UNORDINARY SITUATION ASSESSMENT OF HUMAN FATIGUE AND DROWSINESS IN EXPERT DECISION-MAKING SYSTEMS

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Abstract. The current research aims to augment a platform with complex passive multi-level fatigue and workability evaluation and the monitoring system for integration into professional safety and telehealth domains. The monitoring and decision-making system offers a comprehensive evaluation of human fatigue based on estimating mental and physical types of human fatigue. The aggregated component values express the fuzzy logic-based decision about the overall fatigue level in the system output. The current paper offers a decision-making approach for a rule-based expert system in unordinary situations of fatigue and drowsiness as an additional decision block. Evaluating unordinary situations uses electroencephalography parameters of a wearable device in combination with information from pre-work questionnaires. The unordinary situation model evaluates the presence of 5 additional conditions: insomnia, last sleep, microsleep, daytime sleepiness, and boredom sleepiness. The system performs additional control tasks to trigger alerts based on the new decisions during the monitoring session. The feedback, such as decisions, alerts, and recommendations, is received through a smartphone or wearable equipment. The system addition described in this work uses recommendations for the system user to express the level of fatigue and the proposed alerting expert decision model outputs immediate alerts, thus preventing drivers or operators from falling asleep. The proposed system aims to benefit in areas of work schedule planning and dangerous, responsible work.

Keywords: human fatigue, human drowsiness, expert systems.

Introduction

Human fatigue results from prolonged or unusual work manifesting as attention and work capacity reduction for a certain period [1]. The research [1] conducts that fatigue occurs when the amount of human energy available is less than required. Fatigue is a signal and a demand for rest to restore energy. Determining the level of fatigue can play an important role; for example, during the rehabilitation (recovery) process, it is essential for the patient to continuously monitor the degree of fatigue in his daily activities to prevent deterioration and death. Driver fatigue causes accidents and human casualties, and student fatigue causes early health problems. Fatigue can be mental, physical, sensory, and emotional [2]. However, any fatigue type manifests itself in the body's reactions. Therefore, the fatigue assessment is performed using different indicators [3]. This article is the continuation of the previous research by the authors, where an expert decision-making system was created for adaptable human fatigue evaluation, which was created in collaboration with experts from the Riga Stradiņš University, Kaunas University of Technology and the Lithuanian Sports University. The system described in [4] is designed to evaluate mental and physical components of human fatigue and fuse the decisions in the common recommendation layer. The first level of each component assesses the fatigue type based on the objective (physiological) and subjective inputs, where objective methods use biosensor signal processing and decision making to produce the diagnostic indications used in the expert decision-making system. After analysing the created expert system, the present article describes the proposed addition to the mental fatigue evaluation platform module that accounts for the unordinary situations of the human fatigue and drowsiness that require additional monitoring and immediate reaction from the expert decision system.

Fatigue assessment methods

Fatigue assessment is a complex process and not an easy method to implement. To date, measurements of physiological parameters help assess fatigue: electroencephalography (EEG) and electrocardiography (ECG) [4]. These measurements, standardised for sleep medicine, are performed in laboratory conditions. The authors have previously researched methods of obtaining objective drowsiness indices (eye symptoms) by using video camera image processing that can be applied in a non-stationary environment [5].

Therefore, it is expedient to create a mobile wearable-type fatigue monitoring and decision-making system for individual daily use with real-time decision visualisation and augmentation in several areas of application, such as rehabilitation, sports and fitness centres, vehicle driving [6], operator work, office work and student workload assessment. The possible macrostructure of the fatigue level assessment computer system is shown (see Fig. 1).

