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Evaluation of less Common Independent Component Analysis Algorithms for Brain Computer Interface Preprocessing

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Abstract

Nowadays, one of the most challenging issues in Brain-Computer Interface (BCI) systems is tackling with physiological artifacts like Electrooculography (EOG) and Electrooculography (EMG) as a preprocessing step. It is the first step of each BCI systems that is very substantial because for next steps like feature extraction and classification we need clean signals without undesirable artifacts. Using a linear filter to remove these artifacts is common due to their simplicity and acceptable results in recent BCI preprocessing papers especially among winners in BCI VI competition using the same dataset as this paper (Graz 2A). By means of this, we have decided to compare the performance of band-pass filter with thirty well-known Independent Component Analysis (ICA) algorithms to remove undesirable EOG artifacts from EEG signals. The most common ICA algorithms that have been applied on this dataset are FastICA, SOBI and Infomax, but we tend to try less common algorithms to evaluate the real performance of ICA. In the meantime, we choose three optimized algorithm of ICA (FPICA, SANG and SYM-WHITE) that work better in noise reduction with Graz 2A dataset and compare their results with simple 8 to 40 Hz band-pass filter on 23-24-25 channels for EOG signals. The performance of our three algorithms was measured using the signal to interference (SIR) index. Results indicate that among all tested algorithms, Symmetric Pre-Whitening (SYM_WHITE) algorithm has considerable efficiency for EOG reduction and remarkable high speed in runtime. It is worth noting that it is for the first time that this algorithm is applied on Graz 2A dataset and approximately eliminates all EOG artifacts without destroying the original EEG signals.

Keywords: *Brain computer interface, Independent Component Analysis, ICA, EOG artifact, linear filter, SYM-WHITE*

1. Introduction

A brain computer interface (BCI), also referred to as a brain machine interface (BMI), a mind machine interface (MMI) have become a central part of neuroscience systems [1]. In fact, BCI is a way to interact with the environment, without the use of peripheral nerves and muscle interfaces. BCI provides a non-muscle channels for paralyzed people including those who have suffered spinal cord injury, or in diseases such as stroke [2] amyotrophic lateral sclerosis (ALS) [3], disorders of consciousness [4] and multiple sclerosis (MS) with external devices like computers, neural prosthesis [5], and robotic arms. It should be noted that BCI systems are appropriate for paralyzed people whom their brain injury is not serious, but just disconnected with another part of the body. For instance, BCI systems could be helpful in people with locked-in syndrome, these people are

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completely paralyzed and unable to speak but in terms of consciousness alertness they are healthy. Construction of such interfaces will impressive help to improve quality of life for people with disabilities and reduce their maintenance costs. BCI research, is now a wide-spreading field with more than 100 active research groups all over the world studying the topic [6]. The distinguished and preferable activities in BCI are: The Berlin BCI (BBCI) group has started their effort of training from the human to machine since 2000. The focal point in their work is reducing the intersubjective variability of BCI by minimizing the level of subject training. [7]. The Graz BCI with Pfurtscheller leadership, they use Mu and Beta rhythm of sensory cortex for training and control, one of their substantial approaches is nonfunctional arm grasping for paralyzed people by functional electrical stimulation (FES) that controlled by EEG signals. Some of their works have been reported in references [8-11] A BCI is an artificial intelligence system that can recognize a certain set of patterns in brain signals following five Sequential steps: signal acquisition, preprocessing or signal enhancement, feature extraction, classification, and the control interface [12] (figure1).

