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CLASSIFICATION OF VERBAL AND MATHEMATICAL MENTAL OPERATIONS BASED ON THE POWER SPECTRAL DENSITY OF EEG

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Abstract

A classification of spectral patterns of EEG underlies several cognitive neurotechnologies including passive and active brain-computer interfaces. Despite arithmetic tasks often being used in studies of cognitive workload, there is a lack of findings describing a possibility to recognize EEG patterns related to different types of math operations. In the present work, we have shown that the power spectral density of EEG can be used to classify types of mental operations including a classification of verbal and different mathematical tasks for simple arithmetic operations or logical tasks with arithmetic progressions. The verbal tasks were separated from arithmetic ones significantly better than arithmetic from logical tasks, and verbal from logical tasks. Better discrimination of verbal tasks from arithmetic but not from logical tasks supports the hypothesis of unique EEG patterns associated with verbal activity that apparently differ from mental operations in arithmetic. Additionally, we compared the behavioral performance in problem solving and accuracy of EEG classification in two groups of subjects with education in math or humanities (N = 8 + 8). We obtained the predicted differences related to better performance of the math group in solving math tasks than the humanitarian group. However, the classification accuracy of tasks based on EEG did not differ significantly between groups and was essentially higher than random. Considered together, our results support the hypothesis that EEG patterns reflect individual cognitive states corresponding to mental operations and can be used in classification of different cognitive activity.

Keywords: EEG, power spectral density, mental operations, artificial neural network, classification accuracy.

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Introduction

The modern psychophysiology has accumulated sufficient data about strong association between individual patterns of electric brain activity (electroencephalogram EEG) and cognitive workload and performance (Antonenko, Paas, Grabner, & van Gog, 2010; Chaouachi, Jraidi, & Frasson, 2011; Antonenko & Niederhauser, 2010; Fairclough, Venables, & Tattersall, 2005; Zhu, Maxwell, Hu, Zhang, & Masters, 2010; Ivanitsky, 1997; Tarotin, Atanov, & Ivanitsky, 2017). Given that specific EEG rhythmic patterns correspond to the specific aspects of mental activity, a classification of mental operations based on EEG underlies several cognitive neurotechnologies including passive and active brain-computer interfaces (BCI) (for review: Gerjets, Walter, Rosenstiel, Bogdan, & Zander, 2014: Allison, Wolpaw, & Wolpaw, 2007).

Artificial neural networks, one of the widely used classification algorithms in passive BCI, showed remarkable efficiency (more than 90% accuracy) in recognition of mental operations basing on EEG spectral features while solving verbal and spatial tasks (Ivanitsky, 1997; Tarotin et al., 2017; Atanov, Ivanitsky, & Ivanitsky, 2016). Several studies have demonstrated a potential of EEG as an indicator of cognitive workload during training (Antonenko et al., 2010; Antonenko & Niederhauser, 2010; Fairclough et al., 2005; Fairclough, Gilleade, Ewing, & Roberts, 2013; Zhu et al., 2010), which is defined as a perceived relationship between existing mental abilities and resources required for mental tasks (Hart & Staveland, 1988). Despite arithmetic tasks often being used in studies of cognitive workload (Walter, Rosenstiel, Bogdan, Gerjets, & Spuler, 2017), there is a lack of findings describing a possibility to recognize EEG patterns related to different types of math operations.

Moreover, most of the EEG-based classification algorithms are person-dependent and show a reliable accuracy only when the algorithm training and further classification is performed on EEG data of the same subject (for review: Putze & Shultz, 2014). Person-independent algorithms were actively studied because these algorithms may recognize a cognitive workload of one person having previously trained on EEG data of other subjects (Wang, Hope, Wang, Ji, & Gray, 2012). However, the accuracy of person-independent classification of cognitive states is still near chance level of recognition only if not built on EEG data from a very large sample of subjects (Jarvis, Putze, Heger, & Schultz, 2011).

