Case Study of Interrelation between Brain-Computer Interface based Multimodal Metric and Heart Rate Variability

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Abstract: The Brain-Computer Interface (BCI) can be used for evaluation of the state of individuals during everyday routines. As shown in previous works, there is a relationship between the BCI multimodal metric with functional states of human. We have used power of Theta, Alpha, Beta low and Beta high electroencephalography rhythms and head motion data signals for multimodal metric. Heart Rate Variability (HRV) is common medical method for functional state assessment. In this paper the results of interrelation estimation between multimodal metric and HRV are shown. We used Pearson correlation coefficient (PCC) for estimates of interrelation between multimodal metric and HRV. It was found, the best results for estimates of parasympathetic part of the autonomic nervous system and suprasegmental regulation HRV have value of PCC more then critical value for Pearson correlation.

1 INTRODUCTION

Human body is a phenomenally complex system. Interwoven with a multitude of physiological and mental processes, that overlap and influence one another in many different ways, it is similar in its nature to the Indra's net – each vertex is beaded with many multifaceted jewels, and each jewel is reflected in all of the other jewels (Robertson, 2014).

Given such fractal-like, interconnected structure of our organisms, it would be fair to say that assessment of subject's functional state and mental status is a non-trivial task (Kublanov et al., 2015). Examined signals differs one from another both in their characteristics and origins, and, more often than not, are contaminated with unwanted noise and artefacts. In turn, extracted signal's features, that contain useful insights and information, require usage of sophisticated statistical and mathematical apparatus in order to be properly interpreted (Kublanov et al., 2016).

Despite such associated difficulties, there's a common need in assessment of mental and functional state of a subject, in real-life conditions for healthcare and telemedicine application (Syskov et al., 2017).

Widely accepted methodologies used for that are electroencephalography (EEG) and electrocardiography (ECG), which, while recording signals from different organs (brain and heart, respectively), deal with the same underlying physiological phenomena – electrical activity of our bodies.

Another very common modality used in that setting is the motion activity. In the constant presence of the gravitational force, our bodies maintain continuous state of three-dimensional equilibrium. This self-balancing process produces various bio-mechanical oscillations (for example tremors, clonuses and fasciculations) and shapes our posture – all are indicators of subject's state. "Movement is life" indeed (Borisov et al., 2017). In (Borisov et al., 2018) integrated feature space EEG and motion activity for multimodal metric calculation are used. Statistically significant changes in the assessment of the athlete's functional state for the stages are shown.

In this research, we are testing the hypothesis of existence of common factor between heart rate variability (HRV) and multimodal metric in real-time conditions. To test this hypothesis, we conducted a set of small experiments, whose details, methodologies and final results are described as follows.

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2 MATERIALS AND METHODS

In this research, widespread wireless Emotiv EPOC+ headset was used for EEG and motion data acquisition (Borisov et al., 2017). Its technical specifications are presented in Table 1.

Table 1: Emotiv EPOC+ technical specifications.

Number of channels	14 (CMS/DRL references, P3/P4 locations)
Channel names (International 10-20 scheme)	AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4
Sampling method	Sequential sampling, single ADC
Sampling rate	128 SPS (2048 Hz internal)
Resolution	14 bits 1 LSB = 0.51 μV (16 bit ADC, 2 bits instrumental noise floor discarded)
Bandwidth	0.2 - 45Hz, digital notch filters at 50Hz and 60Hz
Filtering	Built in digital 5th order Sinc filter
Dynamic range	8400 μV (pp)

EPOC+ headset provides information about the induced electrical activity of the brain from 14 channels. This information contains the voltage value for each electrode with a sampling frequency of 128 Hz. Electrode placement locations are shown in Figure 1.

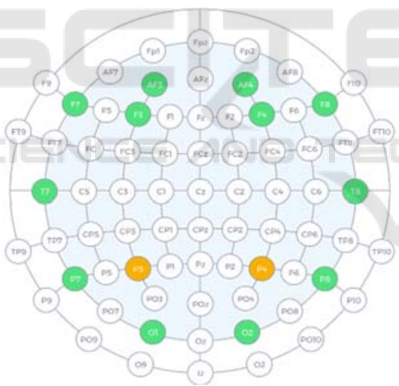

Figure 1: Emotiv EPOC+ electrode locations in standard 10-20 montage scheme.

