KAUNAS UNIVERSITY OF TECHNOLOGY

MINDAUGAS VASILJEVAS

HUMAN-ASSISTIVE INTERFACE MODEL OF PHYSIOLOGICAL COMPUTING SYSTEMS

Doctoral dissertation
Technology sciences, informatics engineering (T 007)

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Scientific supervisor:

Prof. Dr. Robertas DAMAŠEVIČIUS (Kaunas University of Technology, Technological Sciences, Informatics Engineering – T 007).

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MINDAUGAS VASILJEVAS

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TERMS AND ABBREVIATIONS

BCI	Brain Computer Interface. It is a technology that allows communication between a human or animal brain and an external technology.
DHO	Damped harmonic oscillation. It is repetitive harmonic variation, typically in time, of some measure, which amplitude constantly decreases.
ECG	Electrocardiography. It is a process of recording the electrical activity of the heart over a period of time using electrodes over the skin.
ECoG	Electrocorticography. It is a type of electrophysiological monitoring that uses electrodes placed directly on the exposed surface of the brain to record electrical activity from the cerebral cortex.
EDA	Electrodermal activity. It is the property of the human body that causes continuous variation in the electrical characteristics of the skin.
EEG	Electroencefalography. It is a noninvasive electrophysiological monitoring method to record electrical activity of the brain.
EMD	Empirical mode decomposition. It is a signal decomposition method, which extracts so-called intrinsic mode functions of a complex signal.
EMG	Electromyography. It is an electrophysiological monitoring method to record electrical activity of the skeletal muscles.
EOG	Electrooculography. It is a technique for measuring the corneo-retinal standing potential that exists between the front and the back of the human eye.
EP	Evoke potentials. It is an electrical potential recorded from the nervous system of a human following presentation of a stimulus.
ERP	Event-related potentials. It is the measured brain response that is the direct result of a specific stimulus event.
GUI	Graphical user interface. It is a form of user interface that allows users to interact with electronic devices through various graphical elements and visual indicators.
HAMM	Human-assistive multimodal model. It is a software development framework suitable for multimodal systems where input modalities are based on physiological signals.
HASCM	Human-assistive single channel model. It is a software development framework suitable for single channel-based physiological computing interfaces.
HCI	Human–computer interaction (or Human-Computer interface). It is a scientific domain which analyses the design and use of computer technology, focused on the interfaces between users and computers.
HI	Humanistic Intelligence. It is a type of intelligence that results from a feedback loop between a computational process and a human being, where the human and computer are inextricably intertwined.
HMI	Human-Machine Interface. It is an interface which is capable of handling human-machine interactions.
HRV	Heart rate variability. It is a physiological property of the heart, which shows the variation in the time interval between heartbeats.
IMF	Intrinsic mode function. It is any function with the same number of extrema and zero crossings, whose envelopes are symmetric with respect to zero.

IR	Infrared radiation. It is electromagnetic radiation with longer wavelengths than those of visible light.
IR-PCR	Infrared-induced pupil corneal reflection. It is PCR eye tracking technique based on infrared illumination.
NCI	Neural—control interface. It is a technology that allows communication between an external system and human based on physiological signals of neural origin.
NUI	Natural User Interfaces. It is a user interface that is effectively invisible and remains invisible as the user continuously learns increasingly complex interactions.
PCR	Pupil – corneal reflection. It is an eye tracking technique, in which vector between the pupil center and the corneal reflection is used to compute the point of regard.
PCS	Physiological computing system. It is a system that incorporates physiological data from humans into its functionality or displays these data at the interface.
POG	Point of gaze. It is a gaze position measured by eye tracking device.
SCP	Slow Cortical Potentials. Slow cortical potentials are slow event-related, direct-current shifts in the EEG, originating from the large cell assemblies in the upper cortical layer.
SSVEP	Steady state visually evoked potentials. They are signals that are natural responses to visual stimulation at specific frequencies.
TF	Fatigue threshold. It is an eye fatigue metric that is calculated using an empirical formula that depends on the average spatial accuracy of an eye tracker so that the threshold can scale with noisier signals.
UI	User interface. It is the space where interactions between humans and machines occur.
VOG	Videooculography. It is a non-invasive, video-based method of measuring horizontal, vertical and torsional position components of the movements of both eyes.
TSP	Travelling salesman problem. It is an NP-hard problem in combinatorial optimization, which asks the following question: “Given a list of cities and the distances between each pair of cities, what is the shortest possible route that visits each city and returns to the origin city?”

FIGURES

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1 INTRODUCTION

1.1 Relevance of the work

Human-computer interface (HCI) based on physiological interaction, also known as physiological computing, is a very important research area in computer science. This type of interface goes beyond the typical human-computer interaction. Physiological interfaces incorporate human body characteristics into their functionality. Physiological characteristics of the human body could be determined as any quantitative data of physiological nature that are recorded from the human. The concept of physiological interaction or physiological computing systems (PCS) encompasses such well-known paradigms as brain-computer interface (BCI), neural computer interface (NCI), gaze tracking interface etc.

The initial focus of the PCS-based interfaces was on people with disabilities, since their condition often requires an alternative mode of communication. Recently, we can observe an increasing number of applications that primary focus on healthy users. BCI games and entertainment application, for instance, are expected to constitute a large market of potential users (both healthy and disabled) [Ahn et al., 2014]. Although eye tracking has been known as a useful research utility, recent studies reveal that eye tracking provides a more challenging and immersive experience to the PC game players [Antunes and Santana, 2018]. EMG-based interfaces were mostly applied to control of prosthetics [Castellini and van der Smagt, 2009, Cipriani et al., 2008], but nowadays we can find applications of EMG-based interfaces for smartphones [Lee et al., 2015] and serious games [Ghassemi et al., 2019].

One of the main reasons why PCS-based interfaces are more often used in entertainment applications is the growing number of consumer-grade electronic devices for physiological signal scanning. For a long time, systems were bulky, expensive and laboratory-oriented. Recently more consumer-affordable devices based on physiological computing and eye tracking emerged in the market (e.g. Tobii eye trackers for gaze tracking, Emotiv EPOC+ for BCI applications, MYO gesture control armband for electromyography (EMG)-based control). The gaze tracking systems have become more user-friendly and significantly cheaper. However, in many cases higher affordability has been achieved at the expense of accuracy [Maskeliunas et al., 2016].

The control of interfaces based on PCS is rather a demanding task since a user has to carry out often unnatural activity, which results in high cognitive and physical load. The performance of a user controlling this kind of interface varies due training, emerging fatigue or change in mental state. Mental and physical fatigue have negative impact to performance, while training affects user performance positively.

Fatigue is described as extreme tiredness resulting from mental or physical exertion or illness [Pageaux and Lepers, 2016]. It is common for almost every human physical activity. While controlling a personal computer (PC) in conventional ways, a user experiences fatigue after a relatively long period of time. Fatigue while controlling PC or any other digital device using human – machine interface based on physiological computing usually emerges much faster. Fatigue effects in the EMG-based interfaces are usually concerned with tension of specific muscles, which are responsible for muscle control. Users of the eye-tracking-based human – machine interfaces are usually affected by fatigue which eye muscle tension or even tiredness related with continuous looking at a PC screen and low blinking rate cause. In the field of BCI a user encounters mental fatigue because control of BCI applications requires significant mental concentration. User fatigue results in the decrease of performance and accuracy of system control, so that a user is able to perform high quality control just for a relatively short period of time (measured in minutes or hours. To expand time period of high-quality control in human – machine interface, intelligent user interfaces (UI's) are developed or, if possible, multimodal interfaces are applied.

The training effect opposes the fatigue effect. Therefore, the period of high-quality control might be expanded by performing consistent training. Concepts of fatigue and training are common for physiology research. The analytical models of sport athlete's performance, which encompass the muscular fatigue and training components, have been proposed by Banister and other researchers [Banister et al., 1975, Calvert et al., 1976, Morton et al., 1990, Busso et al., 2002] in the eighties of the twentieth century and elaborated later. Nowadays this research has not lost their relevance. Moreover, they can be applied in new research areas, such as physiological computing, multimodal interface, BCI and NCI.

1.2 Object of the work

The object of this work is an intelligent model of user performance-aware HCI.

1.3 Aim of the work

To enable the monitoring, analysis and increase of performance of users working with physiological computing-based user interfaces by proposing the concept and model of the adaptive human-oriented HCI.

1.4 Tasks of the work

For the aim of the thesis to be achieved, the following objectives have been set out:

1. Perform the analysis of the existing HCI models related to physiological computing.
2. Carry out the analysis of the existing human performance models.
3. Develop an extension to the existing physiological models to allow for the development of an adaptive user performance-aware interfaces.
4. Adapt the performance models for EMG-based HCI and gaze tracking-based HCI.

1.5 Scientific novelty

In this work the following novel results are presented:

1. The extension of the biocybernetic loop concept, called human-assistive HCI model, has been proposed. The model has two variants: human-assistive

single channel model (HASCM) and human-assistive multimodal model (HAMM). HASCM is applied to the users who can use only one input modality. HAMM is applied to users who can use more than one input modality. The novelty of the proposed model lies in two aspects: (i) the aforementioned model is derived from the concept of the biocybernetic loop, but it is more specific in the sense that it provides practical framework for user interface design, (II) the proposed model incorporates the performance evaluation in the human-computer communication process.

2. The analytical model of athlete performance proposed by Banister et al. [Banister et al., 1975] was adapted to PCS research area. Based on this analytical model and experimental results, the analytical performance model for a speller based on eye tracking, has been derived. The derived model of eye tracking performance could be applied to develop human-assistive interface systems.
3. The analytical DHO model, applied to evaluate performance of sport's athletes, was adapted to evaluate the performance of users in the context of PC game based on eye tracking. This model is suitable for long-term analysis of performance dynamics. Findings show that this model well describes long-term fatigue and training effects and short-term recovery of user performing abilities.
4. To denoise and smooth the raw performance data of a PC game based on gaze tracking, a signal decomposition method, called BoostEMD [Damasevicius et al., 2015] has been developed. BoostEMD is an extension of a widely known Empirical Mode Decomposition (EMD) method, which is used to decompose time series representing a physiological signal into constituent mono-component signals, also known as Intrinsic Mode Functions (IMFs). In BoostEMD approach, the initial IMFs are further decomposed in lower order IMFs applying the principles of the EMD method and some additional signal transformation, called boosting [Damasevicius et al., 2015].

1.6 Practical value

Human-assistive HCI model provides a framework for the development of human – machine interfaces based on physiological computing. Using human-assistive HCI model, user interfaces based on the performance characteristics of physiological interaction can be designed. The aim of this model is to enhance time period of continuous accurate control of the human – machine interface based on physiological computing.

Typically, one of the biggest application areas of user interfaces, based on various physiological signals, is the systems for disabled. In general, such assistive technologies can be applied everywhere (both at work and home) in our everyday life to increase the quality of our life, sustain work productivity as well as for entertainment. Using such a system user starts feeling fatigue relatively fast, therefore, performance of the system control decreases as well. The performance of a user depends on individual characteristics. The proposed human-assistive HCI model aims to adapt the interface to individual user needs and abilities and helps to prolong the time of effective usage of a certain interface. Moreover, some specific performance evaluation methods, suitable for interfaces based on eye tracking and EMG recording, have been adapted from other domains.

1.7 Thesis statements

1. The proposed Human-assistive HCI model could be applied to develop human – machine interfaces based on physiological signal control.
2. Empirically determined analytical performance model developed by Banister et al. fits well user performance data obtained by using virtual keyboard interface based on eye tracking.
3. Empirically determined analytical DHO performance model fits well user performance data obtained by applying a PC game based on eye tracking.
4. The proposed BoostEMD signal decomposition method can smooth the raw performance data of the PC game based on gaze tracking better than other analyzed smoothing methods (moving average, Savitzky-Golay and median filters).

1.8 Scientific approval

The experimental results were presented and discussed in 4 international scientific conferences:

1. XV International Conference on Human Computer Interaction, Interacción 2014, Tenerife, Spain.
2. 2014 Federated Conference on Computer Science and Information Systems, FedCSIS 2014, Warsaw, Poland.
3. The 19nd International Conference ELECTRONICS 2015, Palanga, Lithuania.
4. 12th International Conference on Intelligent Computer Communication and Processing, ICCP 2016, Cluj-Napoca, Romania.

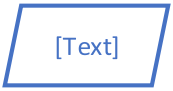
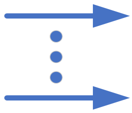
The full list of publication can be found in chapter titled “LIST OF PUBLICATIONS OF MINDAUGAS VASILJEVAS ON DISSERTATION TOPICS”.

1.9 Notation of diagrams

All diagrams in this document are presented based on the below provided notation.

Table 1.1 Notation of diagrams

Concept	Notation	Description
Layer, component	[Text]	Describes a static concept of systems. Layers and components are responsible for a specific set of actions of a particular system.
Medium	[Text]	Describes physical or virtual communication environment.

Process		Describes actions – a dynamic behavior of the system.
Data flow		Describes data type and (or) their flow direction.
Multiple data flow		Describes multiple (undetermined number) types of data and their direction.

1.10 Thesis organization

The work consists of 5 chapters. Total scope of the thesis is 130 pages, 49 figures, 11 tables and 227 literature review sources.

Chapter 1 provides the introduction of the thesis, encompassing a short summary of work relevance, aim, tasks, scientific novelty, practice value, thesis statements and scientific approval.

Chapter 2 gives the analysis of the research object. It is divided into two main sections. The first section provides an overview of PCS paradigms, which enable adaptability, and analysis of physiological signals suitable for fatigue estimation. The second section focuses on the analysis of fatigue detection in different scientific domains.

Chapter 3 describes the proposed Human-assistive HCI model. Two versions of this model (HASCM and HAMM) are described in separate sections.

Chapter 4 describes 3 different experimental researches that aim at adaptation of Human-assistive HCI model.

Chapter 5 provides general conclusions of this work.

The structural organization of the dissertation is demonstrated in Fig. 1.1.

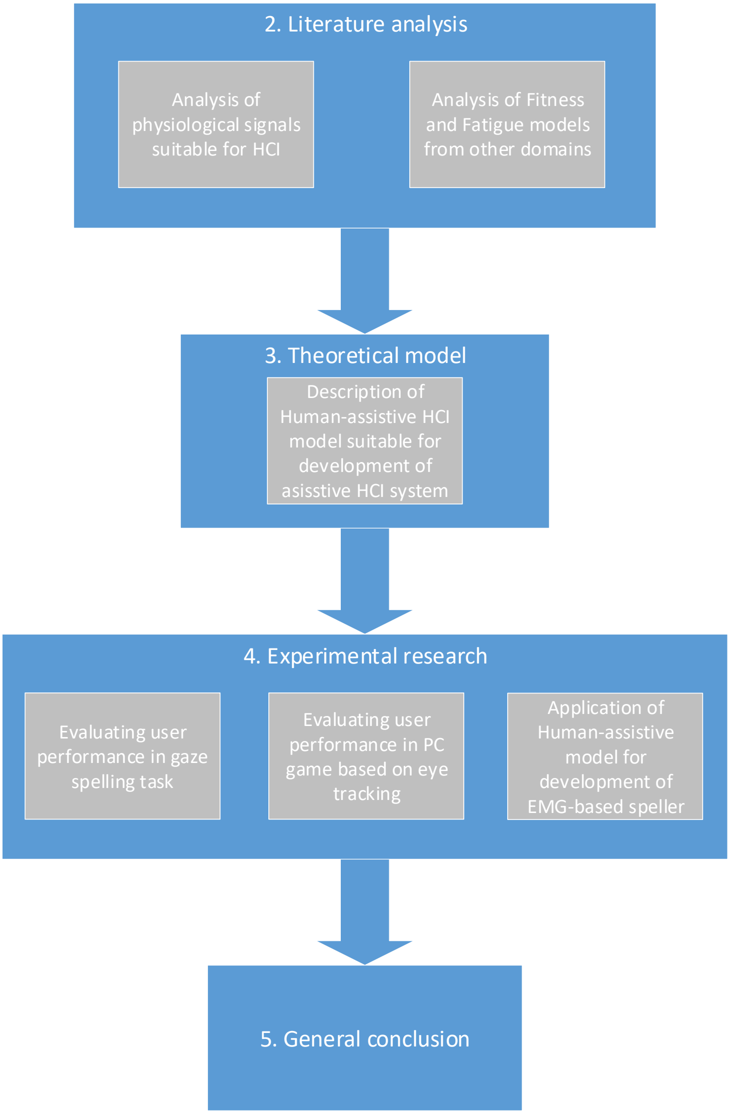


Figure 1.1 Structural organization of the dissertation

2 ANALYSIS OF LITERATURE

In this chapter the analysis of literature is carried out. First, the basic concepts of physiological computing and input modalities are overviewed. Second, the analysis of performance estimation methods in both physiology and HCI domain is conducted. Finally, the idea of combining bio-cybernetic loop and human performance models is elaborated.

This chapter is organized as follows: section 2.1 provides the overview of human-machine interfaces, section 2.2 provides the overview of input modalities used in physiological computing, section 2.3 presents the analysis of user performance estimation methods, section 2.4 presents the idea of combining bio-cybernetic loop and human performance models, finally, section 2.5 provides the conclusion of the chapter.

2.1 Overview of Human – machine interface

2.1.1 Biofeedback

In the first treatise on cybernetic theory and communication as well as control in biological and mechanical systems by Wiener in 1948, the theory of feedback is of the core importance. The concept of feedback here relies on the recognition that the controller of the system can control an appointed variable if it can access information about that variable. Starting with the seventh decade of the 20th century the perception of humans as able to exercise conscious influence over apparently unconscious physiology was seriously dealt with and it was found out that feeding back physiological information to a subject ensured successful physiological control [Allanson and Fairclough, 2004], and this process is called feedback. It relates to a set of therapeutic procedures that handle electronic or electromechanical tools to measure, process and provide information with educational and reinforcing features about both normal and abnormal neuromuscular and autonomous activity to people and their therapists. This helps people to increase awareness of, trust in and control over their physiological processes. With reference to physiological signal feedback loop for a system that includes computer-based signal presentation, the computer is to fetch physiological signals from the sensing hardware, pre-process the signals and exhibit them in real time.

Recently computer-based systems for presentation of physiological signals are to carry out two separate applications, namely clinical biofeedback and physiological signal-driven hands-free human-machine interaction. The same signal pre-processing and presentation requirements apply for both applications.

A long-known application domain for physiological signal-driven hands-free human-machine interaction is EMG-based prostheses [Farina, 2014]. In this case artificial limbs are controlled by healthy muscles from another body place. Biofeedback is considered as a current position of an artificial limb. Nowadays biofeedback is exploited in medicine [Windthorst et al., 2017, Sjödahl et al., 2015], PC games [Parnandi and Gutierrez-Osuna, 2017, Lobel et al., 2016], sports training

[Ortega and Keng, 2018, Paul and Garg, 2012], psychology (e.g. for stress reduction) [Dillon et al., 2016].

A general scheme of biofeedback is presented in Fig 2.1.

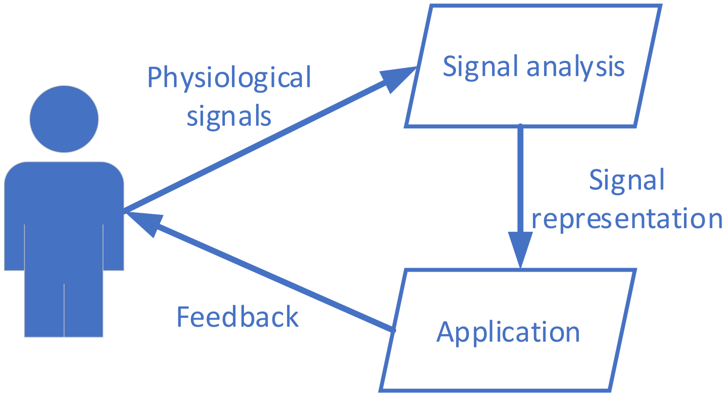


Figure 2.1 A general scheme of biofeedback

The general workflow of biofeedback starts with recording physiological signals. Afterwards, these signals are quantified and processed to produce suitable representation of the signals for specific application. Signal analysis as well as its representation are strongly related with application (e.g. in medical application sampled signals are usually represented in a complex form as time series, whereas in PC games representation of the signals is simplified and can be transformed to colors, emoticons, sounds, etc.). A user receives the feedback as determined by the application. Feedback can be provided as visual, auditory or tactile information.

2.1.2 Biocybernetic loop

The concept of the biocybernetic loop originating from a cybernetic model of control and communication within a closed loop unifies all physiological computing systems. In the feedback loop data are processed in collection, analysis and translation phases, the realization of which depends on the category of a physiological computing system. At the first stage user-worn sensors aim at collection of data, quantification of which as well as identification of artifacts are the main processes of the second phase. To be more precise, quantification of the incoming data in real time and identification of periods with irrelevant or incorrect data are the role that the analysis algorithm should play. For the analysis stage much attention is paid to a certain aspect of psychology or behavior. The final phase explains the way physiological units of measurement are changed into a computer command to be carried out at the human-computer interface. For EMG-based interfaces and certain categories of BCI (e.g. where the cortex helps to capture motor functions), the biocybernetic loop aims at changing patterns of physiological activity into a certain command [Fairclough, 2017].

The concept of the biocybernetic loop encompasses biofeedback (see section 2.1.1). Recording of physiological signals and providing various feedback to the user are common stages of biocybernetic loop and biofeedback. However, a biocybernetic loop is a more complex paradigm. It has additional stages: classification and adaptation. The classification stage aims to classify physiological signals to the interface control commands. In the adaptation stage functionality, or appearance of the system can be modified based on classification results or direct real-time measurement of psychophysiology [Allanson and Fairclough, 2004].

Biocybernetic loop may be designed to: (1) promote and sustain a state of positive engagement with the software/task, (2) minimize any health or safety risks to the user that are inherent within the HCI [Serbedzija and Fairclough, 2009]. Moreover, the biocybernetic loop might provide the following adaptations [Serbedzija and Fairclough, 2009]:

- awareness of user state (seconds/minutes/hours)
- adaptation to stable traits (hours/days/weeks)
- adaptation to trait changes (months/years)

Other categories of physiological computing count on the accurate recognition of spontaneous psychological states to communicate system adaptation, e.g. affective computing technologies the function of which is to detect changes in emotional states [Cambria, 2016]. The adaptive controller is responsible for converting real-time physiological data into computer control, and for pattern-matching algorithms adaptive control is hence direct. For biocybernetic adaption the role of the controller changes. These systems are developed for promoting positive states and forbidding the unwanted. The impact between the user and system changes since biocybernetic control is for shaping and manipulating the psychological state of the user. If the user faces great mental workload, the system interferes to reduce workload and keep the situation stable. If the system user experiences failure, the system might either offer help or adapt itself to reduce the challenge. Certain change in a human-computer duo seeing the computer as a partner or team-player as opposed to a servant-like system is the net result of the closed-loop design.

At different levels of HCI the functions of the biocybernetic loop are different, e.g. with reference to muscle interfaces and BCI, the biocybernetic loop functions as a tool to communicate commands to the interface [Chai et al., 2018, Chowdhury et al., 2017, Lin et al., 2016]. At the meta-level of the HCI, biocybernetic adaptation alters parameters of the interactions (e.g. game difficulty) [Ewing et al., 2016, Labonte-Lemoyne et al., 2018] or intervenes into the system actively (e.g. offers help) [Conrad and Bliemel, 2016]. Hence, in general, the aim of the biocybernetic loop is to adjust settings and make interventions to result in the desired interaction. It is both a model of information flow and all-enclosing concept for physiological computing systems being responsible for having raw physiological data converted into proper response from computer software. The process covering the biocybernetic loop relates to the listed issues [Fairclough, 2017]:

1. physiological measures must be valid for psychological concepts;
2. there must be unobtrusive hardware that can capture these measures in the field with enough fidelity;

3. data must be analyzed and categorized in near-real time to deliver user representation to the system;
4. changes in user representation must be converted into software control and adaptation that is both responsive and coherent.

The scheme of the biocybernetic loop [Karran, 2014] is presented in Figure 2.2. It has 4 components: inference, classification, adaptation and interaction.

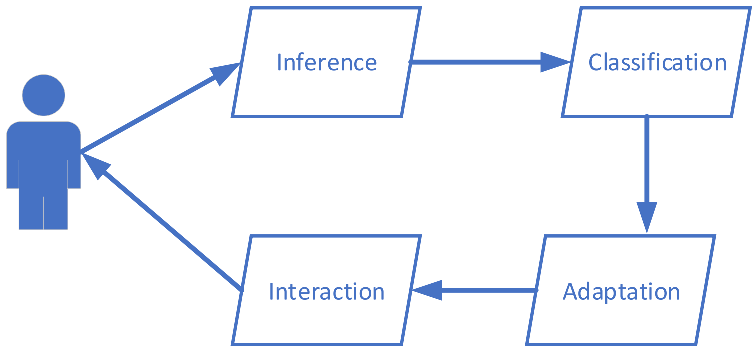


Figure 2.2. The scheme of the biocybernetic loop [Karran, 2014]

Each component of the biocybernetic loop is explained below:

1. **Inference**. Linking the target psychological state with a physiological measure is the main concern of the stage. A psychophysiological construct that best describes the target psychological state (e.g. a state of high cognitive workload) is created and physiological measures which define the most valid operationalization of that psychological state are selected. Choosing sensor technology and signal processing techniques, which must be suitable for application in the field and provide high signal fidelity, is essential for this stage of the loop. The selection of features of the inference model plays the most significant role to the effectiveness of the loop. If the physiological measures do not capture the psychological construct with enough sensitivity and reliability, the inference model does not provide a clear link between the user state and system operation [Karran, 2014].
2. **Classification**. The identification of the psychophysiological state in real-time or near real-time is concerned at the stage. It is important that information passed from this stage be up-to-the minute if dynamic functioning is expected from the loop. Hence, the choice of classification algorithm becomes crucial at this point. The classifier must be capable of processing and categorizing information in a both accurate and timely manner. The cost of misclassification of user responses requires careful examination as ultimately the classifier feeds forward judgements into the adaptation engine and thus shapes the efficacy of system adaptation in response to user behavior [Karran, 2014].

3. **Adaptation**. The psychophysiological response has previously been measured and classified at this stage. The results from the classification are employed to find out the form of adaptations to be used at the interface. Therefore, adaptation is concerned with the application of the governing rule set or purpose of the loop, namely, what actions should be taken at the interface in response to classification findings about the user‘s state [Karran, 2014].
4. **Interaction**. The process of adaptation is a form of the interface between the user and the system. The form of adaptation will shape user perceptions of system efficacy from the psychophysiological inference to classification and adaptation. It must be carefully designed to provide a timely and relevant action or feedback at the interface to cause user confidence [Karran, 2014].

2.1.3 Humanistic intelligence

Humanistic Intelligence (HI) is intelligence that arises because of a human being in the feedback loop of a computational process, where a human and a computer are inextricably intertwined [Minsky et al., 2013]. HI is expressed through three main operational modes: constancy, augmentation, and mediation [Mann, 2001].

- **Constancy**: HI manifests itself as *operationally constant*; which means that despite power-saving modes it never shuts down. Furtheron, it is *interactionally constant*, which refers to always active inputs and outputs of the device. It is important to note that interactionally constant implies operationally constant, but vice versa is not the case. The problem of insufficient comprehension of the significance of the above-mentioned constants has led to the development of portable devices which in their turn stimulate the progress of new forms of intelligence that help the user in new ways.
- **Augmentation**: computing is perceived as the main task in the sense of traditional computing, while HI-based intelligent systems see computing as a separate part. From the HI point of view computing itself is not the result; a human being should be doing something else while computing. Thus, the computer should augment the intellect, but the primary task should not be ignored.
- **Mediatio**n: exemplar manifestations of HI show the human being *encapsulated* [Mann, 2001]. Nonetheless, the basic notion of mediation makes encapsulation of any degree possible for it can offer the user encapsulation of higher extent than traditional portable computers. The mode is like the augmentation mode in the sense of implicit spatio-temporal contextual awareness from sensors. The encapsulation as provisioned by mediation has two characteristics, one or both of which can be implemented in varying degrees. The first one is *solitude* which means that the embodiment of HI starts playing the role of an information filter due to our ability to mediate our perception. To a less intense extent it might merely enable to slightly change aspects of our reality perception. Furtheron, we

are given a possibility to augment or improve desired inputs. This control supplements greatly to user empowerment seen as the most crucial HI issue. The second aspect is *privacy*, which suggests that information that leaves our encapsulated space might be modified or controlled rather than absolutely concealed or blocked. Also, the embodiment of HI can be a mediator for interacting with untrusted systems and hides our otherwise transparent movements in cyberspace and the real world. The system becomes less defenseless against direct attacks if the synergy between the user and computer is close enough. It is important to note that due to the element of the HI encapsulation, diverse physiological quantities can be measured.

- **Combined modes** imply that all three modes are correlating, e.g. constancy is demonstrated via augmentation and mediation. The latter two should not necessarily be implemented in isolation, as real embodiments of HI generally include elements of augmentation and mediation. Thus, HI is the basis for combination and empowerment of various aspects of each of the mode discerned.

In general, six basic signal flow paths are distinguished speaking about intelligent systems embodying HI (see Fig. 2.3). Each path characterizes an HI attribute:

- **Unmonopolizing**: a person is not dissociated from the real world as, for instance, in the game of virtual reality;
- **Unrestrictive**: the device does not interfere with other tasks carried out;
- **Observable**: the output medium is regularly noticeable;
- **Controllable**: a person can always control the device, even in automated processes, e.g. an application opens 20 documents after the user presses ‘Enter’;
- **Attentive**: the device is environmentally aware, multimodal and multisensory which means increased awareness of the situation;
- **Communicative**: the device can serve as a communication medium and enables the user to communicate directly to other or helps in delivering expressive or communicative media.

