Perspectives of subjects’ psychophysiological state identification using dynamic biometric features

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Abstract. The hypothesis on drivers psychophysiological state (PPS) identification before and during driving by dynamic biometric features is analyzed. An experimental evaluation of the reliability of three psychophysiological states identification (normal, drowsiness, alcohol intoxication) in the space of handwritten-signature and voice features was provided.

1. Introduction
Today, with a high level of control processes automation, there is an increase in errors committed by humans. The problem of the "human factor" is especially evident in the field of transport management. According to the data provided by the WHO (World Health Organization [1]), more than 1.25 million people die each year as a result of an accident, between 20 and 50 million people are injured. Among the causes of accidents are excess speed, driving in a state of intoxication or under the influence of psychoactive drugs, distraction, vehicle technical defects. The WHO also reports that almost 90% of accidents on the roads of Europe can refer to the error under influence of "human factor". According to the statistics of the US Department of Transportation, in the United States every day almost 29 people die in alcohol-impaired vehicle crashes. The financial damage in this case is estimated at 44 billion dollars per year [2]. The share of alcohol-related fatalities varies between 5% and 35% for different countries, with a weighted average of 21.8% [3]. The above statistics show that effective methods are needed to eliminate this problem. The present work is devoted to the analysis of perspectives of development and use of the driver’s psychophysiological state recognition system while driving a vehicle using dynamic biometric features.

2. Briefly on shortcomings of existing solutions on driver’s state monitoring
To date, many governments have used different strategies to solve the problem of a road accident before they occur: mass media campaigns, specialized school programs, organization of sobriety checkpoints, and the introduction of drunk driving laws - the level of permissible blood alcohol concentration (BAC).

Concerning the last one, it can be noted that in 47% of countries the BAC level is less or equal to 0.05 g/dl, for a number of countries (19%) this level is below 0.02 g/dl, and such restrictions are introduced currently only in 134 countries. There is a considerable amount of works and even...
industrial model that to some extent solve the problem of alcohol intoxication identification. For example, the ignition interlocks installed in cars measure alcohol on the drivers breath. It keeps the car from starting if the driver has a BAC above a certain level, usually 0.02. However, their use is limited and applied for people convicted of drunk driving and are highly effective at preventing repeat offenses. The most famous solutions include the Attention Assist system, installed on Mercedes-Benz vehicles from 2011. On the signals of the sensors of steering wheel rotation, engine control, interaction with the braking system, traffic stability, etc. an individual driver’s model of the trip (template) is formed. If the computer notices significant deviations of the model parameters during the next driver’s trip on the vehicle, a decision is made to interrupt the further movement. In [4], the drawbacks of the described system are indicated: complexity, which excludes its use in most cars produced, cases of making false decisions are possible.

However, not only alcohol intoxication is the main cause of an accident. In 10-20% of cases, an accident is associated with driver fatigue (with "fatigue" the term "drowsiness" is used). A person driving a car for more than 17 hours awake is also at risk of crashing, as being at 0.05 BAC. Such a risk arises from a combination of several factors: biological, lifestyle, work, etc. [5]. The systems for determining fatigue, depending on the method of obtaining the identifying features/parameters, are divided into two categories: invasive and non-invasive. The first ones include systems based on the analysis of ECG [6] and EEG [7]. Non-invasive systems acquire information about drivers state and vehicle without contact with driver, so the monitoring process will not interfere with the driver. Received data can better reflect real driver behavior and real-time status. Among the identifying parameters in such systems could be determined the following: 1) the frequency of blinking (in particular, the period/ percentage of time when the eyelid is raised/closed) [8]; 2) the characteristics of the steering [9] (angles of rotation); 3) the movement of mouth [10] and other parts of the face for the analysis of facial expressions, on the basis of which the conclusion is made, including drivers fatigue level [11]. Unfortunately, most research in this direction is carried out in the driving simulator, and their effectiveness under real conditions remains unproven. For example, on a real road, a stochastic displacement due to uneven road coverage will impose additional noise on driving characteristics and increase state detection error. When using video cameras to control the eyelid-moving activity or drivers facial expressions, the quality of the images obtained is sufficiently sensitive to lighting and other external factors. When using EEG features (also EDR or ECG), there is a need to use expensive specialized contact equipment, making it difficult for driver to control the vehicle.

There are no encouraging studies and results confirming the applicability, for example, of the alcohol intoxication system for assessing fatigue and same on the contrary. In addition, there are other features (dynamic biometric features) that have proved their applicability in problems of recognition the subjects and their state, exceeding reliability of mentioned above, including by combining several groups of features obtained from different, but economically and technically accessible equipment. These characteristics include voice and handwriting dynamics features.

