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Recognition of human daytime fatigue using keystroke data

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Abstract

Human daytime fatigue has many signs (tiredness, sleepiness, lack of vigilance). The on-set of fatigue during working hours can be dangerous for people of several professions such as lorry drivers or industry workers, however even for office workers it may lead to serious errors. Timely recognition of daytime fatigue using simple computer based tests can reduce fatigue related accidents or errors in workplace. In this paper, we analyze the use of keystroke data derived by typing on computer keyboard to recognize the state of an increased fatigue. Using specific key press and release timing information from text input tasks, we achieve an average daytime fatigue recognition accuracy of 98.11% when only three qualitative classes of daytime fatigue (low, medium and high) are considered.

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Keywords: fatigue recognition, office ergonomics, assisted living, biometrics.

1. Introduction

Fatigue can easily be recognized by human actions. Due to the lack of energy and motivation, a person can no longer work in a regime or tempo that is typical for him, then the symptoms of fatigue develop such as forgetfulness, memory capacity is diminished, and the person can not think clearly about what can happen around him/her in the

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near future. As a result of work-related fatigue, industrial accidents or work-related injuries can happen[1]. In addition, tiredness can lead to poor communication and lack of vigilance, which are very important in daily work. Kim et al.[2] have identified factors that most often determine fatigue and fatigue symptoms. The most important determinants of fatigue are: sleep disturbances; age; lack of physical activity; monotony; and volatile work schedule. Some factors such as lack of physical activity, monotony, or volatile work patterns are common to some individuals[3]. As an example, the concept of monotony is often used in driving behavior studies that have found that fatigue and monotony reduce driver attention[4]. Moreover, the decrease in work monotony has a positive effect in reducing fatigue associated with monotonous and repetitive work operations such as driving[5]. Cognitive fatigue also negatively influences the performance of students during learning tasks or examinations[6].

Daytime fatigue can be recognized by certain signs or symptoms. The most common signs of fatigue are: forgetfulness; poor communication; constant exhaustion; uncontrollable sleepiness; lack of vigilance. Sometimes the symptoms of fatigue are similar to the symptoms of alcohol consumption[7, 8]. Therefore, it is important to track and measure the symptoms of fatigue continuously during working hours. If fatigue exceeds the safe levels allowed for a specific type of a work, a person should take a break or have a rest, because further continuation of work may pose danger to him and his/her colleagues, or may lead to serious errors reducing work output or even leading to the financial losses of an employer. For example, one study estimated the drop in productivity related to fatigue up to 6.1%[9], while another study[10] urged to develop and implement active measures for fatigue risk management in workplaces. Fatigue detection and assessment requires sensitive and effective measures that can be used in everyday environment, but it is especially relevant for assisted living environments (ALE) such as smart offices. Software can be used captures through the computer's input devices such as mouse or keyboard. Biometric personal data may be used to identify a person or his or her status by capturing the response time, accuracy, memory, etc., in executing certain benchmark tasks such as a visual tracking task[11] or a reasoning test[12]. Some studies use speech or voice as data, as these are known to change their characteristics if a person is in the state of stress[13] or fatigue[14].

Biometric data are physical or behavioral features that make each person unique and can be used as a means of personality validation. Biometric data can be divided into physical and behavioral characteristics. Physical features include fingerprints, iris and face. All physical characteristics can only be changed after physical damage. Behavioral characteristics include Keystroke Dynamics (KD), gait, voice, personal signature. These factors have constant and variable components. The constant behavioral component depends on the physical data of the person and does not change. Meanwhile, a variable component of KD, depending on the psychological state of a person, can change[15]. Keystroke dynamics is one of the biometric characteristics that is based on the assumption that different people have different writing manners. The neuro-physiological factor determines the unique signature of a person. This factor also determines the different characteristics of the writing keyboard for different people[16].

KD has been successfully used for user authentication[17, 18], generation of private keys for cryptography applications[19], and automated stress detection using keystroke features[20]. In previous work, we analyzed gaze fatigue during execution of vision demanding tasks[21]. Here we continue our work[22], and analyze the use of keystroke dynamics data for daytime fatigue recognition.

2. Method

2.1. Data

The KD uses a data sequence, which consists of key click and release times. In order to be able to model the person's writing template using the data sequence, it is first necessary to normalize the data. Normalization of the sequence is carried out by replacing the absolute sequence times in consecutive time intervals[23]. Following Morales et al.[24], we distinguish five properties that characterize the subject's KD template: *Hold Time* is the time difference between pressing and releasing the key; *Release - Press delay* is the time difference between the release key and the subsequent key press times; *Press - Press delay* is the time difference between the subsequent keys press times; *Release - Release delay* is the time difference between the time and the time when the keys are released; *Press - Release delay* is the time difference between the key press and the key release times.

