Research Article
Blind Source Separation Based of Brain Computer Interface System: A review

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Abstract: This study reviews the originality and development of the Brain Computer Interface (BCI) system and focus on the BCI system design based on Blind Source Separation (BSS) techniques. The study also provides the recent trends and discusses some of a new ideas for BSS techniques in BCI architecture, articles which discussing the BCI system development were analysed, types of the BCI systems and the recent BCI design were explored. Since 1970 when the research of BCI system began in the California Los Angeles University, the interest and the amount of research in BCI have been increased significantly; especially, when the BSS theory emerged in 1982 by a simple discussion between researchers. A lot of refereed journals and conference papers are reviewed and categorized to make this study in useful form. However, there are a few comprehensive reviews of BSS techniques in BCI literature. The review concludes with a brief discussion and expected future of the BCI.

Keywords: Artifact rejection, Brain Computer Interface (BCI), Blind Source Separation (BSS), Independent Component Analysis (ICA), neurophysiological signal analysis

INTRODUCTION

Brain Computer Interface (BCI) is a communication system that translates the user's intent into control signals. Its research deals with establishing communication pathways between the brain and external world (Mugler *et al*., 2010; Jin *et al*., 2011). Generally the BCI system consists of four components: a signal's acquisition unit; a signal processing system; an output device; and an operating protocol. The second part (i.e., signal processing system) is the most important in BCI, therefore the recent research focus on this part and based on the blind signal processing techniques such as Blind Source Separation (BSS). BSS techniques offer at least a way of improving the effective Signal to Noise Ratio (SNR) and enhance some brain patterns (Cichocki, 2004). Actually BSS algorithms investigate several alternatives and even more promising approaches. These algorithms used not only for noise reduction or artifacts removal, but also in source localization and improving spatial resolution of the brain signal (Musha *et al*., 2002; Cichocki, 2004).

Expert knowledge is required in medicine, in neuroscience and in statistical signal processing to extract the relevant information from the brain for diagnosis, analysis and therapy (Cichocki, 2004). Besides traditional signal processing analysis tools; emerging blind signal processing techniques, especially, generalized component analysis including
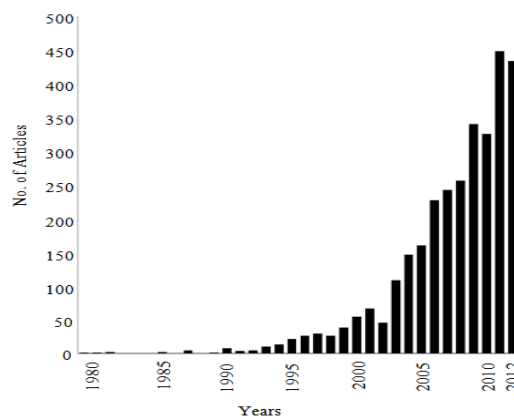

Fig. 1: Graph describing the increase of articles published in BCI from a PubMed search engine with key word: Brain computer interface

Independent Component Analysis (ICA), Sparse Component Analysis (SCA), Time-Frequency Component Analyzer (TFCA) and Nonnegative Matrix Factorization (NMF) are appeared to analyze the brain signals (Makeig *et al*., 1996, 2004; Cichocki, 2004).

Since 1970 when the first basic idea of Brain Computer Interface (BCI) systems appear, the BCI stay in inactive case because the computers were very slow and the treatments of a big streams data were not sufficient (Mileros, 2003; Salim, 2007). Then in late

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1980's, began to develop significantly and attracted much attention by the researchers.

Figure 1 shows the rapid increase in articles published during the last.

BCI have been reviewed in various papers; some of the review's areas are particular**,** like Cichocki (2004) discussed in his review how the various BSS and signal decomposition algorithms applied for analysis and processing EEG data in BCI. Also discuss a promising application of blind source separation in early detection of Alzheimer Disease (AD). Nicolas-Alonso and Jaime (2012) prepare an important reviewed article for BCI system and discuss the developments, advantages, drawbacks, latest advances and survey the numerous technologies reported in the scientific literature to design each step of a BCI.

This study reviews the development of BCI signal processing based on BSS algorithms and touches some new notice from current researches which are very important for this field. The study also reviews the recent trends and discusses some of the new ideas which contribute to the development of BCI in commercial manufacturing and research fields. Authors hope that, this review study is a useful for the researchers to develop the BCI systems and determine further research areas in the field.

