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Use of parallel computing for analyzing big data in EEG studies of ambiguous perception

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ABSTRACT

Problem of interaction between human and machine systems through the neuro-interfaces (or brain-computer interfaces) is an urgent task which requires analysis of large amount of neurophysiological EEG data. In present paper we consider the methods of parallel computing as one of the most powerful tools for processing experimental data in real-time with respect to multichannel structure of EEG. In this context we demonstrate the application of parallel computing for the estimation of the spectral properties of multichannel EEG signals, associated with the visual perception. Using CUDA C library we run wavelet-based algorithm on GPUs and show possibility for detection of specific patterns in multichannel set of EEG data in real-time.

Keywords: Electroencephalogram, multichannel EEG, big data, parallel computing, CUDA

1. INTRODUCTION

Studying of brain neural network and its activity is of a great interest for many researchers in modern science. An intensive progress in developing of methods for experimental investigation and mathematical data processing leads to increasing number of interdisciplinary publications during last years.[1–5] Brain activity analysis is a multidisciplinary task that combines approaches of many fields of natural science such as neurophysiology, mathematics, biophysics, nonlinear dynamics etc.

Neural ensemble of brain is commonly considered as a very complex oscillatory network with great number of elements – neurons. Activity of individual neurons and their clusters along with inter-neural and inter-cluster interactions raise complex dynamics in activity of brain neural networks. Research on such activity is an important task since some features of brain activity can provide information about functional state of living organism.[6]

Main sources of information about brain activity relate to experimental methods that involve registration and analysis of various brain signals. One of the most common methods for obtaining information about brain activity in normal and pathological conditions is electroencephalogram (EEG).[7] EEG method involves non-invasive placing of special electrodes on scalp and recording of EEG signals which represent sum of electric currents generated by a small group of neurons near each electrode.[8] Since brain is a complex oscillatory network, the signal that it generates, namely EEG, also has complex structure. EEG signal is characterized by complex time-frequency structure with number of specific frequency ranges, oscillatory patterns, heavy nonstationarity, significant noise component and intermittent behavior.[9,10]

It is well-known that EEG dynamics in some frequency ranges and forming of specific rhythms and patterns are in strong correlation with functional state of brain and body. Thus, studying of EEG structure along with recognition and classification of EEG patterns is an important task for understanding fundamental mechanisms of brain. It also has quite prospective applications in technics and medicine. One of possible applications is brain-computer interface (BCI).[11]

The BCI is based on real-time recognition of characteristic forms of activity in brain signals (EEG in this case) with their subsequent transformation into computer commands for programs, devices etc. Nowadays BCIs are actively developed and used for number of tasks with interaction between brain and machine systems,

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such as 2D movement control of a cursor, partially speech synthesis, simple movement control,[12] rehabilitation, exoskeletons and robots control,[13] absence-epilepsy seizures prediction.[14,15] On the one hand, BCI operation is highly influenced by the operators possibility to generate and reproduce stable patterns of cognitive activity, which then can be transformed into control commands. On the other hand, processing, analysis and decoding of incoming EEG data is also very significant. This part of BCI should include some advanced methods for EEG analysis and oscillatory pattern detection, that not only provide acceptable quality of pattern recognition, but also can be implemented in real-time.

Complex signal analysis and oscillatory patterns detection are common fields of radiophysics and nonlinear dynamics. Number of reliable and effective methods such as continuous wavelet transform (CWT)[16] were developed for detailed investigation of signals time-frequency structure. Many of these methods found application in EEG signal analysis.[17] Although CWT allows to perform detailed time-frequency analysis of EEG signals and can be effectively used for EEG pattern detection, it requires considerable computational power, especially when applied to big EEG data or in real-time. Thus, BCI intended to use CWT for decoding of multichannel EEG signals in real-time should introduce some special approaches. One of possible solutions is implementation of parallel computing for CWT.

In present paper we propose improvement in approach for BCI for estimation and control of alertness. We demonstrate the application of parallel computing for real-time estimation of the spectral properties of multichannel EEG data, associated with the visual perception. Using CUDA C library we run CWT-based algorithm on GPUs and show possibility for detection of the specific patterns in multichannel set of EEG data in real-time.