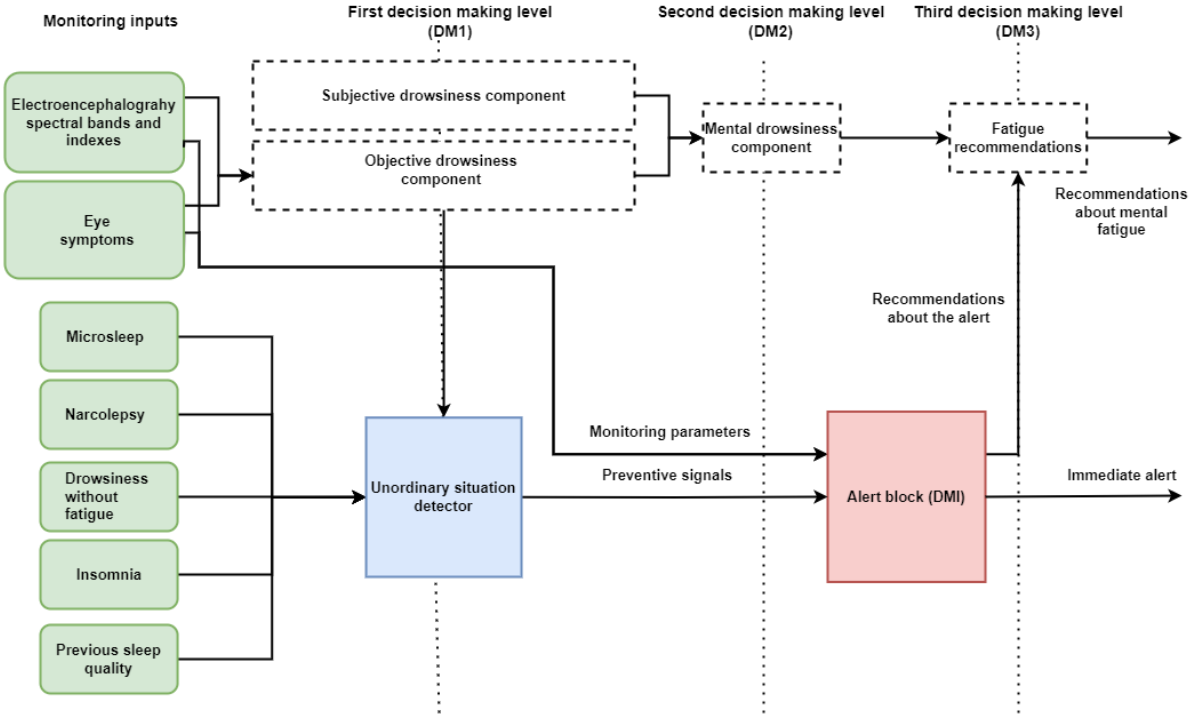

Fig. 1. **General macro structure diagram of a decision-making system**

The first decision level (**DM1**) is intended to select parameters to measure and recognise fatigue components. The expert-system decision platform DM1 level accepts processed inputs from machine-learning algorithms and signal processing of the wearable biosensor devices [4].

The second decision level (DM2) is intended for:

- determination of the overall fatigue level based on the expression levels of the components;
- to determine the importance of components in joint fatigue.

The third level of decision-making (DM3) is intended to develop a set of decisions or recommendations for cases of different applications. The expert system outputs a decision index expressed as the recommendation level. The user interface software reflects this information with the help of custom audio-visual matters and is not a part of the expert system.

By a more detailed study, it can be said that the incoming information of the system is divided into three parts [7]:

- objective, measurable information;
- subjective, humanly expressed information;
- episodic, observed information at the start of work.

A set of human physiological parameters forms the flow of objectively measurable information. Psychological aspects, such as peculiarities of character, thinking, and behaviour, were reflected in a person’s mood, motivation, psychomotor functions, and cognitive functions. It forms a flow of personal information obtained through surveys and tests.

Information observed prior to work shall be included in the system as probable only if such observations are made and the appropriate personnel is engaged in the relevant application. Observations may include manifestations such as stress, emotional agitation, drowsiness, insomnia, and signs of illness before starting work. Drowsiness (**D**) and fatigue (**F**) are associated with all fatigue components. The assessment of somnolence is characterised by physiological, subjective, and objective performance indicators. Manifestations of acute and compensated fatigue are characterised by undesirable drowsiness during the day, characterised by the body’s desire for sleep and rest in the human natural circadian rhythm cycle. Drowsiness is increased due to chronic fatigue or a disturbed daily sleep cycle. Excessive sleepiness during the day: a neurological disorder with a sudden recurrence of uncontrolled sleep. Excessive drowsiness with spontaneous sleep during the day is narcolepsy, which is medically diagnosed as a single illness. Intuitively, these developments are now interconnected. Unfortunately, in practice, they are considered separately. There are approaches in the literature from the coexistence of two events, close ties to complete identity, and fusion. In computer versions such ambiguities should be avoided. In the case of extreme fatigue, insomnia is observed, which generally characterises the stage of fatigue.

- Drowsiness (**D**) expression levels or gradations are like fatigue (**F**) gradation. Unfortunately, there are several different understandings of (**D**) and (**F**) in the studies [8].
- The existence of a close functional link between (**D**) and (**F**) makes it possible to take a variant of the theory of partial overlapping sets as a basis for the development of a computer system and to organise two information channels for measurement of fatigue and drowsiness parameters [9].

Unfortunately, the development of a computer system is hampered by developments in practice, where the link between fatigue and drowsiness is very weak, not visible at all, or of the opposite nature. It can be said that there are situations when (**F**) exists without (**D**) and vice versa. Such extraordinary situations or artefacts include the following five situations.