BRAIN COMPUTER INTERFACE (BCI)

- **Originality and development:** In 1970's the United States department of defense tried to develop a systems helping pilots to interact with their aircraft therefore, this trial gave the basic idea of Brain Computer Interface (BCI) systems. But unfortunately that dream was ahead of its time, because the computers were very slow and the treatments of a big streams data were not sufficient (Mileros, 2003; Salim, 2007). Initial progress and development in BCI research was very slow and limited by computer capabilities, knowledge of brain physiology and brain signal processing analysis. In 1950's the mu and beta rhythms (i.e., sensorimotor rhythms) was first recorded in EEG signals as a prominent oscillatory phenomenon over sensorimotor cortex and known to be associated with movement or movement imagery (Gastaut, 1952). Although in late 1960's, the experimental work with monkeys showed that: can be used the signals from single cortical neurons to control a meter needle. And the systematic investigations with humans really began in the 1970's. The question posted by Vidal (1973) can be observe the electrical brain signals to work as carriers of information in person-computer communication or for the control purpose of prostheses, his BCI was an early attempt to enable computer to be a prosthetic extension of the brain

by evaluate the feasibility of using neuronal signals in a person -computer dialogue (Vidal, 1973; Jerry *et al*., 2012).

In the late of 1970's, Kuhlman demonstrate and used EEG feedback training to enhance the mu rhythm. Based on this information; Wolpaw *et al*. (2002) trained some of volunteers to control on the amplitudes of sensorimotor rhythm and use it to move a cursor on a computer screen accurately in 1 or 2 dimensions (Wolpaw *et al*., 1991; Wolpaw and McFarland, 1994, 2004).

In the 1980s, an experiment on rhesus macaque monkeys by Georgopoulos *et al*. (1989) at Johns Hopkins University (JHU) to measure the electrical responses of single motor cortex neurons and found a mathematical relationship between the measured responses and the direction in which they moved their arms based on a cosine function (Georgopoulos *et al*., 1989).

Since 1990 the BCI researches really scoot, because computer's development, better EEG devices offered new possibilities and appropriate brain signal processing techniques are developed.

There are some eye-catching researches of the current BCI systems based on the modulation of brain rhythms. For example, power modulation of mu(μ)/beta (β) rhythms is used based on the motor imagery (Pfurtscheller and Neuper, 2001). Besides, phase modulation is also employed in a Steady-State Visual Evoked Potential (SSVEP) (Kluge and Hartmann, 2007). Generally there are five major brain waves distinguished by their different frequency ranges. These frequency bands are: alpha (α), theta (θ), beta (β), delta (δ) and gamma (γ).

By 2006, a practical experiment by implanted a microelectrode array in the primary motor cortex of a person with complete tetraplegia. A brain computer interface system enabled the patient to open simulated e-mail, a television, open/close a prosthetic hand and perform simple actions with a robotic arm based on the recorded signals obtained from microelectrode array (Hochberg *et al*., 2006).

In Krusienski and Shih (2011), used the Electrocorticography (ECoG) to record directly the cortical surface signals to demonstrate that signals can be translated by a brain computer interface to allow a person to accurately spell words on a computer screen (Krusienski and Shih, 2011).

In 2012, hybrid brain computer interface that uses the motor imagery-based on mu rhythm and the P300 potential to control a real wheelchair; two experiments were conducted to assess the BCI control system, simulated wheelchair in a virtual environment and a real wheelchair were tested and the subjects steered effectively by controlling the direction and speed (Long *et al*., 2012).

Table 1: Common neurophysiological signals used in Non-invasive BCI (Bayliss, 2001; Salim, 2007)