In addition to that, headset also provides data from a three-axis accelerometer, which allows assessment of the movement of the headset in space during the experiment.

Recorded signal contains the values of the acceleration for each axis and the data recording time. The scheme of the accelerometer axes is shown in Figure 2.

Psycho-physiological telemetric system "Rehacor" (made by Medicom MTD, Ltd., Russia, see technical specifications in Table 2) with a set of cardiograph electrode terminals was used for ECG signal acquisition.

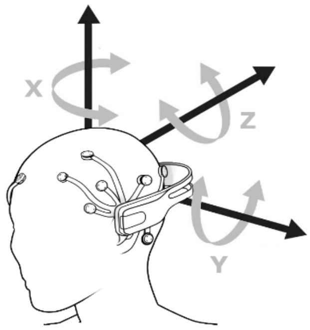

Figure 2: Scheme of accelerometer axes.

Table 2: "Rehacor" technical specifications.

Number of channels	4
Sampling rate	250 Hz
Resolution	24 bits
Dynamic range	5 - 8000 μV (pp)
ECG channel noise	≤ 2 μV (pp)
Low-pass filter cutoff frequencies	30; 40; 100 Hz
High-pass filter cutoff frequencies	0.05; 0.16; 0.5; 1.6; 5; 16 Hz
Callibration signal	5 Hz sine wave; 1 μV amplitude
HRV calculation range	45 - 240 bpm

2.1 Experiment Setup

A series of experiments with the equipment described above was carried out on 9 healthy subjects in the age group of 23±3 years, to study parameters which would describe different functional and mental states of a subject. Each experiment contained five stages as described further.

At the stage of functional rest (RS), the subject sits opposite the monitor of the personal computer and looks at the black screen.

Stage of TOVA test (Test of Variables of Attention) is an intellectual test for the variability of attention (T1 and T2). It is a mental test to evaluate the function of active attention and control reactions.

The Pebl software was used for the test procedure. During the test, squares and circles appears alternately at the top and bottom of the computer screen. The task of the subject is to press a space on the keyboard when a square appears at the top of the screen.

At the stage of hyperventilation (HL), the subject frequently breathes, imitating breathing during heavy physical load. The final stage is aftereffect period (AE). The time-line of the experiment is shown in Figure 3.

Raw EEG, HRV and movement data were recorded and collected during the experiments, before being processed as described in the next sections.

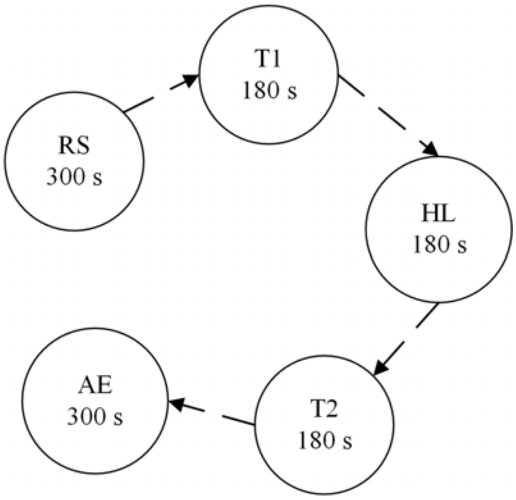

Figure 3: Time-line of the experiment.

2.2 Motion Data Processing

The three-axis accelerometer provides information on the magnitude of the acting accelerations along the three axes, respectively. The acceleration value for each axis is registered through equal time intervals. The signal measured by the accelerometer is a linear sum of three components (Borisov et al., 2018):

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

GA provides information about the spatial orientation of the device, and the BA provides information about the movement of the device and subject's head movement.

The frequency spectrum of accelerations caused by human motion is located in the range from 0 to 20 Hz. The gravitational component is located in the range from 0 to 0.3 Hz. The component containing instrumental noise is located generally in the range above 20 Hz.

To isolate the motion component from the signal, a second-order Butterworth window filter with frequencies from 0.3 to 20 Hz was used.

The most relevant motion data (MD) features of the accelerometer signal are (Borisov et al., 2018):

- Maximum and minimum values of acceleration;
- Average value of acceleration at a given time interval;
- Standard deviation (STD);
- Zero cross rate (ZCR);
- Mean ZCR;
- Mean energy for a current stage;
- Activity (in the equation below);
- Average activity time.

