

Brain Computer Interface Using EEG Signals

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Abstract

Brain-computer interface (BCI) is an emerging technology which aims to convey people's intentions to the outside world directly from their thoughts. It is especially appealing to severely paralyzed patients, since motor ability is no longer a prerequisite for this communication. It also offers a promising tool for normal people to enhance their communications with computers. It has not only introduced new dimensions in machine control but the researchers round the globe are still exploring the possible uses of such applications. BCIs have given a hope where alternative communication channels can be created for the persons having severe motor disabilities. In this paper we will present a brief idea about EEGLAB software which is used for brain computer interface. The basic functions which are used for preprocessing EEG signals will also be discussed.

Key Words: EEGLAB, ICA, preprocessing

1. Introduction

“Mind Control is generally regarded as scary. But recent refinements of brain- machine interfacing (BMI) may redefine the expression to mean totally different”. [2] The need of new communication channels was strongly felt for the disabled people, who can't move their muscles, can't communicate with the outside world, so that they can also be able to lead an independent life. Thus, the idea is why not to use one's brain to control one's own environment. It is now a proven fact in medical sciences that the blockage of neural pathway between the cognitive part of brain (the signal generator) and the part which has to respond causes paralysis[3]. Though the signals are being generated in most of the cases but somehow or the other are not communicated properly because of disorder. So, if such an artificial system could be devised which can use electrophysiological signals of brain to perform the task which brain is trying to instruct, will truly be BCI system. Extracting reach information from brain signals is of great interest to the fields of brain computer interfaces (BCIs) and human motor control.

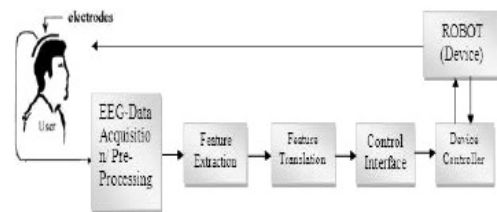


Figure 1. Functional model of BCI

To date, most work in this area has focused on invasive intracranial recordings; however, successful decoding of reach targets from noninvasive electroencephalogram (EEG) signals would be of great interest. BCIs are being developed for a variety of applications ranging from assistive technologies for patients with motor disabilities to entertainment devices. Across the wide range of applications [4], all BCI systems share the same set of underlying components, which can be broken down into three main segments: brain signal acquisition, brain state decoding, and computer-mediated performance of a task. Some BCIs decode the brain state into a set of discrete classes such as yes/no commands, while other BCIs decode continuous data such as a reaching trajectory. One goal of BCI research is to develop systems capable of decoding neural representations of natural movement planning and execution. [8] The large number of degrees of freedom, high complexity, and speed of natural movement pose particular challenges to building BCI systems of this type. **Electroencephalography (EEG)** is the recording of electrical activity along the scalp produced by the firing of neurons within the brain. In clinical contexts, EEG refers to the recording of the brain's spontaneous electrical activity over a short period of time, usually 20–40 minutes, as recorded from multiple electrodes placed on the scalp [6]. In neurology, the main diagnostic application of EEG is in the case of mental task as epileptic activity can create clear abnormalities on a standard EEG study. A secondary clinical use of EEG is in the diagnosis of coma encephalopathy's, and brain death. EEG used to be a first-line method for the diagnosis of tumors, stroke and other focal brain disorders, but this use has decreased with the advent of anatomical imaging techniques such as MRI and CT. Derivatives of the EEG technique include evoked potentials (EP), which involves averaging the EEG activity time-locked to the presentation of a stimulus of some sort (visual, somatosensory, or auditory).