- **The first situation**, insomnia D(I), occurs when there is much fatigue instead of drowsiness, as expected [10]. In this case, the system output will only react to the fatigue decision, and the result is not as strict as when both component decisions are involved;
- **In the second situation -** the moment and level of fatigue depend on the duration and quality of previous sleep from falling asleep **D(Q)** [11]. This is reported by the person and marked as present if the self-evaluated quality of sleep is low and the previous duration of sleep within the last 24 hours is less than 3 hours;
- **The third situation** is micro-sleep **D(M),** when a person suddenly falls asleep for a short time. Here it is difficult to find any connection with fatigue [12]. The short timings of microsleep episodes require additional monitoring with sensors and a decision-making layer capable of preventive reaction before the recommendations;
- **The fourth situation** is narcolepsy **D(N),** when a person falls asleep in the middle of the day for a long time without pronounced drowsiness. One version says that the cause is a side effect of diseases [13];
- **The fifth situation -** drowsiness, occurs without fatigue from monotonous activity or boredom **D(B)** as a psycho-emotional state [14]. Boredom sleep is often measured only by drowsiness monitoring or a subjective evaluation questionnaire and is not classified as a medical condition.

According to the analysis of unordinary situations of drowsiness, one can once again make sure that fatigue (**F**) and drowsiness (**D**) are not identical concepts because, in some situations, the concepts are contractionary. Unfortunately, this analysis also does not answer the question of the relationship between (**F**) and (**D**) and does not help in choosing the proper relationship format from the options mentioned above. At the same time, (**F**) and (**D**) are so closely related that in the subjective plane (interviewing experimental participants using subjective scales), there is no certainty about appropriate selectivity. For example, when asked about the severity of fatigue, the answer may include drowsiness characteristics.

Evaluation of unordinary situations

The expertise procedure from the sleep expert analysis does not show any functional relationship between drowsiness and fatigue in the ordinary sense. For unordinary situations, different solutions are sought to assess them in the overall process of recognition and decision-making by adding a layer of expert decision logic models. This document focuses on the expert decision-making methods to augment the previous expert derived logic. The logic blocks are implemented in the computer system using Mamdani Fuzzy Inference Systems. When solving specific problems, it is concluded that one should not be interested in increasing the gradations of (**F**) and (**D**) expressions or levels. In the current uncertainty conditions, a person cannot assess the situation in the spheres (**F**) and (**D**) in a very nuanced way, just as it is not possible to make decisions about the recommended recommendations in a nuanced way. Therefore, it is proposed to describe the (**F**) and (**D**) levels in a 3-point system **-** low (**L**), medium (**M**), and high (**H**). The Boolean values for the unordinary situation detector inputs and outputs are marked as present (**0**) or not present (**1**). The fatigue and drowsiness level objective measures originate from the expert logic described in [4] and [5]. The unordinary situation evaluations are from subjective evaluation or specialist input. The decision-making expert system rule base example is given in Table 1. Abbreviations used:

- D(Q) – previous sleep quality;
- D(M) – microsleep drowsiness;
- D(I) – insomnia, drowsiness;
- D(N) – narcolepsy drowsiness;
- D(B) – boredom sleep;
- F – fatigue level from the classifier;
- D – drowsiness level from the classifier.

Table 1

Decision-making table for the unordinary situation detector

Input parameters	**Production rules**																	
D(Q) D(M) D(I) D(N) D(B)	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
F	L	L	L	M	M	M	H	H	H	L	L	L	M	M	M	H	H	H
D	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H
Detector result	0	0	1	0	0	1	0	1	1	0	0	1	0	1	1	1	1	1

Table 1 shows the decision rules for the determination of unordinary situations by using fatigue (**F**) and drowsiness (**D**), which include both objectively measurable and subjective (questionnaires and tests) information and on-site condition information. The unordinary subjective information parameters are weighted equally by meaning; if either one is observed and present, the detector will consider the objective states of **(D)** and **(F),** which will trigger the detector output in **(M)** or **(H)** states. The detector can produce output if only the objective inputs are present, but cannot produce a positive detection with only subjective measures. The subjective unordinary parameter activation is **(H)** if only one of the conditions is present. The selected logic consists of 2 linear membership functions for the subjective unordinary situation parameters and three class outputs from the classifiers. The logic is observed during the expertise process and agreed on the parameter gradations for observability and consensus of the expertise process. The number of combinations that the experts require to evaluate decreases at least tenfold if the number of gradations is lowered [15]. Therefore, in this model, the complexity measure (O) is 41, which is described by the given equation (1):

$$O = \sum_{i=1}^{N} T^k = T_{i1}^{k1} + T_{i2}^{k2} = 2^5 + 3^2 = 41 \tag{1}$$

where O – complexity measure of the fuzzy inference controller rule base;
T – number of linguistic gradations for the parameter;
k – number of parameters with the same gradation;
N – total number of parameters.

