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AUTOMATED REAL-TIME CLASSIFICATION OF PSYCHOLOGICAL FUNCTIONAL STATE BASED ON DISCRETE WAVELET TRANSFORM OF EEG DATA

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Abstract: A method for the automated real-time classification of psychological functional state is proposed. The classification is based on discrete wavelet transform of electroencephalographic data. The method consists of two preliminary stages — global feature selection and individual tuning, and the main stage — real-time classification. All stages are fully automated. The software implementation of this method revealed high reliability of classification and good potential of the method for applications dealing with virtual caves, including stress resistance evaluation, training, phobia therapy, etc.

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1. Introduction

The identification of a psychological functional state is important for individual psychological examination, particularly, for stress resistance evaluation. It is also important for teaching, training, phobia therapy and other applications where task difficulties can be varied and incorrectly chosen difficulty level leads to inadmissible results: low efficiency if difficulty is too low and zero or even negative progress if difficulty is too high. In case of using virtual cave as a facility for task generation and performance control, the difficulty level can be easily changed in real time. In addition, virtual cave equipment provides real-time monitoring of psychophysiological characteristics and parameters. In this case highly reliable automated psychological functional state classification based on these data can essentially increase training/therapy efficiency and simultaneously reduce the requirements for expert supervision over the process.

In this paper we describe a method for automated real-time binary classification of psychological functional state (norm vs. stress) based on electroencephalographic (EEG) data. These two classes of psychological functional states are the most important ones for the aforementioned applications. The method does not use any a priori knowledge of the psychological domain.

The rest of the paper is organized as follows. In Section 2 the general scheme of the method is described. This scheme can be formally applied to any collection of estimators. In Section 3 the collection of estimators used in software implementation of the method is defined. The definition of these estimators is based on a discrete wavelet transform, CDF 9/7 wavelet is used. In Section 4 the results of the method testing are discussed.

2. Method Description

2.1. Data Structure. The EEG data are measured by a set of K sensors, so each measurement is a vector $v \in \mathbb{R}^K$. The measurements are performed uniformly M times per second. Thus, the EEG data corresponding to a time window with length N seconds is a point in $\mathbb{R}^{KMN}$. The EEG data is noisy and contains artifacts, but generally these artifacts lie in the low frequency domain or in the high frequency domain (e.g., artifacts related to winking), and medium frequency domain is unaffected. Figure 1 gives an example of data generated by one EEG sensor.

The typical value of K is several dozens (up to 256), the typical value of M is several hundreds (up to 5000). Hence the dimension of the data is extremely high. However, strong dependencies between data corresponding to closely located sensors as well as between data corresponding to close measurements are present. At the same time, the quantity of individuals for which EEG data is available for the purposes of machine learning and algorithm tuning is only several dozens. That is why the straightforward application of standard methods for the automated classification (e.g. SVM — see Cortes and Vapnik [3]; Random Forrest — see Breiman [1]) leads to inadmissible results and a specific method is required.

2.2. The method scheme. The proposed method is based on a widely used voting scheme (e.g., see Littlestone and Warmith [5]), but it has a stage that is non-standard for typical machine-learning methods, but common for various medical and psychological algorithms — a stage of individual tuning.

At the top level, the method includes three stages:

- global learning;
- individual tuning;
- individual testing.

At all stages, the method deals with EEG data processed by the collection of estimators. Here an estimator is an ensemble of mappings $\mathbf{f} = \{f_n\}_{N_0}^{N_1}$, where f_n maps $\mathbb{R}^{Kn}$ to $\mathbb{R}^+$, and $N_0 \in \mathbb{N}$, $N_1 \in \mathbb{N} \cup \{+\infty\}$. A result of a computation of an estimator $\mathbf{f}$ for a time window with length N seconds is a real number $f_n(D)$, where $n = MN$ (here we suppose that $N_0 \le N \le N_1$), and D is raw EEG data corresponding to this time window.

It is supposed that an initial collection of estimators $\mathcal{F}$ is given. Formally, the method can be applied to an arbitrary collection of estimators, but the reliability of the resulting classification essentially depends on the choice of the initial collection of estimators. The collection used in the software implementation of the method is described in Section 3.

The stage of global learning consists in selecting estimators from the initial collection that are generally useful for functional state classification. Currently this stage does not use any a priori psychological knowledge, but this knowledge can be naturally taken into account at this stage (however, it is not required for obtaining a reliable classifier).

