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On the person and psychophysiological state identification using electroencephalogram parameters

A A Nigrey[1], A E Sulavko[2], A E Samotuga[2] and D P Inivatov[2]
[1]Omsk State Transport University, Omsk, Russia
[2]Omsk State Technical University, 11 Mira ave., Omsk, 644050, Russia

Abstract. The development of methods and technologies for the automatic determination of the psychophysiological state (PPS) of a person is an actual scientific and technical task. Early detection of the fact that the subject is in a sleepy state or in a state of intoxication at the workplace will help to avoid accidents, harm to life, health, and causing losses. In this work the EEG data of 30 subjects in normal, sleepy conditions and a state of mild intoxication were collected. As a result of the spectral and correlation analysis of the EEG data features were selected. An amount of information about the difference of the investigated states contained in the features was determined. A computational experiment on the recognition of human state according to EEG data based on the "naive" Bayes classifier was conducted. The following error level was achieved: 10.9% when recognizing the state of “norm” and “intoxication”; 0.2% when recognizing the status of "normal" and "falling asleep."

1. Introduction

The development of methods and technologies for the automatic determination of the psychophysiological state (PPS) of a person (operator in an organization, train drivers, drivers, etc.) is a fairly obvious scientific and technical task. Early detection of the fact that the subject is in a sleepy state or in a state of intoxication (including alcohol) at the workplace will help to avoid accidents, harm to life, health, and causing losses. These PPS are characterized by a destabilizing effect on performance, distracted attention, a decrease in reaction, and other negative effects.

The main reason for the mistakes of operators at production facilities is associated with workers overwork and the use of alcohol [1]. It is about 45% of accidents at nuclear power plants and more than 60% of accidents at hazardous production facilities are the result of employee errors caused by a change in the state of the subject [2]. The number of incidents resulting from the human factor is reduced by selective or complete monitoring of personnel with the monitoring of PPS at the workplace.

Currently, neurointerfaces - devices that record and interpret the electrical activity of the brain (electroencephalogram, hereinafter referred to as EEG) are actively developed and used. They are used to control devices and prostheses, biometric identification and authentication [3], control the functional state of a person and so on. EEG analysis allows us to identify parameters that are associated with certain brain conditions and also correlate with PPS.

2. Problem statement

The purpose of the present work is to evaluate the informativeness of EEG parameters from the point of view of the possibility of identifying on their basis the SFC of the subject. PPS - a set of human properties that reflect the biological aspects of the manifestation of adaptation to changing environmental conditions and evaluated on the basis of the measurement of psychophysiological information [4]. In this paper the alcohol “falling asleep” states and how they differ from calm (normal) state are being studied. Under normal condition is understood that before the start of the experiment the subject was not exposed to any physical or mental stress, was not took drugs affecting the PPS, and his neurological status was assessed as normal (mood, level of attention, quickness and adequacy of responses to questions, the ability to maintain balance were normal).

3. Theory

It is customary to distinguish rhythms that differ in frequency, duration, amplitude and shape of the vibrations when analyzing electrical vibrations recorded by an electroencephalograph. Table 1 presents the known EEG rhythms and describes the features of their manifestation when the state of the subjects is changed.

Table 1. Basic EEG rhythms and their attitude to the state of subjects.