2. METHODS

BCI discussed in present paper is based on EEG signal analysis with help of CWT. In the general case CWT is a convolution of investigated signal $x(t)$ (EEG signal in our study) and a set of basic functions $\varphi_{s,\tau}$:

$$W(s,\tau) = \int_{-\infty}^{\infty} x(t)\varphi^{*}{}_{s,\tau}(t)dt \tag{1}$$

In equation (1) " * " marks cojugation of complex number. Each basic function $\varphi_{s,\tau}$ from this set can be obtained from one function φ_0, the so-called mother wavelet, by its extention/compression and time shifting as following:

$$\varphi_{s,\tau}(t) = \frac{1}{\sqrt{s}}\varphi_0\left(\frac{t-\tau}{s}\right) \tag{2}$$

In equation (2) φ_0 — mother wavelet, s — time scale, which determines extension or compression of initial mother function, τ — time shift of wavelet transform.

There are a lot of different mother wavelets that find application in signal analysis according to the problems of the current study. In present work we used CWT with Morlet mother wavelet with parameter $\omega_0 = 2\pi$:[?,?]

$$\varphi_0(\eta) = \pi^{-\frac{1}{4}} e^{j\omega_0\eta} e^{-\frac{\eta^2}{2}} \tag{3}$$

Common way to use CWT in signal processing is to analyze 3D (or 2D projection) distribution of wavelet energy $W(s,\tau)$ (wavelet spectrum). Further analysis of wavelet spectrum can provide detailed information about time-frequency structure of given signal and its specific rhythms. BCI discussed in present work uses "skeletons" of wavelet surfaces[18,19] for detection of certain rhythms in EEG and their time dynamics. The "skeletons" of wavelet surfaces are constructed to extract dominant EEG frequencies and determine the evolution of oscillatory patterns in EEG data. Process of "skeleton" construction is the following. First, the momentary wavelet energy distribution $E_i(f_s,t_0)$ is constructed for some time moment t_0.

$$E_i(f_s, t_0) = |W(f_s, t_0)|^2 \quad (4)$$

Then the function $E_i(f_s, t_0)$ is examined for the presence of local maxima E_{max}. If several local maxima $E_{max,k}$ are detected in $E_i(f_s, t_0)$, then the highest maximum is selected as first "skeleton" at given time moment t_0, the second highest maximum is second "skeleton" and so on. In order to construct full "skeletons" of wavelet surface the procedure described above should be repeated consequently for all points in time series of given EEG signal.

Proposed BCI algorithm also uses technologies of parallel computing to allow big EEG data analysis in real-time. CUDA is a parallel computing platform and programming model developed by NVIDIA for general computing on graphical processing units (GPUs). With CUDA, it is possible to dramatically speed up computing applications by harnessing the power of GPUs. In GPU-accelerated applications, the sequential part of the workload runs on the CPU – which is optimized for single-threaded performance – while the compute intensive portion of the application runs on thousands of GPU cores in parallel. Using of CUDA allows to program in popular languages such as C, C++, Fortran, Python and MATLAB and express parallelism through extensions in the form of a few basic keywords. In developed algorithm the CUDA Toolkit from NVIDIA is used as it provides all necessary instruments for developing GPU-accelerated applications. The CUDA Toolkit includes GPU-accelerated libraries, a compiler, development tools and the CUDA runtime.

3. BRAIN-COMPUTER INTERFACE

In the paper we propose improvement for approach used for BCI originally introduced in paper,[20] where it is described as BCI for estimation and control of alertness. Original BCI uses CWT and "skeletons" of wavelet surfaces for detection of dominant frequency components in EEG signal during bistable image perception. Special criteria are used to track changes in time-frequency structure of EEG signal during perception and to estimate level of human alertness.

BCI algorithm proposed in present paper has a number of conceptual improvements in comparison to original algorithm. All these features are intended to allow big EEG data analysis in real-time and to improve overall performance. The proposed BCI algorithm includes following steps:

1. Receiving EEG data from 19 channels of "10-20" scheme in real-time
2. EEG signal analysis and "skeletons" construction with help of parallel programming module based on CUDA technology
3. Checking "skeleton"-based criteria for estimation of alertness
4. Audiovisual feedback according to current level of alertness

Step 1 suggests experimental procedure that includes bistable image demonstration and EEG signals recording. We used the EEG recorder Encephalan-EEGR-19/26 (Medicom MTD, Taganrog, Russia) supplemented by a special developed software. A special library from Medicom MTD allowed us to access the data in real-time with a sample rate of 250 Hz. We used the set of N = 19 EEG channels arranged according to "10-20" scheme (see Fig. 1).