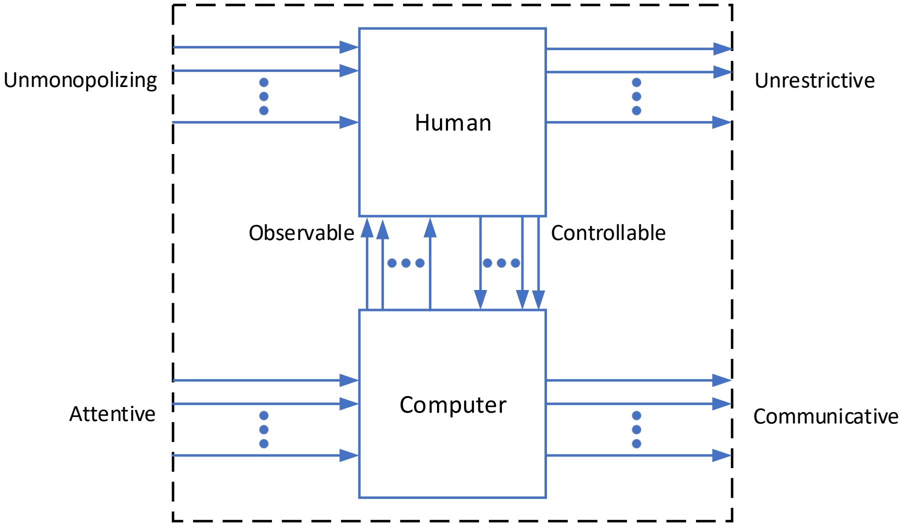


Figure 2.3. The six signal flow paths for intelligent systems embodying HI [Mann, 2001]

2.1.4 Speller as a typical human – machine interface application

Originally, the analysis of a speller application was presented in [Vasiljevas et al., 2014a, Vasiljevas et al., 2014b, Damaševičius et al., 2015].

2.1.4.1 Analysis of the requirements for speller applications

The requirements for speller application can be categorized at different levels depending upon the physical abilities of its users [Quek et al., 2012]: 1) Users with no physical disability, who may use NCI for entertainment or other conditions where physical movement is restricted. 2) Users with minor impairments (such as older persons). 3) Users with severe physical disabilities, who may wish to use NCI as a secondary input. 4) Users who are almost locked-in (having limited muscle control), who may need to use NCI as a method for communication.

First, the speller must follow general requirements for smart systems to be integrated into the AAL environments. Next, the specific requirements for impaired users (and, specifically, for older persons) must be followed. Impaired users need assistance such as automatic learning of user’s behavior to estimate his/her current needs.

Since humans often make mistakes or errors in interacting with machines, for any human-operated system, user interfaces should be designed such that prevent errors whenever possible, deactivate invalid commands, make errors easy to detect and show users what they have done, and allow undoes, reverse, correct errors easily [Mann, 2001].

For smart systems, the following principles (also called “operational modes”) of Humanistic Intelligence Framework [Mann, 2001] must be satisfied:

1) **Constancy**: the interface should operate continuously to read signals from human to computer and to provide a constant user-interface.

2) **Augmentation**: the primary task relies on increasing the intelligence of the system rather than computing tasks.

3) **Mediation**: the interface mediates between human senses, emotions and perceptions and acts as an information filter by blocking or attenuating undesired input to decrease negative effects of interaction (such as fatigue, information overload, etc.) as well as to increase positive effects (such as user satisfaction) by amplifying or enhancing desired inputs.

According to Lopes [Lopes, 2001], the user interface for the disabled must: support user variability allowing to provide the means to adapt to user-specific requirements; support of a wide range of input devices and output modes; provide minimal user interface design; promote interaction and retain user attention on the tasks; and provide strong feedback mechanisms that may provide rewarding schemes for correct behavior (results).

The requirements for interfaces for impaired users can be formulated as follows [Marinc et al., 2011]: 1) Limited access to details: complex and vital details of the system must be hidden to avoid user overwhelming and trapping. 2) Self-learning: detected common patterns in the behavior of the user should be used to automatically create rules or shortcuts that speed and ease up the use of the system. 3) System interruption: in most cases impaired users have no idea how the system is working, therefore, easy cancellation of the system activities must be ensured.

In the questionnaire-based study of potential BCI user requirements towards assisted technologies [Zickler et al., 2010], the participants rated participants rated "functionality" (aka effectiveness) as the most important requirement, followed by "possibility of independent use" and "easiness of use".

2.1.4.2 Overview of speller systems and interfaces

The research in developing and improving speller systems focuses on improving accuracy of spelling, increasing speed of information transfer, developing usable and effective speller interfaces, and combining EEG/EMG-based input with input automation techniques such as word complete and automatic correction of misspellings. For example, Akram *et al.* [Akram et al., 2013] propose a modified T9 (Text on Nine keys) interface with a dictionary to give words-suggestions to the user while typing. Eight keys are associated with several characters and a dictionary is used to suggest words according to the sequence of keys a user presses. Ahi *et al.* [Ahi et al., 2011] use a custom-built dictionary of 942 four-lettered words integrated into the classification system of P300 speller for automatic correction of misspellings. However, the dictionary is used only for word correction and the user has to spell all the characters of a target word. Höhne *et al.* [Höhne et al., 2011] use a German language T9 system with an auditory event-related potential based speller. The user spells on a 3×3 scheme with audio stimuli and suggestions are shown after the user spells a complete word. Mathis and Spohr [Mathis and Spohr, 2007] use tree data structures constructed from a newspaper corpus to automatically complete the spelled words. In this way, identification of all letters becomes unnecessary, and spelling of a word takes less time. However, such a word completion system assumes that the first letter is identified by the classifier correctly, and in case the first letter is misclassified, the system generates erroneous results. Ulas and Cetin [Ulas and Cetin, 2013] propose an approach for incorporation of such information into a BCI-based speller through hidden Markov models (HMM) trained by a language model. To sum up, implementations of the speller application can be characterized by:

Type of data: EEG [Tomioka and Müller, 2010], EMG [Lalitharatne et al., 2013], ECoG [Speier et al., 2013], EOG [Liu et al., 2011].

Type of the analyzed signal: P300 event-related potentials (ERPs), which are series of peaks and troughs appearing in the EEG in response to occurrence of a discrete event, such as presentation of a stimulus or psychological reaction to a stimulus [Adams et al., 2009], Error-related Potentials (ErrPs) generated by the subject's perception of an error [Combaz et al., 2012], Steady-state visual evoked potential (SSVEP), which are signals that are natural responses to visual stimulation at the same (or multiples of) frequency of the visual stimulus [Hwang et al., 2012].

Modality: *Auditory*: the rows and columns of the letter matrix are represented by different sounds, such as spoken numbers [Furdea et al., 2009] or environmental sounds. *Visual:* subjects direct their eye gaze toward the letter they want to select. There are two cases: overt attention when eye gaze is directed towards the target letter, and covert attention when eye gaze is directed to a central fixation point [Brunner and Schalk, 2011]. *Tactile:* stimuli are applied to fingers that represent the letters of the alphabet. First, a group of letters is selected, then, one letter from this group is selected [Waal et al., 2012].

Interface:

*Single character (*or *Linear) speller:* all letters are shown, and each letter is flashed individually until further selection is done [Ortner et al., 2011].

Matrix Speller: All letters are arranged in a matrix. First, a speller flashes an entire column or a row of characters. Then, single letters are flashed in a sequence, and can be selected [Farwell and Donchin, 1988]. Different matrix sizes can be used, e.g., a 6x6 matrix containing all 26 letters of the alphabet and 10 digits (0-9), or even a full QWERTY keyboard [Hwang et al., 2012].

Lateral single-character is a single-character paradigm comprising all letters of the alphabet following an event strategy that significantly reduces the time for symbol selection [Akram et al., 2013].

Chekerboard Speller [Townsend et al., 2010]: the 8x9 matrix is virtually superimposed on a checkerboard which the participants never actually see. The items in white cells of the 8 x 9 matrix are segregated into a white 6 x 6 matrix and the items in the black cells are segregated into a black 6 x 6 matrix. The items in the first matrix randomly populate the white or black matrices, and the users see random groups of six items flashing (as opposed to rows and columns in the Matrix Speller). Such layout controls for adjacency-distraction errors, because the adjacent items cannot be included in the same flash group.

Hex-o-Spell: the speller consists of six circles that all have the same distance to the point of fixation. The circles are flashed while users direct their attention to one of the circles. In the first step, the circle with the desired group of letters is selected. In the second step, letters are redistributed over the circles and the target letter is selected [Treder and Blankertz, 2010].

Frequency-based layout accounts for the relative frequency of character occurrence in a language [Volosyak et al., 2009]. It has a virtual keyboard with 32 symbols surrounded by five boxes flickering at different frequencies. These boxes correspond to commands for navigating the cursor and selecting the intended character. The application starts with a cursor at a central position corresponding to the most frequent character in English (i.e., “E”). Letters with the higher frequency of occurrence are positioned closer to the center while less frequent ones are further away. The user can navigate the cursor to the desired letter and confirm his/her choice with the “Select” command. The further the character is located from the center, the more command selections (cursor movements) are required.

Stimulus type: the way each individual character changes (e.g., flashing, color change, etc.). For example, Rapid serial visual presentation (RSVP) is a method of displaying information (generally text or images) in which the text is displayed word-by-word in a fixed focal position [Acqualagna and Blankertz, 2013].

Stimulus rate: the speed at which individual characters change.

Stimulus pattern: grouping of the symbols in the interface (e.g., QUERTY or DVORAK layouts in a virtual keyboard).

Character set (alphabet): includes all letters of the alphabet as well as some additional symbols (numbers, separation marks, etc.).

Intelligence techniques: additional techniques for improving accuracy of the system and rate of communication such as using language model [Ulas and Cetin, 2013], word autocomplete, spelling correction or word prediction.

The result of the analysis can be considered as a taxonomy of speller application parameters, which can be used for developing new speller applications. Next, we will discuss the model of a PCS and its application to developing the EMG-based systems.

2.2 Input modalities

2.2.1 EEG

EEG signal is a physiological signal generated by the cerebral cortex of the human brain. In HCI applications non-invasive electrodes are usually placed on a human scalp to capture an EEG signal. Standard placement scheme of scalp electrodes is presented in Fig. 2.4 It is known as international 10-20 system.

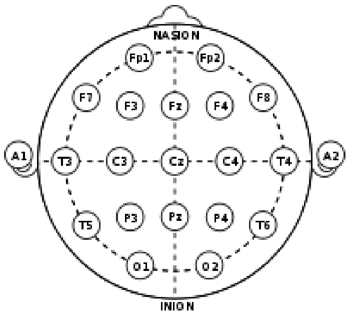


Figure 2.4. The International 10-20 system

Higher resolution system is also applied for capturing EEG. It is known as 10-5 system [Oostenveld and Praamstra, 2001].

In some cases, invasive electrodes are applied to measure an EEG signal. To place invasive electrodes surgical intervention is required. Electrodes are placed directly on the exposed surface of the brain to record electrical activity from the cerebral cortex. This approach is known as ECoG [Hassanien and Azar, 2015].

It is suggested that EEG reading techniques, when electrodes are placed in the skull on the top of human brain should be considered as a partially-invasive EEG or partially-invasive BCI [Ramadan et al., 2015]. However, a partially-invasive EEG requires nearly the same level of surgical intervention as in the case of the invasive EEG.

EEG signal itself is divided into different bands:

- **Delta**. Frequency range of 1-4 Hz. These are the slowest waves of EEG. They also tend to be the highest in amplitude and are usually observed in deep sleep phase. The waves commonly appear in infants and small children brain waves.
- **Theta**. Frequency range of 4-8 Hz. They appear when the subject is relaxed or during meditation. These waves are usually observed in the frontal or temporal lobe of the brain.
- **Alpha**. Frequency range of 8-12 Hz. These waves usually emerge when the subject is in a relaxed state with his eyes closed. This type of waves is observed in parietal, sometimes occipital lobes of the brain.
- **Beta**. Frequency range of 12-30 Hz. Such waves are strongly related with mental activity and psychical stress. These waves are observable in the frontal lobe of the brain.

- **Gamma**. Frequency range of 30-150 Hz. These waves are the highest in frequency. Sometimes they can be subdivided in smaller bands (e.g. High Gamma with frequency range of 80 – 150 Hz). They are observable in the frontal lobe of the brain and related with various mental activities (e.g. perception of senses, understanding of meanings and words, etc.).

Some authors divide EEG in an even complex set of bands distinguishing Mu rhythms (frequency range of 8-13 Hz) [Pfurtscheller et al., 2006, Fox et al., 2016] and SCP (frequency range of 0-1 Hz) [Leins et al., 2007].

Human – computer interface, whereby EEG signals are used as an input, is called Brain – Computer Interface (BCI). A typical scheme of BCI is presented in Fig.2.5. This abstract scheme is common for nearly every HCI based on physiological data.

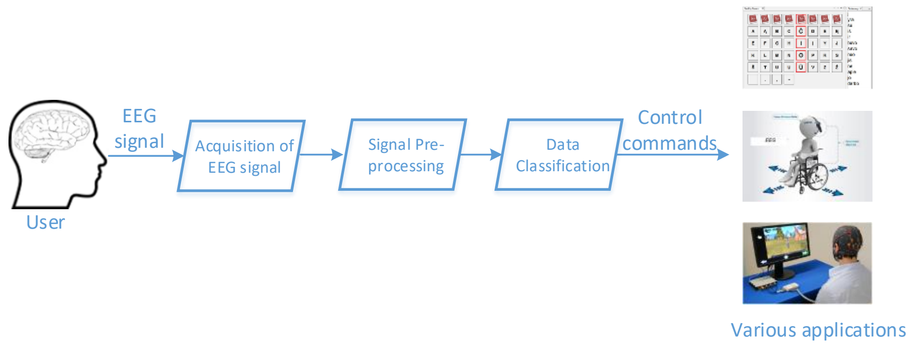


Figure 2.5. A typical scheme of BCI

The stage of the EEG signal acquisition is specific for this type of the spelling system. EEG signal is captured using the techniques described above. The stage of preprocessing is responsible for signal filtering and feature extraction. In data classification stage various machine learning algorithms are applied for recognition of the control commands. A type and number of the control commands depend on an application. One of the most widely spread BCI application is a speller [Dal Seno et al., 2010, Yin et al., 2013, Yin et al., 2015, Benda et al., 2017]. In case of a speller, control commands could be letters, rows and columns in a symbol matrix or navigation commands in a specific set of symbols. Another popular application refers to wheelchair control [Carlson and Millan, 2013, Singla et al., 2014, Waytowich and Krusienski, 2017], computer games [Nijholt et al., 2009, Marshall et al., 2013, Wong et al., 2015], neuromarketing [Wriessnegger et al., 2015], etc. Abdulkader et al. in their study classify BCI application into these groups: medical, neuroergonomics and smart environment, neuromarketing and advertisement, educational and self-regulation, games and entertainment, security and authentication [Abdulkader et al., 2015]

There are two modes of EEG signals for speller control:

- **Spontaneous potentials**. These signals are generated by the cerebral cortex without any stimulus presented to the test subject. Spontaneous potentials provide information about mental state, different cognitive processes and activation processes. Furthermore, different thoughts, actions and mental states can affect EEG rhythms [Martišius, 2016]. The fact that a specific thought can affect the shape of an EEG signal and sustain some pattern over a prolonged period, allows us to see a signal as a control command. In literature the most common way to control a BCI speller using spontaneous potentials is motor imagery [Pfurtscheller and Neuper, 2001]. Similar systems have been presented by Sitaram et al, Perdikis et al and D'albis et al. [Sitaram et al., 2007, Perdikis et al., 2014, D'albis et al., 2012].

- **Event-related potentials** (ERP). These signals are generated by the cerebral cortex when a test subject is stimulated. One can observe a significant change of brain waves after a specific stimulus. The stimulus can be sensory (also known as evoke potentials or EPs), imaginative or evoked by real physical activity, i.e. movement of limbs or other body parts. EPs could be raised by auditory, visual or somatosensory stimulus. Also, EPs can be classified regarding the frequency of stimulation. If stimulation frequency is less than 2 Hz, an observed signal is considered as transient EP. In a similar way, if stimulation rate is higher than 6 Hz, a response known as steady state EP will appear [Martišius, 2016]. A specific case of a BCI speller called steady-state visually evoked potentials (SSVEP) speller is worth mentioning, as recently its development has attracted researchers' attention [Yin et al., 2013, Hwang et al., 2012, Yin et al., 2015, Cecotti, 2010]. The basic principle of that kind of a speller is to perform control tasks, when different visual regions are represented on the screen. To control the speller test, a subject must point his gaze and focus to a certain region.

In scientific studies of BCI, various EEG recording equipment are used. While the high-resolution EEG recording systems are expensive, there is a number of studies where consumer-grade EEG devices are used (e.g. Emotiv EPOC, Neurosky MindWave etc.). Our research shows that these devices are limited in terms of accuracy and feedback. Also, it may increase BCI illiteracy [Maskeliunas et al., 2016].

2.2.2 EMG

Electromyography (EMG) is an electrodiagnostic medicine technique for capturing and evaluating the electromyogram. Electromyogram itself is a physiological signal produced by muscle cells of skeletal muscles [Kamen and Kinesiology, 2004]. The source of an EMG signal is the potential of a single muscle, which value is approximately 90 mV. The amplitude of a surface EMG signal can vary from less than 50 µV to 30 mV [Nigg and Herzog, 2007]. The frequency of an EMG signal that represents a significant EMG activity is in the range of 5 – 450 Hz [Komi and Tesch, 1979, Merletti and Di Torino, 1999]. In literature it is considered as one of the best understood and promising source of a physiological signal suitable for human – machine interaction [Allanson and Fairclough, 2004].

There are two techniques for capturing an EMG signal:

- **Surface EMG recording**. In this technique pre-gelled surface electrodes are applied for capturing an EMG signal. Surface electrodes are placed on the subject's skin. Since the potential difference is measured, two or more electrodes are needed. Skin and fat serve as low-pass filters; hence the signal provides only limited assessment of muscle activity. In case of a classification task, surface technique performs poorly compared to an intramuscular technique [Smith and Hargrove, 2013].
- **Intramuscular EMG recording**. In this technique monopolar needle electrodes are usually applied. These electrodes penetrate the skin above a specific muscle. The EMG signal captured using intramuscular electrodes has a wider band of frequency compared to a signal captured using surface electrodes. The frequency also depends on a specific muscle and the type of a muscle activity (dynamic or isometric). An EMG signal recorded using intramuscular technique gives better results in classification [Smith and Hargrove, 2013].

Most common EMG application for human – computer interaction is control of artificial prosthesis [Saridis and Gootee, 1982, Park and Lee, 1998, Farina et al., 2014]. Often an EMG signal serves as an alternative or concurrent input channel for Hybrid BCI system. In this type of a BCI system additional electrophysiological signal channels are added. Different channels can be recorded simultaneously, or one can switch between different input channels. Recently Hybrid BCI with an additional EMG channel for various applications is often discussed in literature [Minati et al., 2016, Tang et al., 2016, Li et al., 2013, Lin et al., 2015]. A Hybrid BCI system with an additional EMG channel for speller application was proposed by Lin et al [Lin et al., 2015, Lin et al., 2016]. In this system both EMG and EEG SSVEP modalities are used for speller control simultaneously. Both signals are fused using "AND" strategy [Lin et al., 2016].

Single modality EMG-based speller with adaptable stimulus rate and dictionary support can perform similarly as hybrid BCI spellers in terms of input speed, accuracy and information transfer rate [Vasiljevas et al., 2014a]. Input speed can be increased using concepts instead of symbols [Damaševičius et al., 2015].

A variety of studies have proven that a facial EMG can be used to measure and determine emotional response to various stimuli [Dimberg et al., 2000, Van Boxtel, 2010, Gruebler and Suzuki, 2014]. In more recent studies facial EMG technique have been applied for moral evaluation of written information [Hart et al., 2018].

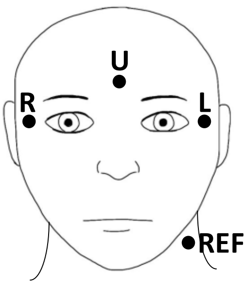
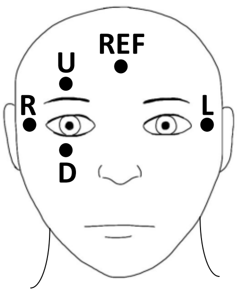
EMG can be considered as one of the best adopted input modalities in physiological computing. For a long period of time various EMG-biofeedback devices have been used for rehabilitation after stroke [Woodford and Price, 2007], treatment of tension headaches [Flor et al., 1983], fibromyalgia syndrome [Ferraccioli et al., 1987], etc. Recently, widely available commercial EMG devices like Mio armband (https://www.myo.com/) and Somaxis Myolink (http://www.somaxis.com/) can be used on a daily basis for gaming, interacting with computers and fitness purposes as well as for physiotherapy [Sathiyanarayanan and Rajan, 2016].

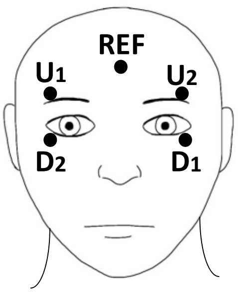
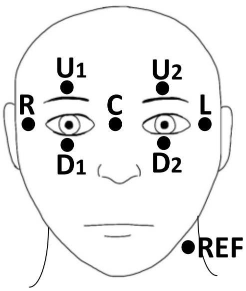
2.2.3 EOG

EOG stands for electrooculography. It is a technique for recoding EOG signal. By its nature EOG signal is an electrophysiological signal generated by eye movements or a measure of the potential difference between the cornea and the retina of the eye [Allanson and Fairclough, 2004]. Voltage is generated due to the potential difference between cornea and Brunch membrane [Creel, 2015]. The recorded potentials are in the range of 15–200 µV, with nominal sensitivities of order of 20 µV/deg of eye movement [Duchowski, 2007].

Recent electrode placement study for recording EOG signal has been presented by Lopez A. et al [Lopez et al., 2016], in which 4 different electrode placement schemes are analyzed.

Table 2.1 Electrode placement schemes [Lopez et al., 2016]

Placement view	Description
	Three electrodes (R, U and L) are used for signal capturing. At this configuration two differential signals are generated (right – up and left – up). EOG is represented in two channels: R – U electrode pair provides channel 1 and U – L electrode pair provides channel 2. Additional electrode represents REF. It is the simplest configuration mainly used for low-accuracy system. Poor estimation quality of eye orientation and blinking is achieved using this configuration.
	In this configuration besides R and L electrodes, which represent right and left, U and D electrodes are placed above and below the eye. This configuration gives an opportunity to capture right, left, up and down eye movements and blinking. This type of placement is very common in an HCI application. EOG is represented in two channels of a differential signal: channel 1 (U - D) and channel 2 (R – L).

	This configuration of electrode placement also known as cross-channels configuration. Signals of the horizontal and vertical axes are recorded at the same time. The EOG is represented in two channels: channel 1 ($U_1 – D_1$), channel 2 ($U_2 – U_2$). In order to get useful information, this approach requires more complex post-processing analyses.
	The configuration of 8 electrodes provides maximum EOG signal resolution and ability to capture various eye movements: right, left, up, down, down right, down left, up right and up left. These eye movements are represented by 4 channels of a differential signal: channel 1 (R – C electrodes), channel 2 (C – L electrodes), channel 3 ($U_1 – D_1$), channel 4 ($U_2 – D_2$).

A single-channel EOG–based speller has been described by He et al. It argues that one can control a proposed system using eye blinks. Each symbol in GUI is presented as a blinking button. In order to select a certain symbol, the user must blink in synchrony with the flash of the button [He and Li, 2017].

Recently, EOG glasses (https://jins-meme.com/en/products/es/) have appeared in the market. Various studies were carried out in the field of HCI [Ishimaru et al., 2014, Kunze et al., 2015, Ishimaru et al., 2016]. The study of using EOG glasses to a control speller application was carried out by Barbara and Camilleri. The performance of EOG glasses is compared with the performance of an eye tracker and EOG captured using wet electrodes. The letter input speed (letters per minute) and accuracy of letter typing were measured. The results show that letter input speed (7.11 lpm) achieved using EOG glasses is nearly as high as input speed (7.37) achieved using an eye tracker. Performance achieved using EOG with wet electrodes concede in both the letter input speed and accuracy metrics [Barbara and Camilleri, 2016].

Literature analyses show that the most common application of EOG (same as EMG) is for hybrid BCI systems, since the artifacts of EOG can be found in the recordings of EEG. Most of the researchers record EOG as a separate channel simultaneous with EEG. Most of the hybrid BCI – EOG systems apply evoked potential (EP) paradigm for speller or PC control [Postelnicu and Talaba, 2013, Koo et al., 2014, Usakli et al., 2009].

The main limitation of the EOG-based HCI is inability to provide point of gaze. Therefore, EOG usage for interfaces with displays is limited. Merino et al. described a method for detection of an eye movement direction using EOG signal, but still it is a limited approach, since four directions of eye movements are not very convenient for navigating the screen [Merino et al., 2010]. For pointing display interfaces gaze tracking techniques are more suitable. Despite this limitation, EOG is used for interfaces, in which a pointing display is unnecessary. EOG signals are widely applied in interfaces for wheelchair control [Champaty et al., 2014, Yathunanthan et al., 2008], driver fatigue detection [Khushaba et al., 2011, Chieh et al., 2005] and human identification using eye blinking.

2.2.4 Gaze tracking

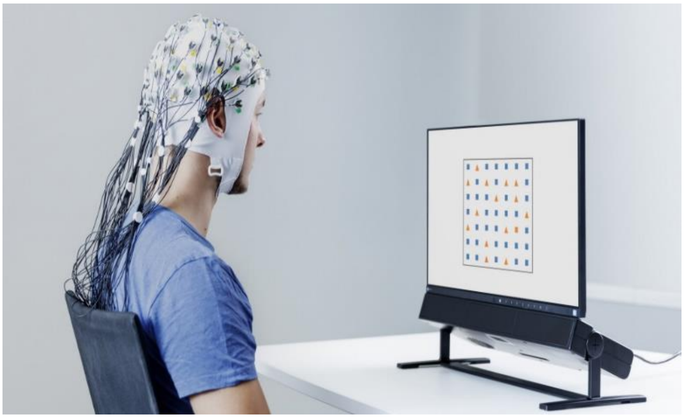
Gaze tracking is probably the most natural way to control assistive interface with display. In general, there are two types of eye movement monitoring techniques: those that measure the position of the eye relative to the head, and those that measure the orientation of the eye in space [Duchowski, 2007].

Duchowski distinguishes between four types of eye movement measurement methodologies: scleral contact lens/search coil-based measurement, Videooculography (VOG)-based measurement, video-based combined pupil-corneal reflection (PCR) and electrooculography (EOG)-based measurement [Duchowski, 2007]. *EOG-based method* was described in previous section (section 2.2.3). EOG-based approaches have been excluded, since these are often referred to as a separate approach for HCI development or as a constituent part of the hybrid BCI. Furthermore, EOG is considered as an electrophysiological signal, which patterns can be recognized as different control commands (similar to EEG or EMG-based HCI). The application of EOG in the field of eye tracking has some limitations, since this technique measures movements of eyes relative to head position. Therefore, to provide point of regard, the head has to be fixed or its position has to be monitored simultaneously [Duchowski, 2007].

Some researchers distinguish only three types of eye movement measurement methodologies excluding video-based combined PCR approach [Zemblys, 2013]. VOG and video-based combined PCR are considered as one approach, since in most cases they share the same principle of eye movement capturing. The distinction between these two methodologies was made by Duchowski regarding the recording of different features of eye movements. Video-based combined PCR approach provides point of regard and VOG approach focuses on eye movement recording without providing point of regard [Duchowski, 2007]. Point of regard is essential for many HCI applications (e.g. speller), therefore, VOG method is not suitable for them.

As mentioned before, the most suitable approach of eye tracking for speller application and other HCI application is video-based combined PCR. In general, there are two types of video-based combined PCR eye trackers: table-mounted (see Fig. 2.6 b) and worn on the head eye tracker (see Fig.2.6 a).

a) Example of head-mounted eye tracker [Raudonis et al., 2009]



b) Example of table-mounted eye tracker *Tobii Pro Spectrum* (https://www.tobiipro.com/product-listing/tobii-pro-spectrum/)

Figure 2.6. Mounting type of video-based combined PCR eye trackers

Video-based eye trackers can be also classified by the type of the light source, used for reflection generation. From this point of view there are two types of eye trackers:

1. **video-based visual light eye trackers**: this type of eye trackers is applied to develop eye-aware or attentive user interfaces that do not strictly require accurate point of gaze tracking [Majaranta and Bulling, 2014]. This method uses one or more head-mounted or table-mounted video cameras. An eye pupil in this kind of a system is detected by usually color segmentation [D'Orazio et al., 2004] or a well-defined pattern recognition [Orozco et al., 2009, Vadakkepat et al., 2008].
2. **video-based infrared-induced (IR) pupil-corneal reflection eye trackers** (IR-PCR eye trackers): this eye tracking technique provides accuracy up to 0.5° of visual angle [Majaranta and Bulling, 2014]. The accuracy of IR-PCR eye trackers is much higher as compared to video-based visual light eye trackers. Therefore, IR-PCR eye trackers has become a preferred technique for gaze-based interaction [Majaranta and Bulling, 2014]. This technique is based on measuring corneal reflection from IR source relative to the location of the pupil center. By measuring corneal reflection and pupil center location at the same time system allows some degree of head movement and can reduce inaccuracies. IR illumination can be aimed at on- or off-axis by creating "bright pupil" or "dark pupil" effect respectively. IR illumination helps to keep eye area well lit, which is necessary for the analysis of eye

features, and does not disturb the test subject, since IR light is invisible to the human eye [Duchowski, 2007, Majaranta and Bulling, 2014].