Name	Frequency and amplitude	Description, localization and attitude to psychophysiological states
Alpha - wave (α-wave)	8 - 14 Hz, 30 - 70 μV	It is recorded in different parts of the cerebral cortex but is most clearly expressed in the occipital and parietal regions. Alpha wave has higher amplitude on the dominant side of the brain. The maximum amplitude is observed in a calm state, with eyes closed in a darkened room. It disappears or weakens with an increase in visual or mental activity [5]. The amplitude increases with the state changing to sleep or with alcohol intoxication (the latter is observed in the band of slow alpha frequencies of the frontal and central parts). The amplitude decreases during stress [6]. The changing normal state to sleepy state is characterized by an increase in amplitude [7].
Beta - wave (β- wave)	13 - 35 Hz, 5 - 30 μV (low frequency: 13-25 Hz, high frequency: 25-35 Hz)	It is well expressed in the central and frontal regions [8]. The amplitude increases when increasing attention, with mental stress, emotional arousal. An increase in the amplitude in the temporal lobes is recorded under stress [9]. In sleepy state a power decreases in the occipital and parietal regions of the beta range [9]. Alcohol affects the power of the high-frequency beta band.
Gamma - wave (γ- wave)	30 - 170 Hz, < 10 μV	It is registered in the frontal, temporal and parietal zones. Observed during the solving of tasks requiring maximum concentration of attention.
Delta - wave (δ-wave)	1 - 4 Hz, > 100 μV	It is observed with low brain activity, deep natural or narcotic sleep, as well as with coma. The predomination of delta waves is characteristic for the 3rd and 4th stages of the slow sleep phase.
Theta - wave (θ- wave)	4 – 8 Hz, 20-60 μV	Theta – wave is registered in the frontal, occipital regions and the hippocampus. It is observed with low brain activity, sleepy state [10], during the REM phase. The increase in amplitude in the first stage of slow sleep. In the frontal lobes a decrease in amplitude is observed during stress and mental stress [11]. Alcohol affects the power of the theta band.
Kappa - wave (κ- wave)	8-12 Hz, 20-30 μV	Kappa - wave is registered in frontal and temporal regions. At the present moment, there is no consensus on the causes of the origin of this wave.
Lambda - wave (λ- wave)	4 до 5 Hz	It is expressed in the occipital regions. Lambda - wave is observed with open eyes when a person's eyes make search movements. They disappear when the eyes are fixed at a certain point.
Tau - wave (τ-wave)	8 до 13 Hz	Expressed in the temporal regions. The tau - wave responds by blocking sound stimuli.
Mu - wave (μ-wave, arcuate, pectinate wave)	7 — 13 Hz	Most clearly expressed in the central regions. It is observed during mental workload and mental stress. It disappears when performing any movements, as well as the mental representation of movement, in a state of readiness for movement or tactile stimulation [12].
Sigma - wave (σ- wave, sleep spindles)	10—14 Hz, < 50 μV	It is recorded throughout the cerebral cortex, but is most clearly expressed in the frontal and central regions [11]. A characteristic feature of the sigma wave is the increase in amplitude at the beginning of the sigma rhythm flash and its decrease at the end of the flash. It is observed in the first and second stages of slow sleep and during the transition to

fast sleep. It disappears in the developed phase of REM sleep.

3.1 State of falling asleep

Sleep is divided into phases of slow (orthodox, NREM) and fast (paradoxical, REM) sleep, 4 stages of slow sleep are also distinguished. According to the adopted method the expert manually analyzes the EEG recordings, divided into segments (30 seconds each), constructs a graphic distribution of the stages of sleep (hypnograms) where each area is assigned to a particular stage of sleep.

The state of falling asleep, decrease in brain activity occurs immediately before sleep. This state is characterized by a decrease in the level of consciousness, yawning, a decrease in the sensitivity of sensory systems, and a decrease in heart rate (HR). The interest at continuous monitoring of EEG employees whose work is associated with danger and high concentration lies precisely in in recognizing the state of sleepiness and the first stage of slow sleep.

It is known that the spectral power density of alpha and theta waves correlates with the state changing from wakefulness to sleep [10]. In this transition the amplitude of the alpha rhythm also increases [7]. Analysis of the power spectrum of EEG signals showed a higher change in power in the occipital and parietal regions in the alpha and beta ranges [9].