Because of the discrete nature of the accelerometer signal, ZCR was calculated as the number of sections where the previous sign differs from the current sign. Activity, the value characterizing the change in the signal over time, was calculated by the following formula (1):

$$Activity = \sum \sqrt{\Delta_x^2 + \Delta_y^2 + \Delta_z^2}, \qquad (1)$$

where $\Delta_x = (x_i - x_{i-1})$.

The average activity time is the ratio of the total activity time, which exceeds the average level by 10%, to the number of stages not exceeding this level.

2.3 HRV Signal Processing

Frequency-domain analysis method was applied to ECG signal and HRV indexes were calculated.

Artifact removal was carried out using 3-sigma rule and moving window algorithm. Mean window value was used for value restoring. Spectral characteristics of frequency ranges, depicted in Table 3, were used for subject's functional state assessment (Borisov et al., 2017).

Table 3: HRV frequency ranges.

Title	Abbreviation	Frequency range (Hz)
High frequency	HF	0.4 – 0.15
Low frequency	LF	0.15 – 0.04
Very low frequency	VLF	0.04 – 0.003
Ultra low frequency	ULF	< 0.003

ULF range is not used in analysis of short-term recordings (3 - 5 minutes in our case). Total spectrum power (TP) is defined a sum of powers in HF, LF and VLF frequency ranges.

Normalized power values in each frequency range (that is HF/TP, LF/TP and VLF/TP) are defined as a percentage ratio of the total power of the spectrum to TP value.

The activity of the parasympathetic link of the autonomic nervous system and the activity of the autonomous regulation loop are characterized by the power of HF/TP index. LF/TP index characterizes the state of the sympathetic center of vascular tone regulation. VLF/TP index is caused by the influence on the rhythm of the heart of the supra-segmental regulation level since the amplitude of these waves is closely related to the mental stress and the functional state of the cerebral cortex.

On all stages of our experiment, sliding window with 100 seconds size was used for assessment of HF/TP, LF/TP and VLF/TP parameters.

2.4 EEG Signal Processing

At the first stage of EEG signal processing, all data were transformed to the frequency domain. To separate EEG rhythms (see Table 4) from the signal, a second-order Butterworth bandpass filter was applied.

Table 4: EEG frequency ranges.

Title	Frequency range (Hz)
θ	4 – 7
α	7 – 15
β_{low}	15 – 25
β_{high}	25 – 31

EEG data in frequency domain is described as 56-dimension (14 channels, 4 frequency ranges each) feature space. This data was passed through EEG signal processing pipeline, as depicted in Figure 4.

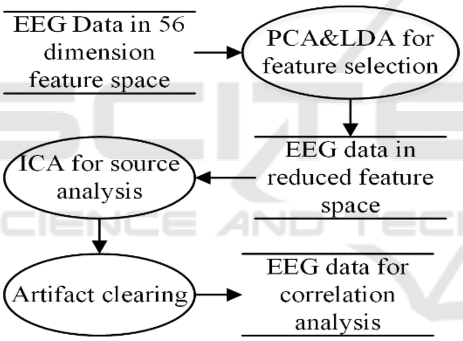

Figure 4: EEG signal processing.

Initially, Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) methods were used for dimensionality reduction and extraction of informative signal (Jolliffe, 2014) and (McLachlan,1992) from the input data.

As a result of PCA and LDA application (covered in more detail in (Islam, 2010)) EEG feature vector was reduced to 10 components, namely AF3, T7, O1, T8, AF4 channels with Theta and Alpha frequency bands.After dimensionality reduction and feature selection step, Independent Component Analysis (ICA) was used for separation of EEG signal from background and inherit system noise. EEGlab scientific package, in addition with supplied guidelines (SCCN: Independent Component Labeling), was used for this task.

Based on spectral analysis of extracted components, frequency bands most likely containing artifacts were selected, on each stage of experiment.

All frequency spectra then were analyzed for presence of eye-movement overshoots, with 1 second size window using 3-sigma method. Signal was filtered in case of overshoot presence. Example of eye movement artifact component is shown in Figure 5.

