Development of a Method for Identifying the Functional State of a Person When Solving Cognitive Tasks According to the Data of the Brain Microwave Radiation

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Keywords: Microwave Radiation, Radio Brightness Temperature, Machine Learning, Cognitive Load.

Abstract: The article described a technique for conducting experimental studies using passive non-invasive thermography in radio bands to study the effect of changes in the psychophysiological state on a person's radio-brightness temperature. The registration of the radio-brightness temperature signals was carried by contact microwave radiometer, which ensures the reception of brain microwave radiation in the frequency range (3.4-4.2) GHz. A data processing algorithm for detecting stable characteristics of patterns in changes in brightness temperature fluctuations, based on continuous wavelet transform, was proposed. A total of 18 parameters were used to estimate the brightness temperature fluctuations. In this study, two machine learning methods were tested that allow the selection of the most significant features: logistic regression using L1-regularization and the decision tree method. The accuracy of determining the functional state on the training data reached 90%. It was shown that the parameter of microwave radiation fluctuations – the median value of the amplitude of fluctuations with fluctuation periods from 40 to 80 s, makes it possible to divide the initial data sample into two subgroups in which the response to cognitive load is significantly different.

1 INTRODUCTION

At each moment of time, a person is in a specific psychophysiological state. This can be a state of sleep or wakefulness, sensory deprivation or information overload, tension or monotony, adaptation or stress. Each of these psychophysiological states is characterized by a specific form of the background activity of the nerve centers, and, accordingly, a special systemic response of the body to external stimuli in the form of changes in basic physiological vital parameters such as heart rate, respiratory rate, temperature and blood pressure. The time for the formation of these responses and, accordingly, changes in the psychophysiological state can be from several seconds to tens of minutes.

The urgency of the problem of analyzing and assessing the psychophysiological state of a person, as a factor determining his behavior and capabilities, is determined by the rapid spread of cognitive disorders among the working-age population of developed countries (Tol et al., 2014). Existing methods for assessing the psychophysiological state are formed on the basis of clinical observations and are, in fact, subjective, since they use rather subjective questionnaires for patients, for example, the depression anxiety stress scale (DASS), as well as clinical interviews, for example, the Hamilton psychometric scale (HDRS-21) for assessing the level of depression. Known instrumental methods in this task analyze changes in the physical characteristics of video images or biomedical signals formed on human skin (Ahn et al., 2019). To study deep processes in human organs and tissues, measurements of own physical fields are used, including microwave radiometers and passive acoustic thermometers.

The aim of this study is to develop a method for identifying the functional state of a person in solving

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cognitive tasks based on the data of the brain's own electromagnetic radiation.

2 MATERIALS AND METHODS

2.1 Research Methodology

Original researches on registration of radio brightness temperature (RBT) on the basis of the Ural Federal University were carried out. The study involved a group of 40 relatively healthy subjects.

The cyclogram of registration of RBT consisted of the following cycles:

- 5 minutes – rest state;
- 5 minutes - cognitive load (verbal counting);
- 5 minutes - aftereffect.

Registration of RBT signals was carried out using a model of a contact microwave radiometer, which ensures the reception of the brain microwave radiation in the frequency range (3.4-4.2) GHz (Vesnin et al., 2019). The working frequency range was chosen in order to be able to receive information about RBT in the piazza and arachnoid meninges (V. S. Kublanov et al., 2020). During the research, the antenna unit of the radiometer was connected to the radiometric receiver using a flexible coaxial cable 20 cm long and was located in the center of the forehead. The radiometric receiver of the radiometer, which provides reception of the brain microwave radiation, had good thermal insulation from the subject's head.

To provide protection against interference, the antenna unit was shielded with a metallized fabric. The experiments were carried out with the lights off. There were no mobile phones in the experiment room.

2.2 Data Processing Methods

A python program was written to process signals. Continuous wavelet analysis was chosen as the main processing method. (Mallat, 2009). The main libraries used were the NumPy library for general math transforms, the PyWT library for numerically computing the continuous wavelet transform (Lee et al., 2019), and scikit-learn library for applying machine learning (ML) models(Pedregosa et al., 2011).

The Gaussian wavelet of the eighth order was used as the basic wavelet. For each signal, the spectral components of the RBT signals with fluctuation periods from 20 to 40 s, from 40 to 80 s, and from 80 to 140 s were calculated.