| Signal	Description
Mu, and Alpha rhythm	Mu is an 8-12 Hz spontaneous EEG rhythm associated with motor activities and maximally recorded over sensorimotor cortex. But Alpha is in the same frequency, but is recorded over occipital cortex.
ERS/ERD	Movement-related increases and decreases in specific frequency maximally located over sensorimotor cortex. Individuals may be trained through biofeedback to alter the amplitude of signals. It exist even when the individual imagines.
Slow cortical potential	Large negative or positive shifts in the EEG signal lasting from 300ms up to several minutes. Individuals may be trained through biofeedback to produce these shifts
P3 component of the evoked potential	A positive shift in the EEG approximately 300-400ms after a task stimulus. Maximally located over the central parietal region, this is an inherent response and no training is necessary.
Short-latency visual evoked potentials	To produce the component, a response to the presentation of a short visual stimulus is necessary. Maximally located over the occipital region, this is an inherent response and no training is necessary.
Steady-State Visual Evoked Potential (SSVER)	A response to a visual stimulus modulated at a specific frequency. The SSVER is characterized by an increase in EEG activity at the stimulus frequency. Typically, the visual stimulus is generated using white fluorescent tubes modulated at around 13.25 Hz or by another kind of strobe light. A system may be constructed by conditioning individuals to modulate the amplitude of their response or by using multiple SSVERs
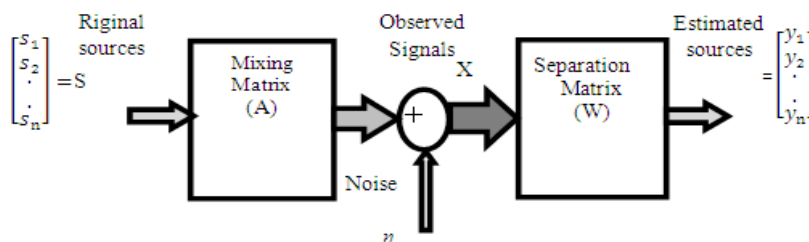
Fig. 2: BSS schematic diagram

To date there have been over than 20 research groups in BCI field, they taken different methods and approaches to the subject, less than half of the BCI research groups have built an online BCI (Lehtonen, 2002; Salim, 2007).

- **Types:** Most of the brain computer interface systems are based on the synchronous experimental protocol in which the subject (individual) must follow a fixed repetitive planner to switch from one mental task to the next. The other rely on more flexible asynchronous protocol where the subject makes self-paced decisions on when to stop doing a mental task and start the next one (Millan, 2003). Electrodes are used to receive neural inputs. Currently there are three main types of BCI systems, based on the acquisition of neurophysiological signals associated with various aspects of brain function (Millan, 2003).

  o **Direct (invasive) BCI:** Direct BCIs involve invasive procedure to implant electrodes in the brain (i.e., Electrode is placed directly into grey matter of patient) (Fig. 2). Thus the signals acquired from single or small groups of neurons used to control the BCI. In most cases the most suitable option for placing the electrodes is the motor cortex region, because of its direct relevance to motor tasks (Ochoa, 2002).

  o **Partially invasive BCI:** Partially Invasive BCIs are implanted inside the skull but outside the brain (i.e., Electrode is placed directly on the surface of the brain (beneath the dura) to record neural signals-also known as Electrocorticography (ECoG)) (Fig. 2). The signal strength for this type

is a bit weaker, but less risk of scar tissue formation (Aarts *et al.*, 2009).

  o **Non-invasive BCI:** Non-invasive BCIs are based on the analysis of Electroencephalogram (EEG) phenomena. These EEG phenomena are acquired through macro electrodes covering the scalp (Fig. 2). The common neurophysiological signals, used for noninvasive BCI control are summarized as shown in Table 1 (Bayliss, 2001; Salim, 2007). Figure 2 show the neurophysiological signals acquisition methods.

- **Components:** The main function of a Brain Computer Interface (BCI) is to convert the person's intent into an outside action by detect and extract the features of brain signals which are measured by electrodes to indicate the user's intentions and to translate these features into device commands that accomplish the user's intent in real time (Fig. 3).

Generally, the brain signals generated from activity of neurons are detected by electrodes located on the (scalp, cortical surface, or within the brain). The brain signals are amplified and digitized. The relevant characteristics of the brain signal are extracted and translated into commands that control an output device such as (a prosthetic limb, a spelling program, a motorized wheelchair and so on). The feedback signal from the device used by user to modify the brain signals in order to maintain effective device performance (Mak and Wolpaw, 2009; Jerry *et al.*, 2012).