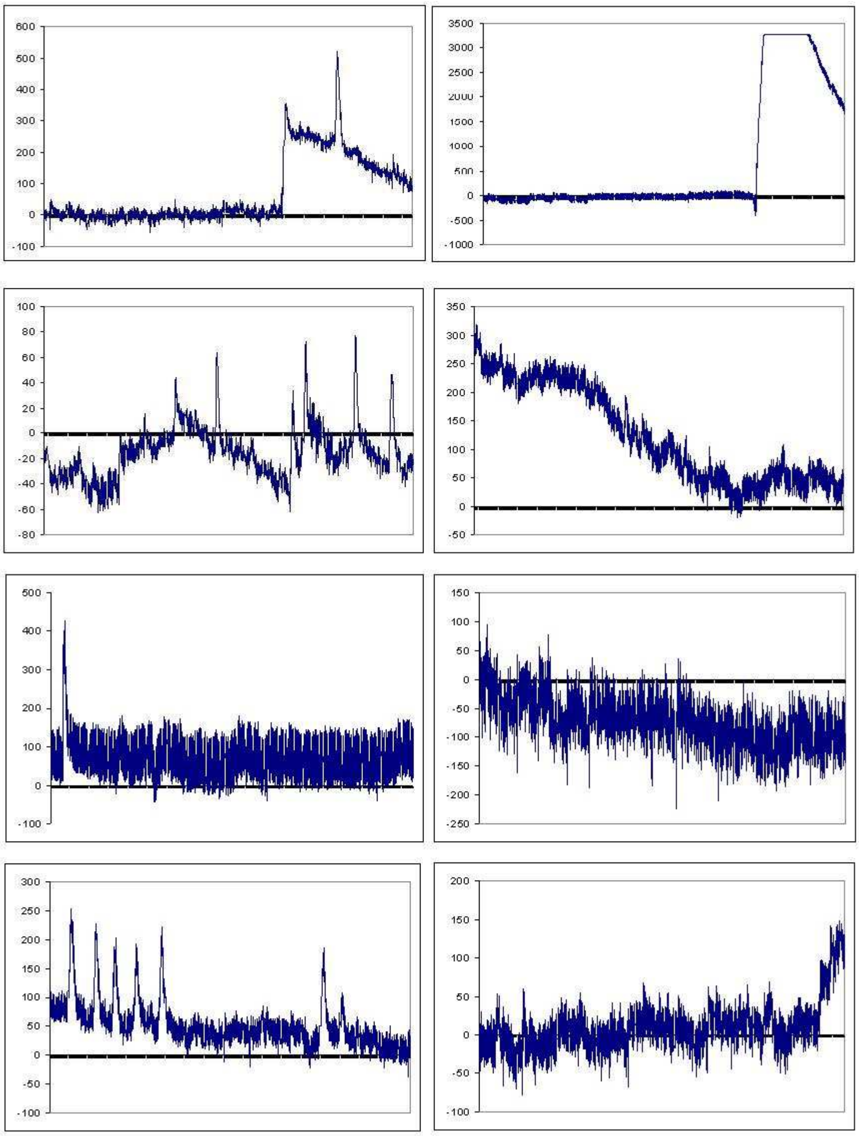

Figure 1: An example of EEG data corresponding to one EEG sensor and four individuals (one individual in each line: left graph corresponds to stress, right — to the normal state). The length of each data block is approximately 12 seconds.

At the stage of individual tuning the data corresponding to one individual is analyzed. Similarly to the previous stage, this information is expertly segmented, and a psychological functional state (norm/stress/other) corresponding to each segment is known. However, due to the requirements of the applications the amount of this information is small: it is considerably smaller than the amount of information at the global learning stage. The task that is solved here is to select a subset of estimators from a set of generally useful estimators that are well applicable to the individual, and to calculate thresholds and other parameters required for the individual testing stage.

At the stage of individual testing a data corresponding to a time window with a fixed length is analyzed and the psychological state (norm/stress) corresponding to this time window is determined.

2.3. The global learning stage. The input for this stage is a set of EEG data blocks corresponding to different individuals. Here a data block is EEG data corresponding to one time window; the length of a time window is typically 1-2 minutes, and longer blocks are split into blocks corresponding to time windows with this length. It is supposed that several blocks corresponding to both normal state and stress are present in input data for each individual, and that the state corresponding to each block is known (determined by experts). Normally, for each individual there should be at least 6 non-overlapping data blocks corresponding to stress and at least 6 non-overlapping data blocks corresponding to the normal state.