To evaluate the obtained spectral components of the signals, the following approach was used, separately for each study cycle and for each spectral component:

- Finding all zero crossing points (green points on Figure 1);
- Estimation for each consecutive pair of points half-period w and amplitude h;
- Estimation of the median value M, standard deviation STD and coefficient of variation CV for the set of values of w and h in the study cycle;

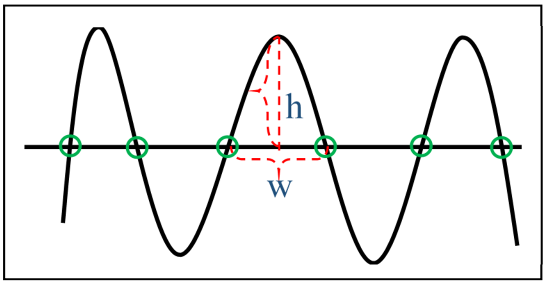


Figure 1: To the method for evaluating signal components.

Thus, for each time stage and for each frequency domain of interest, 6 estimates were obtained: **M w**, **STD w**, **CV w**, **M h**, **STD h**, **CV h**. A total of 18 parameters were used to estimate RBT fluctuations.

2.3 Visualization of the Multidimensional Parameter Space

A popular method for studying the multidimensional data is a method of t-SNE (Maaten & Hinton, 2008). This method has become widespread in the field of machine learning, because it allows one to generate seemingly convincing two-dimensional "maps" from data with hundreds or even thousands of parameters.

The idea behind this method is to take a set of points in a high-dimensional space and find an exact representation of those points in a lower-dimensional space, usually in a 2D plane. The algorithm is non-linear and adapts to the underlying data by performing different transformations in different regions.

A special feature of t-SNE is the configurable “perplexity” parameter. In fact, this parameter reflects how the new lower-dimensional representation balances the local and global features of the original data. The parameter is, in a sense, an assumption about the number of nearest neighbors of each point. Thus, the perplexity value has a complex effect on the resulting images. For small values of this parameter (1-10), the t-SNE method gives preference to the local features of the initial data, at large values (30-50) - the global features of the initial data.

It is worth remembering the stochastic nature of this method: the t-SNE algorithm does not always give the same result with successive runs. Therefore, it is recommended to repeat the run of the t-SNE algorithm several times at certain perplexity values in order to judge general patterns.

2.4 Machine Learning Methods

To solve the problem, an approach based on machine learning was used, which made it possible to form combinations of significant parameters of radio brightness temperature fluctuations to predict the functional state of subjects from the control group. Machine learning is considered in a simple concept

$$y = f(x)\,, \qquad (1)$$

where x is the original data; f is the function obtained using ML methods; y is the expected response. In this study, two ML methods were chosen: logistic regression (*LogR*) using L1-regularization and decision trees (*DT*), which allow the selection of the most significant features (V. Kublanov & Dolganov, 2019).

The *LogR* method (Meier et al., 2008) forms a probability model using a logistic function. L1 regularization or Lasso regularization is a linear model that estimates sparse coefficients. This approach is useful in some problems because of its tendency to give preference to solutions with fewer non-zero coefficients, effectively reducing the number of parameters on which a given solution depends. Mathematically, this model is based on adding a regularization term to the standard *LogR* approach - the modulus of the sum of the weight coefficients.

The *DT* method is also an approach that incorporates the search for the most significant parameters (Lior, 2014). At each *DT* node, there is a search among all available parameters for the one that most optimally divides the sample into classes. The selection takes place sequentially until all data is divided or further separation is less optimal than what was obtained in the previous step.

The cycle of studies is considered as y. The analyzed signal is expected to be related to brain activity and should look different for different study cycles. As the initial data x, 18 parameters of RBT fluctuations were considered.

The following were used as the metrics for evaluating the models of ML:

- *accuracy* - the proportion of responses correctly predicted by the ML model;
- *precision* - the proportion of responses predicted by the ML model are positive and, at the same time, are really positive;
- *recall* - the proportion of objects predicted by the ML model as a positive class out of all objects of a positive class;
- $F1$-*score* - harmonic mean of *precision* and *recall*.

To reduce the effect of overfitting, a 5-fold cross-validation approach was used (Refaeilzadeh et al., 2009). At each stage of the cross validation, each metric was evaluated. The final metrics were assessed as the average of the metrics across 5 rounds of cross validation ($cv5$). Additionally, the overall classification accuracy and the F-1 measure were evaluated for the general model (on the *training* data).

3 RESULTS

3.1 Data Visualization with t-SNE

Figure 2 shows the results of visualizing the application of the t-SNE algorithm for three perplexity values- 2, 10, 30. For each perplexity value, the t-SNE algorithm was implemented several times. Below are the 4 most typical implementations for each perplexity value.

As can be seen from Figure 2, at different perplexity values, green dots, which correspond to cognitive load, quite often turn out to be isolated from red and blue. In this case, the red and blue dots, as a rule, are close to each other. In some cases, green dots are divided into subgroups, due to the nature of the t-SNE algorithm. However, even in this cases these groups are separated from the red and blue dots.

