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Faculty of Engineering

Development and Implementation of Multimodal System for Attention Monitoring in Naturalistic Work Environments

- Ph.D. Thesis –

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“The scientific man does not aim at an immediate result. He does not expect that his advanced ideas will be readily taken up. His work is like that of the planter - for the future. His duty is to lay the foundation for those who are to come, and point the way.”

Nikola Tesla

ПРЕДГОВОР

Првенствено желим да се захвалим мојој вереници Јелени Цветић за пуну подршку током докторских студија. Јелена је још једном несебично подржала моје одсуство током студирања, што је резултирало израдом докторске дисертације, за шта сам јој неизмерно захвалан.

Желео бих да изразим своју захвалност Европској Комисији и фондацији *Marie Curie* за финансијску подршку током израде докторске дисертације, која је реализована кроз пројекат *“Innovation Through Human Factors in Risk analysis and management”, InnHF- FP7-PEOPLE-2011-ITN-289837.*

Посебно сам захвалан мом ментору професору Ивану Мачужићу за предано менторство кроз све фазе докторских студија. Такође, професор Мачужић се снажно залагао за покретање научних истраживања из нове научне дисциплине на катедри за производно инжењерство. Такво залагање и његова подршка су биле од неизмерног значаја, а нарочито у раним данима докторских студија, када су многи сумњали у могућност спровођења неуроергономских истраживања на катедри за производно инжењерство. Професор Мачужићу ми је пружио помоћ и током поставке експеримената, као и у поступку набавке опреме која се користила у експерименталним истраживањима и приликом адаптације лабораторије за неуроергономска истраживања, што је на послетку резултирало објављивањем научних радова, на чему сам му изузетно захвалан. Поред професора Мачужића, професор Бранислав Јеремић је заслужан за покретање истраживања у научној дисциплини неуроергономије. Професор Јеремић је такође био менаџер *InnHF* пројекта на Универзитету у Крагујевцу и самим тим је помогао адаптирање лабораторије за неуроергономска истраживања. Поред тога, професор Јеремић је, кроз пружање критичког погледа у процесу израде експеримената али и приликом писања научних радова у великој мери помогао њихову израду. Изузетно сам захвалан и професору Петру Тодоровићу на помоћи коју ми је пружио при обради сигнала који су добијени током експерименталних истраживања, као и током поставке експеримента, а нарочито за израду *GSR* уређаја и *HR monitor*-а (који су развијени у оквиру *InnHF* пројекта, уз помоћ Саше Славнића).

Неизмерну захвалност дугујем мом “незваничном ментору”, професорки Вањи Ковић (Филозофски факултет, катедра за психологију, Универзитет у Београду) за њену изузетну подршку током истраживања. Желео бих да истакнем да без њеног знања из области експерименталне психологије израда ове дисертације не би била могућа. Такође, професорка Ковић је учествовала у свим фазама израде ове дисертације, укључујући поставку експеримената, као и у анализи и интерпретацији добијених резултата. Поред тога, професорка Ковић је несебично посветила своје време током свих фаза припреме научних радова, укључујући писање, као и одговоре рецензентима, за шта сам неизмерно захвалан.

Ивану Глигоријевићу бих желео да се захвалим што се прикључио тиму у пројекту као искусни истраживач (*Experienced Researcher*). Иван је био спреман да несебично подели своје знање из области обраде биомедицинских сигнала што је представљало један од кључних доприноса изради ове дисертације.. Такође, Иван ми је помагао кроз све фазе истраживања, укључујући поставку експеримента, увођење у област обраде сигнала, анализу и интерпретацију података. Поред тога, Иван је одвојио своје време да буде самном у лабораторији током већег дела експерименталних истраживања. На крају, уз Иванову помоћ сам стекао искуство у писању истраживачких чланака, с обзиром да је он активно учествовао у писању мог првог рада за научни часопис али и осталих чланака који су објављени током *InnHF* пројекта.

Такође, желео бих да одам признање и професору Maarten De Vos-у (са катедре за биомедицински инжењеринг, Универзитет у Оксфорду), који је кроз критичке коментаре на рад који је обављен у нашој лабораторији допринео унапређењу квалитета самог рада. Неизмерно сам захвалан и професорима Милошу Миловановићу и Мирославу Миновићу (Лабораторија за мултимедијалне комуникације, Факултет организационих наука, Универзитет у Београду) за њихову сарадњу током *InnHF* пројекта, као и током припреме конференцијског рада на тему мултимодалне имплицитне интеракције између човека и рачунара. Такође професори Миловановић и Миновић су учествовали у развоју апликације која се користила за снимање покрета тела (помоћу *Kinect*-а), као и софтвера за снимање покрета шака (снимљених помоћу *Leap Motion*-а).

Још један велики допринос самој изради дисертације је пружио мој брат Богдан Мијовић, који ме је на почетку докторских студија увео у област обраде ЕЕГ сигнала. Такође, Богдан ми је помагао током обраде резултата добијених из експерименталних истраживања, као и приликом давања одговора рецензентима, иако није био међу потписаним ауторима објављених радова.

Славици Дамјановић сам веома захвалан на помоћи коју ми је пружила са администрацијом током целог периода студирања и трајања *InnHF* пројекта. Славица је била веома посвећена решавању разних ситуација које су се наметале током трајања пројекта, као и у комуникацији са универзитетом, што је резултирало решавању свих проблема који су настајали. Такође, желео бих да се захвалим колегама из центра за теротехнологију: Милану Раденковићу, Марку Ђапану, Марку Милошевићу, Evanthia-ји Giagloglou, Christos-у Tsiafis-у и Alberto Petruni-jу; за њихову подршку у тешким тренуцима, као и доброј атмосфери која је владала током докторских студија. За то сам посебно захвалан Милану Раденковићу, јер смо доста слободног времена провели у *brainstorming*-у, који је на крају резултирао успешном спровођењу разних идеја до којих смо долазили на тај начин.

Посебну захвалност дугујем деди Гојку, који је изненада преминуо током израде ове дисертације. Наиме, Гојко је био изванредан инжењер и проналазач, а посебно ми је помогао пред сам почетак експерименталних истраживања, тако што је креирао један део импровизоване машине која се користила у експериментима који су спроведени у току израде дисертације. На жалост, деда Гојко није дочекао да види крајњи резултат истраживања, а верујем да би био поносан на то како је његова помоћ допринела изради мог доктората.

Желео бих да поздравим и све колеге које су учествовале у *InnHF* пројекту, и са којима сам квалитетно проводио време током летњих школа, конференција и активности које су биле везане за сам пројекат. Посебно се захваљујем Центру за иновативне људске системе (*Centre for Innovative Human Systems*) са Тринити колеџа у Даблину за то што су прихватили да први део праксе, која је била везана за пројекат, спроведем у њиховој институцији. Такође, посебно бих се захвалио научници Nora Balfe, која је ревидирала све радове на којима сам радио и дала коментаре који су водили побољшању квалитета објављених радова. Поред тога, захвалан сам и колегама из компаније ARIA где сам провео други део праксе. Посебно се захваљујем професорки Micaela Demichela, Gianfranco Camuncoli и Eleonora Pilone, за њихову подршку током тог периода, као и за помоћ у решавању административних проблема који су се јављали током пројекта. Такође, желим да се захвалим компанији Тетрапак из Горњег Милановца, у којој сам провео трећи део праксе. Посебно сам захвалан менаџменту Тетрапака, који је препознао потенцијал истраживања, која су спроведена на Универзитету у Крагујевцу и који су нам омогућили да мерења спроведемо на радницима у индустријском окружењу. За то сам неизмерно захвалан Драгољубу Гајићу и Александру Брковићу.

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У Крагујевцу, 2016. године *Аутор*

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Kragujevac, 2016. *Author*

Р Е З И М Е

РАЗВОЈ И ИМПЛЕМЕНТАЦИЈА МУЛТИМОДАЛНОГ СИСТЕМА ЗА ПРАЋЕЊЕ ПАЖЊЕ РАДНИКА У РЕАЛНОМ РАДНОМ ОКРУЖЕЊУ

Како технологија стално напредује, индустријске несреће које се везују за неисправност техничких система су скоро скроз умањене. Из тог разлога, људска грешка се сматра узрочником око 80% несрећа у индустрији. Један од главних узрочника људске грешке је лимитирана ментална издржљивост људских оператера, која узрокује пад у пажњи радника и последично води до грешака у раду. Класичне ергономске методе које се користе за процену когнитивног стања човека су угланом квалитативне и субјективне, и према томе су прилично непоуздане. Из тог разлога, психофизиолошки сензори су почели да се примењују у ергономиским истраживањима, са циљм да обезбеде објективне и квантитативне мере радниковог когнитивног стања. Пратећи тај тренд, неуроергономија се појавила као научна под-дисциплина ергономије. Предност коришћења неуроергономских метода, је у томе што неуроергономија истражује функционалну зависност између динамике мозга и бихевиоралних параметара и тако заобилази теоретске везе које описују корелацију између ових параметара, а које су коришћене у ергономији.

Ова дисертација представља научни оквир за мултимодални систем који је предложен да се користи за праће пажње радника и који користи психофизиолошке сензоре и бихевиорална мерења. Систем се састоји од психофизиолошких сензора, као што су: галвански реакцију коже (енг. galvanic skin response - GSR), мерење откуцаја срца (енг. heart rate –HR) и елекроенцефалографију (енг. Electroencephalography – EEG); бихевиоралне модалитете као што су: Времена реакција (енг. reaction times – RTs) и сензоре за праћење покрета (енг. motion capture – MoCap), “Kinect” the “Leap Motion”. Иако је представљен оквир за снимање поменутих модалитета у реалном времену, ова дисертација је фокусирана на резултате који су добијени снимањем EEG, RTs и Kinect модалитета.

Главни циљ дисертације је истраживање могућности коришћења савременог преносног EEG-а у индустријским условима, са циљем праћења пажње радника. Претходна истраживања која су користила EEG су била углавном обављана у контролисаним лабораторијским условима и због тога, налази из тих студија се узимају са одређеном дозом резерве. Да би се снимио

EEG у реалном радном окружењу, радно место у којем радници склапају хидраулично црево је веродостојно реплицирано и субјекти у студији су симулирали тај процес.

Дисертација се састоји од четири експерименталне студије. У првој студији, испитивано је како честе микро-паузе утичу на ниво пажње радника, поредећи амплитуде P300 Komponente evociranih kognitivnih potencijala (eng. event-related potential – ERP) пре и непосредно после периода микро-паузе. Главни налаз је да микро-паузе позитивно утичу на ниво пажње радника и предложено је њихово укључење у дневне активности радника. У другој студији, истраживано је да ли радници имају већи ниво пажње уколико им је наметнуто са којом руком да почну склапање црева. Две психолошке парадигме су биле представљене учесницима у студији, паралелно са симулиранм акцијом склапања црева. У првој парадигми, учесници су могли да изаберу да отпочну операцију са било којом руком, док су у другој били условљени да започну операцију руком која одговара смеру стрелице која се приказивала на екрану испред њих. Ово истраживање је открило да су учесници имали већи ниво пажње у случају условљавања којом руком да започну операцију, јер је амплитуда P300 компоненте била значајно виша у поређењу са случајем када су могли слободно да изаберу са којом руком ће започињати задатак.

Преостале две студије су имале за циљ да представе оквир за праћење когнитивног стања радника у реалном времену. Трећа студија је испитивала пропагирање P300 амплитуде и корелација између P300 амплитуде и времена реакција је испитивана. На групном нивоу, јасна негативна корелација између ова два модалитета је пронађена, међутим она није била конзистентна на индивидуалном нивоу. Због тога је наглашена потреба да се овакви резултати пријављују на индивидуалном нивоу у ергономским студијама. Последње истраживање које је представљено је испитивало да ли је количина покрета који нису у директној вези са задатком, негативно повезана са пажњом радника. У том циљу, предложена је метода кватификације ових покрета помоћу концепта енергије покрета. Прелиминарни резултати потврђују да је енергија покрета негативно корелисана са ЕЕГ модаитетима пажње и предложен је научни оквир будућег система за праћење пажње у реалном времену.

Кључне речи*: Неуроергономија, Пажња, Бежична електроенцефалографија, Event Related Potentials, P300 компонента, Индекс ангажовања, Kinect, Задатак Бројеви, Задатак Стрелице*

ABSTRACT

Development and Implementation of Multimodal System for Attention Monitoring in Naturalistic Work Environments

As technology is ever advancing, industrial accidents related to technological malfunctioning have been almost diminished, leaving the human error responsible for up to 80% of the remaining accidents. One of the main causes for this is limited mental endurance of human operators', which causes the attention decline and consequently leads to an operating error. Classical ergonomics methods for assessing the operators' cognitive state are still dependent on the subjective and qualitative methods, thus being unreliable. For that reason, in the recent years the psychophysiological sensors were included in the ergonomics research, with the aim of providing the objective and quantitative measures of the operators' cognitive state. Following that path, the neuroergonomics emerged as a scientific discipline, which investigates the human brain functions in relation to performance at work. The advantage of using neuroergonomics is that it investigates the functional relationship between brain dynamics and behavioral parameters, thus avoiding theoretical constructs that describe the correlation between these two, and which are ubiquitously used in ergonomics research.

The present dissertation introduces a framework for the multimodal attention monitoring system, utilizing psychophysiological and behavioral measurements. The multimodal system consists of psychophysiological sensors, such as galvanic skin response (GSR), heart rate (HR) sensor and electroencephalography (EEG), the behavioral modality of the reaction times (RTs), and the motion capture (MoCap) sensors Kinect and the Leap Motion. Although the framework for synchronous and real-time recording for all the sensors was provided, this thesis was focused solely on the results obtained from the EEG, RTs and Kinect recordings.

The main aim of the presented dissertation is to investigate the possibility of utilization of the recently available wearable electroencephalography (EEG) in industrial setting, with the goal of the operator's attention monitoring. Previously reported EEG studies that were concerned with the attention states of the operators were mainly confined to the strictly controlled laboratory conditions and therefore, the findings from these studies needed to be taken with the certain ambiguity. In order to record the EEG in naturalistic environment, specific workplace where operators' assembly the hoses, used in hydraulic break systems in vehicles, was faithfully *replicated and the participants in the studies simulated the manual assembly operations.*

The present dissertation consists of four experimental studies, where the first two were concerned with investigation how different work conditions influence the cognitive state of the operators', i.e. the studies were concerned with the assembly task design. In the first study, the influence of the frequent micro-breaks on the cognitive state of the workers' was investigated, by comparing the P300 event-related potential (ERP) amplitude prior and immediately following the micro-break period. It was found that the micro-breaks enhance the attention of the operators' and the proposal for their inclusion in the regular work routine was made. Second study investigated the influence of hand alteration on the attention level of the operators'. For that aim, the participants in the study were presented with two distinct task: the one in which they could initiate the assembly operation with whichever hand they preferred, and the one in which they were conditioned with which hand they should initiate the operation. This study revealed that the instructed responding induces the higher attention, as assessed through the P300 component's amplitude, compared to the experimental condition where the participants could freely choose the hand for the initiation of the assembly operation.

Further, a framework for the on-line assessment of the operators' cognitive state was provided. In the third experimental study, the propagation of the P300 component's amplitude was observed and correlated with the RTs. On the group level, a negative correlation was found, confirming the previously reported finding. However, due to individual differences, the correlation on the individual level was inconsistent, emphasizing the necessity for the individualized EEG measurements for the reliable attention monitoring system. Finally, it was investigated whether the quantity of task unrelated movements corresponds to attention of the operator, as previously shown to be negatively related to the attention of operators'. For that aim, the concept of movement energy (ME) was introduced and correlated with EEG attention-related modalities. The initial finding from this study showed that the ME is negatively related to the EEG attention-related modalities and proved that the future attention monitoring system can be built based on these modalities.

***Key words**: Neuroergonomics, Attention, Wearable Electroencephalography, Event Related Potentials, P300 Component, Engagement Index, Kinect, Numbers task, Arrows task*

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Abbrevations

ANOVA	-	*Analysis of Variance*
ANS	-	*Autonomous Nervous System*
AP	-	*Action Potential*
BCI	-	*Brain-Computer Interface*
BOLD	-	*Blood Oxygen Level-Dependent*
CNS	-	*Central Nervous System*
CPP	-	*Centro Parietal Positivity*
ECoG	-	*Electrocardiogram*
EDA	-	*Electrodermal Activity*
EEG	-	*Electroencephalography*
EI	-	*Engagement Index*
EMG	-	*Electromyogram*
EPSP	-	*Excitatory Postsynaptic Potential*
ERN	-	*Error Related Negativity*
ERP	-	*Event Related Potential*
FFT	-	*Fast Fourier Transformation*
fMRI	-	*functional Magnetic Resonance Imaging*
fNIRS	-	*functional Near Infrared Spectroscopy*
GA	-	*Grand Average*
GSR	-	*Galvanic Skin Response*
HCI	-	*Human-Computer Interaction*
HF/E	-	*Human Factors and Ergonomics*
HR	-	*Heart Rate*
HRV	-	*Heart Rate Variability*
ICA	-	*Independent Component Analysis*
IMU	-	*Inertial Measurement Unit*
IPSP	-	*Inhibitory Postsynaptic Potential*
LAN	-	*Local Area Network*
LFP	-	*Local Field Potential*
LSL	-	*Lab Streaming Layer*
ME	-	*Movement Energy*
MEG	-	*Magnetoencephalography*

MMHCI	-	*Multimodal Human-Computer Interaction*
MoBI	-	*Mobile Brain-Body Imaging*
MoCap	-	*Motion Capture*
MRCP	-	*Movement-Related Central Positivity*
MSD	-	*Musculoskeletal Disorder*
OCRA	-	*Occupational Repetitive Actions*
OWAS	-	*Ovako Working Posture Analysis*
PET	-	*Positron Emission Tomography*
PSD	-	*Power Spectral Density*
PSP	-	*Postsynaptic Potential*
RT	-	*Reaction Time*
SART	-	*Sustained Attention to Response Task*
SCCN	-	*Swartz Centre for Computational Neuroscience*
SCL	-	*Skin Conductance Level*
SCR	-	*Skin Conductance Response*
SDK	-	*Software Development Kit*
SNAP	-	*Simulation and Neuroscience Application Platform*
UDP	-	*User Datagram Protocol*
USB	-	*Universal Serial Bus*
VDT	-	*Visual Display Terminal*
XDF	-	*eXtensible Data Format*

1. Introduction

In the early years of industrialization, industrial accidents were reported mainly in terms of technological malfunctions, ignoring the human element as the cause (Gordon, 1998). However, as the technology became increasingly reliable, failures related to it have been dramatically reduced, attributing majority of the remaining accidents to the human elements in the system (Hendy, 2003). Importantly, humans are often characterized as the most fallible element in the production line, mainly due to limited mental and physical endurance that can sometimes cause behavior and responses to be unpredictable (Hamrol et al., 2011). Due to mental strain, human element in the production system is responsible for 80% of all industrial accidents (Reason, 1990; Stanton et al., 2005).

In order to reduce the human participation in production system, industry tends to automate as much processes as possible, thus reducing the probability of human error and increasing productivity. However, although manufacturing industry has aimed to reach “lights-out” manufacturing, i.e. fully automated factories (Topkins et al., 2010) in which the human failures should be reduced as humans would be exempted from the production processes itself, there are still many industrial processes relying on human operators. Important notion is that occupational health and safety (OHS) researchers and specialists are persuaded that significant increase in human operators’ errors are actually linked to the growing incompatibility between workers and modern technology (Fafrowicz and Marek 2008). Thus, studying how human operators interact with the system has received considerable attention in both scientific research and industrial practice (Stanton et al., 2005).

The scientific discipline that investigates the interaction between system and human operators is called human factors and ergonomics (HF/E) or ergonomics (Salvendy, 2012). Classical ergonomics approach for studying human cognitive state and the interaction between humans and operating system mainly utilizes qualitative and subjective methods, such as questionnaires and measurements of overt performance. However, these methods are often unreliable and unable to investigate underlying (covert) cognitive processes of workers during their everyday routine in industrial environments (Parasuraman, 2003). Moreover, classical ergonomics methods are unable to provide the real-time data acquisition and processing. For that reason, neuroergonomics emerged as novel path in ergonomics research (Parasuraman, 2003; Parasuraman and Rizzo 2006). Neuroergonomics merges knowledge form ergonomics and neuroscience, and it is defined as the science discipline that studies the human brain in relation to work (Mehta and Parasuraman, 2013a).

This dissertation, which presents a partial fulfilment of the requirements for the degree of PhD in Engineering, is concerned with the neuroergonomics studies of manual assembly workplaces, where operators are performing monotonous and repetitive manual assembly operations. For that aim, advances in both ergonomics and neuroergonomics are discussed in introductory chapters, following which general methodology for the development of the multimodal system for recording and analysis of multiple signal modalities, which are related to cognitive state of the workers, is presented. Finally, four neuroergonomics studies are presented and the results discussed. The findings from these studies could be used for the manual assembly task design. Finally, the framework for the on-line attention monitoring is presented and discussed.

1.1 The aim of the Dissertation

Existing literature on ergonomics is mainly concerned with the physical ergonomics, i.e. with the postural loads and prevention of potential work-related musculoskeletal disorders (MSDs). However, far less attention is dedicated to the cognitive states of the workers. Moreover, as discussed in previous section, the methodologies that are used for the assessment of cognitive states of workers are unreliable. For that reason, this dissertation aims in investigating the applicability of the neuroergonomics methods for the assessment of the cognitive states of the workers during monotonous and repetitive manual assembly operations. In order to achieve this goal, a workplace replica was create at the Faculty of engineering (University of Kragujevac), where participants in the study were simulating manual assembly operation while wearing wearable sensor network for recording the physiological signals of workers.

The second aim is investigation of the possibilities for recording the body movements of the participants, by using the motion capture (MoCap) devices that relies on structured light technology. In this way, the movements can be recorded without the need for the markers and therefore, the participants in the study are not imposed to any movement constraints. Usually, the studies that used the MoCap devices for the ergonomics were concerned with the prevention of the work-related MSDs. However, the body movements could be an important indicator of cognitive states. Therefore, in presented experimental settings, the MoCap devices were mainly employed for the estimation of the cognitive state of the participants.

In the Chapter 5, a general methodology used for the achievement of the previously mentioned goals was presented. Finally, a relationship between behavioral and brain signal modalities were investigated with the aim of investigating which factors are influencing the cognitive state of the workers' employed on manual assembly tasks.

An important notion is that the multimodal framework presented in the Chapter 5 consists of physiological sensors (electroencephalography (EEG), galvanic skin response (GSR) and heart rate (HR) sensor), MoCap sensors (Kinect and Leap motion) and recording the reaction times (RTs) as a behavioral modality. However, for the aim of present dissertation, only the results for the EEG, Kinect and RTs signal modalities were processed and the results from these studies will be presented and discussed.

1.2 Theoretical background

In order to provide objective parameters of workers' cognitive state Parasuraman (2003) proposed a novel path in ergonomics research, which was tentatively named neuroergonomics (Parasuraman, 2003). The main objective of neuroergonomics is the objective assessment of how the brain carries out every day and complex tasks in naturalistic work environments (Parasuraman 2003; Mehta and Parasuraman 2013a). In its essence, the neuroergonomics is able to provide precise analytical parameters depending on the work efficiency of individuals, by directly investigating relationship between neural and behavioral activity (Fafrovicz and Marek 2007). In this way, unreliable user state evaluation based on theoretical constructs, which are mostly describing cognitive states of the workers related to the task execution, can be avoided (Fafrovicz and Marek 2007).

Widely used technique for neuroergonomics studies was functional near infrared spectroscopy (fNIRS), mainly due to its high mobility and low cost. fNIRS has been successfully applied for objective measurement of mental workload for spatial orientation and for studying the mental fatigue, and attention of the operators (Ayaz et al., 2011; Mehta and Parasuraman, 2013b; Li et al., 2009), etc. However, fNIRS provide indirect metabolic indicators of neural activity and it has low temporal resolution (Mehta and Parasuraman 2013). On the other hand, techniques for direct measurement of neural activity that provide high temporal resolution, EEG and event related potentials (ERPs), were moderately mobile and the most of the research was confined in the laboratory space or simulators, thus limiting the usefulness of such a measurements in neuroergonomics research (Mehta and Parasuraman 2013a; Fu and Parasuraman 2006). However, as technology advanced EEG became increasingly mobile and eventually wearable, providing possibility to directly observe neural activity in applied environments (Wascher et al., 2014; Mijović et al., 2014).

EEG provides the possibility to both timely and objectively detect the critical behavior of humans (e.g. drops in attention, error, etc.) and it has been confirmed as a reliable tool in estimating ones' cognitive state (Klimesch et al., 1999; Luck, et al., 2000; Murata et al., 2005; Yamada 1998). Analysis of the ERPs, extracted from continuous EEG recording, represents commonly employed method in evaluating ones' neural activity (Hohnsbein et al., 1998). Picton et al. (2000) defined ERPs as 'voltage fluctuations that are associated in time with certain physical or mental occurrence'. ERP components are defined in terms of polarity and latency with respect to a discrete stimulus, and these components reflect a number of specific perceptual, cognitive and motor processes (Brookhuis and De Waard 2010). In that sense, so-called P300 (also called P3) component is the positive deflection in terms of voltage, appearing around 300ms after the stimulus presentation (Gray et al., 2004; Polich and Kok 1995). The amplitude and latency of the P300 component are often used to identify the depth of cognitive information processing, being strongly related to the attention level (De Vos et al., 2014a; Johnson 1998; Polich 2007). Another EEG feature that is used for estimation of the level of cognitive engagement in the task is, so called, engagement index (EI, Prinzel et al. [2000]). EI is calculated as the ratio between fast going brain oscillations, which reflect the state of wakefulness and alertness state (so called beta waves) and the summation of waves of low frequency that reflect the state of sleepiness and low alertness (so called alpha and theta waves), i.e. $EI=\beta/(\alpha+\tau)$.

Although Parasaruman (1990) proposed the idea of applying ERP recording in operational environments, in order to address various HFE problem areas, only very recent studies provided possibility of recording ERPs in applied environments by utilizing available wireless connections (Debener et al., 2012; De Vos et al., 2014a; Wascher et al., 2014). This finally allowed merging EEG with the guiding principle of neuroergonomics, and examination of how the brain carries out complex everyday work tasks in realistic environments (Parasaruman and Rizzo 2006). Present dissertation proposes a 'new paradigm' in ergonomics research through utilization of ERP measurement in naturalistic workplace environment, where manual assembly operation was simulated. The research presented in this dissertation is one of the first studies, which utilize a wireless 24-channel EEG recording for the ERP extraction in naturalistic environment (as it will be presented in Chapters 5, 6, 7, 8 and 9). The main aim of the presented dissertation is the investigation of possibility of studying the attention of an assembly worker. As the main disadvantage of the EEG measurement, its immobility is now overcome, it is believed that its utilization in the real workplace environments will be ubiquitous in the years to come.

Another modality that can provide a continuous-like assessment of human attention level is a behavioral measure of the reaction times (RTs, [Larue et al., 2010; Sternberg 1969]). RT represents a time interval from the indicated start of operation (stimulation), until the moment of the action initiation and the main reason for wide usage of RT measurements is that they are easy to obtain and simple to interpret (Salthouse and Hedden 2002). However, the major drawback of experiments involving RT is that they usually consist of a stimulus followed by the response, without direct possibility to observe the mental processing that occurs between stimuli (Luck et al., 2000; Young and Stanton 2007).

Additionally neuroergonomics is concerned with the body movements, since the humans interacts with the systems through a physical body (Parasuraman and Rizzo, 2006). In fact, it was previously shown that the number of task unrelated movements is negatively correlated with the attention of a person (Roge et al., 2001). However, the study of Roge et al. (2001) quantified the task unrelated movements using manual counting of these movements in a *post hoc* analysis. Therefore, this dissertation investigated the possibility for the automation of this analysis, with the usage of the modern MoCap sensors, by using the proposed concept of movement energy (ME) that is presented in Chapter 9 of this dissertation. In this way the estimation of cognitive state of a person could be investigated with MoCap sensors in a unobtrusive way.

1.3 Main Hypotheses

This dissertation is based on the following ground hypotheses:

<u>Hypothesis 1:</u>

Firstly, it will be investigated whether multiple signal modalities, that are heterogeneous in both type and sampling frequency, could be recorded simultaneously and synchronously in naturalistic work environment. If this prove possible, than an overall multimodal system framework (consisting of EEG, GSR, HR, Kinect and Leap Motion sensor) for the assessment of operators' cognitive state will be presented.

<u>Hypothesis 2:</u>

Starting from the assumption that RTs and psychophysiological signals can objectively reflect the operators' cognitive state, the hypothesis is that the RTs will be negatively correlated with the psychophysiological signals that reflects the attention of the operators', i.e. the time needed for performing the simulated operation will be longer once the attention level, observed through psychophysiological signals, shows lower values.

<u>Hypothesis 3:</u>

Studies that are concerned with the relationship between RTs and psychophysiological signals are mainly conducted on the group level. Therefore, the third hypothesis is that, even if the second hypothesis shows to be valid at the group level, the interindividual differences between the participants can influence the consistency of the results on the individual level. If the results shows that there is no consistent correlation between the RTs and psychophysiological signals on the individual level, these results should be further investigated, the advantages and disadvantages of both RTs and psychophysiological signals should be considered, and the most reliable tool should be adopted for further studies of the workers' cognitive state. An important notion is that RTs are more sensitive to strategic responding in comparison to more automated responding that participants cannot control, such as ERPs (that are considered to be the '*21st century RTs*').

Hypothesis 4:

It is hypothesized that the attention level of the operators" can be enhanced through introduction of frequent micro-breaks. In order to confirm the hypothesis the attention of the participants in the study will be assessed prior and immediately after the micro-break period, through investigation of the P300 component's amplitude.

Hypothesis 5:

Another hypothesis that was under investigation is whether the instructed hand responding can enhance the attention level of an assembly worker. In order to test this hypothesis, the participants were imposed to two distinct task conditions. In the first condition, the participants could chose to initiate the assembly operation with whichever hand they prefer, while in the second condition, the participants were requested to initiate the action with the hand that correspond to the direction of the arrow that appeared on the display in front of them.

Hypothesis 6:

Finally, as already reported in the Section 1.2. the quantity of task unrelated movements is negatively correlated with the human attention. Therefore, this hypothesis tested whether this information can be automatically obtained through introduction of the methodology that is based on movement energy (ME). In order to test this hypothesis, the body movements will be recorded with the Kinect sensor and ME will be calculated. Finally, the ME will be correlated with the attention-related modalities obtained from the EEG recordings.

1.4 Methods

Firstly, the replicated workplace was created, in which the participants in the study simulated manual assembly operation. Further, the participants were equipped with the wearable sensor network, which consists of sensors for recording physiological sensors (EEG, GSR and HRV), and the sensors for recording the movements of the participants, namely Kinect and Leap Motion sensor. Upon creation of sensing environment, the data were recorded and processed using following methodology:

- EEG signal processing was performed using EEGlab toolbox (Delorme and Makeig, 2004) and Matlab 2013b (Mathworks Inc., Natick, MA).
- For the analysis of the data obtained from the Kinect sensor the Matlab 2013b was used.
- The analysis of the data obtained from the GSR sensor is meant to be performed in Matlab 2013b and the LedaLab (http://www.ledalab.de, plug-in for the Matlab software)
- The analysis of the heart rate variability (HRV) is meant to be performed in Matlab, 2013b
- The statistical analysis of all data was performed in the IBM SPSS v.20

1.5 Expected Results

The following results are expected upon accomplishment of the research conducted during the doctoral studies:

1) An overall framework for multimodal synchronous recording and analysis of psychophysiological and motion signals for the aim of objective assessment of operator's cognitive state will be provided.
2) The methodology for the objective assessment of operator's cognitive state, using wearable EEG will be provided.
3) Guidelines for the manual assembly task design will be provided, with the aim of enhancing the operators' level of attention.
4) The methodology for quantification of the task unrelated movements, using the movement energy will be provided

5) Reaching above-mentioned goals, it is aimed in reducing the human errors in production lines, more closely in the assembly operations. Finally, timely detection of the drops in attention and deviations in cognitive state of the workers should lead to reduction of work-related injuries, economy loss, influence of human factors in industrial accidents, etc., which should ultimately lead to improvement of the workers' overall well-being in industrial environments.

1.6 Chapter-by-Chapter Overview

Chapter 1 briefly discuss the shortcomings of existing ergonomics methods for objective assessment of the operators' cognitive state in workplace environments. It further briefly discuss about the advantages of neuroergonomics methods over classical ergonomics approaches. This chapter outlines the importance of objective measurement of operators' cognitive state and it provides the outline of the main objectives and main objectives of the present dissertation. It further provides the brief theoretical background of the present work and ground hypotheses. Further, the used methodology for the data processing and statistical analysis was briefly presented.

In **Chapter 2**, a brief overview of scientific field of ergonomics is presented. Further, four main domains of ergonomics research are presented and the advantages and disadvantages of each domain are discussed.

Chapter 3 introduces the Neuroergonomics as a science discipline and the benefits of using neuroergonomics over solely ergonomics principles. Since the neuroergonomics relies on neuroimaging techniques, an overview of neuroimaging techniques that can be used for the neuroergonomics studies is provided. Further, the advantages and disadvantages of each methods for recording the brain activity in naturalistic environment are discussed. As the EEG was used in studies that constitute the present dissertation, special focus was on EEG and wearable EEG studies that were conducted with the aim of investigating the cognitive state of the operators. Moreover, since other physiological sensors (other than neuroimaging techniques) can be used for estimating the cognitive state of the operators', HR and GSR sensor are also introduced and literature review of studies that used these sensors in ergonomics studies is presented. Finally, studies that used multimodal approach, combining EEG, GSR and HR modalities were reviewed and benefit of using such recordings was outlined.

In **Chapter 4**, a literature review of using the MoCap technology for ergonomics studies was provided. The focus was on recently available consumer devices that uses structured light technology and thus does not require external markers for reliable motion tracking of a person. Finally, utilizing the MoCap technology for the aim of assessing the cognitive state of the workers' was proposed, which is based on automated quantification of task unrelated movements.

General methodology that was used in experimental studies, which were conducted for the aim of present dissertation, is provided in **Chapter 5**. This chapter begins with the introduction of the concept of the implicit human–computer interaction (HCI) and its possible application for cognition-aware computing in industrial settings. Further, a workplace replica is presented, where the participants in experimental studies simulated the manual assembly operations. In addition, the sensors used in the studies are presented, together with their technical specifications. Finally, the overall system architecture of the multimodal system for estimating the operators' cognitive state is presented and discussed.

Chapters 6, 7, 8 and 9 are actual experimental studies that were conducted at the Department of production engineering (Faculty of Engineering, University of Kragujevac) as part of present dissertation.

An experimental study in which it was investigated whether the introduction of frequent micro-breaks can have a positive influence on attention level is presented in **Chapter 6**.

Chapter 7 is consisted of an experimental study in which it was investigated whether the attention level of an assembly worker can be enhanced if the he is conditioned with which hand he should start the manual assembly operation.

In **Chapter 8**, the relationship between P300 component's amplitude and RTs was investigated and a general framework for the future real-time attention monitoring of the operators' attention is provided.

Chapter 9, presents an experimental study in which it was investigated whether the cognition-aware computing can be utilized in industrial environments. For that aim, a multimodal study, which consisted of EEG and Kinect sensor, was conducted. The main objective was to present the concept of ME and to investigate the correlation between P300 amplitude, EI and ME.

Finally, general conclusions from all experimental studies is presented in Chapter 10 and the directions of future studies are discussed.

Graphical representation of the chapter-by-chapter overview is presented on Figure 1-1.

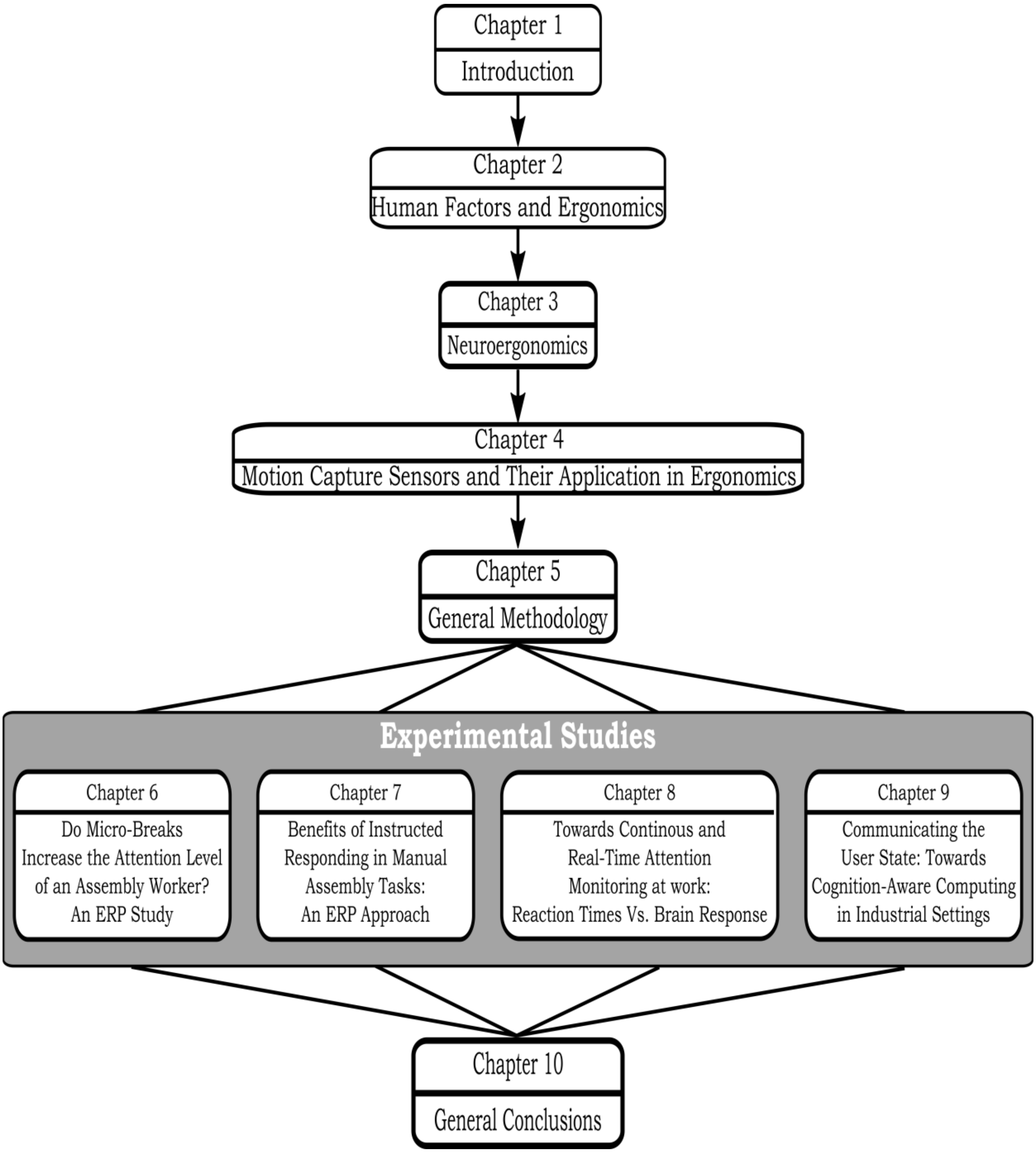


Figure 1-1: Graphical representation of the chapter-by-chapter overview of the present dissertation

2. Human Factors and Ergonomics (HF/E)

Ergonomics is the science discipline which studies the interaction between humans and other elements of a system (Salvendy, 2012), and if successfully applied, it can prevent accidents and improve overall safety and health in industrial environments (Imada 1990). The origin of word ergonomics comes from the Greek "Ergon", which means work and "Nomos", which means law. Therefore, ergonomics is considered as the science of work (Cañas et al., 2011; Salvendy 2102). Another term that is synonymously and interchangeably used with ergonomics is Human Factors and Ergonomics (HF/E, [Salvendy, 2012]).