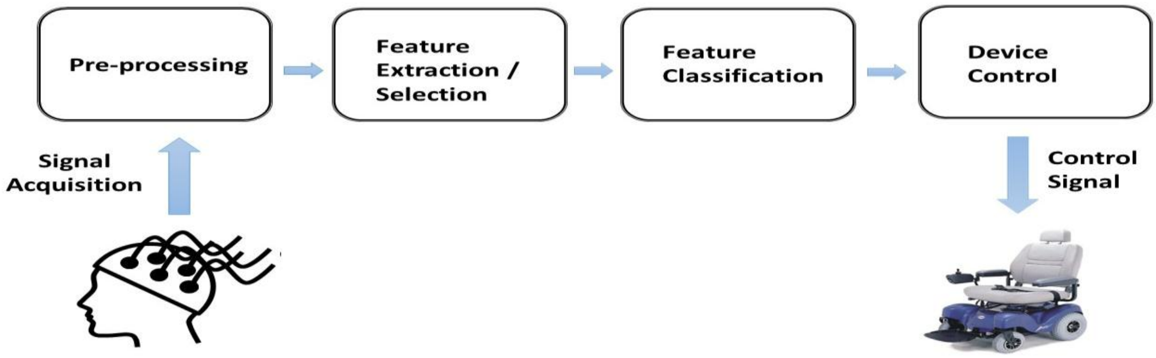

Figure 1: A representation of a conventional BCI.

1.1. BCI preprocessing

In order to better understanding of user's intent, first of all we should clean brain's signals from undesirable artifacts. Artifacts are undesired signals that can introduce noticeable changes in brain signals and eventually affect the neurological phenomenon. Artifacts are divided into two major categories: non-physiological or physiological sources: Non-physiological like changes in electrode impedances, 50/60 Hz power-line noise etc. And physiological artifacts such as potential created by the eye or body movement. However, BCI researchers usually take necessary precautions for handling non-physiological artifacts, physiological artifacts, especially those generated by eye or body movements, remain a noticeable issue in the design of BCI systems[13], for example, we can not to Electrocardiogram (ECG) artifacts can be caused by heart, respiratory artifacts caused by breathing that is synchronized with breathing body movements, skin responses such as sweating, which may cause changes in electrode impedance [14], as regards most of the researches are regarding to tackling with EOG and EMG artifacts. In this paper, we are facing the challenge of removing EOG artifacts. These artifacts are contained of two phenomena: 1) Eye blink; It is demonstrated by a low frequency signal (< 4 Hz) which could be considerable in amplitude. It is asymmetrical activity mainly located on front electrodes (Fp1, Fp2) with a low propagation. 2) Eye movement; it is illustrated by a low frequency signal (< 4 Hz) too but with a higher propagation [15]. As we know, there are different ways of handling with the artifacts that can be mentioned in the following:

1.1.1. Artifact avoidance: In this method users are trained to avoid blinking or moving their body during the experiments. Nevertheless, this method has several drawbacks, for instance, many physiological artifacts like heartbeats are involuntary and it is nagging for users to control eye and body movements during data recording.

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1.1.2. Artifact rejection: This method includes rejection of the trial, which has artifacts, despite this method is the simplest way to tackling with artifacts, but it has its demerits like the loss of useful information about that trial. This can be done manually or automatically, in manual rejection of epochs a human expert has identified all the artifact-contaminated epochs and eliminate them from the analysis that is very time-consuming and frustrating.

1.1.3. Artifact removal: This is one of the most popular and successful method of removing artifacts is in the BCI. There are some common methods for artifact removing that can be highlighted in the following:

1.1.3.1. Linear filtering: Nowadays, one of the most common methods because the simplicity of implementation are linear filtering. These filters are suitable when artifacts are in particular frequency bands and not overlap with the original signal. For example, to remove EMG artifacts, the low - pass filter is appropriate and a high-pass filter can be used for EOG artifacts. Although, for BCI systems that lie in low frequency neurological phenomena like Movement-related potentials (MRPs), these methods are not as prosperous, because these neurological phenomena may overlap the same frequency range as that of the EOG artifacts. But they can be effective for BCI systems that use a neurological phenomenon with high-frequency content (such as Beta or Mu rhythms).

1.1.3.2. Independent Component Analysis (ICA): ICA represents one solution of the Blind Source Separation problem (BSS) that is the extraction of a set of signals based exclusively on their mixtures. [16] Basic ICA model assumes linear combination of source signals namely components, these components should be independent and non-Gaussian:

$$\mathrm{X} = \mathrm{As} \tag{1}$$

Where X is a mixture of source signals, A is the mixing matrix, through which source signals pass, and S is the source signals. Components can be obtained using the following expression:

$$A = A^{-1}\mathrm{X} = \mathrm{WX} \tag{2}$$

Where matrix W is inverse to matrix A.