3.2 State of alcohol intoxication

In the laboratory special instruments are used to evaluate the blood alcohol content as well as the Widmark formula or its modification [13]:

$$M=\frac{p\cdot 0,7\cdot m}{0,8\cdot 0,9\cdot g}$$

, where p – is an achieved level of intoxication in ppm, 0,7 – the proportion of water in the male organism, m – body weight, 0,8 – alcohol density, 0,9 – the proportion of alcohol absorbed into the blood, g – alcohol strength. This formula gives an approximate estimate of the alcohol content in the blood, but can be used to accurately assess the stage of subject intoxication. The result of the developing method for recognizing the stage of intoxication by EEG parameters should be compared with the result of assessing the stage of intoxication using the modified Widmark formula.

With ethanol intoxication a pronounced increase in the EEG alpha activity is noted. Alcohol consumption also affects the power of theta (4–8 Hz) and high-frequency beta (20–35 Hz) frequency ranges. On the other hand, it was noted that subjects who are in a passive state during EEG recording demonstrated a decrease in the power of EEG signals received from the frontal lobe, with significant alcohol consumption [14].

4. Experimental results

In this work, the EEG data of 30 subjects who were in the following PPS were collected: normal, after drinking (stage of light intoxication), falling asleep. In all conditions EEG data recording was carried out under standard conditions (the subject was sitting on a chair with closed eyes). The necessary alcohol doses in order to bring the subject into a state of intoxication were calculated according to the modified Widmark formula (focusing on a quantity of 0.7 ‰, which corresponds to the second stage in the classification in accordance with the classification given in Federal Aviation Regulation (CFR) 91.17). To introduce the subjects to drowsiness they were asked to take 2 motherwort pills of 200 mg each after which the subjects were sitting in a chair for 20 minutes in a quiet and dark room. EEG recordings of 5-6 minutes duration were made for each state of the subject.

While taking the EEG data the arrangement of the electrodes was as shown in figure 1 in accordance with the standard 10-20 scheme (the figure also shows the attachment points for the extended 10-10 scheme).

All EEG records were divided into intervals of 2.5 seconds, after which each interval was converted into a vector of values of the following features (a similar set of features were used in the solution of the biometric authentication by EEG, however in this work, the composition of the features was adjusted taking into account the specifics of the problem):

a) integral amplitude spectra of the EEG signals were received via Short-Time Furrier Transform (STFT) with finding the mean values of each harmonic for all windows. The width of the STFT window was 512, step was 32, only the average amplitudes of harmonics with numbers from 8 till 71 of each signal were used as features (11 signals as in figure 2, 64 harmonics from every signal, a total of 704 features). Indicated harmonics fully cover the frequency range [4; 35.5] Hz that relevant alpha, beta, theta, sigma wave. According to the data of an analytical study of the literature other wave do not contain information about the states of falling asleep and intoxication (Table 1);

b) matrix of pairwise correlation coefficients between EEG signals and their derivatives (11 signals, 11 derivatives, a total of 231 features).

As a result of processing the EEG data for each state, from 3600 to 4000 examples of feature vectors are obtained. These data were divided by the following images: 1,500 random examples of 2.5 second EEG images were used as a training sample, the other were used as a test sample.

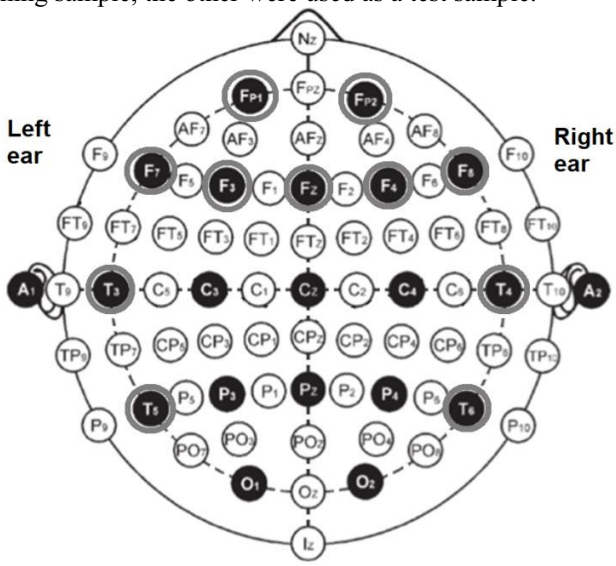

Figure 1. Electrode location (the standard positions of the 10-20 system are marked in black, the additional positions for the 10-10 system are marked in white, the electrodes used in the experiment are marked with gray circles).