The main application fields for eye tracking are: market research and advertising testing [Wedel and Pieters, 2008], usability research [Poole and Ball, 2006, Ehmke and Wilson, 2007], eye control for accessibility [Majaranta and Bulling, 2014], psychology and vision research [Armstrong and Olatunji, 2012], medical research, diagnostics and rehabilitation and car assistant system [Langner et al., 2016].

2.2.4.1 Gaze spelling related metrics

Originally, the overview of gaze spelling related metrics was presented in [Vasiljevas et al., 2016].

Metrics include types of metrics for evaluating typing characteristics (input accuracy, error rate, information transfer rate) [Arif and Stuerzlinger, 2009] related to text entry task using gaze ('gaze spelling').

Typing speed is measured in words per minute (wpm), where a word is any sequence of five characters, including letters, spaces, punctuation marks, etc. [MacKenzie and Soukoreff, 2003]. Both corrected errors and errors left in the entered text are considered.

$$WPM = \frac{|T|-1}{S} \times 60 \times \frac{1}{5} \tag{2.1}$$

Here, S is time in seconds measured from the first key press to the last, including backspaces and other edit and modifier keys. The constant 60 is the number of seconds per minute, and the factor of one fifth accounts for the average length of a word in characters including spaces, numbers, and other printable characters. Note that time is measured from the entry of the very first character to the last, which means that the entry of the first character is never timed. It is expected that due to fatigue typing speed should decrease.

Error Rate (ER) is calculated as the ratio of the total number of incorrect characters in the transcribed text to the length of the transcribed text:

$$ER = \frac{|E|}{|T|} \times 100\% \tag{2.2}$$

here E is the number of errors in the text T. This metric does not consider corrected errors. It is expected that due to fatigue the error rate should increase.

Rate of Backspacing (BR) indicates how often the participants cancelled characters and correlates with errors to a degree. The rate of backspacing is calculated by dividing the total number of characters erased prior to the current position by the total number of characters typed:

$$BR = \frac{|B|}{|T|} \times 100\% \tag{2.3}$$

here B is the number of corrections in the text T. It is expected that due to fatigue BR should increase.

Total Error Rate (TER) combines the effect of accuracy during and after text entry:

$$TER = \frac{|E| + |B|}{|T| + |E| + |B|} \times 100\% \tag{2.4}$$

2.2.5 Electrodermal activity

Electrodermal activity (EDA) also referred to as galvanic skin response (GSR) is the marker of skin conductance that varies depending on moisture content of the skin. The skin becomes moist as sweat is released to the skin surface. Moisture content of the skin is directly proportionate to skin conductance: the wetter skin means the greater skin conduction. This individual's physiological signal is significant for neural computer interface, since glands that produce sweat are controlled by the nervous system.

Skin conductance is measured between two skin points through which very low electric current flows. Under Ohm's law, the voltage across the two points and skin conductance are calculated. The signal of the galvanic skin response varies depending on emotional stimuli such as music, the scenes of violence, etc. [Allanson and Fairclough, 2004].

From a system-theoretical view point, methods of electrodermal recording can be allocated to the below listed three groups [Boucsein, 2012]:

1. **endosomatic recording**: here only those properties of the electrodermal system which follow active changes of the system are examined. The electrical energy is pretended to originate in the polarized membranes in the skin.
2. **exosomatic recording with direct current**: in this case the electrodermal system is supported with electrical energy from an external source, using either a constant voltage or a current. In the appropriate models, passive properties of a system, in which capacitors are charged and changes in the signal result from mainly resistive changes, play a key role.
3. **exosomatic recording using alternating current**: this method is not of frequent use. Here responses of the electrodermal system to oscillatory signals, which also include changes in capacitors or charged membranes in the skin, are investigated.

EDA measures belong to a group of passive physiological signals. It cannot be induced by purpose. Instead, it is triggered by the human nervous system. This implies that EDA is more suitable for psycho-physiological human state detection, e. g. driver fatigue [Craye et al., 2016], visual attention [Sakai et al., 2017], even depression and suicidal behavior [Sarchiapone et al., 2018], etc.

2.2.6 ECG

An electrocardiogram (ECG) is the change of the electrical activity of the heart over a period of time. ECG scan is recorded after electrodes have been attached to the chest skin. ECG scan and interpretation are among the most popular medical tests. ECG signal is captured using dry or pre-gelled electrodes. Electrode placement methodology is standardized. The most popular electrode placement scheme is a standard 12-lead ECG [Chou and Knilans, 1996].

ECG is a direct means to measure the heartbeat rate (the number of contractions of the heart per minute (bpm)). One’s physiological condition can be determined by the value of the speed of the heartbeat. Heart rate variability (HRV) also serves as an indicator of physiological condition. It refers to variation in time interval between heartbeats. If the subject experiences stress or anger, the speed of his heartbeat increases significantly. The same thing can happen in performing a difficult mental task with time constraints and uncertainty.

ECG measurements like HR and HRV represent a psycho-physiological state of the human. It is also highly related with human physical activity. The primal application of ECG which parameters were derived from was in medicine and diagnostics. In the HCI domain HRV together with other physiological signals is also an indicator of driver fatigue [Vicente et al., 2016]. Human emotional state and stress level could be also detected using HRV measurement [Thayer et al., 2012, Appelhans and Luecken, 2006]. HRV might be applied in computer games. The system receives feedback from the subject by evaluating the speed of his heartbeat, thus, it is possible to change the difficulty of game levels and overall game appearance [Dekker and Champion, 2007].

2.3 Performance and its estimation methods

This section provides the analysis of performance estimation methods for both sports and HCI domain, mainly focusing on PCS as HCI sub-domain. The primary focus of this analysis is not to cover all aspects of user or athlete performance estimation, but to conduct the comprehensive overview of mathematical impulse-response (IR) models, which are applied to performance modeling in athletic training. IR models assume that performance is affected by the sum of two factors: (1) fitness, which has a positive impact on performance, and (2) fatigue, which has a negative impact on performance. The nature of fatigue and its detection methods are also within the scope of this analysis.

This section is organized as follows: first, we provide an overview of the performance evaluation methods in HCI domain, second, we provide similar overview in sports domain, third, we analyze IR models and their applicability for HCI domain, and finally, we provide a comparative analysis of fatigue in sports and in HCI domain, since it is a major factor in performance modeling based on IR.

2.3.1 Monitoring of performance in sports

Monitoring of the extent of fatigue is a question of importance to coaches, trainers, or sports scientists who aim at optimization of an athlete's performance as training when a high level of fatigue can lead to no training adaptation. Hence, tracking the athlete's freshness will provide the coach with knowledge on athlete's sensitivity to adaptation and/or his/her performance ability. To say it in other words, the significance and advantage of implementing a fatigue monitoring system is having an ability to identify the athlete's response to training. It becomes critical if it is aimed at maximizing or maintaining performance of an athlete. Knowledge of both when an athlete is responding well to training and when not is crucial from the perspective of a training prescription. Such kind of knowledge enables the coach to adjust an athlete's training programme to prevent overtraining and maximize performance.

For both objective and subjective elements are included in the fatigue structure, it is important to have monitoring protocols that consider both aspects. There are several methods for the collection of data to verify fatigue:

1. **Subjective tests**
    a. *Wellness Questionnaires*: these are simple questionnaires to be filled by athletes to assess their feeling. They often include questions about how athletes slept, pain or tiredness they feel, current stress level. The questions are usually determined by the coach since it is he, who feels what is of the ultimate significance to the athletes, e.g. if the athlete is studying at a university, the question about their school workload is included. Despite there is a variety of wellness questionnaires, there is lack of those scientifically examined and found to be proper to have changes in weekly training regimens [Gastin et al., 2013]. Despite being cheap and able to provide immediate feedback, these questionnaires are used as a fatigue monitoring tool when large groups of responders are examined.
    b. *Rating of Fatigue Scale* – this type relates to most recent methods of fatigue monitoring and is best described by good face validity and highly important convergent validity [Micklewright et al., 2017]. The scale is referred to as a holistic measure to determine how fatigued a person feels – this is conducted via an 11-point Likert scale with diagrammatic selections. For this two-part system participants find the rating easier and a more accurate way of determining perceived fatigue levels is provided. Rating of the fatigue scale highly correlates with physiological markers and is also capable to make a distinction between perceived activity during recovery and exercise [Micklewright et al., 2017].
2. **Objective tests**
    a. *Countermovement Jump* (CMJ) – simplicity and little time needed to measure makes this type of testing a popular approach for fatigue monitoring. These tests are primarily used to measure an athlete's explosive lower-body power [Markovic et al., 2004] and are

conducted either with or without the arm-swing which has proved to increase performance by 10 per cent or more [Cheng et al., 2008]. A current issue with measuring the CMJ is the cost and impracticality of some of the equipment used for the test, though it is reported that the average CMJ height is more sensitive to neuromuscular fatigue than the highest CMJ height [Claudino et al., 2016].

b. *Heart Rate Variability* (HRV) – the method has been of growing interest and is perceived as a means of measuring body's reaction to training and its related levels of fatigue. HRV demonstrates the variation in time between each heartbeat and is affected by mental and chemical as well as physical stress. it is argued to meticulously reflect recovery status, anticipate when performance of an athlete is better or worse, help to determine if an athlete has been overtraining [Flatt, 2016], predict athlete's greater susceptibility to illness or injury [Gisselman et al., 2016]. However, it is time-consuming and requires an athlete to be at complete rest and relaxed to have the test result as exact as possible. Since many variables should be involved in the measurement, it is required that HRV should not be the only test for fatigue and readiness measurement.

c. *Video gesture analysis* – method, which allows to estimate biomechanical features of athletes in a quantitative manner. However, this method also can be defined as a mixed method, which includes both quantitative and qualitative analysis. Preliminary qualitative analysis is usually required to determine bio-mechanical features, which then can be estimated in a quantitative manner [Wilson, 2008].

d. *Saliva, blood and urinary measures* – testing hormone levels in saliva, blood or urine has been found a trustworthy means for fatigue and performance measurement. It has demonstrated that the levels of hormones as cortisol and testosterone taken from saliva sample change during and after physical activity and these changes decide one's biochemical response. Changes in the ration of testosterone and cortisol decide on how an athlete is coping with stress and recovering from it. This type of testing is argued to be very accurate, though requiring expensive equipment and resources.

To sum up, solid baseline measures should be opted regardless of the type of testing. The application of the research-grounded methods contribute to consistent and accurate results.

2.3.2 Monitoring of performance in HCI

In general, the approaches of performance evaluation and fatigue detection can by divided into following groups [Ji and Looney, 2006]:

1. Readiness-to-perform and fitness-for-duty technologies: it relates to the alertness capacity of an operator before the task is carried out. This

technology aims at provisioning the operator to fit for the duration of the task period, or at the beginning of an extra period needed for duty execution.

2. Mathematical models of alertness dynamics combined with ambulatory technologies: this type refers to the appliance of mathematical models to predict operator alertness or performance at different periods of time since interactions of sleep, circadian, and related temporal antecedents of fatigue. Their significance lies in predictive validity.
3. Performance analysis technologies*:* These technologies are aimed at measuring the behavior of the user by monitoring hardware and software systems under control of the user. Vehicle speed variability, steering wheel position, acceleration [Solovey et al., 2014] and lane deviation [Ji and Looney, 2006] are used to evaluate driver fatigue. Time per selection, bit rate, information input speed are suitable metrics to evaluate BCI and NCI performance [Thompson et al., 2014, Damaševičius et al., 2015]. All these metrics and combination of them show that when the user feels fatigued, his behavior or system behavior strays from his nominal behaviors.
4. On-line, user status-monitoring technologies: this group of technologies includes records of bio-behavioral dimension(s) of a user, e.g. parameters defining eye movements [Schleicher et al., 2008], head movements [Ji et al., 2004], facial expressions [Gu and Ji, 2004], heart activity [Patel et al., 2011], brain electrical activity [Huang et al., 2016, Zhang et al., 2015], GSR [Dawson et al., 2014], reaction time [Schleicher et al., 2008] on-line (e.g. repeatedly, when driving). These apply EEG to monitor brain activity, also ocular measures to outline eyelid movement (e.g. PERCLOS) and characterize pupil movement (such as saccade movement v.s. fixation time). Parameters which describe facial muscles, body postures and head nodding are also important. GSR level is directly proportional to fatigue, but is also related with other influencing factors (e.g. sweat, stress). Thus, GSR suitability for detecting work-related fatigue is questionable [Dawson et al., 2014]. In addition, false estimation can also be caused by variability of user's behaviors, e.g. driver sleeping with open eyes [Zhang et al., 2017].

Regarding application most of the researches are conducted in the field of driver fatigue detection. However, there is a variety of fatigue detection and performance evaluation technologies which are mainly organized under the nature of the measurement device. These technologies are to be overviewed in the following paragraphs.

Fitness-for-duty tests: these tests are used to determine an employee's level of alertness to see if it is enough to perform neuro-behavioral tasks, especially executive functions as vigilance or hand-eye coordination. However, there is no evidence if these tests can predict the level of fatigue during task performance. Hence, to check whether the level of fatigue is increased the tests should be re-taken which becomes problematic if, for instance, the companies use non-portable devices and drivers are not near the check-in depots serving as accommodation [Dawson et al., 2014]. Thus, study is needed to see how far ‘fail’ scores can anticipate the probability of fatigue-related accidents.

- For *neuro-behavioural performance* the *psychomotor vigilance test* is a means to evaluate sustained attention and it is considered as a recognized exemplar for fatigue detection. For the test individual’s button-press response to visual stimuli on a computer screen over a period of 5-10 minutes and consequently reaction time and ‘lapses’ (these are when response time is equal to or higher than 500 ms) are measured. The PVT demonstrates that performance decreases due to sleep restrictions, extended vigilance, time-of-day effects, etc. and this counts in numerous applications in industries as rail, aviation, mining or defense. For prominent individual differences in driving performance the PVT may be of greater importance to anticipate fatigue-related driving incidents.
- *Pupilometry* is defined as a technology to assess pupils’ uncontrolled response to highly intense bright light and is an expressed biomarker of fatigue. Longer and slower constriction abeyance is an articulated sign of individual’s fatigue. The parameters are assessed by binocular-type instruments when an individual must watch an eyepiece for a minute or two. Quick administration and alerting time, non-required training and no learning effects are the greatest advantages of the devices. Furtheron, as pupillary responses are uncontrolled, the test cannot be manipulated. Pupillometry is not appropriate to people having head or eye-related problems and to those who are above 50 years old. There are several devices referring to pupillometric technology.
- *EyeCheck* is a hand-hold device which measures pupil diameter and constriction latency. It has been extensively used by the US police for detection of the illegal drug use and fatigue in motorists. However, the effectiveness of the method is doubtful for neither fatigue nor sleeping hours correlate with the EyeCheck scores.
- *Fitness impairment tester* (FIT) measures eye tracking (with the stress on saccadic velocity) as well as pupillometry (pupil diameter, constriction amplitude and latency) and total FIT scores are received from the calculations of these parameters. The results are relative since compared to one’s personal performance. Total FIT scores demonstrate growth in response to sleeplessness and subjective sleepiness of healthy volunteers. Long work hours also complement to increasing FIT scores. Fatigue is not clearly expressed via the parameters of pupil diameter and constriction amplitude because of their sensitivity to ambient light and time of day effects. Furthermore, FIT cannot be applied to people who have excessive blinking or wear thick corrective lenses.
- *Oculomotor measurement* encloses devices to measure the frequency, duration and/or rate of eye closure. Some devices measure ‘PERCLOS’ (the percentage of time when driver’s eyes are 80-100 % shut). PERCLOS scores are better than EEG and head nodding or eye-blinking technologies, though

it alone cannot single out a full set of fatigue subjects. Oculometric devices are non-invasive and appropriate in static environments – these two are considered the greatest advantages. *Optalert* also falls under the category as a means for detecting blink frequency, velocity and duration, though it is not suitable for people with visual or sleep disorders. *CoPilot* is another means for tracing fatigue, but visual and audial warnings are generated only when a threshold of fatigue is reached. The device, however, has a very high false alarm rate when subjects are motionless, which proves it is highly sensitive to movement. *Seeing machines driver state sensor* (DSS) is argued to ignore head movements or partial face occlusion. Its scores rely on facial tracking and absolute eyelid position, but the results become doubtful due to extended wakefulness and subjective sleepiness.

- *Electroencephalography* (EEG) is a noninvasive method for monitoring electrical activity of the brain. There are several technology-based devices that fall under the group. In *Smart Cap* EEG sensors are fixed on either a head band or baseball-like cap. This technology is yet commercially unavailable. *B-Alert* is a device where EEG sensors are embedded in a headband-like device. Alertness levels between healthy subjects and those who suffer from sleep apnea are easy to single out. *Posture/head nodding* devices, usually worn behind the ear, catch posture changes that mark fatigue. A sensor fixes a shift when the head nods forward to a preset angle (usually about 15 degrees) and the alarm starts sounding. However, warning comes rather late, almost at the point of falling asleep. *Galvanic skin resistance* (GSR) also referred to as Electrodermal Activity (EDA) or Skin Conductance (SC) is one of the most sensitive measures for emotional arousal. There are risks for the method, however. External factors as temperature or humidity affect GSR and hence the results might become inconsistent the same as measurements of different locations might result in different conclusions [Picard et al., 2016]. *Engine driver vigilance telematic control system* (EDVTCS) is either a finger- or wrist-worn device with an integrated sensor measuring GSR. It has been found out that GSR levels do not change greatly across 28 hours of continuous wakefulness regardless of changes in subjective sleepiness, driving simulator performance and PVT performance.
- *Performance-based monitoring* singles out indicators that refer to fatigue-related driving incidents. *Embedded performance measures* inspect task performance and establish performance breakage depending on operator's fatigue. These measures are non-intrusive and embedded into the real task. Their face validity is high due to direct measurement of the behavior important to task performance and job safety. Despite being appropriate and well-operating with reference to different road and weather conditions, they find it problematic to deal with driving at night in the rain since the road reflectance increases or there are non-blacktop surfaces in rural settings.

2.3.2.1 Metrics of eye performance

Originally, overview of eye fatigue metrics was presented in [Vasiljevas et al., 2016].

Eye movement refers to the voluntary or involuntary movement of the eyes, helping in acquiring, fixating and tracking visual stimuli. Humans use three types of voluntary eye movement to track objects of interest: smooth pursuit, vergence movements and saccades. McConkie [McConkie et al., 1988] has demonstrated that the distributions of initial saccade landing sites are Gaussian in shape and that the center of these distributions and their standard deviations are determined primarily by oculomotor factors. Variability in human saccades is caused by a combination of uncertainty in target localization and noise in movement planning and execution [Van Beers, 2007]. As mental as well as physical factors affect both target localization and movement execution, the onset of fatigue should lead to higher variability in saccadic movements and target fixation positions.

The evaluation of eye fatigue is usually performed using subjective evaluation questionnaires, e.g., Majaranta *et al.* [Majaranta et al., 2009] asked the participants how tired their eyes were before each test, and again after the test, on a scale of 1 to 7. The fatigue level was calculated by subtracting the first value from the last value. However, the authors did not manage to obtain any relationship of the level of fatigue vs. time or speed of work. It points to the unreliability of the method of evaluation used.

- *Dwell time* is the duration a gaze fixation rests on a certain object. Dwell time helps to differentiate between accidental gazes, gazes during visual search and, e.g., intentional gazes during execution of tasks. The duration of a fixation correlates with the processing that is going on in the brain. It is expected that dwell time should increase due to fatigue.
- *Point of gaze (POG) accuracy.* Given the target, we can compute the distance from the center of the target during each fixation when the eyes are aligned with our target of visual attention. The fixated area is called the point of gaze. Due to fatigue, the POG accuracy should decrease.
- *Fatigue Threshold* (TF) [Lohr et al., 2016] is calculated using an empirical formula that depends on the average spatial accuracy in degrees, θ_{avg}, of the eye tracker so that the threshold can scale with noisier signals, A, difference in FQlS between the first fatigued group of data and the initial FQlS, and μ, the mean spatial accuracy of the data:

$$TF = A \times \theta_{avg} / \mu \tag{2.5}$$

Average spatial accuracy [Lohr et al., 2016] is calculated during calibration by finding the mean gaze point, Gi, for each calibration point, Pi, and then calculating the average distance in degrees, θi, between each calibration point and gaze point:

$$\theta_{acc} = \frac{1}{n} \sum_{i=1}^{n} \left| P_i - G_i \right| \tag{2.6}$$

Fixation Qualitative Score (FQlS) is a metric that represents the distance between the fixation components of the eye movement signal and the stimulus [Komogortsev et al., 2010].

$$FQlS = \frac{1}{n}\sum|p_i - g_i| \tag{2.7}$$

here p_i are stimuli points and g_i are the gaze points. FQlS should increase when a user becomes fatigued.

2.3.3 Analysis of impulse-response models for estimation of performance

Originally, the overview of the impulse-response models also known as fitness-fatigue models was presented in [Vasiljevas et al., 2016]. In this analysis terms impulse-response models and fitness-fatigue models are used interchangeably.

Mathematical and analytical models provide a method for describing and predicting the effect of mental and muscular load on the performance characteristics of a human [Taha and Thomas, 2003]. It is also known as impulse-response models, since they define the performance as the sum of fitness and fatigue factors. Analysing physical performance data one can identify and quantify different effects of loads such as increased performance (fitness or learning) and decreased performance (fatigue). Such models have been extensively studied in sports medicine [Banister et al., 1975, Calvert et al., 1976] as well as in applied physiology [Morton et al., 1990, Busso et al., 2002]. Consequently, there are two research directions: one is for analyzing fitness and fatigue models affecting sport performance of athletes, while another one aims to model muscular response to stress.

One of the most popular fitness and fatigue models was proposed by Banister et al. [Banister et al., 1975]. From the time it was first presented till nowadays this model has had various elaborations [Calvert et al., 1976, Morton et al., 1990, Busso et al., 2002].

2.3.3.1 Original Impulse-Response model

According to this model, any training session will have both fitness-building effect and a fatigue-inducing effect. The total performance is defined as the sum of fitness and fatigue. In this model fitness has a positive impact to performance, while fatigue has a negative impact. This statement is defined in simple mathematical expression as follows:

$$P = F_{fittness} + F_{fatigue} \tag{2.8}$$

Where P is performance, $F_{fittness}$ – fitness and $F_{fatigue}$ – fatigue.

This model is based on empirical observation that at the start of the training fatigue has high amplitude, which decreases fast. At same, fitness has lower amplitude, which decays slower then fatigue. The performance peak at the point where difference of fitness and fatigue is the smallest (see Fig. 2.7).

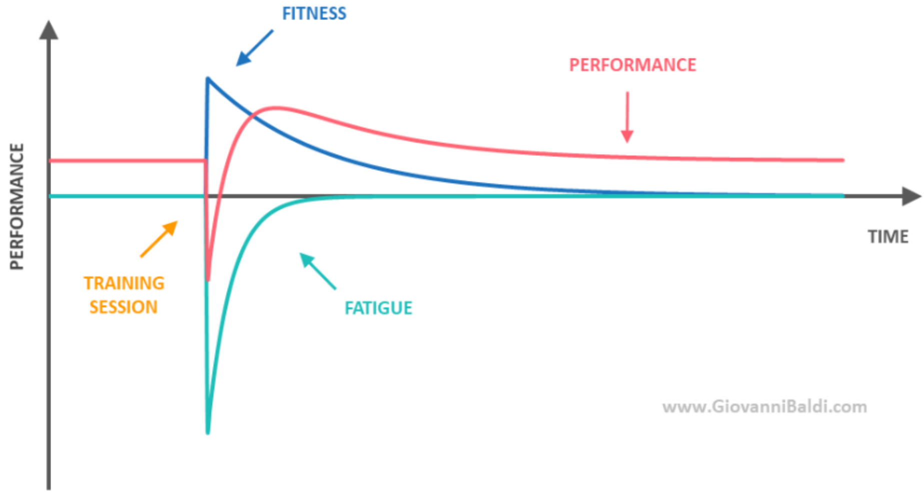


Figure 2.7. Impulse-response model (source: https://www.giovannibaldi.com/dual-factor-theory/)

The impulse-response model describes the dynamics by which an individual's performance capacity changes over time as a function of training and elegantly abstracts the underlying physiology by accurately fitting performance data [Clarke and Skiba, 2013]. The other impulse-response models, presented in the forthcoming sections, are based on this general model, but provide a more sophisticated mathematical expression.

2.3.3.2 Classical Banister model

The term "Classical Banister model" is not common. Here it is used to distinguish the original Banister model from its elaborations. The Banister model is aimed to relate training loads to performance considering the dynamic and temporal characteristics of load sequences over time. These effects can be described by two transfer functions: 1) positive influence (i.e., muscular learning or fitness) that sums up all positive effects leading to an increase in performance, and 2) a negative function that summarizes effects leading to fatigue and having a negative impact on performance. The transfer function is as follows:

$$p_t = p_0 + k_a \sum_{s=0}^{t-1} e^{-(t-s)/t_a} w_s - k_f \sum_{s=0}^{t-1} e^{-(t-s)/t_f} w_s \tag{2.9}$$

where p_t is the modelled performance at time t; p_0 is the initial performance level; k_a and k_f are the fitness and fatigue magnitude factor, respectively; τ_a and τ_f are the fitness and fatigue decay time constant, respectively; and w_s is the known training load per week (or day) from the first week of training to the week (or day) preceding the performance.

2.3.3.3 Calvert model

Calvert *et al.* [Calvert et al., 1976] proposed a model to quantify the training and performance relationship of a swimmer. The model was derived by fitting a mathematical equation and examining its parameters. A single training impulse elicited two fitness responses that increase performance, and a fatigue response that decreases performance. The final form of the Calvert's model is presented as follows:

$$p(t)=\left[e^{\frac{-t}{\tau_1}}-e^{\frac{-t}{\tau_2}}-Ke^{\frac{-t}{\tau_3}}\right]w(t) \tag{2.10}$$

where $w(t)$ is the training impulse, $p(t)$ is performance, τ_1 and τ_2 are the time constants associated with the two fitness functions and τ_3 is the time constant associated with fatigue, and K is the fatigue coefficient specific to the individual, and t is the day of the training impulse.

2.3.3.4 Morton model

Morton *et al.* [Morton et al., 1990] simplified the Calvert's model (Eq. 2.10) to two components (one for fitness and one for fatigue) because the second fitness component was not statistically supported. The Morton's model is as follows:

$$p(t)=\left[e^{\frac{-t}{\tau_1}}-Ke^{\frac{-t}{\tau_3}}\right]w(t) \tag{2.11}$$

2.3.3.5 Busso model

Busso *et al.* [Busso et al., 2002] defined how fitness and fatigue are affected by a training input as follows:

$$\begin{aligned} g(t) &= g(t-1)e^{\frac{-1}{\tau_1}}+w(t) \\ h(t) &= h(t-1)e^{\frac{-1}{\tau_2}}+w(t) \end{aligned} \tag{2.12}$$

where $g(t)$ and $h(t)$ are arbitrary fitness and fatigue response levels at the end of day t, and τ_1 and τ_2 are decay constants of each input.

Eq. (2.12) has been then combined to form a simple linear difference equation

$$p(t)=k_1 g(t)-k_2 h(t) \tag{2.13}$$

where k_1 and k_2 are weighting factors for fitness and fatigue, respectively.

2.3.3.6 DHO model

Damped Harmonic Oscillation (DHO) model is used to describe daily physical performance capacity in team sports [Morin et al., 2016]. The rationale for using this model is based on chronobiology research, in which cosinor-based rythmometry is a common approach [Cornelissen, 2014, Nelson, 1979]. The aim of this model is to represent long-term day-to-day variation in physical performance capacity.

The model is represented as a product of a damped simple sine wave and an exponential resistance component.

$$Single\ DPC_n = -TL_n\ sin(\frac{2\pi t}{T} + \pi)e^{\frac{-t}{\theta}} \tag{2.14}$$

Where *DPC* – performance capacity on day *n*, TL_n – the sum of all training loads of the day, *t* – elapsed time (in days) since the training day, θ – damping parameter in arbitrary units, *T* – time period of one oscillation (in days).

Since the professional sports training is a long-term matter, it is expedient to evaluate cumulative DPC, which is the sum of single DPCs till day *n*.

$$Cumulative\ DPC_n = \sum_{i=1}^{n} DPC_{(n-i)_i} \tag{2.15}$$

where *n* is the number of training days.

