FEASIBILITY STUDY OF PHYSIOLOGICAL PARAMETER REGISTRATION SENSORS FOR NON-INTRUSIVE HUMAN FATIGUE DETECTION SYSTEM

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Abstract. Human fatigue manifests in slower reactions, reduced ability to process information, memory lapses, absent-mindedness, decreased awareness, lack of attention, underestimation of risk, reduced coordination etc. Chronic, decompensated and acute fatigue in form of drowsiness and falling asleep can lead to errors and accidents, ill-health and injury, and reduced productivity of sectors as in equipment operations, transportation. Their detection is necessary where they provide an option for the quantification and objective evaluation of subjective fatigue levels. Many studies are dealing with this topic for automotive and workability usage to design a fatigue detection and countermeasure device. The paper describes research of recent attitude to the development of the fatigue condition detection methods with the usage of human biological signal combinations, like electroencephalography (EEG), photoplethysmography (PPG), electromyography (EMG), galvanic skin response (GSR), temperature, position, respiration and percentage of eye closure (PERCLOS) to obtain diagnostic parameters reflecting the state of central nervous, cardiovascular, respiratory and muscular system and for monitoring of physiological vital changes. The current research focuses on aspects of non-obtrusive sensor signal quality and placement, and selection factors and evaluation of usability and potential integration into a wearable platform with the use of current sensor technologies that extend the application of sensors from laboratory to everyday environment. The sensor review aims to support development of a platform with multi-level fatigue monitoring and workability evaluation system designed in order to provide an integrated service in the area of operational safety.

Keywords: human fatigue, sensor devices, sensor complex, physiological parameters, sensor evaluation.

Introduction

Human fatigue is a construct of multiple components that are characterized from experience, physiology or performance. Fatigue can be seen from two aspects – physiological and psychological side. Fatigue as a physiological phenomenon indicates changes in brain wave activity, eye movements, head movements, muscle tone and heart rate. If a person is tired, his body temperature, heart rate, blood pressure, breathing and adrenaline production are changed. Fatigue affects the person's mind and motivation, as well as psychomotor and cognitive functions. Characteristic features are loss of human motivation, exhaustion of feelings, boredom, discomfort and unwillingness to continue working. When looking at the manifestations of cognitive processes, there are changes in reaction times, memory and coordination of psychomotor functions, information processing and decision making. The measurements of physiological signals therefore require a comprehensive assessment by using a sensor complex.

Fatigue affects operation safety, mental performance and attention. A wide range of wearable sensors and methods exist to this date designed for biomedical applications of monitoring vital parameters and algorithms for analysis of human physiological states [1].

The previous work of the authors resulted in a fully developed mobile telemedicine screening complex (MTSK) with analysis and advice centre software, and research work for development a new set of mobile, portable medical device complex for preventive examinations [2].

Non-invasive sensors for medical devices are even more used in the healthcare market. With the addition of microfluidic chips (Si-based, polymer-based, glass-based) the BioMEMS market, represented by silicon MEMS devices used for life sciences and healthcare applications, is expected to more than double – from 3 billion USD in 2017 to 6.9 billion USD in 2023, with a Compound Annual Growth Rate of 14.9 % from 2017 - 2023 [3].

The current study aims to formalize the most recent advancements in wearable sensors, which could provide measures of mental fatigue. The listed sensors are significant to the selected method of evaluation of fatigue caused physiological parameter changes and are grouped by the organism subsystems. The mental fatigue as a base type for this research is chosen in context with its application in cognitive workability evaluation according to the project requirements.

Sensor evaluation method

The approach for sensor evaluation proposed by the authors is based on compliance criteria and informativity about human functional systems reacting on fatigue. Non-invasive, non-intrusive sensors are indispensable elements of ambulatory and long-term health monitoring systems [4]. Wearable sensors, being progressively more comfortable and less obtrusive, are appropriate for monitoring an individual's health or wellness without interrupting the daily activities. The sensor devices can measure several physiological signals as well as activity and movement of an individual by placing them at different locations of the body.

The following proposed criteria for assessment of sensors have been introduced and discussed further in-detail.

C1. Measurement parameter coverage for the sensor defines the amount of parameters which can be acquired from the following sensor. The sensor complex devices considered in the current research can capture multiple sensor signals. The C1 criterion describes the amount and variety of measureable parameters, where low value means a raw signal from a single sensor, medium value for a sensor with multitude of parameters with also discrete processing on the sensor side, and high value characterizes multi-sensor devices and sensor complexes with two or more measured human functional systems.

C2. Distance to the object is categorized in three groups by the approach used – it can be distant, in a contact with skin or invasive. Invasive sensors are noticeable in an obtrusive way. Distant sensors are not in contact with the human body.