The aim of this study was to explore a possibility to recognize different math operations, both in comparison with each other and compared to verbal tasks in healthy subjects with special higher education in humanities or math based on classification of EEG spectral patterns. We used tasks we had defined in a pilot study according to a similar average time of solution: Verbal Tasks – Anagrams of 5-6 letters and two types of math tasks (arithmetical operations and logical tasks on arithmetical sequences (Chemerisova & Martynova, 2018). Additionally, we combined data from the current and previous datasets in order to study group differences in behavioral accuracy and time of task solution between math and humanitarian subjects. For the purpose of EEG classification we used an artificial neuronal network – the perceptron classifier without hidden layers (McCulloch & Pitts, 1943; Pitts & McCulloch, 1947), which was previously successfully implemented for classification of EEG patterns during solving of verbal and spatial tasks (Ivanitsky, 1997; Atanov et al., 2016; Tarotin et al., 2017).

Methods

Participants

19 healthy right-handed volunteers participated in the study. All the subjects were students or alumni of higher education institutions in Moscow. The subjects were divided into two groups: Math Group (N = 9, 5 males, age 21.8 ± 2.6 years) with specialization in math (3 alumni, 6 students) and Humanitarian Group (N = 10, 6 males, age 23.2 ± 3.8 years) with specialization in humanities (5 alumni, 5 students). Each participant provided a written informed consent to participate in the study. The study protocol met the requirements of Helsinki Declaration and was approved by the ethical commission of Institute of Higher Nervous Activity and Neurophysiology Russian Academy of Science.

Procedure

Subjects were comfortably seated in a sound-shielded room with a distance of 1 m from a square 19" monitor. During EEG recording, subjects were presented tasks and were asked to solve them mentally giving equal priority of accuracy and the shortest solving time. The tasks were presented in a light gray color in the center of the black screen with the sizes of letters and digits being equal for all tasks. We presented 3 types of tasks in pseudorandom order: 60 verbal (to solve anagrams of 5–6 letter words e.g. wnesra answer), 60 arithmetic (to calculate expressions on addition, subtraction, fraction or multiplication) and 60 logical tasks (to extend sequences of integers). The presentation paradigm was implemented on Presentation software (Neurobehavioral Systems, Inc., Berkeley, CA, USA). Interstimulus intervals consisted of answer pronunciation (4 s), then the rest until the subject clicked a mouse button, then an instruction for the next task (2 s) and then a fixation cross (0.5 s). If no answer was given within 40 seconds the task was considered as unsolved and disappeared from the screen, and the next block of task began. The decision time (DT) was calculated between the task start and response time points. Additional long breaks were organized every 20–30 minutes or upon subjects' requests. The entire experiment usually lasted 2–2.5 hours.

Analysis of behavioral data

We used the following behavioral data for analysis of task and group differences: DT, the number of correct answers (CA), false answers (FA), and the number of unresolved tasks (UT). Additionally we monitored subjective reports on tasks after the experiment regarding their complexity and chosen decision strategy.

Since we used the same types of tasks as in the pilot study (Chemerisova & Martynova, 2018) we combined the data of the pilot and current studies in order to get a larger sample size required for reliable statistical analysis of behavioral results. So, we analyzed behavioral data of 39 subjects: 19 with mathematical education and 20 with education in humanities. The behavioral data was analyzed by ANOVA for repeated measures within the factor of task and between 2 groups of subjects with Tukey post-hoc comparison. All significant differences were also confirmed by Mann–Whitney U-test for nonparametric samples.

EEG recording

During the task solving we recorded EEG using "Encephalan" (Medikom MTD, Russia, Taganrog) amplifier with 19 channels placed according to an international 10–20 system (except Oz and Fpz) with 2 additional channels for electrooculogram (EOG) recording. EEG was recorded with reference electrodes located on mastoids under unipolar montage with 250 Hz sampling rate. The default filtering was 0.5–70 Hz bandpass and 50 Hz notch. The electrode impedances were kept below 10 k .