As BCI is intended to estimate alertness during bistable image perception, the core of experimental procedure is bistable image demonstration. Bistable images are images that can be perceived in two different ways and their perception can switch during observation. Visual perception plays an important role in data analysis in brain and cognitive activity, since human brain acquires about 90% of information through eyes. The mechanism of bistable image recognition is not well understood yet, but it is known that the perception is the result of processes in distributed neuronal network of occipital, parietal and frontal cortex areas. Thus, bistable image perception is an exellent task for testing level of human alertness as it involves activity of wide neuronal network and requires certain concentration of attention.

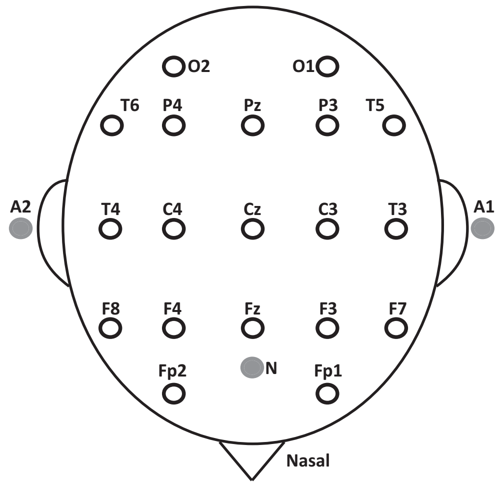

Figure 1. Scheme of setup for EEG recording system according to “10-20” scheme

Step 2 of algorithm implies CWT-based procedure for EEG signal analysis enhanced with application of parallel programming technologies. Since there are 19 analyzed EEG channels with sample rate of 250 Hz and they should be processed in real-time with CWT in frequency range of 4-30 Hz, this step requires considerable computational powers. Proposed solution of this problem is to use parallel computing with help of CUDA. Procedure of paralleling is illustrated on Fig. 2.

As seen from Fig. 2 procedure of paralleling includes several steps. First step is EEG channel paralleling. BCI acquires data in form of time series for 19 EEG channels and the first thing is to provide individual CUDA-powered computational module for each channel. Then each module prepares space in GPU and transmits EEG data from CPU to GPU. When whole time series for each channel are loaded to GPU, next step of paralleling is division of task into several blocks. Task in our case is computation of wavelet energy in time interval corresponded to length of loaded EEG time series and in frequency range of 4-30 Hz. This step of paralleling allows to split given frequency range into number of block and to perform computational task for each block separately. Further paralleling implies division of each block into threads where each thread is assigned to compute wavelet energy in given frequency range (determined by block) and in particular momnet of time series (determined by thread). When computation is over acquired wavelet energy data is transmitted from GPU back to CPU where it is saved to file.

Step 3 of BCI algorithm assumes construction of “skeletons” and checking special criteria for estimation of alertness. On this step “skeletons” are constructed for each of N = 19 EEG channel in two phases: before (I) and during (II) perception of bistable image. The wavelet spectrum of the EEG signals was calculated using a floating window of 2-sec length in the range between 4 Hz and 30 Hz. Each event was analyzed separately in alpha (8-12 Hz) and beta (20-30 Hz) frequency bands on a 1-sec interval preceding the presentation and followed by the moment of the stimulus appearance. A special digital trigger sent by the software together with the presentation of the stimuli initiated the calculation.

Then five “skeletons” are constructed and special characteristics $A_{I,II}$ and $B_{I,II}$ are introduced. These characteristics reflect integral intensity of alpha and beta rhythms before (I) and during (II) perception of bistable image. As a result, the set of values $A_{I,II}$ and $B_{I,II}$ were calculated for each presentation as:

$$A_{I,II} = \sum_{n=1}^{N} \int_{t\in\Delta t_{I,II}} \varepsilon_n(t')dt', where\ \varepsilon_n(t) = \begin{cases} 1 & \text{if } f_1^{max} \in \Delta f_\alpha \\ 1/2 & \text{if } f_2^{max} \in \Delta f_\alpha \\ 1/3 & \text{if } f_3^{max} \in \Delta f_\alpha \\ 1/4 & \text{if } f_4^{max} \in \Delta f_\alpha \\ 1/5 & \text{if } f_5^{max} \in \Delta f_\alpha \\ 0 & \text{if } f_{1-5}^{max} \notin \Delta f_\alpha \end{cases} \quad (5)$$