C3. The environment susceptibility is a grade at which the signal is affected by the environment (noise, motion artefacts). Highly affected devices are considered having a high effect to environmental conditions (temperature, humidity, movement, electromagnetic interference) and based on previous signal processing experience. This criterion can be evaluated by the complexity of signal processing required to compensate the signal correction. Highly affected measurements have a high percentage of corrupted readings (more than 10 % within 5 minutes), correspondingly 3-5 % for medium and up to 3 % for low artefact on the total sample amount.

C4. Type and availability indicates the type of the device used in a medical or consumer grade. The availability is associated with the technological readiness of the sensor, where sensors can be prototype (laboratory) or available in-market. Criteria C4 and C5 have a hierarchy of related sub criteria.

C5. Mobility indicates whether the sensor is stationary or mobile. For mobile sensors the connectivity and battery life are evaluated. Stationary devices have the minimum mobility. For mobile sensors the mobility depends on connectivity and battery life. Low mobility sensors have wired connections and limited battery life (often less than 30 minutes), while high mobility characterizes devices for up to 24hours of battery life and Bluetooth or autonomous data acquisition for more than 3 hours.

C6. Wearability assessment evaluates the sensor placement and alternatives of selected positions on human body. The research (Zeagler, Clint, 2017) [5] considers specific sensor placement separately projected on human body for suitable measurements and also factors that affect the non-intrusiveness of the sensor are taken into account. Highly wearable sensors correspond to the body map zones with the highest on-body location where functional, technical and social factors are considered. Low wearability devices are limited and not adjustable to body position, not practically or socially accepted as a wearable device or obstruct and limit body movement in a stationary or semi-stationary measurement design.

C7. Human functional system coverage criterion for a sensor or sensor complex evaluates the signal relation to human functional system. The systems and signal relations are summarized and listed in Table 1. The sensor complex measurement approach is required to obtain a comprehensive evaluation of the physiological state deviation and the level of fatigue manifestations such as drowsiness, alertness, reaction time and others [6; 7]. This criterion indicates the sensor relation with the physiology and human fatigue manifestation. The C7 criterion consists of mapping the device in a space of seven human functional systems.

Table 1

Summary of human functional systems and measured signals

System	Sensor signal	Literature
S1. Cardiovascular	PPG raw signal R-R interval data Heart rate data Pulse oximeter (SpO2) data	[8] Bonjyotsna, A., & Roy, S. (2014) [9] Thayer JF et al. (2009) [10] Chua et al. (2012) [11]M. Mahachandra et al. (2012)
S2. Central nervous	EEG signal Power Spectral EEG band data	[12] Niedermeyer E.; da Silva F.L. (2004) [13] Tandle, A., & Jog, N. (2015) [14] Stamps & Hamam (2010)
S3. Muscles and movement	EMG signal EMG Spectral (FFT) data EMG RMS data Movement acceleration data (3 axis)	[15] Beck T. W (2005) [16] Jalloul N. (2018). [17] Ugulino, W. et al. (2012)
S4. Respiratory	Respiration rate data	[18] Krehel, M et al. (2014) [19] Makikawa et al. (2014) [20] Lee, Y et al. (2018)
S5. Sensory (vision)	PERCLOS data Eye closure duration data Blink frequency data Eye closure and opening speed Eye angle data	[21] A. R. Beukman et al. (2016) [22] Franco Simini et al. (2011) [23] Luis M. Bergasa et al. (2004) [24] Chang, W.-D. (2016)
S6. Thermoregulatory	Temperature data (°C)	[25] Kräuchi et al. (2006) [26] Shizuka Bando et al. (2017)
S7. Periphery nervous system	GSR signal (μS) GSR component data	[27] Critchley, H. D. (2002). [28] Cole, P.J. et al. (2005)

Results and discussion

A comprehensive approach for selection of sensors based on the criteria and analysis of signal measurement literature and fatigue research published materials is summarized in Table 2. The given seven device sensor applicability is evaluated based on seven criteria and expressed in short form results (i.e. "*High*, "*Medium*", "*Low*"). The evaluation process consists first on the criteria, which originate from the device technical information, design evaluation and preliminary tests. Current results show that S2 specific device D1 has high mobility, yet highly susceptible to noise. The observed devices (D5, D6) of non-contact approach are promising sensors, yet currently available in prototype form. Sensor kit D7 has the most measurement coverage and as a medical device it can be used as a control method, however, it is obtrusive and the sensors distributed with wires across the body. From consumer devices the best suitable is D2, as it has better placement, wearability and measurement parameter coverage than D1, D3 and D4. The next stage of sensor evaluation is based on the experimental results, where the sensitivity of the measured parameters and the sensor signal quality can be statistically evaluated by control methods of voluntary measurements and tests that are specific to the problem domain. The sensor comparison and measurements by following a measurement protocol are reflected in the authors' previous published work [29].