BCI system consists of 4 sequential components:

Fig. 3: Brain signal analysis: Blind source separation problem (Tahir, 2010)

o **Signal Acquisition:** Involves the electrodes which pick up the electrical activity of the brain with an amplifier and filters unit. The signals are amplified to levels suitable for electronic processing and filtering to remove electrical noise or other undesirable signal characteristics. The signals are then digitized and transmitted to a computer (Wolpaw *et al.*, 2002; Jerry *et al.*, 2012).
o **Feature Extraction:** Converts the brain signals into relevant feature components (Alwasiti *et al.*, 2010). It is the process of analyzing the digital signals to distinguish the signal features with strong correlations related to the person's intent. In current BCI systems the most features are: Time-Triggered EEG or ECoG response amplitudes and latencies, power within specific EEG or ECoG frequency bands, or firing rates of individual cortical neurons (Jerry *et al.*, 2012).

The external artifacts and physiologic artifacts signals must be avoided or removed to ensure accurate measurement (Wolpaw *et al.*, 2002).

o **Feature translation:** The feature components are classified into logical controls (Alwasiti *et al.*, 2010). It is converts the features into the appropriate commands that accomplish the user's intent for the output device. For example, a power decrease in a given frequency band could be translated into an upward displacement of a computer cursor, or a P300 potential could be translated into selection of the letter that evoked it (Jerry *et al.*, 2012).
o **Device Output:** In current BCIs, the most devices is a computer screen and the output is the selection of targets, to operate the external device, such as letter or icons selection, cursor control, robotic arm operation and so on. In order to obtain the closed loop system, the output device operation provides feedback to the user (Mak and Wolpaw, 2009).

BLIND SOURCE SEPARATION

Blind Source Separation (BSS) is an important research area in signal and image processing used to extracted or recover source signals from their mixtures
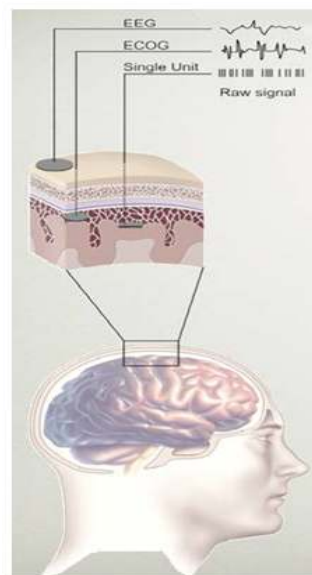

Fig. 4: Brain signals acquisition method

(without/with little) information about source signals or mixing process. Or can be say, the task is to determine approximately the individual source (independent source signals) from their mixtures based on minimum of priori of information. The term blind refers to the fact that there is no specific information about the mixing process or about the existing source signals (Hyvarinen, 1999; Sanjeev *et al.*, 2012).

Generally, the BSS mixture types can be considered as:

- Instantaneous (static) linear mixtures
- Convolutive mixtures
- Nonlinear mixtures

Convolutive Blind Source Separation (CBSS) refers to the separation in a dispersive environment based on procedures that do not have specific knowledge of the source properties or the mixing conditions (Olyaee *et al.*, 2010; Sanjeev *et al.*, 2012). Wide applications of CBSS, in speech, music, underwater signals recorded in passive sonar, radio communications, antenna arrays, astronomical data, satellite images and interpret functional brain imaging data (Hansen and Dyrholm, 2003; Mansour *et al.*, 2006; Pedersen *et al.*, 2007).

In Nonlinear transformations often told that it is information overload or data overload. The task is to arrival large amounts of data containing relatively small amounts of useful information. This is true both in daily lives and within much science (Comon and Jutten, 1996; Basak and Amari, 1999).

