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Procedia Computer Science 192 (2021) 1274–1284

Procedia Computer Science

www.elsevier.com/locate/procedia

25th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems

# An adaptable human fatigue evaluation system

Eglė Butkevičiūtė[a,*], Matīss Eriņš[b], Liepa Bikulčienė[a]

[a]*Kaunas University of Technology, K. Donelaičio str. 73, Kaunas 44249, Lithuania*
[b]*Riga Technical University, 1 Kalku str. Riga 1658, Latvia*

**Abstract**

In medicine and diagnostics bio-signals are recorded in a stationary condition that limits the evaluation of dynamic human body changes in daily activities. There are various types of fatigue including physical and mental. In most cases, prolonged fatigue recognition may lead to various chronic health problems or even disability at work and daily life activities. In this research, a generalized human fatigue evaluation system is proposed that may identify different types of fatigue. A presented system architecture consists of several devices including a headband, chest belt, smartphone, and video camera. Depending on what type of fatigue needs to be monitored, devices may be used separately or all at once. Sensor measurements can be initiated by using wireless or wired communication. In the fatigue recognition a multimodal evaluation system is used for processing of several bio-signals (ECG, R-R, EMG, EEG, IMU) and an expert system is used to perform decision making. Every bio-signal may indicate a different type of fatigue. Furthermore, in this research several fatigue recognition methodologies are proposed: heart rate variability parameter analysis for physical fatigue evaluation and spectral dominant and eye-related symptom analysis for mental fatigue identification. The evaluation of mental or physical fatigue that is associated with low performance or loss of attention or productivity may improve road safety or critical operations. It can be used for the prevention of specific diseases or improving human wellbeing.



*Keywords:* health monitoring system, physical fatigue, mental fatigue, physiological measurments, biosensors.

## 1. Introduction

To monitor the health condition in gyms, working places or even at home, various mobile Applications have been created for those who have specific health conditions, are athletes or beginners in sports activities, elderly people,

* *Corresponding author email address: egle.butkeviciute@ktu.lt*

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10.1016/j.procs.2021.08.131

drivers and others [1][2][3]. Health monitoring systems often require additional devices for data transmission, storage, comparison or any other purpose. Electronic remote-control systems become more and more popular because of the improving technologies (such as sensors and devices). Even though their demand is growing rapidly, every device and application needs to meet today's standards and be user friendly for everyone [4][5]. Therefore, the preliminary research on the sensors was done by the authors to determine the sensors for user-friendly placement on the body [6].

In medical diagnostics, biological signals (like electrocardiogram (ECG), electroencephalogram (EEG), electromyogram (EMG)) are recorded in a stationary condition to make sure that the noise appeared during recording and signal transmission processes is minimized. However, the demand for health monitoring in daily life activities, working places or training sessions is rapidly increasing [7]. Recordings in a stationary condition have limitations when it comes to the evaluation of interactions between different human organism systems and dynamic changes in daily activities. If a person is moving or working intensively, multiple systems work in parallel: cardiovascular, muscular, neural and others [8]. Multimodal biological signal recordings and dynamical change analysis are becoming more and more popular because scientists are trying to find out how multiple human parts interact together as a single complex system [9][10]. The importance of that system appears in the physiological fatigue detection process where dynamic changes may reflect a certain type of fatigue. Mostly, physical fatigue is of very high importance for athletes and employees who work intensively. The unnoticed symptoms can cause permanent heart injuries. For this reason, athletes are interested in new technologies that allow monitoring health condition in real-time. Meanwhile, office workers suffer from mental fatigue, which may end up in a chronic disorder and cause long-term consequences. In this case, the fatigue may result in disability at work.

Prolonged fatigue or reduced work capacity for a certain time [11] is the highest concern in this research. Statistically even 20% of the human population is suffering from daily fatigue that reduces the work capacity and the quality of life. Mostly, tiredness is caused by the slower system response, the reduced ability to process new information, memory gaps, reduced insight or coordination issues. It is important to ensure continuous monitoring of fatigue in day-to-day activities for better rehabilitation (recovery) process. This is very important not only for the prevention of health deterioration but also to decrease fatal accidents.

