

# The EEG-based Emotion Classification in Tactile, Olfactory, Acoustic and Visual Modalities

G. Portnova<sup>1,2</sup>, D. Stebakova<sup>1</sup> and G. Ivanitsky<sup>1</sup>

<sup>1</sup>*Institute of Higher Nervous Activity and Neurophysiology of RAS, 5A Butlerova St., Moscow 117485, Russia*

<sup>2</sup>*Pushkin State Russian Language Institute, Russia*

**Keywords:** EEG, Classification, Acoustic, Visual, Tactile and Olfactory Modalities, Pleasant and Unpleasant Stimuli.

**Abstract:** We perceive pleasant and unpleasant stimuli using different modality systems, such as visual and acoustic tactile and olfactory modalities. In our study we investigated the specificity of emotional perception in four modalities using EEG. 20 healthy participants were instructed to assess the stimuli using emotional scales. We used power spectrum density, alpha-peak frequency, wavelet analysis and method of "emotional spaces" for EEG data and DNN classifier for modality specific and non-specific classification of pleasant and unpleasant stimuli. We found, that difference of EEG power spectrum density and alpha-peak frequency between states of pleasant and unpleasant stimulation varied from one modality to another. Meanwhile, the above-stated differences were more similar between tactile and olfactory modalities and acoustic and visual modalities. the method of "emotional spaces" and DNN classification showed general, modality nonspecific features of pleasantness evaluation.

## 1 INTRODUCTION

The perception of emotionally charging stimuli is possible in variable sensory-specific systems: visual, auditory, olfactory and tactile, each of them should be accompanied by the different brain activity (Wu et al., 2018). Nevertheless, researchers reported, that the assessment of the "pleasantness" and "unpleasant" of stimuli should include sensory-non-specific components (Grabenhorst et al., 2007). The aim of our study was to detect the modalities' specific and non-specific features of emotional perception that could be used for the forehead classification.

Some researchers previously reported about similar physiological mechanisms for assessing emotions in different modalities (Delplanque et al., 2008). One of these mechanisms could be related with the activation of the limbic system. The activation of the limbic system was shown to be accompanied with theta-rhythm activity (Lévesque et al., 2017), responsible for emotional perception in different sensation systems (Diao et al., 2017). Some authors reported, that the emotional perception of pleasant and unpleasant stimuli in visual modality has EEG specific delta- theta- rhythm PSD patterns

(Iosilevich et al., 2012), which was higher for unpleasant stimulation. Moreover, higher alpha-rhythm frequency during visual emotional perception was related with the predisposition to the prevalence of positive emotions (Tumyalis et al., 2010). The emotional perception in tactile modality was also accompanied changes of the theta- and alpha-rhythm PSD (Monosova, 1994). The pleasant pleasurable feeling, induced by light pressure that excites C-tactile fibers, as was shown previously related with processing of the sensation in limbic cortical areas (McGlone et al., 2014, McGlown et al., 2012).

The general mechanisms of emotional perception originate from asymmetry of pleasant and unpleasant emotions (Coan and Allen, 2004). The differential roles of left and right cortex for processing of pleasant and unpleasant emotional information was repeatedly reported (Fernandez-Carriba et al., 2002). Resting EEG measures figure prominently in this literature. These studies have established differential roles of left and right prefrontal cortex (PFC) for processing pleasant and unpleasant emotional information, respectively. For example, Loken and co-authors reported that pleasant tactile stimulation activate left anterior

insula, related with the processing of pleasant emotions (Loken et al., 2009).

Thus, in our study we attempted to investigate both sensory specific and non-specific mechanisms of emotional reception and processing using innovation method of visualization of EEG patterns (Roik et al., 2014) and Deep neural network classifier, which was previously reported as effective tool to detect the emotional states using EEG data (Stuhlsatz et al., 2011).