The output of this stage is a set of generally useful estimators from the initial collection of estimators, and additional information for each generally useful estimator: its relative weight and its orientation flag (it equals 1 if higher values of estimators generally correspond to stress, and equals −1 if higher values of estimators generally correspond to the normal state).

The selection of generally useful estimators is performed as follows. For each individual non-overlapping data blocks $S_1, \ldots, S_k$ corresponding to stress and $N_1, \ldots, N_m$ corresponding to normal state are taken. Then an estimator $\mathbf{f}$ is taken from an initial collection of estimators, and it is examined whether this estimators separates stress and the normal state (in this case the estimator is called *informative* for this individual). More formally, if

$$\max_{i=1,\ldots k} \mathbf{f}(S_i) < \min_{j=1,\ldots m} \mathbf{f}(N_j),$$

the estimator $\mathbf{f}$ is called informative for the individual with the orientation flag −1; if

$$\min_{i=1,\ldots k} \mathbf{f}(S_i) > \max_{j=1,\ldots m} \mathbf{f}(N_j),$$

the estimator **f** is called informative for the individual with the orientation flag 1; and the estimator **f** is called non-informative for the individual otherwise. For the informative estimator **f** with the orientation -1 its individual usefulness for the individual is set to

$$\frac{\min_i \mathbf{f}(S_i)}{\max_j \mathbf{f}(N_j)} - 1,$$

and for the informative estimator **f** with the orientation 1 its individual usefulness for the individual is set to

$$\frac{\min_k \mathbf{f}(N_j)}{\max_i \mathbf{f}(S_i)} - 1.$$

The estimator is called generally useful if for at least given fraction (in current software implementation — 2/3) of individuals it is informative with the same value of orientation flag (in this case, this value is assigned to the orientation flag of the estimator).

The relative weight $w(\mathbf{f})$ of the estimator **f** is calculated basing on the individual usefulness of this estimator for the individuals for which the estimator turned out to be informative, and the fraction of such individuals. All the weights are non-negative real numbers, and the sum of all weights equals 1.

2.4. The individual tuning. Unlike global learning that should be performed only once on a fixed group of individuals, individual tuning is required for all individuals whose psychological functional state would be further automatically classified.

The individual tuning stage allows involving certain information about individual peculiarities. However, due to the limitations imposed by the applications the amount of data available at the stage of individual tuning is low — only one data block S corresponding to stress (with standard length 1-2 minutes) and only one data block N corresponding to the normal state (with the same length).

The individual tuning is performed as follows. For every generally useful estimator **f** values $h^+ = \mathbf{f}(S)$ and $h^- = \mathbf{f}(N)$ are computed. If the orientation flag assigned to the estimator **f** was 1 and $h^+ \leq h^-$, or if the orientation flag assigned to the estimator **f** was -1 and $h^+ \geq h^-$, the estimator is put into a class of estimators that are not well applicable for this individual. Otherwise the estimator is included into the set of estimators well applicable for the individual, and the values of h^+ and h^- are remembered.

2.5. The individual testing. At the stage of individual testing a time window corresponding to latest data is analyzed. The typical length of the window is 1 minute, windows overlap, and a shift of a window is 10 seconds. Thus, the classification results are typically updated every 10 seconds, and the delay of the classification does not exceed 1 minute.

The individual testing is performed as follows. Let $\mathcal{F}_{ind}$ be the set of estimators that are well applicable to the individual for which the classification is performed, and let D be a data block corresponding to the analyzed time window. For each estimator $\mathbf{f} \in \mathcal{F}_{ind}$ its vote $V_{\mathbf{f}}(D)$ is calculated. Vote is a real number that lies between -1 and 1. Negative number means a vote for the normal state, and positive number means a vote for stress. Votes close to zero show the uncertainty of the conclusion, and votes with high absolute values show the confidence.

The vote $V_{\mathbf{f}}(D)$ is a clipping

$$\max\{-1, \min\{1, v_{\mathbf{f}}(D)\}\},$$

where

$$v_{\mathbf{f}}(D) = s(\mathbf{f}) \frac{\log_2 h - (\log_2 h^+ + \log_2 h^-)/2}{|\log_2 h^+ - \log_2 h^-| + 0.05}$$

(0.05 is a regularization parameter), $s(f)$ is an orientation flag for the estimator f assigned at the global learning stage, $h = \mathbf{f}(D)$, and h^+, h^- are the values corresponding to the individual and the estimator assigned at the individual tuning stage.