EEG analysis

Three subjects were excluded from the EEG analysis due to an extensive number of artifacts during the recording. So, EEG data of 16 subjects remained, 8 per group. The EEG was offline filtered in the 1–40 Hz band and then eye movement artifacts were removed (by subtracting EOG signal from EEG channels using linear regression for coefficients calculation). Additionally, muscle and other artifacts were manually cleaned from the EEG. Further, the continuous EEG was segmented into epochs corresponding to task solving and inter-stimulus intervals. Next, the absolute values of the power spectral density from Fast Fourier Transformation (FFT) of these signals were calculated and smoothed with 15 passes of the "three-point filter". The length of FFT window was 4096 bins (~16 s) counted from the end of each epoch. If the epoch duration was lower than needed, we filled the missing part by zeros (with corresponding normalization). The band of interest (5–20 Hz) contained 247 spectral bins. The EEG power spectra obtained for each of 19 EEG channels were concatenated and the resulting vectors were used for classification. The classifying model was a perceptron without hidden layers, i.e. just three McCulloch-Pitts neurons (McCulloch & Pitts, 1943; Pitts & McCulloch, 1947). These classes were the presented task types. Classification of the spectra was carried out at individual levels (N-fold cross validation of the feature vectors of one specific subject). Classification accuracies were compared by ANOVA for repeated measures within factor of task and between 2 groups with post-hoc planned comparison. Additionally values of classification accuracy were also checked for possible association with behavioral scores of performance in task solving using Spearman's rank correlation analysis.

Results

Behavioral performance in solving the tasks

In the joint behavioral dataset (N = 39) we observed significant interaction of factors — 3 Types of Tasks and Group — 2 groups for all criteria of success in solving the tasks. CA: $F(4, 148) = 10.787, p = .000$; DT: $F(4, 148) = 2.489, p = .046$; and UT: $F(4, 148) = 3.518, p = .009$. Both post-hoc comparison and Mann–Whitney U-test revealed that Math Group showed greater CA for arithmetic tasks ($p = .015$), lesser number of UT for logical tasks ($p = .012$) than Humanitarian Group. DT did not differ significantly between the groups after pairwise comparison tests. Both groups solved verbal tasks with similar accuracy and performance (Figure 1).

One-way ANOVA for the current data set (N = 8×8) also revealed no differences in behavioral scores for verbal tasks between groups. DT for arithmetic and logic tasks did not differ between groups but, however, CA was higher for Math Group than for Humanitarian Group for arithmetic and logical tasks: $F(1, 14) = 5.46$, $p = .034$ and $F(1, 14) = 9.33$, $p = .008$, correspondingly. The number of UT was lower in Math Group for logical tasks: $F(1, 14) = 4.83, p = .045$.

The comparison of DT for different task in the math group showed that verbal tasks were solved faster than arithmetical ones with more CA on logical as compared with verbal tasks ($p < 0.05$, Mann–Whitney U-test). Subjects with education in humanities also solved verbal tasks faster that arithmetical and logical ($p < 0.05$, Mann–Whitney U-test), but with similar performance for all tree types of tasks (CA and UT did not differ significantly).

Accuracy of task classification based on EEG spectral values

In all three comparisons, an accuracy of classification was higher than chance level with minimal mean value of 74 % (Table 1). The accuracy of task classification for all subjects (N = 16) was significantly different between the types of comparison. Classification of verbal and arithmetic task was significantly better (83.6 ± 4.67%) than arithmetic and logical tasks on progressions (77 ± 5.5%): $F(1, 15) = 7.78, p = .009$. The accuracy of task classification between groups did not reach a substantial level of probability. We observed only a tendency for better accuracy in the classification of verbal against logical in the math group compared to the humanitarian group ($p = .052$ according to the Mann–Whitney U test).