Multidimensional representation methods can be applied for data visualisation and application of fuzzy logic for alignment of criterion values. The current method relies on study of literature analysis, therefore, equal criterion weights can be applied to use the current dataset for sorted rank decision making about selection of a sensor or device subset. The criterion weights can be applied after conducting experiments with given devices and expert evaluation in relation to indices of human physiological fatigue where measurement parameter sensitivity is statistically calculated in correlation with human reaction time, mental or physical performance scores or subjective evaluation scores, or other problem domain specific generally accepted measures.

Table 2

Device evaluation based on criteria

<table>
<tr><th rowspan="2">Device*</th><th rowspan="2">Sensor</th><th colspan="7">Criteria</th></tr>
<tr><th>C1</th><th>C2</th><th>C3</th><th>C4</th><th>C5</th><th>C6</th><th>C7</th></tr>
<tr><td>D1</td><td>EEG single electrode</td><td>Medium</td><td>Contact</td><td>High noise artefact sensitivity</td><td>Consumer personal use</td><td>Mobile, low mobility</td><td>Low, limited body placement</td><td>S2</td></tr>
<tr><td rowspan="3">D2</td><td>In-ear PPG sensor</td><td rowspan="3">High</td><td rowspan="3">Contact</td><td rowspan="3">Low</td><td rowspan="3">Consumer personal use</td><td rowspan="3">Mobile, high mobility</td><td rowspan="3">High</td><td>S1</td></tr>
<tr><td>In-ear temperature sensor</td><td>S6</td></tr>
<tr><td>Ear accelerometer</td><td>S3</td></tr>
<tr><td>D3</td><td>ECG single electrode chest belt</td><td>Low</td><td>Contact</td><td>Low</td><td>Consumer personal use</td><td>Mobile, high mobility</td><td>High</td><td>S1</td></tr>
<tr><td>D4</td><td>Active measurement GSR</td><td>Low</td><td>Contact</td><td>Medium, sensitivity to humidity</td><td>Consumer personal use</td><td>Mobile, low mobility</td><td>High</td><td>S7</td></tr>
<tr><td>D5</td><td>IR illuminator</td><td>High</td><td>Non-contact</td><td>Medium</td><td>Prototype</td><td>Stationary</td><td>High</td><td>S5</td></tr>
<tr><td>D6</td><td>Radio impulse radar (respiration sensor)</td><td>High</td><td>Non-contact</td><td>Highly sensitive to electro-magnetic noise</td><td>Prototype</td><td>Stationary</td><td>Low, not wearable</td><td>S1, S3, S4</td></tr>
<tr><td rowspan="10">D7</td><td>Bipolar EEG 4 electrodes</td><td rowspan="10">High</td><td rowspan="10">Contact</td><td rowspan="10">Medium, differs from sensor</td><td rowspan="10">Medical device</td><td rowspan="10">Mobile, low mobility</td><td rowspan="10">Low, limited daily usage</td><td>S2</td></tr>
<tr><td>Accelerometer</td><td>S3</td></tr>
<tr><td>Finger PPG</td><td>S1</td></tr>
<tr><td>Respiration belt</td><td>S4</td></tr>
<tr><td>Active measurement GSR</td><td>S7</td></tr>
<tr><td>ECG 4 electrodes</td><td>S1</td></tr>
<tr><td>EMG 4 electrodes</td><td>S3</td></tr>
<tr><td>EOG 4 electrodes</td><td>S5</td></tr>
<tr><td>Temperature</td><td>S6</td></tr>
<tr><td>Pulse oximeter (SpO2)</td><td>S1</td></tr>
</table>

Note: D1 – Mindwave Mobile 2 [30]; D2 – Cosinuss One [31]; D3 – Polar H7 [32]; D4.Mindfielde Sense Skin Response [33]; D5 – Project AWAKE [34]; D6 – Xethru X4M200 [35]; D7 – Nexus 10 MK II [36];

Conclusions

1. A selection of physiological parameters based on multi-criterion evaluation of measurement sensors proposed in the current work shows the multi-sensor consumer device (D2) advantages over single electrical activity sensor devices (D1, D3, D4) in terms of parameter coverage.
2. The medical multi-sensor kit (D7) can be used for control purposes as limited wearability, but the stationary prototypes (D5, D6) do not comply with the mobility requirements.
3. The weights and other criteria, like signal relation with the problem domain, can be obtained from sensor experiments and expert evaluations, so that a target function for candidate ranking is set and defined by a specific field of application.

4. The results of the current research can be used in creation of a decision support system for physiological sensor group selection in novelty applications, like human fatigue assessment.

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