The resulting vote $V(D)$ is a weighted sum

$$V(D) = \sum_{\mathbf{f} \in \mathcal{F}_{ind}} w(\mathbf{f}) V_{\mathbf{f}}(D)$$

of votes corresponding to all estimators well applicable for the individual. The resulting classifier $C(D)$ is a vote's sign:

$$C(D) = \operatorname{sign} V(D)$$

(1 corresponds to stress and -1 corresponds to the normal state).

3. The Collection of Estimators

The initial collection of estimators used in the software implementation of the described method had the following structure. The information from different

EEG sensors was processed independently, so each estimator dealt with the signal obtained from only one sensor. For every sensor 16 estimators were defined: 8 "absolute" estimators and 8 "relative" estimators. All estimators used discrete wavelet decomposition (wavelet filtering) of a signal.

The estimators were defined using the following construction. A data block D was divided into smaller non-overlapping blocks with with length $L = 2^l$ measurements and truncated: for a data block with the initial length T measurements the length of the truncated block was $T_1 = \lfloor T/L \rfloor L$. The value l was chosen in such a way that L measurements corresponded to 8-16 seconds. For the real data used for the method testing l was 15.

A signal d of a single EEG sensor in the data block D was thus split into segments $d_1, \ldots, d_J$, where each d_j is a vector in $\mathbb{R}^L$ space, and $J = \lfloor T/L \rfloor$. A discrete wavelet construction (see Daubechies [4], Ch. 5, Sec. 5.1) provides a decomposition of $\mathbb{R}^L$ in a direct sum:

$$\mathbb{R}^L = \Phi_0 \oplus \Psi_0 \oplus \Psi_1 \oplus \cdots \oplus \Psi_{l-1},$$

where $\dim \Phi_0 = 1$, $\dim \Psi_k = 2^k$ $(k = 0, 1, \ldots, l-1)$. We used the decomposition corresponding to Cohen-Daubechies-Feauveau wavelet CDF 9/7 (see Cohen et al [2]).

This decomposition of $\mathbb{R}^L$ generated the expansion of d_j. In this decomposition low-scale and high-scale terms were discarded (it led to the filtration of noise and artifacts in low frequency and high frequency domains), and only medium-scale terms were further used. In case of $l = 15$ we defined $d_j^i = \mathrm{Pr}_{\Psi_{i+5}}(d_j)$ for $i = 1, 2, \ldots, 8$. For each i vectors d_j^i were then combined into one vector $d^i = (d_1^i, \ldots, \ldots d_J^i) \in \mathbb{R}^{LJ}$.

The vector d^i was divided into overlapping segments with lengths $L/4$ and shift $L/256$, and for each segment its ℓ^2–norm u_k^i was computed $(0 \le k \le 256J - 63)$.

Finally, for $i = 1, 2, \ldots, 8$ the value of an estimator ϕ_i for the data block D were defined as a median of the set $U_i = \left\{u_k^i\right\}_{k=0}^{256J-63}$, and the value of an estimator ϕ_{8+i} for the data block D was defined as

$$\frac{\phi_i(D)}{\sum\limits_{j=1}^{8} \phi_j(D)}.$$

The usage of a median of norms corresponding to relatively short overlapping time windows provided the low influence of artifacts with good time localization on the values of the estimators.

4. Results and Discussion

The study was performed at Moscow State University; it was approved by the Ethic Committee of the MSU Faculty of Psychology. The study used a special scenario for the virtual cave developed by the staff members of the MSU Faculty of Psychology using Virtools software (see the official Virtools homepage [7]). The task in the scenario consisted in the detection of objects with specified features (shape and color) in the set of flying objects. The difficulty of the task depended on the following parameters:

- the maximum time for detection;
- the speed of the objects;
- the frequency of new objects generation;
- the fraction of the objects of interest in the whole set of the objects;
- the fraction of objects similar to the objects of interest (e.g. objects with the same color but different shape or vice-versa) in the whole set of the objects.

The scenarios optionally included disturbing elements such as punishments (e.g. mild electric shock) in case of errors of one or both types (false alarms and misses), and sudden irritating sounds.

The EEG data was collected using BrainAmp equipment including the BrainAmp Standard amplifiers and the BrainCap (see the manufacturer official web site [6]) with 64 sensors and frequency 2500 Hz. The segmentation of data and the identification of psychological functional state corresponding to each segment was performed manually by the experts of the MSU Faculty of Psychology. Only segments corresponding to normal state and stress were used for the method testing.