HF/E is independent discipline of human-artifact interactions (Salvendy, 2012). It is multidisciplinary science, which utilizes and consolidate knowledge from diverse science disciplines including engineering, design, technology and management of human-compatible systems and technology, while taking into account variety of natural and artificial products, processes, living and working environments (Kawrowski, 2005). Steaming from its interdisciplinary nature there is no unique definition of HF/E, rather a large number of definitions were previously reported in the literature (Wogalter et al., 1998). Probably the most concise definition was provided by Dempsey et al. (2000): *"Ergonomics is the design and engineering of human-machine systems for the purpose of enhancing human performance".* As such, HF/E is concerned with the design and evaluation of jobs, tasks, environments, products and system, while it tends to create compatibility of these with the abilities, needs and limitations of people (Salvendy, 2012).

2.1 HF/E Domains

Although HF/E has very comprehensive scope and extensive subject of interests, four main domains of application, which are crucial for investigating the interaction between humans and socio-technical systems, can be recognized nowadays (Stanton et al., 2004; Cañas et al., 2011). These are: physical ergonomics, cognitive ergonomics, organizational ergonomics and recently emerged discipline of psychophysiological and neuroergonomics domain.

2.1.1 Physical Ergonomics Domain

The use of physical ergonomics to assess how work is done is one of the most studied domain in HF/E studies, mainly because many aspects of industrial work are physical in nature (Stanton et al., 2004; Vignais et al., 2013), and it is commonly referred to as 'classical ergonomics' (Hollangel, 1997). Physical Ergonomics is concerned with anatomical, anthropometric, biomechanical and physiological parameters of workers (Cañas et al., 2011). Physical ergonomics issues include working postures, materials handling, repetitive movements, work-related musculoskeletal disorders (MSDs), workplace layout, safety and health (IEA, 2015). The main aim of physical ergonomics is the improvement of musculoskeletal health at work (Vieira and Kumar, 2004).

Exposure to risk factors for work-related MSDs is usually assessed using methodologies, which can be divided into self-reports, observational methods and instrument-based (called Direct) methods (Vignais et al., 2013; Diego-Mas and Alcaide-Marzal 2013).

Self-reports are usually used to quantify discomfort of the workers, since presently the methodology for direct observation of discomfort or objective measurements does not exists (Stanton, 2004). Self-reports include questionnaires, work diaries and interviews. As such, they are highly subjective and unreliable, because the interpreted results depend on both the worker's literacy and on the experience of the experimenter (Vignais, 2013).

Observational methods are based on direct observation of the workers during the course of their operation. The main goal of observational methods is to assess worker's behavior on predefined sheets, e.g. Rapid Upper Limb Assessment (RULA) sheets, by either on field observation or by videotaping workers and then conducting analysis during replying videos (Vignais, 2013). The advantage of these methods is that they are straightforward to use, applicable to wide range of working operations and relatively low cos. However, drawback is that the data collection systems are inaccurate and provide rather broad results (Diego-Mas and Alcaide-Marzal, 2013). Additionally, the presence of the observer during the work routine can influence can lead to higher performance of the workers, due to Hawthorne effect (Adair, 1984).

Instrument-based or direct measurement methods are usually conducted by sensors that are attached to the recording subject, with the aim of objective measurements of the workers' activities (Stiefmeier et al., 2008; Diego-Mas and Alcaide-Marzal 2013). These kind of measurements are preferred, since the data acquisition is accurate. However, it was argued that these measurements are not suitable for use in real-work situation (Diego-Mas and Alcaide-Marzal 2013) and that the recording equipment is costly (Trask and Mathiassen, 2012). Nevertheless, Stiefmeier et al. (2008) presented the case study in automotive industry, while workers were wearing the jacket equipped with Internal Measurement Units (IMUs) and they reported no discomfort during the regular operation. Moreover, with the recent technological advancement and development that relies on structured light technology (Salvi et al., 2004) the direct measurements are possible without the need for workers' to wear recording sensors. Additionally, with the introduction of the e.g. Microsoft Kinect, the costs of such a systems drastically decreased. Therefore, nowadays it is possible to conduct direct observation methods in work environments at relatively low cost, while no posing discomfort to the workers (Dutta, 2012).

2.1.2 Organizational Ergonomics (Macroergonomics) Domain

Organizational ergonomics (also called macroergonomics) domain is concerned with the overall design of work systems (Stanton et al., 2004; Hendrick and Kleiner, 2005). Organizational ergonomics deals with the optimization of sociotechnical systems, including their organizational structure, policies, and processes (IEA, 2015). It emerged as an ergonomics domain back in the 1978, and since then there has been increased interest of practitioners and researchers in studying the human organizational factors (Kleiner, 2008).

In the early years of the HF/E, the industrial accidents were attributed either to failure of technology and latter to the human error (Gordon 1996). However, the accident at the Piper Alpha, which received many research interests, showed dependence of the performance of complex socio-technical systems on technical, human, social, organizational, managerial and environmental elements (Pate-Cornell 1993; Gordon 1996; Mearns et al., 2001). The Piper Alpha disaster increased awareness for both practitioners and scientists that these factors can be important co-contributors to incidents which could potentially lead to a catastrophic event (Gordon 1996), thus emphasizing the need for organizational ergonomics.

Organizational ergonomics mainly promotes the safety climate as one of the most important precondition for safe working environment (Zohar, 1980; Gordon, 1996). In the seminal paper of Zohar (1980), it was found that the strong management commitment to the safety leads to safer production. That is, he reported that in low accident companies the top management was personally involved in safety activities on a routine basis (Zohar, 1990). However, the underlying HF/E factors that affect safety can be defined as organizational, individual and group factors (Gordon, 1996) and therefore, it is important to study interaction between all these factors in order to create the safety climate in industry (Bentley and Tappin, 2010).

It was proposed that workers' attitudes and perception to safety could be measured using safety climate questioners and that safety-related behaviors could be evaluated using checklists, while the organization safety could be evaluated through audits or analyzing the documentation of the industrial (companies) safety management system (Cooper, 2000). However, these measurements related to the individual factors are qualitative and use the overt performance measurement, thus being unreliable (Parasuraman, 2003). For the aim of objective assessment of factors that are influencing the cognition and perception of the workers, the scientific domains of cognitive ergonomics and neuroergonomics emerged.

2.1.3 Cognitive Ergonomics Domain

Cognitive ergonomics domain is concerned with studying cognitive processes at work, with an emphasis on an understanding of the situation and on supporting reliable and effective performance (Cañas et al., 2011). It is concerned with mental processes, such as perception, memory, reasoning, and motor response, as they affect interactions among humans and other elements of a system (IEA, 2015). While 'classical ergonomics' is concerned with the quality of working from the physical ergonomics point of view, the cognitive ergonomics is trying to describe how the work affects the mind, as well as to describe how the mind affect the work (Hollangel, 1997). In that sense, it can be said that cognitive ergonomics represents the merging of 'classical ergonomics' with cognitive psychology.

The ubiquitous implementation of automated processes have shifted the responsibility of the workers from physical activities to the ones that requires the ability of workers to sustain attention over prolonged period of time (Hollangel, 1997), i.e. humans are nowadays shifting their role from active controllers to the one of system supervisors (Warm et al., 2008). Therefore, instead of physical skills, workers are responsible for planning and reasoning and they are required to possess problem-solving skills (Hollangel, 1997).

Studies of risks in workplace are traditionally divided into two directions. On the one hand there are post-analyzes, once when accident has already happen, thus studying the human error (Reason 1990). On the other hand, there are studies that are concerned with the assessment of the risk, specifically the possibility of human erroneous actions, which is known as the human reliability assessment (Hollangel, 1997). The latter can be assumed as the milestone of the cognitive ergonomics, since it is focused on how the workers think, rather than how they act, i.e. how workers maintain control over their work, since if the control fails, then system enters into a state of loss control that could further lead to unwanted dangerous situations (Hollangel, 1997).

Another approach used in cognitive ergonomics is cognitive task analysis (CTA). CTA represents the extension of traditional task analysis techniques, with the aim to assess information about the knowledge, thought processes and goal structures that underlie overt task performance (Chipman et al., 2000). CTA methods mainly focus on describing and representing the cognitive elements that underlie goal generation, decision making, judgments, etc. In its essence, CTA uses a variety of interview and observation strategies to capture a description of the knowledge that experts use to perform complex tasks (Clark et al., 2008). As such, these methods are usually unreliable, the analyses are usually carried in the initial phase of process design (off-line), and there is no possibility for the real-time applications of such methodologies.

2.1.4 Psychophysiology and Neuroergonomics Domain

The major drawbacks of the beforehand mentioned HF/E domains is that all the analyses of the workers' cognitive state are qualitative and they utilize the overt performance measurements, which are usually conducted in *post hoc* analysis. In order to overcome these drawbacks and to provide objective measures of the workers cognitive state the psychophysiological methods, which were initially used solely in the medical field, were recognized for usage in HF/E studies (Stanton, 2004). Andreassi (2013) proposed one of the definitions of psychophysiology: "*Psychophysiology is defined as the study of relation between psychological manipulation and resulting psychophysiological responses, measured in the living organisms, to promote understanding of the mental and bodily processes*".

Psychophysiological methods are divided into the ones that record the activity of autonomic nervous system (ANS) and the ones that are able to record the activity of the central nervous system (CNS). The former group consist of measurement of galvanic skin response (GSR), heart rate variability (HRV), etc. The latter mainly consists of neuroimaging methods, such as electroencephalography (EEG), functional magnetic resonance (fMRI), etc. The main difference between ANS and CNS is that the actions of the ANS are not under direct voluntary control of humans (Janig, 1989), while the CNS is related to behavior and thus it can be related to the voluntary control of humans (Cacioppo et al, 2007).

The overall goal of applying psychophysiological methods in HF/E studies is to improve the design of a system with regard to system effectiveness, as well to workers' well-being (Trimel et al., 2009). The advantages of psychophysiological methods, in comparison to previously mentioned HF/E domains are twofold: they are *objective* and they can be *acquired and processed in real time* (Trimmel et al., 2009). Additionally, the psychophysiological measurements enables the detection of covert reactions to task environments, which are not possible to observe with the overt performance measurements by HF/E professionals (Parasuraman, 2003), making more holistic evaluations of particular design environments possible (Trimmel and Poelzl 2006).

Recently, a novel path in ergonomics emerged, which is mainly concerned with applying psychophysiological measurements for observation of the CNS activity during the regular work operations, i.e. which is interested in how brain carries out everyday tasks in complex environments (Mehta and Parasuraman, 2013a). This novel direction was defined as neuroergonomics (Parasuraman, 2003). The benefits of neuroergonomics methods is that they provide insights in the brain functioning and not only in the physiological response of the ANS. Thus, it provides the possibility for direct linking of the brain dynamics to the behavioral responses of the workers.

The present dissertation mainly focuses on neuroergonomics studies, by utilizing wireless EEG technology for investigation of brain dynamics during simulated work. Further, the multimodal recording of brain dynamics and psychophysiological measurements was performed for better understanding of relationship between ANS and CNS activity. Finally, the motion capture sensors were also applied, mainly in order to relate the behavioral modalities with the physiological signals. All of these will be discussed in detail in further chapters.

3. Neuroergonomics

Parasuraman (2003) pinpointed the importance of studying the human brain processes while executing everyday complex tasks in naturalistic environments, through the new direction in human factors and ergonomics (HF/E) research. The 'official' proclamation of Neuroergonomics was in the year of 2003, when Taylor & Francis group published a special issue of 'Theoretical Issues in Ergonomics Science' that was entirely devoted to neuroergonomics and where the majority of articles were mainly discussing the newly emerged science sub-discipline of ergonomics. Although Parasuraman and Wilson (2008) modestly stated that neuroergonomics should not be thought of as revolutionary, but rather as another step in HFE research, the growing body of neuroergonomics research refuted this statement. In fact, ever advancing technology has facilitated neuroergonomics research and nowadays, only twelve years from its inception, it has become one of the principal directions in HFE research.

Neuroergonomics is defined as the study of the human brain in relation to performance at work and in other naturalistic settings (Parasuraman 2003; Parasuraman and Rizzo 2006; Parasuraman 2011; Mehta and Parasuraman 2013a). It is interdisciplinary area of research that integrates scientific disciplines of HF/E and neuroscience while attempting to exploit the benefits of each (Parasuraman and Rizzo 2006). The goal of neuroergonomics is not solely to study brain dynamics, which is in the field of neuroscience, but to put the brain dynamics in the context of human cognition and behavior at work and other everyday settings (Parasuraman and Rizzo, 2006). Moreover, since the human brain interacts with the environment over physical body, neuroergonomics is correspondingly concerned with the neural basis of physical performance, e.g. moving and grasping objects, etc. (Parasuraman and Rizzo, 2006).

Traditionally, ergonomics research and practice has not considered neuroscience or findings concerning brain mechanisms that underlies human perceptual, cognitive, affective and motor processes (Parasuraman, 2003). This is not surprising, since the HF/E has its roots in a psychology of 1940s that was firmly in the behaviorist camp (Parasuraman, 2003), where researchers were using solely the simplified stimulus-response (S-R) approach, but also due to slow shifts from behavioral to cognitive approach in psychology itself. More recently, however the ergonomics was influenced by the cognitive psychology, but still the neuroscience continued to be ignored (Parasuraman, 2003). One of the main reasons for this is that primary interest of ergonomics is assessment of broad psychological constructs and high-level cognitive functions, which are still not likely to be effectively mapped in the neuronal network of brain functioning (Sarter and Sarter, 2003). For that reason, the focus on 'large' cognitive constructs still represents a major challenge for the neuroergonomics (Sarter and Sarter, 2003).

Nevertheless, in the classic ergonomics perspective cognitive functions are mainly described through the correlation of various theoretical constructs that describe cognitive context (Hanckook and Szalma, 2003) and which are further used as elements for complementing the process of research and design (Fafrowicz and Marek, 2007). On the other hand, the neuroergonomics postulate the elimination of such theoretical constructs from research and design process and it focuses on examining the role of neural systems that are involved in execution of the work tasks, i.e. the neuroergonomics aims in investigating the limits of the efficiency of neural system in executing particular work task (Farowicz and Marek, 2007). As argued in work of Fafrowicz and Marek (2007), in the traditional ergonomics, mental, cognitive and emotional functions are observed through theoretical contstructs, which are defined by the psychologists, and the research is directed towards correlation between behavioral and hypothetic cognitive processes. Whereas from neuroergonomics perspective, the functions of covert neural structures are the main subjects of the research and they are becoming the point of departure (Fafrowicz and Marek 2007). Figure 3-1 graphically depicts the main differences between traditional ergonomics and neuroergonomics approach.

While trying to link brain dynamics with the ever advancing technology at work, neuroergonomics has two key goals: (1) to utilize present and evolving knowledge of human performance and brain function in order to design technologies and optimize work environments, with the ultimate aim of creation of the safer work conditions; and (2) to yield necessary knowledge of brain function in relation to human performance in naturalistic workplace environments (Parasuraman, 2003). In order to achieve these goals, neuroergonomics provides the possibility to enrich the HF/E research by providing precise analytical parameters of brain functioning and behavior in naturalistic settings (Parasuraman 2011; Mehta and Parasuraman 2013a), rather than evaluating human performance solely through unreliable subjective measurements (Parasuraman 2003; Parasuraman and Rizzo 2006). Ultimately, understanding brain processes in naturalistic environments can lead to improvement of existing industrial processes design and to creation of safer and more efficient working conditions (Parasuraman 2003), consequently improving the operators' overall wellbeing.

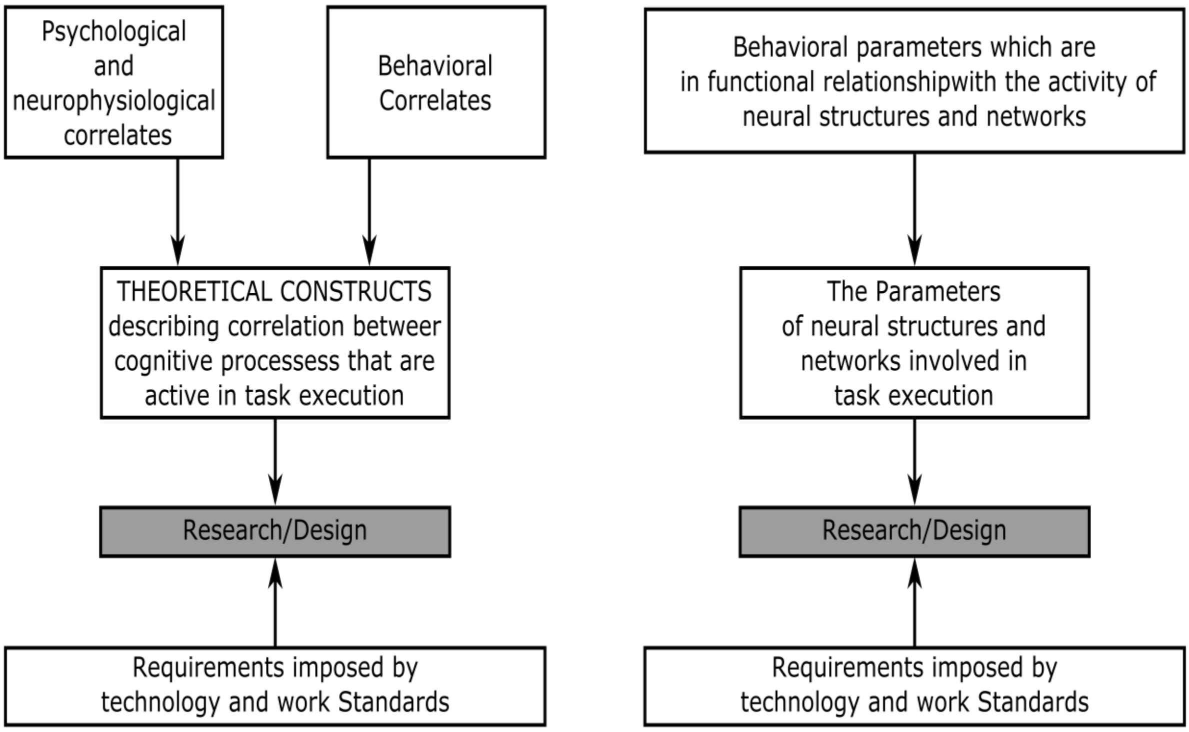


Figure 3-1: Traditional ergonomics approach (left image); and neuroergonomics approach to research and design in ergonomics (right image – Figure adopted from: Fafrowicz and Marek, 2007)

So far, neuroergonomics had significant success in evaluating brain activity in its interaction with automated systems, through the studies of mental workload, dual-task performance (Ayaz et al., 2013) and operators' vigilance (Warm et al., 2008). Additionally, it went a step further with the development of state-of-the-art neuroadaptive systems facilitating the mutual interaction between an automated system and operators, in the sense that both human and the system can initiate the change in the level of automation when needed (Scerbo 2006; Mehta and Parasuraman 2013a). On the one hand this trend is understandable as industry, for over several decades, has tried to reach the 'lights-out manufacturing' concept (Tompkins et al., 2010), i.e. completely automated factories, which can operate without the direct presence of human operators in the production processes. In that case, human supervisory control of automated systems becomes essential (Sheridan and Parasuraman 2005), as human operators would be solely responsible for controlling the automated production systems (Warm et al., 2008). Although automation is becoming ubiquitous in industry and everyday life (Parasuraman et al., 2008), the 'lights-out' concept is still rather futuristic and there is still a need for human manual operations in the production processes. This is especially notable in assembly tasks and processes where costs, related to process automation, are generally not justifiable (Tang et al., 2003).

For these reasons, it is evident that neuroergonomics studies should pay additional attention to more traditional workplaces, through investigation of concurrent physical and cognitive work. This approach has received far less attention in neuroergonomic studies (for review see Mehta and Parasuraman 2013a). For example, in the car manufacturing industries the majority of processes are automated, however human operators play a crucial role in the final car cockpit and interior assembly, i.e. final assembly (Michalos et al., 2010a). Typically, manual assembly tasks require a large number of repetitions and are monotonous in nature, thus leading to hypo-vigilance of operators (Spath et al., 2012). In turn, operators' have difficulty in sustaining the desired level of attention during the task, and therefore, the risk of work-related injuries, material damage or even accidents is increased (Kletz, 2001). Therefore, employing existing neuroimaging techniques to understand the way the brain processes various stimuli in this class of tasks could be beneficial, as the task design could be optimized in such a way as to obtain and maintain sufficient operator attention, thereby avoiding possibly hazardous situations.

3.1 Neuroimaging Techniques in Neuroergonomics

An extensive review of neuroimaging techniques applicable to neuroergonomics research has been recently published by Mehta and Parasuraman (2013a). Neuroimaging techniques can be divided into two distinct groups according to their recording mechanisms (Figure 3-2): one that exploits techniques for indirect metabolic indicators of neural activity (hemodynamic techniques), and the one that employs direct measurements of brain activity based on electromagnetic techniques (Mehta and Parasuraman 2013a). The former consists of techniques such as functional magnetic resonance imaging (fMRI), positron emission topography (PET) and functional near infrared spectroscopy (fNIRS). On the other hand, Electroencephalography (EEG) and therefrom derived event related potentials (ERPs) belong to the neuroimaging techniques that directly measure brain activity (Gramann et al., 2011; Mehta and Parasuraman 2013a).

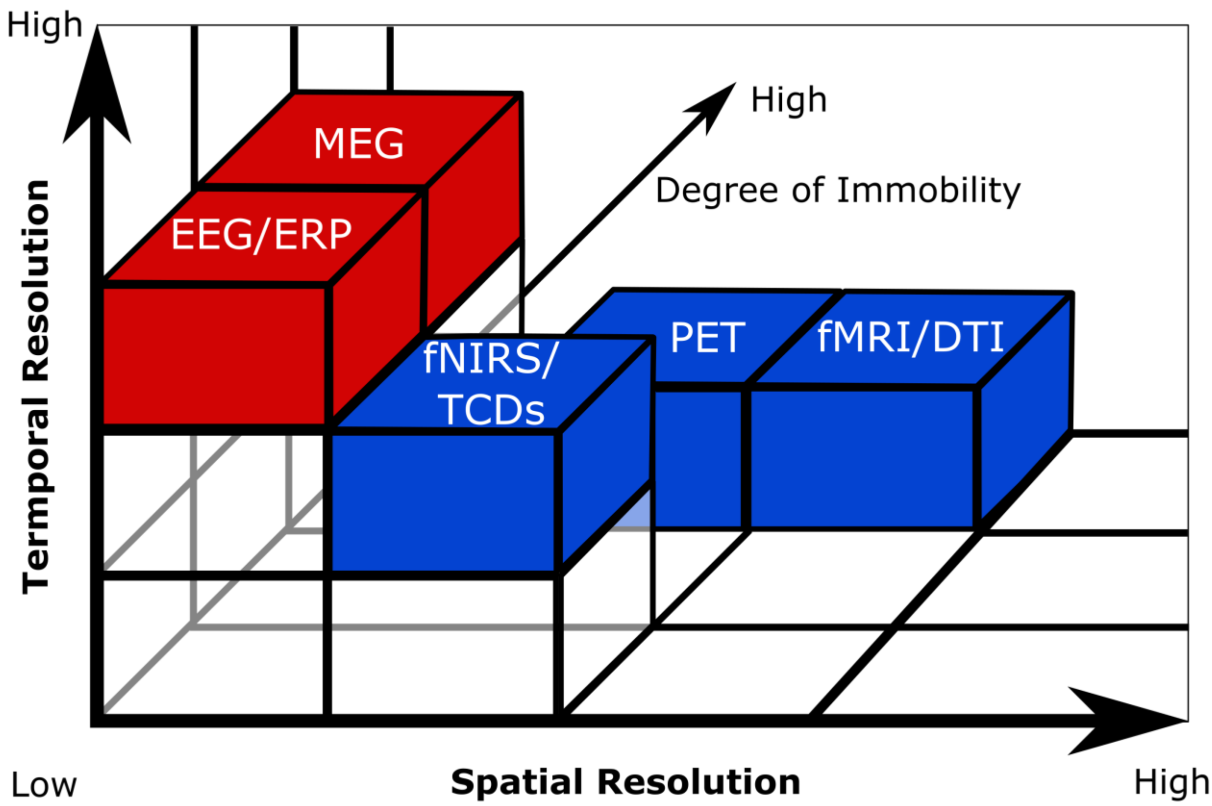


Figure 3-2: A comparison of neuroimaging methods utilized in neuroergonomics studies. Methods for direct observation of brain dynamics are depicted with red color, while the ones for indirect observation of brain processes (Blue). EEG – electroencephalography; ERP – Event-Related Potential (ERP); MEG – Magnetoencephalography; fNIRS – functional Near Infrared Spectroscopy; PET – Positron Emission Tomography; fMRI – functional Magnetic Resonance Imaging; DTI – Diffusion Tensor Imaging (Figure adopted from Mehta and Parasuraman, 2013a).

The main distinction between neuroergonomics and neuroscience is that former aims in investigating the brain functioning in relation to work and therefore when evaluating which neuroimaging method should be used for neuroergonomics study following three important criteria should be considered (Mehta and Parasuraman 2013a):

(1) - Temporal resolution,
(2) - Spatial resolution, and
(3) - The degree of mobility

The temporal and spatial resolutions presents the ability of the recording device to discriminate between two data points in time and space, respectively (Slavin and Bluemke, 2005), while the degree of mobility relates to the dimensions of the recording equipment and its usability for usage in naturalistic environments. Graphical representation of comparison of neuroimaging methods that are mostly utilized for neuroergonomics studies is depicted on Figure 2-2 and they are summarized in table 3-1 (Mehta and Parasuraman, 2013a).

3.2 Hemodynamic Neuroimaging Techniques Applicable To Neuroergonomics

3.2.1 Functional Magnetic Resonance Imaging (fMRI) and Positron Emission Tomography (PET)

fMRI and PET belong to cerebral hemodynamic techniques that can provide valuable information on source locations of diverse neural activation patterns, which are associated with cognitive, motor and affective functions (Mehta and Parasuraman, 2013a). fMRI is capable of noninvasive assessment of relative changes in cerebral oxygenation while a person is engaged in cognitive task (Parasuraman and Rizzo, 2006). A brief description of working principle of fMRI was provided by Calhoun (2006) and here it will be summarized. fMRI relies on the fact that oxygenated blood has different magnetic properties than deoxygenated blood or surrounding tissues. This disparity of blood oxygenation causes the variation of magnetic resonance signal. Once the specific brain region increases in neural activity a small decrease of local oxygenated small pool, following which the cerebrovascular system responds by increasing the flow of oxygenated blood into that region for returning the oxygenated blood level back to normal. At this point however, the supply of oxygenated blood exceeds the neural demand and therefore, the ratio of oxygenated to deoxygenated blood is altered. fMRI is able to acquire this blood oxygen level-dependent (BOLD) signal over the brain regions. Finally, the BOLD signal can be used to associate neural responses to performance of a cognitive tasks, which is measured and compared to baseline of resting state, or to another cognitive task that differs in cognitive task demand (Calhoun, 2006). On the other hand, PET uses injected radioactive tracers in order to measure the dependence of the blood flow related to neural response to stimuli (Mehta and Parasuraman, 2013a).

Table 3-1: List of neuroimaging techniques applicable to Neuroergonomics (Adopted from Mehta and Parasuraman 2013)

Method	Abbreviation	Measures/ Stimulates	Mobility	Cost	Spatial Resolution	Temporal Resolution
Magnetic Resonance Imaging	MRI	Grey matter volume	None	High	High	NA
Positron Emission Tomography	PET	Blood flow and Oxygen consumption of glucose	None	High	High	NA
Diffusion Tensor Imaging	DTI	White matter integrity	None	High	High	NA
functional Magnetic Resonance Imaging	fMRI	Relative Blood Oxygenation	None	High	High	Low
functional Near Infrared Spectroscopy	fNIRS	Oxyhemoglobin and deoxyhemoglobin	High	Low	Moderate	Low
Transcranial Doppler Sonography	TCDS	Cerebral blood flow velocity	Moderate	Low	Low	Low
Electroencephalography	EEG	Summated post-synaptic electrical activity	High	Low	Low	High
Event Related Potential	ERP	Stimulus or response-related electrical activity	High	Low	Low	High
Transcranial Magnetic Stimulation	TMS	Brain Activation or Inhibition	Low	Moderate	High	High
Transcranial Direct Current Stimulation	tDCS	Brain Activation or Inhibition	High	Very low	Low	Low

Both PET and fMRI possess very high spatial resolution, which allows scientists to allocate which brain regions are activated in particular cognitive tasks (Mijović et al., 2012). Thus, they were successfully applied and have had important impact in advancing knowledge on brain functions and mechanisms during relatively simple and static cognitive and motor tasks (Mehta and Parasuraman, 2013a; Gramann et al., 2014).

PET and fMRI were already successfully applied for investigating the brain dynamics during driving (e.g. Calhoun, 2006), in aviation sector (e.g. Cause et al., 2013), etc. However, important limitations of these methodologies is that have poor temporal resolution, mainly because hemodynamic response is a slow signal and each echo-planar image is acquired every few seconds (Mijović et al., 2012). One of the possibilities to increase spatio-temporal resolution of such a recordings, neuroscience research started to focus on multimodal approaches. For that aim, recently a combination of EEG-fMRI modalities has been successfully integrated (Mijović et al., 2012; Mijović et al., 2013). Although this intervention increased the precision of such systems, one of the limitations is that precise signal acquisition requires that participants are lying in the supine position in noisy scanners (Mehta and Parasuraman, 2013a). The first problem of such a recording is that hemodynamics is altered in lying compared to the standing position (Raz et al., 2005). Additionally, the recording equipment is of big dimensions and therefore the mobility of these systems is severely limited, which restricts synchronized brain-body measurements in naturalistic conditions (Maekig et al., 2009). Finally, the assumption that brain activity, which is measured in static position and inside the noisy scanners, reflects a general principle of brain dynamics during cognitive processes is rather inappropriate (Gramann et al., 2011).

3.2.2 Functional Near infrared Spectroscopy (fNIRS)

For above mentioned reasons, scientists adopted neuroimaging methods that offers better mobility features, for the aim of investigating the brain dynamics in everyday settings (Mehta and Parasuraman 2013a; Gramann 2011; Gramann 2014). From the group of techniques that measure brain hemodynamics, fNIRS remains the single convenient technique for the neuroergonomics research in naturalistic setting due to being lightweight and wearable (Ayaz et al., 2010; Ayaz et al., 2012; Mehta and Parasuraman 2013b).

fNIRS is relatively novel methodology that is used in functional brain-imaging studies. fNIRS works on similar principle as fMRI and PET, but it possess lower spatial resolution than these two methods (Mehta and Parasuraman, 2013b). It is noninvasive neuroimaging technique, which utilizes specific light wavelengths that are introduced through scalp surface in order to enable continuous measurement of alteration in the relative ratios of deoxygenated to oxygenated hemoglobin in the capillary beds during brain activity (Izzetoglu et al., 2005). Oxygenated and deoxygenated blood can be contrasted by their optical absorption properties, which allows fNIRS to detect the level of these parameters in response to brain activity. The advantage of fNIRS over PET and fMRI is that it is small sensor that can be mounted on participants' head (Gramann et al., 2011). Thus, it can be utilized for both static and dynamic motor movements, without creating the undesired movement artifacts (Izzetoglu et al., 2005; Perrey, 2008; Gramann et al., 2011).

fNIRS has so far been successfully applied for objective measurement of mental workload within air-traffic controllers (Ayaz et al., 2011; Ayaz et al., 2012), for spatial orientation (Ayaz et al., 2011), studying the mental fatigue (Mehta and Parasuraman, 2013b), attention (Li et al., 2009), dual working memory skill (Ayaz, 2013), and other neuroergonomics studies. However, one of the limitations of the fNIRS studies it that their focus is mainly on prefrontal cortex, which raises the question whether investigation of only one brain region can provide enough insight on overall brain dynamics (Derosiere et al., 2013). Another important limitation for application of fNIRS in dynamic environments is that hemoglobin concentration dynamics are slow and therefore it limits the temporal resolution of fNIRS in the order of several seconds (Gramann et al., 2011; Irani et al., 2007). The former limitation limits the usage of the fNIRS for studying the brain dynamics of goal-directed movements and fast embodied cognitive processes, which are initiated in fractions of seconds (Gramann et al., 2011).

As stated by Gramann et al. (2011), for investigation of sub-second brain processes the neuroimaging technique has to have very good temporal resolution based on the direct investigation of brain processes. Two widely employed methods are EEG and MEG. However, the MEG is still contained solely to laboratory conditions due to the size of the recording equipment (Mehta and Parasuraman, 2013a), thus leaving EEG as unique method for investigating brain dynamics that follows participants' free movements (Gramann et al., 2011).

3.3 Electroencephalography (EEG)

German scientist Hans Bergner introduced the first human EEG signal in 1924 (Berger, 1929; Sanei and Chambers, 2013). Berger placed one electrode over forehead and one over the occipital cortex and has recorded the rhythmic activity at approximately 10Hz, which is known today as the alpha waves (Pizzagalli, 2007). Berger further proposed that the periodic fluctuations of the human EEG may be related to mental processes, e.g. arousal, memory, etc. (Pizzagalli, 2007). Ever since the EEG has been widely used for measuring the electrical brain activity and it has been recognized as the mostly used tool in clinical and experimental neuroimaging, but also in neuroergonomics studies (Gevins and Smith, 2006).

3.3.1 Electrical brain activity

In this section, a brief background on electrical brain activity will be provided, mainly based on the following previous published works (Pizzagalli, 2007; De Vos, 2009; Vanderperren, 2011; Sanei and Chambers, 2013).

A Neuron (Figure 3-3), which consists of a cell body, dendrites and an axon, is an electrically excitable cell that processes and transmits information through electrical and chemical signals. Neurons are electrically polarized in a way that their interior is negatively charged with respect to the outside cell. The main reason for this is unequal distribution of sodium (Na+), potassium (K+), and negatively charged ion chlorine (Cl-) across the cell membrane. This potential difference called the resting potential and it has typical values around -70mV. When cells communicate with each other, they release chemicals known as neurotransmitters, at the synaptic terminals. The neurotransmitter travel from presynaptic to postsynaptic region that disturbs the resting potential, or a so called postsynaptic potential (PSP), by several microvolts and in duration of approximately 10 ms. Since every neuron possess many synapses that are connecting to numerous other neurons, the actual potential over a cell membrane is given by spatial and/or temporal summation of the PSPs. At this stage, both a depolarization (a decrease in negativity) and hyperpolarization (an increase in negativity) are possible. Depolarization of neuronal cell beyond critical level (threshold) generates an action potential (AP) that propagates along the axon. Once it arrives to the synapses, the AP can release neurotransmitters in order to communicate with the next set of neurons. However, since the hyperpolarization is also possible, there are two distinct types of the PSPs: ones that depolarize and eventually lead to generation of AP (also called excitatory PSPs - EPSPs); and the ones that lead to suppression of Aps (known as inhibitory PSPs - IPSPs).

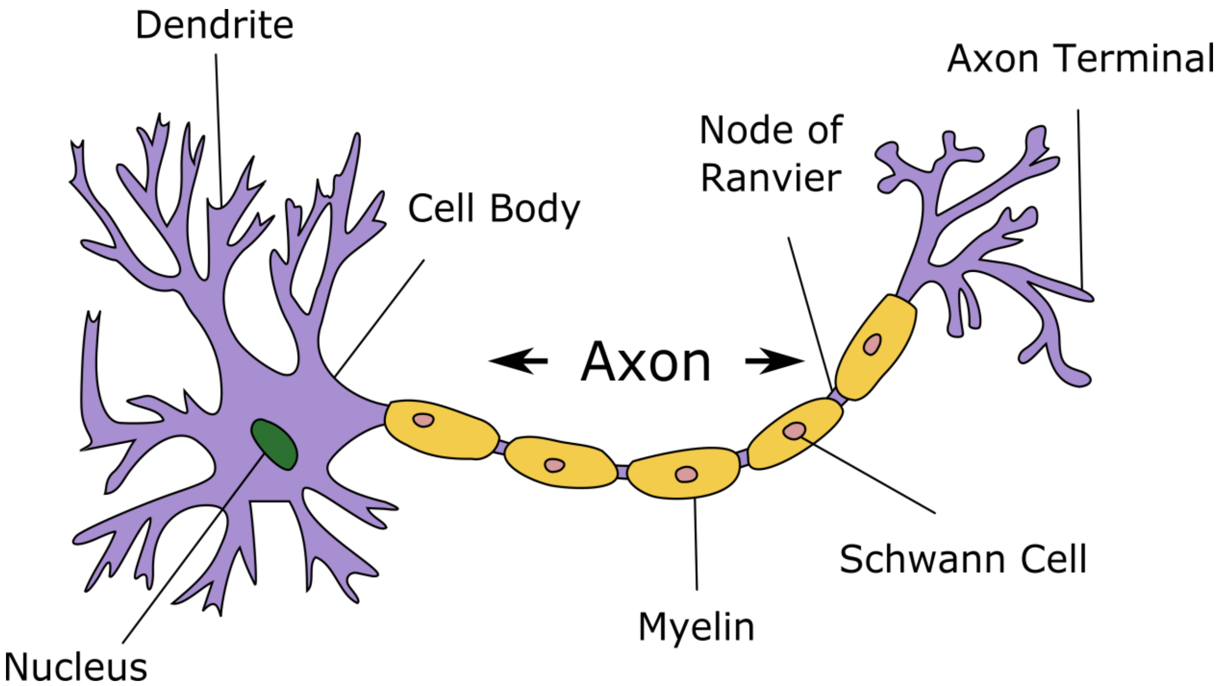


Figure 3-3. The structure of neuron (Adopted from: https://en.wikipedia.org/wiki/Soma_(biology))

3.3.2 EEG signals Measurement

EEG signal measures the generation of currents that flow during synaptic excitations of the dendrites of numerous pyramidal neurons in the cerebral cortex (Sanei and Chambers, 2013), i.e. EEG measures the post-synaptic activity of the human brain. Once the neurons are activated, the synaptic currents are produced within dendrites, which further generates a magnetic field measurable with the electromyogram (EMG), while the secondary electrical field over scalp is measurable with the EEG systems (Sanei and Chambers, 2013). In other words, the neurons possess specific electrical properties that cause their activity to produce electrical field (Vanderperren, 2011). These electrical fields may be recorded from a short distances from the source (local field potentials - LFPs), from a large distance from the source (electrocorticografy - ECoG), or at the subjects scalp (EEG).