The specified characteristics of the subject refer to subconscious movements of human [12]. The authors of [13] found that considering the PPS when creating a users template and in the process of identifying the user by handwriting dynamics, the number of identification errors is reduced by an average of 28%, which indicates the existence of information on PPS hidden in the features of subconscious movements. Later in work [14], it was shown the principal possibility of identifying the PPS using signature parameters that were used earlier to recognize the signers. In [15] the authors investigated the possibility of identifying alcohol intoxication through a handwritten signature and reached a maximum probability of correct decisions of 95% after 35 min from alcohol consumption. It is also known that voice characteristics reflect human emotions [16]. Studies show that the percentage of errors in recognizing some emotions by voice reaches 5%. Attempts are made to determine the stress state of a person by voice [17]. The presented data point to the possibility of creating a system for recognizing an inadequate
human condition based on dynamic biometric features.

3. Biometric features

The basis for this work is a hypothesis: dynamic biometric features (handwriting dynamics and voice features) characterizing the subject also characterize his/her PPS. This hypothesis is confirmed in [14, 18]. The issue of drivers identification is not considered in this paper. Handwritten signature consists of functions of the pen tip position (coordinates) on the tablet \(x(t), y(t)\) and pen tip pressure on the tablet \(p(t)\), where \(t\) is the time in discrete form. As the biometric features in the present study, the following parameters characterizing signers and proposed in [19] were tested:

1. Distances between some signature points, normalized by length of the signature, in three-dimensional space (the third dimension is the pressure \(p(t)\)). Points are selected evenly with a certain step.
2. Some characteristics of the static image of the signature: the ratio of signature length to its width, the center of the signature, the angle of signature inclination, the angle of inclination between the centers of the signatures halves.
3. The energy-normalized amplitudes of the first 16 (most low-frequency) harmonics of the velocity function of the pen on the tablet \(v_{xy}(t)\) and the pen pressure function on the tablet \(p(t)\). The first 16 harmonics contain more than 95% of the energy of the signals \(v_{xy}(t)\) and \(p(t)\), which is typical for all subjects.
4. Correlation coefficients between all pairs of signature functions \(x(t), y(t), p(t)\) and their derivatives \(x'(t), y'(t), p'(t)\).
5. Some values of the functions \(x(t), y(t)\) and \(p(t)\), as well as the speed of the pen on the tablet \(v_{xy}(t)\). Points are selected evenly with a certain step.

The process of voices features extraction is based on the approach from [20]. For digital recording of the speech signal, the sampling parameters were 8 Hz and the number of quantization levels was \(2^{16}\). The use of the parameters makes it possible to obtain sound of good quality, but which does not provide unnecessary information. After receiving the signal, it is processed, after that an array of statistical characteristics of this signal is provided, for which histograms of relative frequencies are built, the column values of which are used as identifying features. Such features include:

1. Characteristics of the integral frequency of speech signal fragments (zero formant).
2. Characteristics of the integral frequency of the transitions of the speech signal through the energy envelope coefficients.
3. Frequency characteristics of positive and negative pressure level.
4. Correlation coefficients of the characteristics of the signal integral frequency and the transitions of the speech signal through the energy envelope.
5. Correlation coefficients of the frequency characteristics of the positive and negative pressure levels.

The resulting discrete signal \(Y\) is divided into intervals \(Y_i\) to 0.025 sec. With the shift \(\tau_{PF} = 0.0125\) sec. The value is 0.025 sec. is explained by the frequency of the pitch (PF) (min (PF) = 80 Hz) due to the vibration frequency of the vocal cords. The frequency - \(\nu_{PF}\) is the smallest significant frequency of the spectrum of the voice signal. The length of the interval is chosen to be twice as long as the period of the smallest frequency min (PF), so that a minimum interval of 1 PF period is placed in a separate interval. The length of the shift is equal to the length of the period min (PF) for more accurate localization in time of changes in the processed signal. For each interval \(i\), the number of transitions of the signal Yi through the zero is calculated.
A correction should be made for the case of the appearance of an active outgoing air pressure deflecting the microphone membrane from a quiet state and subtracting from their sample \( Y^\text{mean} = \sum_{i=0}^{N} Y_i \) value, where \( N = \tau_{RF,D} \) if \( Y^\text{mean} \) is greater than zero, or add \( Y^\text{mean} \) is less than zero. Thus, we get a centered signal - \( Y^0 \). Each interval \( Y_i \) is associated with the number of transitions of the signal \( Y^0 \) through zero - \( T(0,Y_i) \), calculated by the formula:

\[
T(0,Y_i) = \sum_{x=0}^{N-1} (y(x) = \begin{cases} 
1, & Y^0_i(x) \cdot Y^0_i(x+1) < 0 \\
0, & Y^0_i(x) \cdot Y^0_i(x+1) \geq 0
\end{cases}
\]

where \( N = \tau_{RF,D} \). The intervals \( Y_i \) are grouped into arrays of intervals belonging to the interval \( Z_i \) in \( z \) sec., in accordance with which a histogram of the relative frequencies \( G(T(0,Y_i)) \) of the values \( T(0,Y_i) \) of the intervals \( Y_i \) belonging to \( Z_i \) is plotted. The length of the interval \( Z_i - |Z_i| = z \) sec. is chosen due to the number of intervals \( Y_i \), the increment of the number of which to \( Y_i+1 \) gives a change in the histogram \( G(T(0,Y_i)) \) less than 0.03. The set of histogram column values \( G(T(0,Y_i)) \) and will be the signs of the j-th realization of the k-th voiceprint - \( S(G(T(0,Y_i))) \).