Thus, the parameters of RBT fluctuations at the stages of rest state and aftereffect are quite similar, while the parameters at the stage of cognitive load tend to differ from both of these stages. From this, we can conclude that it would be more reasonable to solve the *binary* classification problem: the rest state recording and aftereffect stage was selected as the *first class*, and the cognitive load stage as the *second class*.

3.2 Results of Applying Machine Learning Methods

Table 1 shows the results of evaluating the MO models. For *LogR*, two models are considered - linear combinations of parameters and combinations of second degree polynomials. Increasing the degree of the polynomial to 3 does not increase the performance

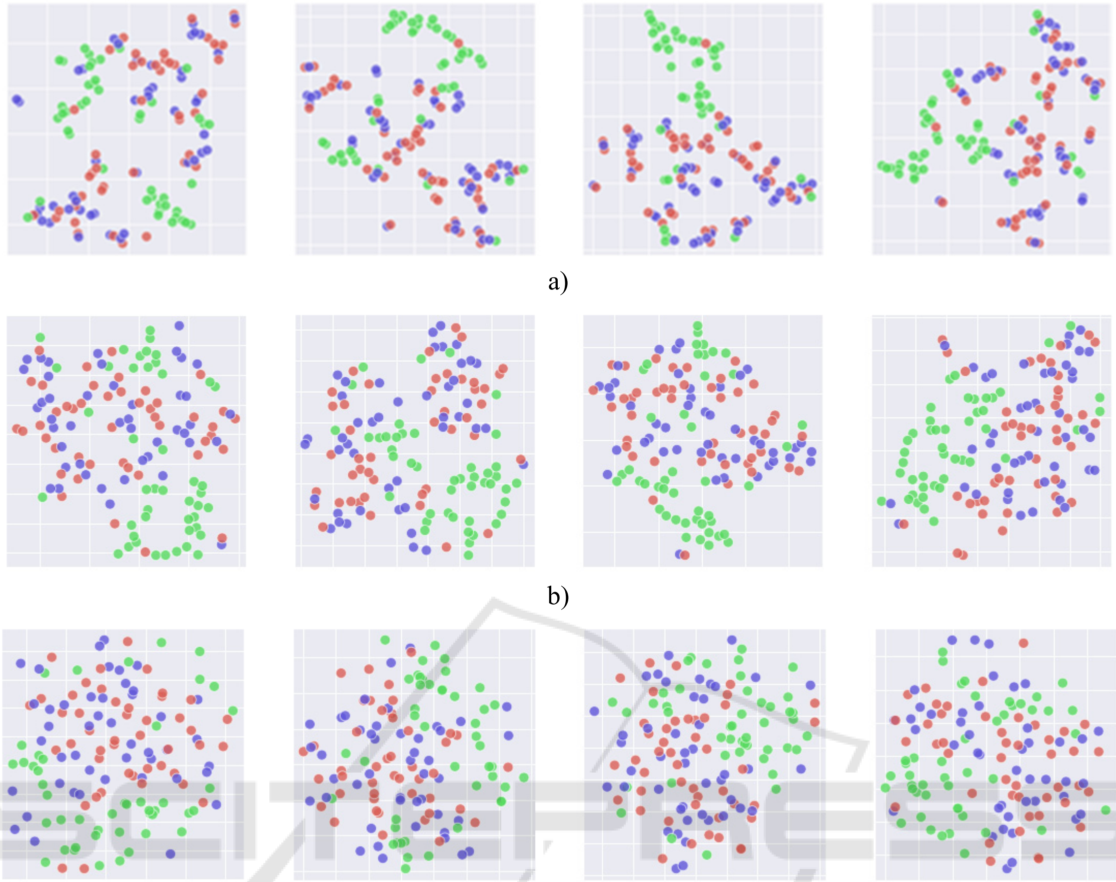


Figure 2: Visualization of RBT parameters by the t-SNE method: a) perplexity = 2; b) perplexity = 10; c) perplexity = 30. Red dots – rest state recording, green - cognitive load, blue - aftereffect.

metrics of the MO model. For *DT*, the parameter maximum depth is set equal to 5. At this value of the parameter, the highest values of the MO metrics are achieved.

Table 1: Perfomance metrics for classification models.