Fatigue may be mental, physical, sensory and affective [12]. However, any type of fatigue may be observed from the body reactions and various system responses. In practice, the following stages of fatigue are known as the compensated phase (if the human offsets the increasing effort) and decompensated phase (when fatigue symptoms increase effort to somatic illness that becomes burn-out syndrome) [13]. Fatigue evaluation is a complex process. Mostly, physiological parameter measurements under laboratory conditions have been used to evaluate fatigue (such as EEG, ECG, eye or jaw muscle movements, leg muscle movements, breathing and respiration rate, oxygen saturation in the blood and others). However, not much research has been interested in multiple daily practices for an individual user with online mode.

Several methods for bio-signal registration and analysis require multiple devices. In this article, the full architecture of different signal recordings is presented for application in physical and mental fatigue recognition and workability evaluation systems. The main purpose of this research is to develop a platform for a complex multi-level fatigue monitoring system as well as a workability evaluation system that is designed to provide an integrated service in the professional safety and health area. Furthermore, real-time decision-making algorithms in everyday use are implemented across multiple application areas, such as rehabilitation, sports and workplaces. Some aspects of fatigue could be directly related to various diseases. Other factors may be sleep disturbance, medication side effects, stressful life events and anxiety [14]. The psychosocial impact of fatigue is considerable because it may prevent participation in everyday activities like work and social pursuits.

## 2. Related works and methodology

### *2.1. Various research about fatigue*

Methods for fatigue detection and evaluation may be divided into subjective and objective (such as blinking, head movement, mouth movement, etc.) and physiological characteristics detection (such as EEG, eye power, EMG, etc.) Subjective testing includes evaluative and physiological response detection. The awakening methods are based on physical, chemical, and biological regulations [15][16].

Physical fatigue is a major health and safety-related problem among workers. Many previous studies are based on interviews and/or questionnaires to evaluate physical fatigue for workers in construction. However, these methods are not only time-consuming but also limited by recall bias. To overcome these limitations, many researchers used physiological metrics (HR, HRV, skin temperature, electromyographic activity, and jerk metrics) to measure real-time physical fatigue. These metrics and online fatigue evaluation can be used only with wearable devices and specific algorithms for artefacts extraction [17]. For muscle fatigue evaluation devices should be non-invasive and accurately identify if fatigue occurs in non-constant loads. This could be achieved by applying two electrodes placed on the skin in the muscle region and recording electric impulses [18]. Among the tools proposed to assess the athlete's fatigue, the analysis of heart rate variability (HRV) and spectrum provides an indirect evaluation of the settings of autonomic control of heart activity [19].

Research in physiology and sports science shows that fatigue as a complex psychophysiological phenomenon has a relevant impact on human body performance and motricity system. In [20] research authors state that the machine-learning system is capable of extracting an individual fatigue description from electromyography signal (EMG) and heart rate variability (HRV) measurements. The fatigue monitoring and early warning system may reduce the accident rate and optimize the working environment. It can be based on heart rate, R-R interval, respiration rate and blood pressure analysis [21]. Some authors consider that fatigue may be evaluated by using only spectral components of the EEG signal. This methodology can be used as a part of mental fatigue evaluation. However, it does not reflect the physical fatigue [22]. One of the highest concerns for the driver's fatigue is to avoid accidents on the road. The real-time monitoring system could be applied to monitor eye movement and head motion. It could be designed together with sound, light, and vibration stimulations to conduct state warnings and physical state [23].