Each feature can be evaluated in terms of its informativeness. The informativeness of any feature can differ significantly for each class of images. The informativeness of a features for a certain class of images is understood as the amount of personal information from the area of intersection of the probability density functions, that characterizes the feature values for some classes of images (figure 2). Empirical probability densities were constructed for characteristics of category (a), probability density was determined for characteristics of category (b) based on the lognormal distribution hypothesis (which was established on the basis of the Pearson chi-square method). The distribution parameters of the corresponding features for each class were calculated on based on the training sample.

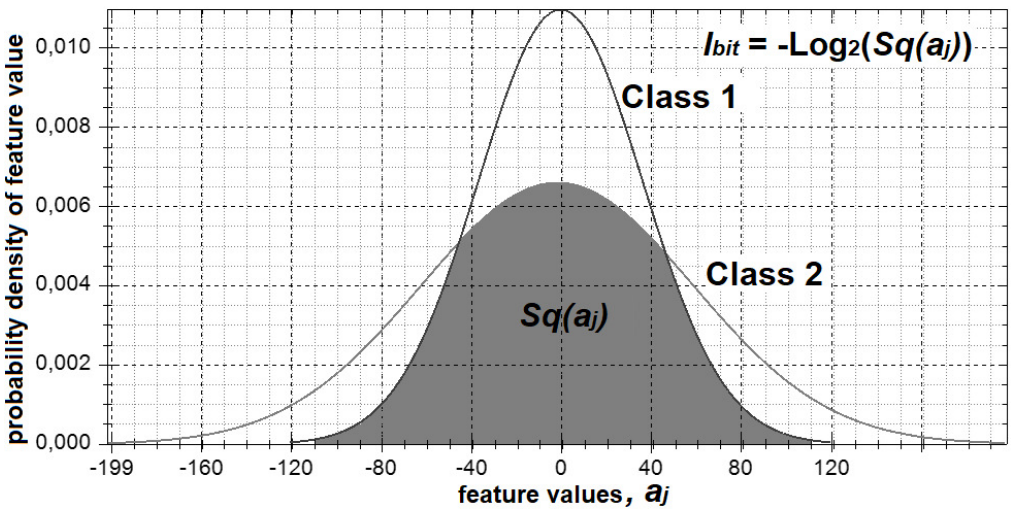

Figure 2. Determination of the amount of feature data for two classes of images

The indicated features were evaluated in terms of the amount of informativeness about the differences for the states of “normal” and “intoxication” (figure 3), as well as “normal” and “falling asleep” (figure 4) in them. As you can see, for each pair of states the information content of the features is different some features are uninformative for recognizing "intoxication", but informative for recognizing "falling asleep", others, on the contrary some features are suitable for both tasks. Therefore, it was decided to build two independent classifiers for recognizing the corresponding images of pairs of states. The naive Bayesian classifier (1) was used to recognize the EEG images, so that in each series of experiments, two hypotheses were determined (“norm” and “intoxication”, “norm” and “falling asleep”). The experimental results shown in figures 5 and 6.