## 2 METHODS

### 2.1 Subjects

20 healthy right-handed subjects participated in our study (9 male, 11 female,  $30.2 \pm 2.7$  years old). Exclusion criteria were: menstrual cycle phase, use of oral contraceptives, previous neurological or psychiatric history, pregnancy, treatment with anti-depressants and anxiolytics and high levels of anxiety or hostility during the examination (Spielberger et al., 1970; Buss and Durkee, 1957). Peers have signed the informed consent for research document indicating willingness to participate in the study.

### 2.2 Stimuli

The experiment consisted of 4 series corresponded to 4 modalities. The quantity of stimuli varied depending on modality: 16 pictures from IAPS (Lang, 2008) (6 pleasant, 6 unpleasant, 4 neutral), 12 sound (4 pleasant, 4 unpleasant, 4 neutral), 10 tactile stimuli (4 pleasant, 4 unpleasant, 2 neutral), 14 odors (5 pleasant, 5 unpleasant, 4 neutral). Participants assessed the pleasantness and arousal of stimuli both during EEG recording (by choosing bottom for most pleasant (9), neutral (5) and most unpleasant (1), the gradient was marked on keyboard (1-9)) and after the experiment using visual scale. Two stimuli (most pleasant and unpleasant) were selected for farther classification. All the stimuli' presentation was randomized separately for each modality and repeated 4 times for tactile and olfactory modalities (these stimuli were presented for 24 seconds) and 40 times for auditory and visual modalities (presented for 8 seconds). The stimuli were presented using Presentation Software (Neurobehavioral Systems, USA).

### 2.3 EEG Registration

During the EEG recording the subjects sat in a comfortable position in an armchair in an

acoustically and electrically shielded chamber. The participants were instructed to remain calm and to hear to the presented sounds (via earphones), watch the visual stimuli (presented in the monitor), smell the odors, and percept tactile stimuli avoiding falling asleep. The auditory olfactory and tactile stimuli were presented while the subject's eyes were closed, to avoid visual interference. EEG was recorded using a recording device Neurotravel-24D (ATES Medica, Italy) with 32-channel Electro-Cap (USA). The amplifier bandpass filter was nominally set to 1.6-30 Hz. The electrooculogram (EOG) was measured with AgCl cup electrodes placed 1 cm above and below the left eye, and the horizontal EOG was measured with electrodes placed 1 cm lateral from the outer canthi of both eyes. The recording was separated on two datasets with 30-40 minute interruption.

### 2.4 Data Processing

EEG intervals corresponding to a specific stimulus were concatenated. These epochs lasting about 300-400 seconds were analyzed further. Eyes movement artifacts were cleaned out using EOG data by EEGLab. Small intervals affected by muscle activity were excluded (cut) manually using visual inspection. All the following processing was performed using EEGLab (Delorme and Makeig, 2004) plugin for MatLab (Mathwork Inc.). The "emotional spaces" calculations were implemented on C# programming language by the lab's engineer.

### 2.5 Power Spectral Density

Fast Fourier Transform (FFT) was used to analyze PSD. The EEG spectrum was estimated for each  $310 \pm 6.8$  seconds long interval. The resulting spectra were integrated over intervals of unit width in the range of interest (2-2.5Hz, 2.5-3 Hz ... 19.5-20 Hz). We analyzed asymmetry of differences between pleasant and unpleasant stimuli over symmetric channels (F7-F8, F3-F4, FC5-FC6, T3-T4, C3-C4, CP5-CP6, T5-T6, P3-P4, O1- O2), the results were presented on figure 2.

### 2.6 Variability of Rhythm (Wavelet SD)

We applied mathematical method the Morlet wavelet (or Gabor wavelet). This is a complex exponential modulated by a Gaussian function which depends on a tunable parameter is related to the time and frequency resolutions (Tallon-Baudry

et al, 1996). We calculated the standard deviation for the intervals of unit width in the range of interest (2-4Hz, 4-6 Hz, ... 18 -20 Hz).

## 2.7 Peak Alpha Frequency (PAF)

PAF was taken as the frequency from range 8-13 Hz with maximal PSD.