The linear mixtures have three global properties (Stone, 2001):
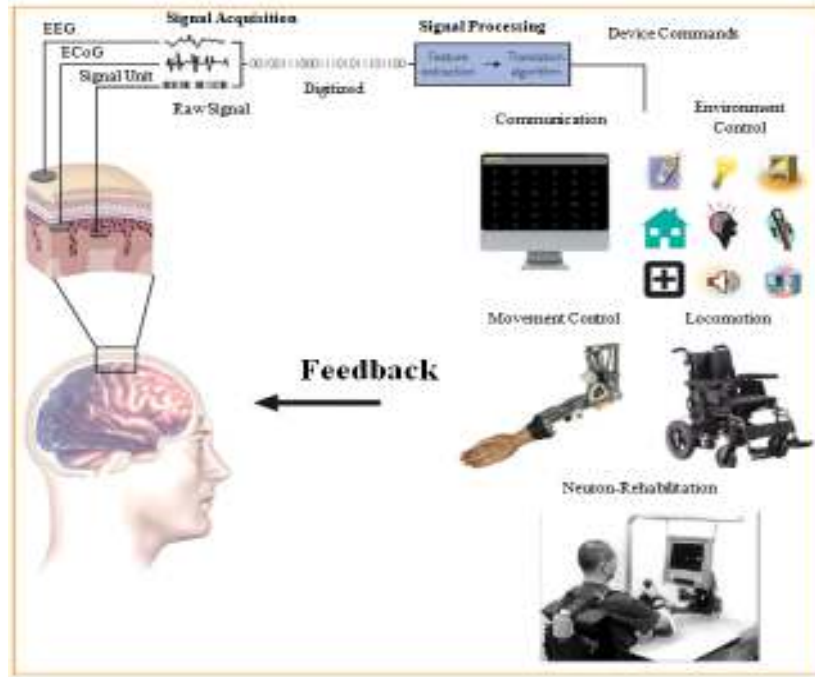
- Temporal predictability.

Fig. 5: Components of a BCI system (Jerry *et al.*, 2012)

- **Gaussian probability density functions:** The probability density function (pdf) of any mixture approximates a Gaussian distribution is greater than (or equal to) any of its component source signals based on the central limit theorem.
- **Statistical Independence:** The degree of statistical independence between any two signal mixtures is less than (or equal to) the degree of independence between any two source signals.

The BSS schematic diagram model is shown in Fig. 4.

In a non-invasive technique (EEG), the sensors (electrodes) are sited at the surface or around the head (scalp) at very close distance. For each action of the human, a lot of numbers of sources (neurons) are active (stimulus). Each sensor (electrode) is measuring a mixture of these stimuli from sources and each sensor measures a different mixture depending upon its distance from the sources as shown in Fig. 5.

No idea about the sources and the mixing process that has occurred inside the head. Therefore, cerebral signal analysis can be considered as a BSS problem.

Typical linear mixing model of BSS for a number of signals emitted by *n* independent physical sources $s_1(t), s_1(t), \dots s_n(t)$; such as (different brain areas emitting electric signals, or mobile phones emitting their radio waves); with *m* observed mixtures $x_1(t), x_1(t), \dots x_m(t)$ is:

$$x_1(t) = a_{11}s_1(t) + a_{12}s_2(t) + a_{13}s_3(t) + \dots a_{1n}s_n(t)$$
$$x_2(t) = a_{21}s_1(t) + a_{22}s_2(t) + a_{23}s_3(t) + \dots a_{2n}s_n(t)$$
$$x_3(t) = a_{31}s_1(t) + a_{32}s_2(t) + a_{33}s_3(t) + \dots a_{3n}s_n(t)$$
$$x_m(t) = a_{m1}s_1(t) + a_{m2}s_2(t) + a_{m3}s_3(t) + \dots a_{mn}s_n(t)$$

Or

$$x_j(t) = \tag{1}$$

$$a_{j1}s_1(t) + a_{j2}s_2(t) + a_{jn}s_n(t) \quad j = 1,2,.m \tag{2}$$

In vector notation:
$$X(t) = A\,S\,(t) \tag{3}$$

where,

$$X(t) = [x_1(t), \dots x_m(t)]^T \tag{4}$$

$$S(t) = [s_1(t), \dots s_n(t)]^T \tag{5}$$

Also, n (k) is a vector of additive noise:

$$n(t) = [n_1(t), \dots n_m(t)]^T \tag{6}$$

Now, the mixing can be expressed as:

$$X(t) = A\,S\,(t) + n(t) \tag{7}$$

The superscript T refers transpose operator.
$A \in R^{m \times n}$ is a mixing matrix.
Symbol (*t*) is time or sample index.

