Searching and Using of Time Intervals of Brain Activity in a Problem of Solving Process by Estimation of Negentropy of EEG

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***Abstract*—In the analysis of a brain activity it is actual to find time intervals that represents only brain activity. We have developed a new software instrument that helps to search and visualize such intervals. The base assumption of this work is that distribution of the amplitude of signal that represents brain activity is significantly different from a Gaussian distribution. So we use negentropy as an indicator of intervals of brain dynamics.As a result, the developed instrument helps to analyze EEG information visually and make further mathematical calculations with the results.**

***Keywords*—Electroencephalography (EEG), Independent Component Analysis (ICA), effective intervals, negentropy, ERSP**

I. Introduction

One of the methods of analyzing brain activity is to calculate an event-related spectral perturbation [1]. ERSP reflects a change in time of a spectral power in different regions of a brain. Search of a time interval in which a brain activity is fundamentally different from a brain activity in adjacent intervals is actual when using this method. That interval represents a time period limited by a moment of an “inclusion” of a brain in a solution of a problem and a moment of a cessation of functional activity that existed at a previous phase. The method of negentropy is used to determine these changes [2]. However, a routine use of this method is to search for intervals of specific activity, for example, to find areas that reflect the oculomotor response. At the same time, it is of interest to search intervals that reflect brain dynamics exactly. These intervals may have different temporal boundaries for different examinees as well as for different brain areas of a single examinee.Such intervals we call “effective intervals”.

The main aim of the current study is to develop a software system that allows to select effective intervals most correctly for the analysis of temporal dynamics of the electroencephalography (EEG), taking into account individual characteristics of a topology of cortical processes. A new instrument should meet the following requirements:

- An interface for settings required parameters for calculating effective intervals.
- Ability to visualize effective intervals on the EEG.
- Searching effective intervals on independent components of the EEG.
- Analysis of negentropy of spectral perturbations.
- Ability to visualize averaged over all trials values of time limits of effective intervals in the ERSP plot.
- Storing numerical values of the ERSP on found intervals.

The result of this work became the finished software product that meets the requirements listed above. It allows selecting and producing further additional mathematical calculations solely on time intervals, that reflect brain activity associated with external events (effective intervals). Also, this product simplifies visual analysis of ERSP and EEG components.

II. Previously developed algorithm

Previously implemented algorithm (Lazarenko, 2005) allowsdetermining effective intervals of EEG and is based on an analysis of negentropy of the signal amplitude. In [3], that algorithm is used to calculate the “event-related desynchronization/synchronization” - ERD/ERS [4].As opposed to the standard method of selecting time limits for the calculation of ERD/ERS, in which they are the same for all stimulus presentations, this technique allows to analyze brain reaction on time intervals when it is most pronounced. So intra- and inter-individual differences in reaction time, that reduce recognizabilityof this reaction,aretaken into account [3]. However, the assessment of negentropy in that algorithm is performed for an averaged EEG signal. The brain dynamics in response to a particular stimulus are reflected not in all brain areas and not in all frequency bands [5]. So determined by this approach intervals are not useful for tasks that require greater accuracy.

III. Methods

In this work our proposal consists of developing a new algorithm that allows to search effective intervals of EEG. Spectral changes of a brain activity typically involve more than one frequency or frequency band [1], so the algorithm of

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identifying time intervals should estimate a negentropy of full-spectrum ERSP. Also, that analysis should be implemented for individual independent components of EEG, allocated on the basis of Independent Component Analysis (ICA) [6,7].

The developed algorithm takes as input names of events' marks, which then used as limitation for searching intervals only near events of interest, as well as left and right temporal boundaries from these points. Algorithm searches effective intervals inside specified boundaries.It should be noted that event's mark is a moment when some event, e.g. stimulus presentation or reaction on it, is occurred, and it is usually stored with EEG data.

The new method of searching effective intervals consists of the following steps:

1. EEG data decomposition using ICA and time phasingobtained components according to input arguments.
2. Time-frequency decomposition of each obtained interval, calculating ERSP.
3. Effective intervals search and selection of the optimal interval for each frequency, obtained in the step 2.

Consider next each step indetail.

A. ICA decomposition

Independent component analysis (ICA) is a computational technic for separating a multivariate signal into additive subcomponents [6]. The concept of ICA was proposed in [8] as a special case of "blind source separation" problem. A simple example for this method is the "cocktail party problem", where the underlying speech signals are separated from sample data consisting of people talking simultaneously in one audience.

The process of decomposing EEG data using ICA involves a linear change of basis from original source data to a spatially transformed "virtual channel" basis.In the original channel data, each row of the EEG data matrix represents the time course of summed in voltage differences between source projections to one data channel and one or more reference channels. After using ICA, each row of the data activation matrix gives the time course of the activity of one component process spatially filtered from the channel data. It is important to note that the base assumption of the ICA is that the source signals are statistically independent [9].