## 2.8 Emotional Spaces

We used “cognitive space” construction method (Roik and Ivanitskii, 2013) to visualize how close/distant these emotional sound and background fragments are according to EEG data. As the stimuli in this study are emotional, the constructed space will be called “emotional” space. The method consists of the following steps (figure 1):

- 1) EEG of each emotional sound and background fragments was divided into small non-overlapping epochs of 8 seconds (approx. 30-40 pieces).
- 2) FFT (absolute value) was calculated for the epochs in 2-20 Hz band for electrodes (F3, F4, F7, F8, FC5, FC6, T3, T4, T5, T6, CP5, CP6, P3, P4, C3, C4, O1, O2 international 10–20 system)
- 3) The distance between each pair of emotional stimuli was calculated: for each frequency bin two samples of FFT values (of the epochs of these fragments) were compared using Mann-Whitney U-test ( $p < 0.05$ ). The distance was equal to the percentage of differing frequency bins.
- 4) Emotional stimuli were placed onto a plane using multidimensional scaling method, namely Sammon projection (Sammon, 1969).

$$E = \frac{1}{\sum_{i < j} d_{ij}^*} \sum_{i < j} \frac{(d_{ij}^* - d_{ij})^2}{d_{ij}^*}$$

Each type of modality is depicted using the shape the pleasant and unpleasant stimuli were depicted using color (see Figure 3 A). So, the distances between the stimuli types on the plane were as similar as possible to the distances calculated by FFT values. This similarity was always good enough to claim the projection is legit.

- 5) The resulting pictures (obtained for each subject) have arbitrary rotation because of Sammon projection algorithm and different sizes because of high individuality of EEG. Before the averaging over group these pictures should be standardized. We used scaling to equalize the size (the sum of squared distances to the figures from the “center of mass”) and rotation/reflection so that pleasant visual stimulus (white rhomb) was on the top of the picture and the unpleasant and pleasant auditory stimuli (circles) were on the left and right sides correspondingly laying on a horizontal line.
- 6) After standardization individual pictures are averaged over groups. So, these pictures show relational distances between emotional sounds based on how much the corresponding EEG data differ in terms of rhythms magnitudes.

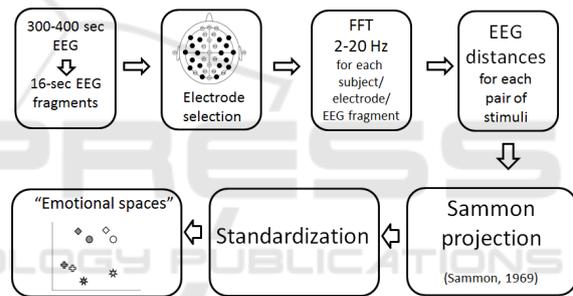


Figure 1: Steps of “Cognitive spaces” method.

## 2.9 Statistical Analysis

A one way ANOVA with Bonferroni correction for multiple comparisons,  $p < 0.05$ , were used to determine lateralization effects on EEG metrics. We analyzed differences of EEG distances using Student’s t-test to compare indices for each stimulus ( $p < 0.05$ ). The Pearson’s correlation coefficient between EEG indices and emotional assessments was calculated. Significant R values were used for further analysis ( $p < 0.05$ ).

## 2.10 Classifier

The Deep neural network (DNN) and Extreme Learning Machines (ELM) was used for the classification of pleasant and unpleasant stimuli recognition using the EEG signals (Han, 2014; Tripathi, 2017). The testing sample was taken from the dataset 1 and then passed on to the trained

network. We had three data arrays, which contained from 32 different channels: power spectral density, alpha-peak frequency, and wavelet data. We prepared two datasets

### 2.10.1 Dataset I

EEG data was taken from a first part of study, when subjects assessed the pleasantness of different stimuli. After the first type of EEG study subjects assessed the stimuli using psychological scales. The most “pleasant” and “unpleasant” stimuli was selected using self-reported assessment and psychometric scales and divided in two groups: training and testing.