For example, consider the EEG recording signals from the brain, EEG data are recorded from different parts of it, so this information is a mixture of different activities of different part of the brain. ICA could separate our desirable brain's part activities by obtaining their independent components. (Figure 2)

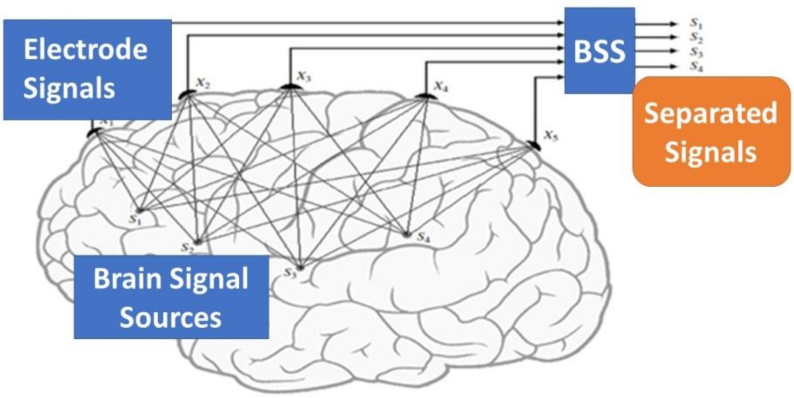


Figure 1: Mixing and blind separation of the EEG signals [17]

However, the major difference between the ICA with other popular methods such as PCA, is that it uses the non-Gaussian data structure. Notice that this method is unsupervised.

1.1.3.2.1. Measures of nongaussianity

1.1.3.2.1.1. Kurtosis: The classical measure of nongaussianity is kurtosis or the fourth-order cumulant. The kurtosis of y is classically denoted by:

$$Kurt(y) = E\{y4\} - 3(E\{y2\})2 \quad (3)$$

Assume that y is of unit variance, the right-hand side simplifies to E {y4} −3. This indicates that kurtosis is simply a normalized version of the fourth moment E {y4}. For a Gaussian y, the fourth moment equals 3(E {y2}) 2. So, kurtosis is zero for a Gaussian random variable. [18]

1.1.3.2.1.1. Negentropy: A second substantial measure of non-gaussianity is given by Negentropy. Negentropy is based on the information theoretic quantity of (differential) entropy. More detail has been reported in [18].

Artifact removal in EEG by ICA was first introduced in with the FastICA algorithm on simulated and real child data filtered by a band-pass filter. After that in 2002 Tang et al applied SOBI algorithm on 122 channel MEG data in source localization. This paper evaluates the possibilities of SOBI usage in MEG data processing [19].

In [20] Infomax algorithm tested on four patients for preprocessing during an epileptic spikes localization task. After that [21] used FastICA for hypnogram estimation from EEG, EOG and EMG data recorded from 14 patients. Korhonen and his colleagues [22] used FastICA algorithm for large muscle artifacts removing from transcranial magnetic stimulation (TMS). The TMS artifacts have been completely removed by this algorithm. Another research during medical usage of the ICA was for the detection of early stages of Alzheimer's disease by AMUSE algorithm in [23]. Regarding Graz 2A dataset, M -Naeem et al [24] compared different ICA preprocessing algorithms (Infomax, FastICA and SOBI) on cross-validated training data as well as on unseen test data, and one of the recent papers according to Graz 2A dataset with ICA preprocessing was [25] that examined their method with three different ICA well-known algorithms (FastICA, Infomax and Extended-Infomax). As mentioned above, most of the papers regarding to ICA artifact removing applications were applied by common ICA algorithms such as FastICA, SOBI, Infomax and AMUSE. In this paper, we apply less common ICA algorithms on Graz 2A for the first time to evaluate the real performance of ICA.

2. Data Acquisition and dataset

In this study, we used dataset 2a from BCI Competition IV. This dataset is provided by the Institute for Knowledge Discovery (Laboratory of Brain-Computer Interfaces), Graz University of Technology (Austria). Compared to datasets from past BCI Competitions there were eye movement artifacts in dataset 2a as a new challenging issue. The data set consists of EEG data from nine subjects. [26] Each subject was sitting in a comfortable armchair in front of a computer screen. The cue-based BCI paradigm consisted of four different MI tasks, to with the imagination of movement of the left hand (class 1), right hand (class 2), both feet (class 3), and tongue (class 4). In two sessions on different days of each EEG recorded for each subject that each session consists of 6 runes which is separated from the short break.

