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Stream Processing of Multichannel EEG Data Using Parallel Computing Technology with NVIDIA CUDA Graphics Processors

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Abstract—Prospects of using parallel computing technology (PaCT) methods for the stream processing and online analysis of multichannel EEG data are considered. It is shown that the application of PaCT to calculation and evaluation of spectral characteristics of EEG signals makes online determination of changes in the energy of the main rhythms of neural activity in various parts of the cerebral cortex possible. The possibility of implementing the PaCT algorithm with CUDA C library and its use in a modern brain–computer interface (BCI) for cognitive-activity monitoring in the course of visual perception.

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In recent years, studying neural networks in the human brain has been of considerable interest, which can be seen in the rapid growth in the number of scientific publications in this field [1–5]. A significant number are devoted to the description of results obtained at the interface between neuroscience and other sciences (physics, mathematics, psychology, engineering, etc.).

Effective analysis of processes in the brain requires developing both the new methods of analysis and the new software and hardware facilities for their implementation. In this context, a promising approach is provided by parallel computing technology (PaCT) intended for online analysis of a large body of data. This is necessary, in particular, for developing brain–computer interfaces (BCIs) [6]. At present, BCIs are extensively created and applied, e.g., for controlling simple movements [7], managing exoskeleton robots [8], detecting absence-epilepsy seizures [9, 10], etc. Further BCI development must employ advanced methods for the interpretation of electroencephalography (EEG) records based on analysis of big input data.

In this Letter, we propose a new algorithm for the stream processing of multichannel EEG records, which employs the PaCT principle. The efficiency of applying this algorithm to BCI based on the Encephalan (Taganrog, Russia) EEG measuring unit and data processing with the aid of CUDA C library is shown.

The main sources of information on human-brain functioning are related to experimental methods involving the measurement and analysis of neural-activity signals. One of the most widely used techniques in both pathological and normal states is EEG recording of brain electrical activity [11, 12]. EEG records are characterized by a complicated time–frequency map structure with a set of frequency ranges and oscillatory patterns, significant nonstationarity, high noise level, and intermittent behavior [13, 14]. The dynamics of the EEG signal in characteristic ranges and the formation of specific oscillatory patterns are known to reflect to a significant degree the functional state of both the brain and the whole organism.

Analysis of complex EEG signals and detection of oscillatory patterns are traditional tasks in radio physics and nonlinear dynamics, where a number of effective methods have been developed that are already finding application in EEG analysis [15]. One of these methods is based on the continuous wavelet transform (CWT) [16], which is frequently used for recognizing characteristic rhythms by constructing "skeleton" plots [17]. Skeleton plots represent the lines of local maxima in a wavelet spectrum and can be used for detecting and tracing dominant components in the EEG signal.

Although the CWT allows detailed time–frequency analysis of EEG patterns to be performed, application of this method requires considerable computational facilities. Thus, special approaches have to be developed in the case of CWT application to online interpretation of multichannel EEG records in BCIs. One possible solution of this task is based in the use of PaCT.