The classifier was trained on two types of EEG data: 1) using most pleasant and unpleasant stimuli separately for different modalities (8 groups, sensory-specific) 2) using most pleasant and unpleasant stimuli averaged over all modalities (2 groups, sensory-non-specific).

### 2.10.2 Dataset II

EEG datasets were taken from the second part of study, when subjects were instructed as previously. The tested EEG data contained pleasant and unpleasant stimuli with the similar emotional characteristics. The percentage of correct classification was measured for each subject separately.

## 2.11 Emotional Assessment of Stimuli

After the first part of the EEG registration subjects were instructed to assess stimuli using specially prepared questionnaire. The questionnaire included: specification of presented stimuli and several scaled, measuring emotional features (“Pleasantness”, “Fear”, “Arousal”, “Disgust” and etc.) Participants were instructed to indicate how the stimuli describe their affective state on a scale from 0 (“not at all”) to 5 (“extremely”).

## 3 RESULTS

### 3.1 Power Spectral Density

The rhythmic spectral activity of more ancient modalities (tactile and olfactory) was differed from more modern modalities (auditory and visual): the slow-wave rhythm PSD was lower and beta-rhythm

BSD was higher for ancient sensory systems ( $p < 0.05$ ).

The differences of PSD between pleasant and unpleasant stimuli showed significant asymmetry (Figure 2). In the right hemisphere we found significant differences of PSD between pleasant stimuli for each modality type. In the left hemisphere only visual and olfactory pleasant and unpleasant stimuli’ PSD had significant differences. The visual pleasant stimuli (compared to unpleasant) had lower delta-rhythm PSD in the left hemisphere and higher alpha- and beta-rhythm bilateral. The auditory pleasant stimuli had lower delta and theta-rhythm PSD and higher beta-rhythm in the right hemisphere. The tactile pleasant stimuli had higher alpha- and beta-rhythm in the right hemisphere. The olfactory pleasant stimuli had higher alpha- and beta-rhythm in the right hemisphere and lower beta-rhythm in the left hemisphere.

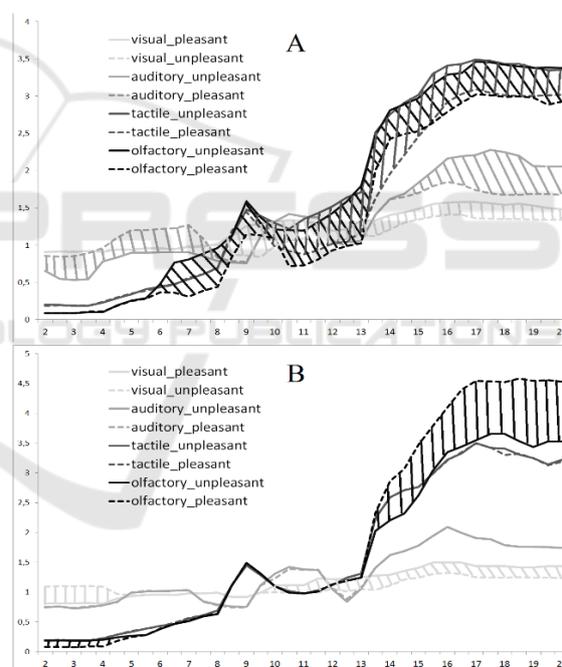


Figure 2: The differences of the PSD in the right (A) and left (B) hemisphere between pleasant and unpleasant stimuli.

### 3.2 Alpha-peak Frequency

The alpha-peak frequency was significantly higher for unpleasant stimuli compared to pleasant in the right central and temporal areas (C4, T4, F8, Cz, Pz). These differences were found for tactile, auditory and visual stimuli.

### 3.3 Wavelet Standard Deviation

Significant differences were found only for visual stimuli. Standard deviation was significantly higher for pleasant visual stimuli: for theta- and delta-rhythm in the right temporal areas (F8,T4,T6) and for the alpha- and beta-rhythm in the central and parietal areas (F8, F4, C4,Cz, C3 T4, T6, T5 Pz, P3, O1).

### 3.4 Classification

The results of sensory-specific and sensory non-specific classification are presented in Table 1.