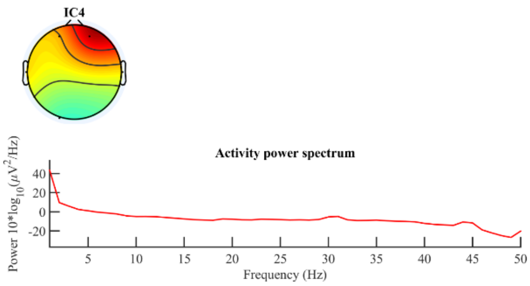

Figure 5: Eye component of EEG.

2.5 Creation of Multimodal Metric

By “metric”, we mean a measure that gives a scalar estimate of “human proximity” to one of the two states, in real time. In this work metric for RS and HL stages are calculated (as shown on Figure 6).

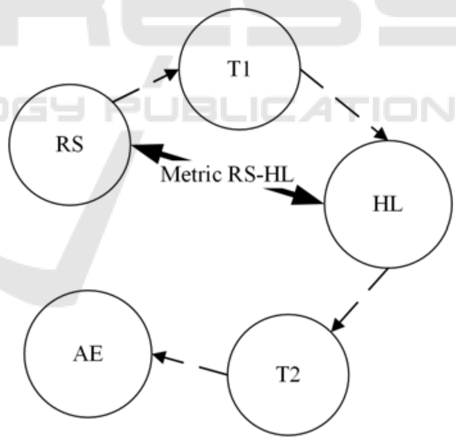

Figure 6: Metric RS-HL definition.

Integrated feature vector is created by concatenation of motion modalities and bio-electrical activity vectors. The model of integrated feature vector is depicted in Figure 7.

After construction, 32 component vector was weighted with coefficients of hyperplane PD separating resting (RS) and hyperventilation stages (HV) for calculating scalar value for each time point, using machine learning as described in (Borisov et al., 2018).

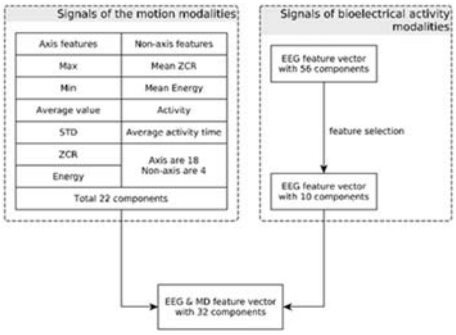

Figure 7: Model of integrated feature vector.

3 RESULTS AND DISCUSSION

Both coefficients of multimodal metric and HRV indexes were calculated using sliding window with 100 seconds size and 5 seconds step. As a result of data processing pipeline, time series with the following structure were obtained:

- 3 minute stages (T1, HV and T2) – 16 data points;
- 5 minute stages (RS and AE) – 40 data points;
- Total record of all stages contains 128 (40 × 2 + 16 × 3) data points;
- For each subject, a total of 8 vectors (7 HRV indexes and 1 PD coefficient) were calculated.

Examples of plotted HRV indexes and normalized coefficient of multimodal metric PD are shown on Figure 8.

Visual analysis of plotted data indicates that there exists a dynamic that reflects changes in the functional state of a subject during the experiment, both in multimodal metric and in calculated HRV indexes.

To test our initial hypothesis of existence of common factor between heart-rate variability signal and time-series of multi-modal metric, Pearson correlation coefficients (PCC) were calculated for RS and HV time-series.

Statistical significance of correlation coefficients was evaluated. Based on table values from (Förster and Rönz, 1979) for p=0.05:

- Sample size N is 112 (56 × 2);
- Number of degrees of freedom DF is 110 (N – 2);
- For given value of DF, critical value of correlation coefficient is 0.2.