2.3.3.7 Linear fitness and fatigue model based on Kalman filtering

Kolossa et al. proposed linear fitness and fatigue model with Kalman filtering, which allows to improve prediction by combining last model state and additional indirect measurements [Kolossa et al., 2017]. The proposed model is a transformation of the well-known 3-time-constant fitness-fatigue [Busso et al., 2002] model to linear, time-variant state-space model.

$$x_{k+1} = A_k x_k + B_k u_k + v_k \tag{2.16}$$

The notation of eq. (2.16) components is as follows:

x is a state vector:

$$x = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \tag{2.17}$$

where x_1 – fitness and x_2 – fatigue;

A_k is the system matrix with exponential decay rates in the diagonal, the decay rates are taken from fitness and fatigue model proposed by Busso et al. [Busso et al., 2002]:

$$A_k = \begin{pmatrix} e^{\frac{-1}{\tau_1}} & 0 \\ 0 & e^{\frac{-1}{\tau_2}} \end{pmatrix} \tag{2.18}$$

B_k is time varying input matrix:

$$B_k = \begin{pmatrix} e^{\frac{-1}{\tau_1}} \\ c_2(k) \cdot e^{\frac{-1}{\tau_2}} \end{pmatrix} \tag{2.19}$$

In addition to two exponential decay rates, it contains $c_2(k)$ – training influence factor on the fatigue component. It is defined as follows:

$$c_2(k) = c_3 \sum_{j=1}^{k} u(j) e^{\frac{-(k-j)}{\tau_3}} \tag{2.20}$$

Under this model, the states of the system cannot be accessed directly. It can only be determined by indirect measurements of y_k

$$y_k = C_k x_k + n_k \tag{2.21}$$

where n_k refers to observation noise (usually gaussian distributed), C_k is the quantity of each state component on the measurement. C_k is defined as follows:

$$C_k = (c_1 - 1) \tag{2.22}$$

In this definition $c_1 - c_3$ are the weighting factors and $\tau_1 - \tau_3$ are time constants.

The main advantage of a linear, time-variant state-space model with Kalman filtering is the ability to correct the estimated model state online. Thus, the tolerance for measurement errors is much higher compared to traditional fitness – fatigue models.

2.3.3.8 Summary of the analytical model overview

There are a few types of training and fatigue models. Banister and its elaborations models are based on the exponential decay function that is widely used to describe natural phenomena such as heat transfer between the object and its medium, rate of enzyme-catalysed chemical reactions, fluid dynamics, metabolization of drugs in patients. These examples provide a logical foundation for application of an exponential decay function for fatigue modelling. Other training and fatigue models are based on DHO [Morin et al., 2016]. These models describe long-term changes in the performance capacity in the context of nonlinear and nonmonotonic processes. However, the fatigue models have been criticized for imprecision and low accuracy due to variability of their parameters [Hellard et al., 2006]. Furthermore, the models also need verification in the context of physiological computing, where signals of a human body are usually registered under normal conditionals rather than considerable strain. Also, the problem of mental fatigue is usually ignored, though over time it leads to decrease of performance in PCS.

2.3.4 Fatigue in sport vs fatigue in HCI

Fatigue as the result of professional sport activities and fatigue resulting from the application of HCI based on physiological signals are similar in their nature. In both fields mental and physical fatigue are operating. From the perspective of time, under time training – fatigue models applied in sports the effects of fatigue come out in the temporal space of months, weeks and days. Meanwhile, a decrease in fatigue-induced performance of HCI based on physiological signals can be expected in hours or even minutes. It should be emphasized that in sports, fatigue can also occur in a relatively short period of time (for example, in sports as sprint, which requires a lot of explosive power), but in this analysis the time scale is determined based on the practice of existing training - fatigue models. The environmental conditions affecting athletes and HCI based on physiological signals are significantly different. Professional athletes train methodically, consistently for a long time. During exercise, physical activeness is very high. This training can eventually lead to mental fatigue. Meanwhile, users of HCI based on physiological signals operate under relatively low physical activity conditions, though control of certain systems using physiological signals has its own specifics. Here, the type and strength of fatigue greatly depends on a specific input signal. Using EMG-based HCI involves muscle tiredness that is of the same nature as during exercise training, but this fatigue is localized in the body where the EMG signal is generated. BCI systems cause mental fatigue, because this type of interface does not involve any physical activity. The use of gaze tracking interface results in visual fatigue, which occurs due to muscular fatigue around the eye and a slight flicker, thus, a distinct form of muscle fatigue. In addition, mental fatigue occurs in both the use of EMG-based HCI and the gaze tracking interface in the long run.

Table 2.2 Comparison of fatigue in sports and HCI

	Fatigue in sports	**Fatigue in HCI**
Origins of fatigue	Mental/Physical	Mental/Physical
Temporal scale	Months/week/days	Hours/minutes
Detection methods	Physiological signals/ Subjective tests/ Objective tests (performance)/Analytical training – fatigue models	Physiological signals/Subjective tests/ Performance-based approaches
Environmental conditions	High physical activity and considerable strain	Low physical activity and low or medium strain

In terms of fatigue detection methods both domains share similar approaches. Fatigue detection using physiological signals, subjective tests and objective tests by their nature are similar in sports and HCI, but in terms of implementation they can differ from each other. However, analytical training – fatigue models are typical only in a professional sports domain.

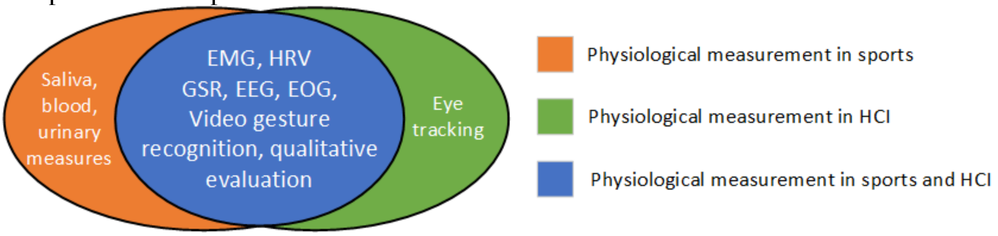


Figure 2.8. Physiological measurements used in sports and HCI for fatigue detection

Most of physiological measurements used for fatigue detection in sports have an equivalent in HCI (see Fig. 2.8). The HRV measurements are used in both a broad and very similar context in both areas [Flatt, 2016, Gisselman et al., 2016, Vicente et al., 2016].

The application of the EMG signal for the detection of local muscle fatigue has long been known in sports workouts (as in rehabilitation and ergonomics). Hence, various devices for monitoring muscle fatigue have been developed using power spectrum shift [Cifrek et al., 2009]. This equipment operates precisely when muscle tiredness is determined by isometric muscle contractions, but while dynamic contractions, measurement accuracy is questionable due to the movement of the electrode. EMG-based HCI control is dominated by dynamic contractions, which cause muscle tiredness to occur relatively quickly. As a result, other methods of the EMG signal analysis are used to detect muscle fatigue in the HCI field. Upper-limb power-assist exoskeletons are constantly exposed to muscle fatigue caused by dynamic muscle contractions. To solve this problem, complex methods are used to measure and analyze several EMG features (e.g., root mean square, mean power frequency and spectral features) at the same time [Lalitharatne et al., 2012].

EDA, EEG and EOG signals are mainly used for detection of mental fatigue. In the HCI field these signals are most commonly used to detect driver fatigue [Craye et al., 2016, Sommer and Golz, 2010]. For studies on athlete fatigue and performance these signals are also applied to: EEG alpha frequency band measurements are applied to estimate audio-visual relaxation and its impact on athletes' performance [Mikicin and Kowalczyk, 2015], EDA and EOG signals are used to measure athletes' sleep quality, as well as for the research on fatigue caused by sleep deprivation [Estivill-Domènech et al., 2018, Düking et al., 2016].

Subjective tests, also refered as as qualitative measures, used in sport trainings enclose various questionnaires, that are criticized for lack of scientific evidence and rating of the fatigue scale, such as the 11-point Likert scale, which are more formalized. In the HCI field, subjective tests are also applied, though they are of rating of scale-type methods, the most popular of which are: Subjective Workload Assessment Technique (SWAT) [Reid and Nygren, 1988], NASA-TLX [Hart and Staveland, 1988], Workload Profile (WP) [Tsang and Velazquez, 1996].

Performance-based approaches are also applied to both HCI and sport. In sport trainings a variety of sports-specific metrics and a universal CMJ metric are applied. In the HCI area performance metrics depend heavily on a particular system (e.g., vehicle speed variability, steering wheel position, acceleration metrics can be used for assessing driver fatigue, while for NCI-based speller metrics of time per selection, bit rate, information input speed, etc. are applied).

Video gesture recognition was long-known in the HCI domain. Video gesture recognition could be classified into 3 major categories: (I) human action and activity recognition [Chaquet et al., 2013], (II) face and head gesture recognition [Mitra and Acharya, 2007] and (III) hand gesture recognition [Rautaray and Agrawal, 2015]. [Xie et al., 2012] applied head gesture recognition to assess driver fatigue. [Li et al., 2014] extended fatigue detection approach by combining head gesture and EEG data. Hand gestures are also used for fatigue studies, e.g. [Ruiz and Vogel, 2015] studied the performance of body and arm gestures and found that soft wrist weight constraints reduced arm fatigue by generating more diverse, non-legacy gestures using different body parts and more subtle movements. Fatigue detection based on human activity recognition mostly uses body sensor networks [Ma et al., 2014, Gordienko et al., 2017].

Video gesture recognition is also applied in sports training and coaching. For decades, coaches have been using video records to analyze performance of athletes. It was a means of qualitative analysis. Recently, a more sophisticated form of analysis, also known as a quantitative video analysis, has been often applied to analyze the performance of athletes. Quantitative video analysis is based on gesture recognition and aims to capture biomechanics of sportsmen movements. It is used in various type of sports (swimming, athletics, different team sports etc.) [Wilson, 2008].

Quantitative video analysis has proven its significance in high performance sports like Taekwondo [de Souza Vicente et al., 2016]. Human body gesture recognition can be used for physical rehabilitation. [Da Gama et al., 2016] presented a clinically-related gesture recognition interactive tool, which improved user engagement and exercise performance outcomes.

There are physiological measurements of fatigue that are specific only for sports domain. Most often they are biomedical markers found in blood, salvia and urine. The known blood-borne markers of fatigue are: Creatine Kinase, Urea, free-testosterone, cortisol [Julian et al., 2017] or blood lactate level [Hoff et al., 2016]. Changes in cortisol and testosterone taken from saliva directly correlate with fatigue, therefore, those hormones are also considered as fatigue markers [Cormack et al., 2008]. Amino acids like taurine, carnosine and others serve as urinal markers of fatigue [Corsetti et al., 2016].

2.4 Combination of biocybernetic loop and performance models

Biocybernetic loop describes how psychophysiological data from the user is captured, analyzed and converted to a computer control in real-life [Serbedzija and Fairclough, 2009]. It helps to achieve the adaptive communication between a user and a system. However, the user in this context is described as not stable system member, since it is affected by many internal and external factors [Serbedzija and Fairclough, 2009]. The wide variety of these factors results in the description of adaptive communication only on a very high level of abstraction.

Although the biocybernetic loop provides some abstract description of the adaptive interaction between a user and a system, it still faces limitation in some domains regarding the integration of physiological sensors, the processing of signals, and the communication between physiological systems and applications [Muñoz et al., 2017]. Moreover, the biocybernetic loop lacks practical system development frameworks, which would facilitate the integration of the biofeedback loop to a specific application. The specific realization of the biofeedback loop highly depends on a user and an application. The application may define the level of instability of the user, since user state measurement depends on the specific system design.

The analysis of performance models based on impulse and response revealed that human performance can be defined by fitness and fatigue factors. A combination of impulse and response models with the biocybernetic loop may result in approximation of user states, since user performance would be defined only by two factors (training and fatigue). Therefore, this extension of the biocybernetic loop could lead to a more detail description of the adaptive system and its interaction with the user. However, impulse and response models lack validation in HCI domain, therefore, it is of high interest to test those models in HCI domain and possibly extend the concept of the biocybernetic loop by including the performance models. The inclusion of performance models to the biocybernetic loop is even more reasonable considering the fact that fatigue factor, which is the key factor in human performance modelling, is of the same origin despite the domain it occurs (see section 2.3.4).

2.5 Conclusions of the Chapter

PCS plays an important role in HCI domain. In PCS actively and passively generated physiological signals (e.g. EEG, EOG, EMG, EDA, etc.) are applied as an interface control method. This way of interface control allows disabled people to communicate with others, control their digital devices and their environment. PCS is also widely used in areas where human hands are occupied but additional control is required (e.g. car drivers, plane pilots, etc.), also other domains like marketing research and advertisement testing, adaptive computer games, prosthetics, rehabilitation, psychology, etc.

However, the conscious use of PCS is hindered by many factors such as availability of low-cost high-quality sensors and the need to develop more effective physiological signal processing and user-state detection algorithms as well as steep learning curve for using PCS. One of the factors, often neglected, is fatigue (both mental and physical one) which reduces accuracy and information transfer rate of the PCS communication channel and leads to input errors.

Fatigue in the field of sport training and physiology is widespread for researchers. Both subjective and objective research methods are applied, also monitoring of human physiological signals is often used to detect fatigue. Furthermore, impulse-response models of physiology domain elegantly includes fatigue factor in mathematical performance models. Although a mathematical impulse-response model abstracts the human performance to two factors (fitness and fatigue), it has still been validated in many studies regarding the performance estimation of athletes. Fitness and fatigue factors are also met in HCI domain, especially in PCS sub-domain. The generation of physiological signals for system control sometimes involves the same muscles (e.g. in EMG-based interfaces) as in an intensive physical activity (e.g. athlete training). This implies that fatigue is of the same nature in both domains. In fact, the analysis carried out in section 2.3.4 shows that fatigue is estimated using similar methods both sports and HCI. Fitness factor is also relevant not only to human physiology. A more general term for fitness is training. The importance of training can be seen in many fields where permanent exercise is required, one of which is the use of certain software. The aforementioned assumptions suggest that impulse-response models are worth to be tested in PCS.

The aim of integration of impulse and response models to PCS interface design is to ensure the adaptiveness of the interface. The common approach of the adaptivity in PCS is the biocybernetic loop. Therefore, the obvious way to introduce the training-fatigue models in PCS is by including these models into the bio-cybernetic loop. This extension of the biocybernetic loop could lead to a more detailed description of the adaptive system and its interaction with the user. Theoretical issues of the integration of performance models are addressed in chapter 3, while in chapter 4 the experiments of application in PCS of training-fatigue models are presented.

3 HUMAN-ASSISTIVE HCI MODEL

In this chapter human-assistive HCI model is presented. It is based on the combination of the bio-cybernetic loop and performance models, which have been analyzed in chapter 2. Two variants of human-assistive HCI model have been proposed: (1) human-assistive single channel HCI model and (2) human-assistive multimodal HCI model.

This chapter is organized as follows: section 3.1 describes the motivation for the development of human-assistive models, section 3.2 provides in-depth description of human-assistive single channel HCI model, section 3.3 provides in-depth description of human-assistive multimodal HCI model, section 3.4 describes the limitation of the proposed models, finally, section 3.5 provides conclusions of chapter 3.

3.1 Motivation

There are various PCS-based communication and control systems. The primary purpose of such systems is to enable alternative or enhance a way to control user interfaces. Physiological computing systems are suitable for work and home activities. These can sustain work productivity and entertain. For disabled people, who do not move hands and (or) legs, it can improve the quality of life. Systems that solve this problem are called assistive systems. Different types of these systems, such as BCI, NCI, gaze tracking systems have been discussed in previous chapters. As discussed in the analysis section, one of the major usability problems of these systems is the decrease in performance due to mental and physical fatigue.

When using assistive interfaces based on PCS systems, performance can decrease radically. A lot of factors have impact on the decrease, but the most important is fatigue. In solving the problem, fatigue is simply bypassed developing a sophisticated user interface and multimodal solutions (e.g. hybrid BCI). However, it must be acknowledged that fatigue effects in similar systems are unavoidable. Often users can control only one input modality, therefore, after fatigue appears and accuracy of the system control decreases, user's motivation decreases as well. Other major factor of the interface control performance is training. Training factor has a positive impact on interface control performance. The training aspect increases, while user constantly uses the interface. Evaluation and prediction of the system control performance in real time would be a natural way to solve motivation problem.

Athlete performance models described earlier in the thesis, used in sport trainings, could be applied to predict fatigue and training effects in PCS-based interfaces. Further in this chapter Human– assistive HCI models, aimed to design assistive interfaces based on PCS, are described. These models rely on a biocybernetic loop and HI principles, though their novelty lies in the performance assessment and prediction element included in the system design. Hence, it is a priori accepted that fatigue and training effects will occur using assistive interfaces-based on PCS. Though the proposed models originate from the concept of a biocybernetic loop, the representation of the aforementioned models focuses on practical aspects of the development of PCS-based user interfaces. In general, Human–assistive HCI models provide a design framework for the PCS-based user interfaces. The distinction between the concept of a biocybernetic loop and human-assistive HCI models also lies in the performance measurement methods. Performance or user states in a biocybernetic loop are measured based on bio-physiological characteristics of the user. In human-assistive HCI model performance can be measured directly from bio-physiological signals, generated by the user, or indirect measures, related with specific application, can be applied (e.g. accuracy, error rate, information transfer rate etc.). Thus, the proposed models are suitable, but not limited to, the development of the PCS-based user interfaces.

There are two types of Human-assistive HCI models: (i) Human-assistive single channel HCI model is aimed at users who can control only one input modality, (ii) Human-assistive multimodal HCI model is for users that can control more than one input modality. Both these types are similar, the only difference between them is the interaction between the user and the system that they describe.

3.2 Human-assistive single channel HCI model

3.2.1 Model description

Human-assistive single channel HCI model (HASCM) is applied for users, who can control only one modality of input (e.g. in BCI input modality is brain wave signal, in some cases it is the only input channel). The input channel is monitored by an intelligent layer of the system. Feedback to the user is provided regarding physical and (or) mental load, which is measured during performance evaluation procedure. Feedback to the user is provided as recover activity, which helps the user to regain lost performance. After this procedure further control of the system can be carried out.

The structure of HASCM is as follows (see Fig. 3.1):

1. **Interaction layer**: it establishes communication between the user and the system. The inner structure of an interaction layer consists of two components: input channel and feedback activity.
   1.1. Input channel represents input modality, which is used for control of the system.
   1.2. Feedback activity – represents response of the system, when fatigue effects appear.
2. Intelligent layer is a central component of the model responsible for coordination of other components and decision-making process.
3. Performance evaluation procedure – responsible for performance evaluation of the user using the system.
4. Control layer – represents application-specific actions to control the system.

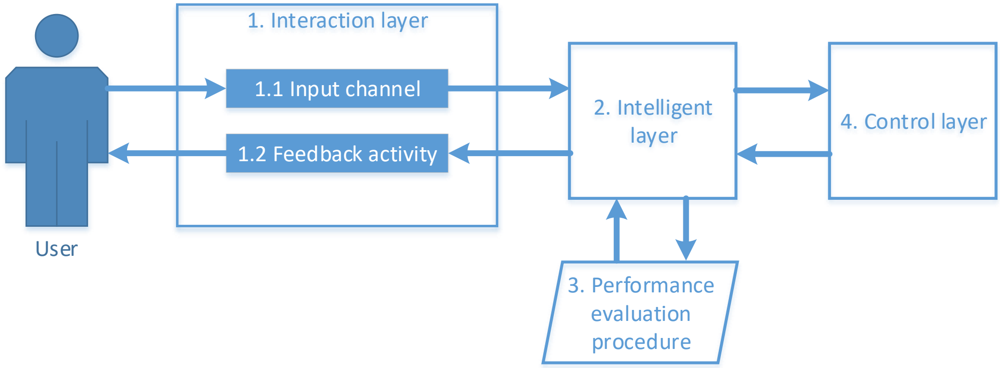


Figure 3.1 Human-assistive single channel HCI model

Human-assistive single channel HCI model consists of several layers:

- **Interaction layer**. This layer provides tools of communication and control of the system. It is divided into two blocks: control channel and feedback activity. Control channel is responsible for capturing an input modality which is presented in the model as a control channel. Feedback activity is a specific response of the system, when intelligent layer triggers a decreased level of performance. The purpose of this activity is to help user to relax and recover from mental and (or) physical fatigue. The type of feedback can be visual, auditory, tactile, somatosensory.
- **Intelligent layer**. This layer is responsible for decision-making process. Each time user sends an input signal to the system the decision must be made whether the signal should be converted to control command or recover activity should be provided to the user. The features of the signal, which represents fatigue, depends on the type of input modality. The extraction of these features is made in an intelligent layer. Afterwards the extracted features are sent to performance evaluation procedure, which returns feedback as an estimate of current performance level. The features of performance also can be received from control layer, as specific metrics of application (e.g. accuracy of user control, input speed, information transfer rate etc.). Then the decision is made whether user should keep controlling the system or the fatigue is too high, and the recover activity should be activated. Furthermore, the classification of a signal to determine the specific control command of application is also made in intelligent layer.
- **Performance evaluation procedure.** It serves as a tool for quantitative assessment of user performance. The performance itself may depend on fatigue and training aspects of specific user. The aforementioned procedure is application-specific and may vary from sophisticated fatigue feature extraction and classification techniques to threshold function, which takes as

an argument certain performance parameters. The output of this procedure is an estimate of performance level. Initial performance model can be pre-defined and if necessary modified online.

- **Control layer.** Control layer determines specific actions which are used to control the application. Application area is wide, technically it encompasses almost any digital device the can receive at least one input modality of any human suitable form and can provide at least one output modality of any human suitable form.

The typical architecture of system adapting MASCM is presented in Fig 3.2. Packages here represent logically related elements. Performance evaluator package corresponds to the performance evaluation procedure presented in Fig. 3.1. The rest of the packages are identical with corresponding elements in Fig. 3.1.

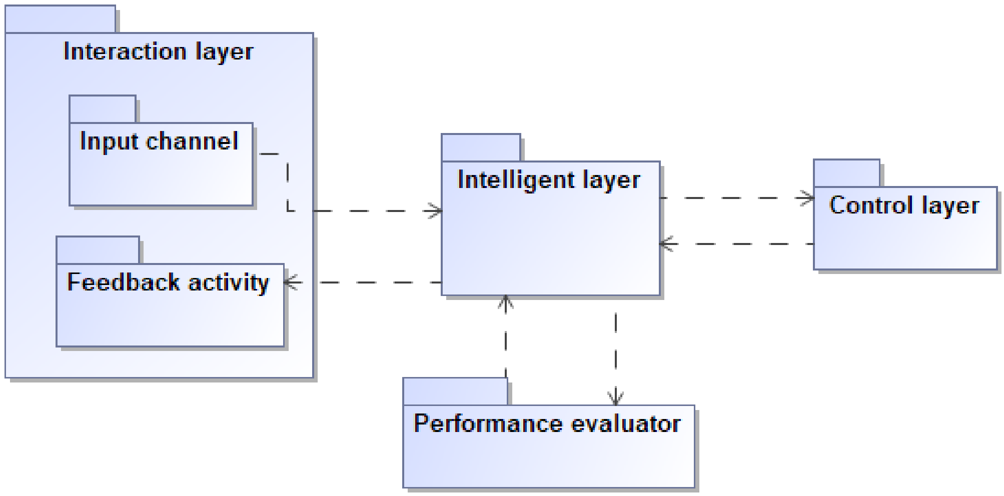


Figure 3.2 Typical HASCM architecture in UML notation

3.2.2 Interaction of model components

From HASCM point of view, a user is also a part of the system. The user can send input commands and get feedback from the system (see. Fig. 3.3). System control tasks can be executed using input modalities, which are determined by the system design. No distinction is made between traditional input modalities (e.g. mouse, keyboard, joystick, etc.) and alternative ones like physiological computing-based (e.g. EEG, EMG, EOG, gaze tracking, etc.) or NUI-based (e.g. human gestures). The user provides input to the system, which later is pre-processed in the Input channel.

The concept “single channel” in HASCM model does not necessarily mean that the user is able to control the system via one input mode. Input channel can receive one unified set of input modalities. A unified set means that input modalities are undetachable from each other in terms of control. For example, a mouse and a keyboard are undetachable from each other in many cases, because one set of control commands are covered by the mouse, and another set by the keyboard. If one input mode cannot cover all control commands, one cannot consider it as an independent input mode (a model which deals with independent input modalities is called HAMM).

Input channel is responsible for pre-processing a task. Not all input types may need pre-processing (e.g. a mouse and a keyboard), in such cases this task is simply skipped. The most pre-processing is needed when system input is based on a physiological signal; then signal sampling and filtering are usually applied. Further analysis of the pre-processed input data is then made in the Intelligent layer.

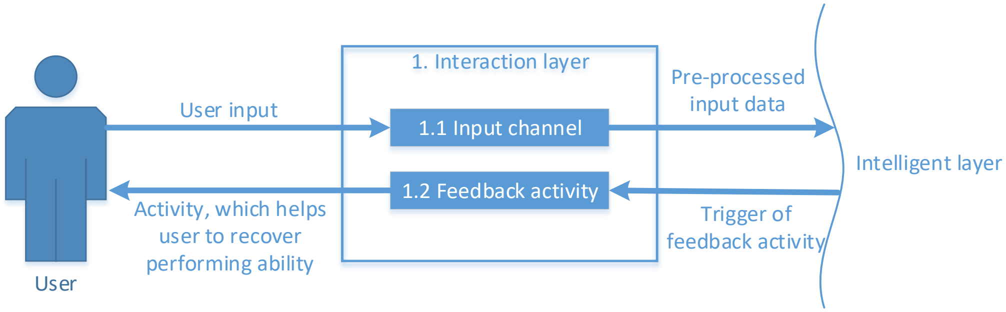


Figure 3.3 Communication between user and the Interaction layer of HASCM

Intelligent layer triggers Feedback activity when the performance of system control decreases. In general, Feedback activity is every activity which helps a user to recover performing abilities. In terms of sensing ability Feedback activity can be classified into (i) sensory feedback activity and (ii) hidden feedback activity:

- Sensory feedback activity can be sensed by the user. The feedback type can be visual, auditory, tactile, or somatosensory. The main purpose of any type of sensory feedback activity is to help a user regain performing abilities. Typical examples of such feedback are GUI change due increased level of fatigue or inserts of relaxing music during control process.
- Hidden feedback activity cannot be directly sensed by the user. In this case, the user can feel improvement of the interface performance or other metrics but cannot sense it. A typical example is adjustment of control parameters (e.g. dwell time adjustments in gaze tracking interfaces).

In terms of how feedback activity is included into a control – feedback loop, it falls into (i) interruptible and (ii) uninterruptible feedback activity:

- Interruptible feedback activity interrupts control process of the system. In this case, control of the system is disabled, instead a user is stimulated by a relaxing activity.
- Uninterruptible feedback activity does not disable the control process. It is carried out simultaneously. Adjustment of control parameters is also a proper example to demonstrate this kind of feedback.

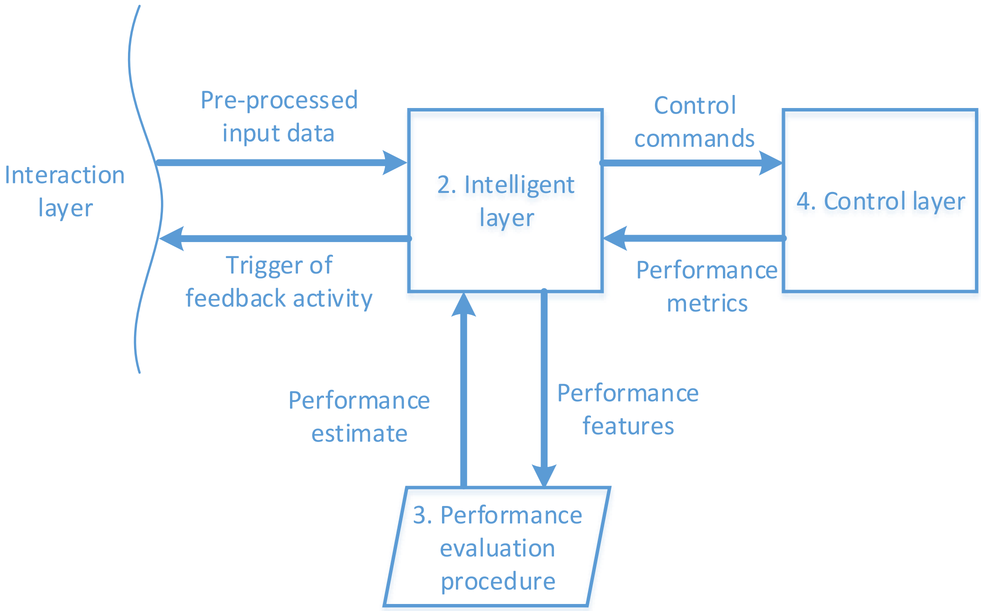


Figure 3.4. Communication between the Intelligent layer and other components of HASCM

The Intelligent layer is the most complex component of HASCM (see Fig.3.4). It is responsible for (i) pre-processed data classification to the control commands, (ii) user performance feature extraction and (iii) decisions of when feedback activity should be triggered.

- Pre-processed data classification to determine control commands. This procedure is common for PCS. The complexity of classification approach depends on application. Physiological signal classification may require sophisticated pattern recognition methods (e.g. artificial neural networks, SVM, etc.). In some cases, additional feature extraction must precede classification to reduce dimension of the data (e.g. PCA). In simple solutions input data can be transformed to control commands by applying threshold function. Some interface types do not require classification at all (e.g. gaze tracking interface provides point of gaze). Therefore, data classification is optional in this model.
- User performance feature extraction is an important process in HASCM. The extracted performance features are used in performance evaluation procedure as input arguments. Therefore, Intelligent layer and Performance evaluation procedure are strongly related. Since performance is usually affected by user fatigue and training factors, the feature extraction tends to search for features in the input signal that are related with user fatigue. To extract features from input data one may need to link a physiological measure to a specific fatigue state. Karran calls this process *inference* [Karran, 2014]. Another way to estimate the performance features is to use pre-set application-specific

performance metrics of the Control layer. Performance metrics like accuracy and input speed are common for many systems and those metrics is strongly related with fatigue, because those metrics decrease in the presence of fatigue. Combined approach, when extracting fatigue features form both input data and performance metrics, may increase accuracy, but it is a more complex approach.