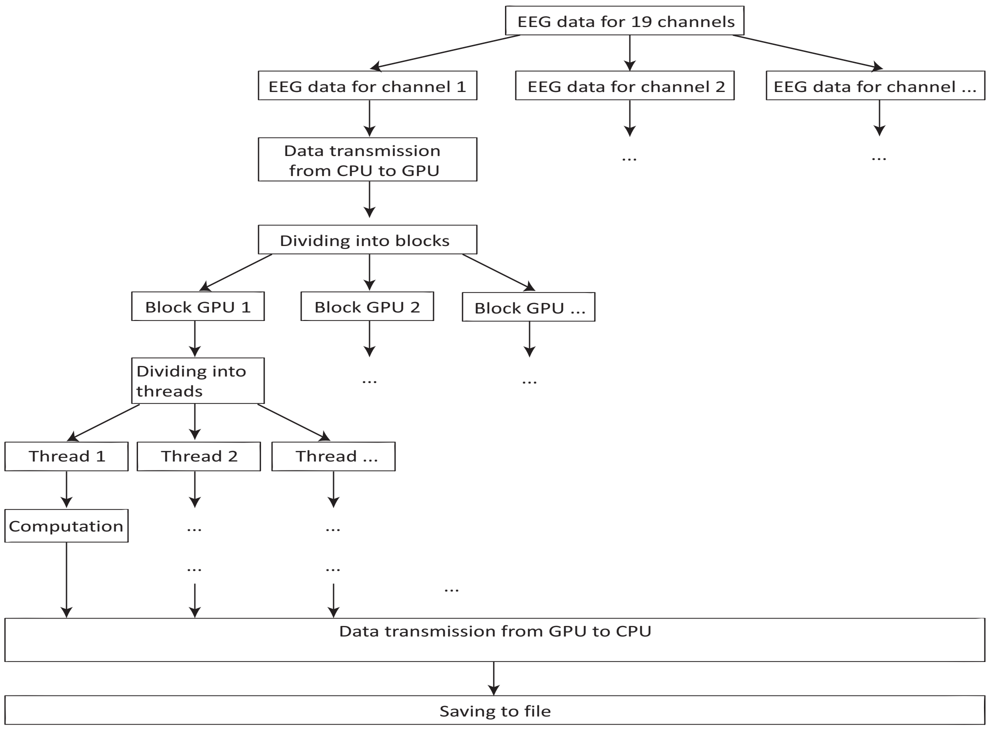

Figure 2. Procedure of paralleling for computation of wavelet energy

$$B_{I,II} = \sum_{n=1}^{N} \int_{t \in \Delta t_{I,II}} \varepsilon_n(t')dt', where\ \varepsilon_n(t) = \begin{cases} 1 & \text{if } f_1^{max} \in \Delta f_\beta \\ 1/2 & \text{if } f_2^{max} \in \Delta f_\beta \\ 1/3 & \text{if } f_3^{max} \in \Delta f_\beta \\ 1/4 & \text{if } f_4^{max} \in \Delta f_\beta \\ 1/5 & \text{if } f_5^{max} \in \Delta f_\beta \\ 0 & \text{if } f_{1-5}^{max} \notin \Delta f_\beta \end{cases} \tag{6}$$

where N = 19 is the number of EEG channels and $f_1 - 5^{max}$ is the location of the maximal spectral component for "skeletons" 1-5.

The obtained values were averaged over six presentations to obtain averaged characteristics $< A_{I,II} >$ and $< B_{I,II} >$ and the control characteristic $G(t)$ was calculated as

$$G_(t) = \frac{(< A_I > - < A_{II} >) + (< B_I > - < B_{II} >)}{2} \tag{7}$$

According to step 4 of BCI algorithm $G(t)$ is calculated and copared to treshold value in real-time. In the experiments with BCI, the feedback control is carried out in the form of a short sonic tone every time $G(t)$ reaches threshold value.

4. RESULTS

Developed BCI was tested in experiment with volunteers. Experimental work for recording EEG signals was held in scientific-educational center "Systems of Artificial Intelligence and Neurotechnologies" of Yuri Gagarin State Technical University of Saratov, Saratov, Russia. Experimental design included standard physiological trials such as opening/closing eyes, audio stimulation, photic stimulation etc.[6] along with specially developed trials for presentation of bistable images.