Upon the number of sensor and sources, the BSS can be divided into three categories (Sanjeev *et al.*, 2012):

- Over-Determined mixing
- No. of sources < No. of sensors
- Determined mixing

- No. of sources = No. of sensors
- Under-Determined mixing
- No. of sources > No. of sensors

The observed signals are the weighted sums of the original source signals, where the coefficients depend on the distances between the sources and the sensors. Where A is the unknown mixing weights. The weights and the original sources are unknown as well as those cannot be recorded directly, this is the Blind Source Separation (BSS) problem. Safely can be assume that, the matrix made by mixing coefficients is invertible (i.e., full rank matrix). Independent Component Analysis (ICA) is one approach for solving this problem, it's assume that $s_i(t)$ are statistically independent at each time. ICA, a method for finding underlying factors or components from multivariate (multidimensional) statistical data, based on the information of independence and nongaussianity then can estimate w_{ij}, which allows us to separate the original source signals $s_i(t)$ from their mixtures $x_j(t)$. Thus there exists a matrix with coefficients w_{ij}, such that we can separate them as Tahir (2010):

$$s_1(t) = w_{11}x_1(t) + w_{12}x_2(t) + w_{13}x_3(t) + \dots w_{1m}x_m(t)$$
$$s_2(t) = w_{21}x_1(t) + w_{22}x_2(t) + w_{23}x_3(t) + \dots w_{2m}x_m(t)$$
$$s_3(t) = w_{31}x_1(t) + w_{32}x_2(t) + w_{33}x_3(t) + \dots w_{3m}x_m(t)$$
$$\vdots$$
$$s_n(t) = w_{n1}x_1(t) + w_{n2}x_2(t) + w_{n3}x_3(t) + \dots w_{nm}x_m(t)$$

(8)

Or based on Fig. 1: the separating model without noise is:

$$E\,Y(t) = W\,X\,(t) \tag{9}$$

E is a permutation and scaling matrix and Y(t) the recovered sources:

$$Y(t) = [y_1(t), \dots y_n(t)]^T \tag{10}$$

BSS problem is to estimate the best separating matrix W and its ideal value equal to:

$$W = A^{-1} \tag{11}$$

BSS BASED BCI

Artifacts are undesirable signals that can interfere with neurological phenomena. They represent one of the limitations in the signal acquisition unit of brain computer interface system, most significant of which are: Ballistocardiogram (BCG), Electrooculogram (EOG), Electromyographic (EMG) and line artifacts, (Tahir, 2010). They may change the characteristics of neurological phenomena or even be mistakenly used as the source of control in BCI systems (Mehrdad *et al.*, 2007). BCG artifact, due to the tiny movement of EEG electrodes because of the pulsatile changes in blood flow tied to cardiac cycle and EOG artifact, by the

movement of eyes (Allen *et al.*, 2000; Sijbers *et al.*, 2000). Currently the most approaches used for the BCG and EOG artifacts in BCI system are:

- Averaged Artifact Subtraction (AAS)
- Adaptive Filtering Techniques (AFT)
- Blind Source Separation (BSS)

Independent Component Analysis (ICA) is a well-established technique for BSS. In biomedical signal analysis, researchers have used this technique for artifact attenuation, rejection and extract the statistically independent components from spontaneous EEG (Niazy *et al.*, 2005; Srivastava *et al.*, 2005). Based on Makeig *et al.* (1996) and Jung *et al.* (2000), the ICA is highly effective when:

(i) The mixing medium is linear and propagation delays are negligible.
(ii) The time courses of the sources are independent.
(iii) The number of sources is the same as the number of sensors.
(iv) Mixing and the independent components (ICs) are stationary.

In the case of neurological signals, assume that the recordings signals are mixtures of underlying brain and artifact signals. Because volume conduction is thought to be linear and instantaneous, assumption (i) is satisfied. Assumption (ii) is also reasonable because the sources of eye, muscle activity, line noise and cardiac signals are not generally time locked to the sources of EEG activity which is thought to reflect synaptic activity of cortical neurons (Jung *et al.*, 2000). Assumption (iii) is questionable, because don't know the effective number of statistically independent signals contributing to the scalp EEG. Finally Assumption (iv) discussed by Blanco *et al.* (1995); The data are considered as random variables in batch ICA algorithms and their distributions are estimated from the whole data set. Therefore, the nonstationarity of the signals is not really a violation of the assumptions of the model (Tahir, 2010). However, the assumption of stationary of the mixing matrix A agrees widely accepted (Scherg and Cramon, 1985; Mosher and Leahy, 1992). More Details about the validity of ICA model for brain signal in Hyvarinen *et al.* (2001). Jung *et al.* (2000) proposes a new and generally applicable method for removing a wide variety of artifacts from EEG records based on ICA/BSS.