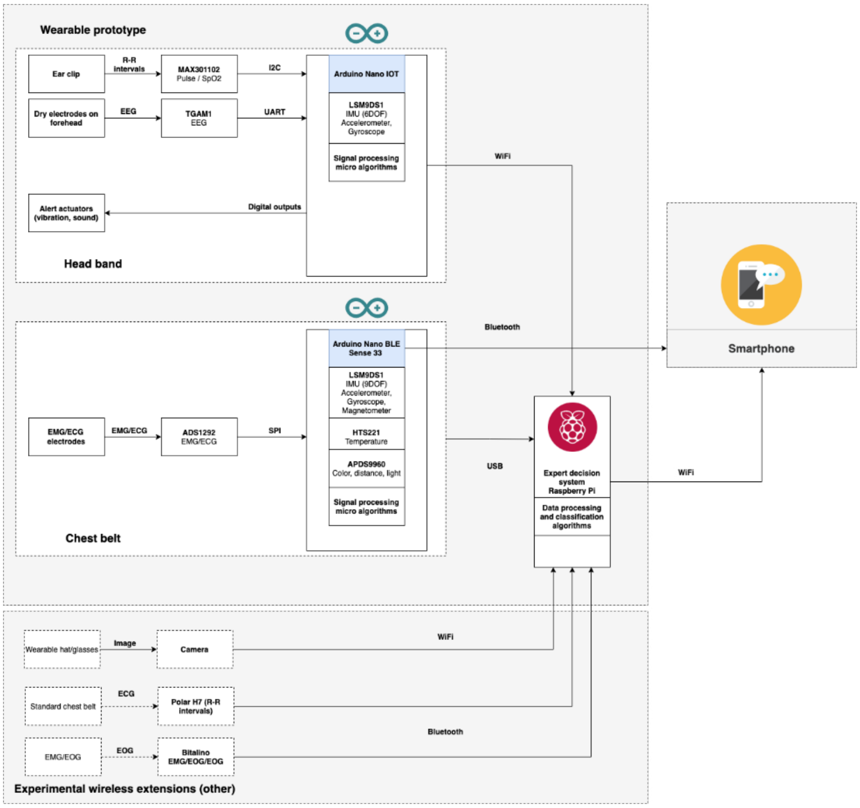
There are several different products for fatigue assessment that are currently being developed by scientists from the USA, Japan, Australia, China and EU countries. However, they mostly cover only specific areas and focus on a certain speciality or risk groups. Also, they do not include wider system access in the evaluation problems. As an example, the most common research areas could be mentioned for drivers [24][25], pilots and employers [26] for the investigation of mental and physical fatigue. Also, those types of fatigue may radically affect individuals or even the future of the entire country. The most popular methods to evaluate or recognize different types of fatigue are web tests or mobile applications [27], image processing by using cameras [28], electroencephalogram signal analysis and sleep coaching [29], which is based on questionnaires [30]. Furthermore, some research is focused on the fatigue risk for people with special diseases such as cancer [31], diabetes and sleep aponia [32]. The quantity of various research also proves that fatigue evaluation technologies are still relevant and popular in different scientific fields. Efficient and user-friendly fatigue assessment with decision-based risk of accidents reduction may be applied and used in different workplaces.

The proposed fatigue evaluation system architecture and methodology is novel and differs from other similar research because it is based on complex systems theory and uses multiple bio-signals. As a result, this architecture suggests a universal computerized monitoring system that may determine the degree of fatigue and the decision making in many application domains (like rehabilitation process regardless of the specific disease, drivers, athletes training process, workers, etc.)

### *2.2. System architecture*

In this chapter, the overall architecture is presented where the solution of the physiological parameter data acquisition is shown (see Fig. 1). The following architecture is hosted on the described electronics components. All services (including the expert decision support) are local and do not involve Cloud components for data acquisition to ensure minimal communication latency. The Cloud itself could be used for data storage and online decision making.

The proposed wearable prototype contains an electronic board with several modules. The prototype is placed in a casing that is attached to the human body or clothing on wearable elastic belts. In the given modular architecture, sensors are placed on separate parts of the body to measure various physiological parameters from the human head and chest. All parts are connected wirelessly to the expert system or smartphone over Bluetooth or IoT wireless connection. This way, human movements are not restricted by wires or sticky electrodes directly placed on the body. The focus of the proposed architecture is on the wireless communication of wearable electronics data acquisition modules. The diagram (see Fig. 1) distinguishes the main communication components - two functionally different wearable belts, a Raspberry PI minicomputer (expert system and IoT protocol services). Also, a smartphone is used for user interaction with the system. The smartphone may use a direct Bluetooth connection to one or more belt




modules or an indirect connection via Wi-Fi to the Raspberry Pi minicomputer. If necessary, the data and commands can be transmitted over a wired connection. Other external additions to the system are possible with additional sensor modules that supply data processing algorithms to the minicomputer.

Fig. 1. The proposed system prototype combines several devices for the health monitoring.

