Functional State Assessment of an Athlete by Means of the Brain-Computer Interface Multimodal Metrics

Vasilii Borisov, Alexey Syskov, and Vladimir Kublanov

Abstract

The estimation in real time of the functional and mental state level for the athlete during the loads is essential for management of the training process. New multimodal metric, obtained by means of the brain-computer interface (BCI), is proposed. The paper discusses the results of the joint usage of data from Emotiv EPOC+ mobile wireless headset. It includes motion sensors (accelerometer) and EEG channels. The features of the Emotiv EPOC+ interface allow to record the deviation of the head from the body axis, which provides an additional channel of information about the physical and mental (psycho-emotional) state of the athlete. Based on this data a new multimodal metric is calculated. Approbation of the metric was performed for functional stress studies on group of 10 volunteer subjects, including evaluations of the TOVA-test and the hyperventilation load. The joint application of different signals modalities allows to obtain estimates level of attention for these functional studies.

Keywords

Brain-computer interface • Functional study
Multimodal interaction

1 Introduction

Traditionally, the assessment of the functional state of an athlete using EEG devices is carried out in the laboratory conditions. The progress of mobile data transmission technologies, the emergence of mobile and energy saving computing technologies allows to create a mobile functional status monitoring systems for personal use (including applications in sport tasks) [1]. The development of user EEG systems brain-computer in the last decade has shown a fundamental difference in approaches for laboratory studies and functional state assessment in everyday life [2]. In this work we use the 14-channel wireless EEG headset Emotiv EPOC+ [3]. Studies have shown that this headset is a worthy replacement for EEG laboratory instruments in everyday life [4, 5].

Multimodal signals paradigm allows to increase the accuracy of classification the functional state of a person in real world conditions. So, the accelerometer signal indicates the daily activity type and allows to increase accuracy of classification in HRV feature space [6]. On the other hand, human motion data depends of vestibular system in almost all aspects of life [7]. In this way, the information on the movements of the head can be used to assess the cognitive status: self-perception of movement, spatial perception, including moving objects.

In [8], EEG and accelerometer signals from Emotiv Epoc+ are used for assessing the functional state in integrated multimodal feature space. Integrated feature space was constructed and verified for telemedicine and workout applications with multimodal intelligence user interface [9, 10]. The averaged data for a stage (3–5 min duration) was used for feature extraction and classification. It is more useful to have a metric for continuous athlete functional state assessment during each stage.

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The purpose of this work is the development of metrics, the detection of physiological patterns with changes in the functional state of the athlete in the training process. An example of a metric is the calculated values of the level of focus, stress, etc. at certain points in time.

2 Materials and Methods

2.1 Stages of the Experiment

To receive signals during the experiments, Emotiv Epoc+ headsets with Community SDK for data processing were used. The Emotiv EPOC+ headset contains 14 EEG channels and a three-axis accelerometer. The location of the electrodes of the EEG corresponds to the standard scheme 10–20: AF3, F7, F3, FC5, T7, P7, Pz, O2, P8, T8, FC6, F4, F8, AF4. The sample rate is 128 Hz. The number of digits of the ADC are 14. As additional software, Pebl was used to monitor the training program, Matlab was used for analysis and data processing.

The program of the experiment was sharpened as follows in order to simulate changes in the functional state during the training:

- Rest state (RS) during 300 s;
- TOVA test (T1) during 180 s;
- Hyperventilation load (HL) during 180 s;
- TOVA test (T2) during 180 s;
- Aftereffect (AE) during 300 s.

At the stage of functional rest, the subject sits opposite the monitor of the personal computer and looks at the black screen. Stage of TOVA test is an intellectual test for the variability of attention. It is a mental test to evaluate the function of active attention and control reactions. During the test, squares and circles appear alternately in the upper and lower parts of the computer screen. The task of the subject is to press a space on the keyboard when the square appears at the top of the screen [11]. At the stage of hyperventilation, the subject often breathes during the whole time, imitating breathing during heavy loads.

For functional state control purpose, ECG signal during all stages was registered. The spectral characteristics of HRV are investigated in the frequency bands indexes. The changes in VLF index were significant during the stages [3]. It is known [12], that fluctuations of VLF index of HRV signal with periods in range (0.04–0.003) Hz is complex and is due to the influence on the heart rhythm of the suprasegmental regulation level, since the amplitude of these waves is closely related to the mental stress and the functional state of the cerebral cortex.

2.2 Formation of Feature Space

2.2.1 Primary Signal Processing

Signals of motion modalities. During the experiments, the data was saved from the built-in three-axis accelerometer of the Emotiv EPOC+ headset; it provides data: time; acceleration values along the 3-axis.

The signal measured by the accelerometer is a linear sum of three components:

- Body Acceleration Component is acceleration resulting from body movement;
- Gravitation Acceleration Component is acceleration resulting from gravity;
- Noise inherent to the measuring system.