Results

It is easier for a person to assess drowsiness than the degree of fatigue, which is much less clear [16]. Therefore, it is proposed to perceive **(D)** and **(F)** as fundamentally separate states, which do not prevent them from often complementing or converging. It is proposed to create separate information channels from the physiological inputs and the decision-making level **(DM1)** at the level for **(D)**, **(F)** and unordinary situations **(DMI)** without trying to find theoretical connections between them. The aggregation of information can be implemented in decision-making procedures in the form of production laws, as shown in Table 2. The decision rule complexity for the **(DMI)** block is 18 due to the low number of input parameters.

Table 2

Decision-making table for the alarm block (DMI)

Input parameters	**Production rules**																	
Electroencephalography spectral bands and indexes	L	L	L	L	M	M	M	M	L	L	H	H	H	H	M	M	H	H
Eye symptoms	L	L	L	M	L	L	M	M	H	H	L	L	H	H	H	H	M	M
Unordinary fatigue situations	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
Alert output index	0	1	1	1	1	1	2	3	3	3	3	3	3	3	3	3	3	3

The computer implementation of the resulting expert modules in the MATLAB software package for alarm decision making is shown in Table 1 and Table 2. The triangular geometry is used for the input data of the decision system membership function module, which characterises the discrete quantities for the corresponding gradations of the input parameters: L-0, M-1, H-2. Furthermore, accordingly, the belonging output function "Alert output index" uses four output gradations for the alert actuator control and the recommendation block **(DM3),** which is a strict value (0-3). The expert system contains decision-making rules linking the input parameters and output decisions and uses the Mamdani Type1 fuzzy inference system. The product method combines the logical branches (AND), but the maximum method is used for the logical (OR) implementation. Defuzzification is implemented using the mean-of-maximum (MOM) method, which is experimentally tested by using known input-output rules and compared to the system input class. Each module of the decision system implemented in work is checked, and 100% compliance is expected when the system module with the given expert data is validated. The experts evaluate the given matrix tables and use the average expert rating to correlate each expert opinion to the output. Next, the output is corrected to match the expert consensus. The given expert system contains 100% coverage for the expert decisions and production ruleset with the number of theoretical combinations. The system is implemented without duplicate laws and covers the entire decision space. The system assumes that three input values are used, of which the missing value of any parameter results in a low input parameter setting. In this case, electroencephalogram and eye estimates are obtained by algorithms and sensors, which assume that both parameters can be obtained simultaneously during monitoring. Extraordinary features are calculated for the person after the first data entry when the questionnaire is submitted or before the work survey. If an abnormal symptom is detected after at least one of the operational conditions described in the description of the unordinary situation block, there must also be a single (H) activation by the objective measures. The parameters of the physiological measurements have a high priority, and any of them at a high value results in a maximum alarm output rating.

The logical impact of the unordinary situation and alert **(DMI)** blocks on the level **(DM3)** of the expert recommendations is shown in Figure 2. Four classes of recommendations are defined. First, the case of the pre-flight survey is considered, in which the objective fatigue component is excluded, and only subjective input information is used, as well as alarms, the input source of which is available from the block of unordinary situations. In this case, the gradation of mental fatigue can use **(L)** or **(M)** fatigue classes. Consequently, the resulting decision only after the survey is to continue working (1) or take a short break (3). Suppose a block of extraordinary situations is involved as part of an additional survey. In that case, a formal recommendation is also used and only after the survey it is possible to provide recommendations on the potential risk and deter the person from performing their duties by recommending rest or other ways to reduce fatigue.