Table 1: The percentage of correct classification (averaged over the group).

DNN for 8 classes		
	Pleasant	Unpleasant
Visual	0.81±0.02	0.84±0.05
Auditory	0.78±0.06	0.85±0.07
Tactile	0.80±0.01	0.71±0.05
Olfactory	0.88±0.04	0.89±0.03
Sensory-non-specific		
DNN for 2 classes		
	Pleasant	Unpleasant
Visual	0.65±0.01	0.71±0.04
Auditory	0.64±0.06	0.61±0.02
Tactile	0.72±0.02	0.58±0.01
Olfactory	0.69±0.03	0.76±0.05
Sensory-non-specific	0.64±0.07	0.67±0.04

### 3.5 Emotional Spaces

EEG differences represent the both sensory-specific and sensory-non-specific differences between stimuli (Figure 3). The unpleasant stimuli for each modality were in the left side of the emotional space, compared to pleasant stimuli. The more ancient sensory systems were separated from the more modern sensory systems. EEG distances between pleasant and unpleasant stimuli positively correlated with the distances of emotional assessment by the scale “Pleasantness” ( $r>0.48$ ,  $p<0.05$ ). To calculate distances of emotional assessment we analyzed difference between scores of pleasant and unpleasant stimuli.

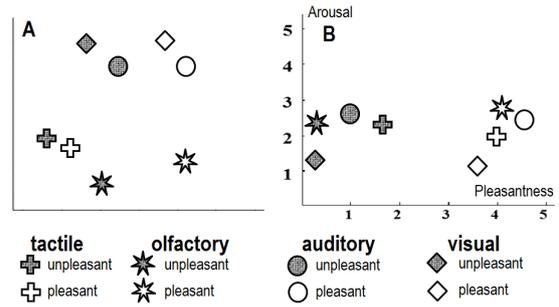


Figure 3: A: “emotional spaces”, B: the subjective assessment of stimuli using scales “Arousal” and “Pleasantness”.

## 4 DISCUSSION

In our study we found that modern sensory systems (visual and auditory) had similar EEG patterns and differed from more ancient sensory systems (olfactory and tactile). In spite of a small amount of data, which analyzed emotional perception in four different modalities simultaneously, some researchers reported about similarity of the EEG rhythmic activity in alpha- and beta-bands between visual and auditory systems (Jessen and Kotz, 2011). These data correspond to our results showed similar beta-rhythm PSD between pleasant and unpleasant stimuli in visual and auditory modalities.

We hypothesized that modality-independent mechanisms of emotional processing always accompany the emotional perception of pleasant and unpleasant stimuli; the results of our study seem to confirm this assumption. For example, we found the good level of classification accuracy trained on sensory-non-specific EEG distances. This modality-independent difference between pleasant and unpleasant stimuli also could be visualized using “Emotional spaces” method. Other researchers also reported about modality non-specific emotional stimuli processing, which occurs when subjects solve tasks, presented in different sensory systems (Brosch, 2009). Previous research has demonstrated that emotions from faces and emotions from voices are also represented using similar mechanisms, for example, both types of emotional stimuli have been shown to be processed in the superior temporal sulcus (Haxby et al., 2002; von Kriegstein and Giraud, 2004).

Our results also demonstrated the asymmetry of EEG changes during of emotional perception. This data is consistent with the previous studies reported about the brain asymmetry during processing of

pleasant and unpleasant stimuli and hypothesized that positive emotions correspond to the right hemisphere, and negative – to the left (Fernandez-Carriba et al., 2002). For example, the emotion-modulated asymmetries, related with processing pleasant and unpleasant emotional information were found in the frontal cortex (Coan and Allen, 2004). The clinical EEG studies have shown that depression is associated with the greater activation of the right prefrontal cortex (Davidson et al., 2002), other researchers also reported about the higher activation of the right amygdala (Abercrombie et al., 1998). Furthermore, our results showed that most pronounced differences of the EEG between pleasant and unpleasant stimuli were found in the right hemisphere. Previously, a general right hemispheric advantage for emotion processing was reported (Martin and Altarriba, 2017; Kesler-West et al., 2001).