Changes in acceleration along the axes caused by human movements correspond to frequencies from 0 to 20 Hz in the signal spectrum. The gravitational component can be isolated in the range from 0 to 0.3 Hz. A component containing instrument noise is usually in the range above 20 Hz. To isolate the BA component, a second-order Butterworth window filter with frequencies from 0.3 to 20 Hz is used [13]. The study used the characteristics of the accelerometer signal from [6].

Signals of bioelectrical activity modalities. In the first step, all EEG data were transformed to the frequency domain. To separate EEG—rhythms from the signal, a second-order Butterworth bandpass filter were applied. Rhythms borders were: Theta (4–7) Hz, Alpha (7–15) Hz, Beta-Low (15–25) Hz, Beta-High (25–31) Hz. Discrete Fourier transform method was used for frequencies magnitudes extraction. As result, four coefficients are calculated for each of 14-th channel. Each coefficient is sum of magnitudes for one of the rhythms. Thus, EEG data in frequency domain are described as 56-dimension feature space [8].

2.2.2 The Model of the Integrated Feature Vector

Further, in order to build feature space and exclude artifacts components, the methods of the principal components (PCA) [14, 15], and linear discriminant analysis (LDA) [16] are used. Pairs of main components with the maximum explained variance and better classification accuracy are used to identify the most informative characteristics, for this purpose, the information on loads for EEG channels is used [8]. Data sets for pairs of states (RS and HL; RS and T1; T1 and HL) are used for building cross all stages feature space. The Fig. 1 contains data sets units, data processing unit descriptions and example of classification as described above.

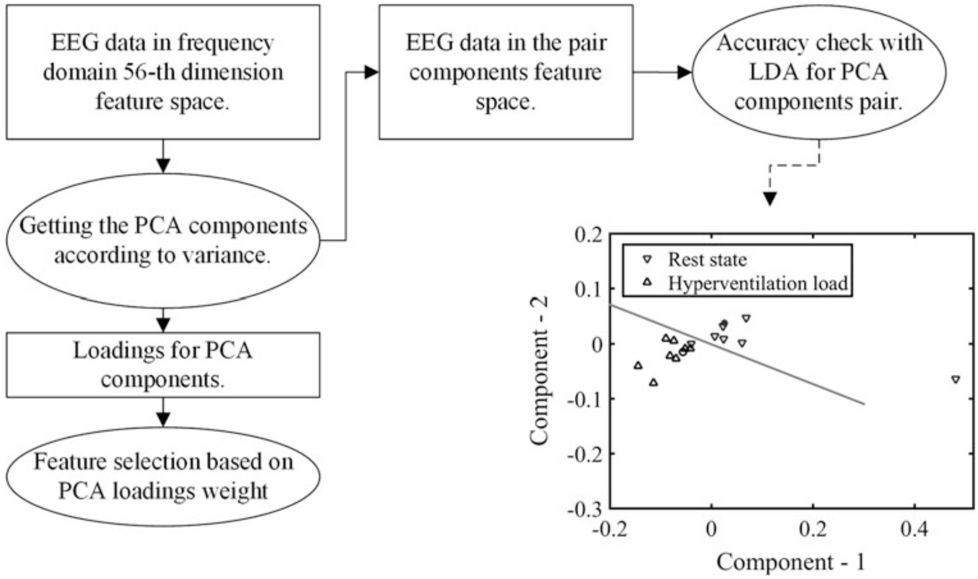

Fig. 1 The diagram of data processing for feature selection purpose

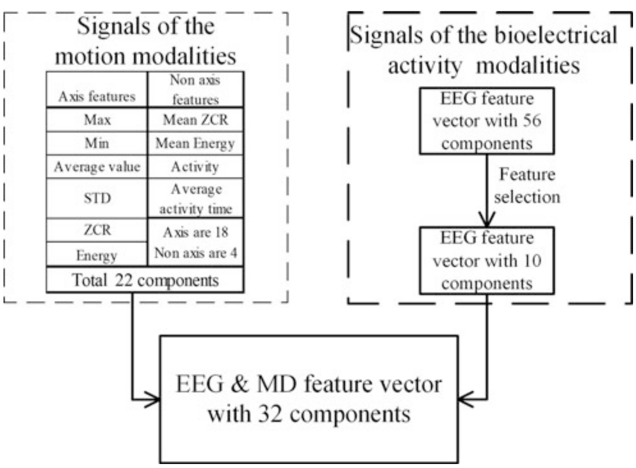

Fig. 2 The process of integrated feature vector creation

The result of feature selection is EEG feature vector, which contains AF3, T7, O1, T8, AF4 channels with Theta and Alpha rhythms components, correspondingly. Therefore, the new EEG vector size is 10 versus 56 in initial EEG data.

After that, new EEG feature space was expanded by adding the 22 components of accelerometer features as it depicted in Fig. 2.