Table 1. The proposed heath monitoring system configuration.

| Settings | ECG configuration | EEG configuration | PPG pulse sensor configuration | Accelerometer sensor configuration | Actuator configuration |
|---|---|---|---|---|---|
| Module | SPI commands | UART commands | chip settings or I2C commands | chip settings or built-in commands | Digital outputs assignment |
| Algorithm | transmission frequency, averages, buffer size | transmission frequency, averages, buffer size | transmission frequency, averages, buffer size | transmission frequency, averages, buffer size | sound tone, vibration parameters |
| Parameter | ECG signal, R-R intervals | raw EEG, EEG frequency bands, e-sense parameters | R-R intervals, SpO2 settings | accelerometer filters (AHRS, Complementary) | |
| Enable feature | if the module is on the board | if the module is on the board | if the module is on the board | | |

To reach the integrity of a system the same set of generalized functions are implemented into all types of communication technologies and it is called the communication interface. The communication interface defines three main functional groups: configuration, data acquisition and actuator control. The proposed system configuration is described in Table 1. The data recording and transfer start when the device starts streaming parameter values from sensor modules according to the set of configuration parameters. The BLE may be used if it is required for the direct belt communication with a smartphone.

### *2.3. Fuzzy expert system*

An expert system is a part of a computer program that allows solving a particular problem by using the knowledge of experts in a specific domain and computational decision procedures. In this article, the described expert system for physiological fatigue evaluation is split into two components. In the first part mental fatigue and drowsiness decision rules are described with several input groups: eye blink frequency and ratio, brain activity dominant frequency, previous sleep disorders, mental activity scores, and demographic indicators. The parameters for mental fatigue evaluation expert system values are presented in Table 2. The other component contains parameters of physical fatigue evaluation. It consists of five input groups: central nervous system (CNS) state, heart recovery time, heart possibility to adapt the load, sympathetic/parasympathetic system balance, and compensatory movements in motion tracking. Parameter values for the physical fatigue evaluation expert system are presented in Table 3. Both fuzzy logic parts are in the same expert decision logic base (see Fig. 2) which is combined of logical rules synthesized from the expertise of professionals in sleep, sports medicine, and rehabilitation. The components of mental and physical fatigue apply different membership functions with low, average and high fatigue indicators, which are the outcome of previous research and can be expressed as transparent and human-readable logic. The partial decisions are expressed as a crisp continuous numerical value in the classic Mamdani fuzzy logic [33], which was chosen over the Sugeno type of more constant classes to be further used in the next levels of the recommendation process. The decision output is produced by using a first order weighted average inference engine, which is experimentally validated in MATLAB and later implemented as a Java microservice.

Table 2. Measured parameters and values for the mental fatigue evaluation in the proposed expert system.

| Input variable | Resulting value and units | Low value threshold | Average value threshold | High value threshold |
|---|---|---|---|---|
| Target game | Average reaction test value (ms) | >550 | 550 – 750 | <750 |
| Sector memory | Number of memorized sectors | >9 | 9 – 6 | <5 |
| Mathematical test | Number of correct answers per minute | >24 | 24 – 17 | <17 |
| Previous night sleep duration | Hours | >7 | 6 – 5 | <4 |
| Sleep quality | Self-evaluation | Good sleep | Hard to fall asleep/Often awake | Feeling lack of sleep in the morning |
| Eye blink frequency | Times per minute | >14 | 14 – 8 | <8 |
| Average eye blink closure | Duration (ms) | >130 | 130 – 400 | >400 |
| Camera evaluation | Classifier drowsiness grade | Low | Medium | High |
| Dominant EEG frequency | Dominant time (s) | <3 | 3 – 10 | >10 |

Table 3. Measured parameters and values for the physical fatigue evaluation in the proposed expert system.

| Input variable | Resulting value and units | Normal value threshold | Abnormal value threshold |
|---|---|---|---|
| Pulse | Pulse value in bpm / 2 | ≤52 | >52 |
| Discriminant of RR intervals and QRS complexes | Percentage, % | <10 | ≥10 |
| RR interval ratio of low and high frequencies | Grade of low and high frequency ratio | 45 – 60 | <45 and >60 |
| Tapping test | Number per second | ≥5 | <5 |

| | | | |
|---|---|---|---|
| Compensatory movements | Number of compensatory movements per second | ≤10 | >10 |