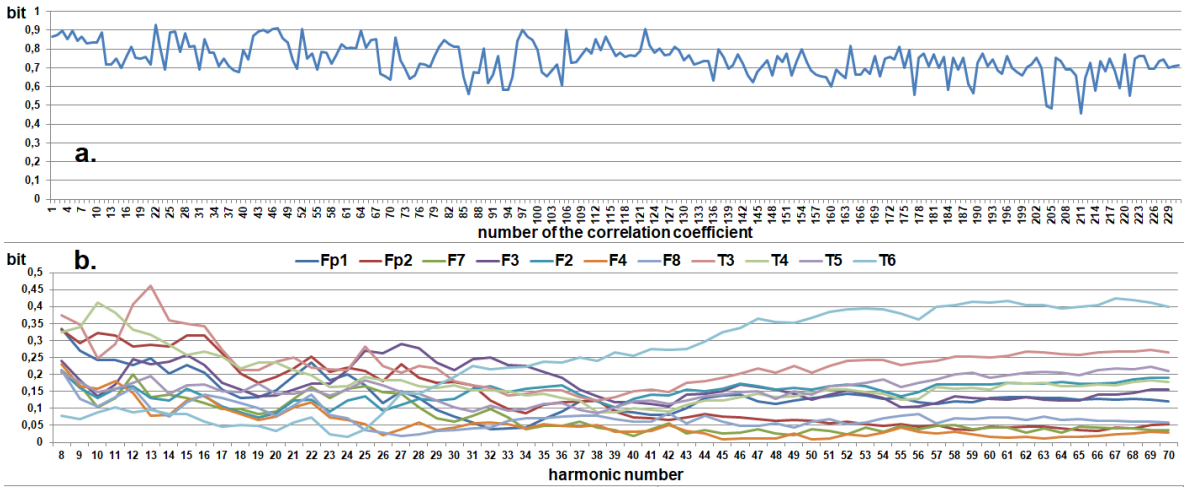

Figure 3. The informativeness of features of the corresponding categories (a, b) for the task of pattern recognition of “norm” and “intoxication” PPSs.

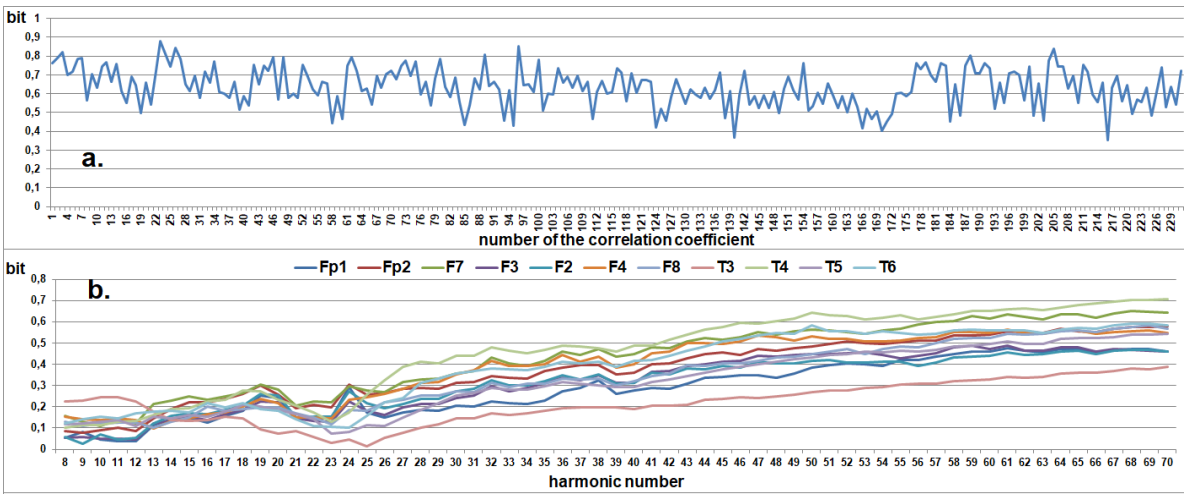

Figure 4. The informativeness of features of the corresponding categories (a, b) for the task of pattern recognition of “norm” and “falling asleep” PPSs.