2.3 Calculating a New Metric

The LDA method was used for creation the metric. Data sets for analysis contained EEG and MD recordings in integrated feature space for all subjects and the following pairs of stages: RS and HL, RS and T1. Test data were obtained from the experiment data using a cross-validation test (leave-one-out-cross-validation).

In our case, the accuracy obtained was 100% for all test samples. To determine the level of the athlete functional state, the formula derived in [17] is used to estimate the distance of each subject from the hyperplane *PD* separating the two load tests:

$$PD = \frac{\sum_{i=1}^{32} k_i x_i + C}{\sqrt{\sum_{i=1}^{32} k_i^2}}, \tag{1}$$

where

- k_i are the coefficients of the hyperplane separating the two functional states;
- C is constant;
- x_i are the coordinates of the state of the subject in the characteristic space.

3 Results

The metric values were calculated on the basis of the averaged data for each stage and each subject. Boxplots were obtained for the states of the RS-T1 metric (as shown in Fig. 2)

This metric describes statistically significant state changes for the RS and T1 stages. For the stages HL, T2 and AE, the changes are not significant. In Fig. 3 shows scatter graphs for the RS-HL metric. From these graphs it is clear that:

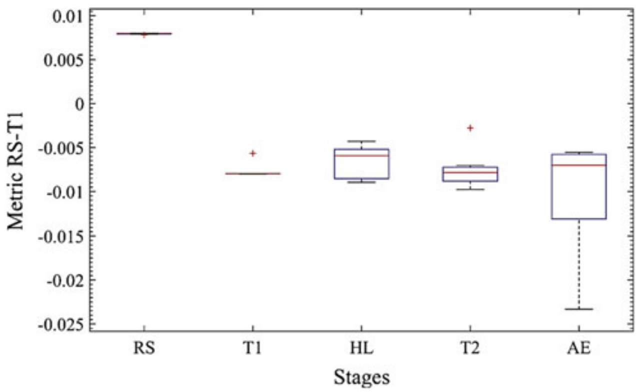

Fig. 3 The metric values calculated for RS-T1 stages

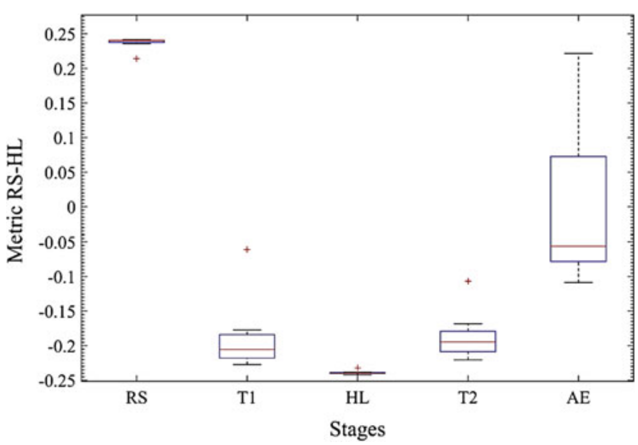

Fig. 4 The metric values calculated for RS-HL stages

- There are statistically significant differences in the metric values for the following stages: RS, T1, HL, and AE levels;
- There are no statistically significant changes for stages T1 and T2;
- There is a dynamic reflecting changes in the metric in the state AE towards recovering RS values after cognitive and physical exertion (Fig. 4).

4 Conclusions

One of the problems in developing an intelligent, multimodal interface is to obtain a model for combining modalities to calculate various metrics for assessing a person functional state. In this work, metrics to determine the physiological patterns of changes in the functional state of athletes in the process of training were obtained.

To calculate each metric, the coefficients of the LDA model were used. The coefficients of LDA models were obtained on training samples in the integrated feature space of EEG modalities and an accelerometer for pairs of functional states:

- Rest state (RS) and TOVA test (T1) is the metric of RS-T1;
- Rest state (RS) and Hyperventilation load (HL) is the metric of RS-HL.

The value of the metrics was calculated for the following functional states: Rest state (RS); TOVA test (T1); Hyperventilation load (HL); TOVA test (T2); Aftereffect (AE). The calculation was made for the averaged characteristics of the modalities of each athlete. As a result, boxplots of metric values were obtained for each stage of the experiment.

Based on the results of the boxplot diagram analysis, the following conclusions can be drawn:

1. for the RS-HL metric, it is possible to obtain statistically significant changes in the assessment of the athlete functional state for the stages: Rest state (RS); TOVA test, Hyperventilation load (HL); Aftereffect (AE);
2. for the RS-HL metric, there is a dynamic that reflects the changes in the metric in the state AE towards the recovery of RS values after cognitive and physical exertion.

The revealed dynamics of the RS-HL metric in our opinion is associated with a change in the controlling effect of the cerebral cortex. What causes changes in the activity of alpha rhythm and changes in patterns of head movements. Changes in the patterns of movement of the head are associated with the search for the most stable position of the head relative to the gravitational vector.

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Conflict of Interest The authors declare that they have no conflict of interest.

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