- Decisions of, when feedback activity should be triggered, depend on Performance evaluation procedure. Performance evaluation procedure returns the performance estimate to the Intelligent layer. The performance estimate can be numeric value or pre-defined user state. In order to activate the trigger, when performance estimate is numeric value, threshold or sigmoid function can be used. When a pre-defined user state is an indicator, the Intelligent layer should recognize this state and execute the necessary actions.

Performance evaluation procedure defines means of performance measurement in the specific system. It can be a set of logic rules, mathematical equations or complex dynamic structures like Kalman filters and artificial neural networks (ANN). A performance model can be passive or adaptive. Passive performance model is a pre-defined analytical model which does not change its behavior during control process. Adaptive performance model changes over time and can be optimized during control process (e.g. Kalman filter).

Control layer represents the logic of application. It receives control commands from Intelligent layer. These control commands are used to control the main application. The Control layer also sends back the performance metrics, which can be used for performance evaluation.

3.3 Human-assistive multimodal HCI model

3.3.1 Model description

Human-assistive multimodal HCI model (HAMM) represents the case when more than one input modality is used to control the application. It is more complex compared to HASCM, since an increased number of input modalities requires additional input channel selector component (see Fig. 3.5). Intelligent layer and performance evaluation process in this case are also more complex because different input modes may require different performance estimation techniques. Therefore, additional fatigue feature extraction techniques should be considered. Despite structural differences from HASCM this model also differs in terms of feedback type. Feedback in this case is a change of input channel or a group of input channels. When performance of the system decreases, the current input channel is switched to alternative input channel (or a group of input channels).

The structure of HAMM is as follows (see Fig. 3.5):

1. Multimodal interaction layer consists of a set of control channels and Input channel selector. Each control channel carries out specific pre-processing techniques.
    1.1. Input channel selector – works as a switch, which enables specific input modality to take part in control, and links it with specific control channel.

    1.2. Control channel - represents the specific input modality, which is used for control of the system.
2. Intelligent layer - is a central component of the model, which is responsible for coordination of other components and decision-making process.
3. Performance evaluation procedure – responsible for performance evaluation of the user using the system.
4. Control layer - represents application-specific actions to execute the system.

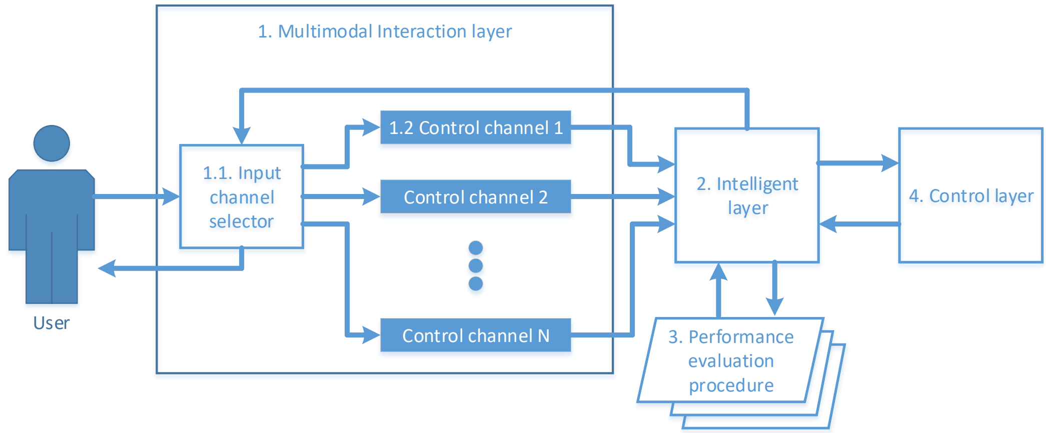


Figure 3.5 Human-assistive multimodal HCI model (MAMM)

HAMM consists of several layers, which is common for HASCM as well, however, the functionality of those layers to some extent is different from HASCM. The MAMM layers are listed below:

- **Multimodal Interaction layer.** This layer is responsible for capturing an input signal of each modality. It consists of many Control channels. Each Control channel represents a specific input modality. The number of input modalities depends on the user. Some of the input modalities could be used to control simultaneously (but not all together), others as an alternative control channel. If needed, some low-level signal pre-processing actions are carried out in each Control channel. Input channel selector is one of constituent parts of the Multimodal interaction layer. It is responsible for switching a specific input channel or a group of channels regarding data received from the intelligent layer. Furtheron, it is responsible for feedback to the user. Input channel selector sends information about a channel, which is currently in control in any suitable form to the user. Input channel selector restricts to activate all control channels at once. At least one Control channel must remain in reserve.
- **Intelligent layer**. Intelligent layer is responsible for decision making and signal classification to determine specific control command of application

layer. Since in this case there are more than one input modality, the system must decide which one or a group of input modalities should take control. Possible outcome of this decision is: (i) leaving the same input modality or a group of them in control or (ii) switching to other input modality or a group of them. This decision is made based on performance estimate of a current system state. Different input signals captured from a specific input modality may require different features for performance evaluation, therefore one may require additional methods of feature extraction. The extracted fatigue features are sent to performance evaluation procedure, which later returns the performance estimate. Finally, the intelligent layer must decide which input mode or group of modes will take control. This decision is sent to the input channel selector. Those actions are repeated each time user initiates control command. Same as in HASCM, the performance can be estimated based on performance parameters received from the Control layer.

- **Performance evaluation procedure**. Performance evaluation procedure may contain one or more performance models. Separate performance models may be applied to a specific Control channel. It is possible to use only one performance model, when the model is based on the performance metrics of the Control layer. The output of this procedure is current performance estimate of the user.
- **Control layer.** Control layer determines specific application which is controlled by the user. Application area encompasses almost any digital device that can receive two or more input modalities of any human suitable form and can provide at least one output modality of any human suitable form.

The typical architecture of system adapting MAMM is presented in Fig 3.6. In this example 3 different control channel are utilized. Packages here represent logically related elements. Performance evaluator package corresponds to the performance evaluation procedure presented in Fig. 3.5. The rest of the packages are identical with corresponding elements in Fig 3.5.

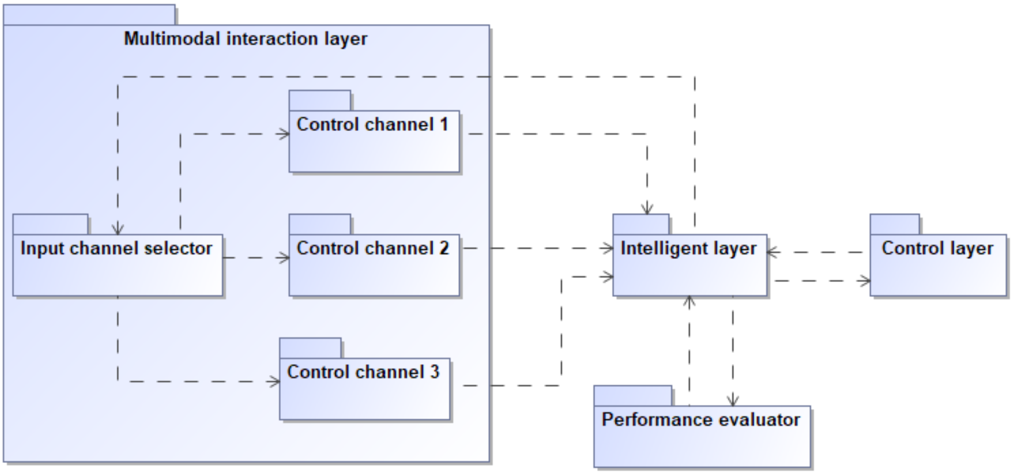


Figure 3.6 Typical architecture of HAMM with 3 control channels in UML notation

3.3.2 Interaction of model components

A user in a human-assistive multimodal HCI model (HAMM) is considered as a separate component of the model. The user can generate multimodal input. The workflow of the system based on HAMM is as follows:

1. A user generates multimodal input which is used for system control.
2. The system detects when performance level decreases.
3. Current input modality or a set of modalities are disabled.
4. An alternative input modality or a set of modalities are activated.
5. A user gets notification of the system decision on which input modality is now active.

Input modalities are managed in the Multimodal interaction layer (see Fig. 3.7). The number of input modalities depends on user abilities and system design. Each input modality should be independent from each other. It means that every single input modality must cover all control commands of the system. The Input channel selector, which is one of the constituent parts of the Multimodal interaction layer, manages which input modality must take control over others. At the start of the control input channel selector sets default input modality in control. Later switching of input modalities is determined by Intelligent layer, which sends a control command that enables input modality. In general, Input channel selector works as a switch controlled by Intelligent layer. Besides switching functionality, input channel selector notifies the user which input modality is in control, so that user will always know which input modality should be used. Input channel selector can activate a set of input modalities in control, still one restriction remains – all exiting input modalities cannot be activated at once, at least one should remain in reserve.

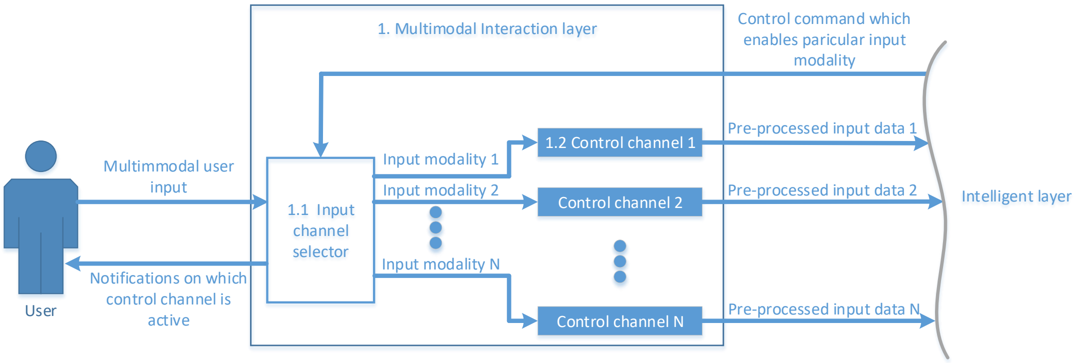


Figure 3.7 Communication between the user and Multimodal interaction layer of HAMM

Multimodal interaction layer also consists of a set of Control channels. The exact number of Control channels depends on user ability to generate different input modalities. Same as in HASCM, Input channel in HAMM is responsible for pre-processing. Not all input types may need pre-processing (e.g. a mouse and a keyboard), in such cases this task is simply skipped. The most pre-processing is needed when system input is based on a physiological signal; then signal sampling and filtering are usually applied. Different types of input signals may require different pre-processing techniques; therefore, the number of Input channels coincide with the number of input modalities. The output of the Input channel is the pre-processed input data, which is further analyzed in the Intelligent layer.

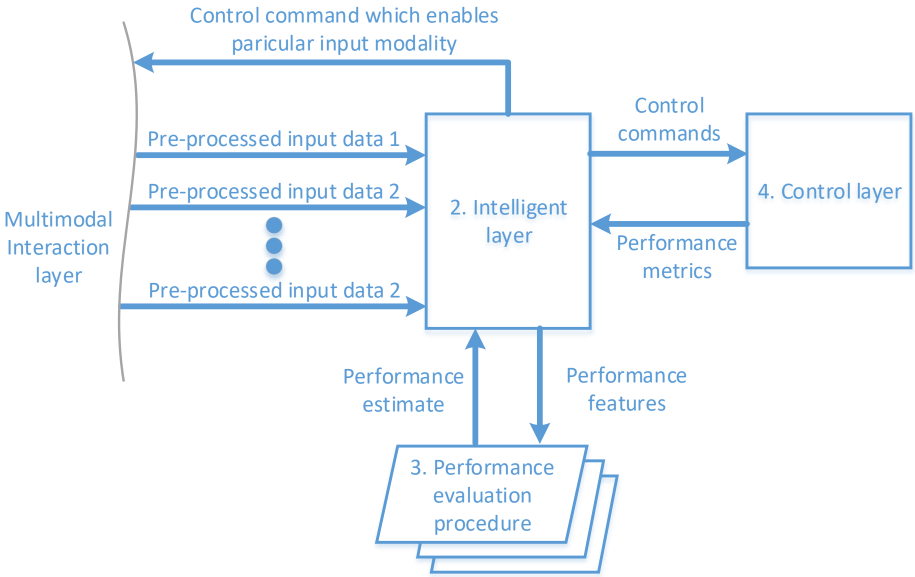


Figure 3.8 Communication between the Intelligent layer and other components of HAMM

The Intelligent layer of HAMM operates in the same way as in HASCM. It is responsible for (i) pre-processed data classification to the control commands, (ii) fatigue feature extraction and (iii) decisions when input modality needs to be switched. This functionality fits the one presented in Section 3.2.2. The only difference here lies in decision-making process. The intelligent layer of HAMM is responsible not only for activating the multimodal interaction layer when the increased level of fatigue is detected, but also must decide which input channel should be activated.

Performance evaluation procedure in HAMM differs from the HASCM in the sense that it might contain a set of different performance procedures or models, since different input modalities are used. Performance or features received from the intelligent layer help to identify a suitable performance model. If performance or fatigue features cannot be distinguished from each other, additional identifiers may be required.

Control layer is the same for both, HASCM and HAMM. It is responsible for (1) controlling particular application based on the received control commands from intelligent layer and (2) sending back the performance metrics, which can be used for the evaluation of performance.

3.4 Model limitation

The main drawback of the model lies in variability of performance estimation metrics. CMJ metric used in sport trainings is suitable to evaluate athletes' performance or fatigue level in many sports [Markovic et al., 2004]. However, to objectively evaluate performance in the HCI domain, no similar metrics are distinguished. Performance assessment methods in the HCI and PCS areas are greatly dependent on the scope and the type of input modalities used for control. The arguments of mathematical performance functions based on training and fatigue will also vary from one system to another. Using the same system does not change the analytical model for different users, but the parameters of this model will be different for different users (this is demonstrated by studies presented in Chapter 4). Hence, every user must necessarily undergo trial testing before using a certain system to find the right model or, at least, suitable parameters.

After using the system for a longer period, the user trains himself, thus, controlling the system becomes smoother. For the same reason performance evaluation procedure can also change. Then the need for re-optimization of the analytical model emerges. This problem might be solved by adjusting the model online as proposed in Kolossa et al. [Kolossa et al., 2017].

3.5 Conclusion of the chapter

Human-assistive HCI model describes interaction between a human and a computer, including the evaluation of user performance. 2 variants of the model have been suggested: (i) Human-assistive single channel HCI model, (ii) Human-assistive multimodal HCI model. When the system is managed by only one channel, the system responds to decrease of the performance by offering the user an opportunity to relax or by facilitating the management process. In the case of multimode control, the system detects decrease of performance in one channel that can transfer control to an alternative control channel.

The proposed models originate from the concept of a biocybernetic loop. They focus on practical aspects of the development of PCS-based user interfaces. In general, Human–assistive HCI models provide a design framework for the PCS-based user interfaces. The distinction between the concept of a biocybernetic loop and human-assistive HCI models also lies in the performance measurement procedure, which was inspired by impulse-response models, initially used in human physiology domain, and renamed after training-fatigue models in this study.

The main limitations of the proposed model are related to the performance evaluation procedure itself. Predicting performance or user fatigue can be a complicated process, as parameters of performance or user fatigue to different individuals can vary widely. It is, therefore, very difficult to apply the same model parameters to different individuals.

4 ANALYTICAL PERFORMANCE MODELS FOR HUMAN-ASSISTIVE HCI

In this chapter all experiments and their results are described. The predominant focus of those experiments is (1) to investigate performance models and their applicability to PCS (Section 4.1 and Section 4.2) or (2) to apply a simple fatigue evaluation procedure and test the effect of its application to system performance (Section 4.3). All experiments have been carried out on a specially-developed application. Theoretical models described in Chapter 3 (HASCM and HAMM) have been applied for the development of these applications. The results presented in this chapter, have also been published in these papers [Vasiljevas et al., 2014a, Vasiljevas et al., 2014b, Vasiljevas et al., 2015, Vasiljevas et al., 2016, Damaševičius et al., 2015, Damasevicius et al., 2015].

This chapter is organized as follows: in Section 4.1 experiments on modelling user performance in gaze spelling task are provided, in Section 4.2 experiments on modelling user performance in PC game based on eye tracking are presented, in Section 4.3 EMG-based speller prototype is described and its performance experiments are provided, finally, in Section 4.4 conclusion of this chapter are presented.

4.1 Modelling user performance in gaze spelling task

Research in this section was originally presented in [Vasiljevas et al., 2016].

4.1.1 Methodology

4.1.1.1 Proposed eye performance model

Let $\underline{X}$ be a time series consisting of spatial gaze landing positions $X=(x_1,x_2,...,x_n)$ measured at time $T=(\mathrm{t}_1,\mathrm{t}_2,...,\mathrm{t}_n)$ when performing the gaze fixation task. For simplicity, we consider only one dimensional (horizontal one), though the model can be applied to the vertical dimension as well. Given *X* and assuming normal distribution of the landing site position, we can construct the probability density function (PDF) of *X* as $pdf(X)$.

Let us perform the segmentation of time-series using the sliding window with the length of the local sliding window *w* and the step between adjacent sliding windows *s*. This transformation transforms *X* into a sequence of vectors $\overline{X}=(\{x_1,...,x_W\},\{x_{S+1},...,x_{S+W}\},...,\{x_{kS+1},...,x_{kS+W}\})$, here $k=\lfloor (n-w)/s \rfloor$.

Let *M* be a time series constructed from the maximal values of $pdf(X)$ meaning the largest probability value of landing. PDF is calculated for each member (aka vector) of sequence $\bar{X}$. Finally, we result in a sequence $M=(m_1,m_2,...,m_k)$, where m_i is the maximum PDF value of i-th $\bar{X}$ member, $i=[1;k]$. *M* value can be used to characterize the performance of a subject: the higher the value, the more accurate the subject is, the lower the value, the less accurate the subject is.

The probability distribution depends upon many different factors such as the skill of a subject in using the gaze-based interfaces as well as the complexity of the gaze tracking task. Therefore, we must normalize M to remove inter-subject and inter-task variability as follows. Let S be a set of subjects $S = \{s_1, s_2, \dots, s_p\}$. Let M_S be a matrix constructed of M for subjects S. The normalization procedure consists of diving each element of matrix $\overline{M_S}$ by square root of a product of a mean value of each subject and the mean value of all subjects at each time step. The normalized matrix $\overline{M_{S,t}}$ is defined as:

$$\overline{M_{s,t}} = {M_{s,t}} \Big/ \sqrt{E\left(M_{\forall s,t}\right) \cdot E\left(M_{s,\forall t}\right)} \tag{4.1}$$

here $E(\cdot)$ is the mean (expectation) operator.

Let the grand mean of $\overline{M_{S,t}}$ be $\overline{\overline{M}} = E\left(\overline{M_{S,t}}\right)$. Finally, we perform the fitting of $\overline{\overline{M}}$ to a variant of Banister's model:

$$P(t) = k_1 \cdot e^{-t/\tau_1} - k_2 \cdot e^{-t/\tau_2} \tag{4.2}$$

here $\mathrm{P}(t)$ is performance, k_1 and k_2 are learning and fatigue parameters, t is time, τ_1 and τ_2 are decay parameters for learning and fatigue respectively.

The Banister model assumes that, in response to a training impulse, performance first decreases and then returns to the initial level after a time t_n and then peaks at a higher level after time t_g [Fitz-Clarke et al., 1991]. Therefore, we calculate two additional t_n and t_g parameters to evaluate time needed for the subject to rest after the gaze tracking session as follows:

$$t_n = \frac{\tau 1\, \tau 2}{\tau 1 - \tau 2} \ln\left(\frac{k_2}{k_1}\right) \tag{4.3}$$

$$t_g = \frac{\tau 1\, \tau 2}{\tau 1 - \tau 2} \ln\left(\frac{\tau 1\, k2}{\tau 2\, k2}\right) \tag{4.4}$$

4.1.1.2 Gaze spelling system

4.1.1.2.1 Architecture

The architecture of the developed prototype gaze speller system is quite simple (see Fig. 4.5). It consists of the gaze tracking device (Eye Tribe), which is connected to a PC via USB 3.0 connection. On the PC, the core modules are responsible for calibration procedure and gaze feedback. A more detailed description of the architecture and implementation can be found in [Vasiljevas et al., 2015].

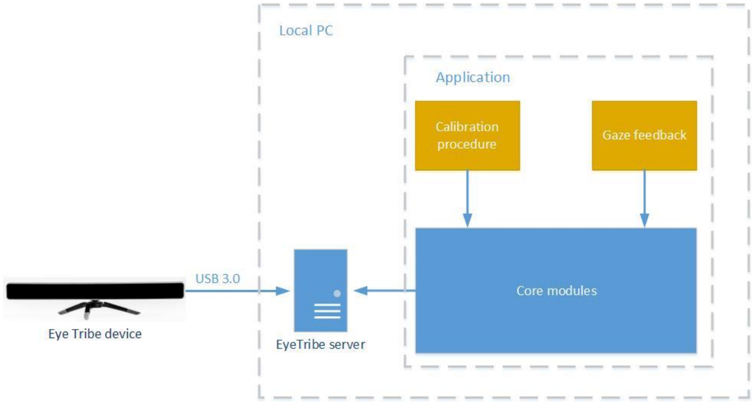


Figure 4.1. Architecture of the gaze speller prototype system

4.1.1.2.2 Application of HASCM to system design

In the sense of HCI, gaze speller architecture is based on HASCM model (see Fig. 4.2), where eye movements are used as an input channel. An adaptive dwell time described in Section 4.1.1.2.5 serves as an initial recover activity. The dwell time is adapted in accordance with rate of typing errors detected by the intelligent layer of the system. In this study we also investigate a more complex training and fatigue model described in 4.1.1.1, input of which is based on accuracy of the sight landing position. The intelligent layer of this application is responsible for gaze mapping on a PC screen, detecting typing errors and initiating the feedback to the user. Error rate threshold function serves as the initial fatigue evaluation procedure. The threshold indicates how many errors can be made before initiating the recover activity. The specific threshold value is set by the user. In general, system control workflow is as follows: first, the user enters a text by his eye movements, second, the system monitors how many unwanted selections (errors) the user has made, after the error threshold is reached, dwell time adjustment is made (dwell time is increased at the specific value). The opposite adjustment (decrease of dwell time) is made, when the user reaches some defined number of the intentional selections.

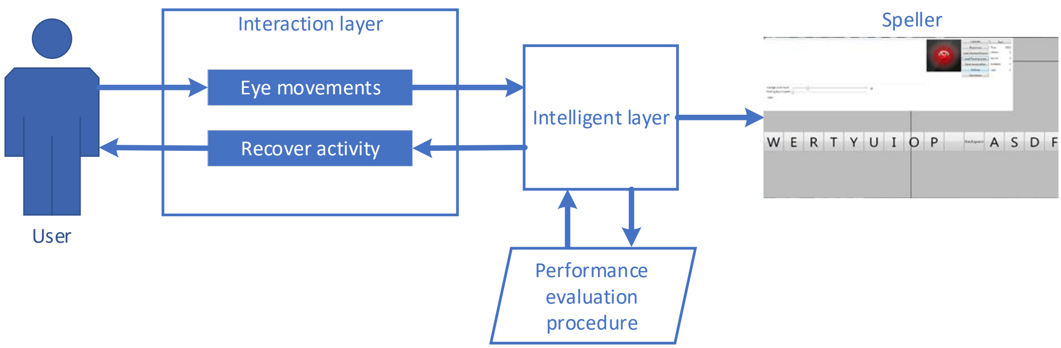


Figure 4.2. The HASCM model for gaze speller

4.1.1.2.3 Interface

The primary motive for designing a user interface for a gaze speller is usability as good user experience would also enhance user acceptance of the system. Our developed interface was inspired by Špakov *et al.* [Špakov and Majaranta, 2009] and is based on the concept of a "scrollable keyboard" (see Fig. 4.3).

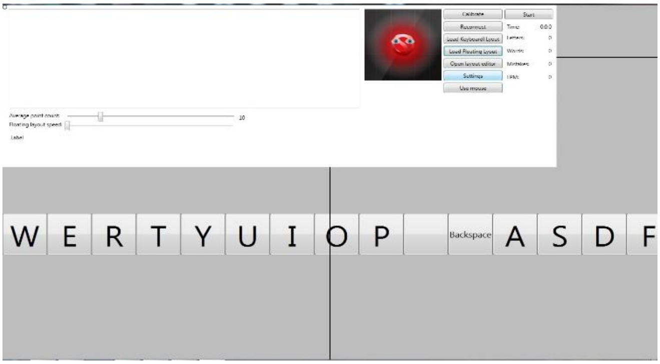


Figure 4.3. Interface of the gaze speller

Current implementation uses two scrollable keyboard layouts: 1) a standard QWERTY layout mapped to a single scrollable line of letters, 2) and a letter bigram optimized layout described in Subsection 4.1.1.2.4. Feedback is ensured by the black line which always stays at the center of the screen while the one-line keyboard moves underneath it, depending on the horizontal position of the gaze. Letter selection for input is provided by eye dwelling. Additional menu buttons are for calibration, connection to the gaze tracking device, loading of the alternative keyboard layouts, and setting program options. Layout editor has been implemented for the design of other keyboard layouts.

4.1.1.2.4 Letter bigram optimized layout

We have developed an alternative layout for the letter scrollbar based on the frequency of bigrams in the language under consideration. First, we have computed the number of occurrences of each bigram in text corpora (we used "Alice in Wonderland" from Project Gutenberg) as follows.

Let s_i and s_j be a sequence of two symbols or bigram in alphabet L. Let the frequency of a bigram be $f(s_i, s_j)$. The sum of all possible bigram frequencies in alphabet is equal to 100%. We compute the distance from s_i to s_j, as inverse of frequency:

$$D(s_i, s_j) = 1/(1 + f(s_i, s_j)) \tag{4.5}$$

To make the matrix D a true distance matrix, the elements at the main diagonal of the matrix are assigned a zero, i.e. $D(s_i, s_j) = 0$, for all $i = j$.

Next, we consider the problem of optimally placing the letters on the 1D scrolling band as a separate case of the Travelling Salesman Problem (TSP). We can describe the letters as nodes of a graph, and the pairwise distance between nodes is inversely proportional to the frequency of occurrence of bigrams composed from the corresponding letters. The result of a solution to the TSP problem is the shortest path connecting all letters in alphabet. In our case it would be the optimal placement of the letters on the 1D scrolling band. This type of letter placement requires minimum demand of horizontal scrolling. The problem is computationally difficult and can be solved exactly using brute force search or dynamic programming methods for a small number of nodes (usually <15). As we have 26 letters in English alphabet as well as several other symbols (delimiters, numbers, etc.), the brute force search approach is not feasible. We used a simple implementation of Ant Colony Optimization (ACO) to find a near optimal solution to this problem. ACO is a probabilistic technique to solve computational problems which can be reduced to finding good paths through graphs. As the ACO algorithm is probabilistic, each time a different solution is provided. We have repeated the algorithm 100 times and selected the solution with the shortest length of path. Finally, we shifted the solution so that the symbol with the largest frequency is placed in the middle of the scrolling bar. The solution for scrolling bar used in this paper is:

```
YWVXQZGKJBURE STHANDICOFMPL
```

4.1.1.2.5 Adaptive dwell time and word autosuggestion feature

Using gaze as the input method can be problematic, since the same modality is used for both perception and control. The system needs to be able to distinguish casual viewing of an object from intentional control. Eye movements are also largely unconscious and automatic. Gaze can be easily distracted by movement in the peripheral vision, resulting in unwanted glances away from the object of interest. When necessary, humans can control gaze at will, which makes voluntary eye control possible. For systems based solely on gaze-control, the most common method for preventing erroneous activations is to introduce a brief delay, a so-called ‘‘dwell time’’, to differentiate viewing and gaze-control. The duration should match the specific requirements of the task and the user. Expert eye typists require only a very short dwell time (e.g. 300 ms) while novices may prefer longer dwell time periods (e.g. 1000 ms) that give them more time to think, react and cancel the action. A long continuous dwelling (fixation) can be uncomfortable and tiring to the eyes. On the other hand, the possibility to adjust dwell time supports efficient learning of the gaze-controlled interface and increases user satisfaction [Majaranta et al., 2009].

When using dwell time, the user only initiates the action; the system executes it after a predefined interval. Appropriate feedback plays the essential role in gaze-based interfaces; the user must be given clear indication of the status of the system: if the user is entering text by gaze, he or she cannot see the text appear in the text input field while simultaneously selecting a letter on an on-screen keyboard. Proper feedback can significantly reduce errors and increase interaction speed.

The implemented gaze speller also has the adaptive dwell time and word autosuggestion feature implemented similarly to the ones implemented in the EMG speller [Vasiljevas et al., 2014a, Damaševičius et al., 2015]. The developed speller application is adaptive (input speed can be adapted dynamically in response to the user's state) and intelligent (uses word complete and word frequency features). A common way to implement word prediction is to present a list of predicted words for the user. The words are based on the letters the user has written so far and is sorted based on the frequency of words in the text corpora of the language. The list is dynamically adjusted as more letters are written and the number of possible continuations of the word decreases.