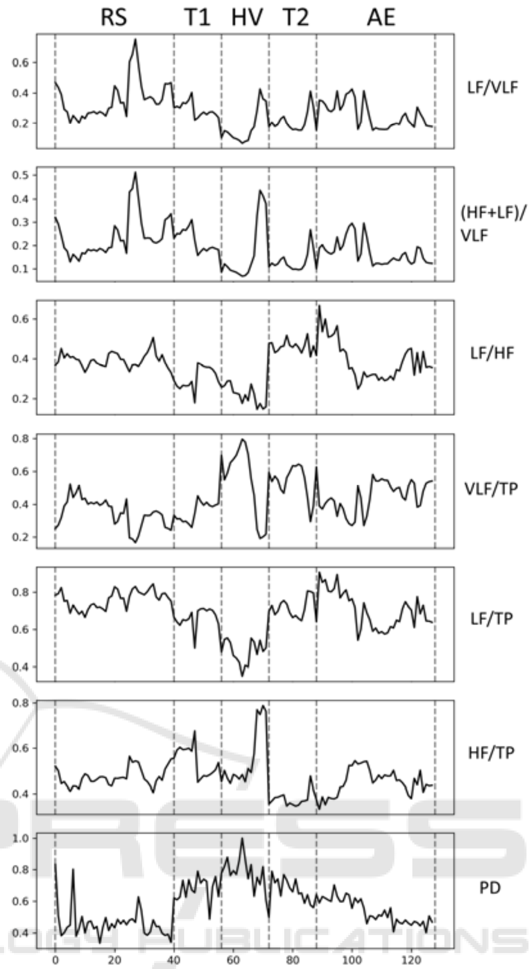

Figure 8: HRV indexes and multimodal metric (PD).

Upon evaluation of PCC correlation coefficients, it was found that data series, consisted of concatenated RS and HV intervals, has a statistically significant Pearson's correlation value. Results are shown on the graphical plot below (see Figure 9), with absolute correlation values on horizontal axis and calculated HRV indexes on vertical axis; each subject is depicted with unique color point on each stage.

The presence of a significant correlation allows us to formulate a hypothesis about the presence of factors that are common to the parameters of the functioning of the central nervous system, the autonomic nervous system and the vestibular apparatus, which can be identified using the proposed multimodal metric.

The explanation of such factors may be based on the following phenomena identified during the research: the spectral components of the HRV signal in the VLF frequency band changed significantly,

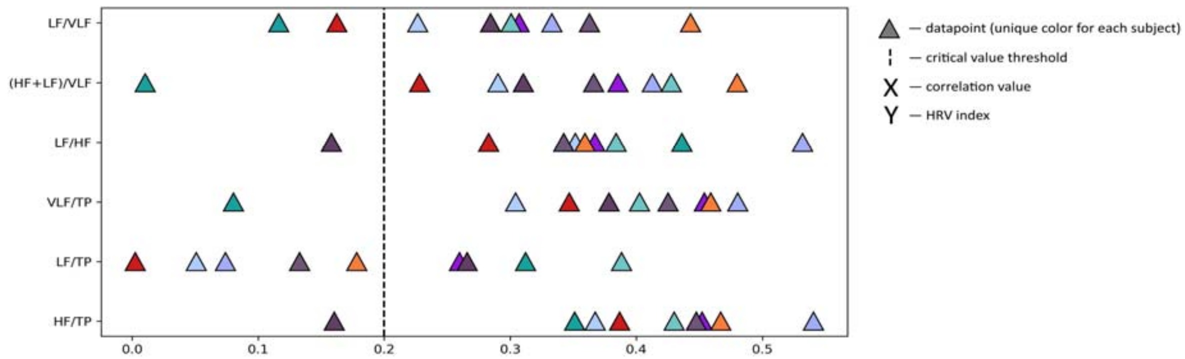

Figure 9: Correlation of vector of concatenated RS and HV intervals with HRV indexes.

which can be explained by the influence of the supersegmental control of the autonomic nervous system on the heart rate.

4 CONCLUSION

In this paper, we verified a multimodal metric of Brain-Computer Interface. For verification, the assessment of the functional state was carried out using the parameters of HRV. Integrated feature space for accelerometer and EEG allows to get more accuracy and accessibility for different function states. Multimodal metric based on this feature space useful for assets "human proximity" to desired function level during training or rehabilitation.

We used PCC for estimates of interrelation between multimodal metric and HRV. The common correlation factor develops itself individually in each subject. Thus, it may serve as a diagnosis feature for functional processes that occur in subject's body. It's tightly bound to the sustenance of the homeostatic state of individuals (Yee and Rabinstein, 2010).

Since the study was conducted on relatively healthy people, such a factor may be the state of human health. Further studies involving people with different nosologies and neurophysiological states.

There are should allow for the identification of additional of physiological patterns. For example, the above results can be developed in the development of methods for assessing changes in the functional state of a person with sympathetic correction for patients with depression and disorders of the function of the vestibular apparatus (Kublanov et al., 2018).

Further investigations need to be carried out in order to pinpoint the nature and origins of this factor for real world assessment of humans.

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