Available online at www.sciencedirect.com

SciVerse ScienceDirect

Procedia - Social and Behavioral Sciences 00 (2013) 000–000

Procedia
Social and Behavioral Sciences

www.elsevier.com/locate/procedia

V Congress of Russian Psychological Society

Automated real-time classification of functional states based on physiological parameters

Ekaterina M. Lobacheva[a], Yulia N. Galatenko[b*], Rozaliya F. Gabidullina[c], Vladimir V. Galatenko[d], Eugene D. Livshitz[d], Taras P. Lukashenko[d], Dmitriy P. Vetrov[a], Alexey E. Lebedev[e], Vladimir E. Podol'skii[d], Vyacheslav V. Lebedev[f], Sergey A. Isaychev[f], Alexandr M. Chernorizov[f], Yuriy P. Zinchenko[f]

[a]*Faculty of Computational Mathematics and Cybernetics, Lomonosov Moscow State University, Leninskiye Gory 1-52, Moscow,GSP-1, 119991, Russia*
[b]*National Research University Higher School of Economics,Myasnitskaya str. 20, Moscow, 101000, Russia*
[c]*Laboratory of tactile diagnostics, Lomonosov Moscow State University, Leninskiye Gory 1-46, Moscow,GSP-1, 119991, Russia*
[d]*Faculty of Mechanics and Mathematics, Lomonosov Moscow State University, Leninskiye Gory 1 (Main Building), Moscow,GSP-1, 119991, Russia*
[e]*The Research-and-Technique Bioclinicum,Ugreshskaya str. 2-85, Moscow, 115088, Russia*
[f]*Faculty of Psychology, Lomonosov Moscow State University,Mokhovaya str. 11-5, Moscow,GSP-1, 125009, Russia*

Abstract

An automated real-time classification of human functional states is an important problem for stress resistance evaluation, supervision over operators of critical infrastructure, automated teaching and phobia therapy. In this paper we propose a novel method for binary classification of functional states based on the integrated analysis of (peripheral) physiological parameters: galvanic skin response, respiratory rate, electrocardiographic data, body temperature, electromyographic data, photoplethysmographic data, muscle contraction. The method is based on Gradient Boosted Trees algorithm. A testing of the method showed that in case of stress vs. calm wakefulness differentiation a reliability of the method exceeds 80%.

Keywords: Functional state; Stress; Automated classification; Gradient Boosted Trees; Individual tuning; Galvanic skin response; Electromyogram; Respiratory rate; Body temperature; Muscle contraction.

* Corresponding author. Tel.: +7 495 772 95 90 *22 25 ; fax: +7 495 939 45 36.
E-mail address: ugalatenko@hse.ru

1. Introduction

An automated classification of a human functional state is an important problem for stress resistance evaluation, supervision over operators of critical infrastructure, functional and genomic-functional studies of sportsmen, medical diagnostics, automated teaching and phobia therapy [1]-[3]. The most important functional states for these applications are stress and state of calm wakefulness (also referred to as a normal functional state).

A method for the automated real-time differentiation of stress and calm wakefulness state based on electroencephalographic (EEG) data was introduced in [4]. This method utilized CDF 9/7 wavelet transform [5] and included an individual tuning stage that essentially increased the classification reliability [6].

In this paper we propose a novel method for an automated real-time binary classification of the same functional states based on the integrated analysis peripheral physiological parameters including galvanic skin response (GSR), respiratory rate (Resp), electrocardiographic (ECG) data, body temperature (Temp), electromyographic (EMG) data, photoplethysmographic (PhPG) data, muscle contraction (MContr). The dimension of these data is essentially lower in comparison with EEG data, and hence other approaches to the classification algorithm design can be applied. We show that a reliable classification can be obtained by the utilization of the Gradient Boosted Trees algorithm [7]; however, peripheral physiological parameters are less informative for the functional state classification than EEG data.

The rest of the paper is organized as follows. In section 2 we describe the structure of the proposed method. In section 3 we present results of experimental evaluation of the method.

2. Method

2.1. Structure

The classification is based on the integrated analysis of parameters (features) listed in Table 1 (see [8], [9]). These parameters are computed for data segments corresponding to a time window with duration equal to 30 seconds.

Similarly to [4], the method has three main stages:

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

However, in contrast with [4], the method utilizes the Gradient Boosted Trees algorithm [7] and constructs a set of decision trees [10] that are used for the classifier value computation. Individual tuning is a non-standard stage for the Gradient Boosted Trees algorithm, but this stage essentially increases the reliability of the classification (see section 3).