2. EEGLAB Software

EEGLAB is an interactive Matlab toolbox for processing continuous and event-related EEG, MEG and other electrophysiological data incorporating independent component analysis (ICA), time/frequency analysis, artifact rejection, event-related statistics, and several useful modes of visualization of the averaged and single-trial data. EEGLAB provides an interactive graphic user interface[6] (GUI) allowing users to flexibly and interactively process their high-density EEG and other dynamic brain data using independent component analysis (ICA) and/or time/frequency analysis (TFA), as well as standard averaging methods. EEGLAB also incorporates extensive tutorial and help windows, plus a command history function that eases users' transition from GUI-based data exploration to building and running batch or custom data analysis scripts [5]. EEGLAB offers a wealth of methods for visualizing and modeling event-related brain dynamics, both at the level of individual EEGLAB 'datasets' and/or across a collection of datasets brought together in an EEGLAB 'study set.' For creative research programmers and methods developers, EEGLAB offers an extensible, open-source platform through which they can share new methods with the world research community by contributing EEGLAB 'plug-in' functions that appear automatically in the EEGLAB menu for those who download them.

2.1. EEGLAB Main Features

- a) Graphic user interface: EEGLAB graphic interface may not be as refined as in commercial software. A lot of the processing is performed on the command line; the EEGLAB graphic user interface (GUI) is only a convenient way to automate such processing. In future, it may be separate the graphic interface functions from the rest of the EEGLAB distribution
- b) Multiformat data importing : Importing various data formats include 1)Importing a Matlab array, 2) Importing Biosemi .BDF files, 3) Importing European data format .EDF files, 4) Importing EGI .RAW continuous files, 5) Importing Neuroscan CNT continuous files, 6)Importing Neuroscan .CNT continuous files 7) Importing sets of data averages into EEGLAB, 8) Importing Snap master .SMA files, 9) Importing ERPSS .RAW or .RDF data files, 10) Importing Brain Vision Analyzer Matlab files, 11) Importing sets of data averages into EEGLAB.
- c) High-density data scrolling : The EEGLAB scrolling data review function, `eegplot()` allows the user to process high
- d) Defined EEG data structure: This is intended for users who wish to use EEGLAB and its functions in Matlab. Various scripts in EEG structures are made transparent so that advanced users can use them to efficiently process their data.
- e) Open source plug-in facility: EEGLAB also has a `_plug-in_` facility that automatically searches for functions loaded into a specified plug-in directory, causing them to appear in the EEGLAB menu. EEGLAB plug-in functions can be offered for download and use by anyone, independent of the EEGLAB distribution, or may be included in the EEGLAB distribution itself.
- f) Interactive plotting functions: For instance `pop_erpimage ()` along with `erpimage ()` plot a colored image.
- g) Semi-automated artifact removal: In EEGLAB for artifact rejection is using 'statistical technique to suggest epochs to reject from analysis.
- h) Event and channel location handling: To remove data based on events in continuous data for internal as well as external file has been modified with the help of `op_chan ()`, `pop_chanedit ()`, `pop_chanplot ()` functions.
- i) ICA and time/frequency measures Independent Component Analysis separate EEG sources with tangential as well as radial orientations. ICA decomposes the data into sources with independent time courses, scalp maps irrespective of head geometry or electrode locations.

2.2. EEG Structure

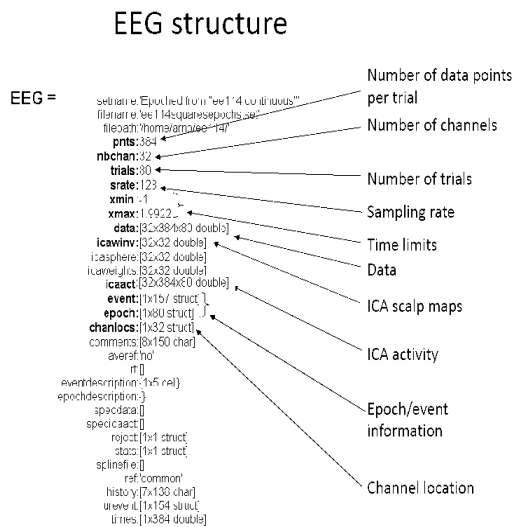


Figure 2. EEG Structure

3. Preprocessing Of EEG Signals

EEGLAB allows reading of data, event information, and channel location files in several different formats including binary, Matlab, ASCII, Neuroscan, EGI, Snap master, European standard BDF, and Biosemi EDF.[3] Standard data analysis functions available in EEGLAB include data filtering, data epoch extraction, baseline removal, average reference conversion, data resampling and extraction of data epochs time locked to specified experimental events from continuous or epoched data. EEGLAB also includes methods allowing users to remove data channels, epochs, and/or components dominated by non-neural artifacts, by accepting or rejecting visually cued EEGLAB recommendations derived from signal processing and information measures. EEG scalp maps and channel locations can be converted between several widely-used Cartesian, polar and spherical coordinate systems and then visualized in two or three dimensions. Continuous data and data epochs of any number of channels can also be scrolled (both vertically and horizontally).