## 5 CONCLUSIONS

Visual and auditory sensory systems had similar EEG patterns and differed from olfactory and tactile sensory systems. The good level of classification accuracy trained on sensory-non-specific EEG distances was found. The advantage of the right hemisphere for emotional processing was found. The modality-independent difference between pleasant and unpleasant stimuli is primarily visualized with the “Emotional spaces” method. Further work is needed to be done with the increased number of healthy participants. Moreover, we are going to include the patients with emotional impairments in our study. The techniques used for classification should be extended to support reported findings

## ACKNOWLEDGEMENTS

We would like to thank engineer Kashevarova O, researchers Atonov M, and Portnov V for assistance in programming of “Cognitive spaces”, calculations of the EEG parameters and DNN + EML classification

## REFERENCES

- Abercrombie H, Schaefer S, Larson C, Oakes T, Lindgren K, Holden J, et al. , 1998 .Metabolic rate in the right amygdala predicts negative affect in depressed patients. In *Neuroreport*, 9(14):3301–3307.
- Brosch T, Grandjean D, Sander D., Scherer K. R. 2009. Cross-modal emotional attention: emotional voices modulate early stages of visual processing. *J Cogn Neurosci*. 21(9):1670-9
- Buss A, H., Durkee A., 1957. Inventory for assessing different kinds of hostility. In *J Consult Psychol* 21:343–9.
- Coan J, Allen J., 2004. Frontal EEG asymmetry as a moderator and mediator of emotion. In *Biological Psychology*, 67:7–49
- Davidson R, Pizzagalli D, Nitschke J, Putnam K., 2002. Depression: Perspectives from affective neuroscience. In *Annual Review of Psychology*:53(1):545–574.
- Delorme, A., Makeig, S. 2004. EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *J. Neurosci. Methods*, 134, 9–21.
- Delplanque S, Grandjean D, Chrea C, Aymard L, Cayeux 2008. I, Le Calve B, Velazco MI, Scherer KR, Sander D. Emotional processing of odors: evidence for a nonlinear relation between pleasantness and familiarity evaluations. *Chemical Senses. Apr* 9;33(5):469-79.
- Diao, L., Qi, S., Xu, M., Fan, L., and Yang, D. 2017. Electroencephalographic theta oscillatory dynamics reveal attentional bias to angry faces. In *Neuroscience letters*, 656, 31-36.
- Fernandez-Carriba, S., A. Loeches, A. Morcillo, and W.D. Hopkins, 2002. Functional asymmetry of emotions in primates: new findings in chimpanzees. In *Brain Research Bulletin*. 57: 561–564.
- Han, K., Yu, D. and Tashev, I., 2014. Speech emotion recognition using deep neural network and extreme learning machine. In *Fifteenth annual conference of the international speech communication association*.
- Haxby, J., Hoffman, E., and Gobbini, I., 2002. Human Neural Systems for Face Recognition and Social Communication. In *Biological Psychiatry*. 51(1):59-67
- Grabenhorst, F., Rolls, E. T., Margot, C., da Silva, M. A. and Velazco, M.I., 2007. How pleasant and unpleasant stimuli combine in different brain regions: odor mixtures. *Journal of Neuroscience*, 27(49), pp.13532-13540.
- Iosilevich E. A., Chernysheva E. G., Chernyshev B. V., 2012. Psychophysiological study of the connection between the valence of the emotional response and the EEG spectral power indicators of human. In: *Modern Psychology: Theory and Practice: Materials of the V International Scientific and Practical Conference, Moscow, July 3-4, M.: Special book*, 2012. S. 21-27. (in Russian)
- Jessen S, Kotz S. A., 2011. The temporal dynamics of processing emotions from vocal, facial, and bodily expressions. In *Neuroimage. Sep* 15;58(2):665-674
- Kesler-West, M., Andersen, A., Smith, C., Avison, M., Davis, C., Kryscio, R., Blonder, L. 2001. Neural substrates of facial emotion processing using fMRI. *Cognitive Brain Research*, 11(2):213-26