$$P_h(\bar{a}) = \frac{0{,}5\prod_{j=1}^{n} p_h(a_j)}{\sum_{i=1}^{\Gamma}(0{,}5\prod_{j=1}^{n} p_i(a_j))} = \frac{\prod_{j=1}^{n} p_h(a_j)}{\sum_{i=1}^{\Gamma}\prod_{j=1}^{n} p_i(a_j)}, \quad (1)$$

where $P_h(\bar{a})$ – posterior probability of the h-th hypothesis, depending on the j-th feature, $p_h(a_j)$ – conditional probability of the$h$-th hypothesis (in this case, it is assumed to be equal to the probability density of the transmitted value of the j- th feature, G is the number of hypotheses, $G = 2$). Since an equal number will be

obtained in the denominator for each hypothesis, it is permissible to decide in favor of a particular hypothesis based on the maximum $P^*_h(\bar{a})$ (2):

$$P^*_h(\bar{a}) = \prod_{j=1}^{n} p_h(a_j), \tag{2}$$

EEG data were recognized in batch mode. In each of several series of experiments that were simulated only those feature were used which informativeness was not lower than a certain level.

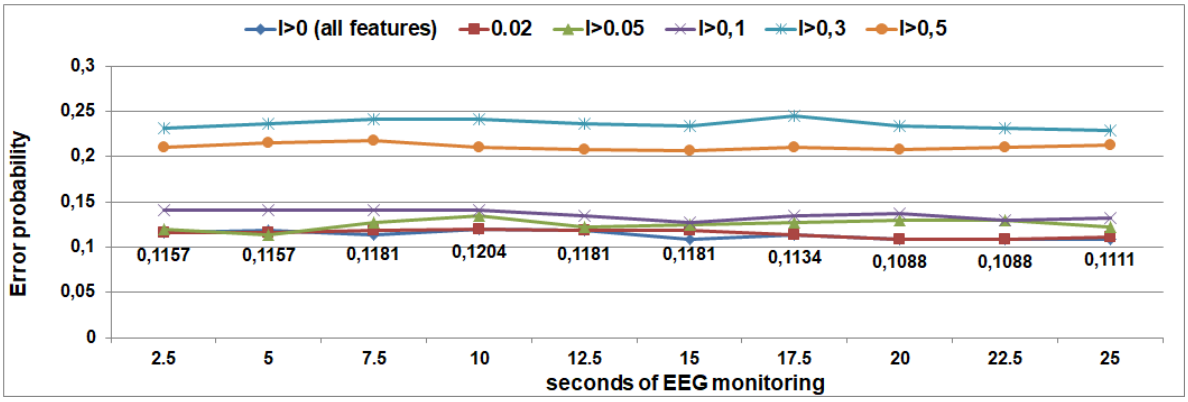

Figure 5. The results of recognition of the "normal" and "intoxication" states by EEG depending on the duration of monitoring and the minimum level of informativeness of features.

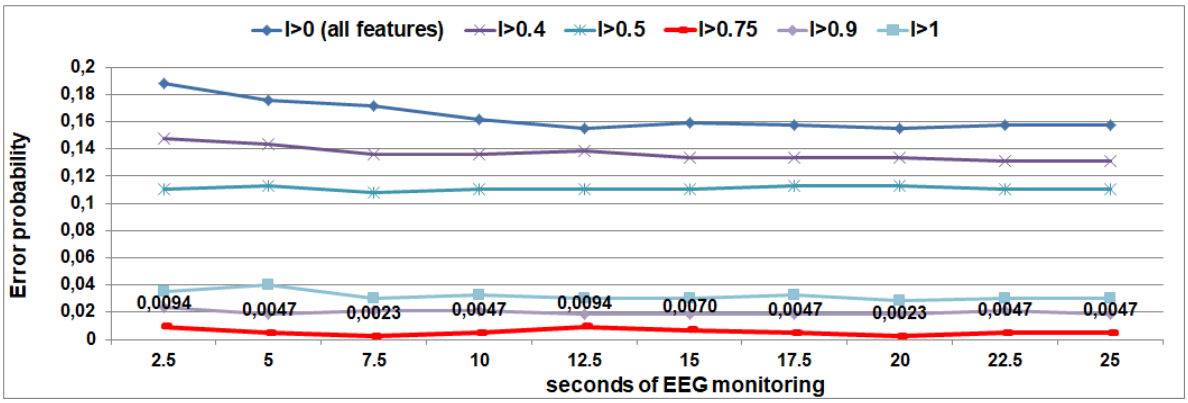

Figure 6. The results of recognition of the "normal" and "falling asleep" states by EEG depending on the duration of monitoring and the minimum level of informativeness of features.