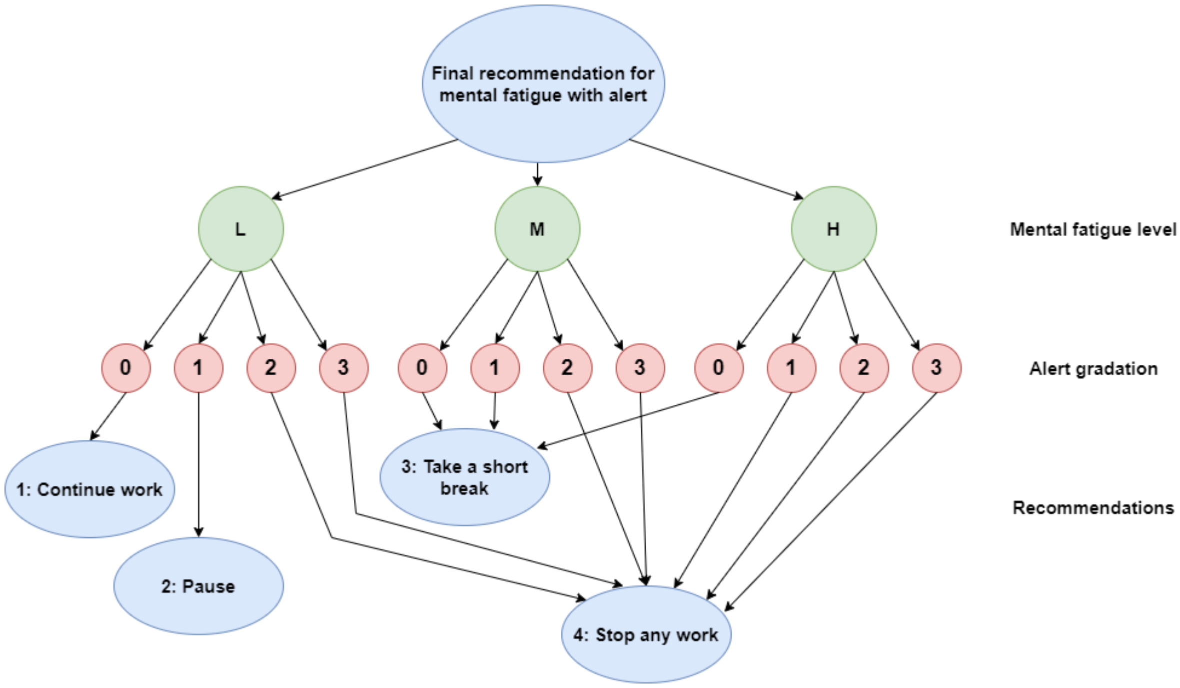

Fig. 2. **Expert decision tree for mental fatigue gradations including alerts**

Discussion

The discussion topic for this article is the consideration to prioritise the objective fatigue and drowsiness means over the subjective ones. There is an opinion in the literature [13] that microsleep and narcolepsy are diagnoses (diseases) and not normal functional conditions due to fatigue. Consequently, they should be considered as contraindications to driving, as should epilepsy, and should not be included in the fatigue detection system; as such, people should be screened at the beginning of the decision-making process. Due to technical limitations, a computer system used for driver drowsiness evaluation does not have access or means to trust the sources or verify medical conditions. On the other hand, the transport flow is not limited to professionals for whom these contraindications may be established at the initial medical examinations [17]. Amateur drivers are not subject to such inspections. Therefore, it is desirable to control extraordinary situations, detect unexpected falling asleep and use extraordinary measures to prevent disaster. In the case of micro-sleep, road transport will require a reaction with intervention in the process, except in rail transport, where the stopping distance can be as high as 1.5 km, and a few seconds cannot affect the process in either a good or a wrong direction. The explanation is that if there is only microsleep, there is no fatigue and drowsiness, and no signal is expected from the decision block **(DM3)** to the recommendation block, without microsleep should be evaluated. If there is not only **(D)** but also **(F) > 0** and **(D) > 0**, then a decision is made by **(DM3)**. Some research [18] emphasises the case of narcolepsy **D(N)**. The process always goes to the "stop" decision.

Conclusions

1. A solution with three information flows complicates solutions where only physiological parameters are considered inputs. It is necessary to find parameters that would indicate unordinary situations and pay more attention to the anamnesis, questionnaires, tests, and on-site observations before the activities. Thus, the resulting determination of the fatigue level and development of the recommendation block **(DM3)** in ordinary situations is ensured by drowsiness **(D)** and fatigue **(F)** level blocks and the decision block **(DMI)** with an extended decision scale.
2. The article presents two expert system modules to evaluate unordinary situations and alerts in case of five drowsiness related problems. The unordinary situation evaluation block contains 41 expert rules derived from the expertise process. After the system evaluation, the alerting block consists of 18 expert rules derived from expert consensus. The system development and validation time in the expert decision systems depend on complexity reduction by decisions on the number of significant parameters and the number of linguistic rules.

3. In extraordinary situations, decision-making **(DM3)** is entrusted to an additional module **(DMI)**, collecting subjective information from the unordinary fatigue and drowsiness evaluation module and direct objective physiological parameters. The proposed solution can be used to augment a recommendation by giving an expert system monitoring capabilities and producing alerts in real-time applications.

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