Automatic removal of electro-ocular artifacts from EEG data procedure based on blind source separation (BSS) is presented in Carrie *et al.* (2004). Two ICA algorithms InfoMax (I-ICA) and Extended-InfoMax (EI-ICA) were utilized to extract eye movements and power noise of 50Hz in EEG data is proposed in Xue *et al.* (2006), it is proven that (EI-ICA) method can isolate both superguassian artifacts (Eye blinks) and subguassian interference (line noise), but (I-ICA)

method is only restricted to remove superguassian artifacts (eye blinks).

Erfanian and Erfani (2004) are used ICA approach to design a new EEG-based BCI for natural control of prosthetic hand grasp and suggest the possibility of using ICA to separate different independent brain activities during motor imagery into separate components.

In 2006, a comprehensive study (Nakamura *et al.*, 2006) has been conducted on different conventional ICA algorithms to evaluate their performance for the BCG artifact attenuation from EEG signals measured inside MRI.

James and Wang (2006) present a technique for applying BSS to single channel recordings of Electromagnetic brain signals. Single channel recordings of brain signals are pre-processed through the method of delays and the delay matrix processed with the BSS technique called LSDIAGTD, which uses temporal decorrelation to implement the ICA. BSS applied to extracts a series of codebook vectors representing the spectral content underlying the recorded signal then identify and extract particular rhythmic activity underlying the recordings (James and Wang, 2006). Shoker and Sanei (2006) propose a hybrid Blind Source Separation-Support Vector Machines (BSS-SVM) approach for distinguishing between left and right finger movements in EEG signal. SVM is used to classify the extracted features incorporating BSS and Directed Transfer Functions (DTF), where 200 trials of 64 electrodes trained the classifier and tested the system.

Halder *et al.* (2007) propose a combination of blind source separation techniques with support vector machines for signal decomposition into (artifacts, non-artifacts) and automatic classification that are designed for online usage. Three ICA algorithms (JADE, Infomax and FastICA) used in order to select a suitable method and one BSS algorithm (AMUSE) are evaluated to determine their ability to isolate Electromyographic (EMG) and EOG artifacts into individual components

However BSS/ICA has some disadvantages:

- The number of independent components is equal to the number of observations.
- Neither the energies nor the signs of independent components can be predefined.
- Ordering of independent components is random.
- Possibility of breaking up of the artifacts into multiple independent components, making the selection task even difficult.

As a result of these disadvantages, seriously began to study new or modified approaches, such as: Tahir (2010) proposes algorithm which tries to overcome the disadvantages of the conventional as well as the existing spatiotemporal algorithm. A complete artifact

Table 2: Summarized the two important techniques related with BSS used in BCI system (Nicolas-Alonso, and Jaime, 2012)

Method	Properties
PCA	• Linear transformation.
	• Transform a set of possibly correlated observations in to a set of uncorrelated variables.
	• Data representation in terms of minimal mean-square-error.
	• No guarantees for a classification
	• Valuable noise and dimension reduction method.
	• Artifacts must be uncorrelated with the EEG signal
ICA	• Separate a set of mixed signals into its original sources.
	• Assume statistical independence of underlying sources.
	• Powerful and robust tool for artifact rejection.
	• Artifacts and EEG signal are independent.
	• May corrupt the power spectrum.

rejection system based on constrained independent component analysis (cICA). The proposed system can remove BCG and EOG artifacts from EEG signals measured inside MRI. It has some advantages compared to the conventional system e.g. automatic artifact rejection system and any reject any number of artifacts at the same time (Tahir, 2010).

The Nonlinear blind source separation methods are also used to extract the brain signals in BCI system, where (Torse *et al.*, 2012) propose a Nonlinear BSS/ICA neural network model to analyze the complex epileptic EEG signals and remove the artifacts . The epileptic recorded EEG signals are highly complex and non-Gaussian. Thus the conventional methods are limited to extract the blind signals.