The EEG measures the electrical communication between neurons as a function of time (De Vos, 2009). However, the occurring potential changes can only be detected if many neurons synchronously depolarize or hyperpolarize. Therefore, it is believed that the synchronous firing of many vertically oriented large pyramidal cells in the cortex specifically generates the EEG, since these neurons are aligned and amplify each other's extracellular fields and the currents generated by these neurons summate in the extracellular space (De Vos, 2009; Vanderperren, 2011). Although the currents are attenuated through meningeal coverings, spinal fluind, skull and scalp, they can still be detected since the sum of the simultaneously active neuron's potential is between 10 and 150 µV (De Vos, 2009). These signals can be measured by placing at least two electrodes on the scalp, which constitutes the EEG signal measurements (Figure 3-4; De Vos, 2009; Vanderperren 2011; Sanei and Chambers, 2013).

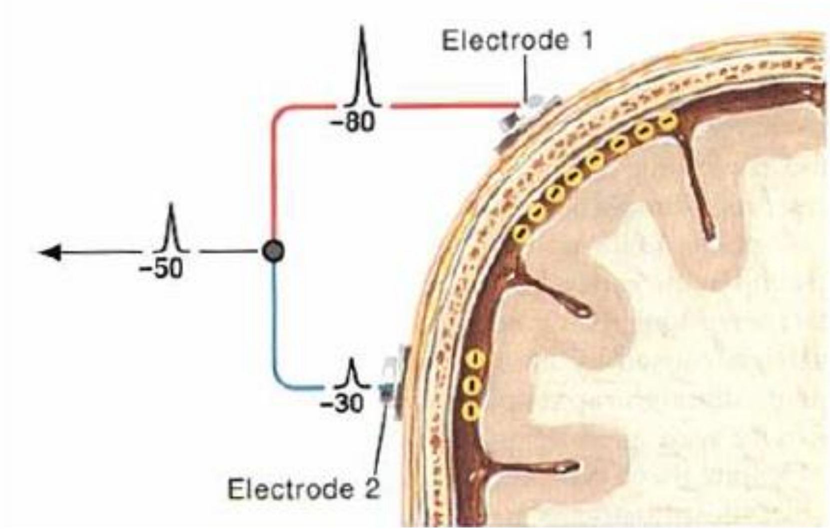


Figure 3-4: The sum of electrical brain potential recorded from two-electrodes placed on the scalp (Addopted from De Vos, 2009)

Berger introduced the two-electrode system for measuring the EEG activity, however nowadays, these systems improved and there is a recommendation that EEG should be measured with at least 24-channel EEG (Nuwer et al., 1998). Since the localization of the specific brain activity is of great importance, there is a general recommendation that the recording electrodes should be placed on well-defined positions on the human scalp, by following the international 10-20 system (Nuwer et al., 1998). The 10-20 system recommends electrode placement based on intersections at 10 or 20% intervals of distances between specific anatomic landmarks on the head (Figure 3-5). According to this system, the electrode positions are specified with a combination of two or three letters and/or digits. The first letter normally corresponds to the specific scalp region at which the specific electrode is located. As such, capital letter F indicates electrodes on the frontal lobe, T on the temporal lobe, O on the occipital lobe, P on the parietal. The letter C indicates the electrodes on the central line. For most electrodes, a second letter or a digit is added to this letter, e.g. FP represents a fronto-parietal region, etc. In addition, a letter Z is added for all electrodes on the midline and odd and even numbers for electrodes on the left and right hemisphere, respectively. For setting a larger number of electrodes, electrodes are equidistantly placed in between the above electrodes and the same naming approach is preserved (Vanderperren, 2011).

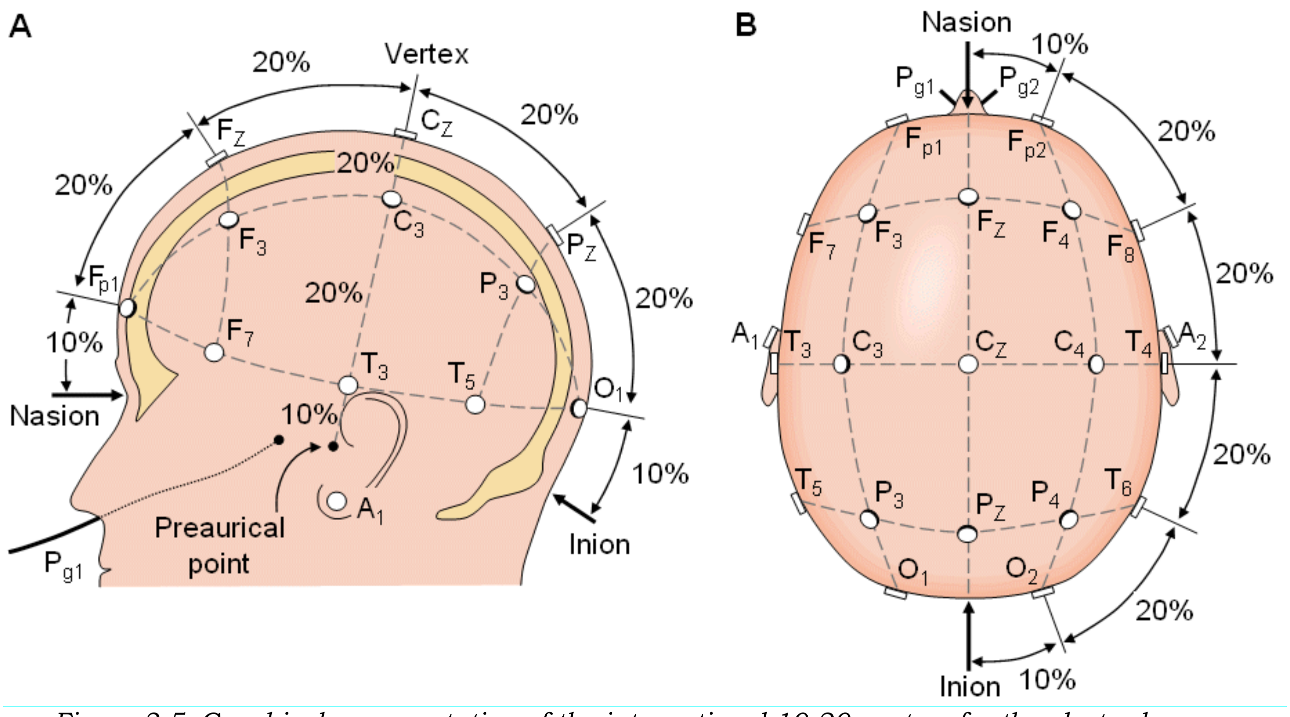


Figure 3-5: Graphical representation of the international 10-20 system for the electrode placements in EEG recordings, seen from above (Image A) and side view (Inage B). Adopted from (Malmivuo, J., and Plonsey, 1995)

In order to measure the potential differences between electrode sites on the scalp, one or several referenced electrodes needs to be used (De Vos, 2009; Vanderperren

2011; Sanei and Chambers, 2013). Mostly used reference systems are bipolar reference, the Laplacian derivation, the average reference and the linked-ears reference (De Vos, 2009). When using the average reference, the potentials on all recording sites are recorded with the average value of all electrodes. In linked-ears reference, the EEG signal is recorded with respect to the average potential on ear lobes. Both of these references are good for visualizing the widespread coherent waveforms, since these waveforms occur with similar amplitude and phase (De Vos, 2009). When using bipolar and Laplacian montage, the EEG signals are obtained by subtracting neighboring electrode signals and they are mainly used for viewing highly localized activity over specific scalp area, since the usage of these methods filters out the widespread waveforms (De Vos, 2009).

3.3.3 Brain Rhythms

In the healthy adults, the amplitudes and frequencies of the brain rhythms change depending on the person's cognitive state, e.g. arousal, vigilance, sleep, etc. (Sanei and Chambers, 2013). The brain rhythms are generally divided in frequency bands and are depicted on the Figure 3-6 (Sanei and Chambers, 2013): δ (delta: < 4 Hz), τ (theta: 4-7.5 Hz), α (alpha: 8-12), β (beta: 13-35 Hz) and γ (gamma: >35 Hz). Depending on the literature, the spans of the frequency bands can vary. However, this is not surprising since these bands are person specific, but also depends of the age. For that reason Klimesch (1999) proposed that for each subject, the frequency bands should be adjusted for alpha and theta windows, before further analysis. Nevertheless, generally, the above mentioned values are used, with a certain ambiguity, in variety of EEG studies.

Delta waves are mainly observable in the deep sleep, however they could be observable also in the wakeful state (Sanei and Chambers, 2013). Theta waves are observable in the wakeful state and they can represent the consciousness slips towards drowsiness of a person (Sanei and Chambers, 2013). Moreover, theta waves are observed when a person is fallen into a light sleep (De Vos, 2009). Alpha waves indicate both a relaxed and awareness state, but without attention or concentration (Sanei and Chambers, 2013), i.e. they show that a person is awake, but it is not actively processing information (De Vos, 2009). Thus, the alpha waves are commonly observed when a person is relaxed but inattentive (De Vos, 2009). Beta waves are the most prominent in the wake state when person is engaged in active thinking and solving complex problems. Moreover, beta is observable during attentive states and when a person is focused on the task (Sanei and Chambers, 2013). Gamma wave, also sometimes referred to as fast beta waves, are generally rare and rarely studied waves, and can be used for detection of certain brain functioning disorders (Sanei and Chambers, 2013).

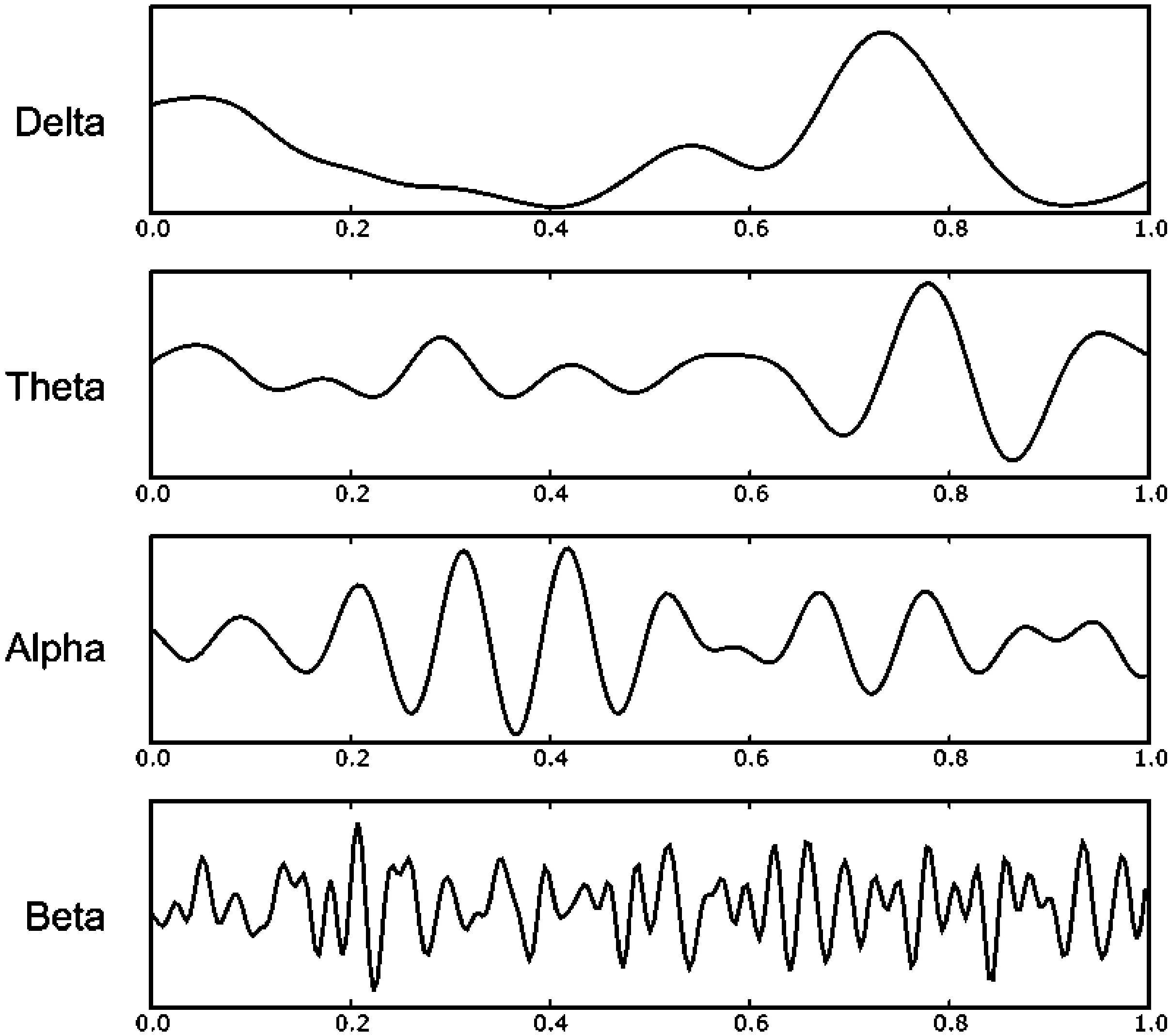


Figure 3-6: Graphical representation of the specific brain rhythm frequencies (Adopted from http://econtact.ca/14_2/ortiz_biofeedback.html)

3.3.3.1 Engagement Index (EI)

When assessing the cognitive state from EEG frequency domains one could use the basic index, which consists of solely calculating power ratios for each of the frequency bands, or the ratio index that is derived from the ratio between power of frequency bands (Cheng and Hsu, 2011). Engagement index (EI) is a ratio index, derived from the EEG frequency bands and it represents how much is person cognitively engaged in the task, reflecting changes in alertness (Pope et al., 1995; Prinzel et al., 2000; Jacko, 2012; Laure et al., 2015). As mentioned in previous chapter, the low frequency waves are usually high in amplitude and are notable in the state of rest, relaxation, sleepiness, low alertness etc. On the other hand, the high frequency and low amplitude waves are reflecting the alert state, state of wakefulness, state of task engagement, etc. The EI represents the ratio between the high frequency waves (β), and the summation of the low frequency waves (α+θ), i.e. EI = $\beta/(\alpha+\theta)$. Therefore, higher EI indicate the higher engagement of the person to the task, while the low values of EI indicate that person is not actively engaged with some aspect of the environment during the task (Jacko, 2012). An important notion is that one should be careful when using the EEG frequency analysis, since the continuous EEG signal can be contaminated with the recording artifacts, such as e.g. muscle artefacts (prozafir and Mutulu, 2012). For that reason, it is important to ensure that all the artefacts, which are unrelated to brain dynamics, need to be removed from the signal prior to the EI calculation.

3.3.4 Event-related Potentials (ERPs)

Event-related Potentials (ERPs) can be recorded from the human scalp and extracted from the continuous ongoing EEG signal (Picton et al., 2000). ERPs emerged from the fact that the EEG signal in its raw form is a rough measure of the brain activity and in the initial years of EEG recordings it was very difficult to use it for assessment of specific neural processes (Luck, 2014). However, the EEG carries the neural responses that are associated with specific sensory, cognitive and motor events, and these responses can be extracted from the ongoing EEG by means of simple averaging and other more sophisticated techniques (Luck, 2014). These methods are necessary, since the ERPs are small in voltage (1-30 μV) relative to the ongoing EEG activity and EEG recording artifacts (Sanei and Chambers, 2013). Thus, the averaging techniques are used to increase signal-to-noise ratio (SNR), by canceling unrelated brain activities and recording artefacts (Luck, 2014). The name Event-related potentials denotes that ERPs are EEG voltage fluctuations that are associated in time with some physical or mental occurrence, i.e. with specific event (Picton et al., 2000; Luck, 2014). Apart from using ERPs for assessing the patients' various clinical conditions, over the past 40 years ERPs were recorded from healthy individuals for assessing various covert cognitive mechanisms, e.g. the mechanisms of attention (Luck et al., 2000).

In order to extract time-locked ERPs from the continuous EEG signal, the participants must be presented with stimulus, which can be auditory, visual, tactile, etc. Figure 3-7 depicts the segment of continuous EEG signal and time-locked periods of signal presentations and the duration of ERP waveforms, which can be used for further analysis (Luck et al., 2000). As can be seen on the Figure 3-7, the segment of EEG following each stimulus (or each response) is extracted from the EEG, and these segments are then lined up in time and averaged obtaining grand average (GA) ERP (as depicted on the lower-right corner of the Figure 3-7). As previously mentioned, the averaging suppress any brain activity that is unrelated to the stimulus to zero (assuming a large number of trials), and any brain activity that is consistently time-locked to the stimulus will remain in the average (Luck et al., 2000).

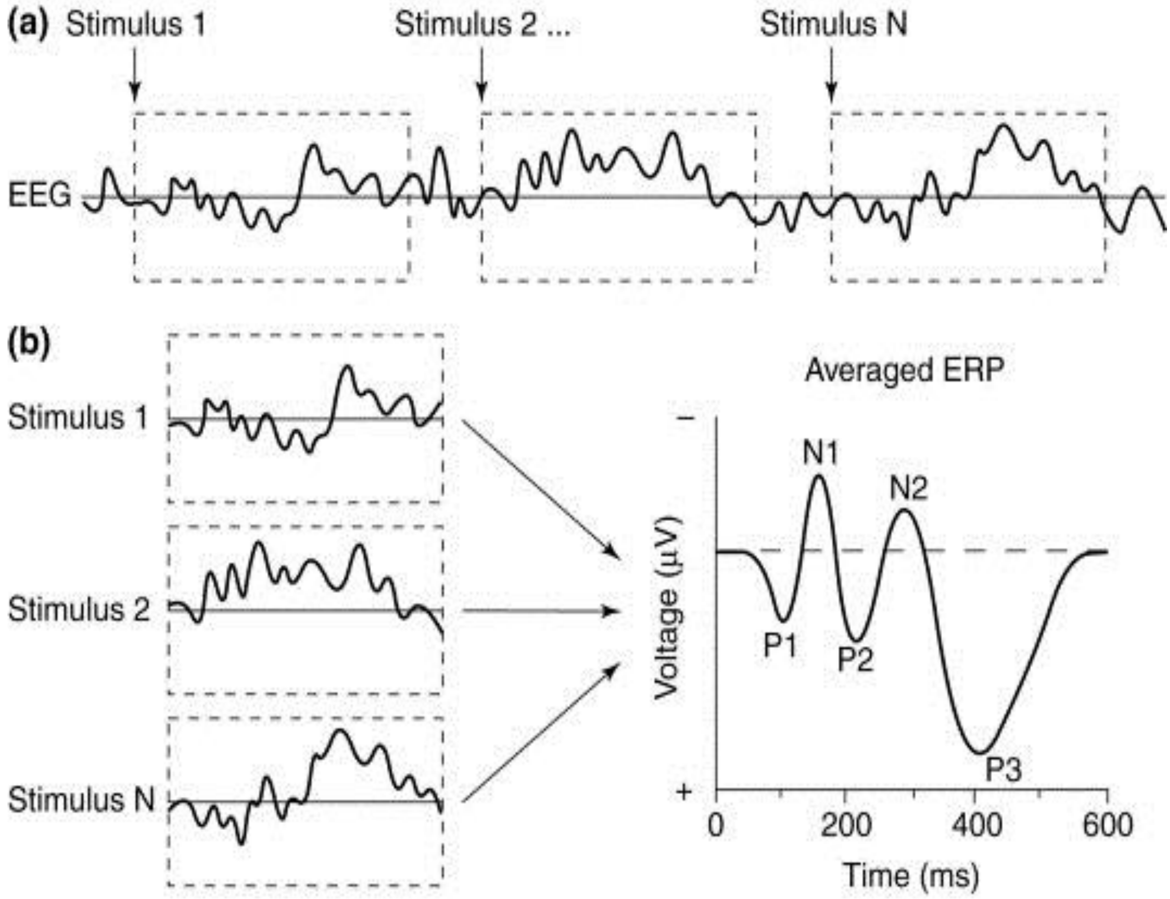


Figure 3-7: The ERP extraction from the ongoing EEG. Image a: The participant is presented with the stimuli (1…N), while the ERP is being recorded; Image b: In order to isolate the ERP from the continuous EEG signal, the time-locked EEG segments following each stimulus are extracted and averaged with the aim of obtaining the GA ERP (Adopted from Luck, 2014).

The resulting GA ERP waveform consists of several positive and negative deflections that are called 'peaks,' 'waves,' or 'components,' (Luck, 2014). The ERP components are typically named in the standardized fashion, in a way that first there is a capital letter P or N, indicating positive or negative going wave, followed by the number, which indicate the timing of the peak in milliseconds (Picton et al., 2000; Luck 2014). As such, e.g. P300 component presents the positive going wave that occurs around 300 ms after the time-stamp of the presented stimuli. The sequence of components that are following a stimulus usually reflects the sequences of the neural processes that are triggered by the stimulus (Luck, 2014). The distinction between early and late components is that the former represents the early sensory processing, while the latter are representative of decision and response-related processing (Luck, 2014). Thus, the ERPs span a continuum between the exogenous potentials (i.e. obligatory responses, which are influenced by the physical characteristics of the eliciting event) and the endogenous potentials (i.e. related to the information processing in the brain that may or may not be invoked by the eliciting event; Picton et al [2000]).

Since ERPs are derived from the EEG, the spatial resolution limited mainly by the numbers of the recording sites of the electrodes. However, the temporal resolution can be increased by increasing the recording channels. This can allow the estimation the intracerebral locations of these cerebral processes (Luck, 2014). Another possibility for increase of temporal resolution is through multimodal EEG-fMRI measurements (Mijović et al., 2012; Mijović et al., 2013). Nevertheless, information provided by ERPs may be used in many different research programs, with vide application area, ranging from understanding how the brain implements the mind to making specific analyzes in medicine, psychology (Luck, 2014), but also for analyzing the brain dynamics in naturalistic environments (Debener, 2012; De Vos, 2014a). Moreover, the ERPs were also successfully applied in brain-computer interfacing (BCI), both in laboratory conditions for the e.g. P300 speller (De Vos et al., 2014b), or in naturalistic environments (De Vos et al., 2014a).

The amplitude and latency of the ERP peaks can be used to measure the time course of cognitive processing, and the distribution of voltage over the scalp can be used to estimate the neuroanatomical loci of these processes (Luck, 2000). Moreover, since the temporal resolution of ERPs is in the order of milliseconds, they can be used to measure the when brain processing activities actually take place and according to Luck et al. (2014) ERPs are considered to be the "Reaction time of the 21st century", since the behavioral reaction time (RT) and performance based measurement measurements are unable to provide the insights of what is happening between the stimulus presentation and the ones response (Luck, 2000; Parasuraman 2003).

In order to successfully apply ERP study, the experimental paradigm should be specifically designed to elicit the desired cognitive processes (Picton, 2000). The most commonly used paradigm is the, so called oddball paradigm in which the improbable target stimulus should be detected in the train of the standard stimuli (Picton, 2000; Luck, 2014). The amplitudes and latencies of the ERPs elicited over both the target and standard condition are then calculated separately and compared, in order to investigate how the brain discriminates stimulus and evaluates the probability

(Picton, 2000; Luck, 2014). The oddball task paradigms usually elicit the P300 ERP component of higher amplitude magnitude over target stimuli, compared to standard ones (Polich, 2007; De Vos et al., 2014a) and it usually reflect the depth of cognitive processing, e.g. memory processing, attention processing, etc. (Polich, 2007; Luck 2014; De Vos et al., 2014a).

3.3.4.1 P300 ERP Component

The P300 component of the ERPs represents the positive deflection of the ERP waveform that occurs around 300 ms after the stimulus presentation and it is the most prominent over central and centro-parietal scalp sites (Picton, 1992). It is also commonly called the P3 component, since it is the third major positive peak in the ERP waveform (Picton, 1992). It was discovered in 1965 (Sutton et al., 1965; Walter et al., 1965) and it was reported as the late positive ERP wave that is evoked by meaningful, task relative stimuli (Picton, 1992). Ever since, the P3 encouraged the use of ERPs for assessment of the neural basis of cognition (Polich, 2007).

Although the early studies were concerned solely with functional analysis of the P3 component (as related to stimulus probability), nowadays it is widely accepted that the P3 component is actually reflecting information processing, when brain mechanisms are engaged in attention and memory processing (Picton, 1992; Johnson, 1993; Polich, 2007). In other words, the P3 component is often used to identify the depth of cognitive information processing, being strongly related to the attention level (De Vos et al., 2014a; Johnson 1988; Polich 2007). It is usually considered that P3 component is not influenced by the physical attributes of the stimuli (Grey et al., 2004; Murata et al., 2005). However, the recent study demonstrated that if P300 is indeed equivalent to centro-parietal positivity (CPP) in the gradual target detection task, physical attributes could influence the P3 component (O'Connell et al., 2012).

Although, the P3 component was studied as a single waveform, recent studies support the notion that there are generally two distinct P3 subcomponents, namely P3a and P3b subcomponents, depending on the target/standard discrimination difficulty (Polich, 2007). Generally, the P3a subcomponent is stimulus driven and it reflect frontal attention mechanisms during the task, while the P3b component has more temporal-parietal scalp distribution and it reflects attention mechanisms, which are related to subsequent memory processing (Polich, 2007). The main functional distinction between these two components is that P3a is related to low-level attentional processing and it reflects the exogenous attention processing mechanisms (Daffner et al., 2000). On the other hand, P3b subcomponent is related to high-level attention processing and processing of the endogenous aspects of stimuli, context-updating information (working memory) and memory storage (Polich, 2007). The latency of P3a and P3b can vary depending on the stimulus events which elicit them, nature of task, and population of participants included in the study, etc. (Polich, 2007). Although, P3a and P3b are mainly elicited separately, both subcomponents can be elicited simultaneously, forming bifurcated P3 component, which contains both subcomponents (Polich, 1988). The main cause of this is that the ERP represents the summation of the electric potentials and thus, both components could simultaneously, contributing to bifurcated P3 peak.

3.4 EEG applications in Neuroergonomics Studies

The application of the EEG systems for the measurements of the operators cognitive state are dating even before the neuroergonomics was established as the science discipline. For example back in 1990s, Parasaruman discussed on the application of the ERP recordings for various HF/E problem areas and he argued that the majority of previous research that was conducted on measurement of the mental workload (Parasuraman, 1990). Shortly after, Gevins et al. (1995) also discussed on the benefits of the EEG applications for the measurement of brain functions in operational environments, and especially those positions that require sustained attention of the workers. Further, Jung et al. (1997) demonstrated how the alertness, in the tasks that require sustained attention, can be monitored in near real-time, using EEG power spectra and they proposed that their system could be applied for non-invasive measurement of the cognitive state of human operators in attention critical settings. Following these research, and with the development of the technology, the EEG received much more attention for estimating the operators' cognitive states in the operational environments, but also for the ergonomics task design (Parasuraman, 2003; Mehta and Parasuraman, 2013a). The application of EEG in neuroergonomics studies covers both physical and cognitive work domains (Mehta and Parasuraman, 2013a).

Regarding physical work, the EEG studies were mainly conducted on repetitive work, mainly by utilizing EEG derived movement-related cortical potential (MRCP), but also combining EEG and electromyography (EMG) signal modalities (Mehta and Parasuraman, 2013a). The usage of the MRCP for physical work was encouraged by the fact that MRCP provides valuable information regarding the role of cortical motor commands on the control of voluntary muscle activations (Mehta and Parasuraman, 2013a). For example, it was found that MRCPs, from the supplementary motor area and contralateral sensorimotor cortex, are highly correlated with the force generation during elbow flection and associated muscle activities (Siemionov et al., 2000). In another study it was found that extension and flection result from separate cortico-spinal projections to the motor neurons, while thumb extensions resulted in lowered EMG it also elicited greater MRCPs than flection movements (Yue et al., 2000). It was emphasized that these findings may provide important information for understanding the etiology of work-related MSDs, caused by repetitive work (Mehta and Parasuraman, 2013a).

Regarding cognitive work, EEG was previously mainly used for studying of the mental-workload, vigilance and mental fatigue, and neuroadaptive systems (Mehta and Parasuraman, 2013a). Studying mental workload is important since if its values are too high, or too low, human-system interaction can be compromised, which could further lead to potentially hazardous situations (Mehta and Parasuraman, 2013a). It was reported that EEG correlates of mental workload are highly sensitive to changes in working memory load (Berka et al., 2007). Moreover, during problem solving and analytical reasoning EEG indices of mental workload also increase (Berka et al., 2007). Further, EEG was also proposed for the on-line detection of changes in mental workload, with the aim of improving the operators' performance (Kohlmorgen et al., 2007).

EEG has been recognized to be powerful method for detecting mental fatigue of the workers, but also to investigate the ability of operators' to sustain attention over prolonged period, i.e. vigilance (Jung et al., 1997; Boksem et al., 2005; Parasuraman and Wilson, 2008; Marcora et al., 2009). Studies of vigilance are among the most important, since the general trend in industry is to automate as much processes as possible, both to reduce human error and to increase productivity (Sheridan, 1980). This way, the automation changes the role of the operators from the ones where they are actively engaged in the production process to the ones of system controllers, which serve in fail-safe capacity and should react only when problem occurs (Warm and Parasuraman, 2008). However, the operators of automated systems, who perform monotonous but attention demanding tasks, largely face difficulty to maintain constant level of vigilance during their work shift (Jung et al., 1997). Thus, in the recent years there is increasing interest in investigation of the possibility of application of the on-line vigilance monitoring. This eventually directed the field of neuroergonomics to the development of the neuroadaptive systems, which should enable mutual interaction between automated system and the operators (Hettinger et al., 2003; Scerbo, 2006). The main principle of work of neuroadaptive is that both human and system could initiate the change in level of automation, i.e. the mental workload to which human operator is exposed, depending on the vigilance level of the operator (Scerbo, 2006).

Apart from these three main domains of EEG in neuroergonomics studies, another important application of EEG is for prediction of human error (Eichele et al., 2008; Eichele et al., 2010; Fedota and Parasuraman, 2010). Neural signal that is associated with the human error is, so called, error-related negativity (ERN). Eichele et al. (2008) have reported that the maladaptive brain activity, related to the preceding error, can be detected around 30 sec before the error occurs. Similarly, the work of Fedota and Parasuraman (2010) states that studies of the ERN indicate that the brain has specific error monitoring and feedback system, which is in strong relation with brain networks that are involved in decision making and learning. Thus, ERN provides the possibility to understand how errors are made, which could provide the basis for creating the error prevention strategies (Fedota and Parasuraman, 2010).

Another application of EEG in neuroergonomics studies can be seen through concurrent studies of physical and cognitive work, which did not received as much attention in the neuroergonomics studies as previously mentioned directions (Mehta and Parasuraman, 2013a). For example, Kamijo et al. (2000) examined how are the cognitive function influenced by the exercise activity. They reported that intensity of exercise influenced the P300 ERP component, which followed an inverted U-shaped curve depending on exercise intensity. Another study used EEG- and EMG-derived corticomuscular measure and it was found that corticomuscular coupling significantly decreases during mentally stressful condition (Kristeva-Feige et al., 2002). Importantly, this was not observable during traditional EMG and force production measurements, which emphasize the importance of studying also the brain function during physical tasks (Kristeva-Feige et al., 2002). Studies in this area of neuroergonomics generally agree that it is important to obtain brain dynamics together with more conventional ergonomics methods in order to understand the overall demands placed on human operators during the work that requires physical and cognitive processing (Mehta and Parasuraman, 2013a).

Although, it was shown that EEG was successfully applied in variety of neuroergonomics studies, all of the previously mentioned studies shares the common limitations. These are mainly related to the recording equipment and procedures. In fact, traditional EEG recording systems suffers from long wiring, which creates huge movement artifacts, thus restricting natural movements of the participants during experimental procedures. Moreover, these studies were mainly confined to strictly controlled laboratory conditions, which require electro-magnetically shielded rooms with attenuated sound and lightning sources. Thus, the ecological validity of such a studies has been recently questioned by Gramann et al. 2011. Indeed, it is an invalid assumption that brain activity measured in dimly lit cubicles and with restricted movements reflects a general principle of the brain dynamics during cognitive processes in everyday life (Gramann et al., 2011). Thus, there is increasing interest in studying the brain dynamics in the naturalistic environments, by utilizing recently available wireless and wearable EEG systems (Makeig et al., 2009; Gramann et al., 2011; Debener et al., 2012; De Vos et al., 2014a; Wascher et al., 2014; Gramann et al., 2014).

Makeig et al. (2009) proposed the mobile brain/body imaging (MoBI) system in order to investigate how is spatially distributed brain dynamics related to natural human cognition. It was emphasized that for such a recording, the EEG sensors must be small and lightweight, battery powered, equipped with wireless data transmission technology and without the need for skin preparation (Makeig et al., 2009). Following these requirements, Debener et al. (2012) demonstrated it is possible to reliably record the EEG signals and even extract the ERPs, while the participants were freely walking outdoors. They created the EEG system by combining consumer EEG driver and EEG recording cap and compared the results obtained from the auditory oddball task in both indoor and outdoor conditions. Finally, they concluded that it is possible to extract ERPs in the naturalistic environment with high accuracy (Debener et al., 2012). Following this study, the possible application of the ERPs, extracted in everyday environment, for the BCI systems was confirmed by De Vos et al. (2014), confirming the reliability of wireless EEG systems. Moreover, Wascher et al. (2014) was among the first to demonstrate that reliable EEG recordings could be performed in simulated working tasks. In this study, the participants needed to move boxes around improvised workplace environment and the information on the cognitive context was reliably extracted and analyzed using eye-blink related potentials, and it was confirmed that eye-blink related potential are able to provide reliable information about cognitive processes in realistic working environment, i.e. in applied context (Wascher, 2014).

Even though, EEG eventually became wearable and nowadays fulfills the most of the criteria imposed by Makeig et al. (2009), an important limitation for the on-sight recordings in the industrial environments is that they still require preparation of participants for recording (Gramann et al., 2011). This is mainly attributed to the usage of the gel-based, so-called “wet” electrodes. This kind of electrodes are uncomfortable, as the electrolyte gel must be placed on the head of the recorded person but previously the head surface should also be prepared in order to ensure good contact between electrode and recording site (Zander et al., 2011; Gramann et al., 2011; Mihajlović et al., 2015). Apart from time consuming for the preparation, there is also possibility of the skin irritation (Zander et al., 2011). In addition, upon usage of these electrodes, the recorded person should clean the hair from the gel, which is also time consuming and impractical. All of these put current EEG devices far from being user-friendly (Mihajlović et al., 2015). In fact, Chatterjee and Price (2009) argued that if wearable technology will be persuasive, they must be more user-aware, ambient-aware and context-aware. However, at this stage this is not the case with the EEG systems, but there is a large amount of work conducted in order to make the EEG systems more attractive to human beings, both for medical and other everyday situations (for review see, Mihajlović et al., 2015).

One of the current directions of research in bringing close EEG systems closer to healthy users and making them more persuasive is the development of dry (Chi et al., 2010; Gargiulo et al., 2010; Zander et al., 2011; Mihajlović et al., 2015) and even skin contactless electrodes (Mathews et al., 2007; Chi et al., 2010; Chi et al., 2012).

Additionally, moving away from medical applications, a clear momentum in the development of the consumer-based and dry-electrode EEG devices can be seen in recent product developments, emotive (www.emotiv.com), Mindo (http://mindo.com.tw/en/index.php), Muse (http://www.choosemuse.com/), etc. However, the desired signal quality (low signal to noise ratio) with dry-electrode based EEG systems cannot be achieved yet and they are still unable to reduce the movement artifacts, which are related to the relative movement of electrodes against the head surface (Chi et al., 2010; Chi et al., 2012) that are mainly caused by the fragile and complex electrode-tissue interface (Mihajlović et al., 2015). For that reason, reliable wearable EEG recording for neuroergonomics research can still be made solely with the wet electrodes, still somewhat limiting its usage for on-site industrial applications (Mihajlović et al., 2015). Nevertheless, operators' brain dynamics can nowadays be successfully investigated with wearable EEG in faithfully replicated workplaces, where the ambient conditions and spatial dimensions could be preserved, by simulating the work activity (Mijović et al., 2016). This can provide insight in how the brain responds to complex industrial tasks and these findings can contribute to more efficient task designs.

3.5 Multimodal Physiological Recordings in Neuroergonomics

Multimodal systems in neuroergonomics studies that include EEG are usually used either in order to enhance temporal resolution of brain imaging techniques such as fMRI, fNIRS, etc., or to support EEG with increasing its spatial resolution, i.e. to be able to more closely locate specific brain regions of interest. Nevertheless, EEG can be simultaneously recorded also with other physiological sensors that record the activity of ANS (e.g. HR and GSR sensors), with the aim of better understanding of nervous system processes that are related to mental state, such as e.g. arousal, alertness, stress, etc.

Heart rate variability (HRV) is non-invasive measure used to detect cardiovascular conditions and ANS activity (Sharma and Gedeon, 2012). Electrocardiogram (ECG) measures the electrical activity of the heart as it progresses through the stages of contraction (Ortiz-Perez et al., 2010). Main feature of the ECG signal is PQRST complex, where the R-R peak intervals are parameters that determines HRV (Rangayyan, 2015; Sharma and Gedeon, 2012). The differences in the time-course of these R-R intervals (heartbeats) are calculated when one wants to extract the HRV, as depicted in Figure 3-8. Another sensor that is used for robust but rough measurements of the HRV is the HR sensor. HR sensors mostly record just the intervals of the heartbeats in time, providing relatively simple signal. HRV can then be obtained in time domain, as the differential between these successive time-stamps of the beats. Alternatively, the time-frequency analysis can also be employed for calculating the power spectral density (PSD) of HRV (Task Force of the European Society of Cardiology, 1996).