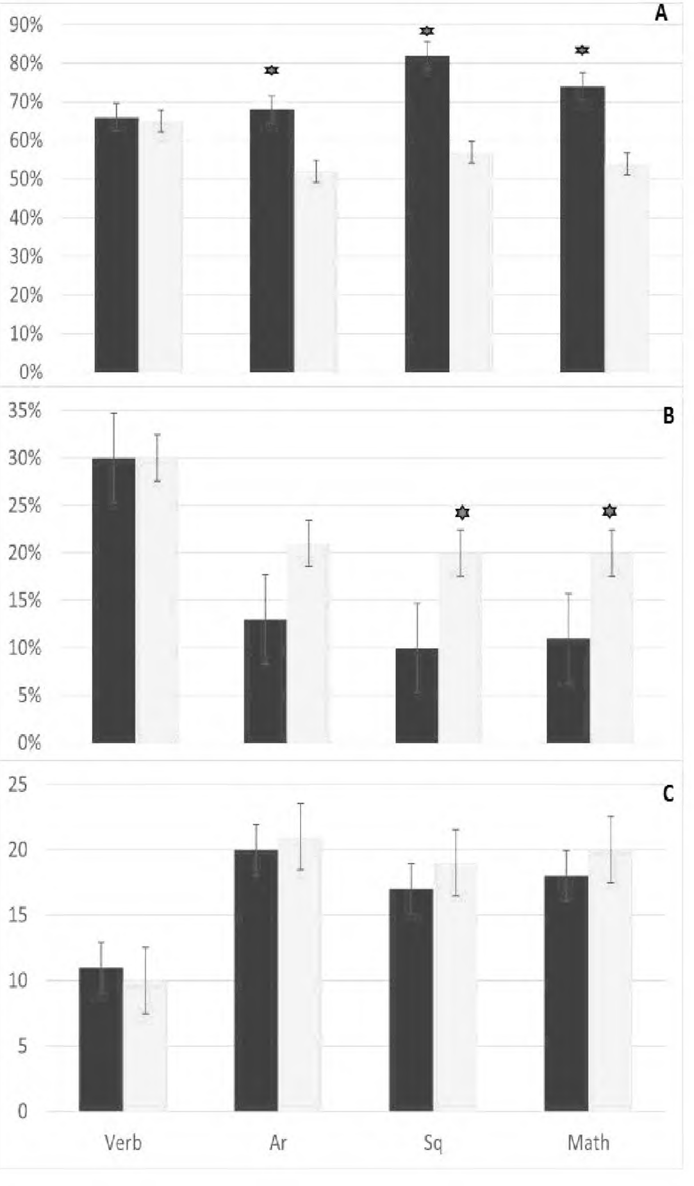
Correlation of classification accuracy with behavioral scores of task solving

The accuracy of classification of verbal and arithmetic tasks for all subjects from both groups correlated positively with CA ($r = -.78$, $p = .0004$), and negatively with UT of arithmetic tasks ($r = -.69, p = .003$).

The correlation coefficients of classification accuracy and behavioral scores were insignificant for the math group. As for the humanitarian group, we observed the following significant correlations: accuracy of classification arithmetic against

Figure 1

Indices of the task solving performance



Note. Verb — verbal; Ar — arithmetic; Sq — arithmetic tasks for progressions, and Math — all math tasks (arithmetic plus arithmetic tasks for progressions). The results of the task performance for the mathematical group are marked by dark grey columns, for the humanitarian group -by light grey. Significant group differences are marked by * ($p < .05$). A — on the criterion of "correctness", B — on the criterion "unsolved tasks for 40 sec.", C — according to the criterion "decision time".

Table 1

The average classification accuracy of classification of three types of tasks based on the EEG power density for 16 subjects (8 with math education and 8 with humanitarian education)

Accuracy of task classification	Math Group	Humanitarian Group	All subjects
Arithmetic vs Logical	79.93 ± 7.3%	74.77 ±7.1%	77.35 ± 7.5%
Verbal vs Arithmetic	86.66 ± 4.8%	81.8 ± 6.2%	84.23 ± 5.9%
Verbal vs Logical	84.6 ± 6.3%	78.04 ± 7.0%	81.32 ± 7.3%

logical tasks positively correlated with CA of arithmetic (r = .74, p = .036) and logical tasks (r = .76, p = .028) and negatively with UT (r = −.86, p = .006; r = −.77, p = .027) of arithmetic and logical tasks correspondingly. DT of logical tasks correlated negatively with the accuracy of classification of verbal against logical tasks (r = −.77, p = .025).