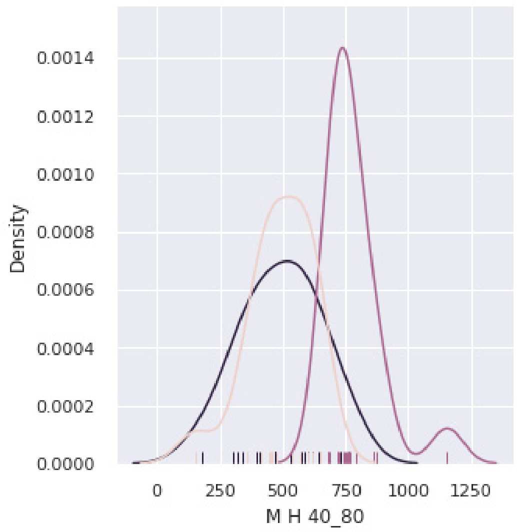
Metric	LogR (linear)	LogR (Quadratic)	DT
Accuracy_cv5	**0.650**	0.625	0.591
Precision_cv5	**0.798**	0.727	0.705
Recall_cv5	0.662	**0.725**	0.700
F1-score_cv5	**0.719**	0.716	0.693
Accuracy_Train	0.675	0.800	**0.900**
F1-score_Train	0.738	0.850	**0.923**
Number of parameters	**3**	13	10

As can be seen from the results shown in Table 1, the highest *accuracy* for training data is achieved using the *DT* method. Moreover, for this method, the MO metrics on cross validation are lower than for *LogR*.

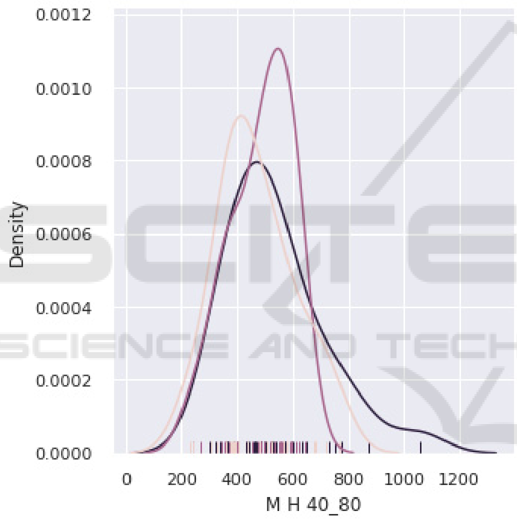
Analyzing the list of parameters for different ML models, it is worth highlighting the parameter **M H 40-80** (median value of the RBT amplitude with a fluctuation period from 40 to 80 s). This parameter was present in all ML models. If one analyzes this parameter separately, it can be seen that the distribution of this parameter for the functional state of the cognitive load looks biased in relation to the states of rest state and aftereffect.

Let's divide the initial sample into two: parameter **M H 40-80** in the state of cognitive load ≥678 (*the first group*); parameter **M H 40-80** in a state of cognitive load <678 (*the second group*).

Visualization of the distribution of the parameter **M H 40-80** for different functional states for these two groups is shown in Figure 3. It can be seen that the first group is characterized by an increase in this



a)



b)

Figure 3: Distribution of the parameter **M H 40-80**: a) *the first group*; b) *the second group*. In light highlighted the distribution for the rest state stage, in pink - for the cognitive load stage, in dark - for the after-effect stage.

parameter in a state of cognitive load. For the second group, the distributions of this parameter are similar.

Estimates of the Student's t-test for the first group showed that the difference in means is statistically significant:

- in comparison with the rest-state stage, record *t-test* = 3.87, *p-value* = 0.0002;
- in comparison with the after-effect stage *t-test* = 2.62, *p-value* = 0.0103.

For the second group, the Student's t-test did not show the statistical significance of the difference in means. This result may indicate that the original sample can be divided into two subgroups in which the response to cognitive load is different. These two subgroups require a more detailed comparison, taking into account the psychophysiological and motivational characteristics of the subjects.

4 CONCLUSIONS

The article describes a technique for conducting experimental studies using passive non-invasive thermography methods in radio bands to study the effect of changes in the psychophysiological state on a person's radio brightness temperature. The study consists of three stages - background recording, cognitive load (verbal counting) and aftereffect. To register the brightness temperature fluctuations, a model of a contact microwave radiometer was used, which ensures the reception of brain microwave in the frequency range (3.4-4.2) GHz.

Correction of data processing algorithms is proposed to detect stable characteristics of patterns in changes in radio brightness temperature fluctuations, which are determined by changes in the psychophysiological state of a person. For each signal, a wavelet analysis was performed to calculate the spectral components of the brightness temperature signals with fluctuation periods from 20 to 40 s, from 40 to 80 s, and from 80 to 140 s. For each stage of the study, 18 parameters were assessed: mean value M, standard deviation STD and coefficient of variation CV for the set of values of the width and amplitude of the oscillation for each of the three spectral components.

An assessment of the performance of algorithms based on machine learning methods for the formation of an objective assessment of the psychophysiological state of a person by recording the brain microwave radiation, has been carried out.

The results presented made it possible to single out a special parameter of brightness temperature fluctuations - the average value of the amplitude of fluctuations with fluctuation periods from 40 to 80 s. This parameter makes it possible to divide the initial data sample into two subgroups in which the response to cognitive load is significantly different.

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