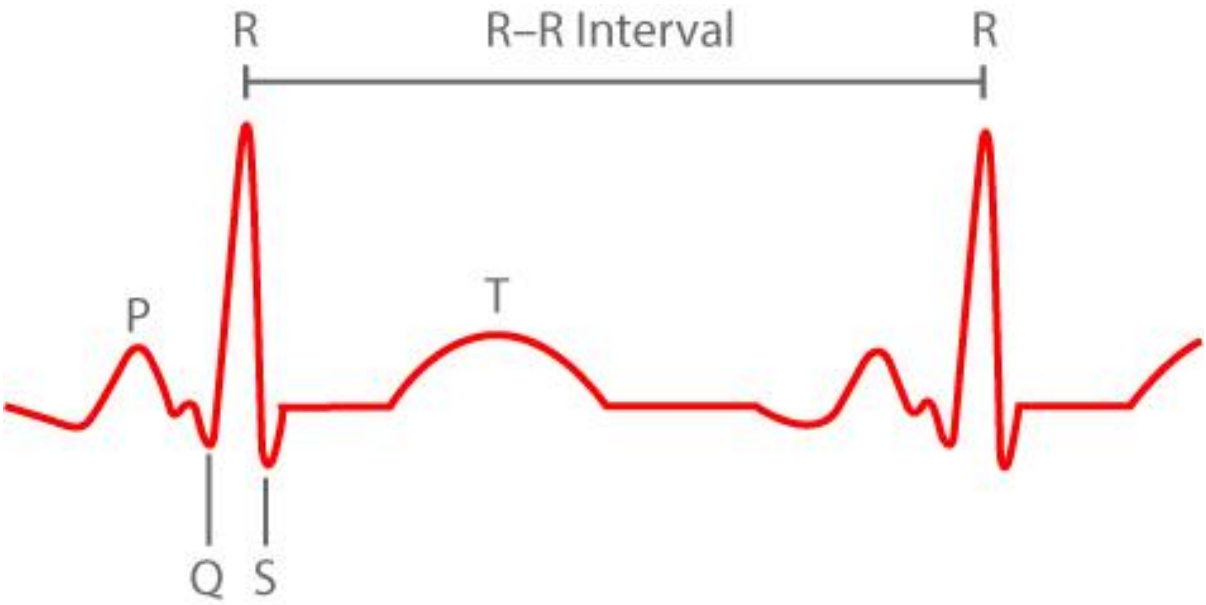


Figure 3-8: Graphical representation of the PQRST complex and R-R interval (adopted from Ortiz-Perez et al., 2010)

HRV can be an important indicator of the stress states (Sharma and Gedeon, 2012), variations in alertness (O'Hanlon, 1972), fatigue (Lal and Kraig, 2011), drowsiness (Vincente et al., 2008), mental workload (Murata, 1994) and other physiological states. For example, stress cause increase in frequency of heart beats and decrease of amplitude of the heart beats in healthy individuals (Sharma and Gedeon, 2012). O'Hanlon (1972) was among the first to report the relationship between HRV and driver's fatigue. In fact, he found that HRV increased with the driving time and related it to the drivers' fatigue. Recently, Wijesuriya et al. (2007) confirmed this finding and proposed a HRV as the reliable measure for estimating drivers' fatigue. Moreover, O'Hanlon proposed that a HRV can be also reliable measure of alertness, since HRV substantially dropped after reactivating the driver in his study. Further, Murata

(1994) found that mental workload influenced the HRV, in sense that ratio between low and high frequency power ratio increased linearly with the work level, confirming sensitivity of mental workload to HRV measures.

Another physiological measure of ANS used abundantly in estimating mental states is GSR, also known as electro dermal activity (EDA) measures flow of electricity through the skin of recorded person (Sharma and Gedeon, 2012). There are three different measurement principles for GSR measurement; however, the most abundantly is exosomatic measurement where skin conductance is measured by applying direct current with constant voltage and using silver-silver chloride (Ag/AgCl) electrodes and an electrolyte gel (Fowles et al., 1981). It is one of the oldest methods for measuring the physiological signals from humans and the reason for its use in the present time is that the data are easy to obtain and the GSR is simple waveform (Lim et al., 1997). Specific features of interest, which are obtained from GSR recording, are skin conductance response (SCR) and skin conductance level (SCL) that can be associated with specific aspects of cognitive state (Lim et al., 1997). The former (SCR) provide an measure of phasic increase of sweat rate that is related to occurrence of some stimuli, while the latter (SCL) are obtained in response free recording, as the number of non-stimulus specific SCRs (Bouscein, 2012). Thus, SCR represents fast varying skin conductance value, over time course of seconds. Figure 3-9 depicts specific characteristic parameters of the SCR waves. First characteristic is its latency, i.e. time elapsed between stimulus presentation and the rise of the SCR wave (Bouscein, 2012). Next important parameter is the rise time, or the time needed for SCR to reach its upper peak amplitude, which is the next important parameter that can be obtained from SCR. Finally, half recovery time, that is, how much time is needed for peak to return to its half amplitude value (Bouscein, 2012).

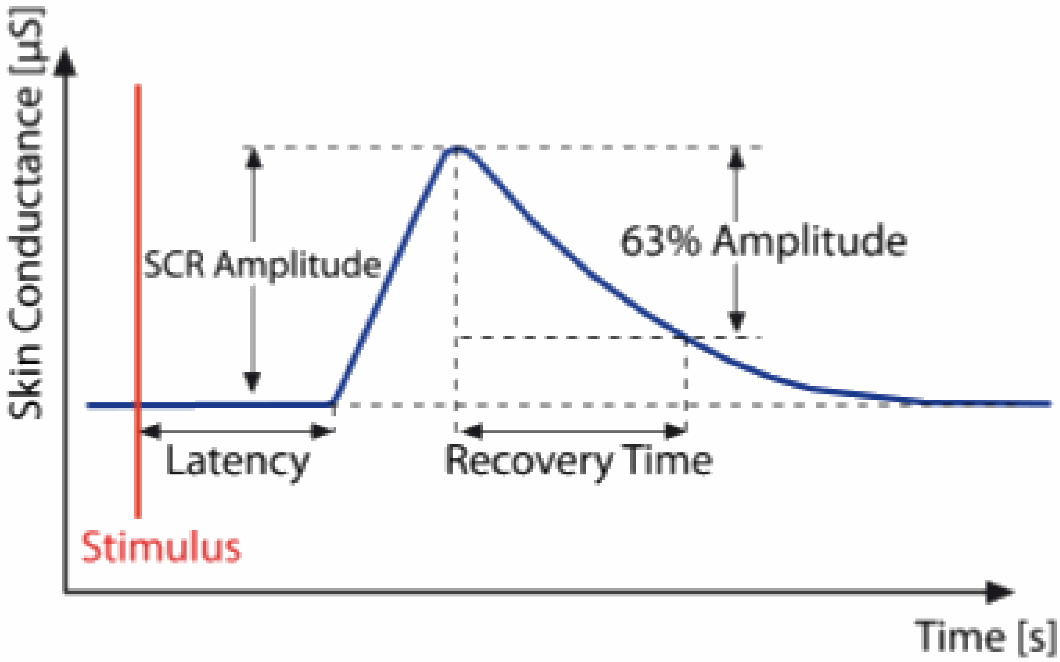


Figure 3-9: Graphical representation of the SCR wave, with its main characteristics (Addopted from Kappeler-Setz et al., 2013)

Similarly to HR measurements, GSR studies confirmed that SCR and SCL could be used for assessing various cognitive state from changes in ANS. For example, Blakeslee (1979) analyzed SCRs before and immediately after stimulus presentation and he reported that SCR magnitudes declined with the performance decrease over the experiment and he proposed that these changes are in close relationship with vigilance performance and attentional processes. It was also previously reported that movements, motor preparation and effort convolved with the increase in EDA, since the motor-related autonomic responses are causing sympathetic arousal that is necessary for support of motor behavior (Vissing et al., 1991). Further, Wilson (1991) showed that the pilot's EDA measures are highly correlated with the changes in responses in various demands of the flights, thus relating them to changes in mental workload to which pilots are exposed. Similarly, Baldauf et al. (2009) found that EDA activity strongly increases with the increasing cognitive workload during simulated driving, while it remain unchanged during the low cognitive demands imposed to the driver. Further, Bundele and Banjeree (2009) proposed that EDA measures significantly correlate with the mental fatigue during the driving, showing possibility of timely detection of fatigued driver.

From all mentioned studies, it is clear that each of the signal modality, namely GSR, HRV and EEG can reflect various cognitive states. However, the multimodal system that simultaneously measures and investigates the relationship between these signal modalities would be beneficial for better understanding both the CNS and ANS activities in applied environments (Dunaway and Steelman, 2013). Following this notion, Dunaway and Steelman (2013) proposed the investigation of relationship between multimodal cognitive load measurements during simulated economic activities in order to provide the most optimal measure for the examination of cognitive load during these activities. Further, Giusti et al. (2009) proposed a multimodal system for investigating the driver's vigilance level in real time, with the aim of reducing the probability of car accident due to lapses in attention. They reported that their system showed the promising results for detection of micro-sleeps and lapses in attention, however, they reported that this system is not ready for the real-life driving since it utilizes EEG measurements, which at the time were conducted with the traditional EEG system susceptible to motion artefacts. Another multimodal study in study in driving and transportation domain was conducted on locomotive train operators for the aim of estimating the operators' arousal (Song et al., 2014). They also reported that the system based on the multimodal physiological signal acquisition and processing is indeed relevant and that it could contribute to increasing safety in public transportation systems (Song et al., 2014). One of the drawback of such systems could be that such a system could be uncomfortable, as the workers should wear the physiological sensors over the work shift. However, the recent study of Doty et al. (2013) stated that their participants in the study reported moderate to high comfort while wearing HR, GSR and EEG sensor over eight hour of consecutive recording. Thus, it seems that miniaturization of recording sensors have increased the comfort for the workers and supported the use of such a systems in real-working environments. Another important limitation of usage of such a systems is that in case of real-life recording in applied industrial environments, the company managers would have full access to the physiological data of the workers, which raises privacy concerns. Fairclough (2014) recently yielded this concern, where he argued that physiological data are personal belonging and that before the actual use of systems for physiological recordings in applied environment, the recorded person must at least provide his/her consent for the recording. Finally, he argued that a system of keeping the obtained data should be confidential, as it is in medical records.

An important notion at this point is that all above-mentioned studies were concerned with the utilization of the physiological measurements mainly in domain of drivers' safety, aerospace sector, transportation sector in general and office work. There is an obvious lack in the literature regarding the recordings of operators' physiological state during either simulated or real work in industrial environments. For that reason, this dissertation mainly aims in investigation of possibilities of utilization of physiological recording during simulated industrial work, with the aim of timely detection of deviations in operators' state during monotonous and repetitive work.

4. Motion Capture and its application in ergonomics

Industrial operators perform physically intensive tasks on a daily basis, since the majority of industrial tasks are physical in nature, thus being constantly exposed to risks of injury (Martin et al., 2012). There are many industrial tasks requiring manual action of the operator, e.g. object manipulation, lifting, pushing, pulling, etc. that are one of the major sources of work-related musculoskeletal disorders (MSDs, Hoozemans et al. [1998]). Although automation has somewhat reduced the need for physical activity for operators, the operators of automated systems are usually required to observe the automated process through visual display terminal (VDT) unit, sitting or standing over prolonged period of time, which can also lead to development of work-related MSDs (Carter and Banister, 2007). Therefore, the use of methods from physical ergonomics to assess the work performance is still one of the most studied directions in HF/E research (Hedge, 2005).

As mentioned in the section 2.2.1 (Physical Ergonomics Domain), diverse methods and tools exists for the ergonomic assessment of manual tasks and postures of the workers, such as self-reports, observational measurements and direct methods (Vignais et al., 2013). Even though the researchers are continuously working on developing supportive tools for identification and evaluation of potentially hazardous human motor tasks and postures, such as QEC, manTRA, RULA, REBA, HALTLV, OWAS, LUBA, OCRA, Strain Index, SNOOK tables and the NIOSH lifting equation, etc. (Andreoni et al., 2009), the fact is that the self-reports and observational methods still have certain drawbacks, the biggest being that the analyses require an off-line analysis and are subjective in nature (Patrizi et al., 2015; Mijović et al., 2015a). Moreover, these methodologies are mostly consider during the design conditions, but they are not used for modification of the existing work conditions (Patrizi et al., 2015). Therefore, there is necessity for the direct on-site evaluation of operators' postures that can be carried out in real-time and in an objective, accurate and quantitative manner (Partizi et al., 2015). Ultimately, the direct measures of operators' postures, by utilizing biomechanical analysis, could provide benefits in practice (Vignais et al., 2013).

Apart from usages in pose estimation, MoCap sensors can be utilized for affective computing (Karg et al., 2013; Kleinsmith and Bianchi-Berthouze 2013). As stated by

Kleinsmith and Bianchi-Berthouze (2013), technological advancement pushed the body motion analysis beyond that of solely gesture analysis and in multimodal interaction with physiological measurement, it was shown that body expressions could be powerful estimator of affective states. Affective phenomena refers to human emotions, moods, feelings, attitudes, temperament, affective dispositions and interpersonal stances (Schrer, 2005; Karg et al., 2013). Affective states can be recognized from body movements, speech, facial expression and physiological parameters (Karg et al., 2013). Although psychological research indicated over a century ago that affective states are expressed through body movements, the systems for automatic recognition of affective states became available only from 1990s, which largely attracted engineers and computer scientist to this area of research (Karg et al., 2013). In the early years, facial expressions were mostly studied modality in the area of affective computing, however it was found that the body expressions are as powerful as facial expression in conveying emotions (Kleinsmith and Bianchi-Berthouze 2013). Moreover, one of the advantages of using body motion, in comparison to the other modalities, is that it is capable to recognize the affective states from the distance (Karg et al., 2013).

Another area of research where MoCap systems can be used, but are not utilized yet, is in the area of human cognition. Although it is closely related to affective states, there is an obvious lack in motion recognition literature related to the application of MoCap systems for investigation of the relation between movements and vigilance or attention. Typically, when performing a specific task, human shows two types of behavioral activities, those directly related to the task performance, and those that are task unrelated behavioral activities (Roge et al., 2000). Based on the various research from 1970s, Roge et al. (2000) classified these task unrelated activities in five categories:

1. 'Postural adjustments' – movements of one or several parts of the body in space
2. 'Verbal exchanges' – Those communications which does not include any piece of information related to the work activity itself
3. 'Ludic activities' – movements indicating the manipulations of the movements
4. 'Self-centered gestures' – movements of one or both hands towards the body
5. 'Non-verbal activities' – practically equivalent to facial expressions

Generally, it was reported that the number of these task non-specific activities progressively increases with the duration of the work, regardless of the time of the day (Rogue et al., 2000). Although, Roge et al. (2000) also confirmed that the number of task unrelated movements were negatively related to the vigilance level, their analysis consisted of recording the participants with the red-green-blue (RGB) camera and the movements were quantified in the post-hoc analysis, through manual counting of these movements. However, this kind of analysis is equivalent to observational methods and therefore, unreliable. On the other hand, the MoCap systems could be engaged in such analysis and automate the process of recording and analyzing the human movement, with the aim of assessing the human cognitive state during the regular work routine (As it will be presented in Chapter 9).

4.1 MoCap Devices in Ergonomics

The direct analysis of human movement is mainly based on pose estimation, which refer to the process of estimating the configuration of the underlying kinematic skeletal articulation structure of a person (Moeslund, 2006). Various sensors can be utilized for pose estimation, starting from classical RGB cameras (Nakajima et al., 2000), and variety of range cameras and depth sensors (e.g. structured light technology; Zhang, [2012] or through combination of wearable sensors, e.g. internal motor units (IMUs; Stiefmeier et al. [2008]). In industry setting, researchers are working on applying this approach in defining work processes (Hori et al., 2006), preventing improper worker positions (Li & Lee, 2011) and proper training and monitoring of new workers (Ray & Teizer, 2012).

An overall research of software and hardware available on the market for biomechanical analysis indicated a number of largely diverse solutions (as presented in Mijović et al., 2015a). Larger companies (especially automotive) have made considerable financial investments in Motion Capture (MoCap) devices in recent years (Horejsi et al., 2013). The devices that are mostly used for ergonomics evaluation are: Impuls X2, motion capture system (PhaseSpace, Inc.); The ART Motion Capture (Advanced Realtime Tracking, Inc.); MOTIONVIEW™ (AllSportSysrems, Inc.), etc. These devices are well known, i.e. from the entertainment industry, where it is possible to animate a virtual character as a result of capturing real actor movements (Hojresi et al., 2013). These expensive MoCap device, provide the possibility to acquire positions of points (called markers) on a character´s body in real time. Once the data has been acquired, there is a need to import it to the 3D simulation software, e.g. JACK (Siemens, Inc.), 3DSSPP (developed at university of Michigan, http://www.umich.edu/~ioe/3DSSPP/index.html), OpenSimulator (http://www.opensimulator.org) etc. in order to perform subsequent ergonomics analysis.

Even though MoCap systems could offer highly precise ergonomic analysis, there are still certain bottlenecks in performing the on-line measurements in real-life industrial environments (as discussed in Mijović et al., 2015a). The majority of commercial MoCap devices are financially demanding and for reliable on-the-fly recording, it is often needed to devote an entire room (Hojresi et al., 2013). This presents one of the major drawbacks for their use in industry and especially in small to medium enterprises (SMEs). Further, MoCap Systems mainly used external sensors (Led diodes, Depth Of Field targets, etc.), which are attached to the recording person, thus posing movement limitations to the workers and being uncomfortable for the use in the industrial settings.

Up to date, there are only two systems that could possibly be used for the on-line recordings and analysis: Real-time Siemens JACK & PSH Ergonomics Driver (Synterial, Inc., http://www.synertial.com) and Cognito system (developed within EU project Cognito, framework FP7, http://www.ict-cognito.org and results were published in Vignais et al., 2013). However, the first system can be used when company is addressing the ergonomic aspects of manual operations during early stages of product design and manufacturing planning and there is a need to use the IGS Synertials motion captures suits. On the other hand, the Cognito system uses on-body sensor network. These sensors are composed of tri-axial accelerometer, a tri-axial gyroscope and a tri-axial magneto- inductive magnetic sensor (Vignais et al., 2013). Cognito systems does not record the movements of the worker, but uses the sensor readings as an input data to computer based RULA ergonomic assessment method and provide feedback when certain thresholds are reached (Vignais t al. 2013). Therefore, both of the systems are dependent on the external sensors attached to the person (presented on the Figure 4-1), which still limits their use in the naturalistic industrial environment.

(a) (b)

Figure 4-1. (a) Combination of Synertial IGS suit with Siemens JACK software for ergonomics evaluation of car assembly, a case study from Skoda automotive (adopted from: www.synertial.com); (b) – IMUs sensor network developed on Cognito project. In this case, apart from possibility to track the workers motion, the Cognito system provides also support to the worker in sense of information on head-mounted VDU, as seen on figures bellow (adopted from http:// www.ict-cognito.org)

With the technological advancement in the computer vision technology, new MoCap systems emerged that does not require neither external markers nor IMUs for the precise acquisition of the human motion. These systems are based on structured light technology (Zhang et al., 2002). Since the introduction of such systems, the gaming industry accelerated the development of consumer based products, which were primarily aimed for contactless interaction between the user and the game itself, in form of Microsoft Kinect. However, the Microsoft provided an open source software development kit (SDK) for Kinect, which attracted many scientists to investigate the possibilities to apply Kinect for various applications, such as gait recognition (Milovanović et al., 2012; Milovanović et al., 2013), ergonomics assessment (Dutta, 2012; Diego-Mas and Alcaide-Marcal, 2013; Partizi et al., 2015), etc. Another, more recent sensor that has been developed, which is essentially based on the same principle as Kinect is the Leap Motion™. Although it was primarily developed for the explicit HCI between user and computerized system, its SDK is also freely available which opened possibility to investigate the potential for its application in various application fields (Zubrycki and Granosik, 2014; Bassily et al., 2014). The main difference between the Kinect and Leap Motion is that the Kinect is capable of recording the full body motion, while the Leap Motion has much smaller recording range and it is used for hand pose estimation.

4.1.1 Kinect and its Application in Ergonomics

Kinect consists of several sensors that are placed in one compact device (Figure 4-2a). Practically, Kinect belongs to the group of 3D depth camera, since it contains a depth sensor, a color camera and a four-microphone, that provide a 3D full-body MoCap device (Zhang, 2012). The depth sensor contains of IR projector and IR camera (as depicted on Figure 4-2b). The Kinect working principle is based on structured light technology. The IR projector is an IR laser that passes through diffraction and it fires a set of IR dots in the acquisition area (Zhang, 2012). Once the dots land on a certain 3D object, the IR camera acquires the reflected pattern and the device performs the analysis using structured light algorithm's in order to compute the depth map and it is capable of 3D object recognition (Zhang, 2012; Patrizi et al., 2015). More closely, a depth value is assigned to each pixel of the image acquired by the RGB camera with the aim of image production, which pixels combine the information about red, green and blue color, and the distance from the Kinect sensor. Further, the acquired color and depth map is segmented in order to recognize the human body (Partizi et al., 2015). Kinect has also inbuilt algorithms for skeletal tracking, in which the human body is represented by specific key-points that represents human joints, e.g. hand, neck, etc. (for review see Zhang, 2012).

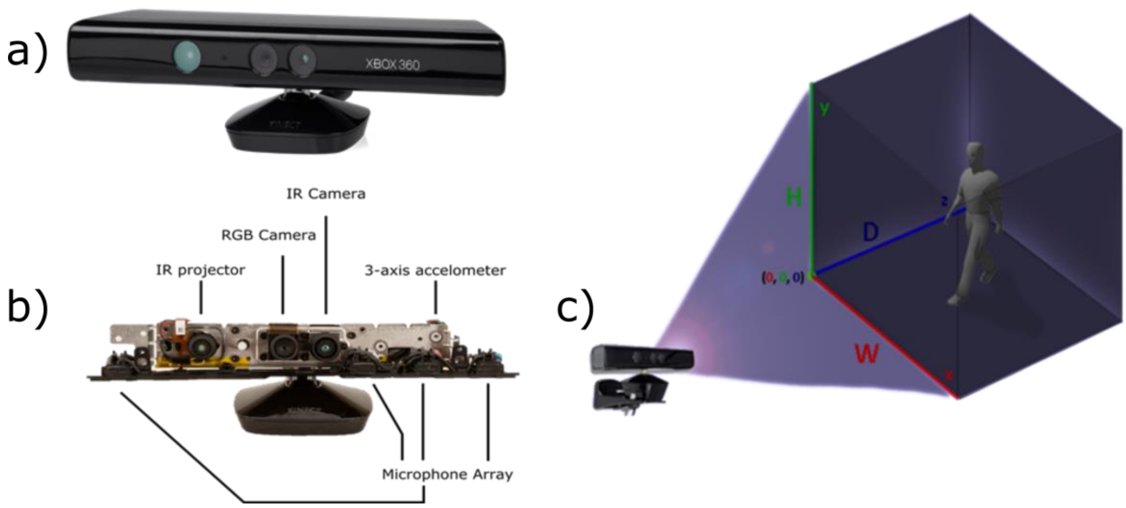


Figure 4-2: (a) - Kinect Sensor; (b) - Position of the sensor inside the Kinect; (c) - Graphical representation of the Kinect acquisition space (Addopted from Milovanović et al., 2013)

The acquisition are of the Kinect sensor is from 0.8 m to 4m frontally from the sensor placement in the z-axis, and the x and y axis are determined by the recording angle in a way that in horizontal axis it covers 57.5^0, while vertically it can cover $43.5^0 \pm 27^0$, depending on the tilt of the device (Milovanović et al., 2013). The acquisition space is graphically depicted on the Figure 4-2c.

Kinect has shown strong potential for the ergonomics studies. For example, Martin et al. (2012) proposed its usage for the real-time pose estimation during the lifting tasks, and particularly in training the operators. Similarly, Clark et al. (2012) investigated the usage of Kinect for clinical application, where frontal and lateral reach were investigated and they compared it to the results obtained by reliable Vicon MoCap system (which requires the on-body markers). Their results support the Kinect for future ergonomics assessment in clinical application, since it is less intrusive and far less expensive than benchmark Vicon system (Clark et al., 2012). Further, Diego-Mas and Alcaide-Marzal (2013) demonstrated the Kinect's capability to support the observational method OWAS (Ovako Working Posture Analysis), by automated acquisition of joint position and translating them directly to the scoring sheet of work postures as proposed by OWAS. Moreover, they compared the results obtained by Kinect and Vicon system and showed that Kinect proved to be reliable tool for motion tracking of workers during the work tasks (Diego-Mas and Alcaide-Marzal, 2013). Another recent study compared the performance of the low-cost Kinect sensor and high-end marker-based MoCap sensor BTS SMART and they provided the support for the future use of Kinect in ergonomics assessment (Partizi et al., 2015).

Above-mentioned studies highly support Microsoft Kinect and its technology for future application in ergonomics for the online posture assessment of the workers. Thus in this dissertation it is aimed to utilize marker-less sensor for the recording of the participants during the simulated working activities, with the aim of developing model for the on-line posture estimation. Moreover, as discussed previously, the body motion can be related to the cognitive state of the person through the evaluation of the task unrelated movements, thus it is aimed in investigating the correlation of these movements with the attention level as estimated by the EEG recordings.

4.1.2 Leap Motion controller and its Applications

The Leap Motion controller is a small and affordable consumer-based motion sensor (Figure 4-3a) that is available on the market since July 2013 (Fanini, 2014). Working principle of the Leap Motion controller is similar to the one from the Kinect, where the biggest difference is that Leap Motion was developed for hand gesture recognition, while Kinect is capable of acquiring full body motion and facial expressions (Marin et al., 2014). Another important difference is that the Leap Motion controller provides a more limited amount of information, in sense that it provide just the information about the key points, rather than complete depth map (Marin et al., 2014). Further, the acquisition area of this sensor is much smaller than the Kinect's one (Figure 3-2b), but it provides much more accurate data points (Marin et al., 2014), in the range of sub-millimeter accuracy (Bassily et al., 2014). As depicted at Figure 3-3a, the Leap Motion controller consists of 2 IR cameras and 3 IR Light-Emitting Diode (LEDs) that are able to track hands, fingers and a few tools in mid-air inside a specific field of view (Figure 4-3b). Generally, it should be placed on the desktop facing upwards in order to operate accurate with high tracking frame-rate inside of designated field of view (Marin et al., 2014).

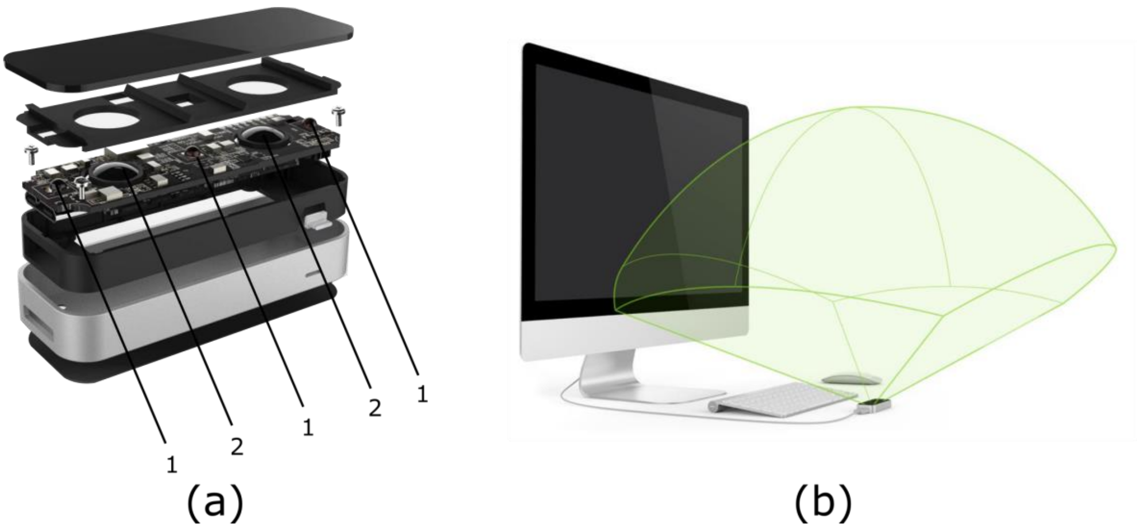


Figure 4-3: (a) - Leap Motion Controller and its inner structure: 1 – IR LED, 2- IR camera; (b) – Graphical representation of the Leap Motion's field of view, where the acquisition space limitations are as follows: 150⁰ angle on the long side, 120⁰ on the short side, 600 mm above the controller and 600 mm wide on each side (Figures adopted from https://www.leapmotion.com/product/desktop accessed on 6/11/2015)

The accuracy of the Leap Motion measurements were confirmed in the work of Weichert et al. (2013). They used the industrial robot with a reference pen that was placed above the Leap Motion controller, which allows the accuracy of the position coordinates down to 0.2 mm. They confirmed that the Leap Motion controller was precise in tracing the pen tip with the accuracy lower than 0.2 nn, thus they concluded that the obtained results were accurate and robust (Weichet et al., 2013). As its accuracy was confirmed, the follow-up studies were conducted in order to investigate the possibility of applying the Leap Motion controller in medical applications. Ebert et al. (2014) created the plug-in for the OstriX medical image viewer that was based on the Leap Motion controller, i.e. they connected the hand gesture analyzer based on Leap Motion controller to the OstriX medical system in order to allow the interaction with the viewer solely through the hand gestures (Ebert et al., 2014). They finally proposed that these hand gesture technologies should be standardized for use in medical applications (Ebert et al., 2014). Another medical application was proposed by Khademi et al. (2014), as a tool for stroke rehabilitation in order to practice the finger individuation. Apart from medical applications, Leap Motion controller was proposed as a tool for remotely controlling the robotic arm, by hand gestures (Bassily et al., 2014; Zubrycki and Granosik, 2015).

From all above mentioned, it is clear that the Leap Motion can be utilize for the various application fields of HCI and human-robot interaction (HRI). However, currently there are no studies that proposes the utilization of the Leap Motion for the ergonomics assessment. One of the ways in which it could be applied is for the estimation of the hand position during material manual handling and especially for hand pinch and grips. The problem of hand pinch and grips has been included in the occupational repetitive actions (OCRA) analysis and discussed in international ergonomics standard ISO 11228-3:2007. Inappropriate pinches can lead to muscle strain and should be avoided (ISO 11228-3:2007) and therefore they should be avoided in low-load material handling. However, in the real-life working environment this is not feasible and therefore the evaluation of these actions should be performed in working environment. Since the Leap Motion can provide the precise acquisition of the key-point position, the pinches (as depicted on Figure 4-4) could be evaluated in real-time, with the aim of reducing possible injuries and long-term exposure of the irregular material pinches and grips.

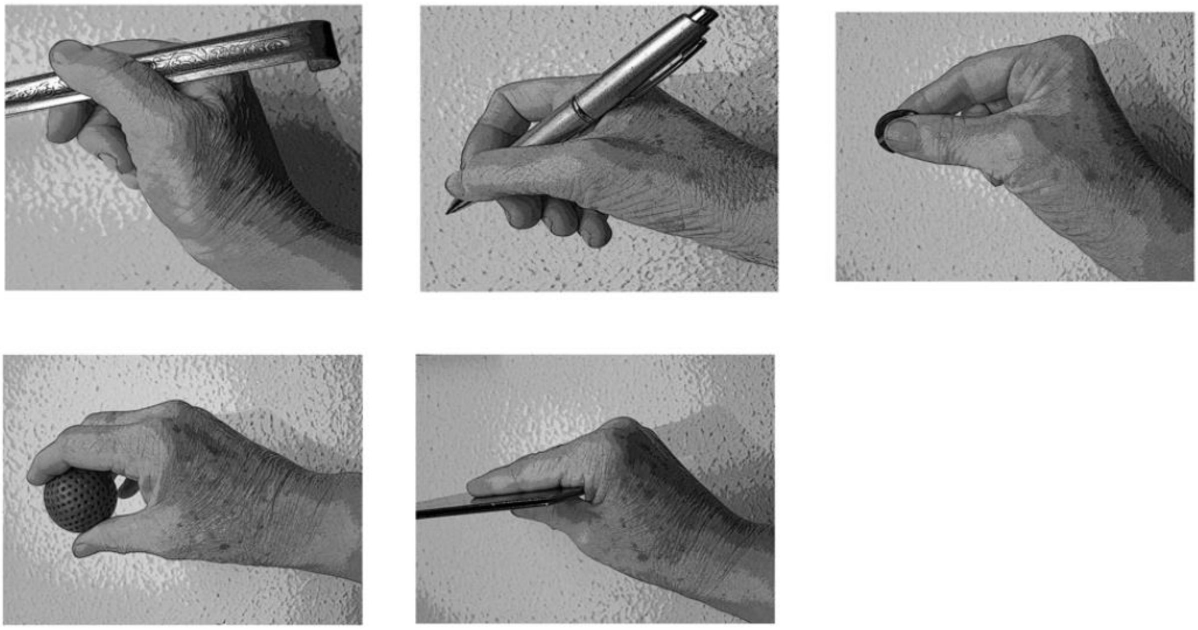


Figure 4-4: A few example of low-load material pinches (Adopted from ISO 11228-3:2007)

5. General Methodology: Towards Creation of Multimodal System for Cognition-aware Computing

The third and fourth Chapter discussed on how different signal modalities could be used for the assessment of user cognitive state and their application in the industry. It was discussed how physiological sensors can be used independently, but also in the multimodal interaction, for better understanding of human cognition in naturalistic environments. Moreover, chapter 4 discussed on utilization of MoCap devices for pose estimation, but also for the aim of assessing the information on the mental state of the person.

In this chapter, which is based on the work of Mijović et al. (2015a) that was presented on “Human Computer Interaction International conference (HCII 2015)”, the multimodal system that consist of physiological (EEG, GSR, HR) and motion capture (Kinect and Leap Motion) sensors will be presented. The objective of the system is to synchronously record the operators’ physiological and motion signals during simulated work routine, with the aim of detecting the deviations in the user state, so that appropriate actions could be timely performed once the physiological parameters starts deviating from the optimal conditions. However, this thesis is concerned solely with the post-hoc analysis and investigation of the relationship between these signal modalities. Nevertheless, the real-time estimation of the workers’ cognitive states will be performed in the future studies. Another objective of the multimodal recording is to investigate how different parameters influence the workers cognitive states. These results from post hoc analyses could be used in the workplace design phase and will be presented in Chapter 6 and Chapter 7.

The multimodal system can be considered as a system that is capable of implicit multimodal HCI (so called MMHCI; Jaimes and Sebe, 2007; Mijović et al., 2015a). Traditionally, MMHCI is used with the main aim of investigating the possibility to bring closer computer technologies to the users (Jaimes and Sebe, 2007). However, MMHCI research was mainly concerned with an explicit, rather than implicit interaction. In order to fulfill this gap current thesis is mainly aiming in investigating possibility for employing implicit MMHCI, particularly in industrial environment (As presented in Mijović et al., 2015a). In the following chapters, the term of implicit HCI will firstly be introduced (chapter 5.1). In order to develop the implicit MMHCI system the replicated workplace from industrial partner "Gomma Line" (Kragujevac, Serbia) was used and it will be presented in chapter 5.2. The simulated assembly operation is described in the Section 5.3.1. Since one of the aims of the studies was the investigation of the P300 ERP component, the participants were presented with the psychological tests, which are described in Section 5.3.2. Further, the participants in the study were equipped with the wearable sensors network for physiological recording as presented in Section 5.4.1. and their movements were recorded with the MoCap devices as presented in the Section 5.4.2. Finally in order to synchronously record each of the signal modality, the Lab Streaming Layer (LSL) was used and the overall system architecture will be presented in the Section 5.5.

5.1 Implicit HCI system for Cognition-Aware Computing

As already stated in the introduction section, HF/E investigate how the human interacts with the system. Similarly, the HCI is a cross-disciplinary area of research that deals with design, theory, implementation and evaluation of the way that humans interact with the computer devices (Kim, 2015). Presently the interaction between human and devices is becoming increasingly important for human success in daily life (Schmidt, 2000). Traditionally, HCI was mostly concerned with the explicit interaction, i.e. it was concerned with the interface design (Hartson and Gray, 1992). In explicit interaction the user provides the computerized system with an input, in a certain level of abstraction through a command line, graphical user interface (GUI), gesture or speech input, and expect that the system further process that information and provide certain output (Schmidt, 2000). In that view, explicit HCI technological context casts a view on computers that are regarded as solid-state machines relying on explicit interaction through mouse, keyboard and monitor or in more recent years through speech, gesture and touch screens.

Although users became familiar with the devices that are enabling explicit HCI, they undoubtedly limit the speed and naturalness of HCI (Pavlović et al., 1997). Alternatively, specific challenge for the improvement of existing HCI studies is to bring it closer to the communication patterns of human beings, and hence to create more "natural" interaction. Schmidt (2000) provided a definition of implicit HCI as "*An action performed by the user that is not primarily aimed to interact with a computerized* *system, but which such a system understands as an input*". This definition was preceded by the notion that the most of the interaction between people, and situation in which they are interacting, is implicitly exploited in communication (Schmidt, 2000). This notion clearly outlines that an important part of natural interaction actually depends on implicit interaction. In that direction, the development of small, reliable and affordable mobile sensors opens a whole set of opportunities for natural interaction with computing entity through sensitive workplace environment (Mijović et al., 2016c).

Present thesis investigated the possibility of introduction of the implicit HCI system for monitoring the workers cognitive state, i.e. for cognition-aware computing (Bulling and Zander, 2014) in industry. Cognition-aware computing was recently defined as the computing system that senses and adapts to cognitive aspects of personal context (Bulling and Zander, 2014). The introduction of cognition-aware computing in industry would be beneficial, since the industrial workers that are working in assembly positions, which require performing monotonous repetitive tasks, are susceptible to boredom, mental fatigue and loss of concentration as time progresses (Smith, 1981; Fisherl, 1993). Their activities often require execution of tasks dependent on use of tools and/or operating a machine, and in such a context explicit interaction with computer becomes impractical. Therefore, a new approach for communication is needed that can be introduced through an interaction model that is more natural. Stable foundation in building such interaction model in production workplace should be on different communication modalities that can ensure implicit interaction between worker and workplace, such as movement, voice, psychophysiological signals, etc. In order to reach this goal, a truly unobtrusive sensing environment was created through the introduction of sensitive workplace (Mijović et al., 2015a; Mijović et al., 2016c).

Proposed sensitive workplace consists of unobtrusive MoCap technology and wearable physiological sensors, which both provide the possibility for monitoring the work activities, without interfering with standard work routines of industrial workers (As it will be presented in the following Section). In essence, the proposed approach should provide a continuous and real time monitoring of worker activities in realistic production environment, which could enable timely detection of deviations in the worker's cognitive state. In this way the system could be capable of preventing the operating error, thus decreasing the number of injuries at the workplace and in the same time increasing the productivity and improving an overall workers' well-being. In comparison to existing systems that require workers' adoption to designed workplace, the approach proposed here should enable continuous improvement of the work process according to specific profile of the worker.

The proposed model of the sensitive workplace system, which will rely on novel human-computer interaction system founded on implicit input, is depicted on Figure 5-1. Underlying idea is to use unobtrusive motion tracking sensors to record worker's body movements (BodyMovement), identify gestures (GestureRecognizer) and develop a model of optimal worker movement on a workplace (GestureAnalyser), Figure 5-1. Using structured light technology captivated in the Kinect and Leap Motion devices, it is possible to capture body movements represented with estimated stick figure of body and hand pose estimations retrieved in near real-time. Based on this input it is intended to develop a Gesture recognizer, able to recognize generic gesture patterns on a workplace. Output from this module will feed in to application Gesture analyzer, which is in the development phase, in order to specify models of worker behavior on a specific workplace (Mijović et al., 2015a).

On the other track, physiological signals were acquired, using EEG, GSR and HR sensors to record workers physiological signal (physiological signal), distinguish physiological features (physiological feature extractor) and attempt to detect worker attention state, mental fatigue, vigilance, engagement and emotional state (physiological analyzer), Figure 5-1. All physiological sensors were connected to recording computers via Bluetooth connection, thus the movement artefact that are usually caused by the long wiring were suppressed. Upon data acquisition and processing, it is intended to build a physiological feature extractor and physiological analyzer that should be used for the real-time assessment of the worker's cognitive state. However, these modules are still under development.

Finally, in order to improve the physiological analysis, and reach more stable conclusions on the workers' cognitive state, future research will be conducted to investigate the possibility of including the output from gesture analysis in to physiological analyzer decision-making process (Figure 5-1). Since body movement represents a final result of cognitive effort, establishing correlation between noticed disturbance in worker gestures and mental state of the worker (acquired through his physiological signals) should enable early recognition and prevention of possible mental or physical strain of the worker.