- Lévesque, M., Cataldi, M., Chen, L. Y., Hamidi, S. and Avoli, M., 2017. Carbachol-induced network oscillations in an in vitro limbic system brain slice. *Neuroscience*, 348, pp.153-164.
- Löken, L. S., Wessberg, J., McGlone, F., and Olausson, H. 2009. Coding of pleasant touch by unmyelinated afferents in humans. *Nature neuroscience*, 12(5), 547-548.
- Martin, J. M. and Altarriba, J., 2017. Effects of valence on hemispheric specialization for emotion word processing. *Language and speech*, 60(4), pp.597-613.
- McGlone F., Olausson H., Boyle J. A., Jones-Gotman M., Dancer C., Guest S., et al. 2012. Touching and feeling: differences in pleasant touch processing between glabrous and hairy skin in humans. *Eur. J. Neurosci.* 35, 1782–1788
- McGlone F, Wessberg J and Olausson H, 2014. Discriminative and Affective Touch: Sensing and Feeling. In *Neuron*, 82, May 21, pp. 738-755
- Monosova A. J. 1994. PhD theses. Analysis of the features of the emotional sphere in normal and affective disorders by olfactory stimulation. M, (in Russian)
- Roik A. O, Ivanitskii G. A., 2013. Neurophysiological Model of the Cognitive Space // *Neuroscience and Behavioral Physiology*. V 43(2):193-199.
- Roik A. O., Ivanitskii G. A., Ivanitskii A. M. 2014. The Human Cognitive Space: Coincidence of Models Constructed on the Basis of Analysis of Brain Rhythms and Psychometric Measurements. *Neuroscience and Behavioral Physiology*. 44 (6): 692-701.
- Sammon J. W. 1969 A nonlinear mapping for data structure analysis // *IEEE Transactions on computers*. V 18(5): 401-409.
- Spielberger C. D., Gorsuch R. L. and Lushene R. E. 1970 Manual for the State-Trait Anxiety Inventory. Consulting Psychologist Press, Palo Alto, CA
- Stokes, D., Matthen, M., and Biggs, S. (Eds.). 2014. Perception and its modalities. Oxford University Press, USA.
- Stuhlsatz, A., Meyer, C., Eyben, F., Zielke, T., Meier, G., and Schuller, B. 2011. Deep neural networks for acoustic emotion recognition: raising the benchmarks. In Acoustics, speech and signal processing (ICASSP). *IEEE international conference on* (pp. 5688-5691).
- Tallon-Baudry, C., Bertrand, O., Delpuech, C. and Pernier, J., 1996. Stimulus specificity of phase-locked and non-phase-locked 40 Hz visual responses in human. *Journal of Neuroscience*, 16(13), pp.4240-4249.
- Tripathi, S., Acharya, S., Sharma, R.D., Mittal, S. and Bhattacharya, S. 2017. Using Deep and Convolutional Neural Networks for Accurate Emotion Classification on DEAP Dataset. In *AAAI*, pp. 4746-4752.
- Tumyalis, A. V., Korenkov V. V., Brak I. V., Makhnev V. P., Reva N. V., Aftanas L. I. 2010. The Individual frequency of alpha activity and emotions negative positive emotions // *Bulletin RAS*, V. 30(4).
- Von Kriegstein, K. and Giraud, A.-L. 2004. Distinct functional substrates along the right superior temporal sulcus for the processing of voices. *NeuroImage*, 22(2), 948-955
- Wu, Y. H., Uluç, I., Schmidt, T. T., Tertel, K., Kirilina, E., and Blankenburg, F. 2018. Overlapping frontoparietal networks for tactile and visual parametric working memory representations. *NeuroImage*, 166, 325-334.

## APPENDIX

The work was supported by the grant of Russian Foundation for Basic Research № 16 – 04 -00092 A and the Russian Academy of Science.