4.1.1.2.6 Limitations

The application of the developed gaze speller for disabled or impaired people may be limited. Some medical conditions cause involuntary head movements or eye tremor, preventing good calibration or may even restrict eye movements to one direction (vertical) only. Our implementation uses a horizontal scrolling bar layout only. QWERTY and bigram frequency-based layout may not be the best choice for the disabled who have no previous experience with the QWERTY layout and might, thus, find another kind of the layout (for example, an alphabetically ordered layout) more familiar. The dwell time sets a limit to the maximum typing speed because the user must wait for the dwell time to elapse before each selection. A long dwell time is good for preventing false selections, but a long fixation on the same target can be tiring to eyes.

4.1.2 Experiments and results

4.1.2.1 Apparatus

The EyeTribe eye tracker (tracking range 45cm – 75cm, tracking area 40cm x 30cm at 65cm distance) was connected to a HP Ultrabook notebook running Microsoft 8 OS 64-bit with an Intel Core i5-4202Y 1.60 GHz CPU and 4 GB RAM. The application was displayed on a 14" flat LCD display with LED backlight and screen resolution of 1920x1080 pixels. The eyeTribe eye tracker communicates with notebook via USB 3.0 interface.

4.1.2.2 Subjects

For the experiment, 8 volunteers (aged 25-32 years, 7 male and 1 female) took part in the test. They were students or staff at Kaunas University of Technology. All were fluent in English and had no known vision problems. All subjects provided a written consent prior to the experiment. After the experiment was performed, the initial screening of data showed that the data for one subject were not recorded due to a software glitch. Therefore, only data from 7 subjects were used for further analysis.

4.1.2.3 Datasets

For the experiment, an easy-to-memorize phrase was chosen from a set of 500 phrases proposed in [MacKenzie and Soukoreff, 2003]. This phrase set is considered the *de facto* standard for text entry evaluations. Punctuation was removed, and the phrases were made case-insensitive.

4.1.2.4 Procedure

Prior to collecting data, the experimenter explained the task and demonstrated the software. The experiment was carried out with one disabled person, who could not control his legs and his hand movements were limited. The subject was instructed on the method of text entry, early word selection, error correction, and the audio feedback. He was instructed to enter the given phrases as quickly and accurately as possible and make corrections only if an error was detected in the current or previous word. The subject could enter a few trial phrases to become familiar with the gaze-controlled selection and correction methods. Then the subjects were instructed to eye type the phrases as rapidly and accurately as possible.

4.1.2.5 Usage scenario

Usually gaze-tracking interfaces are designed to imitate operation of a standard pointing device such as a mouse. The gaze tracker either head mounted or attached in front of the user then tracks the user's gaze and transforms it to the screen coordinates. During eye typing, the user first locates the letter on a virtual keyboard by moving his/her gaze to it. The gaze tracking device follows the user's point of gaze while software records and analyses the gaze behavior. For input, the user must fix his/her gaze at the letter for a pre-defined time interval (dwell time). When the dwell time passed, the letter was selected by the system and users could move on to gaze to the next letter. Feedback was shown both on focus and on selection.

4.1.2.6 Data analysis

The experimental data collected (spatial positions of the gaze landing sites at the central letter of the gaze speller interface) are presented graphically in Fig. 4.4

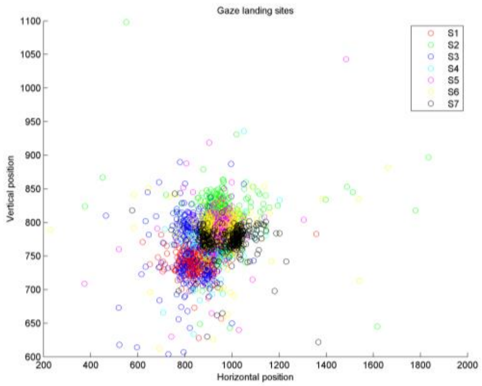


Figure 4.4. Gaze landing site positions (all subjects)

To illustrate the effect of fatigue, we constructed PDFs of the first 100 gaze landing sites (horizontal position only) and PDFs of the last 100 gaze landing sites. Only horizontal position was considered since the scrollable keyboard of the gaze speller we used in our experiments required the subjects to use horizontal movements of gaze. The results are presented in Fig. 4.5 and Fig. 4.6, respectively.

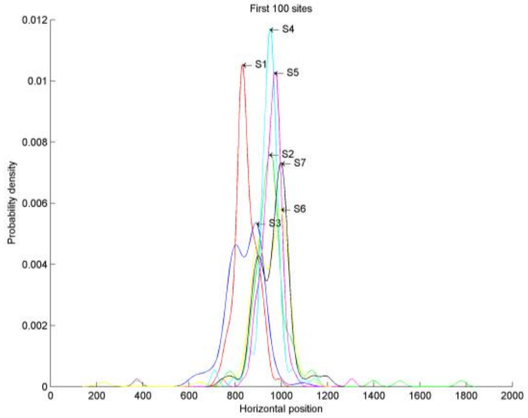


Figure 4.5. Probability density functions of all subjects for horizontal gaze landing sites (first 100 sites)

Note that the shape of PDFs has changed: for most subjects the PDF has flattened, i.e., the spread of values has increased as is visible from the 'thicker' tails of the distributions. From the shape of PDFs we also can see the bimodality of distribution for 3 of 7 subjects indicating that two factors may be in effect.

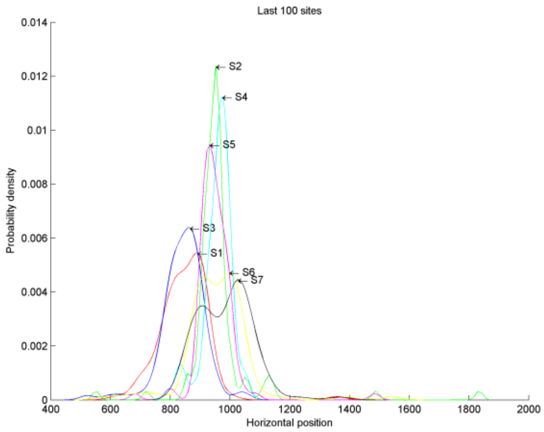


Figure 4.6. Probability density functions of all subjects for horizontal gaze landing sites (last 100 sites)

To model user fatigue during the experiment, we assume that subject accuracy to land their gaze follows the classical exponential decay model with two components: the positive one is corresponding to learning (training), and the negative one is corresponding to user fatigue (as defined in [Banister et al., 1975] model).

4.1.2.7 Model fitting

The model proposed in Section 4.1.1.1 was used. The model parameters were estimated for each subject using the non-linear least squares iterative method, by minimizing the residual sum of quadratic differences between the real and the modelled performances (RSS) with a Trust-Region-Reflective Least Squares Algorithm. Computations were performed using Matlab 2013a (version 8.1, Mathworks). 95% confidence bounds were calculated for the estimated parameters. The model fitting results are presented in Fig. 4.7.

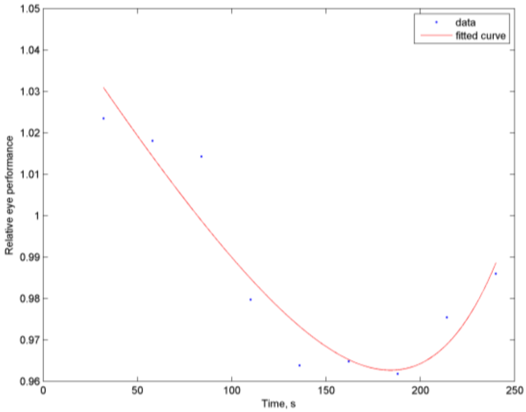


Figure 4.7. Model fitting

The parameters of the best fitted model (w = 62, s = 26) are presented in Table. 4.1-2.

Table 4.1. Model parameters (mean and confidence bounds)

Parameter	Mean	95% confidence bounds	
k1	1.051	1.021	1.081
t1	1471	-265	2677
k2	-0.0013	-0.012	0.015
t2	55.8	-15.8	127

To evaluate fitness of the model, the determination coefficient was calculated as: $R^2 = 1 - (RSS / TSS)$, where *TSS* is the total sum of squares, as well as the degree-of-freedom adjusted coefficient of determination. The sums of squares due to error (SSE) and root mean square error (RMSE) values were computed to evaluate difference between the modelled and real data values (see Table. 4.2).

Table 4.2. Model fitness characteristics

Characteristic	Value
SSE	0.0005
Degrees of freedom	5
R-square	0.9027

Adjusted R-square	0.8442
RMSE	0.0098

4.1.2.8 PCA analysis

For data analysis, Principal Component Analysis (PCA) was performed on the covariation matrix of the horizontal gaze landing position matrix. Factor 1 accounted for 73% of the total variance. This factor was highly negatively related to the performance and can be attributed to fatigue. Factor 2 accounted for 17% of the total variance. This factor was positively related to performance and could be attributed to learning (training).

4.1.2.9 Statistical validation

An important question is how many data points are needed per parameter to enable statistical analysis. For multiple linear regression, 15 observations per parameter is recommended. Since the Banister model is a non-linear one, more data points per parameter may be required. In our experiment we used 338 observations per 4 parameters, which should be enough for a non-linear model.

To analyse stability of this model, iterative computation was performed with the same data but minus one subject, chosen randomly following the methodology described by Hellard *et al.* [Hellard et al., 2006]. A method is considered unstable if small perturbations in the data can cause significant changes in the estimations. One hold-out 7-fold cross validation was done to evaluate the stability of results. In each fold, the data of one subject was removed, and the computation of the model repeated. Different models obtained during the cross-validation procedure are presented in Fig. 4.8. The models differ from each other due to individual factors of each subject. Moreover, the sample of 7 subjects is not enough to generalize the model. However, the shapes of the curves are similar, which shows that the Banister model is suitable to describe user fatigue effects of eye-controlled interface.

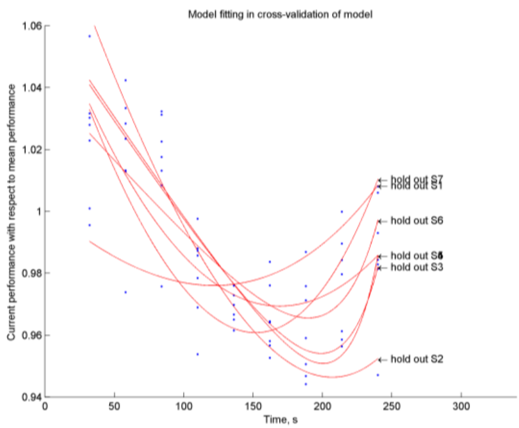


Figure 4.8. Models obtained using one hold out cross-validation

The model parameter results are summarized in Table 4.3.

Table 4.3. Results of cross-validation using one hold-out

Model parameter	Mean value	SD of value
k1	0.974	0.136
k2	-0.085	0.135
t1	1131	654
t2	-149	147
tn	308	244
tg	177	31

Finally, the PDFs of the decay parameters of fatigue and learning obtained during the cross-validation procedure are given in Fig. 4.9. We can see that the effect of fatigue is developed earlier and is stronger than the effect of learning.

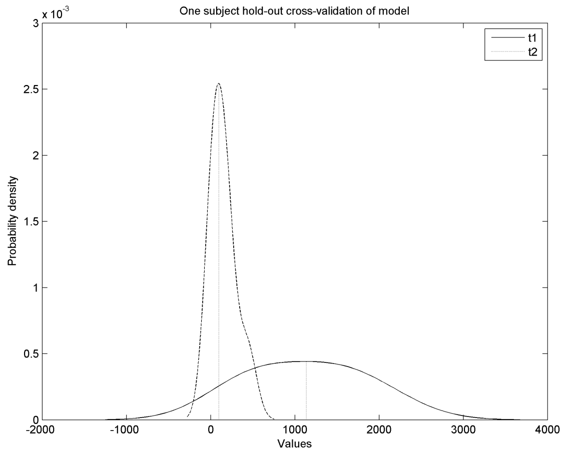


Figure 4.9. Probability density of model's decay parameter values

4.1.3 Conclusion of the section

Our initial experiments with evaluating user fatigue when a subject is working with the gaze spelling system suggest that the classical model of Banister *et al.* proposed to evaluate performance of sports athletes, is applicable to the domain of physiological computing as well. We have analysed the accuracy of gaze landing in performing text entry task. Experimental data were fitted to the proposed fatigue model adapted from Banister *et al.* The proposed model has been validated using the one hold out cross-validation procedure.

The variability between user performance is significant and is larger than intra-user variability due to learning and fatigue effects. PCA analysis shows that intra-user variability can be explained by two factors: fatigue (73% of variance) and learning (17% of variance). Both these factors explain 90% of intra-user variance. Since the learning acts slower than fatigue and has less effect on the results, time-to-peak value is smaller than time-to-initial performance (which is contrary to sports athletes' performance). Therefore, it is recommended to use the time-to-initial performance as an estimate of rest time. The model allows to calculate the time needed to rest after each session. The mean time to rest calculated from all user data is 308+-244 s (5+-4 min). The large SD of the total estimate is due to large variability of user performance. In fact, the analysis of data shows that the length of the test session was too short for two users, which does not allow for the fatigue effects to show up. The rest time can be calculated for each user individually. The prevalence of fatigue effect over learning effect means that the usability of the gaze tracking-based interface is low due to negative reinforcement. Until the fatigue issue could be solved, the users are not likely to be using this kind of interfaces.

The results of the study confirm that the stimulus induced fatigue on users' eyes among the tasks conducted. The main findings of this study are that: 1) learning and fatigue effects are present in the gaze tracking data; 2) learning is slower process than fatigue; 3) the parameters of learning and fatigue can be evaluated using Banister model; 4) time required for eye rest break can be evaluated.

Further research is needed to analyse long-term effects of eye fatigue, which were not covered by this experiment. A larger (in terms of the number of subjects) and longer study is needed to validate the values of the model parameters.

4.2 Modeling user performance in PC game based on eye tracking

4.2.1 Methodology

4.2.1.1 The game

Eye fatigue is a major negative factor of eye performance. Eye fatigue usually emerges after active pursuit eye movements, since the surrounding eye muscles are involved. Such movements can be carried out by supervision of an expert, which is a monotonic and frustrating activity. Other approach is to apply serious games solution [Wouters et al., 2013]. Serious games have been proposed as an attractive mean to engage people in performing useful activities such as learning [Danevičius et al., 2018] through an accomplishment of certain in-game tasks. Therefore, eye-controlled game was introduced.

The idea of the game is based on a widely known Pac-Man game, which is a type of maze chase games. The player navigates Pac-Man through a maze containing resources (dots), and adversaries (ghosts). The aim of the game is to collect the dots while avoiding the ghosts. We have implemented a simpler version of the game, in which the player must move vertically or horizontally in the maze and collect pills. Note that while the aim of the game is to collect pills, the desired eye movement are made by navigating in the maze. The alternating vertical and horizontal movements of eye are the important part of visual therapy that has been demonstrated to improve eyesight [Brunyé et al., 2009], treat amblyopia [Fronius et al., 2006] and eye movement disorder.

There are two modes of the game: simple mode and timed mode. While playing in simple mode, the player needs to collect all pills in the maze to win. In timed mode, the aim is to collect as many as possible pills in a specified period. When a specific pill is taken, it will appear after some time in the same place. The game mechanics of each mode have been modelled using the Machinations diagrams [Dormans, 2011] presented in Fig. 4.10. Elements of machinations diagram are described in Table 4.4. The developed game is easy to play and implements the principles of the effective human-computer interaction outlined in [Shneiderman et al., 2016]: strive for consistency (a familiar graphics and game mechanics from well-known Pac-Man game is used), informative feedback (score is counted to reflect game actions), support internal locus of control (the player initiates the action).

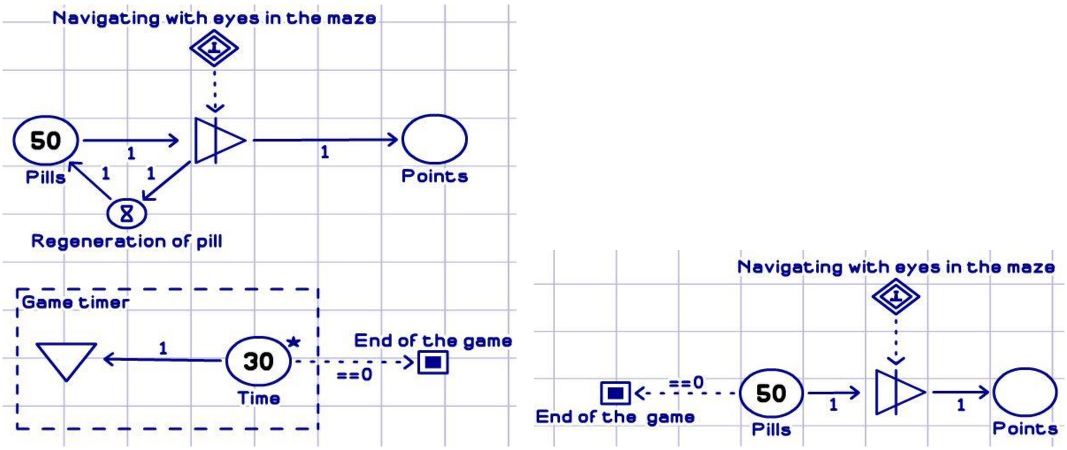
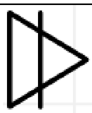
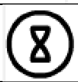
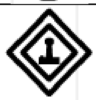


Figure 4.10. Game mechanics (in Machinations [Dormans, 2011]) of timer mode (left) and simple mode (right)

Table 4.4. Explanation of Machinations elements used in the diagrams

Name	Shape	Description
Pool		Pool is a node where resources are stored. The number in the middle of the circle represents the number of resources. In present game resources are considered as pills.
Drain		Drain is a node where resources are consumed.
Converter		Converter is a node, in which one resource is transmuted into another.
Delay		Delay is a node, where the flow of resources is delayed as they get distributed in the diagram.
Gate (indication of player skills)		Gate is a node, which immediately redistribute resources, once activated. Machination framework contains many different types of

		gate nodes. In this case, the shape represents interactive player skills.
Resource connection	⟶	Resource connection determines how resources flow through a diagram.
State connection	- - -›	State connection determines the modification of the current state of elements in a diagram.

The main window of the game is presented in Fig. 4.11 (left). The movements of the main character are restricted by the walls of the game maze. The main character of the game (represented by blue point) is controlled by eye movements of the player. The control principles of the game are represented abstractly in Fig. 4.11 (right). The area around the main character is divided in four equal sectors. Each sector is defined by 90° angle areas from the starting point, which corresponds to the main character. Each of the four sectors represents one of the four directions of movement. When the gaze landing point of the player is captured at the specific sector, the main character moves at the direction specified by that sector.

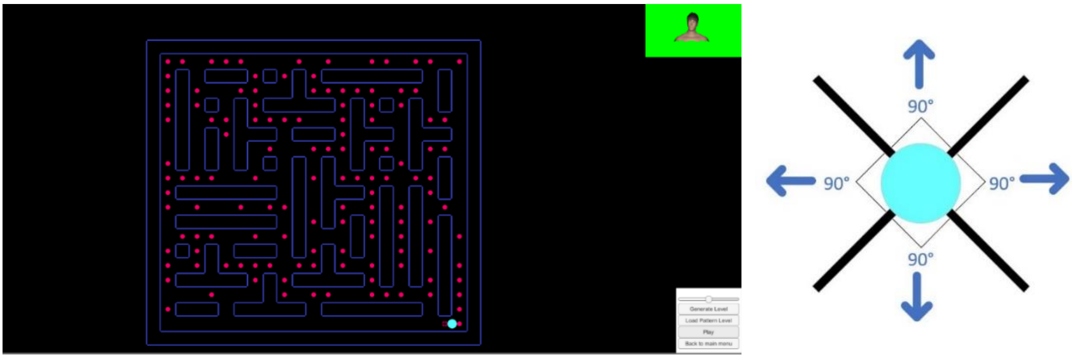


Figure 4.11. Screen of the game with the main character (blue) (left) and control of the main character (right).

4.2.1.2 Application of HAMM

The present version of the Pac-Man game also extends the original game by the means of control mode. Eye movement control mode is introduced. The user can control the game by either eye movements or a keyboard. Since the primary task of the system is to play the game via eye movements, the keyboard control is introduced only after certain fatigue indicators emerge.

The HAMM framework for an eye-controlled game is presented in Fig. 4.12. This application of the HAMM consists of the components listed below:

1. **Multimodal interaction layer.** It describes the means of communication and feedback. The user can use one of the following control channels: (1) eye movements and (2) keyboard control. The eye movement control is established via *Tobii Eye Tracker 4C*. Both control channels are switched

alternately based on the supervision of intelligent layer. The component of the input channel selector is responsible for switching the control channels and informing the user of which control channel is active at the moment.

2. **Intelligent layer**. It is responsible for analysing the control channel parameters and making decision related with switching between control channels. The control using eye movements is a more demanding activity, which leads to fatigue more prominently. However, it is the primary control mode of the presented game, thus, the prolonged usage of it is of interest. The relation between the eye movement parameters and fatigue is not clear enough, therefore, it is the research task of this study. The keyboard control is enabled, when the eye movement parameters indicate fatigue. It is basically a layover of the eye movement. Keyboard control is terminated after a defined period.
3. **DHO-based performance model.** This model is chosen, since it has demonstrated promising results in modelling training effects on physical performance capacity [Morin et al., 2016]. It is investigated further in the following sections.
4. **Eye-controlled game**. A detailed description of the eye-controlled game is presented in Section 4.2.1.1.

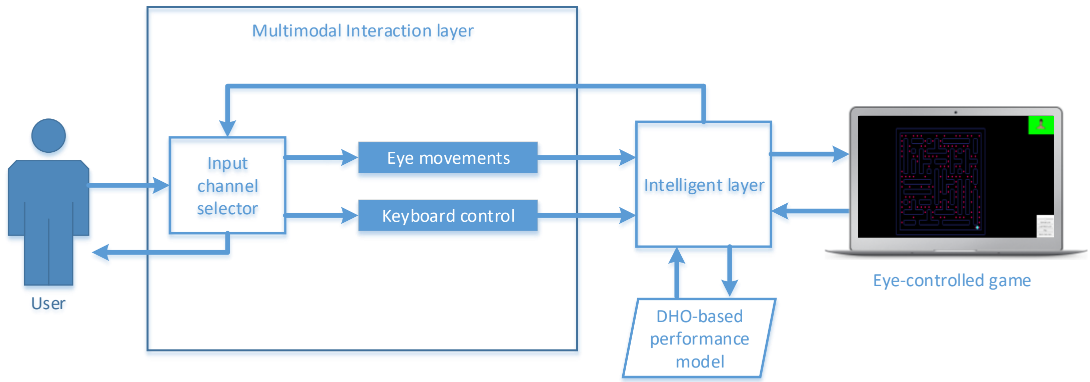


Figure 4.12. Application of HAMM framework for eye-controlled game

4.2.1.3 Evaluation of eye performance

During the game the following eye and game performance characteristics have been collected:

– Direction, amplitude and velocity of saccadic movements;

– Distribution of the number of turns while navigating in the maze.

The saccadic characteristics are further analyzed using the statistical and linear regression methods. The game characteristics are analyzed by fitting the data to the proposed eye fatigue model.

4.2.1.4 Analysis of saccadic velocity and directional distribution

We use circular statistics [Fisher, 1993] to analyze the distribution of saccade velocity and movement direction over time and direction. We analyze the data during the first half and second half of the game session. The results represented as Wind Rose plots are used for comparison to detect the effects of eye fatigue. We also use linear regression to validate the trends observed in the data.

4.2.1.5 Eye training and fatigue model

Two major factors influence the cognitive performance of the player during the game: learning, which represents the improvement of characteristics due to practice and mastery of control, and fatigue, which shows the decrease of abilities to perform game action due to eye muscular and mental fatigue. To evaluate the effects of fatigue and performance recovery on the capability to perform tasks by gaze, we have adopted a well-known model of damped oscillation. A damped oscillation wave is an exponentially decaying sinusoidal wave whose amplitude of oscillation diminishes over time. This model represents the effects of long-term fatigue interrupted by short-time recovery of the performing abilities of biological structures such as eyeball controlling muscles. The DHO was successfully applied for modelling training effects on the physical performance capacity in team sport [Morin et al., 2016]. The model can be considered as generalization of the Fitness-Fatigue models such as the Banister model, which represented the muscular adaptation to physical training as a sum of two exponential functions representing a positive effect (fitness) and a negative effect (fatigue) on sports performance [Calvert et al., 1976].

The adopted model of the change of game performance characteristic f over time t is described as follows:

$$f\left(t\right)=Ae^{-\lambda t}\times\cos\left(wt+\phi\right) \tag{4.6}$$

here A is the initial amplitude, λ is the damping factor, ω is angular frequency, and Φ is the initial phase angle. Note that if the damping factor is positive, the performance decreases due to fatigue, whereas in case of negative damping the performance increases due to the learning effect. To represent the data graphically, we use the phase space plots [Damasevicius el al., 2014], which show the value of $f(t)$ vs. $f(t+1)$

4.2.1.6 Preprocessing of data fitting to the model

To analyse the change of player performance during the game, the temporal distribution of the number of successful turns while travelling in a maze is considered. Each turn requires that a user performs a saccadic movement of an eye in the horizontal or vertical direction, which is the serious aim of the game. The game is started in the timed mode and the number of new turns is registered every 20s. As the resulting time series is very rugged and poorly handled by model-fitting algorithms, the smoothing of the time series is performed. Here the extended version of the Empirical Mode Decomposition (EMD) denoising method, also known as BoostEMD

[Damasevicius et al., 2015], was used. First, the time series is decomposed into independent components (modes) representing variability of the time series at different frequency scales. Then the first mode of the signal with the highest frequency of oscillation is considered as noise and is subtracted from the original time series. The resulting time series is used for fitting a model described by Eq. (4.6) and finding its coefficients using the Levenberg–Marquardt fitting algorithm. The reliability of fitting is evaluated using the odd-even reliability test by correlating scores on the odd-numbered items with scores on the even-numbered items.

4.2.1.7 BoostEMD: proposed extension of EMD method

Originally, the description of BoostEMD method was presented in [Damasevicius et al., 2015].

EMD [Huang et al., 1999] is a signal processing method based on local characteristics of data in the time domain. The EMD method is based on the concept of instantaneous frequency defined as the derivative of the phase of an analytic signal [Cohen, 1989]. A mono-component signal will have positive and well-defined instantaneous frequency. A signal with multiple modes of oscillation (such as biophysical signals) must be decomposed into its constituent mono-component signals, called Intrinsic Mode Functions (IMFs). The IMF is an indivisible component of the signal.

The idea behind the proposed BoostEMD method is to continue the analysis of the derived IMFs using the principles of the EMD method. However, we cannot submit the derived IMF to EMD as it is, as the result of the procedure would be the same IMF. Therefore, the IMFs must be transformed before processing further. A transformation must satisfy a set of principles as follows:

1) It should not increase signal amplitude.
2) It should be reversible, i.e. an inverse of the transformation should be unambiguously computable.
3) It should have a different number of extrema than the original IMF.

Here we propose to decompose each IMF into a pair of positive and negative semi-definite functions denoted as IMF^+ and IMF^- as follows:

$$IMF^{+(k)}(t) = \begin{cases} IMF^{(k)}(t), IMF^{(k)}(t) > 0 \\ 0, otherwise \end{cases} \tag{4.7}$$

$$IMF^{-(k)}(t) = \begin{cases} IMF^{(k)}(t), IMF^{(k)}(t) < 0 \\ 0, otherwise \end{cases} \tag{4.8}$$

It is obvious that each original IMF can be reconstructed from its decomposition unambiguously as follows:

$$IMF^{(k)}(t) = IMF^{+(k)}(t) + IMF^{-(k)}(t) \tag{4.9}$$

Then, to enable extracting higher frequency components of a signal by EMD, each pair of functions IMF^+ and IMF^- is up-sampled by a factor of 2 using a standard low-pass interpolation filter.

Next, the standard EMD procedure is applied and two sets of higher-order IMFs are obtained:

$$IMF^{+(k)} \leftarrow EMD\left(\uparrow\left(IMF^{+(k-1)}\right)\right) \tag{4.10}$$

$$IMF^{-(k)} \leftarrow EMD\left(\uparrow\left(IMF^{-(k-1)}\right)\right) \tag{4.11}$$

here $\uparrow(.)$ is the up-sampling operator, and $EMD(.)$ is the EMD procedure.

Such operation henceforth is called *boosting*, and the proposed extension of the EMD method is called *BoostEMD*.

The original lower-order IMFs can be reconstructed from higher order IMFs easily using down-sampling by a factor of 2 as follows:

$$IMF^{(k)} = \downarrow\left(\sum_i IMF_i^{+(k+1)}\right) + \downarrow\left(\sum_i IMF_i^{-(k+1)}\right) \tag{4.12}$$

here $\downarrow(.)$ is the down-sampling operator.

4.2.1.8 Application of BoostEMD for denoising the signal

Turns made by a player per time unit is considered as a temporal signal. It has been observed that this signal includes random spikes, which handicap the model fitting. The signal to be fitted to a training – fatigue model, at first must be pre-processed by removing random spikes. To smooth the signal, BoostEMD method has been applied.

First, the signal has been decomposed to several IMFs (see Fig. 4.13). Later, lower order IMFs have been discarded from the signal leaving just two higher order IMFs and the residue of the signal.

$$\hat{S}(t) = R(t) + IMF^{(n)} + IMF^{(n-1)} \tag{4.13}$$

where $\hat{S}(t)$ – smoothed signal, t – time, R(t) – the residue of decomposition, in this case it denotes the trend of the signal, n – number of decomposition components (IMFs), $IMF^{(n)}$ – n-th order IMF or the last IMF, $IMF^{(n-1)}$ – n-1 order IMF or penultimate IMF.