Each RUN consists of 48 trials (12 per class, 12 * 4 = 48) thus each subject has 48*6=288 trials. Twenty-two Ag/AgCl electrodes (With 10-20 system electrode montage) were used to record the EEG from each subject; all signals were recorded monopolarly with the left mastoid serving as a reference and the right mastoid as ground. All signals were sampled with 250 Hz and band-pass filtered between 0.5 Hz and 100 Hz. The sensitivity of the amplifier was set to 100 μV. Also 50 Hz notch filter was enabled to repress line noise. In addition to Twenty-two EEG channels, three monopolar EOG channels (23-24-25) positioned above the nasion and below the outer canthi of the eyes [27] were recorded and sampled with 250 Hz too, They were band-pass and notch filter as same as EEG signals but the sensitivity of the amplifier was set to 1 mV. The EOG channels are provided for the sake of artifact processing methods and must not be used for classification.

3. Analysis methods

Forasmuch as the mu (8–13 Hz) and beta (16–25 Hz) frequency bands play a key role in classification of motor imagery [28] the 8–40 Hz frequency band was investigated for the simple band pass filter. Our band-pass filter design method is Elliptic that according to our experiments, it works better than IIR method, we designed band-pass filter in 110 ordering illustrates at experimental results (figure 3). As we mentioned above, we evaluate thirty different ICA algorithms and we choose three optimized algorithms of ICA (FPICA, SANG and SYM-WHITE) that work better in noise reduction with Graz 2A dataset and compare their results this simple 8 to 40 HZ band-pass filter on 23-24-25 channels that are due to EOG. In the following we introduce our desired algorithm briefly:

3.1. Fixed-Point ICA (FPICA): FPICA is a family of batch learning rules for hierarchical neural networks, which extracts the source signal from their mixtures sequentially. The convergence of this algorithm is cubic (or at least quadratic), under the assumption of the ICA data model, in contrast to gradient descent methods that their convergence is only linear. This algorithm is easy to use because Contrary to gradient-based algorithms, there are no step size parameters to choose. The fixed-point algorithm inherits most of the merits of neural algorithm like, it is parallel, computationally simple, distributed and requires little memory space.

3.2. Self-Adaptive Natural Gradient algorithm with nonholonomic constraints (SANG)

Algorithms SANG, NG-FICA, NG-OnLine, ERICA belong to the family of natural gradient (NG) algorithms that are described in detail in Chapters 6 – 8 of . SANG is a batch algorithm which can be demonstrated in the following form:

$$W \leftarrow W + \eta \quad [D - < f(y) g^T(y) >] w \tag{4}$$

Where the diagonal matrix D's entries satisfy the nonholonomic constraints:

$$d_{ii} = < f(y_i) y_i > \ , \quad d_{ii}\,, \quad for\ i \neq j. \tag{5}$$

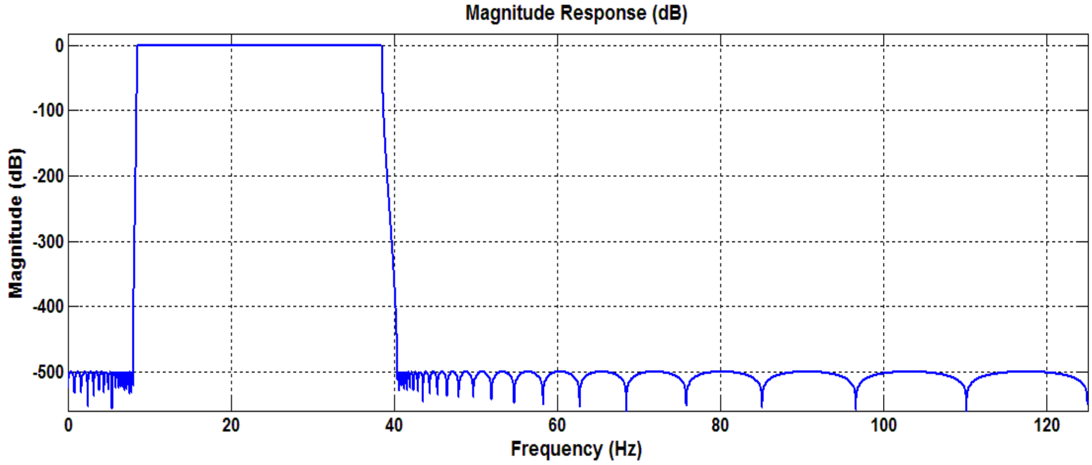
The learning rate matrix η is a diagonal matrix with entries:

$$ii = [d_{ii} + < f'(y_j) >]^{-1} \tag{6}$$

3.3. Symmetric Pre-Whitening (SYM_WHITE): This algorithm is another algorithm is provided for ICA, but not well-known like the conventional ICA algorithms, but has a very high speed and good accuracy in especially EOG removing. This algorithm is based on high-order statistics, causing a shift in the output vector. For more detail, please refer to [29-30].

4. Experimental Results

For our experiments, we choose a subject that approximately has a high rate of EOG artifacts(subject 4), first of all we applied band-pass filter (8-40 Hz) with Elliptic design method (that has better performance than IIR one [31]) to channels (23-24-25) of subject 4, after that we do the same for the SYM - WHITE algorithm, after running this algorithm we eliminate (1-2-3-4-6-7-8-9-10-13-17-22-23) sources visually, notice that this step really depends on the expertise of observer (expert person) which could separate sources that most closely resembles to EOG artifacts. We set ordering of the algorithm to kurtosis, itsruntime with Matlab 2011a



and Core™ i5 2.50 GHz, Ram 4GHz is 5.56 seconds. This algorithm has the highest rate of speed among all tested algorithms. Another optimized algorithms is FPICA that we eliminate) 1-2-3-4-5-6-7-8-9-11-21) sources visually after running. Its runtime is 96.35 seconds. And finally SANG algorithm, the best ordering state of this algorithm is skewness, the eliminated sources is (1-2-3-4-5-7-8-13-1-6-22-23-24) and its runtime is approximately 50.93 seconds. The final result of above ICA algorithms plus band-pass filtered and the original one on subject four, channel 25 for instance illustrate in figure 4 as following:

Figure 3: The designed band-pass filter (8 to 40 Hz)

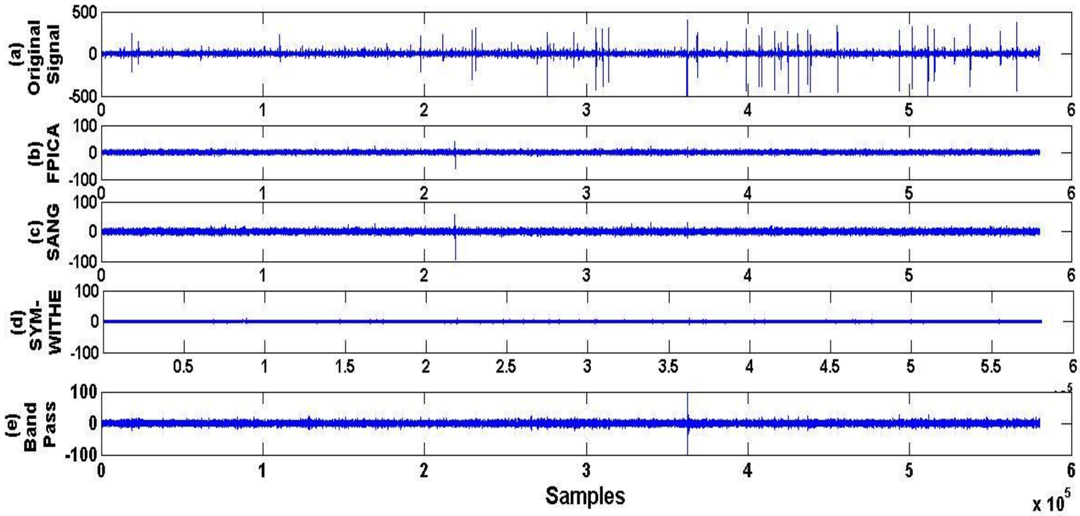


Figure 4: The designed band-pass filter (8 to 40 Hz)