The components obtained by ICA can represent synchronous or partially synchronous activity of a particular area of the cerebral cortex or non-cortical activity (eye movement, muscle activity, the external electric fields, etc.).

There are various algorithms for the ICA decomposition. In the currentstudy, we primarily use algorithm "runica", implemented in the EEGLAB package.

In this work, after applying the ICA, we allocate time-slots from component activations data, which thenis used forsearching effective intervals of brain activity. The length and location of these slots are determined based on the time of appearance of event marks,left and right boundaries (input arguments of the algorithm) and sampling rate of the processed EEG.

B. Time-frequency decomposition

One of three measures of time-frequency decomposition implemented in the EEGLAB are event-related spectral perturbations, or ERSP. The ERSP is used to display average event-related dynamic changes in amplitude of the broad band EEG frequency spectrum.

Calculation of anERSP involves computing the spectral power for each data trial and then averaging the results. Typically, ERSP is calculated by the following formula:

$$ERSP(f,t) = \frac{1}{n}\sum_{k=1}^{n}|F_k(f,t)|^2, \tag{1}$$

where$n$ – number of trials, f – frequency, t – time and $F_k(f,t)$ – spectral estimate of trial k [10]. In this work we use sinusoidal wavelet transform to compute $F_k(f,t)$.

The new algorithm calculates ERSP for each interval independent, i.e. coefficient$n$ is equal to 1. It uses the implementation of the ERSP calculation in EEGLAB and the output are matricesthat represent the time course of normalized for each specified by the algorithm frequency.

C. Searching effective intervals

The base assumption of that work is that distribution of the amplitude of signal that represents brain activity is significantly different from a Gaussian distribution. Therefore, a distribution of the amplitude on effective intervals differs from a distribution on intervals of background activity.

It is the practice to express discrete EEG signal as a sample of a random variable:

$$x: x(0), x(1), x(2), \dots, x(N), \tag{2}$$

$$N = f * L, \tag{3}$$

where$L$ – length of an experiment, f– sampling rate (Hz).

In information theory and statistics, one of the measures of non-Gaussian distribution is negentropy:

$$J(x) = H(y) - H(x), \tag{4}$$

$$H(x) = -\sum P(x = x_i)\log\left(P(x = x_i)\right), \tag{5}$$

where$J$ – negentropy, x – study sample, H – entropy, y – random variable with Gaussian distribution and with the same mean and variance as$x$. The normal distribution has the highest entropy among all the distribution with the same mean and variance.Negentropy measures the difference in entropy between a given distribution and the Gaussian distribution with the same covariance matrix. Thus, it is always nonnegative, and equals zero if and only if the signal is Gaussian.As negentropy computational complex, we use its approximation [11]:

$$J(x) \approx \frac{1}{12}E^2(x^3) = \frac{1}{48}kurtosis^2(x), \quad (6)$$

where*kurtosis* is:

$$kurtosis(x) = E(x^4) - 3E^2(x^2), \quad (7)$$

At the third step, the developed algorithm iterates over all rows of matrices obtained in the second step for each frequency and searches subintervals with the maximum value of negentropy for each row and frequency. As a brute-force search of all subintervals is computational complex, algorithm uses Variable Neighborhood Descent (VND) [12] modified for decision of the current problem.

D. Tools and technologies

As a tool for implementing effective intervals search algorithm and visualization instrument EEGLAB [13] was chosen. EEGLAB is a Matlab toolbox for processing continuous and event-related EEG, MEG and other electrophysiological data. This toolbox allows to calculate ICA and ERSP, so it is perfect for the current study. In addition, Matlab includes many other applications needed for the current task and has sufficiently high performance for mathematical calculations.

The developed product is a plugin for EEGLAB. It allows users to work with a familiar interface. The next EEGLAB's functions was used for basis of this plugin:

- *Runica* – realization of ICA decomposition.
- *Newtimef* – function, that calculates and visualize ERSP.
- *Pop_eegplot* – EEG data visualization.

User interface is implemented with standard features and styles of EEGLAB. Input form of algorithm parameters consists of the following fields:

1. Left interval from event (ms) – the number of milliseconds before an event mark;
2. Right interval from event (ms) – the number of milliseconds after an event mark;
3. Left constraint from interval start (ms) – the number of milliseconds after the beginning of the interval specified by the parameters (1) and (2). A zero value of that parameter corresponds to the value specified by parameter (1);
4. Right constraint from interval start (ms) - the number of milliseconds after the interval specified by the parameters (1) and (2);
5. Coefficient of superiority (>1) - the coefficient of superiority. If algorithm analyzes on some iterationsubinterval that is not in the interval specified by (3) and (4) but between (1) and (2) and negentropy multiplied by coefficient of superiorityis greater than current maximum, algorithm takes that subinterval as a candidate for result.
6. Minimal interval length (ms) - the minimum length of an effective interval;
7. Select events – event marks. Algorithm searches

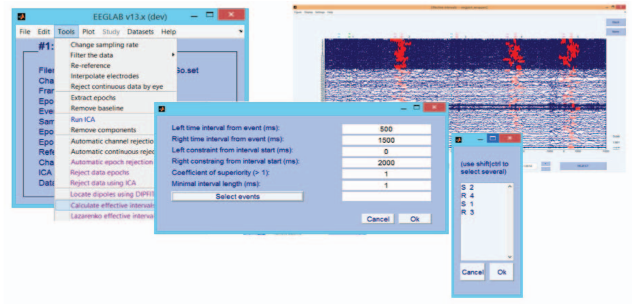


Fig.1. User interface of developed EEGLAB module.

effective intervals only near specified events.