Within a few days, a full-scale experiment was conducted to collect a database of the features, involving 60 subjects being in following states (confirmation of the "transition" to the corresponding PPS was done on Holter’s monitor "Cardiotechnics-04", since it is the cardiovascular system that is one of the main markers for assessing the current psychophysiological state or changing this state):

1. Adequate (or normal) state, in which the subject was not exposed to any influences. The experiment was conducted at the beginning of the working day.

2. Drowsiness. To simulate this state, participants took natural herbal sedative remedies, which include motherwort, mint, valerian, and listened to soothing music.

3. Alcohol intoxication. The subject took alcohol, the dosage was calculated according to the Widmark formula. The weight of the drink corresponded to the amount of alcohol in the blood, for which the concentration was more than 0.5. This level exceeds the permissible level of alcohol concentration for drivers of vehicles in Russia and other countries and leads to statistically significant changes in the parameters of the cardiovascular system.

4. Evaluation of the effectiveness of the driver’s PPS identification based on the Bayesian hypothesis formula

Recognizing the PPS, it is more convenient to use the Bayesian strategy, since in this case, it is not necessary to expose a number of parameters characteristic, for example, for the neural network approach: the number of inputs of neurons, the Hamming distance between the generated code and the correct one. The optimal values of these parameters should be determined separately for each subject based on a computational experiment, which in practice is problematic to implement. Integral estimates of the proximity of the sample presented to the PPS standards during the identification stage can be obtained by repeatedly applying the Bayesian rule [21] in a number of steps equal to the number of features. Each template of subjects PPS is associated with a hypothesis. At each step, the a posteriori probabilities of the hypotheses are calculated using formula (2), considering the value of one of the feature, while the a priori probability of the hypothesis assumes its a posteriori probability calculated at the previous step. In the first step, all hypotheses are equally probable

\[
P(H_i | A_{j-1}) = \frac{P(H_i | A_{j-1})P(A_j | H_i)}{\sum_{i=1}^{n} P(H_i | A_{j-1})P(A_j | H_i)}
\]
where $P(H_i|A_j)$ is the posterior probability of the i-th hypothesis, calculated at the j-th step at entrance of the j feature, $P(A_j|H_i)$ is the conditional probability of the i-th hypothesis at the j-th step (equal to the probability density attribute $A_j$, obtained from the parameters of the i-th template).

A computational experiment was performed in which biometric data of 60 subjects received in the normal (adequate) state, as well as in drowsiness (after using sleeping pills) and light alcohol intoxication (blood alcohol concentration from 0.5 to 1) were fed to the entrance method of consistent application of the Bayesian hypothesis formula. Identification of PPS was carried out separately for each subject according to a vector of features values, obtained from one sample of biometric data, which means: 1 signature, 8-12 seconds of continuous speech of arbitrary content. For the training of the network, 20 samples of the signature and the voice of each person participating in the experiment were used. For each examinee, the number of errors was calculated. The error was the situation when the wrong hypothesis had the maximum a posteriori probability at the last step in making Bayes strategy decisions. The error probability for each subject was calculated as the ratio of the number of errors in the last step of the Bayesian strategy to the total number of experiments. Next, the mean $\bar{M}_e$ of error probabilities for all subjects was determined, as well as the root-mean-square deviation $S_e$ of these probabilities. The results are shown in Figure 1.

Figure 1. Results on drivers’ PPS identification.

5. Conclusion
In the present study, the hypothesis about the possibility of recognition of PPS by dynamic biometric features was tested. The results on identification of 3 psychophysiological states (normal, intoxicated, drowsiness) of vehicle drivers on the basis of real biometric data of 60 subjects with a confidence of 0.99 were obtained. The number of PPS identification errors, depending on the characteristics used for different subjects, was: from 0.5% to 29.7%, the average error was 14.5%. Thus, this hypothesis is confirmed, but it is not performed for all subjects. It is necessary to carry out additional studies to determine the dependence of the error probability on such “personal factors” as the type of human temperament, gender, etc. Another important point that limits the use of this method in practice: the need to create a template for each recognizable state of a person. In order to avoid this limitation, using these biometric features, it is required to develop a model that allows to go from the template of the normal state of subject to the template of the changed state. This model should be created.
considering "personal factors". The question of the possibility of developing such a model is still open and waiting for special studies.

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