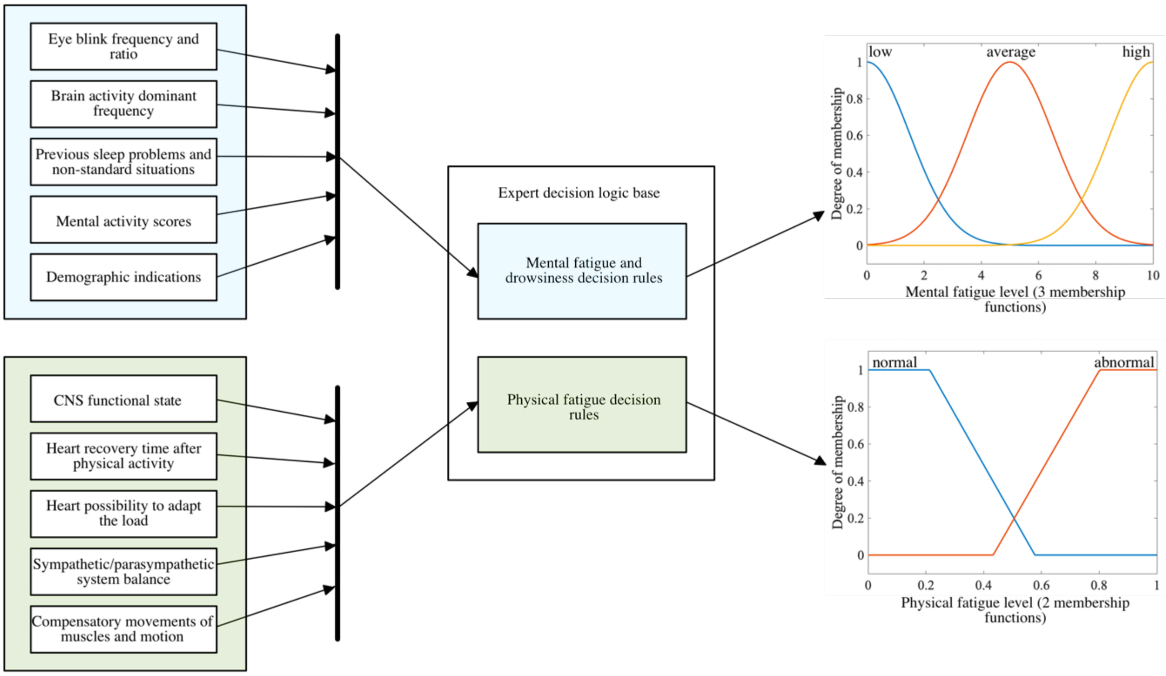



Fig. 2. The expert systems for mental and physical fatigue evaluation.