2.2. Global learning

At the global learning stage a learning sample is processed and a set of decision trees is constructed. A learning sample contains data segments with standard length (30 seconds) corresponding to stress and to calm wakefulness for a representative group of individuals. Data segments corresponding to stress are labeled by +1, and data segments corresponding to calm wakefulness are labeled by –1. A set of decision trees is constructed by the OpenCV library [11] implementation of the Gradient Boosted Trees algorithm [7] with the square loss function $\frac{1}{2}(y-f(x))^2$, by defaults the set contains 100 trees with the maximum depth equal to 3.

Table 1. A list of peripheral physiological parameters used for the classification of functional states.

Signal	Parameters (features)
EMG	Standard deviation
ECG	Heart Rate Standard deviation of RR interval Low frequency rate for power spectral density of RR sequence High frequency rate for power spectral density of RR sequence Low-to-high frequency ratio for power spectral density of RR sequence
PhPG	Mean value of response amplitude Mean value of IBI (inter-beat interval) sequence Standard deviation of IBI sequence Low frequency rate for power spectral density of IBI sequence High frequency rate for power spectral density of IBI sequence Low frequency to high frequency ratio for power spectral density of IBI sequence Signal mean value Number of responses
Resp	Signal mean value Mean value of response amplitude Standard deviation of response amplitude Mean value of IBI (inter-beat interval) sequence Low frequency rate for power spectral density of IBI sequence High frequency rate for power spectral density of IBI sequence
GSR	Signal mean value Number of responses Mean value of response amplitude Mean value of response rise time Energy (sum over all peaks)
Temp	Mean value Standard deviation
MContr	Mean value Standard deviation

2.3. Individual tuning

If one or several data segments are available for an individual, and a correct functional state (stress / calm wakefulness) is known for each data segment (e.g., functional states were manually identified by experts), but this data is essentially insufficient for a construction of a reliable totally personal classifier for the individual, a simple procedure can be used to adapt a constructed set of decision trees for the individual, or, in other words, to perform individual tuning. This procedure simply applies each decision tree from a set to each data segment, and if a classification result provided by a decision tree is incorrect (i.e., positive for calm wakefulness and negative for stress) for at least one data segment, the tree is excluded from a set that is used at the individual testing stage for this individual.

A typical number of data segments used for the individual tuning is 2-4: 1-2 corresponding to stress, and 1-2 corresponding to calm wakefulness. If no data segments with known correct functional state are available, an individual tuning stage can be simply skipped.

2.4. Individual testing

The classification of a functional state for a data segment with a standard length (30 seconds) consists in a straightforward application of the decision trees from a set constructed at the global learning stage, that were not excluded at the individual tuning stage, summation of the results and the comparison of the sum with zero: if the sum is negative, then functional state, associated with the data segment, is classified as calm wakefulness, otherwise it is classified as stress.

3. Results

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 virtual cave technology, and changes of functional states were attained using special scenarios for a virtual cave system developed by the staff members of the MSU Faculty of Psychology. Data segmentation and identification of a functional state for each segment were performed manually by experts of the MSU Faculty of Psychology basing on a complex analysis of peripheral physiological data, EEG data and task performance parameters.

Data was collected for 19 individuals of different gender (m:f 9:10) with different stress resistance levels aged between 18 and 25, and a standard leave-one-out testing procedure [12, Sect. 7.10.1] was applied: one individual was excluded from the sample and global learning was performed for the remaining subset of 18 subjects, then individual tuning and individual testing was applied to non-intersecting collections of non-overlapping data segments, and this procedure was repeated 19 times (one time per individual). Only data segments corresponding to stress and calm wakefulness were used for the global learning, tuning and testing.

Testing showed that average classification reliability equals 81%. Exclusion of the individual tuning stage decreased the average reliability of classification to 61%, therefore, individual tuning appreciably increases classification reliability. It is worth noting that for certain individuals an application of individual tuning stage leads to the reduction of classification quality, but the reduction is generally small, while in case of individuals with essential individual peculiarities the increase of the classification quality provided by individual tuning, is significant (see Fig. 1).

Additional analysis of the distribution of peripheral physiological parameters over the decision trees revealed the following facts.

A list of parameters with the highest frequency of occurrence in the set of decision trees (or, in other words, a list of most informative parameters) includes MConv mean value, Temp mean value, GSR signal mean value, EMG standard deviation, Resp signal mean value.

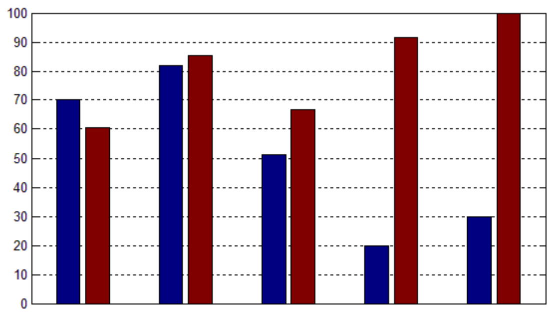

Fig. 1. . Classification reliability (%) for 5 individuals. Blue bars: reliability for the classification without individual tuning; red bars: reliability for the classification with individual tuning.

