

Advanced Electroencephalogram Processing: Automatic Clustering of EEG Components

Diana Rashidovna Golomolzina, Laboratory of Intel-NSU, Novosibirsk State University, Novosibirsk, Russia

Maxim Alexandrovich Gorodnichev, Institute of Computational Mathematics and Mathematical Geophysics SB RAS, Laboratory of Intel-NSU, Novosibirsk State University, Novosibirsk, Russia

Evgeny Andreevich Levin, Novosibirsk Research Institute of Circulation Pathology, Novosibirsk, Russia & Institute of Physiology and Fundamental Medicine, Novosibirsk, Russia

Alexander Nikolaevich Savostyanov, Institute of Physiology and Fundamental Medicine, Novosibirsk State University, Novosibirsk, Russia & Tomsk State University, Tomsk, Russia

Ekaterina Pavlovna Yablokova, Novosibirsk State University, Novosibirsk, Russia

Arthur C. Tsai, Institute of Statistical Science, Academia Sinica, Taipei, Taiwan

Mikhail Sergeevich Zaleshin, Tomsk State University, Tomsk, Russia

Anna Vasil'evna Budakova, Tomsk State University, Tomsk, Russia

Alexander Evgenyevich Saprygin, Novosibirsk State University, Novosibirsk, Russia

Mikhail Anatolyevich Remnev, Novosibirsk State University, Novosibirsk, Russia

Nikolay Vladimirovich Smirnov, Novosibirsk State University, Novosibirsk, Russia

ABSTRACT

The study of electroencephalography (EEG) data can involve independent component analysis and further clustering of the components according to relation of the components to certain processes in a brain or to external sources of electricity such as muscular motion impulses, electrical fields induced by power mains, electrostatic discharges, etc. At present, known methods for clustering of components are costly because require additional measurements with magnetic-resonance imaging (MRI), for example, or have accuracy restrictions if only EEG data is analyzed. A new method and algorithm for automatic clustering of physiologically similar but statistically independent EEG components is described in this paper. Developed clustering algorithm has been compared with algorithms implemented in the EEGLab toolbox. The paper contains results of algorithms testing on real EEG data obtained under two experimental tasks: voluntary movement control under conditions of stop-signal paradigm and syntactical error recognition in written sentences. The experimental evaluation demonstrated more than 90% correspondence between the results of automatic clustering and clustering made by an expert physiologist.

Keywords: *Algorithms for Automatic Selection and Clustering, Brain, Clustering, EEG Data Processing, Independent Component Analysis, Neuroimaging, Neuroscience*

Figure 1. The subject wearing the EEG cap



INTRODUCTION

Electroencephalography (EEG) is a method of noninvasive exploration of functional brain activity. It records electric potentials generated by cortical and, in lesser extent, subcortical neurons by reading the signal from electrodes placed over the head (see Figure 1). EEG plays an important role in investigation of neurocognitive processes, in diagnosis, treatment and prognosis of some diseases.

Different brain processes can take place simultaneously. Some of these processes are

spatially separated, other processes take place in the same areas of the brain, and EEG recordings reflect superposition of all the signals originating from many brain processes and noise. For example, non-brain noise can occur from eye movement or from external electrical sources such as power mains. Brain activity can be connected with sensory, motor, emotion processes, etc. In order to understand brain functioning, a researcher should be able to distinguish the contributions of physiologically different sources to the measured EEG signals.

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