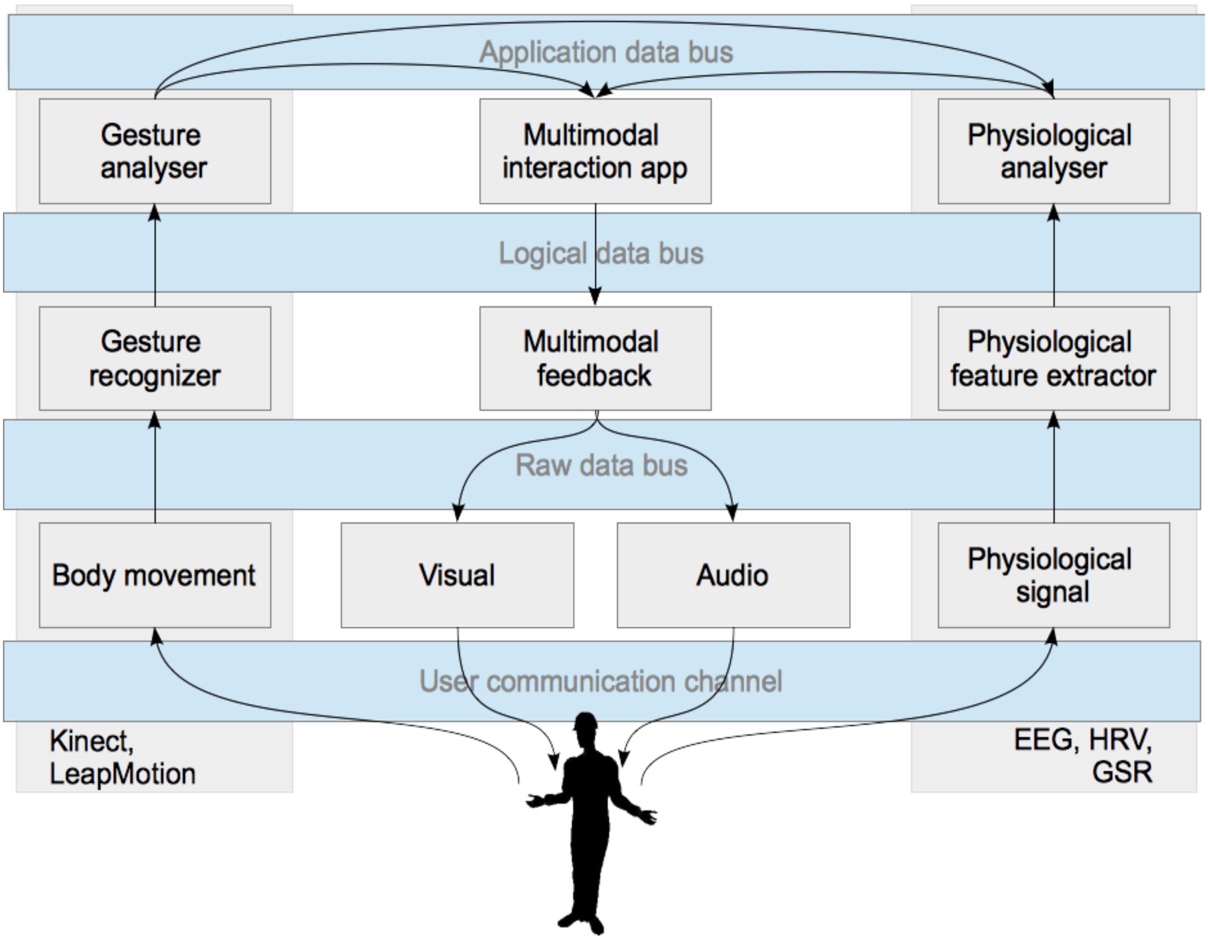


Figure 5-1: Visual Representation of the Multimodal system of the sensitive workplace (Addopted from Mijović et al., 2015a)

5.2 Development of the Sensitive Workplace

For the purpose of investigation the feasibility of the sensitive workplace concept, a full scale workplace replica was created, through consultancy with the car sub-component manufacturing company, at the Department for the production engineering, Faculty of engineering, University of Kragujevac. Since reliable EEG recording still relies on wet electrodes, the on-site industrial EEG recording cannot be performed yet. For that reason, we simulated the production process of the rubber hoses, used in the hydraulic brake systems in automotive industry, in a faithfully replicated workplace (Figure 5-2). In order to create a naturalistic environment all major elements from the real factory settings have been included while preserving respective spatial ratios and mimicking the ambient conditions. Figure 5-2 (left image) depicts the real-life workplace, while the laboratory replica of the workplace is presented on Figure 5-2 (right image).

Figure 5-2: Graphical representation of the real workplace (left image) and the faithful replica of the existing workplace (right image)

The laboratory was air-conditioned and microclimate conditions controlled, keeping the ambient temperature at 24±1°C while the measured relative air humidity value was between 40% and 60%. The luminance at the real workplace was also replicated from the industrial settings, using the same lightning and maintaining the luminance value at 810 lx. Finally, the noise trace was obtained by recording sounds in the vicinity of the original production facility, using cardiodid condenser microphone AT2020USB (Audio-technica, Japan), and this was replayed during the experiments with an SW-HF 5.1 6000 surround multimedia speaker (Genius, Taiwan). The ambient (light, noise) and microclimate (temperature, humidity) condition values were obtained using multifunctional environmental meter device PCE-EM882 (PCE instruments, UK).

Once the replicated workplace was created, the participants in the study were equipped with the wearable physiological sensors network, as depicted on the Figure 5-3. Additionally their movements were recorded using Kinect sensor, which was placed in front and above the participants (as shown at the Figure 5-3) and hand gestures were recorded with the Leap Motion sensor, which was placed in the table, bellow the hands of the participants (Figure 5-3). The detailed description of the sensors used in the study will be provided in the following Section 5.4.

Figure 5-3: Figure 3. Replicated workplace and the sensors placements

5.3 Experimental Task

5.3.1 Simulated Assembly Task

In the production process, an operator carries out the crimping operation in order to join a metal extension to a rubber hose. This single operation, carried out in a sitting position, consists of eight simple steps (actions). Step-by-step simulated operation, carried out by participants in the replicated working environment, is graphically presented in Figure 5-4 and explained in detail further in the text.

During the simulated operation, a single functional modification in the replicated workplace was introduced. In order to elicit the P300 ERP component during the simulated task, an information for the initiation of the simulated operation was presented to the participants in the study in the form of the visual stimuli (explained in detail in the following Section). This was necessary, since the covert cognitive context is usually encrypted in the brain dynamics and in order to isolate and analyze specific cognitive processes, they should firstly be evoked and co-occurring factors should be isolated (Bulling and Zander, 2014). The ecological validity of such a modification lies in the fact that workers on an assembly line would often be provided with the information about the performed task at any given moment (Stiefmeier et al., 2008). Thus the simple stimulus, which informed the operator when to start the assembly operation during the experiment, did not significantly differ from industrial practice. Importantly, the appearance of the visual stimuli was programmed to match the pace of operations and be comparable to the industrial setting.

Simulated operation consists of eight major production steps that can be summarized as follows (Figure 4-4): first, the information to initiate the simulated assembly operation is presented to the participant, in the form of visual stimulus (step 1), upon which he is instructed to instantly initiate the operation by taking the metal part (step 2) and the rubber hose (step 3). Following this, participants should place the metal part on the hose (step 4) and place both inside the crimping machine (step 5). Once the rubber hose and metal part are correctly placed inside the opening, the industrial green lamp lights and it presents a visual cue to the participant, informing him that the part has been correctly placed. Participant then proceed by promptly pressing the pedal, which initiates the improvised machine and replicates the real machines' crimping sound with a duration of 3500 ms (step 6). The real crimping operation that would happen upon pressing the pedal was avoided, preserving its major aspects from operator's perspective - the sound it produces and the cessation of which indicates the end of machine operation, analogously to the real case. Upon completion of the simulated crimping process, the participant removes the component and places it in the box with completed parts (step 7). Finally, following these steps, the participant sits still, waiting for the subsequent stimulus (step 8) indicating the next-in-line operation.

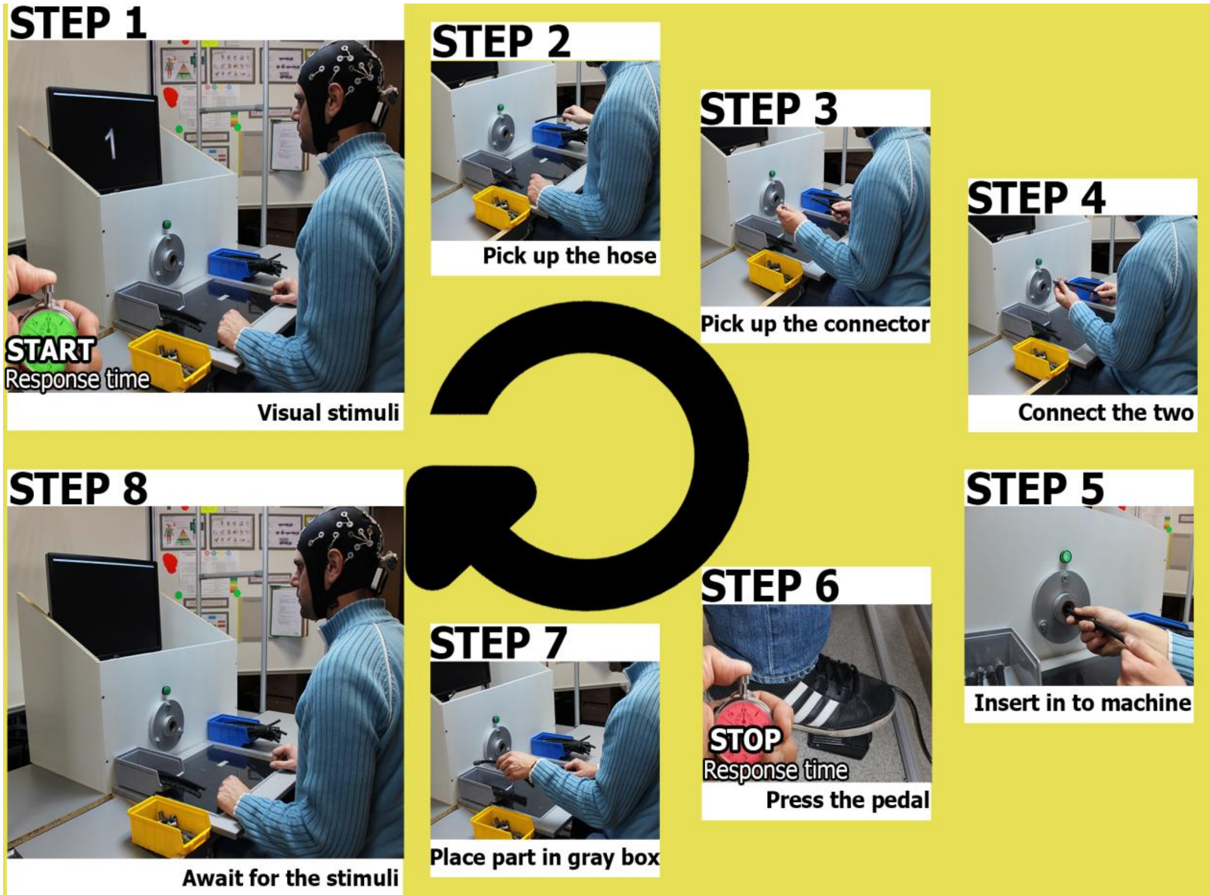


Figure 5-4: Graphical presentation of the step-by-step simulated crimping operation

An important notion is that in presented experimental design, the recording of the reaction times (RTs) could not be measured in the traditional fashion, as the time elapsed between the stimulus presentation and the response by the participants (usually executed with the right index finger). Instead, the RTs here were measured as the time elapsed between the stimulus presentation (step 1) and the pedal press (step 6 from the, also depicted on the Figure 5-4). The pedal used in our study was actually a modified mouse button and it was connected to the recording computer via USB connection. This allows the calculation of RTs, as the difference between timestamps from stimulus presentation (operation initiation) and the beginning of the machine simulated crimping process (As indicated with the chronometer presented on the image of Step 1 and Step 6 from the Figure 5-4).

5.3.2 Experimental Procedure

Experimental procedure was similar for all the experiments and it was described in detail in Mijović et al. (2016a), and this section is based on previously published work (Mijović et al., 2015a; Mijović et al., 2015b; Mijović et al., 2016a; Mijović et al., 2016b).

During the experiments, at least two experimenters were constantly present in the laboratory in order to assure that experimental procedures were strictly followed. The experimenters were seated behind an opaque board (so that participants could not see them during the task) and they observed the participants through a RGB camera that recorded the whole experiment.

Participants were seated in a comfortable chair in front of an improvised workplace including the improvised machine (Figure 5-4). As stated in Section 5.2, in order to extract the ERP component from continuous EEG recording, a functional modification in information presentation was presented to the participants, simultaneously with the simulated assembly process. The participants were subjected to the modified SART, which was named Numbers (Figure 5-5) and Arrows (Figure 5-6) task to prompt initiation of the assembly operation. Both tasks were presented on the 24” screen from a distance of approximately 100 cm. The screen was height adjustable and the center of the screen was set to be level with participants' eyes. Upon presentation of the stimuli on the screen, the participants were instructed to complete the previously explained assembly operation (as graphically presented in Figure 5-4). An important notion here is that in experimental studies presented in the Chapter 6 and 8, participants were completing solely the Numbers task, while in the studies presented in the Chapters 7 and 9, the participants were completing both the Numbers and Arrows task in the balanced order (with a 15 minutes break between the tasks).

As explained in Mijović et al. (2016a), the original SART paradigm consists of consecutively presenting digits from ‘1’ to ‘9’ and participants are required to give the speeded response on all stimuli, with the exception of digit ’3’ (Robertson et al., 1997). The main difference between the original SART and Numbers paradigm is that the digits in Numbers are randomized, with the condition that forbid the appearance of two consecutive digits ‘3’ (‘no-go’ stimulus) and in between two ‘no-go’ conditions at least two ‘go’ conditions must appear. Thus, in our study participants were unaware of the timing when the 'no-go' stimulus would appear. Further, in the original SART paradigm it is requested that participants provide the speeded response with the index finger upon the stimulus presentation. However, this would impede the simulation of the real working operation, since it would require an additional, task un-related operation from participants. Instead, in the Numbers paradigm, participants were instructed to initiate the assembly operation as soon as the visual (target) stimulus appeared on the screen, with whichever hand they felt more comfortable (they could freely choose between step 2 and 3 explained beforehand). Additionally, similarly to Dockree et al. (2007), five randomly allocated digit sizes were presented to increase the demands for processing the numerical value and to minimize the possibility that subjects would set a search template for some perceptual feature of the "no-go" trial (the digit '3'). Digit font sizes were 60, 80, 100, 120 and 140 in Arial text font.

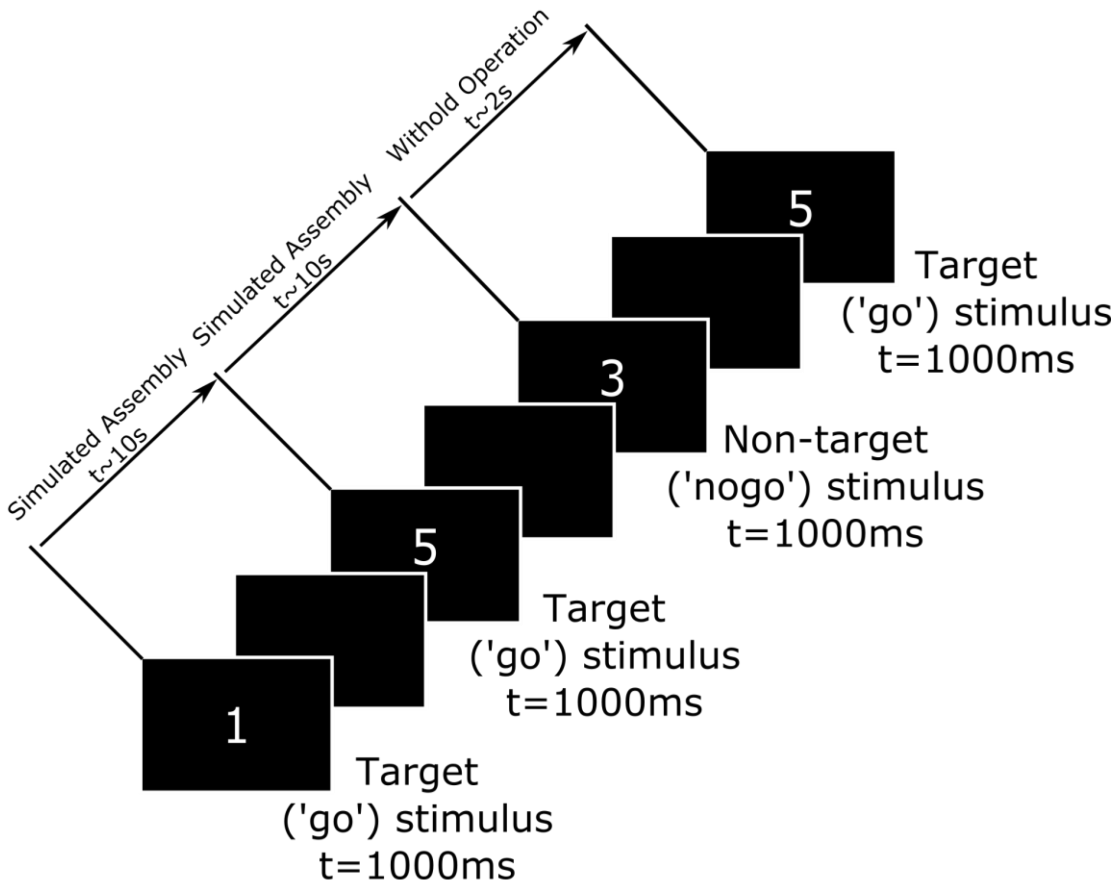


Figure 5-5: Graphical representation of the Numbers task (Adopted from Mijović et al., 2016b)

The Arrows task was presented and explained in Mijović et al. (2016a). The stimuli and procedures for the Arrows task were adopted from the Donkers and Boxtel (2004). The Arrow task is also a "go/no-go" task, where the arrows pointing to the left and right appear on the screen; the white arrows represent the 'go' (target) condition, while the red arrows represent the "no-go" stimulus. Similarly to the Numbers task, the stimuli sequence in Numbers was randomized with the condition that forbade two consecutive appearances of the "no-go" stimuli. The main difference between the Numbers and Arrows tasks was that in the Numbers task participants could freely choose the hand with which they would initiate the assembly operation, while in the Arrows task, participants were required to initiate the action altering the hand according to the direction in which the white arrow on the screen was pointing. In other words, in the Arrows task the participants should initiate the action with the right hand (step 2) if the white arrow was pointing to the right, or with the left hand (step 3) if pointing left.

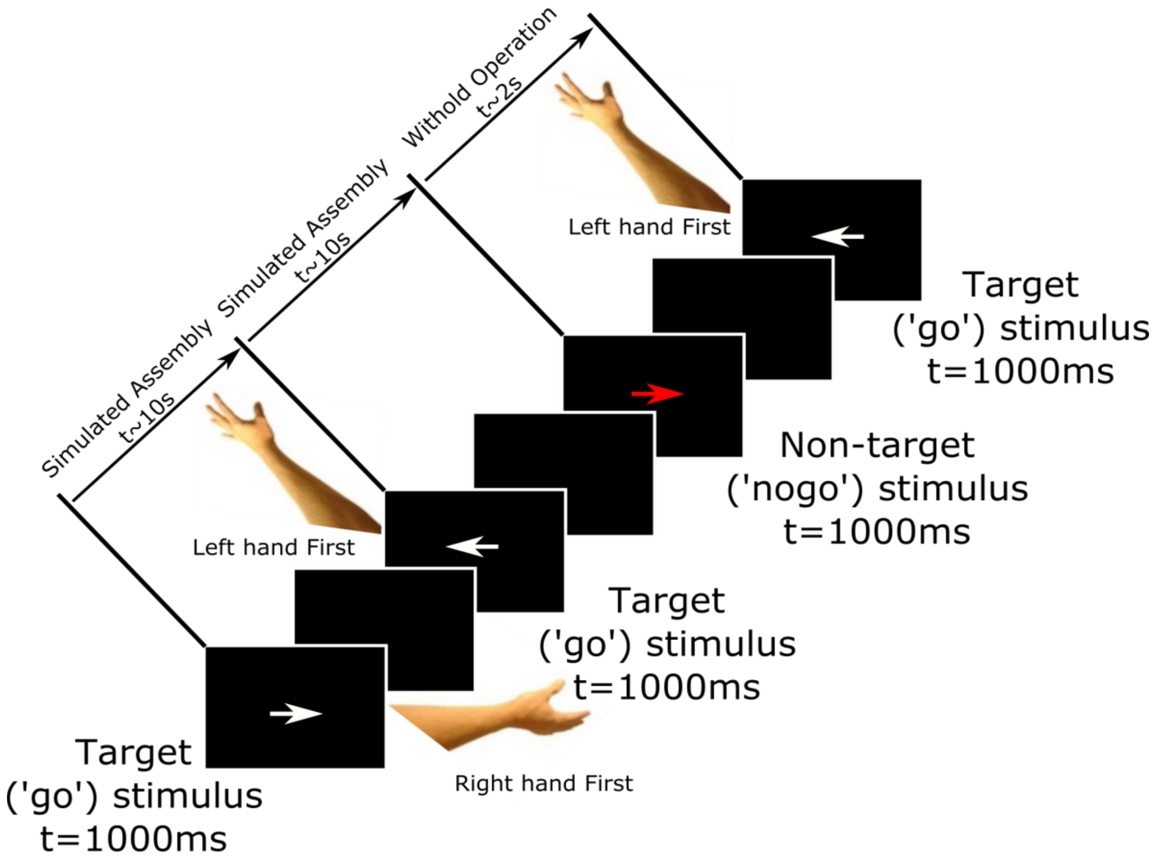


Figure 5-6: Graphical presentation of the Arrows task (Adopted from Mijović et al., 2016b)

Regardless of the task, all the stimuli were presented for 1000ms on a black screen background. Each task consisted of 500 stimuli, where the probability of appearance of 'no-go' stimuli was set on 10% (50 in total), while the 'go' stimuli was presented 450 times. The inter-stimulus interval (ISI) between two consecutive 'go' stimuli was on average 11240ms (STD = 410ms), while between 'no-go' and following 'go' stimuli the average ISI was 3210ms (STD= 120ms). The duration of the each task was around one and a half hours, upon which participants had a 15 minute break, before starting the second task. Thus, the whole experiment lasted around three hours and fifteen minutes.

The task specifications were programmed in Simulation and Neuroscience Application Platform (SNAP, available at https://github.com/sccn/SNAP), developed by the Swartz Center for Computational Neuroscience (SCCN). As explained in Bigdely-Shalmo et al. (2013) and Gramann et al. (2014), SNAP is a python-based experiment control framework that is able to send markers as strings to Lab Streaming Layer (LSL, available at https://code.google.com/p/labstreaminglayer/). The LSL working principle will be explained in detail in Section 5.5.

5.4 Devices used in the study

5.4.1 Physiological Sensors

5.4.1.1 Wireless EEG System SMARTING

EEG data acquisition was performed using state-of-the-art wireless EEG system SMARTING (mBrainTrain, Serbia), with the sampling frequency of 500 Hz and 24-bit data resolution (Figure 5-7a). The small in size and lightweight EEG amplifier (85x51x12mm, 60gr) is tightly connected to a 24-channel electrode cap, (Easycap, Germany) at the occipital site of the participants' head, using an elastic band. The connection between the EEG amplifier and recording computer was obtained using Bluetooth connection (Bluetooth v2.1). The design of the cap-amplifier unit ensured minimal isolated movement of individual electrodes, cables, or the amplifier, which strongly reduced electromagnetic interference and movement artifacts. Further, small dimensions of the recording system provided full mobility and comfort to the participants, as movement constraints were not imposed. The electrode cap contained sintered Ag/AgCl electrodes that are placed based on the international 10-

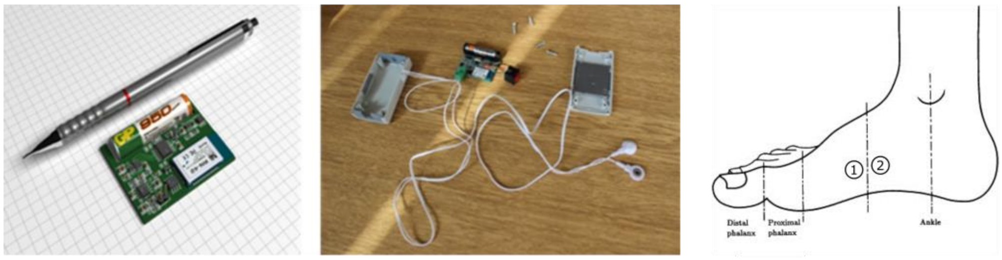
20 System: Fp1, Fp2, Fz, F7, F8, FC1, FC2, Cz, C3, C4, T7, T8, CPz, CP1, CP2, CP5, CP6, TP9, TP10, Pz, P3, P4, O1 and O2 (as presented on the Figure 5-7b). The electrodes were referenced to the FCz and the ground electrode was AFz. Before initiation of the experiments, procedure set imposed that the electrode impedances must be below the 5kΩ value, which was confirmed by the device acquisition software. The device acquisition software is also capable of real-time data streaming through LSL to the lab recorder.

(a) (b)

Figure 5-7: (a) – wearable EEG system SMARTING and its position on the scalp of the recorded person; (b) Electrodes placement

5.4.1.2 Wireless GSR device

The wireless GSR device used in studies was developed at the University of Kragujevac. The GSR device is capable of exosomatic recording, using direct current. Sampling frequency is 40 Hz and the skin conductivity can be measured in the range between 0-120uS. Wireless operation: Bluetooth 2.4GHz, Class 2 is embedded in the device, for the real-time data acquisition on the recording computer, which are further streamed through LSL to the lab recorder. This was enabled through the stand-alone application developed at the department. The GSR device is also small and compatible, with the overall dimensions of 50x40x10 mm. The amplifier is connected to two Biopac-EL507 electrodes that have following specifications: Ag/AgCl contact (11 mm diameter), electrolyte wet liquid gel of 0.5% chloride salt, size 27x36x1.5 mm. The electrodes are placed on inactive (left) foot, in order to reduce the movement artifacts, according to the recommendation from Bouscein (2012). The Device and electrode placements are graphically presented on the Figure 5-8.



(a) (b)

Figure 5-8: (a) - Wireless GSR device; (b) - electrode placement (as depicted by numbers 1 and 2) for exosmotic recording, as recommended by the Bouscein (2012)

5.4.1.3 Wireless Heart Rate Sensor

For the measurement of the Heart Rate, the CNS-SW5 (Canyon, Taiwan) commercial device was used (Figure 5-9a). The Canyon CNS-SW5 consists of chest strap (recording/transmission belt) and a watch, which is capable of receiving the instances of heartbeats' occurrence being transmitted from the chest strap using frequency of 5500Hz. Due to this frequency, the transmitting range is short. In order to increase the transmitting range, the ECG monitor was developed by the Department of production Engineering, University of Kragujevac. The ECG monitor consists of signal receiver (from the transmitting belt) and AM transmitter, which sends impulses on frequency of 433.92 MHz. In this way, the transmitting range can be significantly improved. Finally, the radio receiver sends the radio impulses to the recording computer over the USB connection to the recording computer, and the stand-alone application was developed for the real-time signal acquisition and streaming the data to the lab recorder from the transmitting belt. The radio transmitter and radio receiver are depicted on the Figure 5-10.

(a) (b) (c)

Figure 5-9: (a) - Chest strap; (b) - Positioning the chest strap on the participants' body; (c) – Graphical sketch of the chest strap, with the belonging elements (Adopted from device's user manual)

The chest strap was placed on the participants chests (Figure 5-9b), as recommended by the supplier. Further, the conductive gel was placed on the conductive pads, in order to ensure a good contact with the skin at all times, during the experimental recording (Figure 5-9c). The CNS-SW5 is capable of recording the heart beats in the range between 30 and 240 beats/minute.

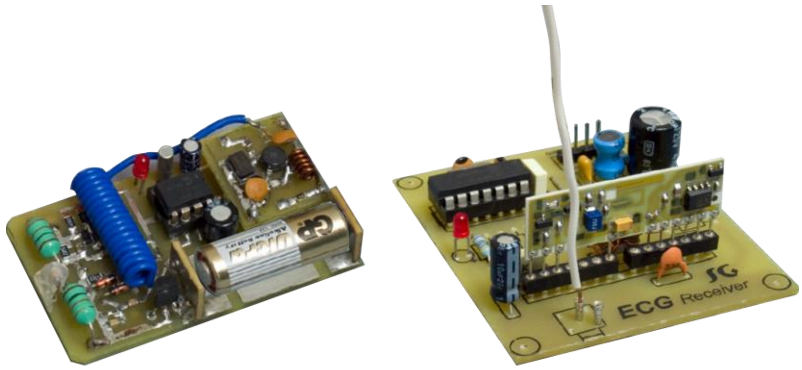


Figure 5-10: Visual representation of the ECG monitor; left image: The receiver from the chest belt that sends the impulses (over transmitter) to the sends the radio receiver (right image), which sends the impulses to the recording computer via USB connection

5.4.2 Motion Capture (MoCap) Devices

5.4.2.1 Kinect

During the simulated assembly operation, the upper-body movements of participants was recorded with Kinect™, which was placed in the replicated workplace, in a position above and in front of participants (as shown in the Figure 5-3). The motion data are interpreted in a form of a stick figure with the 10 key-points seated model that represent the key-points of the upper body (Figure 5-11). The Kinect was connected to the recording computer via USB connection and it is capable of recording with the sampling frequency of 30 frames per second (fps). Other technical characteristics of the Kinect device were already discussed in the Chapter 4.1.1. Real time data acquisition was obtained utilizing a MMK recorder, which was adopted and developed at the Laboratory for Multimedia Communications, Information Technologies (IT) department of Faculty of Organizational Sciences (FON), University of Belgrade. MMK recorder was developed in a way that it can independently record the obtained signals, but also it can stream the signals to the lab recorder over a LAN network (through the LSL).

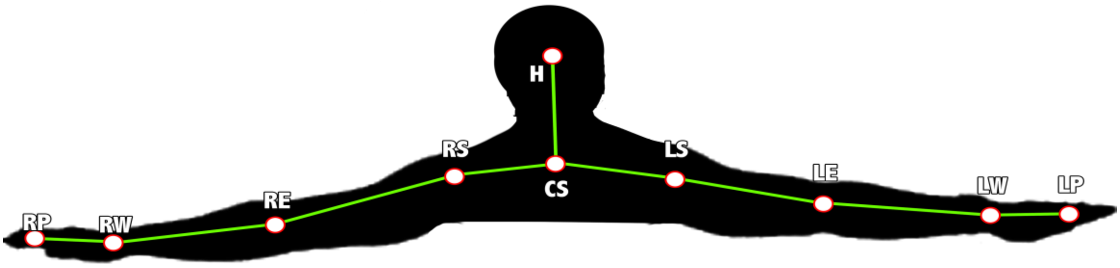


Figure 5-11: Graphical representation of the upper-body seated model and key points: R/L P – Right/Left Palm, R/L W – Right/Left Whist, R/L E – Right/Left Elbow, R/L S – Right/Left Shoulder, H – Head, and CS – Central Shoulder

5.4.2.2 Leap Motion

Leap Motion device was used for estimation of the position of the hand key-points during manipulation of the low loads (rubber hose and metal extensions) at high frequency repetitions of manual assembly tasks. Leap Motion is capable of recording 120 fps images for estimation of the hand key points (as depicted on the Figure 5-12). For that aim, the Leap Motion device was placed in the working table, below the hands of the participants and under a transparent Plexiglas in order to prevent the potential damage to the device. As already discussed in the Section 4.1.2, the Leap Motion sensor is more precise than the Kinect sensor, with the limitation that it can only record objects in close proximity. For the real-time data streaming to the lab recorder, a stand-alone application was developed by Miloš Milovanović, member of Laboratory of Multimedia Communications, FON, University of Belgrade. Other technical characteristics of the Leap Motion Sensor were provided in the Section 4.1.2.

5.5 System Architecture: Data Synchronization

Section 5.4 briefly described the devices, used in the studies conducted for the aim of the presented dissertation. However, all the devices were developed separately and the biggest challenge was to synchronously record the different signal modalities that are heterogeneous in both, type and sampling rate. The synchronization should be precise down to millisecond order, since the ERP extraction requires the millisecond precision. This would not represent a major problem in the case where a common signal reference could be provided for each device. However, this would require that all the devices have separate channel for physical synchronization, which would give rise to movement constraints for the participants in the study, thus limiting the application of the proposed system in the naturalistic environments.

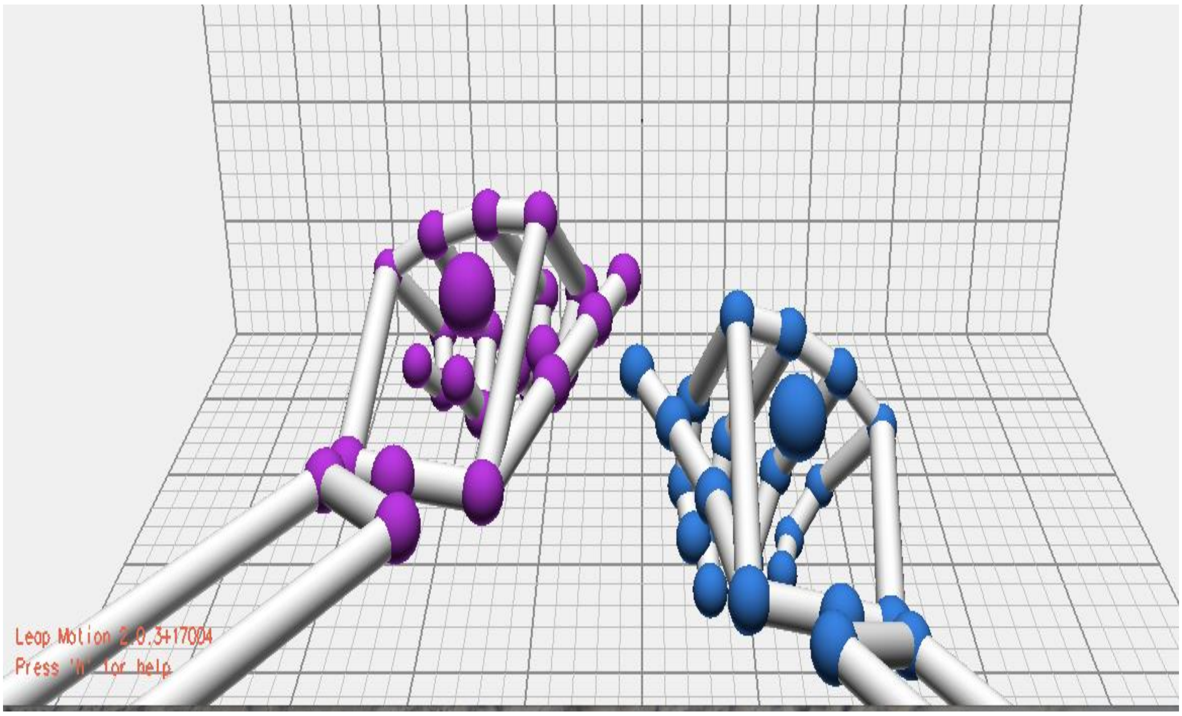


Figure 5-12: Graphical Representation of the projections of the hand key points when recorded with the Leap Motion Controller

In order to overcome this difficulty the SCCN developed the Lab Streaming Layer (LSL) framework (https://code.google.com/p/labstreaminglayer/, accessed on 11/12/2015). As explained in Bigdely-Shalmo et al. (2013) Gramann et al. (2014), LSL is a real-time data collection and distribution system that allows multiple continuous data streams as well as discrete marker timestamps to be acquired simultaneously in the lab recorder, in an eXtensible Data Format (XDF, available at https://code.google.com/p/xdf/, accessed on 11/12/2015). This data collection method provides synchronous, precise recording of multi-channel, multi-stream data that are heterogeneous in both type and sampling rate (Bigdely-Shalmo et al., 2013; Gramann et al., 2014), and is obtained via a local area network (LAN).

LSL is capable of managing data collection in the experiments that involves concurrent recording through different devices. The usage of the LSL drivers requires all the recording computers to be on the same LAN network, since the LSL uses the

User Datagram Protocol (UDP) to collect the data on one or multiple LAN computers (Gramann et al., 2014). Finally, LSL saves the data streams with the time markers that allows joint analysis of synchronous phenomena, as obtained from the diverse sensors modalities (Gramann et al., 2014). This allows the real-time computation of the obtained data streams. Moreover, it is possible to visualize the data in near-real time during acquisition, which allows better experiment control and supervision (Gramann et al., 2014).

As the LSL library is an open-source project, acquisition software for each device was built in such a way to support data streaming over the LSL. Since the LSL was designed to achieve sub-millisecond accuracy (https://code.google.com/p/labstreaminglayer/, accessed on 11/12/2015), it was assumed to be precise enough for synchronizing EEG data with the other signal modalities used in the presented studies.

For synchronously recording all the data streams, a lab recorder that was also developed by SCCN was used. As stated on the webpage of the LSL project, the lab recorder comes together with the LSL and it allows simultaneous recording of all streams on the lab network into a single XDF file. The XDF file format was developed simultaneously with the LSL and it supports all features of the LSL streams.

Apart from the fact that all the devices' drivers were capable of real time streaming the data to lab recorder, the SNAP environment, which was used for running the experimental protocols (described in the Section 4.4), is also capable of sending the precise time stamps of appearing stimuli from both Numbers and Arrows tasks to the lab recorder. SNAP was built on top of the open source Panda3D game engine (www.panda3d.org) and uses Python as its primary scripting language (Gramann et al., 2014). SNAP allows relatively simple, script-level development of complex, interactive experimental paradigms and it can retrieve the signals from various input devices. This feature was used to attach the pedal through an USB port to the recording computer, with the aim of extraction of the behavioral modality of RTs.

The overall system architecture for synchronous recording of all described streams is graphically depicted on Figure 5-13.