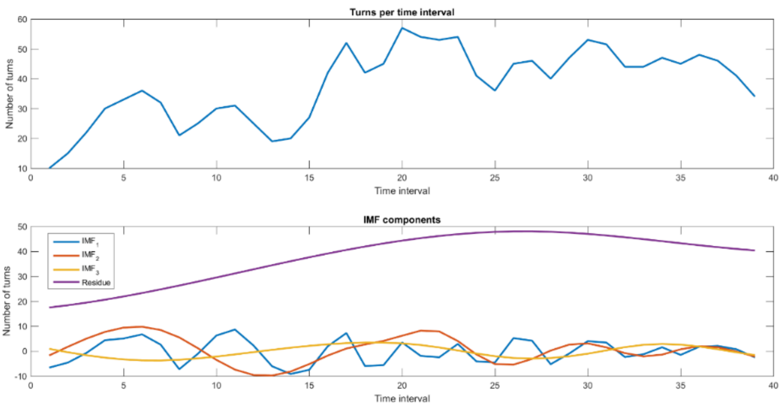


Figure 4.13 Example of signal decomposition to IMFs using BoostEMD

The example of the signal smoothed by BoostEMD is provided in Fig 4.14. After the smoothing procedure signal contains fewer local extrema points (outliers), which is crucial for fitting the signal to DHO model using the Levenberg–Marquardt optimization algorithm.

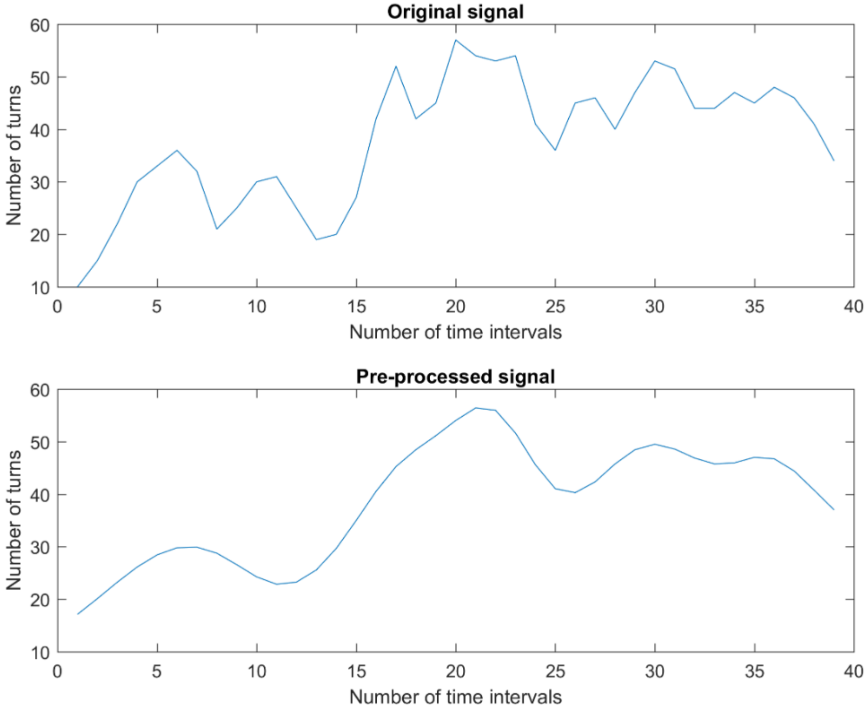


Figure 4.14 Example of the signal smoothing results using BoostEMD

4.2.2 Experiments and Results

4.2.2.1 Experimental setup

12 healthy subjects (6 males and 6 females), aged 21 – 42, participated in the experiment. All subjects filled an informed consent form and the principles of the Helsinki declaration were adhered to. The subjects were asked to play the game in a timed mode for 15 min. To capture eye movements and control the main character of the game by the gaze of the player, Tobii Eye Tracker 4C device was used. See a photo of a subject playing the game in Fig. 4.15.

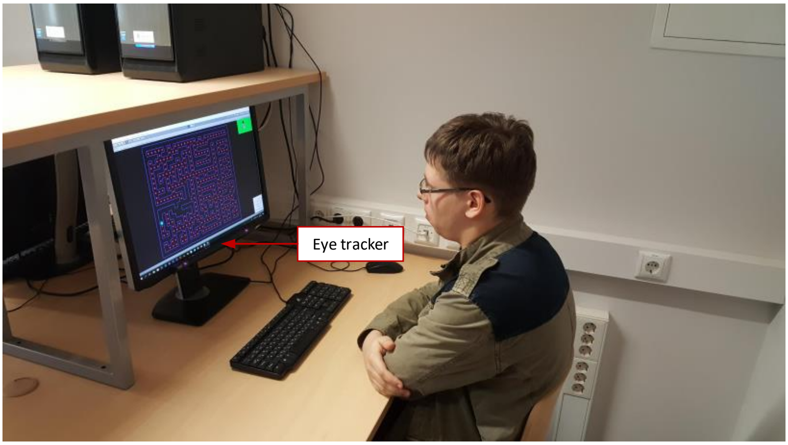


Figure 4.15 Subject playing the game

4.2.2.2 Comparison of the denoising methods

Our method requires that the time series of the game performance measure, first, must be smoothed to allow successful model fitting. To validate the used EMD-based denoising method, we compared it with other popular smoothing methods (moving mean, Savitzky-Golay and median filters) using time series smoothness characteristics (standard deviation, standard deviation of derivative, standard deviation of the normalized derivative, number of sign changes, path length and cumulative jerk) [Hogan and Sternad, 2009].

We used the smoothness results to rank the smoothing methods and performed the Nemenyi test to check if the differences between methods are statistically significant. The results of the Nemenyi test demonstrating the suitability of the EMD-based smoothing method for preprocessing the game performance measure time series over other smoothing (filtering) methods are presented in Fig. 4.16-17. The results showing the superiority of the EMD-based smoothing for this particular kind of data over other smoothing methods (5 out of 6 tests ranked the EMD-based smoothing method as the best one). The numeric values of smoothness metrics are presented in Table 4.5. BoostEMD method demonstrates the best results in terms of standard deviation of a derivative, standard deviation of a normalized derivative, number of sign changes, path length and cumulative square jerk. In terms of standard deviation it is in the second place, after the moving mean filter.

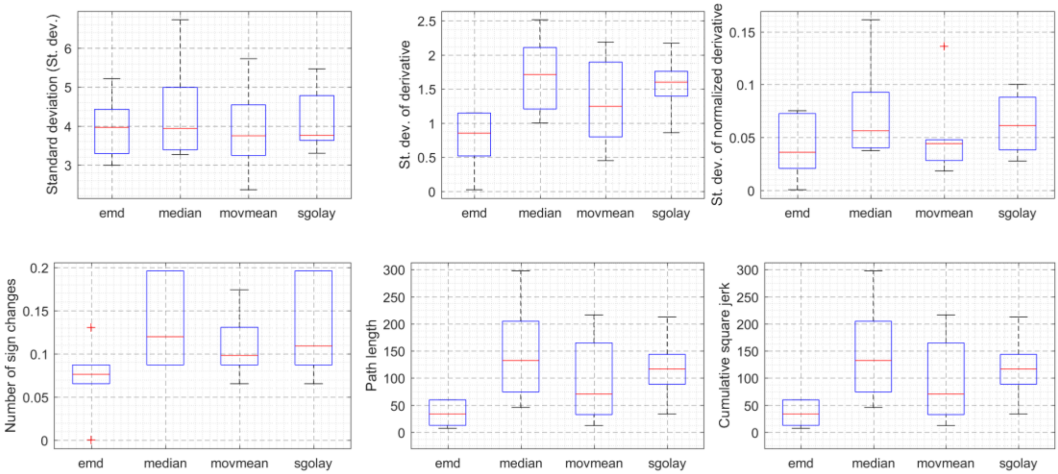


Figure 4.16 Comparison of different smoothing methods in terms of standart deviation, standart deviation of a derivative, standart deviation of a normalized derivative, nuber of sign changes, path length and cumulative square jerk

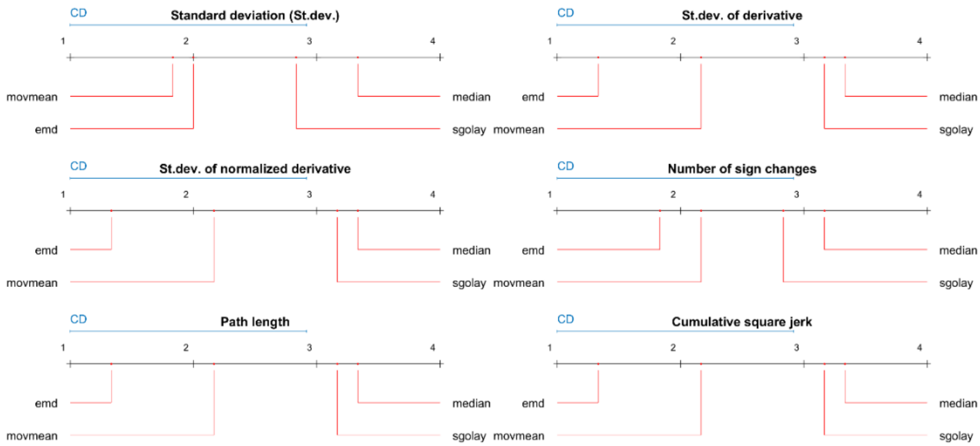


Figure 4.17 Results of Nemenyi test comparing EMD-based smoothing method with moving mean, Savitzky-Golay and median filters when preprocessing the game performance time series

Table 4.5. Comparison results of smoothing methods

		Method			
		BoostEMD	Median	Movmean	Sgolay
SD	mean	3.97	4.37	**3.89**	4.11
	med.	3.96	3.93	**3.75**	3.76
SDoD	mean	**0.76**	1.71	1.3	1.56
	med.	**0.85**	1.71	1.25	1.6
SDoND	mean	**0.04**	0.07	0.05	0.06
	med.	**0.04**	0.06	0.04	0.06
NoSC	mean	**0.07**	0.13	0.11	0.13
	med.	**0.08**	0.12	0.1	0.11
PL	mean	**34.44**	147.75	94.41	118.57
	med.	**33.76**	132.25	70.35	116.5
CSJ	mean	**34.44**	147.75	94.41	118.57
	med.	**33.76**	132.25	70.35	116.5

4.2.2.3 Results of model fitting

The game performance data was fitted to damped oscillation wave model (Eq. 4.6). The model parameters were estimated for each subject using Levenberg–Marquardt algorithm (LMA). Computations were performed using Matlab 2013a (version 8.1, Mathworks). The results of model fitting for all subjects are given in Table 1. The overall reliability of model fitting using the odd-even test was 0.82±0.08 (mean ± std. dev.). Interestingly, we noted r = 0.82 correlation between amplitude and damping factor (Pearson correlation coefficient was calculated for certain model parameters presented in Table 4.6), which could be described as strong positive relation based on the guidelines for interpreting the Pearson correlation coefficient [Ratner, 2009]. That means that good starters usually have faster fatigue rates, whereas slow starters have less fatigue and even improve their game performance during playing. The model parameters can be used to categorize players according to their playing behavior into learners (with negative damping factor) and fatiguers (with positive damping factor).

Table 4.6. Model parameters of each subjects according to damped oscillation wave model

Subject No.	Coefficients of the model				Odd-even reliability
	Amplitude	Damping factor	Angular frequency	Phase	
1	7.6393	0.0317	-0.5407	-2.0307	0.8945
2	4.7579	0.0348	0.2657	0.5575	0.8046
3	15.1602	0.0667	0.3611	-2.9749	0.7480
4	4.1099	0.0114	-0.7830	0.8002	0.9819
5	1.5840	-0.0862	-0.2036	-1.1776	0.7852
6	0.5918	-0.0933	-0.4659	1.7690	0.8982
7	6.2494	-0.0060	0.5168	0.8993	0.7780

8	0.3761	-0.1147	0.3136	2.3527	0.7217
9	7.1254	-0.0062	-0.1551	-2.8604	0.7979
10	1.9880	-0.0483	-0.3842	-0.8683	0.8071
11	8.4314	0.0404	0.8598	-1.1648	0.9275
12	1.6275	-0.0571	0.2378	2.0307	0.8512

Fig. 4.18 represents the changes in game performance using phase space plots. They show how the abilities to play are influenced by two processes: (1) learning, which improves abilities and is represented by outward spiral in the phase space plot, and (2) fatigue, which decreases abilities and is represented by inward spiral. The shape of the curve also indicates the stability or instability of user performance. The denser the curve is, the more stable user control is and vice versa. Each subject has his/her own characteristic abilities, which prevent from generalization of results.

A trend of variation in performance can be determined by the direction of the spiral, therefore users can be classified into learners and fatiguers. If the phase diagram spirals inwards, it means that the performance variation tends to weaken, such users are considered as fatiguers. If the phase diagram spirals outwards, it indicates the upward trend of the performance variation, such users are learners. The example of those performances types is presented in Fig. 4.19

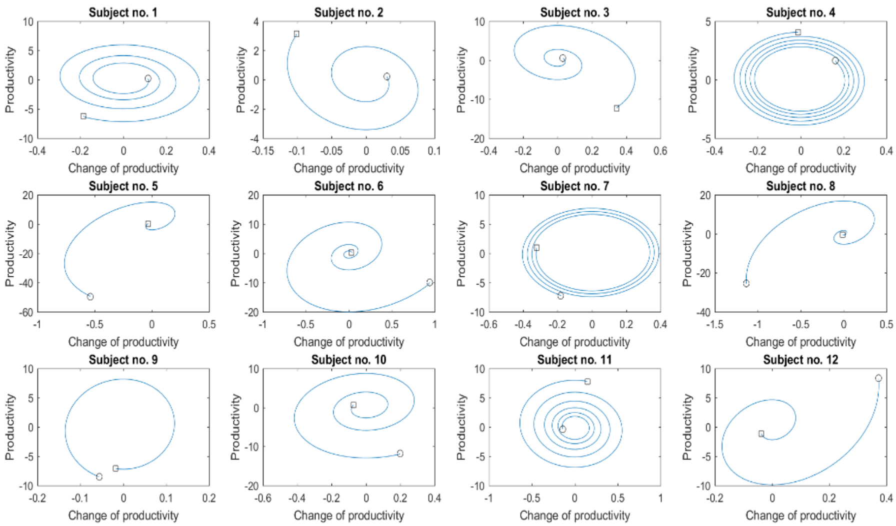


Figure 4.18. Phase space plots game performance characteristic fitted to damped oscillation model (☐ - begin of game, ○ - end of game).

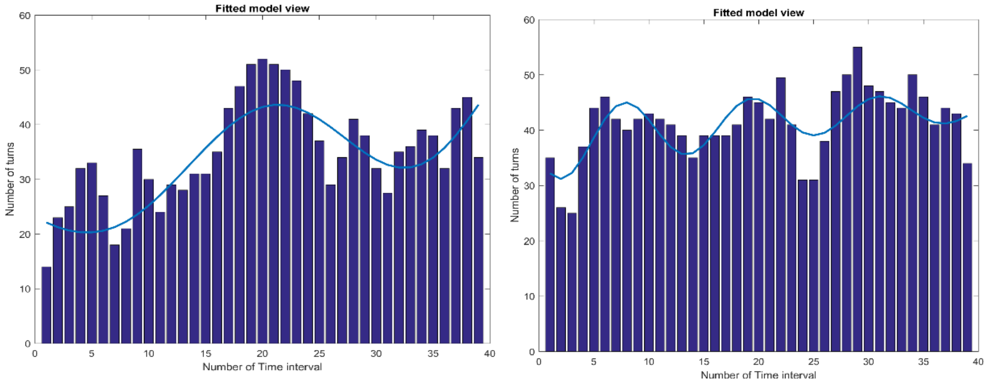


Figure 4.19. Different types of players in terms of performance: left – increased learning with negative damping factor (subject no.12), right – increased fatigue with positive damping factor (subject no. 1)

4.2.2.4 Results of saccadic velocity and directional distribution

The results of changes in saccade velocity and spatial distribution (see an example in Fig. 4.20) show that saccade velocity decreases in time while spatial distribution of gazes becomes blurred and less focused on the main control axes (i.e., horizontal, W-E, and vertical, N-S) of the game indicating both the loss of ability to follow the game and the loss of accuracy in control.

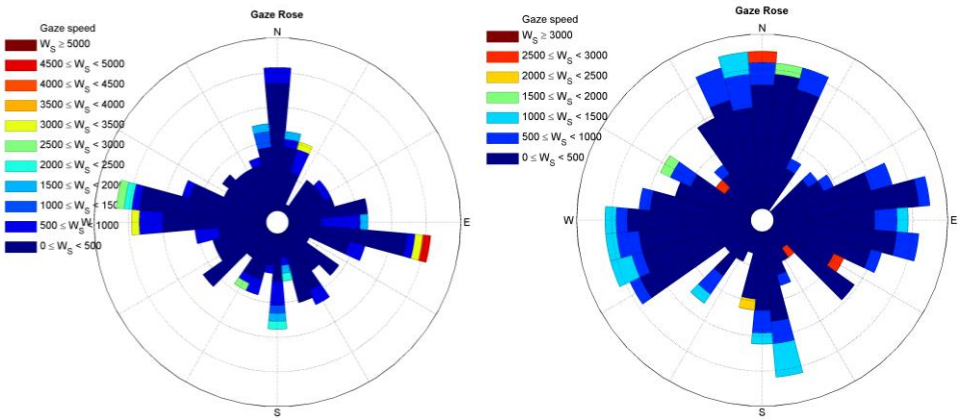


Figure 4.20 Changes in saccade velocity and distribution during the game (Subject 5): first half (left) and second half (right)

To validate the claim, we have calculated the comparison operator

$$C(\Delta t) = \sum_{\Delta t} \left[v(t + \Delta t) < v(t) \right], \tag{4.14}$$

here $[\cdot]$ is the Iverson bracket operator, v is saccade velocity, Δt is time difference.

Then we performed the linear regression of C with respect to Δt as $C = b_0 + b_1 \Delta t$ for all subjects. The negative trend (i.e., decrease of saccade velocity) was confirmed for all subjects with $b_1 = -0.53 \pm 0.09$ and mean linear regression model correlation of 0.98. The values of Pearson correlation for each subject are presented in Fig. 4.21.

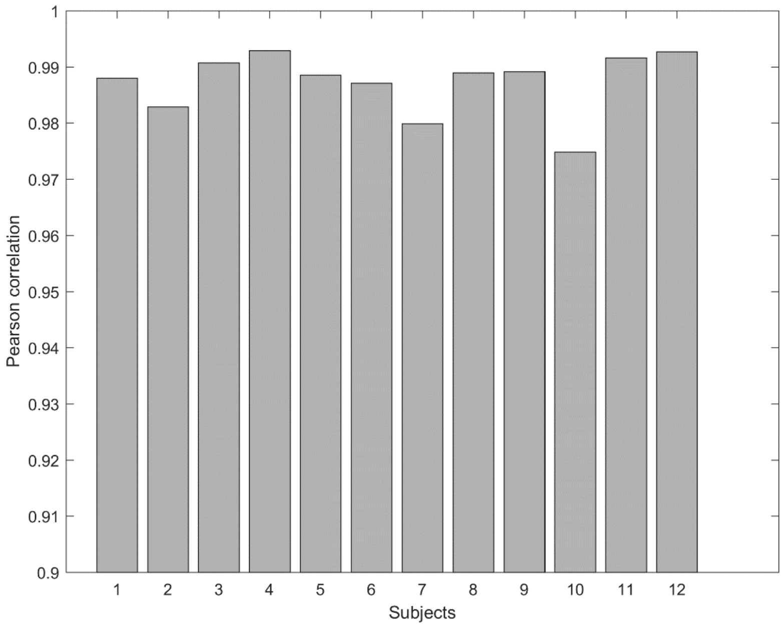


Figure 4.21 Pearson correlation values confirming negative trend in saccade velocity

4.2.3 Conclusion of section

A serious game controlled by gaze to support eye exercising was developed. The game logic requires the user to perform conscious and precise eye movements in the horizontal and vertical directions to achieve in-game aims while at the same time training the ocular muscles. Game sessions data was collected from subjects to analyze changes in temporal and spatial gaze characteristics and game performance.

Our results show that the damped oscillation model can be used to analyze the interaction of learning and fatigue effects during the game. Individual characteristics of subjects established via the damped oscillation model could be used for categorization of players according to their playing skills and abilities as well as for implementing personalized eye exercising programmes, while switching the game control to keyboard when the onset of fatigue is detected to avoid further strain on eyes. The players can be categorized to learners and fatiguers based on damping factor. Learners tend to increase their performance abilities as the dumping factor of the model is negative. Fatiguers lose their performing abilities as the dumping factor of the model is positive. Moreover, a strong r = 0.82 positive correlation between amplitude and damping factor is observed, which indicates, that good starters usually have faster fatigue rates, whereas slow starters have less fatigue and even improve their game performance during playing. However, the temporal and directional analysis of saccade velocity indicates, that in the long term saccade velocity and gaze movement accuracy tend to reduce during the game due to eye fatigue. The regression of comparison operator C, which describes the change in saccade velocity, indicated negative trend with mean linear regression model correlation of 0.98 for each test subject.

4.3 Research of adaptive EMG-based speller

Research described in this section was originally presented in [Damaševičius et al., 2015, Vasiljevas et al., 2014a, Vasiljevas et al., 2014b].

4.3.1 Methodology

4.3.1.1 Adaptation of Human-assistive single channel model for EMG-based speller design

EMG-based speller system design is based on proposed Human – assistive single channel model (HASCM) (see section 3.2). This model includes 4 main components: (i) Interaction layer, (ii) intelligent layer, (iii) fatigue evaluation procedure and (iv) control layer. Input channel and recover activity are distinguished in the interaction layer. Input channel determines the input modality used for system control. Recover activity represents the system reaction to fatigue state of the user.

A more detailed human-assistive single channel model representing the concept of the EMG-based speller is shown in Fig 4.22. The components of this model in detail are as follows:

1. **Interaction layer**. The interaction layer of the EMG-based speller describes input channel, which in this case, is established as EMG signal and recover activity, which in this context, affects the user by setting convenient dwell time of the speller. Some low-level pre-processing of the EMG signal is done in this layer as well (e.g. sampling of EMG signal to data stream). In general, interaction layer, establishes connection between the user and the system and provides feedback in the context of fatigue.

2. **Intelligent layer**. On this layer, data is aggregated and events corresponding to specific patterns of data are generated. This layer also serves as a mediator between all other layers. Intelligent layer is responsible for: (i) EMG signal transformation to control commands, (ii) transformation of EMG signal and speller performance metrics to a suitable form for fatigue evaluation procedure, (iii) adjustment of the system, so that user could control the system as long as posable without fatigue effect.

4. **Pre-set performance model**. The pre-set fatigue model cannot be changed during system control tasks and is set before user starts using the system. The model itself, is based on threshold function (more information on this matter in the next section).

5. **Speller**. Speller represent the application of human-assistive single channel model. The detail description of EMG-based speller interface is provided in sections 4.3.1.5 and 4.3.1.6.

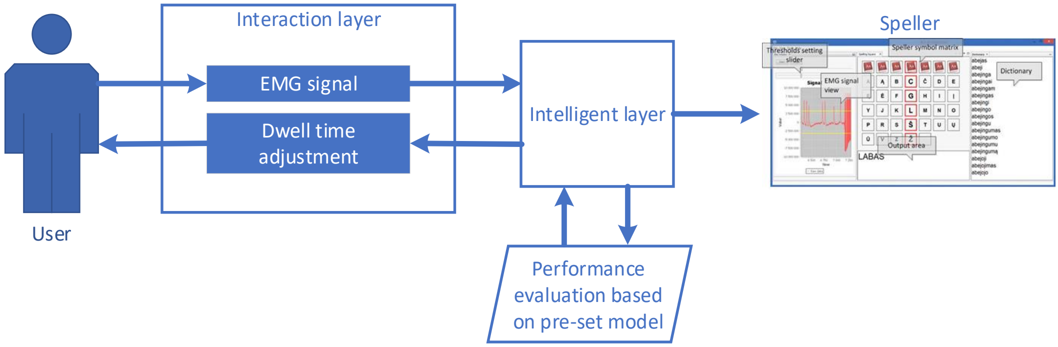


Figure 4.22. Framework of the system based on HASCM

4.3.1.2 Pre-set performance model of EMG-based speller

The pre-set fatigue model is based on dwell time adaptation. Dwell time is adjusted to each user regarding to typing errors and successful letter selections. The model is described as follows:

$$t_{dwell\ time} = \begin{cases} t_0 + n_e t_e - n_s t_s, t_{dwell\ time} > 0 \\ 0, t_{dwell\ time} \leq 0 \end{cases} \tag{4.15}$$

here $t_{dvell\ time}$ – current dwell time, t_0 – initial dwell time, t_e – error dwell time or time value to be added, when error occurs, t_s – selection dwell time, or the time to be subtracted, when successful letter selection occurs, n_e – number of errors and n_s – number of selections. The typing error is considered when a symbol or a word is deleted. The selection is event after the letter is typed.

Error dwell time always has bigger value than selection dwell time, $t_e > t_s$. It means that typing error has larger impact to current dwell time. This restriction helps to balance the dwell time dynamics and avoid the permanence of dwell time, which is undesirable in terms of training effects.

4.3.1.3 Components and architecture of speller

A NCI system generally comprises the following components: (i) a device that records the muscular activity signals; (ii) a signal preprocessor that reduces noise and artifacts; (iii) a decoder that classifies the de-noised signal into a control commands for (iv) an external device or application (e.g., a robotic actuator, a computer program etc.), which provides feedback to the user [Mora-Cortes et al., 2014].

Our speller application has three layers as follows: 1) on the lowest layer, the physiological signal is sampled into a data stream of physiological data. Downsampling can be used to decrease amount of data and increase information processing speed at higher levels. 2) On the intermediate layer, data is aggregated and events corresponding to specific patterns of data are generated. Machine learning techniques such as artificial neural networks may be used to recognize such events and generate decisions. 3) On the highest layer, decisions are processed and used to generate control commands for external applications (systems).

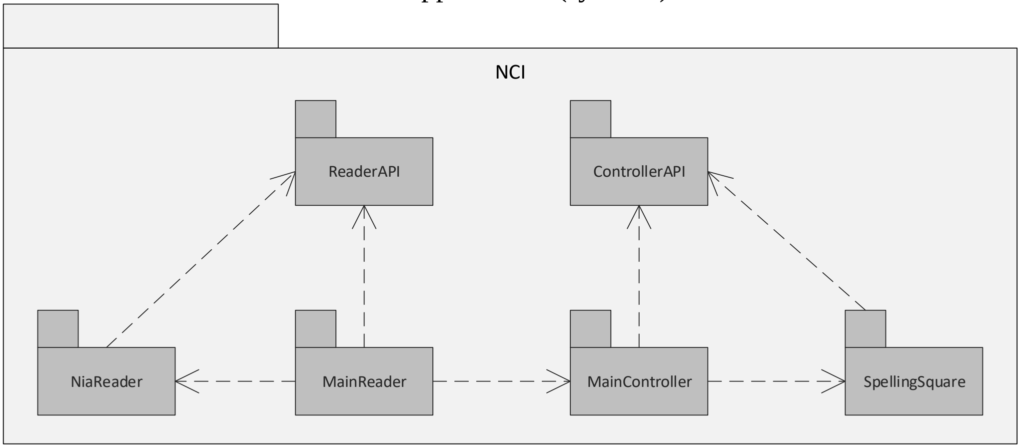


Figure 4.23. Architecture of developed speller application

Architecture of the developed speller application is shown in Fig. 4.23. The speller consists of 6 main components:

- *MainReader* – system module responsible for control of data reader which is selected to use.
- *ReaderAPI* – public external interface module. All third-party modules must implement this component for full system integration.
- *MainController* – system module responsible for the selected control module (executes commands).
- *NiaReader* – third-party module implemented for the “OCZ NIA” data reader device.
- *SpellingSquare* – third-party module implemented for text input in the symbol matrix using EMG-based commands.

The dashed rectangle separates system components (inside the dashed rectangle) from external components, which are either the sensor controllers (EMG readers) or actuator controllers (software or hardware applications such as robots). The speller system is based on *Java NetBeans* framework. The speller was developed with considering its future extension and maintenance so that external components are easy to add or remove.

4.3.1.4 Control

There are two types of control commands of the speller: “Select” command – selects a column or types a symbol of that column. “Cancel” command – exits the selected column or deletes the selected symbol. Those control commands can be initiated by the movements of facial muscles. In practice, eye blinks are used to generate each control command (left eye blink for “select” and right eye blink for “cancel”). The user can see the EMG signal feedback in EMG signal view area (see Fig. 4.24). The particular control command is performed when the amplitude of the

EMG signal is higher than the specified threshold value. The thresholds are marked as yellow horizontal lines in the EMG signal view area. The upper threshold indicates the “select” command, and the lower threshold indicates the “cancel” command. Threshold values can be adjusted using threshold setting sliders.

The signal view of EMG, while spelling the word “hello”, is presented in Figure 4.24. In Figure 4.24 (top), the word “hello” is spelled without mistakes. In Figure 4.24 (bottom), the spelling contains has a few mistakes. For correction of those mistakes cancellation commands must be performed. The spikes indicate the “select” command. One trial (selection of one character) contains two positive signal spikes, the first spike is for column selection, the second for letter selection in the corresponding column.