(a) Original Signal: contains original signal with EOG artifact of subject four, channel 25

(b)FPICA filtered signal: The original noisy signal after FPICA algorithm filtering

(C) SANG filtered signal: The original noisy signal after SANG algorithm filtering

(d) SYM-WHITE filtered signal: The original noisy signal after SYM-WHITE algorithm filtering

(e) Band-Pass filtered signal: The original noisy signal after linear band-pass filtering

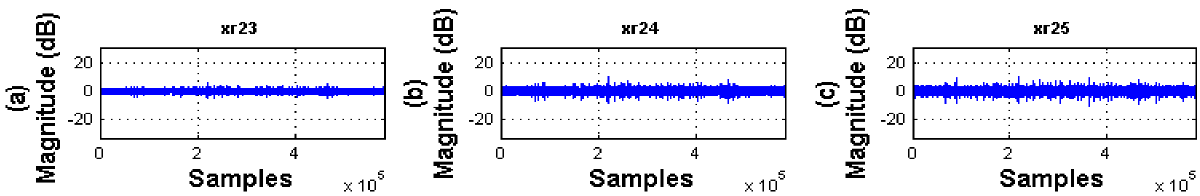


Figure 5: (a) channel 23 of EOG channels, subject four, after SYM_WHITE filtering

(b) Channel 24 of EOG channels, subject four, after SYM_WHITE filtering

(c) Channel 25 of EOG channels, subject four, after SYM_WHITE filtering

The performance of our three algorithms was measured using the signal to interference (SIR) index (equation7), quantifying the distance of the obtained permutation matrix, P = (WA) [32], from the optimum permutation matrix. The lower the SIR index, the better the achieved separation. For instance, a SIR index of zero implies a perfect separation [33].

$$SIR(P) = \frac{1}{n}\sum\left(\sum\frac{|p_{ij}|}{max_k(|p_{ij}|)} - 1\right) \quad (7)$$

Table 1 indicates the efficiency of all three ICA algorithms:

Table 1: The efficiency of all three ICA algorithms, the SIR index of SYM-WHITE algorithm is the lowest one and tends to zero; it indicates that this algorithm implies the best separation.

ICA Algorithms	Signal to Interference(SIR) index	Run Time (Second)
SYM-WHITE	0.0827	5.56
FPICA	0.1619	102.05
SANG	0.1416	53.93

As you can see both in figure 4 visually and table 1 numerically, the best noise removing performance belongs to SYM_WHITE algorithm that has the highest runtime speed too without destroying original signal. According to this, we demonstrate all (23-24-25) channels of it to prove our claim in figure 5.

CONCLUSION

As we know, to provide more accurate BCI system, physiological artifact removal in the preprocessing step plays as a key role for next steps. To sum up, forasmuch as the use of linear filter to remove biological artifacts is so common due to their simplicity and acceptable result in recent BCI preprocessing papers especially among winners in BCI VI competition (2th,3th and 5th winner) that use our intended dataset (Graz 2A) we tended to compare the performance of band-pass filter with thirty well-known Independent Component Analysis (ICA) algorithms to removing undesirable EOG artifacts from EEG signals, most of papers were used common ICA algorithms such as FastICA, SOBI, Infomax and AMUSE, In this paper we applied less common ICA algorithms on Graz 2A for the first time to evaluated the real performance of ICA. Thus we chose three optimized algorithms of ICA (FPICA, SANG and SYM-WHITE) that worked better in noise reduction with Graz 2A dataset and compared their results with simple 8 to 40 HZ band-pass filter on 23-24-25channels that are regarding to EOG signals. Because visual inspection really depends on the expertise of an expert person which could separate sources that most closely resembles to EOG artifacts, the performance of our three algorithms was measured using the signal to interference (SIR) index, our experiments indicated that SYM-WHITE algorithm, has the best performance of EOG removing and it also has the highest speed at runtime.

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