The input for the general learning stage contained data for 15 individuals of both genders aged between 18 and 25 with different levels of stress resistance. As the result of general learning 71 generally useful estimators were selected out of the initial collection that consisted of 1024 estimators. The generally useful estimators included both “absolute” and “relative” estimators. “Absolute” estimators belonged mainly to the lower and medium ranges of the studied frequencies while “relative” estimators covered the whole range of the studied frequencies. The total number of sensors associated with the generally useful estimators was 32. For a significant part of these sensors (15 sensors)

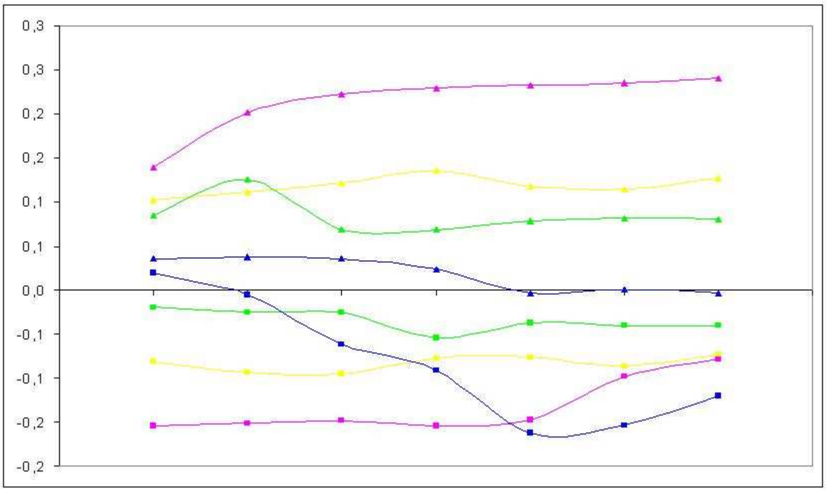

Figure 2: The results of individual testing for four individuals: upper curves correspond to votes $V(D)$ for the stress data, and lower - for the normal state data. Curves with the same color correspond to one individual. The resulting classifier $C(D)$ equals $\operatorname{sign} V(D)$.

only one estimator was associated with each sensor. However, several sensors were associated with a considerable number of estimators (one sensor — with nine estimators, one sensor — with six estimators, and three sensors — with 4 estimators).

The individual tuning and individual testing were performed for four subjects of both genders aged between 18 and 25. Figure 2 illustrates the results of individual testing. As one can see, for three subjects the classification results were totally correct, and for one subject the classification results were correct in approximately 84% of cases. An additional examination showed that this subject had considerable individual peculiarities. Particularly, up to 65% of generally useful estimators turned out to be not applicable to this subject, while this fraction does not generally exceed 25–35%.

Thereby, the study showed that the proposed method provides a highly reliable classification.

The reliability of individual testing remains nearly unchanged if it is performed basing on data corresponding only to a small fraction of most informative sensors (e.g., ten sensors that are associated with 42 of the generally useful estimators).

The reliability can be further increased using more informative individual tuning. In certain cases such individual tuning even allows to avoid general learning stage. However, more informative individual tuning requires more data, and thus this approach is not applicable in case of the problem statement considered in the study. Anyway, the classification using discrete wavelet transforms seems to be a good choice in both cases.

Another way to increase the classification reliability is to analyze certain physiological parameters (ECG data, GSR data, etc.) along with the EEG data. The appropriate modifications can be naturally applied to the proposed method: in this case the initial collection of estimators simply includes polytypic subsets associated with each data source. In frames of the described study these modifications allowed to increase the classification quality for the subject with considerable individual peculiarities from 84% to 91% while the classification for the other three subjects remained error–free. However, additional sensors are required for the collection of the physiological data, and it makes the study procedure technologically more complicated.

Data Availability

The details of the study as well as the EEG data and additional physiological data are available upon request from the authors.

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References

[1] L. Breiman, Random forests, *Machine Learning*, **45** (2001), 5-32.

[2] A. Cohen, I. Daubechies and J.-C. Feauveau, Biorthogonal bases of compactly supported wavelets, *Communications on Pure and Applied Mathematics*, **45** (1992), 485-560.

[3] C. Cortes and V. N. Vapnik, Support–vector networks, *Machine Learning*, **20** (1995), 273-297.

[4] I. Daubechies, *Ten Lectures on Wavelets*, SIAM, Philadelphia (1992).

[5] N. Littlestone and M. K. Waumuth, The weighted majority algorithm, *Information and Computation*, **108** (1994), 212-261.

[6] The Brain Products GmbH official web site, http://www.brainproducts.com/.

[7] The official Virtools homepage, http://www.3ds.com/products/3dvia/3dvia-virtools/.