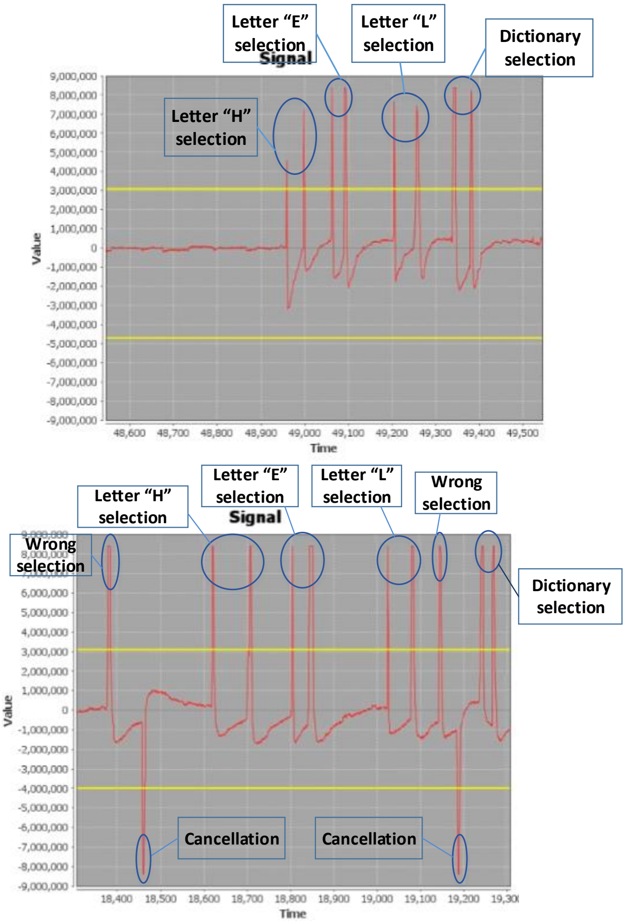


Figure 4.24. Signal view of spelling word “hello”. Top: no spelling mistakes were made and only three characters (“hel”) were selected from the symbol matrix. Bottom: two spelling mistakes were made, therefore after each wrong selection cancellation command was performed. In both cases, dictionary selection was made to complete the word.

4.3.1.5 Traditional speller interface

The developed EMG speller has two different user interfaces. One is a traditional matrix-based speller interface presented in Fig. 4.25. Another one is a novel concept-based interface presented in Fig. 4.26. The most important part of the visual interface is a symbol matrix. The matrix is adaptable so that various symbols (including special or national) could be added into the matrix. The red-colored column indicates the current position of the speller cursor. The cursor moves coherently from column to column until the user activates the “select” command. Next, the cursor moves through each symbol in a particular column. After another “select” command, the particular symbol is selected. That symbol appears in the output area (see Fig. 4.25). The speller cursor moves by the step which varies from 500 to 1500 milliseconds. The step value depends on the number of mistakes the user is making. A smaller number of mistakes means the faster speed of cursor movement. The mistake is considered as the “cancel” command.

The first row of the speller symbol matrix contains a dictionary selection. This selection allows to enter the dictionary. When a few symbols or a stem of the word is written, the dictionary gives an opportunity to complete the particular word faster. The system logs dictionary selections, therefore, common used words are on top of the dictionary, thus, the dictionary adapts to the user.

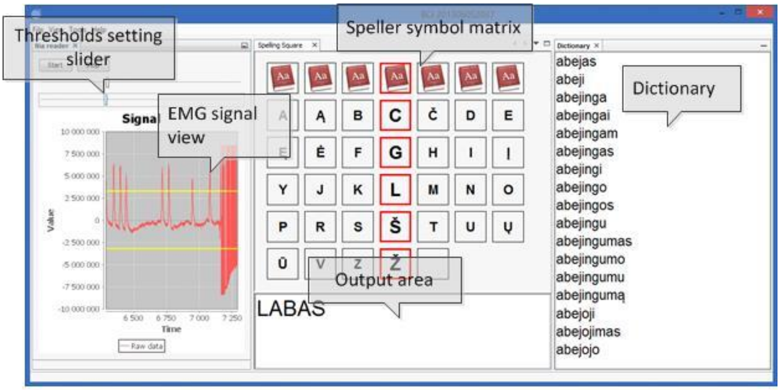


Figure 4.25. Traditional interface of the developed EMG speller

4.3.1.6 Visual concept-based speller interface

We have also implemented a completely different interface of the EMG speller. Traditional spellers use common letters of an alphabet rearranged in different layouts. We have implemented a visual concept-based interface that is based on graphical symbols (graphemes). Graphical symbols enable an alternative form of communication that uses visual elements as opposed to a formal written (textual) language to convey meaning or an idea. Pictograms or ideograms are used to signify the concepts that are communicated. Pictograms are pictures that resemble what they signify, and represent a concept, object, activity, place or event by graphical illustration. An ideogram is a graphical symbol that represents an idea, rather than a group of letters arranged according to the phonemes and grammar of a spoken language, as is done in textual languages.

Visual symbols form a part of our daily lives through their use in medication, transport, computers, etc., because they indicate, in a concise and easily understandable form, places, directions, actions or constraints on actions in either the real world or virtual space. Thus, visual symbols can be used in a number of situations in which textual messages are not possible or adequate due to context or user-based constraints.

While textual (letter-based) languages are good for expressing all kinds of human communication, they require many typing efforts for human-computer communication, which for specific groups of users such as users with impaired motor capabilities, may be a tiresome burden. A visual concept-based interface allows to express high-level concepts succinctly using a notation tailored to a set of specific user problems. Such interface could be tailored towards a specific domain and could be based only on the relevant concepts and features of that domain.

A snapshot of the developed visual concept-based interface of the EMG speller is given in Fig. 4.26. The visual concept-based interface is organized using a hierarchical structure. It consists of symbol matrixes connected with each other by references. Each reference is represented as an icon of a particular domain. Currently, we have included visual symbols from 8 main concept domains: emotion domain, location domain, action domain, time domain, object domain, body part domain, person domain and special symbol domain.

Most of the visual icons we use are adopted from The Noun Project (http://thenounproject.com/), while the remaining ones are custom-built.

Each domain matrix as well as the root matrix can be extended easily by adding new icons (concepts) to the particular domain matrixes. Furthermore, each icon (concept) in particular domain could contain a reference to the specific subdomain matrix. The taxonomical tree of concept matrixes is summarized in Fig. 4.27.

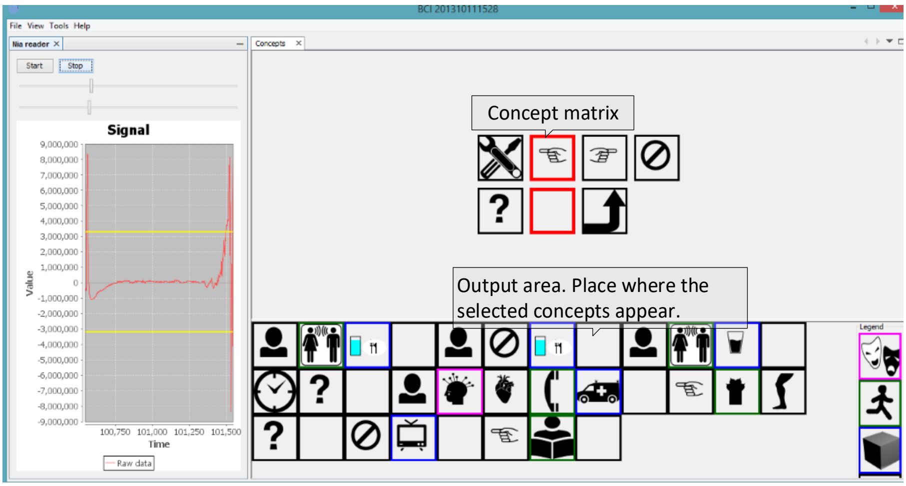


Figure 4.26. Visual concept-based interface of developed EMG speller

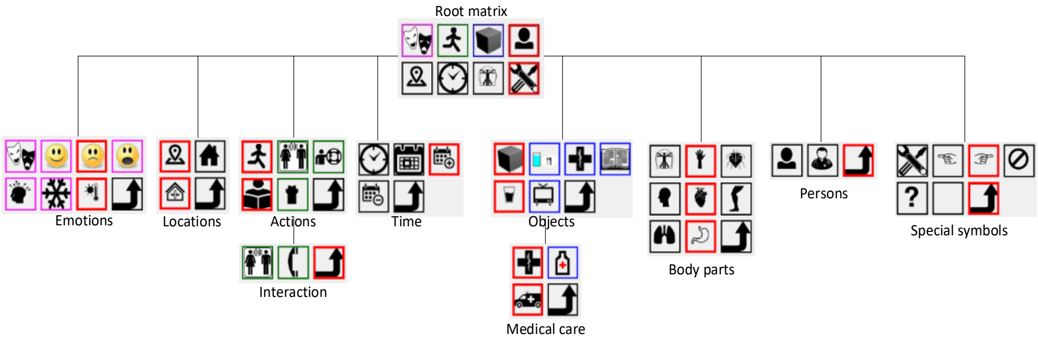


Figure 4.27. The tree of concept matrixes

The meaning of visual concepts is presented in Table 4.7.

Table 4.7. Taxonomy and meaning of visual symbols in speller interface.

	Return sign brings back cursor to the root matrix.	
	Emotions/feelings:	
		Happy
		Sad
		Amazed
		Pain
		Cold
		Hot/warm
	Location (current location):	
		Hospital
		Home/house
	Actions:	
		To read a book
		To ineract:
		To call
		To scratch
		To help
	Time:	
		Past
		Today
		Future

Objects:		
	Drink	
	Meal	
	TV	
	Medical care:	
		Ambulance
		Medicine
	Book	
Body parts:		
	Head	
	Hand	
	Heart	
	Stomach	
	Back	
	Leg	
Person (Me):		
	Medic/doctor	
Special simbols:		
	Question sign	
	Left pointer to object or subject	
	Right pointer to object or subject	
	“Not” sign	

4.3.2 Experiments and Results

4.3.2.1 Experiment with text-based interface

We performed the experiments with 5 subjects (3 males), aged 24–54 (mean = 33) year. Subjects did not have any neurological abnormalities, reported normal or corrected to normal vision, and did not use medication. All subjects gave informed consent prior to the experiment. The EMG data was recorded using OCZ Neuro Impulse Actuator equipment. Visual stimuli were presented on a 13.3" size TFT LCD screen with 1360 × 768 pixel resolution and a refresh rate of 60 Hz. Subjects were seated in front of a table. The screen was in the middle of the table at a distance of approximately 100 cm from the subject. The size of each character was 1.5 × 1.5 cm (0.86 × 0.86° visual angle) and the entire speller matrix was 9.5 × 13 cm (5.44 × 7.42° visual angle). Stimuli consisted of intensifications of the rows and columns in sequential order. Intensification was achieved by increasing the size of all characters in the row or column with a factor 500 for 1500 ms.

A trial is defined here as spelling of one character. All trials started with the speller being displayed on the screen, together with an instruction indicating which letter to select. Each stimulation sequence was followed by feedback on the screen, showing which letter or group of letters had been selected.

Three text paragraphs were given to the experiment participants. Their task was to input the proposed text paragraphs using speller. All text paragraphs were presented in Lithuanian language. The first text paragraph contained 126 characters and its content covered a daily conversation. The second text paragraph contained 111 characters and its content covered a scientific speech. The third text paragraph contained 120 characters and covered a scientific speech with mathematical equations. Each experiment participant repeated the experiment 4 times. The average accuracy, input speed and bit rate values were calculated.

Quantitatively, the performance of speller application can be evaluated using accuracy, information transfer speed and input speed metrics. Accuracy is calculated as the percentage of correct decisions. Bit rate (or information transfer rate) indicates how much information can be communicated per time unit (calculated using Wolpaw's formula [Wolpaw et al., 2000]). Finally, input speed is measured as the average time required to enter a set of benchmark texts. The experimental results are presented in Table 4.6 and Figures 4.28-30.

Accuracy values of the BCI/NCI spellers achieved by other authors (Table 4.6) are within 80-95% range (82.77% using ECoG [Speier et al., 2013], 87.58% using SSVEP-based BCI [Furdea et al., 2009], 87.8% for EOG-based speller [Liu et al., 2011], 91.80% [Acqualagna and Blankertz, 2013], 94.8% for RVSP based speller [Wolpaw et al., 2000]). Bit rate values achieved by other authors are within 19-41 bits/min (19.18 bits/min [Acqualagna and Blankertz, 2013], 40.72 using SSVEP based BCI [Furdea et al., 2009], 41.02 using ECoG data [Speier et al., 2013]). Input speed values achieved by other authors are within 1-9 sym/min (1.38 sym/min for EOG-based speller [Liu et al., 2011], 1.43 sym/min for RVSP-based speller [Wolpaw et al., 2000], 4.33 sym/min [Acqualagna and Blankertz, 2013], 9.39 sym/min for SSVEP-based BCI [Furdea et al., 2009]).

The information transfer rate (aka bit rate) of the BCI/NCI-based speller applications achieved by other authors are within 7-41 bits/min (7.43 bits/min [Käthner et al., 2013], 17.13 bits/min [Shahriari and Erfanian, 2013], 19.18 bits/min [Pires et al., 2012], 11.58-37.57 bits/min [Vilic et al., 2013], 40.72 using SSVEP based BCI [Hwang et al., 2012], 41.02 using ECoG [Speier et al., 2013]).

The symbol input speed of the BCI/NCI-based speller applications achieved by other authors are within 1-12 CPM (1.38 CPM for EOG-based speller [Liu et al., 2010], 1.43 CPM for RSVP based speller [Acqualagna and Blankertz, 2013], 4.33 CPM [Pires et al., 2012], 4.91 CPM [Vilic et al., 2013], 9.39 CPM using SSVEP based BCI [Hwang et al., 2012], 10.16 CPM [Cheng et al., 2013], 12.75 CPM [Wang et al., 2012]).

Table 4.8. Evaluation of speller application

Quantitative metric	**Average Value**	**Peak value**
BASIC SETTINGS		
Accuracy	96.29	98.25
Information transfer rate	34.78	41.83
Input speed	6.37	7.57

ADAPTABLE STIMULUS RATE		
Accuracy	88.61	93.64
Information transfer rate	42.53	49.79
Input speed	8.19	9.60
WITH DICTIONARY		
Accuracy	92.65	96.06
Information transfer rate	43.55	49.26
Input speed	8.22	9.35
WITH ADAPTABLE STIMULUS RATE AND DICTIONARY		
Accuracy	89.16	92.53
Information transfer rate	58.69	65.53
Input speed	11.35	12.42

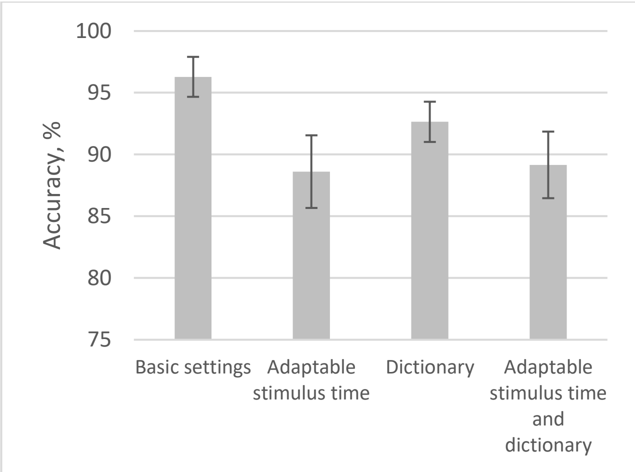


Figure 4.28. Accuracy of character input

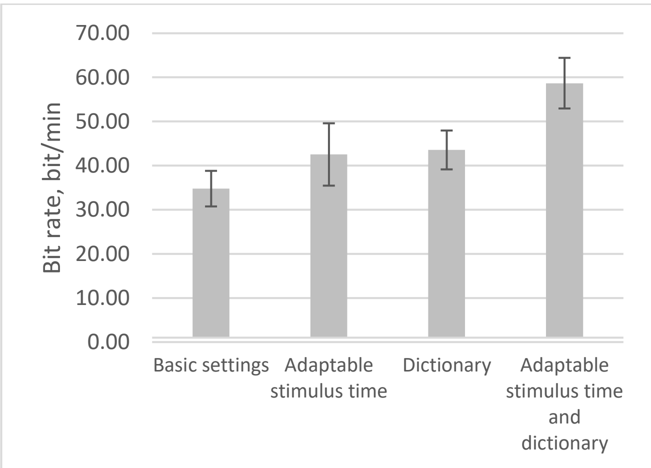


Figure 4.29. Information transfer rate

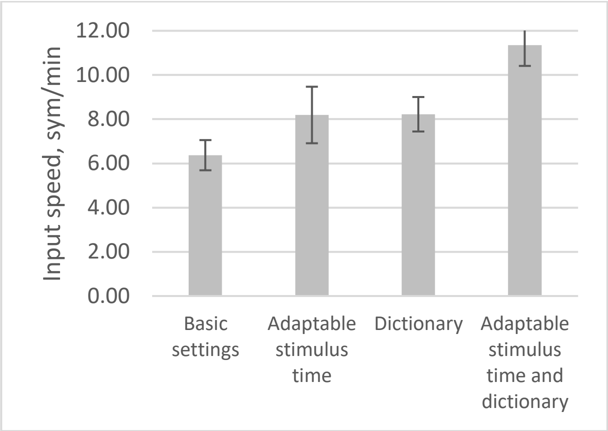


Figure 4.30. Input speed

4.3.2.2 Experiment with the visual concept-based interface

The experiment with the visual concept-based interface was performed under the same conditions as the experiment with text-based interface. The participants had to enter one paragraph of text (196 symbols) which represented daily conversation topics. This paragraph contained simple formulations of basic needs of a user (see an example of message in Figure 4.31). The experiment was performed with 2 subjects (both male, aged 24-28 years). The duration of experiment task was measured, and the input speed is presented in Figure 4.32.

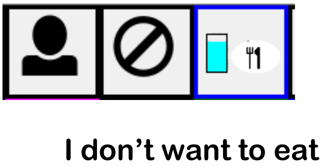


Figure 4.31. Example of a message entered using visual language

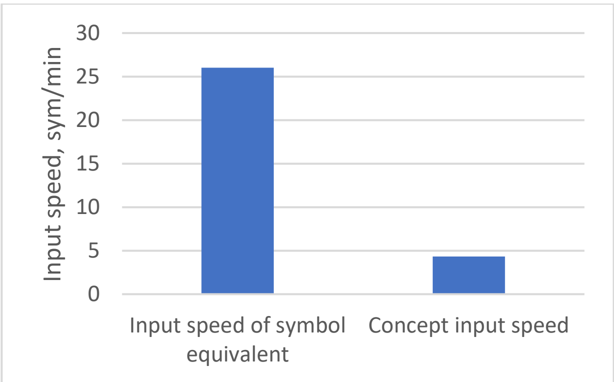


Figure 4.32 Input speed of a concept-based speller

Two metrics of input speed are presented in Figure 4.29: concept input speed (number of valid concepts entered in a time unit) and input speed of letters in a textual language, which would be required to enter in a time unit in order to convey the same message. The results show that using the visual concept-based interface can increase input speed to 26.03 sym/min (equivalent to 4.31 concepts/min) as compared to 11.35 sym/min (see Table 4.8) using the traditional text-based interface of the EMG speller.

4.3.3 Conclusion of the section

Development of the EMG-based speller application based on the HASCM was described. The pre-set training and fatigue model used in HASCM was based on dwell time adaptation. Adaptable stimulus time feature-based on this fatigue model was installed in the system. This system feature together with dictionary increased bit rate of the system from 34.78 to 58.69 bit/min. The input speed of the system increased from 6.37 to 11.35 sym/min. This system is controlled by voluntary muscular movements, particularly the orbicular ones (i.e., eye blinking), which are translated into text input commands.

The developed speller application is adaptive (input speed can be adapted dynamically in response to the user's state) and intelligent (by using word complete and word frequency features). The combination of speller settings of adaptable stimulus rate and dictionary showed the best results in terms of information transfer rate (mean value: 58.69 bit/min, peak value: 65.53 bit/min) and input speed (mean value: 11.35 CPM, peak value: 12.42 CPM). The same speller settings are related with decrease of accuracy, which indicate that adaptable stimulus rate and dictionary enable user to type faster and transfer more information, but also increase number of typing mistakes. Ability to control system faster, also helps user to correct his mistakes faster, so the overall input speed increases.

Two types of interfaces: traditional letter matrix-based interface and visual concept-based interface have been developed and evaluated. The visual concept-based interface has been evaluated using concept input speed and compared with the equivalent text input speed. The results show improvement of input speed by a factor of 2.3 as compared to the best results achieved using a letter matrix-based interface with a dictionary and adaptable input speed, which could be explained by conciseness of the visual language (both in terms of the size of dictionary and the length of visual „words") as well as by reduced user effort required to communicate a message. The main limitations of concept-based interface are the lack of expression scale and ambiguous expressions.

4.4 Recommendations for user interface developers

General recommendations for the HCI designers when developing human-assistive interfaces are formulated as follows:

1. Analyze requirements for user performance introduced by the specific domain of application and the developed system.
2. Analyze the communication modalities used by the system and any user-related effects on performance such as introduced by fatigue.

3. Adopt the Banister or DHO model presented in this dissertation for the developed HCI of the system. The choice of the analytical performance models is not limited to the models presented in this dissertation.
4. Implement biocybernetic feedback loop to allow the adaptability of the HCI characteristics depending upon human performance when working with the system in real time.
5. Evaluate usability of the developed interface and test with users in real-world application environment.

4.5 Conclusion of chapter

The chapter has examined if human-assistive HCI model might be applied in the PCS domain. 3 studies have been carried out on different systems: (i) spelling system based on gaze tracking, (ii) PC game based on gaze tracking, (iii) spelling system based on EMG. In the first and the third system a single channel variant of human-assistive HCI model have been successfully applied. In the PC game based on gaze tracking a multimodal variant of human-assistive HCI model have been applied. Human-assistive HCI model revealed its ability to deal with different applications (PC game and spelling system) and different input modes (EMG and gaze tracking). However, the presented experiments cover only a small part of possible applications and input modes, therefore, there is a need to test the proposed model on a wider variety of applications and input modes.

For modelling eye performance in the spelling system based on gaze tracking, Banister et al. model has been used. The accuracy metric based on a gaze landing position has been taken for fatigue evaluation. The gaze typing experiment has been carried out with 7 volunteers. The results of this experiment reveal that Banister et al. model fits to evaluate user performance in the gaze spelling task. PCA analysis of the data collected during experiment suggests that fatigue effects in this case appears faster than training effects and have major impact on performance. However, the experiment has been executed in a relatively short period of time, thus, one can assume that training effects could have higher impact in the long-term.

The fatigue effects in the PC game based on eye tracking have been measured for a longer period compared to previous research. For this purpose, the DHO model of training and fatigue has been applied. The main reason for choosing this model is the wavy nature of data collected during the PC game experiment. DHO model is suitable for describing the data which reflect both long-term fatigue and training effects and short-term recovery of performance. DHO model validity is determined with sufficient even-odd reliability (r=0.82). However, DHO model has shown high variability in terms of deferent user control.

Banister et al. training – fatigue model fits well the empirical data gathered during gaze spelling task. However, it failed to fit the data obtained from PC game based on eye tracking. Therefore, in this application DHO model was employed, since it showed significantly batter result. The experiments with gaze spelling system and PC game based on gaze tracking differed in terms of duration. This implies that

Banister et al. model is possibly suitable for describing the performance in the short term, as the DHO model deals well the performance in the long term. Some research suggests that user begin to sense the fatigue after 13 minutes of using gaze tracking system [Suzuki et al., 2015]. However, to prove this assumption on aforementioned performance models additional experiments are required.

We also noticed large variability of user-parameters suggesting the need for personalization in physiological computing-based HCI. Training and fatigue models like Banister or DHO cannot be generalized for all population. On the contrary, they can be applied for specification of individual users and even can serve as performance classification tool, as it is shown in section 4.2.2.3, where users are classified into learners and fatiguers.

5 GENERAL CONCLUSION

1. Mental and physical fatigue is the major factor of performing abilities decrease in physiological computing systems (PCS). Despite the significance of the fatigue factor, previous research in PCS domain are conducted only in a fragmented manner and lack a complex approach to the fatigue problem. On the other hand, fatigue research in sports training domain is of high interest and far advanced. Since the nature of fatigue in both sports training and PCS is similar, the approaches of the fatigue estimation and prediction known in sports domain could be adopted in PCS.
2. The proposed Human-assistive HCI model describes the interaction between a human and PCS from the user performance perspective. Two variants of the model are proposed: Human-assistive single-channel HCI model (HASCM) and Human-assistive multimodal HCI model (HAMM). The main novelty is the performance evaluation procedure, which interacts with the standard UI components of the PCS and describes how the system should react to loss of productivity (performance). The applicability of the Human-assistive HCI models has been demonstrated by the design of 3 different applications: (1) gaze spelling system (see section 4.1.1.2), (2) eye-controlled game (see section 4.2.1.2) and (3) EMG-based speller (see section 4.3.1.1).
3. Analytical user performance model developed by Banister et al. is applicable for evaluation of training and fatigue effects in using the gaze tracking-based spelling system (see section 4.1). To validate the model, the accuracy of gaze landing in performing text entry task has been analyzed for 7 subjects. The analysis results have been fitted to Banister et al. model. The most accurate model reached good fitness results ($R2=0.9027$, $RMSE = 0.0098$, $SSE=0.0005$), however, the variability between user performance is significant and is larger than intra-user variability due to learning and fatigue effects. PCA analysis shows that intra-user variability can be explained by two factors: fatigue (73% of variance) and learning (17% of variance). Since the learning acts slower than fatigue and has less effect on the results, time-to-peak value is smaller than time-to-initial performance. Therefore, it is advised to use time-to-initial performance as an estimate of rest time.
4. An analytical user performance model based on damped harmonic oscillation (DHO) is suitable to describe variability in performance of a PC game based on gaze tracking (see section 4.2). The validity of the DHO model fitting has been tested using odd-even analysis, which has shown strong positive correlation (0.82 ± 0.08). Individual characteristics of subjects established via the damped oscillation model could be used for categorization of players under their playing skills and abilities. As initial experiment results show players can be categorized as learners, whose damping factor is negative, and fatiguers, whose damping factor is positive. A strong $r = 0.82$ positive correlation between amplitude and damping factor is observed, which indicates that good starters usually have faster fatigue rates, whereas slow starters have less fatigue and even improve their game performance during

the play. A temporal and directional analysis of saccade velocity indicates that in the long-term saccade velocity and gaze movement accuracy tend to reduce during the game due to eye fatigue, since linear regression models demonstrate negative trends for each subject with mean correlation of 0.98.

5. The extension of the EMD method called BoostEMD has been used to pre-process data of the PC game based on gaze tracking (see section 4.2.2.2). BoostEMD method helps to smooth the signal and reduce the impact of outliers, which complicate model fitting procedure. This method has been compared with other popular smoothing methods (moving mean, median and Savitzky-Golay filters) using time series smoothness characteristics. Nemenyi test has been performed to rank the smoothing results. 5 out of 6 tests rank BoostEMD as the best one. BoostEMD more than twice outperforms nearest competitors in terms of path length and cumulative square jerk (see Table 4.5), which are important smoothness indicators.
6. The developed EMG-based speller adapts HASCM model (see section 4.3). The pre-set performance evaluation procedure based on dwell time adaptation together with a dictionary has been introduced. Those system features have increased bit rate (from 34.78 to 58.69 bit/min) and input speed (from 6.37 to 11.35 CPM), at the same time dropping the accuracy (from 96.29 % to 89.16 %). It indicates that dwell time adaptation and dictionary enable the user to enter the text faster, but also increase the number of mistakes. However, the ability to control the system faster also helps user to correct mistakes faster, since input speed is calculated only for correctly-entered symbols.

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LIST OF PUBLICATIONS OF MINDAUGAS VASILJEVAS ON DISSERTATION TOPICS

The theses authors contribution to each article is as follows:

- Article No. 1 – carried out some of the experiments.

- Article No. 2 – carried out experimental research, description of the experiments, presentation of the results.
- Article No. 3 – development of the EMG-based speller, carried out experimental research, description of the system design and experiments.
- Article No. 8 – development of neural interface, carried out the experiments, description of the conducted experiments.
- Articles No. 4,5,6,7,9,10 – most of the work related with the articles carried out by the thesis author.

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2. Damaševičius, Robertas; **Vasiljevas, Mindaugas;** Martišius, Ignas; Jusas, Vacius; Birvinskas, Darius; Wozniak, Marcin. BoostEMD: an extension of EMD method and its application for denoising of EMG signals // Elektronika ir elektrotechnika = Electronics and electrical engineering. Kaunas : KTU. ISSN 1392-1215. eISSN 2029-5731. 2015, vol. 21, iss. 6, p. 57-61. DOI: 10.5755/j01.eie.21.6.13763.

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4. **Vasiljevas, Mindaugas**; Gedminas, Tadas; Ševčenko, Artūras; Jančiukas, Mindaugas; Blažauskas, Tomas; Damaševičius, Robertas. Modelling eye fatigue in gaze spelling task // 2016 IEEE 12th International Conference on Intelligent Computer Communication and Processing (ICCP): Cluj-Napoca, Romania, September 8-10, 2016: proceedings / edited by Rodica Potolea Radu Razvan Slavescu. New York, NY: IEEE, 2016. ISBN 9781509038992. eISBN 9781509038992. p. 95-102. DOI: 10.1109/ICCP.2016.7737129.
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