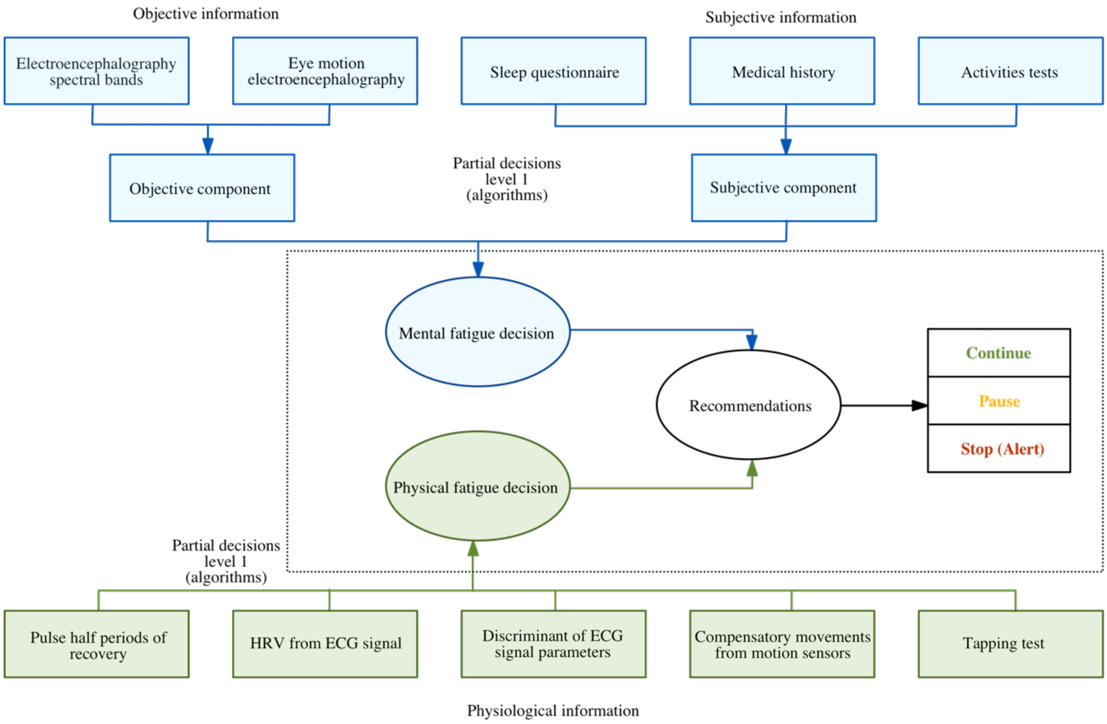


Fig. 3. Input signals and components of the expert system.

In the proposed fuzzy logic expert system several input signals are considered. For the mental fatigue evaluation, the EEG signal and subjective information (sleep questionnaire, medical history and activity tests) are evaluated. Physical fatigue decision rules are based on ECG, EMU, EMG signals, their parameters and tapping test results. The partial decisions in signal processing part of physiological signal acquisition use algorithms in the smartphone or more complex signals involve processing them on a minicomputer to produce input parameter numerical values or even partially solved classification tasks i.e., machine learning algorithm from the camera image produces classes of the human recognized level of alertness. A similar example is the usage of an inertial movement sensor that produces a partial recognition of human movement when microprocessor computational power allows hosting partial decision-making in the data acquisition process. Even though mental and physical types of fatigue have different input parameters and decision rules, the recommendation part is generalised for both parts. Feedback is generated to stop, pause or continue the particular work or activity (see Fig. 3) or to enable the physical prototype light, sound and vibration alert and stimulation.

## 3. Experiments and results

The experiments for fatigue recognition use several environments for various bio-signals registration and physical or mental fatigue evaluation. The main physiological signals are ECG, EEG and EMG. R-R intervals signal may be recorded separately by using a chest belt or can be calculated from the ECG signal. One-minute (60 sec) recordings of different bio-signals are presented in Fig. 4. In part (a) the EEG signal example is presented with eye blinks every 10 sec. Some amplitude values deviations could be seen in every blink. Also, in part (b) the ECG signal recording is shown during exercise. Movement artefacts could be seen in this picture. The last recording is the EMG signal in the back stretching movement. From this picture (see Fig. 4) a back muscle tension and fatigue appearance could be seen.