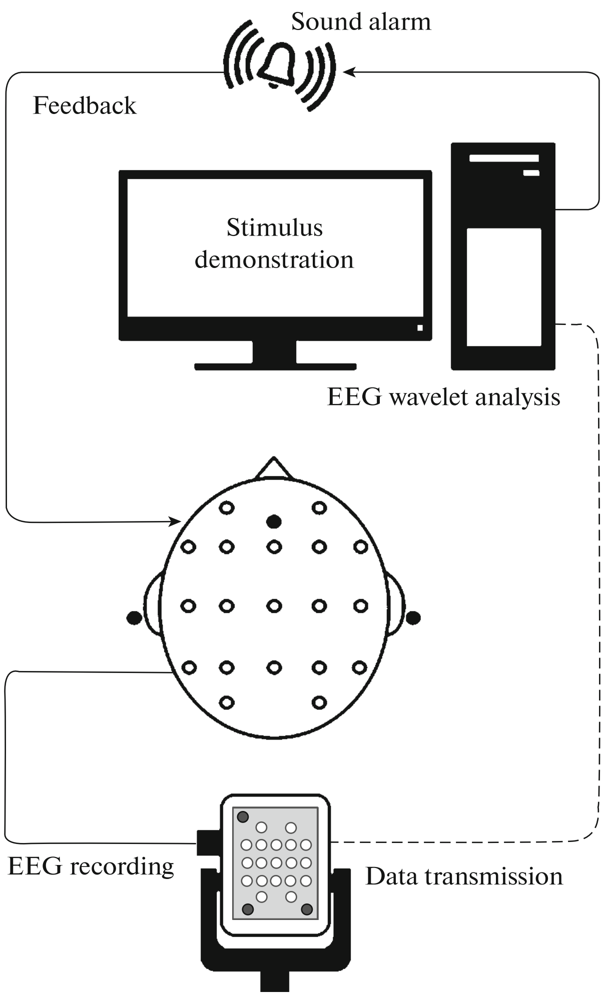

Fig. 1. Scheme of the proposed brain–computer interface showing the operator head with electrodes from which EEG signals are fed into a recorder and transmitted to a computer, where bistable images are presented and the wavelet energy is calculated. The feedback chain is implemented using acoustic signals.

In the present work, the method of EEG analysis based on PaCT algorithms has been verified in a BCI intended for estimating and monitoring the level of attention concentration associated with visual perception [18]. An original BCI employed signals from five EEG channels in the occipital lobe as input data. It is expected that the use of PaCT will allow the volume of processed data to be increased up to nineteen EEG channels.

Figure 1 shows a diagram illustrating the BCI algorithm. The BCI functioning proceeds according to the following scheme: (i) online recording of EEG signals, (ii) wavelet analysis of EEG data using the PaCT algorithm with the CUDA C library, (iii) verification of skeleton-based criteria for determining the level of attention concentration, and (iv) feedback response based on the current level of attention concentration.

Multichannel EEG records were obtained using an Encephalan EEG measuring unit. The EEG signals were taken from 19 EEG electrodes according to a 10–20 scheme at a time resolution of 250 Hz. A software package developed by the Medical MTD company and that we modified allowed EEG data to be obtained online.

The EEG signals were processed by the CWT method so as to calculate the wavelet energy spectrum for each of the nineteen EEG channels in the 4–30 Hz frequency range. The online processing of EEG data was ensured by PaCT on the CUDA platform. Figure 2 shows a scheme of this parallel computing process schematically. As can be seen from Fig. 2, the PaCT algorithm is implemented in several stages. At the first stage, parallelism between EEG channels is introduced and the BCI receives data in the form of time series for 19 channels that are fed into individual CUDA computing moduli. In each module, data are transferred from a central processing unit (CPU) to a graphics processing unit (GPU), which corresponds to the second stage of parallelism. The separation into blocks allows the entire frequency range to be split into M parts and perform the CWT procedure in each block over the entire length of time series. At the third stage, each block is separated into L threads corresponding to one moment of the time series. After the termination of calculations in all threads, data are transferred back to the CPU for further processing.

Then, skeleton plots are constructed and criteria of the neural response to visual-stimulus presentation are checked. The skeleton plots have been constructed for $N = 19$ EEG channels in two phases: (I) before and (II) during the perception of a bistable image. Every presentation of a stimulus was separately analyzed in frequency intervals of the alpha ($\Delta f_\alpha = 8$–12 Hz) and beta ($\Delta f_\beta = 20$–30 Hz) rhythms. Five skeleton plots were constructed for every stimulus presentation and the corresponding spectral characteristics $A_{\mathrm{I,II}}$ and $B_{\mathrm{I,II}}$ were introduced to reflect the intensity of alpha and beta rhythms before (I) and during (II) perception as calculated by the following formula:

$$A_{\mathrm{I,II}}, B_{\mathrm{I,II}} = \sum_{n=1}^{N} \int_{t\in\Delta t_{\mathrm{I,II}}} \varepsilon_n(t')dt',$$

$$\varepsilon_n(t) = \begin{cases} 1, & f_1^{\max} \in \Delta f_{\alpha,\beta}, \\ 1/2, & f_2^{\max} \in \Delta f_{\alpha,\beta}, \\ 1/3, & f_3^{\max} \in \Delta f_{\alpha,\beta}, \\ 1/4, & f_4^{\max} \in \Delta f_{\alpha,\beta}, \\ 1/5, & f_5^{\max} \in \Delta f_{\alpha,\beta}, \\ 0, & f_{1-5}^{\max} \notin \Delta f_{\alpha,\beta}, \end{cases} \tag{1}$$

where $f_{1-5}^{\max}$ are the values of maximum spectral components for skeletons 1–5, respectively. The obtained

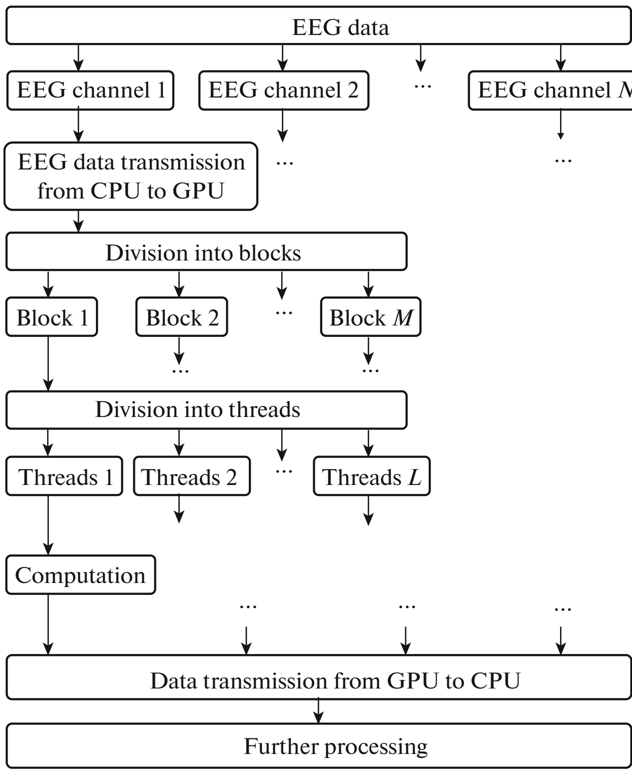

Fig. 2. Scheme of the PaCT algorithm for CWT calculation on the CUDA platform for one EEG channel, one block, and one thread. Calculations for other channel/block/thread units are performed by analogous schemes, after which the results from all threads are collected for further processing.

values of $A_{\mathrm{I,II}}$ and $B_{\mathrm{I,II}}$ are averaged for six stimulus presentations to yield $\langle A_{\mathrm{I,II}}\rangle$ and $\langle B_{\mathrm{I,II}}\rangle$ values, respectively, and the control characteristic $G(t)$ was calculated as

$$G(t) = \frac{(\langle A_{\mathrm{I}}\rangle - \langle A_{\mathrm{II}}\rangle)(\langle B_{\mathrm{I}}\rangle - \langle B_{\mathrm{II}}\rangle)}{2}. \quad (2)$$

At the fourth stage of the BCI algorithm, the current value of $G(t)$ is compared to a preset threshold and, if this level is exceeded, the BCI generates an acoustic signal that evidences reduction in the operator attention concentration, thus acting as feedback.

The verification of BCI functioning based on the proposed PaCT algorithm demonstrated high efficiency of processing of the neurophysiological data. The comparison of performance of the original algorithm and that implemented on a GPC using CUDA revealed a 60-fold increase in the speed of EEG data processing. This result opens up the possibility of analyzing cognitive processes localized in various lobes of cerebral cortex, which requires detailed spatial arrangement of EEG electrodes.

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