Discussion

In the present work, we have shown that EEG can be used to classify types of mental operations including a classification of different mathematical tasks for simple arithmetic operations or logical tasks with arithmetic progressions. The verbal tasks were separated from arithmetic ones significantly better than arithmetic from logical tasks, and verbal from logical tasks. Better discrimination of verbal tasks from arithmetic but not from logical tasks supports the hypothesis of unique EEG patterns associated with verbal activity that apparently differ from mental operations in arithmetic (Wilson & Fisher, 1995). On the other hand, logical tasks for arithmetic sequences are likely to involve verbal cognitive functions, as they require formulating rules describing different numerical sequences (Chaouachi et al., 2011), which may explain more difficult recognition of similar EEG patterns. However, the accuracy of classification was higher than 80 % on average for all subjects and all types of tasks. Importantly, the accuracy of classification was similar for two groups of subjects with education either in math or humanity, while behavioral performance of these two groups significantly differed. We observed better performance in arithmetic and logical tasks in the math group than in the humanitarian subjects and the performance on solving verbal tasks did not differ between groups. These findings were predicted as we expected that humanitarian students and alumni should have more difficulties in solving math tasks without the extensive practice that is usual for math students. The current behavioral data confirmed the previous findings of the pilot study with the same types of tasks (Chemerisova & Martynova, 2018); we also obtained similar results when we combined data of the current and previous studies.

The classification of math tasks significantly depended on the behavioral performance for all subjects but mainly because of the humanitarian group: the better the performance was, the higher was the classification. Remarkably, while behavioral data had a vast dispersion, especially in the humanitarian group, the classification accuracy results had very low dispersion. Despite the higher variability of behavioral data, the higher classification rate and its low dispersion also suggest that it is feasible to use spectral patterns EEG for detection of different mental operations at individual level.

Conclusion

We tested an offline classification algorithm based on the spectral power density of EEG in recognition of three types of mental operations: solving verbal, arithmetic and logical tasks with arithmetic progressions. Additionally, we compared the behavioral performance in solving tasks and the accuracy of EEG classification in two groups of subjects with education in math or humanities. We obtained the predicted differences related to better performance of Math Group in solving the math tasks than Humanitarian Group. However, the classification accuracy of tasks based on the EEG did not differ significantly between the groups and was essentially higher than random. Considered together, our results support the hypothesis that EEG patterns reflect individual cognitive states corresponding to mental operations and can be used in classification of different cognitive activities.

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Классификация вербальных и математических ментальных операций на основе спектральной плотности мощности ЭЭГ

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Резюме

Классификация спектральных паттернов ЭЭГ лежит в основе нескольких когнитивных нейротехнологий, включая пассивные и активные интерфейсы мозг — компьютер. Несмотря на то что арифметические задачи часто используются в исследованиях когнитивной нагрузки, мало результатов, описывающих возможность распознавания паттернов ЭЭГ, связанных с различными типами математических операций. В настоящей работе мы показали, что спектральная плотность мощности ЭЭГ может использоваться для классификации типов умственных операций, включая классификацию вербальных и разных математических задач на простые арифметические операции или логических задач с арифметическими прогрессиями. Вербальные задачи классифицировались от арифметических значительно лучше, чем арифметические от логических задач и вербальные от логических задач. Лучшая точность классификации вербальных задач от арифметических, но не от логических задач, поддерживает гипотезу об уникальных паттернах ЭЭГ, связанных с вербальной деятельностью, которые, по-видимому, отличаются от умственных арифметических операций. Кроме того, мы сравнили эффективность решения задач испытуемыми и точность классификации ЭЭГ у двух групп студентов с математическим или гуманитарным образованием (N = 8 + 8). Мы получили ожидаемые групповые различия, связанные с лучшими показателями решения математических задач у математической группы, чем у гуманитарной группы. Однако точность классификации задач, основанная на ЭЭГ, достоверно не отличалась между группами и была существенно выше, чем случайная. Полученные данные подтверждают гипотезу о том, что паттерны ЭЭГ отражают определенные когнитивные состояния, соответствующие умственным операциям, и могут использоваться при классификации различной когнитивной деятельности.

Ключевые слова: ЭЭГ, спектральная плотность мощности, ментальные операции, искусственная нейронная сеть, точность классификации.

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