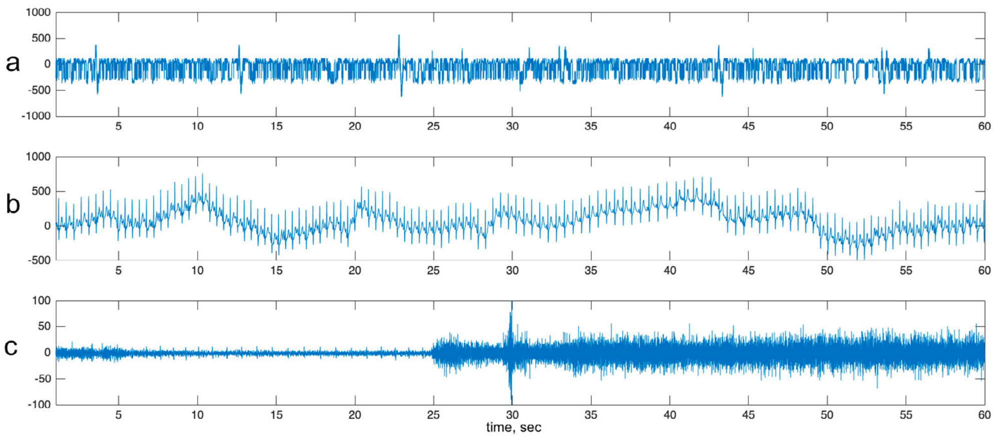


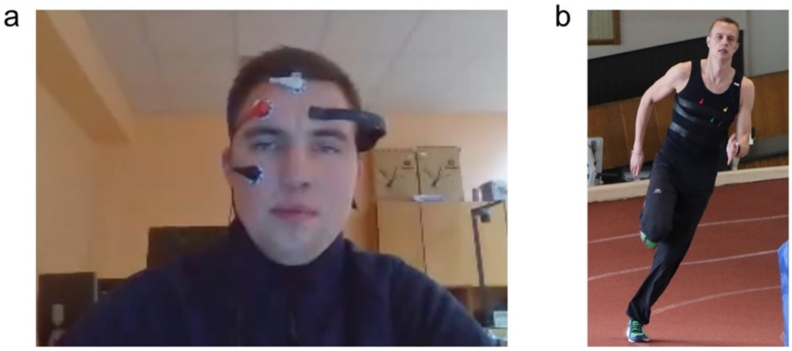
Fig. 4 (a) EEG signal with blinks every 10 secs; (b) ECG signal recordings during exercise; (c) EMG signal when electrodes are placed on the back in back stretching.

Fig. 5. Recording examples for different fatigue evaluation: (a) for mental fatigue EEG signal; (b) for physical fatigue ECG signal.

For better mental fatigue recognition, EEG sensor and a camera control was used that records eye blinks and other facial expressions. The example of recorded eyes blink is presented in Fig. 5 (part (a)). Also, in this figure, a head-belt could be seen that was used in this experiment and described in the proposed system architecture. Meanwhile, for physical fatigue evaluation, the ECG signal was recorded before, during and after the training session (Fig. 5 part (b)).

For the proposed system testing full-day recordings were made. The experiment can be divided into three separate parts for different fatigue recognition: instantaneous muscle fatigue, physical fatigue and mental fatigue (drowsiness).

1. In the instantaneous muscle fatigue, recognition process electrodes were placed on the back of the human body while the participant was performing back stretching. This experiment was repeated several times with several people and the results were similar. Instantaneous muscle fatigue recognition using EMG signal recording is shown in Fig. 4.
2. For the physical fatigue evaluation (that appears not necessarily in movement) several ECG recordings per day




were made before exercise and after exercise. The heart rate variability analysis (HRV) was applied, and various parameter values were estimated using R-R interval values. This experiment was repeated for 60 days, and results are presented in Fig. 6 where bean plots are shown. In this research for R-R interval values the average ($\overline{RR}$), standard deviation ($SDRR$), root mean square of successive differences between normal heartbeats ($RMSSD$), and standard deviation of successive differences ($SDSD$) were estimated. Also, additional HRV frequency parameters were calculated: normalized spectrum of high frequencies ($HR$) and normalized spectrum of low frequencies ($LF$). These bean plots (see Fig. 6) represent each HRV parameter data distribution before exercise (part(a)) and after exercise (part (b)). It could be seen that if a person is physically fatigued the HRV parameter values are differently distributed compared to values in a stage without fatigue.

3. For the mental fatigue recognition experiment, full-day EEG recordings were made. After analysis of various experiments with different eye blinks (double blink, slow, fast blinks, no blinks) it was noticed that EEG signals have significant indices to evaluate mental fatigue or sleepiness. In Fig. 7 could be seen the frequency analysis of the EEG signal. If a person is awake and with opened eyes, gamma or beta waves are more frequent. Also, eye blinks are more consistent. However, if a person starts to feel mental fatigue, the alpha and delta waves become more dominant. The bolded black line (see Fig. 7) represents the moment when a person starts to sleep detected by a person for the experiment to see the dominant EEG spectral frequency band.