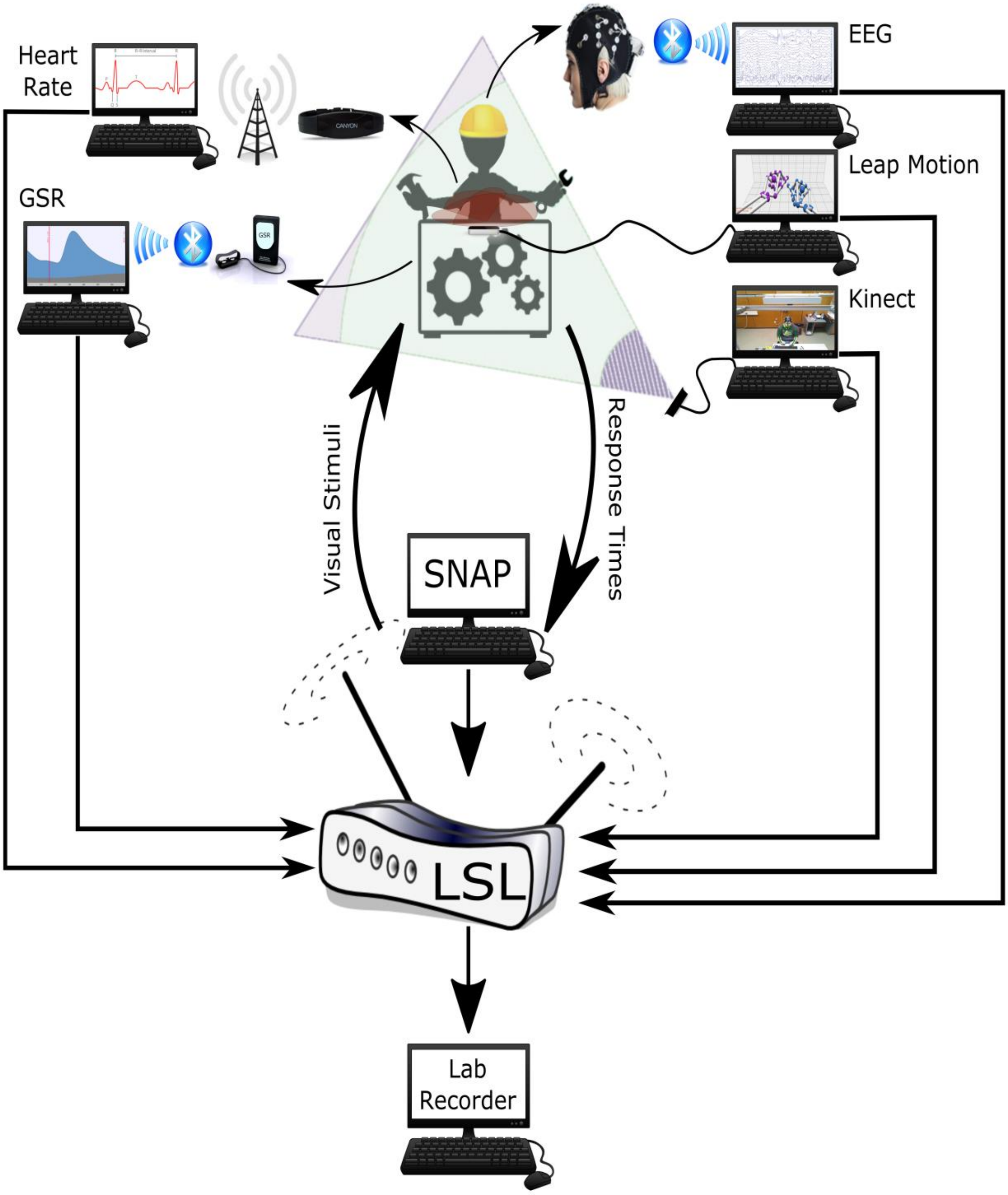


Figure 5-13: Overall system architecture design

6. Do Micro-Breaks Increase the Attention Level of an Assembly Worker? An ERP Study

6.1 Introduction

This Chapter is based on the published work, presented at the International conference "Applied Human Factors and Ergonomics (AHFE 2015)", Mijović et al. (2015b). This study investigated the influence of micro-breaks on the attention of an assembly worker, by utilizing wireless EEG measurements.

Manual assembly work is often highly repetitive and monotonous in nature, as workers are repeatedly completing the same operation up to few thousand times during the work-shift. This kind of work can lead to boredom, attention decline and mental fatigue of the workers (Fisherl, 1993). Moreover, the extended monotonous work is followed by decrease in motivation and morale of the worker that in the long-term leads to mental stress, productivity decline and it can influence the end-product quality. In even worse scenario, the workers' attention decline could lead to error in operating, causing work-related injuries, accidents and material damage (Kletz, 2001).

Majority of existing literature on manual assembly task is concerned with the physical aspects of such a workplaces, rather than mental states of the operators (Rasmussen et al., 1994). This is also reflected in studies of work/rest conditions in the workplace, where major concerns are related to the prevention of work-related musculoskeletal disorders (MSDs) through proposition of various physical exercises in rest periods (Galinsky et al., 2007). However, far less attention has been dedicated to the influence of rest breaks on cognitive state of the workers.

Understanding how the employees recover from work is important area of research in organizational and behavioral psychology (Trougakos and Hidieg, 2009). The influence of work vacations, weekends and end of the day activities breaks on job performance and well-being has been largely documented, while the influence of within the work-day breaks has received far less attention (Trougakos and Hidieg, 2009; Fritz et al., 2013). During the work days, workers spend one-third of the day in the workplace, however they do not spend every moment engaged in the work task, but also short breaks occupy one part of the work-day (Fritz et al., 2013). These breaks from the task can be structured performance-related and the ones relevant for maintaining the workers well-being, such as lunch or rest breaks (Fritz et al., 2013). On the other hand, there are less structured forms of shorter breaks during the work, so called micro-breaks. The studies on micro-breaks suggest that they can be effective in reducing fatigue effects and increase in productivity of the worker (Trougakos and Hidieg, 2009).

Although micro-breaks are frequently proposed as a method of reducing the strain and increasing the task engagement in work with VDU, such as data entry work position (Galinsky et al., 2007; Morris et al., 2008), their effect should be similar if applied in the manual assembly work, as both work position consist of sustained work repetitiveness in static work postures. The importance of micro-breaks was emphasized by OSHA through the following recommendation (OSHA, 2015): “High repetition tasks or jobs that require long periods of static posture may require several, short rest breaks (micro-breaks or rest pauses). During these breaks, users should be encouraged to stand, stretch, and move around. This provides rest and allows the muscles enough time to recover.”

As previously stated, the majority of literature on influence of micro-breaks was mainly concerned with the prevention of work-related MSDs. Another path in studying the micro-breaks was the measurement of workers’ productivity and performance before and after taking a break. However, the main drawback of these studies is that methods for measuring overall performance are unreliable and they are unable to investigate underlying mental processes that are occurring before and after the break period (Parasuraman, 2003). In order to address this problem, the methodologies from the emerging field of neuroergonomics could be employed. As discussed in Chapter 2, the main advantage of neuroergonomics, over classical ergonomics approach, is that it provides precise analytical parameters depending on the work efficiency of individuals, by directly investigating relationship between neural and behavioral activity (Fafrowicz and Marek, 2007). In this way, it is possible to avoid unreliable user state evaluation based on theoretical constructs, which are describing cognitive states of the workers related to the task execution (Fafrowicz and Marek, 2007).

Neuroimaging technique that was used in present neuroergonomics experimental study was wireless EEG. Specific EEG feature of interest in studying attention is the P300 ERP component, since it has been widely documented that the amplitude magnitude of the P300 component is directly related to the level of person's attention (Murata et al., 2005). The P300 component is sometimes bifurcated, containing two sub-components P3a and P3b and although the P300 component is generally related to attentional processing, the mechanisms that generate P3a and P3b subcomponents significantly differ. It has been reported that the P3a component is more related to novelty preference and low-level attentional processes, while P3b component was found to be more related to high-level attentional processing and processing of endogenous aspects of stimuli (Polich, 2007).

In this work the influence of the micro-breaks on the attention level of an assembly worker was investigated, through the analysis of P300 ERP component's amplitude. The study was conducted in faithfully replicated workplace (as presented in Chapter 5, Section 5.2), where participants simulated manual assembly work, explained in Chapter 5, Section 5.3.1. The hypothesis that the higher P300 component, and especially the P3b subcomponent, amplitude would have higher magnitude following the period of micro-break than preceding it, was tested.

6.2 Methods

6.2.1 Participants

Nine healthy subjects, all right-handed males, aged between 19 and 21 years volunteered as participants in the study. Study was restricted to male participants in order to exclude possible inter-gender differences and to replicate the selected job task more faithfully. Participants had no past nor present neurological or psychiatric conditions and were free of medication and psychoactive substances. They were instructed not to take any alcoholic drinks on the day before and the day of participation in the study, as well as not to drink coffee at least three hours prior their participation in the study. All participants had normal or corrected-to-normal vision. They have agreed to participation and signed informed consent after reading the experiment summary. The study was approved by the Ethical committee of the University of Kragujevac.

6.2.2 Experimental Setup

Experimental setup was explained in detail in Chapter 5, Section 5.2

6.2.3 Experimental Procedure

Each of the participants arrived in the laboratory at 9:00 a.m. Upon carefully reading the experiment summary and signing the informed consent for participation in the study, participants started the 15-minute training session in order to get familiar with the task. Finally, EEG cap and amplifier were mounted on the participants' head and the recording started around 9:30 a.m. Participants were seated in the comfortable chair in front of the improvised machine. In this study, solely the Numbers paradigm (explained in the Chapter 5, Section 5.3.2) was used. The Numbers task was presented on the 24" screen from a distance of approximately 100 cm. The screen was height adjustable and the center of the screen was set to be in level with participants' eyes.

6.2.4 ERP processing

EEG analysis was performed offline using EEGLAB (Delorme and Makeig 2004) and MATLAB (Mathworks Inc., Natick, MA). EEG data were first bandpass filtered in the 1-35 Hz range. The EEG signals were then re-referenced to the average of Tp9 and Tp10 electrodes. Further, an extended Infomax Independent Component Analysis (ICA) was used to semi-automatically attenuate contributions from eye blink and (sometimes) muscle artifacts (De Vos et al., 2011; De Vos et al., 2010; Viola et al., 2009).

Upon EEG data pre-processing, ERP epochs were extracted from -200 to 800ms with respect to timestamp values of "go" stimuli preceding and following "no go" stimuli indicated by SNAP software. Baseline values were corrected by subtracting mean values for the period from -200 to 0 ms from the stimuli In the ERP analysis. The identified electrode sites of interest for the ERP analysis in this study were Fz, Cz, CPz and Pz, as the P300 component is usually distributed and is most prominent over the central and parieto-central scalp locations (Picton, 1992). Further, mean grand average (GA) values of the ERPs were extracted and the magnitudes of the P3a (250-350ms window) and P3b (350-500ms window) components were calculated, using the mean amplitude method (Luck 2014). Finally, a repeated measures ANOVA was performed in SPSS, with the aim to compare the amplitude values in the P3a and P3b window, before and after the micro-break period.

6.3 Results

The GA values of ERPs preceding and following the micro-break periods are graphically represented on Figure 6-1. It is notable that the amplitude of the P3b subcomponent had higher magnitude for the trials following the micro-break period (red line), than preceding it (grey line), on all electrode sites. However, this was not obvious in the P3a amplitude window.

P3a analysis (250-350ms): Repeated measures ANOVA with 2 within-subject factors (electrode SITE - Fz, Cz, CPZ and Pz and TIME - before vs. after the micro-break, i.e. 'no-go' trial), revealed a significant effect of SITE ($F(3, 24)= 11.86$, $p<0.01$), but no significant effect of TIME and there was no interaction effect. Amplitudes at Cz and Fz were significantly higher in comparison to the amplitudes at CPz and Pz sites ($p<0.05$).

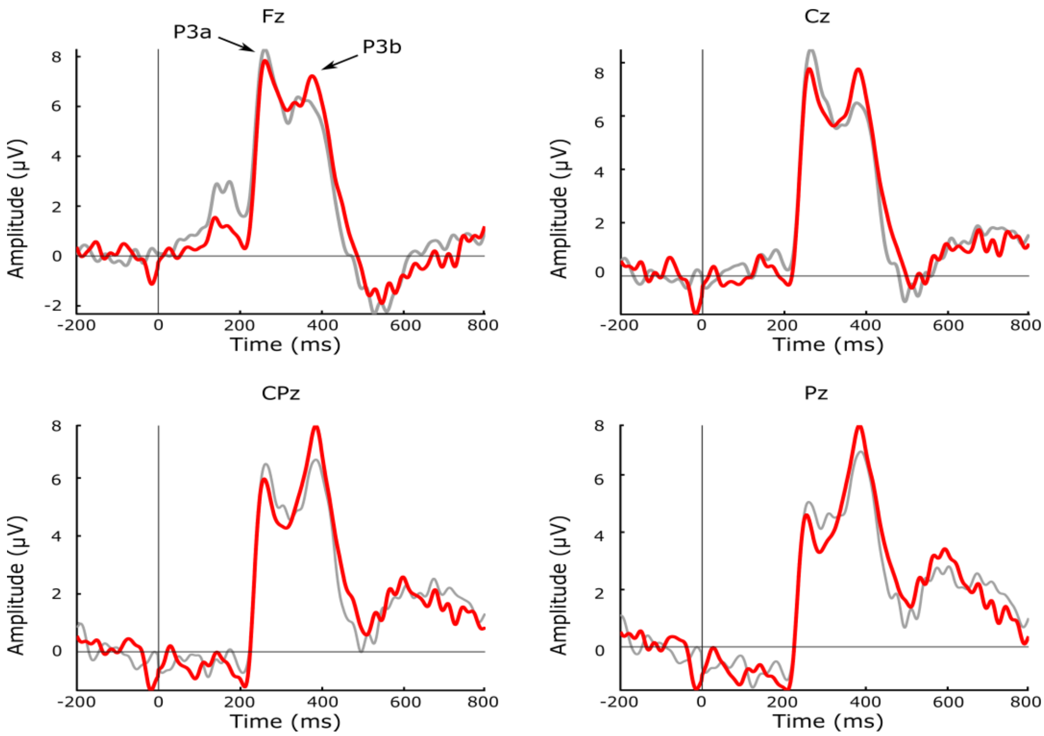


Figure 6-1: ERP waveforms on Fz, Cz, CPz and PZ electrode sites. Red line – GA ERPs following the micro-break period; Grey line – GA ERPs preceding the micro-break period. The P3a and P3b sub-component are depicted on the upper-left image.

P3b analysis (350-500ms): Repeated measures ANOVA with 2 within-subject factors (electrode SITE - Fz, Cz, CPZ and Pz and TIME - before vs. after micro-break, i.e. 'no-go' trial), revealed a significant effect of TIME ($F(1, 24)= 5.43$, $p<0.05$), but there was no significant effect of SITE and the interaction between SITE and TIME was also not significant. The detailed comparisons revealed that the amplitudes at all four sites were higher after the micro-break in comparison to the amplitudes before the break ($p<0.05$), in P3b window (see Figure 6-2).

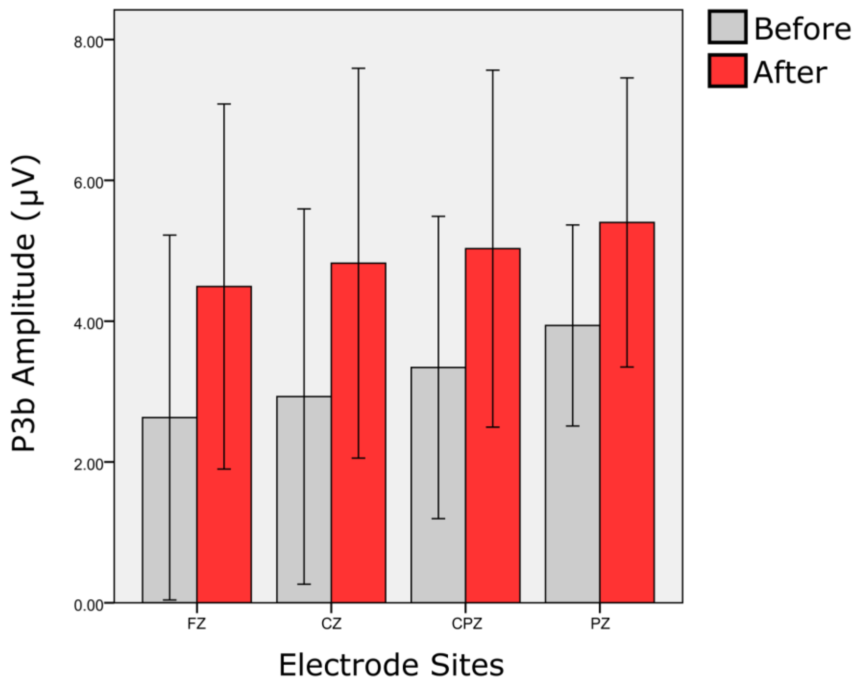


Figure 6-2: Comparisons between the P3b amplitudes before (grey bars) and after (red bars) the micro-break period (p<0.05). Error bars: +/-2 SE

6.4 Discussion

The results of this study indicated that there is a significant difference in the P3b amplitude between the conditions preceding and following the micro-break period, while this was not the case with the amplitude of the P3a sub-component. This finding supports the main hypothesis and confirms that the amplitude of the P3b sub-component, which is related to the higher-level attention processing (Polich, 2007), was affected on all electrode sites and it had higher magnitude following the micro-break period than preceding it. On the other hand, the difference in the amplitudes of the P3a sub-component, which reflects the low-level attention processes (Polich, 2007), before and after the micro-break period did not reach the statistical significance.

Regarding the industrial work organization, one could argue about the timing and the length of the rest periods during the shift. The most common approach of managing the rest periods is that workers are allowed to take one long, lunch break (approximately 30 minutes), and up to two additional break periods of shorter duration (Dababneh et al., 2001). However, it was found that limited rest-break opportunities are significantly related to MSD and that shortcomings in work-rest schedules increase the likelihood of near misses and injury events (Faucett et al., 2007). Another approach, proposed by NIOSH is that workers should be provided with additional 5-minute breaks for each hour working and it was suggested that modified rest break schedules have resulted in significant reductions of these symptoms among workers, while modestly improving the productivity (Dababneh et al., 2001; Faucet et al., 2007). Present study differs from (Dababneh et al., 2001) in a way the participants were provided by the breaks and in total, in this study participants had shorter total-time break period than in (Dababneh et al., 2001). In fact, in our experimental settings participants had 50 micro-break periods (of 5s) during the experiment, which is cumulatively, approximately 3-minute break period for one hour of active engagement to the task. We have shown that higher frequency of short breaks produce the higher attention level of the workers, following the break periods. Therefore, the attention level of the workers could be maintained throughout the workday by including frequent micro-breaks, potentially preventing the workers injuries that are caused by attention decline, while not affecting the productivity of the workers.

Although this study showed that frequent micro-breaks period increases the attention level of workers engaged in assembly tasks, it should be further extended. The future work should include the variation of the length of micro-breaks, with aim to investigate whether the longer breaks would produce higher attention levels. Finally, an optimal micro-break period should be defined with the aim of increasing the attention level of the worker and improve the workers well-being, while enhancing productivity.

6.5 Conclusion

Recently available wireless EEG sensors provided the possibility to examine how the brain process various stimuli in applied environments. Presented study utilized the wireless EEG measurements in simulated assembly task, with the aim of examination whether the frequent micro-breaks periods are influencing the attention level of the assembly workers. The main finding was that the amplitude of P3b ERP sub-component, which is directly related to the high-level attention processing, had higher magnitude following than preceding the micro-break period. The results indicate that the workers on manual assembly line should have frequent short-breaks in order to maintain their attention level during the work-shift. In this way, the attention decline and boredom of the workers could be suppressed, improving the overall assembly workers' well-being. Finally, the introduction of frequent micro-break periods in regular work routine could yield less frequent occurrence of the work-related injuries, which could be caused by the attention decline of the workers.

7. Benefits of Instructed Responding in Manual Assembly Tasks: An ERP Approach

7.1 Introduction

This Chapter is based on the work of Mijovic et al. (2016b). The main notion is that the majority of neuroergonomics studies are focused mainly on investigating the interaction between operators' and automated systems; while far less attention has been dedicated to the investigation of brain processes in more traditional workplaces, such as manual assembly, which are still ubiquitous in industry.

The aim of this paper is the investigation of assemblers' mental states, by utilizing ERPs in a realistically replicated workplace. Neuroergonomics governs that overt performance measurements are unreliable (Parasaruman, 2003), since they do not provide the possibility for timely investigation of the underlying covert cognitive processes during everyday tasks. To get better insights into the time course of the underlying attention processes engaged in manual assembly operation, we selected two tasks in which we triggered goal-directed actions of workers by presenting them either digits (in one) or arrows (in the other task) prior initiating the operation. In this way we wanted to elicit the P300 ERP component (Also called P3 or P3b), which is represented by the positive ERP voltage deflection that usually appears between 300 and 500ms after appearance of the task-relevant stimuli (Verleger et al., 2005; Polich and Kok 1995). The P300 component is often used to identify the depth of cognitive information processing and its amplitude and latency are considered to be related to the human attention level (De Vos et al. 2014; Johnson 1998; Polich 2007).

The P300 complex is the most prominent over the midline scalp sites (Polich 2007) and it is among the most prominent ERP components (Verleger et al., 2014), thus being one of the most studied components of the human ERP. However, it is still argued about what brain functions the P300 component represents (briefly summarized in the Verleger et al., 2014). One influential view is that the P300 component can be explained through the context updating hypothesis that was proposed by Donchin (1981) and which governs that the P3 reflects the updating of working memory that is related with task-relevant and unexpected events. The context updating theory assumes that the mental process that elicit the P3 component reflects a revision of the model of the environment rather than it serves for organizing response to the eliciting stimulus (Verleger et al., 2005). In other words, it is assumed that following an initial sensory processing, an attention-related process evaluates the presentation of the previous event in working memory and if a new stimulus in a train of standard stimuli is detected, the attention-related process updates, which is followed by production of the P300 component (Polich, 2007). However, we have also witnessed arguments against the context updating theory (Verleger et al., 2005; Verleger et al., 2014). In fact, Verleger et al. (2005) proposed a new hypothesis in which they stated that the P300 component is related both to stimuli processing and organizing the response. In order to prove this hypothesis, Verleger et al. (2005) compared the P3 amplitude in stimulus- and response-locked ERPs and they found that both P3 amplitudes were comparable. Therefore, it was confirmed that P300 amplitude does not reflects just the simple reaction to stimulus change. Rather, P300 reflects a process that mediates between perceptual analysis and response (Verleger et al., 2005), i.e. it is related to the organization of the response and it depends on the stimulus-response links (Verleger et al., 2014).

Based on these findings, the present study investigated whether and how the neural correlates of goal-directed actions would differ if the operators were requested to initiate the simulated assembly operation spontaneously (upon seeing a digit), as opposed to the condition where participants were instructed with which hand to commence the operation (upon seeing an arrow). In the spontaneous condition (the Numbers task), we adopted the stimuli from the original SART paradigm that is a simple 'go/no-go' task, which consists of consecutively presenting digits from '1' to '9' and participants are required to give the speeded response on all stimuli, with the exception of digit '3' (Robertson et al., 1997). The main difference between the original SART and the Numbers paradigm (used in our study) is that the digits in Numbers are randomized. Further, in the original SART paradigm it is requested that participants provide the speeded response with the index finger upon the stimulus presentation. However, this would impede the simulation of the real working operation, since it would require an additional, task unrelated operation from participants. Instead, in the Numbers paradigm, participants were instructed to initiate the assembly operation as soon as the visual (target) stimulus appeared on the screen, with whichever hand they felt more comfortable (the assembly operation is explained in detail in Section 2.3). For the instructed responding (the Arrows) task, we adopted the stimuli and procedures from the Donkers and Boxtel (2004). The Arrows task is essentially the choice reaction task, where the arrows pointing to the left and right appear on the screen; the white arrows represent the target ('go') condition, while the red arrows represent the 'no-go' stimulus. The main difference between the Numbers and Arrows tasks was that in the Numbers task participants could freely choose the hand with which they would initiate the assembly operation, while in the Arrows task, participants were instructed to commence each operation with the hand that corresponds to the direction in which the white arrow on the screen was pointing. An important notion is not only the simple stimuli difference between the tasks was varied (digit vs. arrow), but also the informational value of those stimuli: the Arrows task arguably requires stimulus-response mapping, which in turn requires more cognitive evaluation, which consequently induces higher-level attentional processing than in simple 'go/no-go' task. In both, the task specific and spontaneous condition, the visual stimuli (digits and arrows) appeared in the center of the screen that was placed in front of the participants.

We expected attention, when assessed through the P300 amplitude, to be more enhanced in the instructed responding (Arrows) task, compared to the one where participants could initiate the assembly operation upon seeing the task unspecific cue (Numbers task). Further, we wanted to investigate whether the difference in the task condition would also influence the reaction times (RTs), as the performance of the participant's is also important, since this study simulates the naturalistic assembly task replicated from the industry. In other words, we wanted to investigate whether the participants would be slower in the case when they are instructed with which hand hey should start the assembly operation, as compared to the condition when they can spontaneously initiate the assembly operation with whichever hand they prefer.

7.2 Methods

7.2.1 Participants

Seventeen healthy subjects, from which one was left-handed, aged between 19 and 21 years volunteered as participants in the study. Due to abnormalities in the recording three subjects were excluded from further analysis, leaving fourteen participants. The study was restricted to male participants both to exclude possible inter-gender differences and to replicate the selected job task more faithfully, since in company that supported this research only male population occupy the specific workplace under study. Participants did not report any past or present neurological or psychiatric conditions and were free of medication and psychoactive substances. They were instructed not to take any alcoholic drinks prior to, nor on the day of participation in the study. All participants had normal or corrected-to-normal vision. They agreed to participate in the study and signed informed consent after reading the experiment summary in accordance with the Declaration of Helsinki. The Ethical Committee of the University of Kragujevac approved the study and procedures for the participants.

7.2.2 Experimental Setup

Experimental setup was explained in detail in Chapter 4, Section 4.2

7.2.3 Experimental Procedure

Each of the participants arrived in the laboratory at 9:00 a.m. Upon carefully reading the experiment summary and signing the informed consent for participation in the study, participants started the 15-minute training session in order to get familiar with the task. Finally, EEG cap and amplifier were mounted on the participants' head and the recording started around 9:30 a.m. Participants were seated in the comfortable chair in front of the improvised machine. In this study, both, the Numbers and the Arrows paradigm (explained in the Chapter 4, Section 4.3.2) were used in balanced order, and the participants had a 15-minutes break between the tasks. Both tasks were presented on the 24" screen from a distance of approximately 100 cm. The screen was height adjustable and the center of the screen was set to be in level with participants' eyes.

7.2.4 ERP Processing

EEG signal processing was performed offline using EEGLAB (Delorme and Makeig, 2004) and MATLAB (Mathworks Inc., Natick, MA). EEG data were first bandpass filtered in the 1-35 Hz range, following which the signals were re-referenced to the average of the mastoid channels (Tp9 and Tp10). Further, an extended infomax

Independent Component Analysis (ICA) was used to semi-automatically attenuate contributions from eye blink and (sometimes) muscle artifacts (as explained in Viola et al., 2009; De Vos et al., 2010; De Vos et al., 2011). After this data preprocessing, ERP epochs were extracted from -200 to 800 ms with respect to timestamp values of 'go' and 'no-go' stimuli indicated by the SNAP software. Baseline values were corrected by subtracting mean values for the period from -200 to 0 ms from the stimuli. The identified electrode sites of interest for the ERP analysis in this study were Fz, Cz, CPz and Pz.

Following the ERP extraction, the mean grand average (GA) ERPs were calculated. For the 'go' condition, the GA ERP was calculated for the ERPs that preceded the 'no-go' condition. The P300 amplitude was calculated for both 'go' and 'no-go' conditions and for each experimental condition, using mean amplitude measure (Luck, 2014) in the time window from 230 to 450 ms, with regard to the time stamps of the stimuli. Finally, the statistical analysis on the obtained results was carried out.

7.2.5 Reaction Times

As already stated in Section 5.2, the experimental design did not allow subjects to react with the button press upon seeing the visual 'go' stimulus. Therefore, the reaction time (RT) could not be measured in the traditional fashion, as the time elapsed between the stimulus presentation and the response by the participants (usually executed with the right index finger). Instead, the RTs here were measured as the time elapsed between the stimulus presentation (step 1) and the pedal press (step 6 from the 5.3.1 section, also depicted on the Figure 5-4). The pedal used in the study was actually a modified mouse button and it was connected to the recording computer via USB connection. As LSL is capable of real-time recording of the timestamps of the mouse button press, it enabled us to gather precise information regarding the time when pedal was pressed. This allows the calculation of RTs, as the difference between timestamps from stimulus presentation (operation initiation) and the beginning of the machine simulated crimping process.

7.2.6 Error Processing

The errors of omission were classified as the errors when participants omitted the appearance of ‘go’ stimuli. The commission errors processing was challenging, since our task did not require speeded button press and therefore, the errors of commission were difficult to interpret. In fact, the most obvious classification of commission errors would be when participants completely execute the simulated operation upon appearance of the ‘no-go’ stimuli. However, it is important to note that participants sometimes made slight movements upon appearance of the ‘no-go’ stimuli (in sense that they showed intention to initiate the action) and then they inhibited the response upon realization that it was a ‘no-go’ stimuli. This kind of errors we classified as the near-misses. The quantification of the near misses and commission errors was conducted by the experimenters in the room, but also in an off-line analysis by replaying the videos recorded with the RGB camera during the experiment.

7.2.7 Statistical Analysis

The statistical analysis was performed using IBM SPSS software. The ERPs used for statistical analysis included all ERPs related to the “no-go” condition and 50 ERPs related to “go” preceding the “no-go” condition. The 4x2x2x2x2 repeated measures ANOVA was conducted with SITE (Fz, Cz, CPz and Pz) and Period of measurement (first vs second half) as within subject factors and Task (Arrow vs SART), ‘go/no-go’ and Order of presentation (first vs second) as between subject factors, respectively. Additionally, the 2x2x2 ANOVA comparing reaction times (RTs) across Period of measurement (first vs second half) as within subject factors and Task (Arrow vs Numbers) and Order of presentation (first vs second) was conducted. Finally, the 2x2x2 ANOVA was performed, comparing commission errors and near misses across Period of measurement (first vs second half) as within subject factors and Task (Arrow vs Numbers) and Order of presentation (first vs second). Greenhouse-Geissser corrections (FG) were applied where necessary.

7.3 Results

7.3.1 ERP Results

The GA ERPs for each task (Arrows and Numbers), each condition ('go/no-go') and each electrode site under study (Fz, Cz, CPz and Pz) are depicted on Figure 7-1.

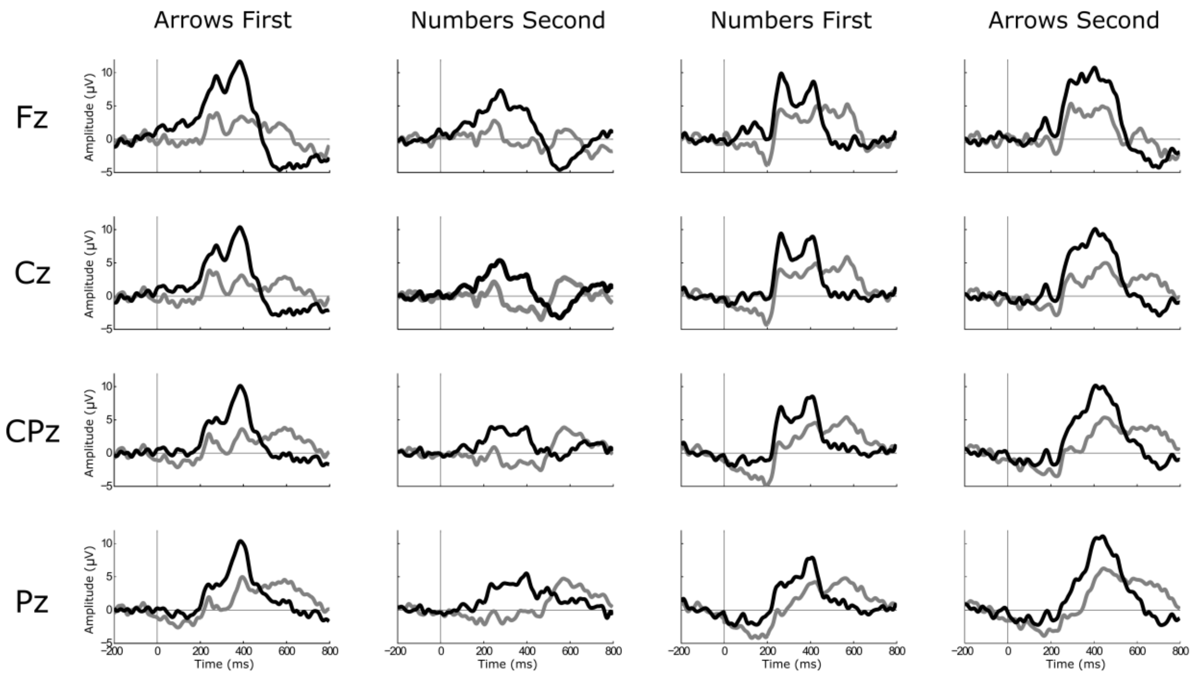


Figure 7-1: Graphical representation of the GA ERPs for each task and each electrode location under study. The black line represents the 'go' condition, while the grey line depicts the GA ERPs for the 'no-go' condition.

The ERPs differed depending on the condition (Go/No-Go: $F(1,96)=25.74$, $p<.000$, $\eta=0.21$), the task (Task: $F(1, 96)=13.43$, $p<.000$, $\eta=.123$), the order of presentation (Order of presentation: $F(1,96)=10.75$, $p<.001$, $\eta=.10$) and across the scalp (SITE: $F(3,94)=11.41$, $p<.000$, $\eta=0.11$). Namely, the P300 amplitudes elicited for 'go' trials were higher than for 'no-go' trials (M =5.73, sd = 4.19; M =2.25, sd = 3.85, respectively). Further, the Arrow task produced higher amplitudes in comparison to Numbers (M =5.24, sd = 4.33; M =2.73, sd =4.07, respectively). The P300 amplitudes elicited with regard to the Order of presentation demonstrated higher amplitudes for whichever task was presented first in comparison to second task (M =5.11, sd = 4.28; M =2.86, sd = 4.19, respectively). Finally, amplitudes elicited at Pz were significantly higher than the amplitudes at the other three sites and amplitudes at CPz site were higher than at Cz and Fz sites at the $p<.05$ level. All the other comparisons were significant in the same direction apart from the Fz-Cz difference.

Figure 7-2 depicts the GA ERPs elicited over all four electrode sites under study for the 'go' condition.

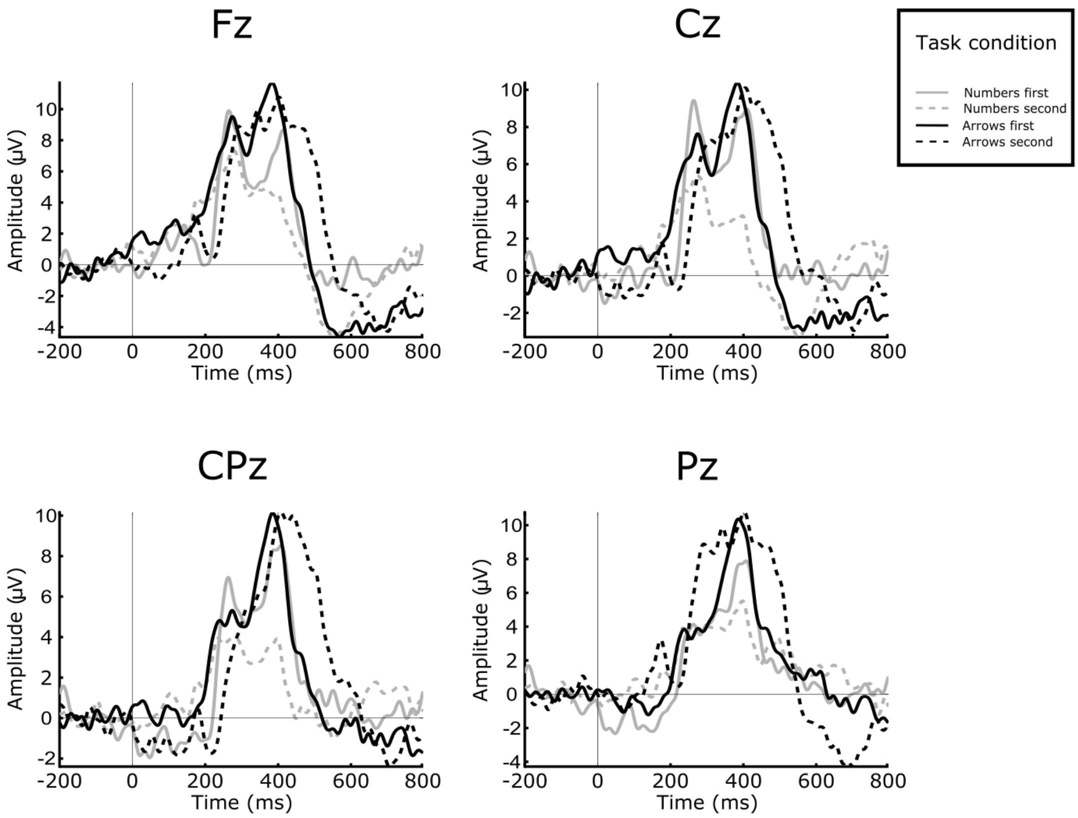


Figure 7-2: The GA ERPs elicited for 'go' condition in all four experimental conditions. ERPs elicited for The Numbers task are represented with the grey color, while the ERPs elicited in the Arrows task are depicted with the black color. The full line represents that the task was presented as a first task and the dashed line if the task was presented as second task.

Besides these main effects, we observed a significant two-way interaction effect between SITE and Order of presentation ($F(3,94)=5.49$, $p=.014$, $\eta=.05$), a significant two-way interaction effect between Task and Order of presentation ($F(3,94)=9.4$, $p=.003$, $\eta=.09$), as well as a three-way interaction between SITE, Task and Order of presentation ($F(3,94)=6.78$, $p<.006$, $\eta=0.07$). The amplitudes were smaller for the Numbers task only when it was presented as a second task and this was true at Cz, CPz and Pz, but not for the Fz electrode (all post-comparisons were significant at $p<.05$).

The P300 amplitude differences for all four sites and depending on the task representation order are presented in Figure 7-3.