We assume that the level of fatigue is associated with the natural rhythm of the activities during the day. Based on this assumption, the time of day is divided into three classes: morning – the person is fully rested and has no signs of fatigue; afternoon - the person is after some hours of work (or other activities), so there is a moderate level of fatigue experienced by a person; evening - the person is tired and experiences a high (elevated) level of fatigue. The key logging software collects keypress time data during the appropriate time of day (morning, afternoon or evening) by the person entering the standard text.

2.2. Feature selection

Before training classifiers, it is necessary to form the most efficient set of properties with which to achieve the most accurate prediction. To achieve this purpose, we first generated a set of features representing statistical characteristics of keystroke data. The full list of features was given in[22] and includes both simple statistical features such as mean, standard deviation, skewness, and higher order statistical features such as statistical moments, L-moments and cumulants[24]. To select most relevant features for classification, we used a generalized linear discriminant analysis based on trace ratio criterion algorithm (GLDA-TRA)[25].

We used linear regression between a set of generated features as independent features and the dependent variable, representing the linear increase of human fatigue during daytime (as our data has only three classes of increasing fatigue, value '1' denotes the morning, value '2' denotes the afternoon, and value '3' denotes the evening), and performed feature ranking based on the value of the coefficient of determination (R^2).

2.3. Classification

Suport Vector Machine (SVM) is one of the most commonly used classification methods proposed by V.N. Vapnik in 1995[26]. This method is based on the idea that the data contained in high-dimensional space can be distinguished from the n-dimensional hyperplane.

The classification system uses the features of each consecutive pairs of keys pressed. In order to evaluate the effect of fatigue on each key pair dynamics, a system is created in which a three-class model is created for each fixed key pair separately. Our classification model consists of four stages: 1. Preparation of training and testing samples - for the selected time interval, the system forms the training and testing data samples. 2. SVM classifier training - for each key pair, the SVM classifier is trained with such values and values that the probability of classifying keypress data to a correct fatigue class is maximized. 3. Selection of SVM classifiers – the SVM classifiers are selected, which have higher prediction accuracy than the threshold value at the training stage. 4. System testing - the model presented in Fig. 1 is used to test the system. The output of the system is the accuracy of the classification, which defines how many probability class predictors satisfy the value of the threshold function.

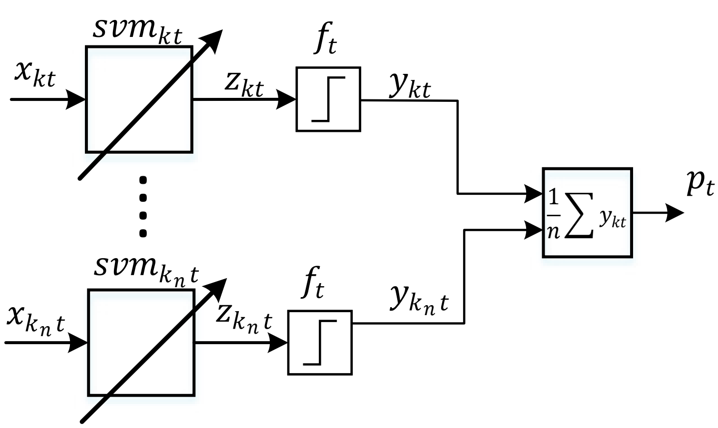

Fig. 1. Model of classifier system.

Our case study has three classes (states of fatigue), so we uses a classification system, where each classifier separates one particular class from the rest (1-vs-all). See Table 1 for explanation of the classification model.

Table 1. Classification system.

Classifier	Predicted class	Input classes	
1.	Morning	Afternoon	Evening
2.	Afternoon	Evening	Morning
3.	Evening	Afternoon	Morning

3. Experiments

3.1. Subjects and texts

The experiment analyzed the data of four participants in the study. All participants of the study gave an informed consent, while all required ethical principles were adhered to. Three of the participants in the study were employed, one was a student. Their age was between the ages of 22 and 33. The study lasted for two weeks, during which the subjects participated in the trials of the text provided by the program three times a day. The text was modified three times during the study. The study was conducted with the assumption that the time of day, when the text is being entered, correlates with human fatigue. It is believed that the keypress characteristics of the text entered in the morning represents a person who does not feel tired, at afternoon - a person who is feeling moderate fatigues, and in the evening – a person is fatigued. Therefore, we have three classes representing free levels of fatigue: low, moderate, and high.

The text dataset used in the study consisted of three fragments of texts: 1) a fragment from the book “Partisan” by Lithuanian author V.V. Landsbergis (129 words, 856 letters); 2) a fragment from the book “The Elephant Vanishes” by Haruki Murakami (117 words, 737 letters); 3) 100 most frequent words (at least 3 letters long) in Lithuanian language (100 words, 547 letters).