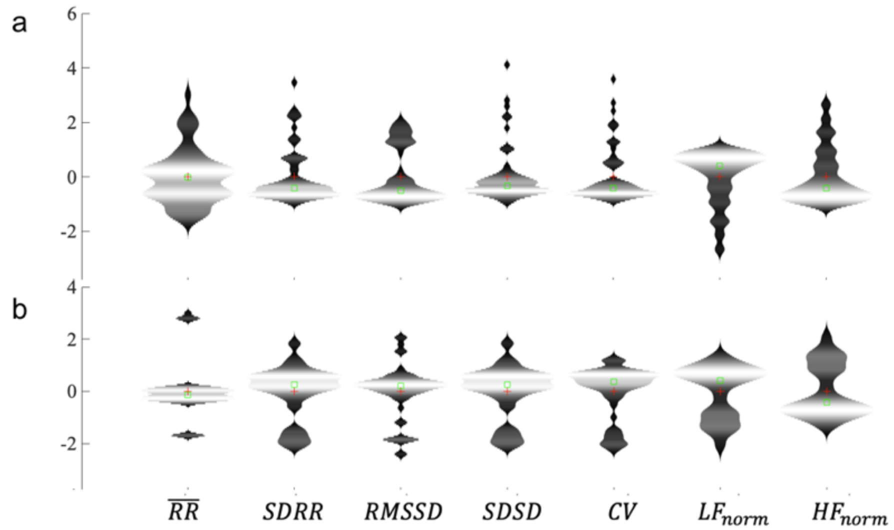



Fig. 6. Bean plots of R-R signal HRV parameters: (a) before exercise; (b) after exercise.

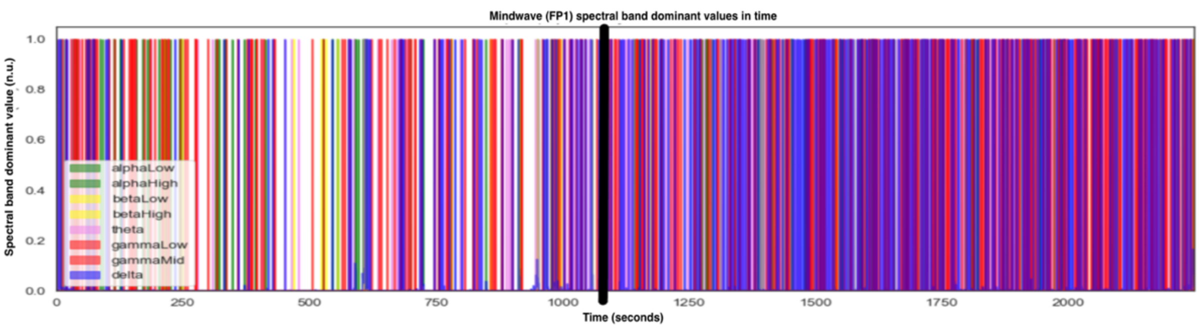



Fig. 7. EEG time-spectral dominant frequency bands plot.

The health monitoring for fatigue evaluation should be made by combining several bio-signal recordings at the same time because every bio-signal may indicate a different fatigue type.

## 4. Conclusions and future work

In this research, a generalized human fatigue evaluation system is proposed that may identify different types of fatigue in workplaces, rehabilitation processes, elderly people, and others. A presented system architecture mainly consists of a headband and chest belts, smartphone, and video camera. Depending on what type of fatigue needs to be monitored, devices may be used separately or all at once. Data transmissions can be initiated using Bluetooth, Wi-Fi or USB. The proposed system combines several devices that could be applied to various people of different ages and professions. Accordingly, to what type of fatigue needs to be measured, different devices can be selected. If necessary, all the signals (ECG, R-R, EMG, EOG, EEG, IMU, images) could be recorded.

In the current work, a two-layer decision-making architecture that relies on modern devices capable of signal classification and partial solutions to some higher-level problems is combined with an expert system that allows creating solutions for more abstract and domain-specific problem models like human fatigue. This solution can facilitate domain experts to build a digital knowledge logic base that is transparent and intuitive. As the expertise in the areas of human fatigue research grows, the system allows to improve the logic base with newly formulated expert rules.

For the fatigue evaluation system that is described in this article there are plenty of possible applicable areas: institutions that use medical treatment and patient rehabilitation (sanatoriums, retirement homes, etc.), the industry and construction companies that production includes hazardous substances, the finance and IT companies if precision and accurate results are required, the operator or controllers to reduce errors and mistakes, the military, rescue teams that experience a high level of stress, sports federations, educational sports institutions that include activities with training loads, and the leaders of various organizations.

## Acknowledgement

This research is supported by the EUREKA program project „Non-intrusive human fatigue assessment" E! 11169 Fatigue.

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