3.1. Independent Component Analysis (ICA)

A primary tool of EEGLAB is to facilitate the process of applying and evaluating the results of independent component analysis (ICA) of EEG data. ICA algorithms have proven capable of isolating both artifactual and neutrally generated EEG sources whose EEG contributions, across the training data, are maximally independent of one another. ICA was first applied to EEG by Makeig et al. (1996) and is now widely used in the EEG research community, most often to detect and remove stereotyped eye, muscle, and line noise artifacts

The temporal independence assumption of ICA is readily understood as a basis for separating artifact sources, since their activities will ordinarily not be reliably phase-locked to one another, given enough training data. In practice, however, ICA also has proved capable of separating biologically plausible brain sources whose activity patterns are distinctly linked to behavioral phenomena. In fact, many of the biologically plausible sources ICA identifies in EEG data have scalp maps nearly fitting the projection of a single equivalent current dipole, and are therefore quite compatible with the projection to the scalp electrodes of synchronous local field activity within a connected patch of cortex. EEGLAB contains an automated version, *runica()*, of the infomax ICA with several enhancements both as a Matlab function and as a stand-alone binary C program that allows faster and less memory-intensive computation. The toolbox also allows the user to select any of over 20 available ICA algorithms including JADE and fixed-point ICA. In short, ICA finds a coordinate frame in which the data projections have minimal temporal overlap. [2]The core mathematical concept of ICA is to minimize the mutual information among the data projections or maximize their joint entropy. ICA can be viewed as an alternative linear decomposition to principal component analysis (PCA). PCA applied in the temporal domain would specifically make each successive component account for as much as possible of the activity uncorrelated with previously determined components – whereas ICA seeks maximally independent sources. This difference in goals leads to dramatic differences in their results. PCA components are both temporally and spatially orthogonal, a constraint unrealistic for actual EEG sources, which arise in domains (spatial regions) of partially synchronous activity in electrically, oriented cortical neurons (and possibly glia). Because the density of cortical connections is weighted towards local connections ($\ll 1$ cm), particularly in the network of inhibitory cells that sustain cortical oscillations, the partially synchronous domains giving rise to EEG activity recorded on the scalp should be mainly compact though the extent and density of these partially synchronous activities are not known. Through simple volume conduction, the projection of synchronous activity within nearly any patch of cortex will be widespread on the scalp. Any electrode will therefore sum contributions of EEG sources in a large portion of cortex. EEG source contributions to scalp electrode potentials depend on source strengths and orientations as much as source locations. The scalp projections of actual brain EEG sources, therefore, are nearly always overlapping and non-orthogonal, contrary to the assumption of PCA. Indeed, because of the spatial orthogonally constraint, projections of smaller principal components to the scalp typically resembles checkerboard maps that could not represent coherent activity within a connected patch of cortex. Therefore, to find biologically plausible sources, PCA must be followed by an axis rotation procedure.