3.2. Data and results

Table 2 shows the characteristics of the aggregated data of the whole study of each participant in the study and derive the average of key dynamics for the corresponding time of day. The results of feature selection using linear regression are presented in Fig. 2 (10 most significant features are shown).

Table 2. Mean values of the KD properties of the subjects for the corresponding time of day.

Subject	Class	Press-Press time, s	Press-Release time, s	Release-Press time, s	Release-Release time, s
1	morning	0.272	0.377	0.166	0.271
	afternoon	0.299	0.416	0.183	0.299
	evening	0.299	0.424	0.175	0.299
2	morning	0.211	0.301	0.122	0.211
	afternoon	0.220	0.311	0.129	0.220
	evening	0.189	0.296	0.083	0.189
3	morning	0.332	0.428	0.237	0.333
	afternoon	0.323	0.420	0.226	0.324
	evening	0.302	0.411	0.195	0.304
4	morning	0.229	0.337	0.122	0.229
	afternoon	0.217	0.327	0.107	0.217
	evening	0.190	0.303	0.077	0.190

The classification results are presented as the confusion matrices for each subject in Table 3. The average correct classification rate is 98.11% (98.01% for low (aka 'morning') fatigue, 96.75% for moderate (aka 'afternoon') fatigue, and 99.55% for high (aka 'evening') fatigue). The combined confusion matrix for all subjects is presented in Table 4. From confusion matrix we can see that most of classifications errors were between consecutive (morning/afternoon or afternoon/evening) states of fatigue.

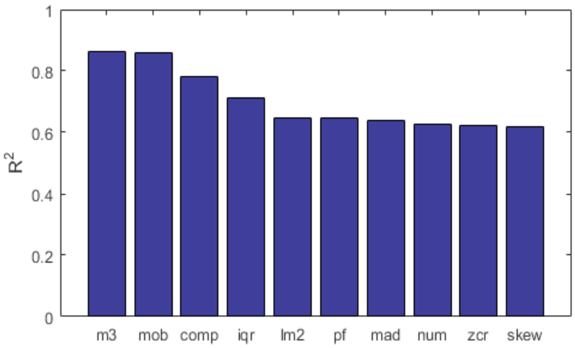

Fig. 2. Significant features ranked by coefficient of determination: 3rd moment (m3), Hjorth's mobility (mob), Hjort's complexity (comp), interquartile range (iqr), 2nd L-moment (lm2), peak frequency from DCT (pf), median absolute deviation (mad), number of ourliers (num), number of mean zero-crossings (zcr) and skewness(skew)

Table 3. Confusion matrices for each subject: keystroke class (predicted) vs. fatigue class (actual)

Subject	**1**			**2**			**3**			**4**		
	Morning keystroke	Afternoon keystroke	Evening keystroke	Morning keystroke	Afternoon keystroke	Evening keystroke	Morning keystroke	Afternoon keystroke	Evening keystroke	Morning keystroke	Afternoon keystroke	Evening keystroke
Morning fatigue	**99.63**	0	0	**93.91**	1.40	0.10	**99.78**	0	0	**98.75**	0	0
Afternoon fatigue	0	**89.90**	0	4.91	**97.79**	5.54	0	**99.89**	0.00	0	**99.45**	0
Evening fatigue	0	0	**99.02**	0	0	**99.69**	0	0.11	**99.52**	0	0.28	**100**

Table 4. Overall confusion matrix: keystroke class (predicted) vs. fatigue class (actual)

	Morning keystroke	Afternoon keystroke	Evening keystroke
Morning fatigue	**98.02**	0.35	0.03
Afternoon fatigue	1.23	**96.76**	1.39
Evening fatigue	0	0.10	**99.56**

4. Conclusion

We proposed and analyzed a method for an objective evaluation of the level of human fatigue during the working day. We used the standard text entered three times during the course of the day. Then a set of statistical features was generated from the keystroke dynamics data, and feature ranking was performed using linear regression. Feature selection was performed based on the value of the coefficient of determination (R^2). The top-ranked features were used to train SVM classifiers for each of the consecutively pressed keys in the text. Finally, only classifiers with classification accuracy above threshold were selected to form a classification system. The classification results show an average accuracy of 98.11% accuracy in recognizing the correct state of daytime fatigue, while the confusion matrix showed that most of misclassifications were between the neighboring (morning/afternoon or afternoon/evening) states of fatigue.

Achieved results are important for assisted living environments (ALE) and, especially, for smart offices, where a keystroke test can be devised using the method proposed in this paper and an appropriate recommendation for an office worker can be issued based on his/her state of daytime fatigue. Limitations of the study are a low number of tested subjects, and difficulty to control the subjective factors of fatigue, which are independent of daytime.

Future work will involve the collection and analysis of data from a larger number of subjects, as well as selection and analysis of different kinds of text for fatigue recognition.

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