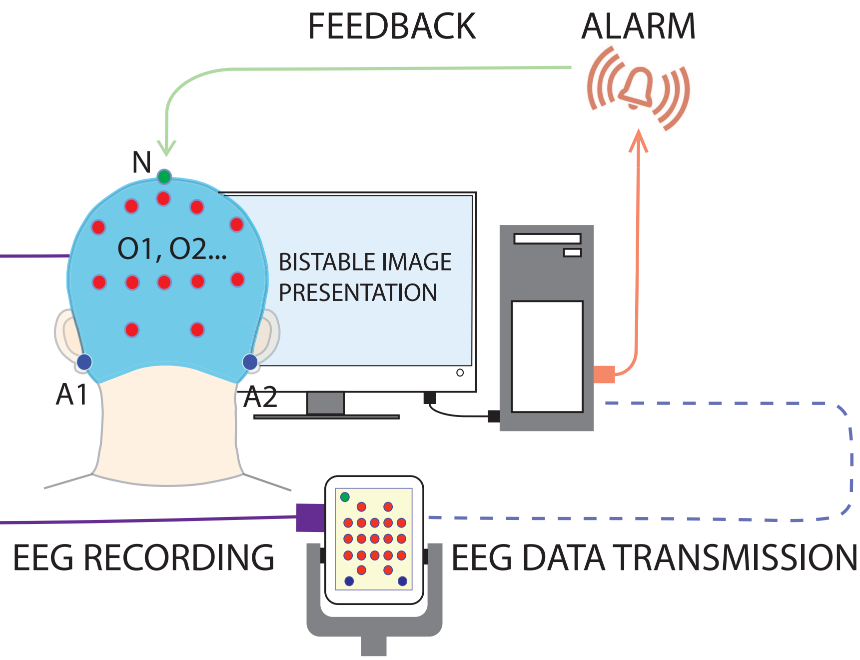

Figure 3. Scheme of BCI

EEG signals were recorded with use of standard International scheme "10-20".[21] Frequency range of EEG records was 0.016 – 70 Hz with band-pass filter on 49.5 – 50.5 Hz to prevent influence of power grid. Experiments were held for 20 healthy men and women in age of 18 – 40. Duration of each record was $\sim$ 35 minutes. During experiments volunteers observed number of bistable images each for short period of time – 1.5-2 s. Since bistable image can be perceived in two different ways, volunteers were instructed to push one of two buttons on input device according to the way they perceive each image.

BCI described in present paper was implemented during these experiments. Final scheme of BCI is shown on Fig. 3. Fig. 3 shows volunteer's head with placed EEG electrodes: ground electrode (N), referents (A1 and A2), rest electrodes according to scheme "10-20" (O1, O2...). Link "EEG RECORDING" corresponds to electric wires that transmit EEG signals from electrodes to electroencephalograph. Then through wireless link "EEG DATA TRANSMISSION" EEG data is transmitted to PC, where it is processed. According to acquired control characteristic $G(t)$ BCI sends "ALARM" sound and thus provides "FEEDBACK". "ALARM" starts when $G(t)$ exceeds certain threshold value which is estimated for each subject individually, based on the previous value of $G(t)$ averaged over a 4-min interval. The comparison between the current value of $G(t)$ and its threshold value was made for every bistable image presentation.

Performance of proposed BCI was tested and compared to performance of the original BCI. Proposed BCI was implemented on laptop with following characteristics: CPU Core i7 4700MQ 2.4 GHz, GPU GeForce GTX 860M, 2 Gb RAM. While new BCI algorithm works with 19 EEG channels (instead of 5 in original BCI) and with 5 skeletons (instead of one) its performance is 60 times faster thanks to parallel computing.

5. CONCLUSION

The present work is devoted to the improvement of BCI algorithm for estimation and control of alertness by addition of CUDA parallel programming technologies. Application of such technology allows to implement big EEG data real-time analysis by increasing number of analyzed EEG channels from 5 to 19. Also "skeleton" analysis is improved by increasing number of analyzed "skeletons" which gives new BCI algorithm more flexibility.

Since performance increase of proposed BCI algorithm is essential further research will go towards addition more EEG channels for even more precise estimation of alertness. It can be achieved by using advanced EEG recording equipment and expanded EEG placement schemes.

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