Previously proposed procedures, such as Promax and Varimax, were drawn from the factor analysis literature. ICA can be viewed as a more powerful rotation method, though in practice ICA is usually applied to the original data without PCA preprocessing. ICA seeks to find component time courses that are mutually independent, meaning that component cross correlations as well as all the higher-order moments of the signals are zero. ICA is free to adapt to the actual projection patterns of EEG generators if their activity time courses are (near) independent of one another. ICA is now being applied to many biomedical signal processing problems including decomposing fMRI data and speech and noise separation.[9] Performing ICA decomposition is most appropriate when sources are linearly mixed in the recorded signals, without differential time delays. These assumptions are precisely met for brain (and non-brain) generator processes summed by volume conduction in scalp EEG data. Because ICA does not attempt to maximize the variance of each component, ICA components may account for more equal portions of the total signals than PCA components. For example, in 32-channel decompositions ICA component activities typically account for near 0% to about 5% of the total signals. ICA may usefully be applied to data with 128 or 256 channels, though meaningful results are also possible using 32 or fewer channels. Some earlier studies applied ICA to collections of ERP data averages. However, this approach requires care and caution in interpretation of results. To separate two or more processes, ICA requires that their independence be expressed in the data. A small set of data averages may not include enough conditions in the training set to demonstrate the independence of the underlying processes. If, for example, several processes are partially phase reset in similar ways, the resulting event-locked response averages may not express their underlying functional and temporal independence. Data averages, by their nature, contain sums of activities occurring at similar latencies relative to some class of events. When two or more sources invariably contribute to a set of response averages at the same latency, ICA, trained on these averages, may assign their summed activities to a single component. Trained on the unaveraged data however, ICA may use their relative variability in single trials to separate them. A second problem with applying ICA to data averages is that the averaging process nearly cancels out the activity of many of the EEG sources.[8] Thus applying ICA to the unaveraged EEG data also allows ICA to separate ongoing activity of EEG sources even if they are only partially phase-locked for brief time periods. This is most useful when there are a sufficient number of channels to fit the most active EEG and artifact processes. Theoretical assumptions underlying the use of ICA to decompose EEG data include: (1) the data must contain enough data points for the temporal independence of the underlying sources to be expressed. (2) No electrode activity should be a linear mixture of other electrode activities (as may occur for, e.g., average-

reference data). If so, before running ICA training, EEGLAB *runica* () function automatically performs PCA pre-processing to reduce the number of data dimensions to the rank of the input data. (3) ICA assumes that each data source is spatially stationary throughout the training data. This restriction may be partially relaxed in more recent ICA methods. (4) ICA assumes that the distributions of activation values for each EEG source are not precisely Gaussian. The current distribution of EEGLAB therefore focuses on applying ICA directly to continuous EEG data or, typically, to concatenated collections single EEG data trials. Fig. 4 illustrates the use of infomax ICA applied to the 80 EEG epochs of the EEGLAB sample dataset. The lower the component index returned from *runica* (), the more EEG data (neural and/or artifactual) it accounts for. To determine which components are behaviorally relevant and should be selected for further investigation, EEGLAB allows the user to plot component contributions to the raw data spectrum and/or to the trial-average ERP at all (or specified) channels.

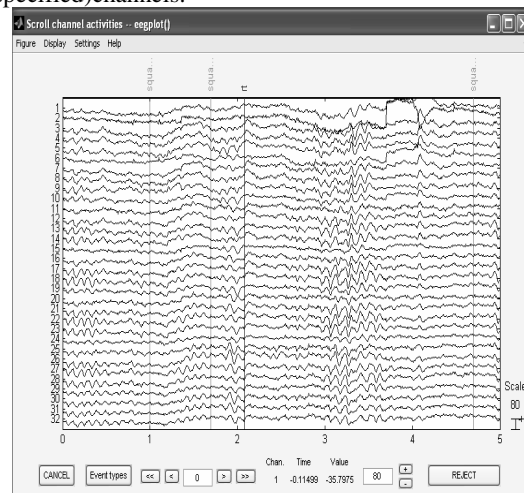


Figure 3. Preprocessing using ICA

4. Conclusion

The EEGLAB software available in the market is the most reliable source used for preprocessing of EEG signals. ICA can be viewed as an alternative linear decomposition to principal component analysis (PCA). PCA applied in the temporal domain would specifically make each successive component account for as much as possible of the activity uncorrelated with previously determined components whereas ICA seeks maximally independent sources. This difference in goals leads to dramatic differences in their results. To find biologically plausible sources, PCA must be followed by an axis rotation procedure. In practice ICA is usually applied to the original data without PCA preprocessing.

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