Parameters (3) and (4) could be used to define boundaries of the most probable position of effective intervals.

For calculation and visualization of effective intervals on the ERSP plot, we have implemented *effint_newtimef_full*function based on EEGLAB's *newtimef*. It could be called from Matlab command line with the same parameters as *newtimef*.

IV. Results

As a result of this work, the new plugin for EEGLAB was developed. It allows calculating and visualizing effective intervals on component activations plots and on ERSP plots. It was primary tested on EEG data recorded during the game "Hunt" based on the stop-signal paradigm. As a measure of "effectivity" of found intervals, next criteria were chosen:

- Similarity and frequency of results ceteris paribus;
- Effective intervals should be concentrated between presentation of a stimulus and a reaction of probationer;

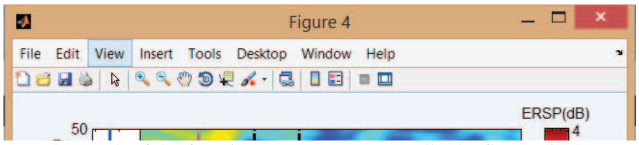
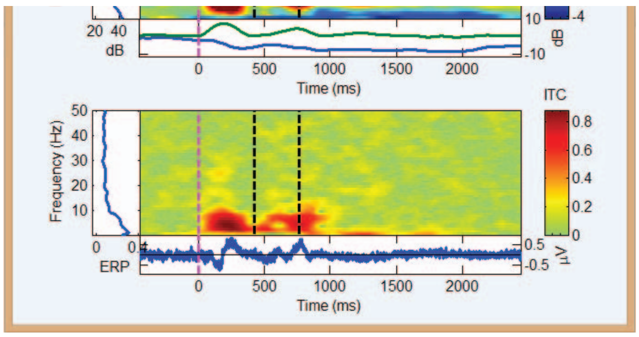


Fig.2. The result of the function *effint_newtimef_full*. The figure displays ERSP and inter-trial coherence (ITC) of the one component of EEG. Dashed lines indicate the boundaries of the averaged effective interval.



- Existence of intervals whose borders coincide or close to events;

- Visual assessment of experts in the field of neurophysiology.

The best results were achieved with an option of algorithm, which choose not subinterval with the maximum value of negentropy among all frequencies, but calculates mean values of left and right borders among 25% of intervals with maximum negentriopy obtained for each frequency.

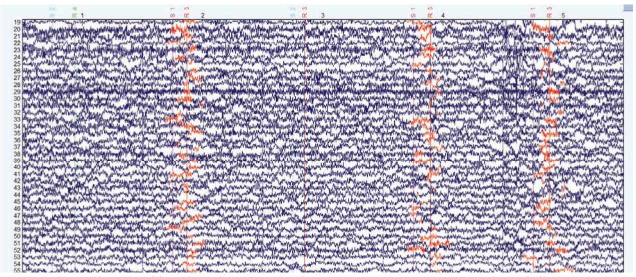


Fig. 3. Visualized effective intervals for components №19-59 of five trials. Effective intervals are marked by red color.

Figure 3 shows effective intervalsfound by algorithm. In this example, the boundaries were set from -500ms to 1500ms from "S1" marks. The large number of intervals are concentrated between "S1" marks (stimulus presentation at 0ms) and "R3" marks (pressing the button at 500-700ms). Also, similarity of effective intervals at different trials could be seen.

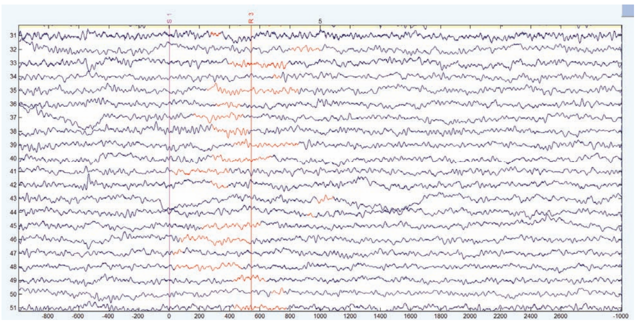


Fig. 4. Visualized effective intervals for components №31-51of the one trial. Effective intervals are marked by red color.

Figure 4 shows the presence of intervals whose boundaries are match with event marks or located near from them. It meets one of the criteria.

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