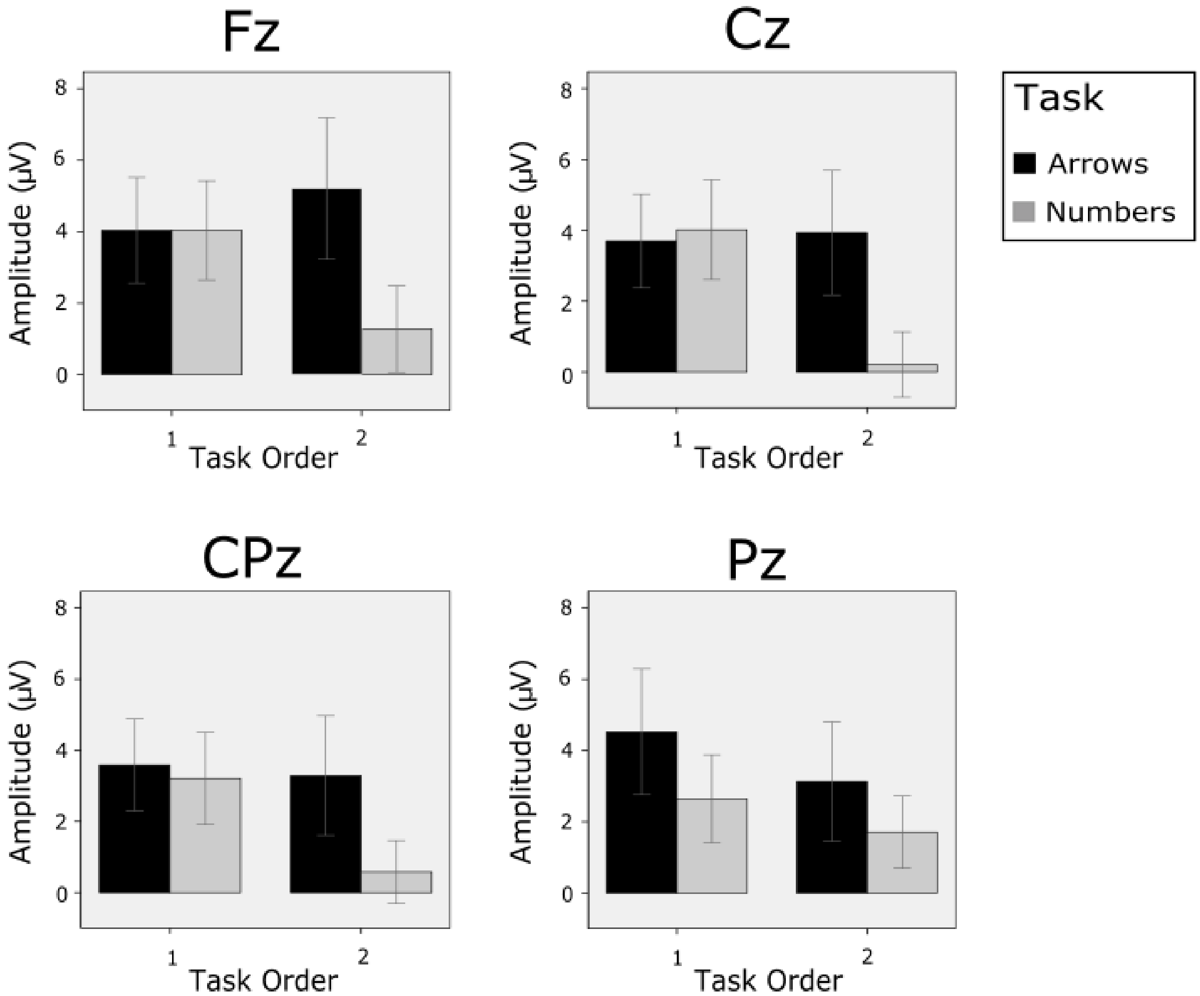


Figure 7-3: The amplitude values for all four-electrode sites and for all experimental conditions. The black color depicts the Arrows task, while the Numbers task is represented with the grey color.

7.3.2 Reaction Times Results

The 2x2x2 ANOVA comparing reaction times (RTs) across Period of measurement (first vs second half) as within subject factors and Task (Arrow vs SART) and Order of presentation (first vs second) revealed neither significant main effects, nor interaction effects.

7.3.3 Errors

The participants did not make any omission errors. Regarding commission errors, across all the participants and all the experimental conditions, we observed only seven errors. Statistical analysis revealed neither main effects nor interactions in this case. However, regarding near-misses, the ANOVA revealed only a significant effect of task ($f(1,94) = 17.26$, $p < .01$) with the participants making more near-misses in Numbers compared to the Arrows task.

7.4 Discussion

The present study investigated whether operators' attention is enhanced when they are instructed with which hand to initiate the manual assembly operation, as compared to spontaneous and free choice of preferred hand. The attention was assessed through the P300 amplitude, as it is widely accepted that the P300 amplitude is positively related to the human level of attention (Ford et al., 1994; Polich 2007; De Vos et al., 2014). For this aim we simulated a manual assembly operation, where we provided the participants with two distinct psychological tasks (Numbers and Arrows) simultaneously with the simulated operation.

The P300 components' amplitude was significantly higher in magnitude for the frequent 'go' (target), than for the infrequent 'no-go' condition (as presented on the Figure 3). This finding is in contrast to the majority of previously reported studies where an infrequent target condition elicits a higher magnitude of the P300 amplitude, since the participants are usually required to note the occurrence of infrequent targets by button press or by silent counting (Struber and Polich, 2002). On the other hand, in our task target stimuli were the frequent ones, as the continuity of operation in manual assembly is essential, while the participants were instructed just to sit still and with no actions during the infrequent 'no-go' condition. As such, it is not surprising that the lower magnitude of the P300 amplitude were elicited in infrequent non-target condition, as passive stimulus processing induces smaller P300 amplitudes than active tasks (Polich 2007). This was also supported by the results from the study of Potts et al. (2001), where they reported that the P300 amplitude was larger in frequent 'go' condition as compared to rare non-target condition in the task where the ratio between 'go' and 'no-go' condition was 80/20.

Moreover, it was found that the inter-stimulus interval (ISI) between target stimuli influences the P300 amplitude, in sense that short ISI lead to decrease in amplitude, while relatively long ISIs elicit the higher P300 amplitude, which is the case even in the single-stimulus paradigm (Struber and Polich 2002; Polich 2007). This was the case also in our study, since the ISI was relatively long (approximately 11s) and we believe that it was suitable for eliciting the P300 amplitude even in the frequent target condition.

The main finding of the present study is that the P300 amplitude was conclusively higher in magnitude when participants were instructed with which hand to initiate the simulated assembly operation, as compared to the case when participants could freely choose the preferred hand for the operation initiation. This may not be surprising, since in the choice reaction task (Arrows) participants were subjected to slightly higher demands of the incoming stimuli evaluation, as they were un-aware of the direction in which the white arrow stimuli would point. On the other hand, the digit stimulus carries considerably lower information, as participants are required just to make distinction whether it is a 'go' or 'no-go' stimuli and to perform their action accordingly, i.e. the participants may stop evaluating the content of the stimuli after some time. Therefore, the response selection requirements during the Arrows task are substantially higher than in Numbers task, which may lead to increased P300 amplitude in condition which required instructed responding of the participants (Verleger et al., 2005; Verleger et al., 2014). Interestingly, even though it was expected that the RTs could differ between the two tasks, this was not the case. The number of commission errors was relatively low and it did not differ between the tasks. However, there was significantly higher amount of near-misses in the Numbers than in the Arrows task. The fact that there was larger number of near-misses in the Numbers task may be expected, as the Arrows task imposes a higher workload to the participants, due to the higher response selection requirements, and as it was previously reported, the errors and mental workload are related according to the U-shaped curve (Desmond and Hoyes, 1996). From all discussed above, it may be proposed that the workers on repetitive and monotonous assembly task should not receive information solely on whether they should initiate the operation or not, but it should be beneficial if they would receive information that carries slightly higher cognitive demands. In fact, the task that consisted of the stimuli with the higher cognitive demands induced the higher P300 amplitude, which may be related to the attention of the worker for the task in hand. Another important notion is that the difference between the task conditions was not visible in the measured RTs, which may constitute one of the important findings of the present study: that the overt performance based measures in a naturalistic environment are not accurate enough, which is in line with one of the main postulate of the Neuroergonomics (Parasuraman 2003). This study supports the notion of the Parasuraman (2003) that the measurement of covert cognitive processes should be adopted in HF/E studies.

Although we showed that the Arrows task produced a higher P300 amplitude than the Numbers task, one could argue about the selection of the tasks, as the stimuli type between task conditions significantly differ (digits vs. arrows). The main reason for not investigating the difference between instructed and non-instructed condition with the same type of stimuli was the avoidance of the interference effect (Pashler 1994). In fact, if only stimuli from Numbers task were used and dedicated the directions to specific digits in hand instructing task (e.g. odd numbers means left and even numbers right hand first), it would be highly likely that the memory would strongly influence the attention processing. On the other hand, if we only used the Arrows stimuli type, the undesired bias would be included in the condition when participants could initiate the operation with their preferred hand. An additional concern is whether the two distinct psychological tests trigger different attentional resources, given that they are composed of different stimulus types and that the Arrows task alternates the response hand, while in the Numbers task participants could respond with whichever hand they preferred. The answer to this doubt could be found in premotor theory of attention (Rizzolatiet al., 1994), which governs that the attention orienting processes are triggered during unimanual response preparation and that the orienting processes are assumed to be equivalent to the processes elicited during instructed endogenous shifts of spatial attention (Eimler et al., 2005). Moreover, Ranzini et al. (2009) also used the tasks with Arabic digits and Arrows and they demonstrated that processes evoked by these cues are alike and that the volitional and non-volitional attentional shifts rely on the same fronto-parietal brain networks. Thus, both Numbers and Arrows tasks should evoke the same cognitive resources of attention, which gives the legitimacy to the choice of the tasks used in this study.

Another interesting finding from this study could be implemented in job rotation strategy. Job rotations in assembly lines are often proposed as method for reducing the monotony of the task, thus keeping the workers more focused (Michalos et al., 2010b). In fact we found that the lowest P300 amplitude values were obtained when the numbers (less demanding task) was presented as a second task, i.e. the data revealed that if a less demanding task follows a more demanding task, the participants' attention was lowered. Thus, we propose that job rotations on assembly tasks should be organized in such a way to avoid that the more demanding task is followed by the task which is more monotonous in nature. However, this notion should be investigated thoroughly in future studies.

One of the limitations of the present study is that it was conducted in a simulated working environment, instead of a real factory setting. The main reason for this was usage of the wet-electrode EEG recording system, which is still uncomfortable for application in actual industrial environments. Nevertheless, we replicated both the spatial dimensions and ambient conditions and performed the wearable EEG study, demonstrating its applicability for the investigation of covert cognitive processes in naturalistic environments for HF/E studies. Another limitation is that, simultaneously with the simulated operation, we used two distinct psychological tests, with the aim of eliciting the P300 ERP component. Although it could be argued that psychological tests could interfere with the simulated operation, an important notion is that the assembly workers should be provided with timely information regarding the performed operation (Stork and Schubo 2010). Therefore, we believe that this modification did not significantly differ from the actual assembly operation in industrial environments. Moreover, in naturalistic settings it is usually hard to isolate and analyze the specific cognitive process, since they should first be evoked and co-occurring cognitive factors should be isolated (Bulling and Zander 2014). Thus, this modification in the information presentation to the participants was necessary in order to elicit the anticipated P300 ERP component during the simulated assembly operation. Unfortunately, the present study is unable to compare brain responses between self-paced (as in this specific workplace) and externally paced work routines that we used in our study. This issue should be addressed in future studies.

The present study demonstrated that wearable EEG recording could be beneficial for task design in HF/E studies. Future studies should investigate whether the reported findings also hold for similar job positions, which are monotonous and repetitive in nature but require continuous focus of the worker on the industrial task (e.g. quality control tasks). Although the present study utilized wearable EEG in a faithfully replicated workplace environment, it seems that it is just a matter of time until EEG systems will be willingly accepted for everyday use (Van Erp et al., 2012; Mihajlović et al., 2015). This could even lead to the application of passive brain-computer interfaces, which could be used for real-time assessment of the cognitive user states in industrial environments (Zander and Kothe, 2011). Nevertheless, the fact that it is nowadays possible to investigate brain dynamics during natural movements (without imposing movements constraints) of the recorded individual brings us a step closer to the guiding principle of the neuroergonomics, that is, to investigate how the brain carries out the complex tasks of everyday life and not just simplified and artificial tasks in the laboratory settings (Parasuraman and Rizzo, 2006).

7.5 Conclusion

Comparing monotonous ('go/no-go') Numbers task to the choice-reaction (Arrows) task, which instructs the participants with which hand to initiate the assembly operation, we found that the latter was more suitable to preserve participants' attention during the externally paced assembly task. This finding was achieved through investigation of the ERP waveform, where it was found that the P300 amplitude, which is related to the level of attention, was enhanced in the task that instructed the participants with which hand to initiate the simulated assembly operation. Regardless of the order of presentation, the P300 amplitudes were comparably high, whereas, the drop of attention was evident in the Numbers when presented as a second task. Our findings suggest that in monotonous assembly tasks, instructed responding, or a similar method of engagement, should be imposed on operators as it enhances their attention level. Finally, stemming from the notion that a drastic drop in P300 components' amplitude was notable when the Numbers task was performed as second, we propose that job rotations on the assembly line should be organized in such a way that the demanding task should not be followed by the more monotonous one.

8. Towards Continuous and Real-Time Attention Monitoring at Work: Reaction Time versus Brain Response

8.1 Introduction

This chapter is based on the published work (Mijović et al., 2016a) and it is concerned with the Continuous and objective measurement of the operators' attention state, which still represents a major challenge in the ergonomics research. Studies in the HF/E regarding mental, cognitive and emotional functions are perceived through theoretical constructs and are still dependent on behavioral indicators (Farfowicz and Marek 2007), subjective questionnaires and measurements of operators' overall performance (Parasaruman 2003). However, as mentioned in previous chapters, these methods are often unreliable (Lehto, and Landry 2012; Parasaruman and Rizzo 2008; Parasaruman 2003; Simpson et al., 2005). Additionally, they are unable to provide a real-time and continuous performance and attention measurement at work places (Jagannath and Balasubramanian 2014), where the continuous focus is essential (Jung et al., 1997). On the other hand, wearable EEG provides the possibility of continuous and objective assessment of the attention level of the operators, which may provide a new paradigm in ergonomics research for human performance monitoring. In this way, unreliable user state evaluation based on theoretical constructs, which are mostly describing cognitive states of the workers related to the task execution, can be avoided (Fafrovicz and Marek 2007).

Throughout the industrial history, studies of human performance in assembly tasks were mainly concerned with postures of the operators (Fish et al., 1997; Li and Haslegrave 1999; Rasmussen et al., 1994), which are still one of the main causes for work related musculoskeletal disorders (Leider et al., 2015). However, far less attention has been dedicated to the cognitive and perceptual factors that can cause errors in operating (Fish et al.1997). For example, the decrease in attention often precedes human error (Arthur et al., 1991; Kletz 2001; Reason 1990; Wiegmann and Shappell 2012; Wallace and Vodanovich 2003), and therefore, its timely detection could help avoidance of dangerous situations including workers injuries, material damage and even accidents with casualties.

EEG provides the possibility to both timely and objectively detect the critical behavior of humans (e.g. drops in attention, error, etc.) and it has been confirmed as a reliable tool in estimating ones' cognitive state (Klimesch et al., 1998; Luck, et al., 2000; Murata et al., 2005; Yamada 1998). Analysis of the ERPs, extracted from continuous EEG recording, represents commonly employed method in evaluating ones' neural activity (Hohnsbein et al., 1998). Another modality which can provide a continuous-like assessment of human attention level is a behavioural measure of the reaction times (RTs, [Larue et al., 2010; Sternberg 1969]). RT represents a time interval from the indicated start of operation (stimulation), until the moment of the action initiation and the main reason for wide usage of RT measurements is that they are easy to obtain and simple to interpret (Salthouse and Hedden 2002). However, the major drawback of experiments involving RT is that they usually consist of a stimulus followed by the response, without direct possibility to observe the mental processing that occurs between stimuli (Luck et al., 2000; Young and Stanton 2007).

In this study the propagation of the P300 ERP component peak amplitude and latency was investigated in order to assess the operators' level of attention, utilizing recently available mobile EEG equipment that did not alter the working process and enabled a 'truly unobtrusive' paradigm. In parallel, the propagation of behavioral component (RT) was examined. This study tested the hypothesis that the decreased level of attention, reflected in the reduced P300 amplitude, would also be followed by the longer duration of RT, as the operator would need more time to complete the operation, and vice versa. Further, the relationship between the RTs and P300 peak latency was examined, in order to investigate whether the RT duration would influence the latency of the P300 peak.

8.2 Materials and Methods

8.2.1 Participants

Fourteen healthy subjects, all right-handed and white skin color males, of age between 19 and 21 years volunteered as participants in the study. Two participants were excluded from further analysis, due to abnormalities during the recording.

Participants had no past or present neurological or psychiatric conditions and were free of medication and psychoactive substances. They have agreed to participation and signed informed consent after reading the experiment summary. The Ethical committee of the Medical Faculty (University of Kragujevac) approved the study and procedures for the participants.

8.2.2 Experimental Task

Experimental Task was explained in detail in the Chapter 5, Section 5.3.1.

8.2.3 Preparation and Experimental Procedure

Experimental procedure was explained in detail in the Chapter 5, Section 5.3.2. An important notion here is that in this study, solely the Numbers task was used, for the aim of eliciting the P300 ERP component.

8.2.4 Data Analysis

The RTs were calculated as the difference between timestamps from the operation initiation and actual beginning of the crimping process. In other words, RTs are here regarded as the time elapsed between the stimulus presentation (step 1) and the moment when participant presses the pedal (step 6), as indicated in Figure 4-4 (Chapter 4, Section 4.3.1).

EEG analysis was performed offline using EEGLAB (Delorme and Makeig 2004) and MATLAB (Mathworks Inc., Natick, MA). EEG data were first bandpass filtered in the 1-35 Hz range. The EEG signals were then re-referenced to the average of Tp9 and Tp10 electrodes. Further, an extended Infomax Independent Component Analysis (ICA) was used to semi-automatically attenuate contributions from eye blink and (sometimes) muscle artifacts (as explained in De Vos et al. [2011]; De Vos et al. [2010]; Viola et al. [2009]). ERP epochs were extracted from continuous EEG signal in the time range -200 to 800 ms with respect to timestamp values of stimuli. Baseline values were corrected by subtracting mean values for the period from -200 to 0ms from the stimuli. The identified electrode sites of interest for the ERP analysis in this study were Fz, Cz, CPz and Pz, as the P300 component is usually distributed and is most prominent over the central and parieto-central scalp locations (Picton 1992).

8.2.5 ERP Processing – P300 Amplitudes and Latencies

In the ERP analysis, firstly the mean grand average (GA) values of the ERPs for the 'go' and 'no-go' conditions were calculated. The GA methodology provides only the single value for the whole measurement period, thus the continuous evaluation of the ERP components was impossible. On the other hand, single trials ERPs could be used for the continuous evaluation of ERP components, but they would have low signal-to-noise (SNR) ratio. However, it has been reported that good quality ERPs could be obtained with as few as 11-repeated stimulus trials (Humphrey and Kramer 1994; Prinzel et al., 2003). Therefore, in order to create a trade-off between reliability and temporal resolution we decided to employ a moving window on single trial ERPs elicited by 'go' condition, averaging the last 15 trials for selected electrodes. The usage of this one-trial-step overlapping window left the total of 435 averaged ERPs for further analysis.

The P300 component obtained in this study was bifurcated containing two subcomponents, P3a and P3b. Whilst the P3a is more frontally distributed, the P3b is more prominent in the centro-parietal region (Polich, 2007). However, their latency vary depending on the stimulus events which elicit them, nature of task, population of participants included in the study, etc. In order to quantify and examine the propagation of P3a and P3b component amplitude and latency for 435 averaged ERPs, the following strategy was used: for the P3a and P3b sub-components, the latency of the maximum peak on the grand averaged ERPs for each subject was found and the 100ms interval window surrounding the peak was chosen for the calculation of the amplitude, utilizing mean peak amplitude method proposed by Luck (2014). Similarly, the latency value on each of the 435 averaged ERPs was calculated using peak latency measures (Luck, 2014).

8.2.6 Comparison of ERP and RT

Similarly, to the ERP analysis, the data for RTs were also averaged using a 15 trials moving-window, thus allowing examination of the RTs propagation during the task. This provided continuous-like time series of RTs, together with the P3a and P3b amplitude and latency values, further enabling the observation of common trends between these two modalities of attention monitoring. In this way it was possible to examine the correlation between the values of the P3a and P3b amplitudes and RTs.

8.2.7 Statistical Analysis

In order to examine the difference of the GA ERPs between ‘go’ and ‘no-go’ condition, a paired t-test was performed. The ERPs used for ‘go/no-go’ comparison included all ERPs related to the ‘no-go’ condition and 50 ERPs related to ‘go’ stimuli preceding the ‘no-go’ condition. To identify latencies with significant difference of go and no-go stimuli, mean amplitude values of GA ERPs across subjects were extracted over fixed 20ms time windows. ‘Windows of interest’ were defined as follows: where successive bins achieved statistical significance, one after first, and one before last bin in this significant ‘run’ respectfully marked its beginning and ending. That is to say, times were treated as the windows of interest only if neighboring 20 ms bins were also significant ($p < .05$). After identification of these windows, mean amplitudes across the window were computed and further analysis was conducted. Due to multiple comparisons, Bonferoni corrections were applied where necessary and the reported pattern of data did not change.

The correlation between the values of the RTs and P3a and P3b peak amplitudes and latencies, were statistically analyzed: vectors of P3a and P3b mean amplitude/latency values, calculated from the 435 values of the averaged 15 ERPs, and analogous values of the RTs were fed to the IBM SPSS software and Pearson correlation coefficients were extracted.

8.3 Results

8.3.1 EEG Results

ERPs were successfully extracted confirming the validity of the setup and accurate synchronization of the stimuli-inferred marking of EEG stream. Figure 8-1 depicts GA ERPs for the go (full line) and no-go (dotted line) tasks for Fz, Cz, CPz and Pz electrode sites. The P3a and P3b values in the ‘go’ condition were significantly higher than in ‘no-go’ condition ($p< .05$), while the more prominent N2 component was elicited over ‘no-go’ trials ($p< .05$), as marked on the upper-left image of Figure 3. Further, the P300 peak elicited in our task was bifurcated, containing its both sub-components (P3a and P3b), as shown on the upper-left image of Figure 8-1.

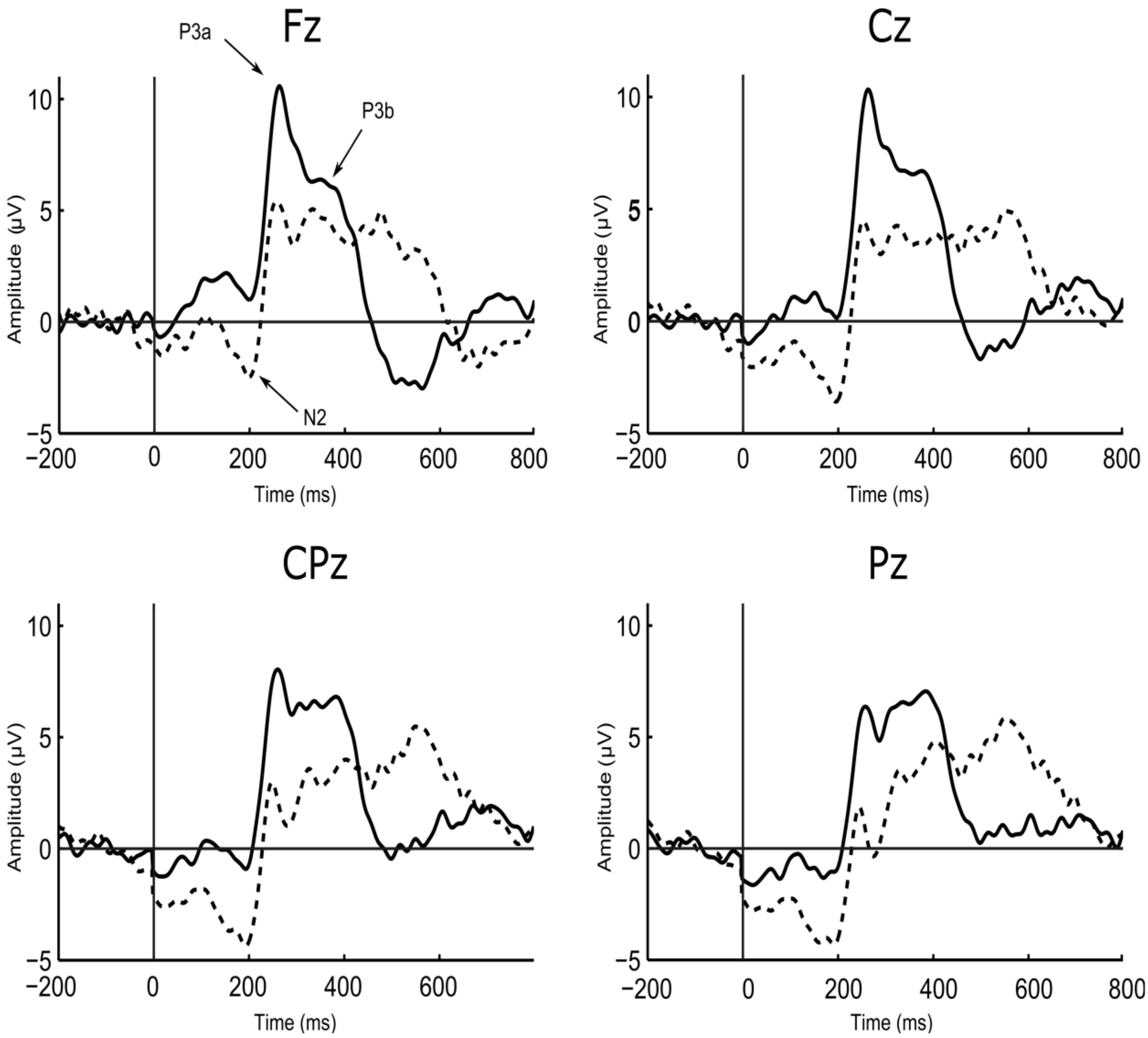


Figure 8-1: Grand average ERP waveform for 'go' (full line) and 'no-go' (dotted line) conditions across electrode sites under study. The N2, P3a and P3b ERP components are indicated on the upper left image.

The P3a and P3b components were consistent throughout the trials, which is represented in the colour maps, on the upper trace of Figure 8-2 (a, c, d and f), that represents an example of data obtained from subject 11 (Table 8-1). The lower traces of Figure 8-2 (a, c, d and f) represent the average ERP waveform on the single subject level, which confirmed that our task paradigm was suitable for electing the P3a and P3b ERP waveforms for 'go' conditions in simulated workplace environment. Additionally, Figure 8-2b and 8-2e represent the topographic maps and the distribution of the P3a and P3b sub-components across the scalp locations.

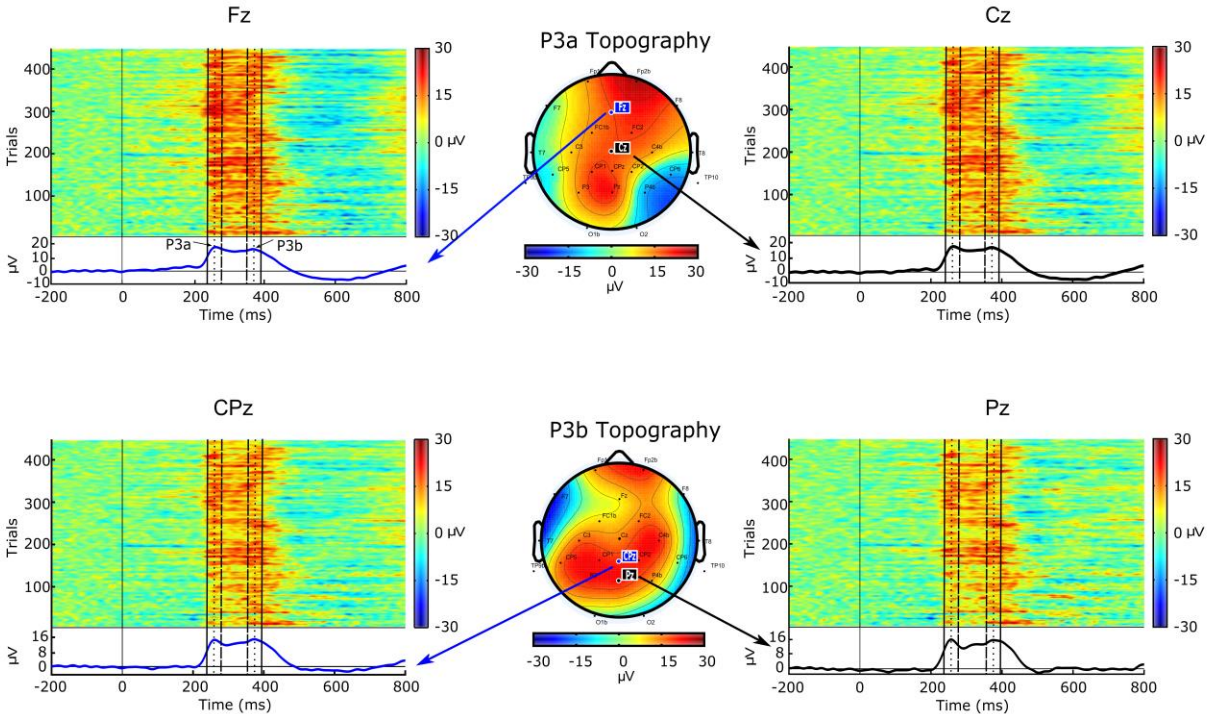


Figure 8-2: The average ERP waveforms, from subject 11 (Table 1) and for 450 go trials (a, c, d, f – lower traces); P3a and P3b sub components of bifurcated P300 peak are indicated in the lower trace of image (a); the amplitudes were calculated for the window between the full lines for both P3a and P3b (as marked on images a, b, d, f). Further, the topography of P3a and P3b components are represented on images (b) and (e).

In order to visualize the correlations between the RTs and P300 ERP component, the trials were sorted according to the RTs in ascending order. Corresponding ERPs were also rearranged according to the sorted RTs. These results are shown in Figure 8-3, where upper images represent results for a participant having the pronounced negative correlation (subject 11 from Table 3) and the lower images shows results for a subject with the positive correlation (subject 7, from Table 8-1). Lower traces of the images (both, a and b) represent the average ERP waveforms. Color map represent 435 averaged ERP amplitudes across trials (the ERP data were additionally smoothed for the better visualization). In the upper trace of the left images, the averaged RTs are presented as the black line (its axis portrayed on the upper side). In these unsorted RTs the intra-individual RT variability across trials can be observed. Similarly, the intra-individual variability of the P300 component amplitude is presented in the color map of the left images of the Figure 8-3. The effect of correlation sign becomes visible after sorting the ERPs according to ascending RTs

(Figure 8-3, right upper traces of the images). It is visible that in case of negative correlation, P300 amplitude (especially P3b) increases as RT is decreasing (the arrow on the right shows the direction of increasing P300 amplitude values, and thus, the correlation "sign"). Analogously, for the subject that shows positive correlation this trend is opposite, also indicated for visualization purposes by a lower arrow on the right.

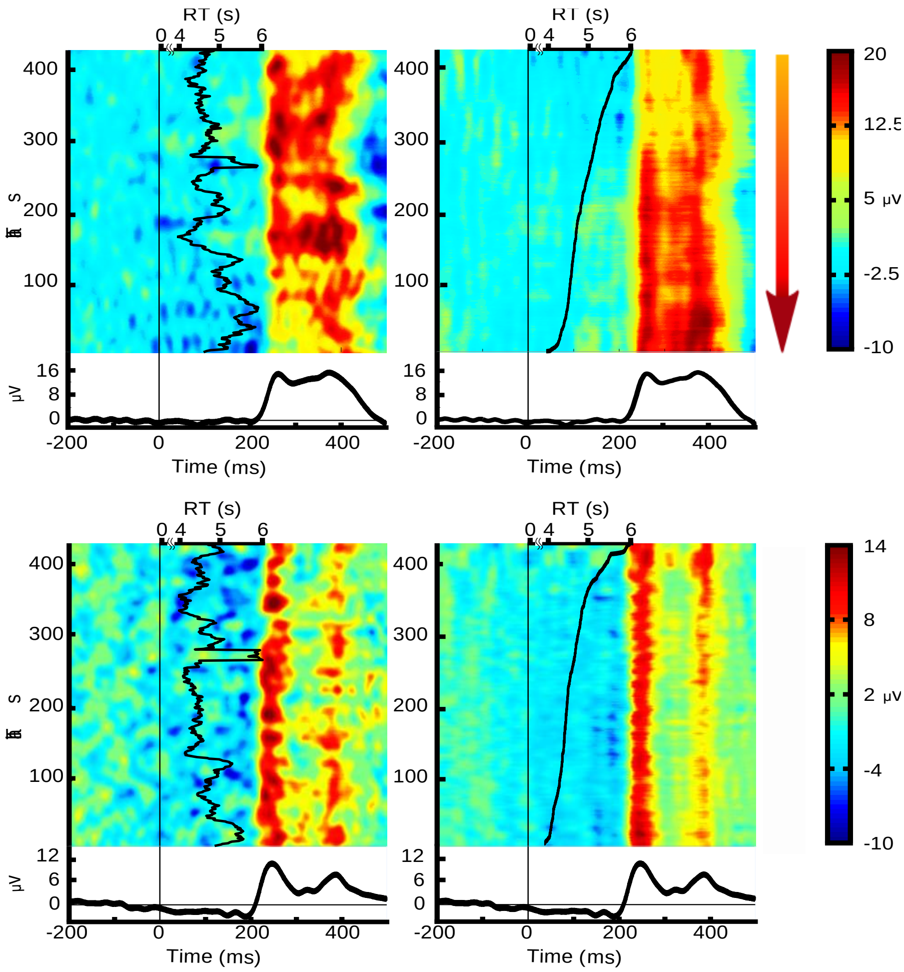


Figure 8-3: Comparison of two subjects having negative (upper) and positive (lower image) correlation between P300 amplitude and RTs. Respective left sides show (averaged/smoothed) ERPs and RTs ordered as recorded during the measurements, while the right sides depict ERP and RT values sorted with respect to ascending RTs. Axes indicate the trial number as well as ERP latency, but also the value of RTs. Arrows on the right side indicate the direction of increasing P300b components (corresponding to correlation sign).

Finally, the time series of the 435-averaged P3b components' mean amplitudes (upper panel of the Figure 8-4) and the corresponding averaged time series of the RTs (lower panel of the Figure 8-4) are presented for the visualization of the effect of variation of the P3b ERP component and RTs. Vertical full lines indicate moments when P3b mean amplitude starts dropping, eventually reaching its lower peak (depicted with dashed lines). Red arrows on the top of the Figure 8-4 represent the direction of the decrease in P300 amplitude. It is notable that when the P3b amplitude is decreasing, opposite trend in RT can be observed.

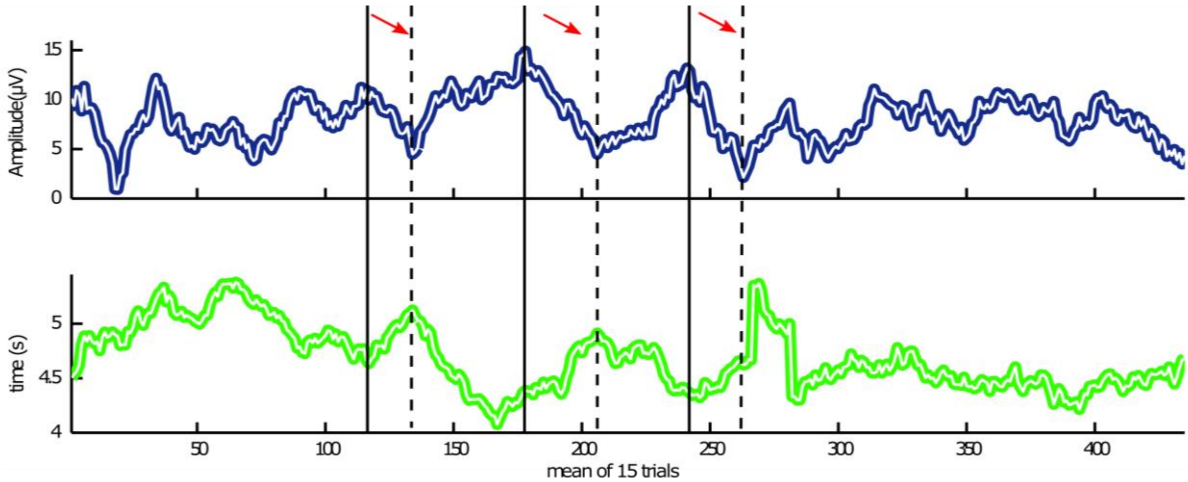


Figure 8-4: Visual representation of the time series of the 435-averaged P3b mean amplitude values (upper trace) versus 435-averaged RT values (lower trace).

8.3.2 Errors of Commission

There was only one participant who executed errors on the 'no-go' trials (six errors of commission, approximately 10% of all 'no-go' trials). Additionally, none of the participants committed errors of omission. Given that there were very few errors in total, we did not carried out further analysis regarding this matter.

8.3.3 Go-No-go Comparison

Paired sample t-test for the N2 ERP component at all four electrode sites revealed statistically significant difference between 'go' and 'no-go' trials (Fz: $t(1,11)=3.42$, $p<.01$; Cz: $t(1,11)=3.26$, $p<.01$; CPz: $t(1,11)=3.40$, $p<.01$; Pz: $t(1,11)=3.31$, $p<.01$). Similarly we observed statistically significant differences across 'go/no-go' trials at all four channels for P3a (Fz: $t(1,11)=3.30$, $p<.01$; Cz: $t(1,11)=3.80$, $p<.01$; CPz: $t(1,11)=4.55$, $p<.001$; Pz: $t(1,11)=4.64$, $p<.001$) as well as for P3b (Fz: $t(1,11)=2.54$,

$p<.05$; Cz: $t(1,11)=3.40$, $p<.01$; CPz: $t(1,11)=6.11$, $p<.001$; Pz: $t(1,11)=8.72$, $p<.001$) ERP components.

8.3.4 Pearson's Correlation Results

In order to evaluate the correlation between ERPs and RTs the Pearson correlation was used. To further examine the strength of obtained correlation results the Bootstrapping and Fisher-Z transform methods was applied to the data, verifying the consistence of the obtained results. The results of correlation between the RTs and P3a and P3b mean amplitudes are presented in the Table 8-1. These revealed that, on the group level, the correlation was negative on all electrode sites under study, with the high statistical significance ($p< .001$, Table 8-1).

However, compared to the group level, the overall significance of Pearson correlation varied substantially between individual participants at all four sites and in both P3a and P3b ERP windows. The results were less variable in the P3b compared to P3a window (values of correlation are presented in lower part of Table 8-1). Moreover, even in the P3b window, as obvious from the Table 8-1, only 4 out of 12 participants followed the general trend of negative correlation between ERPs and RTs at all four sites. Another four participants had significant negative correlations at 3, 2 or only 1 electrode site. Finally, one participant even had positive correlation over all sites, while the remaining three participants had positive correlations at 2 or 3 electrode-sites under study.

Unlike the mean P3a and P3b amplitudes, the correlation between RTs and P3a and P3b latencies was inconsistent. Moreover, the distribution of latencies at all four sites of interest (Fz, Cz, CPz and Pz), across both P3a and P3b windows significantly differed from normal distribution. For that reason, the log instead of raw values was used, which approximated normal distribution somewhat better. At the group level, the P3b sub-component showed only two marginally significant negative correlations (at CPz and Pz electrode sites). On the other hand, P3a subcomponent latencies showed positive correlation at all electrode sites ($p<0.05$) at the group level. However, when analyzed for the individual subjects, the pattern of results was inconclusive.

Table 8-1: Pearson's correlation values between the RTs and P3a and P3b mean amplitudes on the group level (upper part) and on the individual level (lower part of the table).