A list of parameters with the lowest frequency of occurrence in the set of decision trees (or, in other words, a list of the least informative parameters) includes GSR mean value of response amplitude, Resp low frequency to high frequency ratio for power spectral density of IBI sequence, PhPG low frequency rate for power spectral density of IBI sequence, ECG low frequency rate for power spectral density of RR sequence, PhPG low frequency to high frequency ratio for power spectral density of IBI sequence.

A list of parameters with the highest frequency of occurrence in decision trees excluded at the individual tuning stage includes Temp standard deviation, Resp high frequency rate for power spectral density of IBI sequence, ECG Low-to-high frequency ratio for power spectral density of RR sequence.

A list of parameters with the highest frequency of occurrence in decision trees excluded at the individual tuning stage includes for individuals with essential individual peculiarities includes GSR mean value of response rise time, MConv mean, EMG standard deviation. Here individuals with essential individual peculiarities are a group of individuals with lowest classification reliability in case if individual tuning is avoided.

4. Conclusion

A reliable binary real-time classification of functional states can be achieved by the integrated analysis of the peripheral physiological parameters using a set of decision trees automatically constructed by the Gradient Boosted Trees algorithm. However, the average reliability of the resulting classifier is expectedly lower in comparison with the classification based on the EEG data [4], [6]. A maximum classification reliability can be achieved by combing the analysis of EEG data and analysis of peripheral physiological parameters.

Similarly to [6], testing results proved the essential increase of the classification results provided by individual tuning stage. Testing also revealed key parameters for the functional state classification. A list of these parameters includes MConv mean value, Temp mean value, GSR signal mean value, EMG standard deviation, Resp signal mean value.

5. Data availability

All data and the detail of the study are available upon request from the authors.

Acknowledgement

The research was supported by the state contract no. 11.G34.31.0054, the state contract no. 13G36.31.0002, the state contract no. 14.514.11.4025, grants RFBR-11-01-00476, NSh-979.2012.1, NSh-6406.2012.1.

The research used the equipment purchased in frames of the MSU Development Program.

The authors thank the staff members of the MSU Faculty of Psychology for the valuable comments and discussions.

References

[1] Danilova NN. *Psikhofiziologicheskaya diagnostika funkcional'nyh sostoyaniy* [Psychophysiological diagnostics of functional states]. Moscow: MSU publishing. 1992.

[2] Hockey GRJ, Gaillard AWK, Burov O. *Operators functional state assessment: the assessment and prediction of human performance degradation in complex tasks*. Amsterdam: IOS Press; 2003.

[3] The RTO Human Factors and Medicine Panel (HFM) Task Group HFM-056/TG-008. *Operator functional state assessment. Technical report*. Neuilly-sur-Seine: NATO; 2004.

[4] Galatenko VV, Livshitz ED, Podol'skii VE, Chernorizov AM, Zinchenko YuP. Automated real-time classification of psychological functional state based on discrete wavelet transform of EEG data. *IJAM* 2012;25:871-882.
[5] Cohen A, Daubechies I, Feauveau J-C. Biorthogonal bases of compactly supported wavelets. *Comm. in Pure and Appl. Math.* 1992;45:485-560.
[6] Galatenko VV, Livshitz ED, Chernorizov AM, Zinchenko YuP, Galatenko AV, Podol'skii VE. Automated real-time classification of functional states: the significance of individual tuning stage. *Psych. In Russia: State of the Art* 2013:6 (in press).
[7] Friedman JH. Greedy Function Approximation: A Gradient Boosting Machine. *Ann. Statist*. 2001;29:1189-1232.
[8] Gao Y. *A Digital Signal Processing Approach for Affective Sensing of a Computer User through Pupil Diameter Monitoring*. PhD Dissertation. Florida: Florida International University; 2009.
[9] Shi Y, Nguyen MH, Blitz P, French B, Fisk S, de la Torre F, Smailagic A, Siewiorek DP, al' Absi M, Ertin E, Kamarck T, Kumar S. Personalized Stress Detection from Physiological Measurements. *International Symposium on Quality of Life Technology* 2010.
[10] Breiman L, Friedman J, Olshen R, Stone C. *Classification and Regression Trees*. Belmont: Wadsworth; 1984.
[11] Bradski G, Kaehler A. *Learning OpenCV*. Sebastopol, CA: O'Reilly Media; 2008.
[12] Hastie T, Tibshirani R, Friedman J. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. 2nd ed. New-York: Springer Science+Business Media; 2009.