5. The discussion of the results

Table 2 summarizes the results of studies on the recognition of the stages of sleep and sleepiness. The accuracy of the above methods is usually estimated by comparing the result of the method with the conclusion of an expert. Table 3 shows the results of the recognition of alcohol intoxication. The result obtained in this work as can be seen corresponds to the world level and even exceeds the estimates obtained earlier in the accuracy of the decisions.

Table 2. Automatic research results by recognition of stages of sleep by EEG.

First author / year	Mounting location and number of electrodes / EEG database	Number of subjects	Classifier	Accuracy
Ogino (2018) [10]	Fp1, A1	29	SVM	72,7%
Schmitz A. (2011) [15]	Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5, T6, Fz, Cz, Pz	10	Neural network	83,3%
Rhudy J.L. (2014) [16]	P3, P4, O1, O2	9	Student's t-test	-
Zunhammer M. (2017) [17]	32 electrodes	12	SVM, Neural network ,	93-97%

			random forest and k-NN	
Basar (2019) [18]	32 electrodes	6	SVM, k-NN	95%
Antipov O.I. (2012) [19]			Hurst Normalized Span Method	52,2%
Rajendra Acharya (2010) [20]			Analysis of the higher order spectra	88,7 %

Table 3. Results of research on recognition of alcohol intoxication by EEG.

First author / year	Volume of taken alcohol / EEG database	Mounting location of detectors	Decision making algorithm / Result
Tzimourta (2018) [21]	3 servings of 50 ml of 40% alcohol	AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8, O1, O2	Grammatical Evolution / 89,95% 4 classes of states (before taking alcohol and 3 degrees of intoxication). The signal is segmented in periods of 1 s. with an overlap of 0.5 s., from each epoch of the signal, 11 significant features are distinguished
Karungaru (2012) [22]	The first subject consumed three cans of beer of 250 ml (750 ml), and the other two consumed six cans of beer of 250 ml (1500 ml) each.	detector FP1	The average accuracy of identifying 2 classes (sober and after drinking) using the neural network was 92.3%. The average accuracy for the identification problem of 7 classes (sober and 6 levels of intoxication) did not exceed 59.2%.
Sarraf (2017) [23]	50 sober subjects and 50 subjects after taking alcohol (40 for training and 10 for testing). EEG base of State University of New York was used.	64 electrodes	Neural network: 300 epochs of study - 80% accuracy 600 epochs of study - 87% accuracy 1200 epochs of study - 95% accuracy

For each time interval of 2.5 seconds, a separate feature vector was calculated, which was used to recalculate $P^*_h(\bar{a})$ posterior probabilities by formula (2). The probability of errors slightly depends on the time of monitoring as it can be seen (Figs. 5 and 6). From the presented data it can be seen that for identification of the state of "falling asleep" is better to use features with informativeness of $I_{bit} > 0.75$ and for identifying the SFC "intoxication" all features can be used.

6. Conclusion

It can be concluded according to the results of the analytical study of the literature that in order to recognize the states of intoxication and drowsiness, it is necessary to analyze the frequency range from 4 to 35 Hz. In this work the EEG data of 30 subjects who were in the normal, stage of light intoxication PPS falling asleep were collected. As a result of the spectral and correlation analysis of the EEG data, features were identified. The amount of information which is contained in the features on the difference between the states under investigation is determined. A computational experiment was carried out to recognize a person's state according to EEG data based on the "native" Bayes classifier. The following error level has been achieved: 10.9% when recognizing the "normal" and "intoxication" states; 0.2% when recognizing the "normal" and "falling asleep" states. Further research to solve the problems will be associated with the use of methods of "deep" training convolutional neural networks.

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