Pearson's Correlation Values								
Component	P3a				P3b			
Electrode site	Fz	Cz	CPz	Pz	Fz	Cz	CPz	Pz
Group level	-.23	-.16	-.15	-.03	-.24	-.25	-.27	-.18
Individual Subjects	P3a				P3b			
	Fz	Cz	CPz	Pz	Fz	Cz	CPz	Pz
1	-.04	-.01	.03	.07	-.27	-.26	-.23	-.18
2	-.16	-.13	-.05	-.05	-.14	-.18	-.19	-.20
3	-.14	.01	.09	.09	.12	.23	.18	.08
4	-.33	-.35	-.36	-.36	-.10	-.14	-.20	-.27
5	-.03	.02	.02	.03	-.19	-.15	-.11	-.06
6	-.05	-.03	-.03	-.02	-.15	-.10	-.07	-.04
7	.22	.22	.16	.14	.15	.23	.22	.19
8	-.18	-.07	-.03	-.01	-.18	-.07	-.05	-.08
9	.03	.19	.13	.10	.17	.17	.02	-.05
10	-.07	.13	.16	.16	-.01	-.14	.02	.06
11	-.53	-.60	-.61	-.52	-.46	-.46	-.46	-.40
12	.36	.44	.41	.36	.15	.12	.02	.19

(dark grey)	- Negative correlations (p<0.05)
(light grey)	- Positive Correlations (p<0.05)
(white)	- Non significant values (p>0.05)

Based on the results reported beforehand, two groups of participants were identified, i.e. five participants who showed negative correlation between RTs and P3b amplitude in one group, and four who showed positive correlation in the other. Regarding RTs, participants with negative correlation between RTs and P3b were faster (t(RT)=2.2, p<.05), with higher P3b amplitudes (t(Fz)=35.21,p<.001; t(Cz)=38.91,p<.001; t(CPz)=39.68,p<.001; t(Pz)=28.36,p<.001) and shorter P3b latencies (t(Fz)=36.31,p<.001; t(Cz)=30.74,p<.001; t(CPz)=30.43,p<.001; t(Pz)=34.61,p<.001). On the other hand, the positively correlated participants showed slower RTs, lower P3b amplitudes and longer latencies.

Similarly, with regard to P3a component, two groups of participants (four in each) demonstrated the same pattern of results. Negatively correlated had higher amplitude (t(Fz)=22.2,p<.001; t(Cz)=26.5,p<.001; t(CPz)=27.14,p<.001;

t(Pz)=16.84,p<.001) and shorter latencies (t(Fz)=18.77,p<.001; t(Cz)=11.05,p<.001; t(CPz)=7.51,p<.001; t(Pz)=9.89,p<.001), and vice versa for positively correlated. However, there were no significant group differences regarding RTs.

8.4 Discussion

The grand average comparison between ERPs extracted for 'go' and 'no-go' stimuli revealed that the higher P300 amplitude values are elicited for frequent 'go' condition. This finding was similar to the findings reported in previous study (Chapter 7). However, this is in contrast to most of the other findings, where participants were required to respond to deviant (infrequent) stimuli. Nevertheless, this manipulation (with responding to frequent stimuli) was necessary, given that the study was conducted in simulated working environment, whereby the continuity of operation is essential. Therefore, the lower amplitude value of the 'no-go' P300 component is not surprising (Figure 8-1), since the passive stimulus processing generally produces reduced P300 amplitudes, as non-task events engage attention resources to reduce the amplitude (Polich 2007).

The Pearson's correlation between the RTs and P3a and P3b amplitudes, on the group level at all four sites of interest, showed significant negative correlation (Table 8-1). This confirms the main hypothesis, proving that the higher P300 amplitude values, which reflect the higher level of attention allocated to the task (Hohnsbein et al., 1998; Murata et al., 2005) correspond to the shorter RTs needed to complete the action. Additionally, higher values of negative correlation were obtained for the P3b, compared to P3a sub-component. However, the correlations between these modalities on the individual level were not consistent as within the group (Table 8-1), which constitutes one of the main finding of this study. This inconsistency could be attributed to the inter-individual differences, as the P300 component is influenced with the various factors, e.g. intelligence, introversion/extraversion, etc. (Picton 1992), but there can be also individual differences that are not functional but anatomical, such as scull thickness (Hagemann et al., 2008). Furthermore, the RT variability is also known to be subjected to inter-individual differences (MacDonald et al., 2007). Therefore, this study supports the notion of Hockey et al. (2009), where the importance of studying individual level data when performing psychophysiological measurements in ergonomics studies was emphasized.

The Pearson's correlations results between RT and P3b, identified two groups of participants: the one of which was negatively correlated and the other one positively correlated. Negatively correlated group was faster with higher P3b amplitudes and shorter P3b latencies, whereby the positively correlated group showed slower RTs, lower amplitudes and longer latencies. Similar pattern of the results was observed for the P3a component (except for the RT comparisons, which were not significant). Therefore, it may be concluded that participants who showed negative correlation between P3b component and RTs were more focused on the task (given that they had higher P3b amplitude values) and were more efficient (given shorter RTs) than the positively correlated group. However, this finding should be examined in future studies and the consistency of the correlation results on individual basis needs to be confirmed through repeated measures on a single subject basis.

Another interesting comparison would be between ERPs on 'go' trials preceding correctly withhold 'no-go' trials and on 'go' trials preceding commission error on 'no-go' trials, as this could be an useful information on alerting the attention system (Robertson et al., 1997). However, the fact is that there was only one participant who executed actions on 'no-go' trials (6 errors in total, app. 10%). Interestingly enough, this was the participant (No.12, from Table 8-1) who showed a positive correlation between RTs and P3 amplitudes, in contrast to the generally observed trend (negative correlation between RTs and P3 amplitudes). It is noteworthy that it was hard to set an objective criterion as to what action to mark as an error, given that participants would sometimes demonstrate slight movements without executing the action. Therefore, the stricter criterion was chosen, based on which the errors of commission were defined as completion of the action on 'no-go' trials (including the pedal press).

Although the P300 component is generally related to attention processing, the mechanisms that generate P3a and P3b subcomponents differ significantly. P3a component is more related to novelty preference, processing of exogenous aspects of stimuli, i.e. low-level attention processes (Daffner et al., 2000; Polich 2007). This component usually follows the N2 component, which was also found to be increased in response to novel or deviant stimuli processing (Daffner et al., 2000), as also shown on Figure 8-3.On the other hand, P3b component was found to be more related to high-level attention processing, processing of endogenous aspects of stimuli, context-updating information (working memory) and memory storage (Polich 2007). The P3b component is also related to decision processes (O'Connell et al., 2012), in which it mediates function between stimulus processing and required response (Verleger et al., 2005). This is in line with our findings, since the P3b was more prominent in response to go-stimuli, which required action, particularly in central and centro-parietal sites.

Further examination of continuous-like time series of the RTs and P3a and P3b amplitudes revealed visible trends of fluctuation of these two modalities over time (Figure 5). Existing literature suggests that both RTs (Flehming et al., 2007) and P300 component (especially P3b, Polich et al. [2007]) are closely related to the attention, thus it can be inferred that fluctuation of these modalities correspond to the attention fluctuation on the neural as well as on the behavioral level. However, it is apparent from the results that not all the participants showed negative correlation between RTs and P3a and P3b components, which arises an obvious question: which data are more closely related to the attention and should ERP or RT measures be used for evaluation of the assembler attention? Bishu and Drury (1988) pointed out that in assembly tasks translational stage from input information into output action is more complex than in conventional RT tasks and therefore, the structure of the response may influence the performance. Moreover, in RT experiments there are many possible processes that contribute to the RT and therefore it is difficult to isolate and address specific feature of interest, such as attention (Salthouse and Hedden 2002). On the other hand, the P3b component is found to be the direct correlate of the higher-level attention processing (Verleger et al., 2005). Following this logic, we speculate that findings in this study demonstrate that ERP correlates of attention offer a more detailed and sophisticated understanding of the nature of attention decline compared to robust, but rough RT measures. Not only that the ERPs provide the precision of measurement (which is recognized as 'reaction time of the 21st century', Luck et al. [2000]), but also they provide possibility to gain more insightful understanding of the nature of the process as demonstrated through the analysis of P3a and P3b sub-components. However, further studies are desirable to confirm the generality of this finding.

The analysis of the relationship between RTs and P3a and P3b peak latencies, revealed no statistically significant correlations between these components. Although Murata et al. (2005) proposed that the P300 peak latency corresponds to the stimulus evaluation time and that it can be also directly correlated to the level of attention, this was not observed in present study. This finding is consistent with the recent work of Ramchurn et al. (2014) and it confirms that only the P300 component amplitude variation, but not its latency, correlates with the variation of the RTs. The P300 amplitude, on the other hand, was recognized as an index of the attention allocated to the task in numerous studies (Murata et al., 2005; Polich 2007; De Vos et al., 2014 and Ramchurn et al., 2014).

It was reported that the sudden drops in the attention, during a monotonous task, could be attributed to the e.g., daydreaming and mind wandering (Fisher, 1998). However, the neural correlates of these phenomena are still not fully understood (Hasenkamp et al., 2012). For instance, potential benefit of real-time attention monitoring, would be to provide the feedback to the operator once the attention level starts decreasing, thereby attempting to keep the attention level high and prevent possible human errors. The presented study indicates that "periods of attention oscillation" are sufficiently long to make such a feedback system meaningful. However, one of the limitations of the present study is that the results were obtained in an off-line analysis. Therefore, one of the directions of future studies will be utilization of one of the existing Brain Computer Interface (BCI) software packages for real-time data processing in the desired time window and to provide proper visual, auditory or mechanical (e.g. vibration) feedback. The process could be automated in sense that once the amplitude values of the P3b component start decreasing with an obvious trend, as indicated by red arrows on Fig 5. (e.g. between 180th and 200th averaged trial), the feedback could be provided. It is important to investigate the effects of such a feedback also in relation with its content, all the while taking care of workers privacy and mental well-being.

Although, Mijovic et al (2016) believe that the measurement of covert attention-related modality (P3b) offers better understanding of attention processes than the overt performance measure of RTs, one of the limitations of present study is that EEG is still uncomfortable for everyday use and on-site recordings in naturalistic industrial environments. The main reason for this is that the reliable EEG recordings still depends on the wet gel-based electrodes (Mihajlović et al., 2015) and an ethical question of EEG recording arises, in sense that the supervisor could have information about the physiological signals obtained from employees, raising privacy concerns (Fairclough 2014). Nevertheless, if the positive/negative correlation between P3b component's amplitude and RTs is holds on a single subject basis, then proposed methodology can be applied as that a primary (entry) test for workers. The benefits of such a testing can be twofold: firstly, the company management could be able to early detect whether the worker, for particular work position, is focused on the task (based on which group he belongs - positively/negatively correlated); secondly, the reliable, comfortable and low-cost attention-monitoring system could be created based solely on non-invasive RTs recordings. Thus, the future studies should be directed towards investigation of the reliability of correlation between P3b and RTs on single subject basis, upon which the proposed methodology could be applied in industrial settings.

The presented methodology was applied on a manual assembly work, where a single functional modification of the real workplace was needed, in the sense of on-screen stimulus presentation for the aim of eliciting the anticipated P300 ERP component. This modification was necessary, since the covert cognitive context is usually encrypted in complex brain dynamics and in naturalistic settings it is hard to isolate the specific cognitive processes, since they should firstly be evoked (Bulling and Zander, 2014). Therefore, at current stage this methodology cannot be directly applied for the on-site recording in realistic industrial settings and other workplaces, as we would have had to modify the work routine. For that reason, either a more general approach needs to be developed for further application to this work position, or another work position has to be identified, where such attention monitoring systems can be readily applied. These represent an additional direction for future research in this area.

8.5 Conclusions

This study extended existing psychophysiological approaches in ergonomics by providing novel methodology for workers' continuous attention monitoring, during the course of a monotonous assembly task and in the realistic workplace environment. It was observed that, while on the group level P3a and P3b attention related ERP component amplitudes, and the RTs correlated in the negative fashion, that did not hold on individual subjects' level. This constitutes one of our major findings: overt performance measure of RTs alone are not reliable attention level measure *per se*, and covert physiological data needs to be employed for this task. Oscillating attention justifies the use of future feedback systems that would serve both to increase the attentiveness of workers and to prevent work-related errors. In that way, the potential accidents, which could lead to workers injuries and material damage, could be prevented, consequently increasing the workers overall well-being. Future studies are still needed to confirm the applicability of proposed methods, as well as to tune and sufficiently generalize them.

9. Communicating the User State: Towards Cognition Aware Computing in Industrial Settings

9.1 Introduction

This chapter is based on the work that is in preparation for submission, and explores the utilization of the wearable EEG and Kinect devices for the aim of the attention monitoring of operators, employed on monotonous repetitive assembly tasks.

As discussed in Chapter 5 (Section 5.1), wearable sensors provide the possibility to move from conventional, explicit human-computer interaction (HCI), to more natural implicit HCI. In an implicit HCI context (Schmidt, 2000), the computer interprets human physiological and behavioral data as its input, enabling the development of cognition-aware computing for the user state monitoring. This is mainly attributed to a rapid development of sensing technology and improvement of algorithms that can interpret the acquired signals. Following that path, sensing technology is not only providing means for computers to obtain a better image of our environment (such as in smart cities, houses, vehicles etc.), but it also opens a new way of understanding humans, as the technology is deployed to monitoring our behaviors and states. In this context, cognition-aware computing was recently defined as the computing system that senses and adapts to cognitive aspects of personal context (Bulling and Zander, 2014).

Despite the fact that manufacturing industry has aimed to reach “lights-out” manufacturing (i.e. fully automated factories, Tompkins et al., 2010) for decades, there are still many industrial processes relying on human operators. However, humans are often characterized as the most fallible element in the production line and due to limited mental and physical endurance that can sometimes cause behavior and responses to be unpredictable (Hamrol et al., 2011). Therefore, introduction of cognition-aware computing in industrial settings could be beneficial and these effects of deviation in operators’ cognitive state could be lessen.

Although industry has conceived the usage of wearables for over a decade now (Stanford, 2002), the majority of their applications are still oriented towards physical activity recognition (Stiefmeier et al., 2008), rather than activity recognition for the mind (Kunze et al., 2013). In order to get closer to applicability of cognition-aware computing (Bulling and Zander, 2014) in workplaces, this study propose a system that is capable of synchronous recording and analysis of brain dynamics and active behavior in replicated industrial environments.

As discussed in Chapter 3, currently the only available technologies for investigating the brain dynamics in naturalistic environments are fNIRS and EEG (Gramann et al., 2014). Although fNIRS is still less obtrusive than EEG, it is an indirect metabolic indicator of brain dynamics and it suffers from low temporal resolution (Gramann et al., 2014). On the other hand, the EEG provides the direct measure of the neural activity and it possess high temporal resolution (Gramann et al., 2014). As EEG recently became wearable, it currently represents the most powerful tool for investigation of brain dynamics in naturalistic environments. The EEG has been successfully applied in BCI, which has already moved from assistive care to other everyday applications (Van Erp et al., 2012). BCI appears to be increasingly accepted for everyday use, since various companies have started developing consumer based EEG devices for e.g. gaming purposes (Van Erp et al., 2012). Exploring additional applications of BCI, a novel direction of so-called passive BCI has emerged (Zander and Kothe, 2011). Passive BCI is oriented towards continuous analysis of the recorded brain signals in human-machine interaction, with the aim of objectively assessing user states. A clear momentum of passive BCI technology recently enabled new additions to application in industry, empowering the research area of neuroergonomics (Parasuraman, 2003). The only obstacle in wearable EEG recording is that reliable EEG measurements could still be made solely with wet electrodes (Mihajlović et al., 2015), which is still uncomfortable for the workers. However, as discussed in previous chapters, it provides the possibility to investigate the brain dynamics in faithfully replicated workplaces and the findings from these kinds of experiments can be translated to the industry, once the EEG becomes fully comfortable.

Another major challenge in ergonomics and HCI research is the investigation of movements and postures of workers in real time. For that aim, internal measurement units (IMUs) and MoCap sensors can be used, as they have already achieved a degree of success. However, the majority of IMUs and MoCap Systems use external sensors (e.g. Depth of Field targets), which are attached to the person being recorded (discussed more in detail in Chapter 3). Even though workers reported no issues wearing the IMUs sensor network during work (Stiefmeier, 2008), the precise monitoring using contactless sensors would bring an additional comfort. As an emerging alternative, the gaming industry opened a new path in affordable multi-sensor technology, which is capable of precise motion capturing without the need for wearable sensors, in the form of e.g. Microsoft Kinect. Apart from its primary use, researchers extended its applications in the ergonomics domain, since it provides the possibility to effectively observe the workers' movements and postures in real-time and in real-world environments.

The majority of research related to operators' motion is related to posture estimation or action recognition (e.g. Stiefmeier et al., 2008) , whereas much less attention has been dedicated to linkage of cognitive processes to motor actions. An important notion is that the cognition is closely related to motor actions in naturalistic and dynamics environments (Parasuraman and Rizzo, 2008). For example, a recent study reported that variability in quantity of movements, which are not directly related to the task, could be an important indicator of the user state (Roge et al., 2001). This study investigated behavioral activity off-line and indirectly, since the participants were recorded with the RGB (Red Green Blue) camera and manual analysis was subsequently performed, which consisted of counting the number of identified activity types (Roge et al., 2001). However, advances in HCI and computer vision technology allow on-line and automated processing of these. Sensors that rely on structured light technology in unison with additional sensors opens the possibility of automatic acquisition of information on behavioral activities, as it can directly record the position of human body key points (joints) in time. This enabled the development and usage of a simple behavioral model, based on movement energy (ME). Ultimately, the combination of brain dynamics and behavioral modalities can open a deeper understanding of human mental states during complex work activities (Gramann et al., 2014).

In order to investigate above described concept, the specific workplace was replicated from our industrial partner and enhanced it with a sensor network, thus creating the sensitive workplace (As described in Chapter 5, Section 5.5). The next step was synchronous and in real-time recorded the EEG and behavioral signals and investigated the correlation between these modalities. The goal is to achieve a system that will be able to perform online detection of deviations in user states. Such a system should be able to detect a drop in mental and physical performance so that appropriate action (e.g. a break or a change in task) can be taken. Ultimately, such a system could prevent the occurrence of operating errors and improve the worker experience.

9.2 Methods

9.2.1 Participants

Twenty male subjects (aged between 19 and 21), without industrial working experience, participated in the study. The study was restricted to male participants both to exclude possible inter-gender differences and to replicate the selected job task more faithfully, since in company that supported our research only males occupy the specific workplace under study. Participants did not report any past or present neurological or psychiatric conditions and were free of medication and psychoactive substances. They were instructed not to take any alcoholic drinks prior to, nor on the day of participation in the study. All participants had normal or corrected-to-normal vision. They agreed to participate in the study and signed informed consent after reading the experiment summary in accordance with the Declaration of Helsinki. The Ethical Committee of the University of Kragujevac approved the study and procedures for the participants.

9.2.2 Experimental Setup

Experimental setup was explained in detail in Chapter 5, Section 5.2

9.2.3 Experimental Procedure

Each of the participants arrived in the laboratory at 9:00 a.m. Upon carefully reading the experiment summary and signing the informed consent for participation in the study, participants started the 15-minute training session in order to get familiar with the task. Finally, EEG cap and amplifier were mounted on the participants' head and the recording started around 9:30 a.m. Participants were seated in the comfortable chair in front of the improvised machine. In this study, both, the Numbers and the Arrows paradigm (explained in the Chapter 5, Section 5.3.2) were used in balanced order and participants had a 15-minutes break between the tasks.

Each task was presented on the 24” screen from a distance of approximately 100 cm. The screen was height adjustable and the center of the screen was set to be in level with participants’ eyes.

9.2.4 ERP Processing

EEG signal processing was performed offline using EEGLAB (Delorme and Makeig, 2004) and MATLAB (Mathworks Inc., Natick, MA). EEG data were first bandpass filtered in the 1-35 Hz range, following which the signals were re-referenced to the average of the mastoid channels (Tp9 and Tp10). Further, an extended infomax Independent Component Analysis (ICA) was used to semi-automatically attenuate contributions from eye blink and (sometimes) muscle artifacts (as explained in Viola et al., 2009; De Vos et al., 2010; De Vos et al., 2011). After this data preprocessing, ERP epochs were extracted from -200 to 800 ms with respect to timestamp values of ‘go’ and ‘no-go’ stimuli indicated by the SNAP software. Baseline values were corrected by subtracting mean values for the period from -200 to 0 ms from the stimuli. The identified electrode sites of interest for the ERP analysis in this study were Fz, Cz, CPz and Pz, as the P300 component is usually distributed and is most prominent over the central and parieto-central scalp locations (Picton, 1992).

Similarly to study presented in Chapter 7, a one-step moving window was employed on single trials ERPs elicited by go condition, by averaging the last 15 trials for selected electrodes. Finally, the P300 amplitude was calculated for averaged ERPS and for ‘go’ conditions, using mean amplitude measure (Luck, 2014) in the time window from 230 to 450 ms, with regard to the time stamps of the stimuli.

9.2.5 Engagement Index (EI) Calculation

EI is a measurement of a person’s cognitive engagement in a task, reflecting their level of alertness (as mentioned in Chapter 2, Section 2.3.4). The EI represents the ratio between the high frequency waves (β), and the summation of the low frequency waves (α+θ), i.e. $EI = \beta/(\alpha+\theta)$. Higher EI indicates the higher engagement of the person in the task, while the low values of EI indicate that person is not actively engaged with some aspect of the environment during the task (Prinzel et al., 2000).

In order to obtain the EI values, the raw EEG signal was bandpass filtered in three frequency bands (θ, α and β), following which the signals were re-referenced and the artifacts were removed using ICA. The EEG signal was then segmented according to the timestamps of the stimuli appearance and the signal segments of 1s preceding the stimulus appearance were used for further analysis. Further, the Fast Fourier Transform (FFT) was applied to the signals and the Power Spectral Densities (PSDs) were calculated for each frequency band and each simulated operation. Finally, this allowed us to calculate the EI as seen in Figure 9-1.

9.2.6 Movement Energy (ME) Calculation

In order to investigate whether the task unrelated movements could be quantified automatically, we recorded the upper body movements of the participants with the Kinect. As a first step towards this goal, a correlation between task-unrelated ME and the level of attention, with the reference to the EEG attention-related modalities of P300 amplitude and EI was investigated.

In experimental setting, the 10 key-points seated model was used, as the replicated machine occluded the lower-body part of the participants (Figure 9-1). Further, the methodology for automatic quantification of the task unrelated ME was applied, which was based on movement of the key-points and the simple equation of the kinetic energy adopted from classical mechanics. The motion data were extracted and analyzed in the period between the operators' completion of each operation and the consecutive stimuli that was presented to the participants. In that period, during conductance of the step 8 from Figure 5-4 (Chapter 5), the participants had no prescribed activity and the expectation was that they would spend that time relatively still. Further, the kinetic energy of movement was calculated for each simulated operation and for each of the key-points in all-three axes. Finally, the ME for each trial was calculated as the summation of kinetic energies in all three axes (Figure 3c).

9.2.7 Reaction Time Calculation

As stated in previous section (8.1), it is considered that shorter RTs indicates higher attentive state and vice versa, except in case of speed-accuracy trade-off. In this study, the RTs were calculated for each simulated operation, as a time elapsed between stimulus presentation and the beginning of the simulated machine crimping action, i.e. as the time elapsed between step 1 and step 6 from Figure 4-4.

9.2.8 Data Averaging

With the aim of investigating the correlation between obtained modalities, the same approach for averaging (using one-step moving window) was applied to the ME, RTs and EI signal modalities, prior to the statistical analysis. Figure 8-1 graphically depicts the algorithms that were used for the data analysis in this study.

9.2.9 Statistical Analysis

An off-line data analysis was conducted in order to investigate the relationship between EEG and behavioral signal modalities. Upon data averaging, the matrices of 435 data points for each participant and task were fed into IBM SPSS and the data were aggregated according to the number of trials. First, a Spearman's correlation was performed, mainly to investigate whether the any of the recorded modalities reflected the decline in user state over the trials (as an approximation of time). Further, Pearson's correlation was carried out, with the aim of investigating whether behavioral modalities correlate with the EEG derived modalities and to determine whether ME could be used as a reliable modality for estimation of user state.

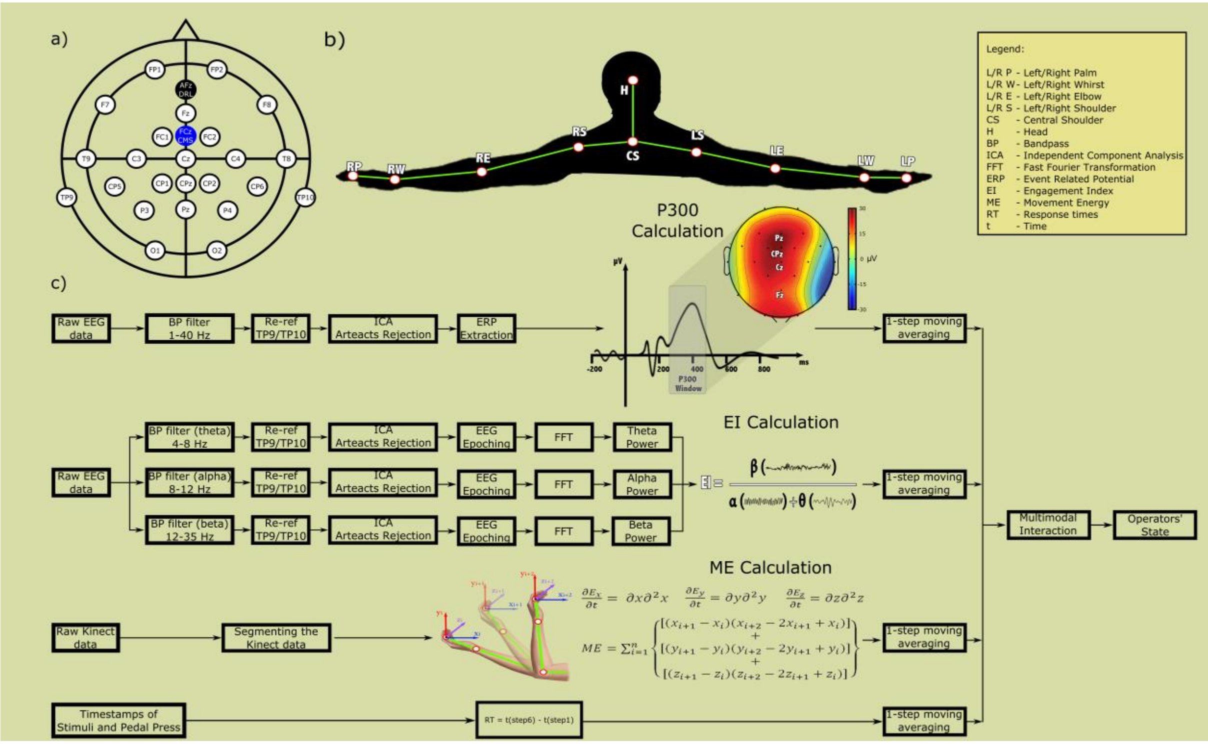


Figure 9-1:Graphical representation of the alghorithms used during the signal processing for each signal modality.

9.3 Results and Discussion

Regarding the Spearman correlation it was found that, regardless of the task order, the monotonous task (Numbers task) induces an attention and engagement decline, as reflected by the decline of the P300 amplitude and EI. Additionally, ME increases as the tasks progress (Figure 8-2 in the upper left table). On the other hand, results in the more mentally demanding task (Arrows task) depended on the order in which it was presented to the participants. This is especially notable through evaluation of the P300 amplitude, as it increased during the task if the Arrows followed the SART task. Although the EI still decreased, proving that mental engagement of the participants decreased during the task, the evaluation of the P300 amplitude revealed that the participants were able to maintain higher attention state during the task. This is also notable through evaluation of ME, as only in the case where the Arrows was the second task, the ME decreased with time elapsed, i.e. the participants made less task unrelated movements. It is noteworthy that RTs were independent from both task type and task order and it decreased with the time-on-task, probably caused by the effect of rehearsing as the task progressed.

The bottom part of Figure 8-2 depicts the Pearson's correlation results. It is notable that the expected negative correlation between P300 amplitudes and ME is more distinct in the case of low demand, monotonous task (SART), than in the more mentally demanding (Arrow) task. This finding is not surprising, as in the existing literature the quantity of movements that are not related to the task are reported to be linked to attention decline in monotonous tasks (Roge et al, 2001). Further, when the more monotonous task is presented first, the EI was negatively correlated for each key-point, while in the more demanding task almost no correlations were found between EEG and behavioral signal modalities. Finally, if the Arrows were presented as the first task, the only negative correlation with the P300 amplitude was at the LP, LW, RP and RW key-points, while the EI was positively correlated with the ME on almost all key-points. This could be explained through the notion of re-activation, as participants in the more mentally demanding task use task unrelated movements in order to re-activate the attention related resources in the brain (Roge et al., 2001), thus staying more focused on the task. This was not obvious if the SART task followed the Arrow task. In fact, again in the more monotonous task, the P300 amplitude was negatively correlated with the ME on the majority of key-points. From all these results, it can be infer that during low demand, monotonous tasks the ME that is unrelated to the task is negatively correlated with the attention level.

The presented results supported the intention of assessing the user state by synchronously recording and analyzing behavior and EEG modalities, with a relatively simple and low-cost unobtrusive sensor network. However, an obvious limitation is that all the analysis was done *post hoc*, and for that reason the future studies will be concerned with the on-line data analysis. The future steps will include the development of advanced algorithms for automated, real-time acquisition and analysis of presented modalities, which could further be implement in an industrial environment. Such a system could ultimately lead to increase of workers' alertness and task engagement, consequently leading to the improvement of workers overall well-being.

9.4 Conclusion

Monotonous and repetitive tasks, commonly seen in manual assembly production lines, often lead to mental strain, due to limited mental and physical endurance of humans. This work focused on exploiting advances in EEG and behavioral sensing technology in order to detect users' states that indicate the occurrence of attention and engagement decline. The final goal is to prevent errors that might lead to product waste or injuries caused by deviations in user state.

This study demonstrated that EEG and behavioral markers can provide a more detailed insight into user state. This was achieved in a realistic workplace environment and represents a first step towards the described HCI model paradigm. ME, which can be analyzed in real time, is less obtrusive than EEG and may provide a reliable, stand-alone tool for attention monitoring, especially in industrial scenarios. An obvious follow-up is to provide real-time processing of these features and put them in a feedback loop with an indication communicated to workers. In this way, operators could be informed about their cognitive state in a close-to real-time manner, which could serve to prevent errors and dangerous consequences. This could then become basis of a true future cognition-aware computing in the industrial environments.

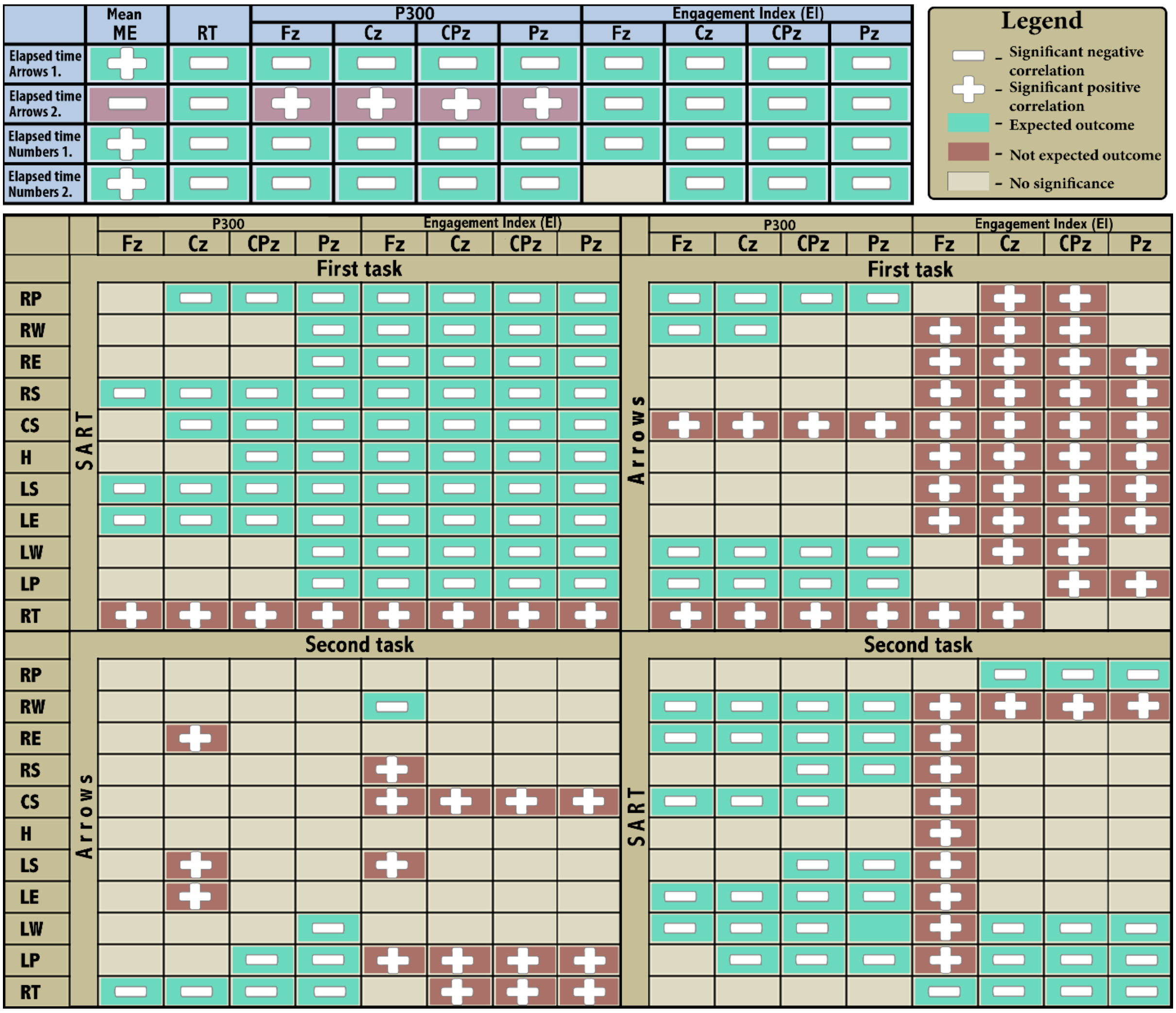


Figure 9-2: Results retrieved from experimental study. Upper left table – Spearman's correlations of elapsed task time with physiological and behavioral factors; Bottom table – Pearson's correlations between behavioral and physiological factors; significance is treated at a p<0.05 level. Fz, Cz, CPz and Pz represent the electrode sites from which we calculated P300 amplitudes and EI. The rows in the lower table represents the key point locations derived from Kinect, explained on Figure 3. The last rows represent the response times (RTs).

10. General Conclusions

Present dissertation investigated the possibility of objective assessment of the operator's cognitive state in the naturalistic workplace environment. For that aim, faithfully replicated workplace was created, where participants in the study performed the simulated assembly operations. The framework for synchronous multimodal physiological and motion signals acquisition and processing was presented and the benefits of instating such a system for both manual assembly task design and for the real-time user-state monitoring were discussed. Although the multimodal framework was proposed, for the aim of this dissertation, the results from the EEG, RTs and Kinect were presented, while investigating the relationship between these and HR and GSR signal modalities will be the subject of the future studies.

In the first experimental study, the potential benefits of inclusion of frequent micro-breaks on the attention level was investigated. In order to investigate the influence of the micro-breaks on the attention level of the participants, the P300 component's amplitude was calculated for the period prior to, and following the micro-break period. It was found that the micro-breaks enhance the attention level of the operators, as the magnitude of the P3b component were significantly higher following the micro-break period than preceding it. This finding can be used for the manual assembly operations task design, in a way that the workers' should receive frequent short breaks during their shift. However, it is important to note that in the presented study, only one time-window was used and therefore, the future studies should investigate what duration of the micro-breaks would be the most desirable, taking into account the productivity and the well-being of the workers.

Second experimental study investigated whether the hand alteration influences the attention of the workers'. In order to investigate this hypothesis, the participants were subjected to two distinct psychological tests that were presented to the participants in the balanced order, and simultaneously with the simulated assembly operations. In the first experimental paradigm, the participants could initiate the assembly operation with whichever hand they prefer, while in the second they were conditioned with which hand to initiate the assembly operation. The findings indicated that the participants in the study had significantly higher attention level in the case when they were imposed to the hand alteration condition. The attention was assessed through the P300 component's amplitude and RTs. Although, the P300 amplitude was significantly higher in magnitude in hand altering condition, there was no difference in RTs between conditions. This finding supports one of the main premises of the neuroergonomics, where it is sated that the overt performance based measurements (such as RTs) are unreliable and that ergonomics should be directed towards investigation of the covert cognitive processes. Another interesting finding was that, in the case where hand-altering task was followed by the less demanding task, the P300 component's amplitude magnitude significantly dropped, i.e. the participants had significantly lower attention level. This finding can also be utilized for the job rotation strategy, in a way that less demanding task should not follow the more demanding task, as the worker's in this case face decrement in the attention. However, this finding should be further investigated in the future studies.

Finally, the possibility for utilization of the EEG and behavioral signal modalities, with the aim of real-time assessment of the user cognitive state, was investigated. Regarding the brain dynamics, both the P300 component's amplitude and the EI were investigated and their propagation over time was assessed. Simultaneously, the RTs and the proposed concept of the ME were also calculated and their correlation with the brain dynamics was calculated. Although the research was conducted in an off-line analysis, the findings from these studies suggested that the proposed multimodal system can be successfully applied for the timely assessment of the workers' cognitive state. Generally, it was found that the EEG modalities are related in negative fashion to the behavioral data, i.e. the participants in the study were slower in executing the action when in the brain signals showed lower attention (assessed through P300 component's amplitude). Moreover, the amount of task unrelated movements was higher; when the brain derived attention-related modalities showed the decreased level of attention. Future studies should be concerned with the development of the algorithms for the on-line acquisition and analysis of the EEG and behavioral data, by utilization of one of the recent BCI software packages. This should lead to possibility of timely detection of the deviation in workers' cognitive states, which could ultimately lead to safer production environments.

Experimental studies, presented in the dissertation, were concerned with investigating the relationship between EEG and behavioural modalities. Since the multimodal system that was proposed includes also HRV and GSR measurements, an obvious follow up studies should be directed towards investigating the interaction between all these modalities. For example, it was reported that the HRV increases with lowering the alertness of humans. Similarly, it was reported that increased SCR and SCL reflects higher attentiveness. For that reason, the relationship between HRV, SCL, SCR, P300 ERP component (and/or EI) and behavioural modalities should be investigated, with the aim of increasing the precision of the user state estimation in the workplaces. Ultimately, once the relationship between all mentioned modalities is investigated, the usefulness of the proposed system can be fully evaluated.

The work presented in this dissertation outlined the vulnerability of the existing ergonomics methods for the assessment of the cognitive states of the workers, and proposed that the cognitive states should be assessed by utilizing the neuroergonomics methods. Not only that neuroergonomics provide the possibility of objective quantification of the human cognitive states, but it also provide the possibilities for the real-time assessment of it. The recent development in sensing technology aided in emergence of the wearable physiological sensors, which can nowadays be used for the recordings in the naturalistic environments. The physiological sensor that was of the most importance for the neuroergonomics studies was the development of wearable EEG. Therefore, it is nowadays possible to directly observe the brain dynamics in applied environments. On the other hand, the MoCap technology also advanced, which can be observed through recently available sensors that are based on the structured light technology, but which are also inexpensive. This dissertation presented the overall framework for utilization of the wearable sensors and the MoCap, with the aim of the real-time user state monitoring. The presented system can be foundation for the future implicit HCI system that can be employed for the cognition-aware computing in industry, which can ultimately lead to decrease of human errors in industry, which are caused by the attention decline, consequently increasing the overall workers' well-being.

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