Finally**,** can be summarized the two important techniques related with BSS theory used in BCI system:

- **Principal Component Analysis (PCA):** PCA has been used to determine the artifactual components in a reasonably successful way in EEG based BCI system and to recover the signals (Boye, 2008; Nicolas-Alonso and Jaime, 2012). But, must be there are no correlations between artifacts are EEG. The feature space dimensionality has also been employed by principle component analysis (Lin and Hsieh, 2009).
- **Independent Component Analysis (ICA):** ICA has usually been used as a preprocessing technique before the feature extraction step, to remove the artifacts in BCI (Flexer *et al.*, 2005; Gao *et al.*, 2010). Although ICA has been proven to be a powerful and robust technique for reject the artifact in BCI system, some studies have indicated that artifact rejection may also corrupt the power spectrum of the underlying neural activity (Wallstrom *et al.*, 2004) In addition, the artifacts must be independent in relation to the EEG. Also some of researchers have been used it as a classifier (Nicolas-Alonso and Jaime, 2012). ICA can be modified for classification process by fitting

the generative ICA model and employing Bayes'rule to create the classifier (Chiappa and Barber, 2006; Nicolas-Alonso and Jaime, 2012). The properties for these methods are shown in Table 2.

CURRENT RESEARCH DIRECTIONS

Recently, the BCI achievements research and development remain almost in the laboratory and based on the data gathered from the volunteers. One of the main aims of BCI system has barely begun to improve the daily lives of people with disabilities (Jerry *et al*., 2012). The Analysis of brain signals depending on the signal processing techniques are seen as a very important key to the interpretation of user's intent, where in 2011, the research team in Colorado State University has obtained a five year, ($1.2 Million) grant to develop BCI that could help people with severe motor impairments do something as simple as turn on a TV by changing what they are thinking about, the development based on advanced signal processing techniques.

Neurophysiological signals have a significant temporal structure and it is clear to use the BSS based on the time lagged covariance matrix for the separation process. As mentioned by Mukul and Matsuno (2011) which present a novel signal pre-processing technique to enhance the rhythmic information related to movement imagination based on the BSS/AMUSE algorithm to estimates the separating matrix by an eigenvalue decomposition of a single time lagged covariance matrix of the EEG signals.

Some of the recent technologies toward merging of Translation Invariant Wavelet and ICA to obtain a better result in noise filtering, as demonstrated by Williams and Li (2011) where they present a new algorithm called Cycle Spinning Wavelet Transform ICA (CTICA).

A good way of gaining further insights on the EEG signals is to introduce nonlinear ICA as introduced by Torse *et al*. (2012), where the main aim is to design of a nonlinear BSS/ICA neural network model, which can be used to analyze the complex epileptic EEG signals which are assumed to be blind signals. The epileptic signals are highly complex and non-Gaussian. Thus the traditional methods are limited to extract the desired signals from blind mixtures. The proposed work consists of two stages: removing and separation, the Nonlinear BSS algorithm is used for the separation and NBSS learning rule is used for ICA estimation. Also the suggestion for future work suggested, by connect the ICA algorithms with soft-computing techniques like Fuzzy logic (FL) and Genetic Algorithms (GAs) to extend their tasks to many other developed tasks such as classification and feature extraction of EEG waveforms.

In recent years, to increase the accuracy of BCI systems by increase the number of electrodes causes a non-linear increase in computational complexity (i.e. decrease transfer rate). Therefore (Ghanbari *et al*., 2012; Sun *et al*., 2008) discus this problem and try to solve it by Genetic Algorithm (GA) to select the effective number of electrodes and to reduce the redundancy, where the proposed a scheme combine the liner filtering, Genetic Algorithm (GA) and Neural Network (NN) classifiers for EEG signal classification. The liner filtering is used to artifact removal. The GA select essential EEG channels and the best features then selected features serve as input feature vector for the classifiers. Two neural networks, including probabilistic neural network (PNN), Multilayered Perceptron (MLP) and support vector machine (SVM) were employed and their effects were compared; finally Ghanbari *et al*. (2012) suggested future works, based on another intelligent method and evolutionary algorithms such as partial swarm optimization (PSO) for selecting the most suitable features and channels (Ghanbari *et al*., 2012).

Allison *et al*. (2012); introduce a hybrid new type of brain computer interface to control on two dimensional cursor movement. Where the vertical position control via ERD activity associated with imagined movement while horizontal position control with SSVEP activity resulting from visual attention, , this type of hybrid system, processed by signal processing techniques based on blind source separation for artifact rejection and separation.

CONCLUSION

Various blind source separation algorithms have been clearly contributed to develop the brain computer interface systems in artifact rejection and separation process to extract the relevant information. The invention of a new designs for BCI will going on for more progress, simple, ease of use, an affordable, on-line and high bit transfer rate, less number of electrodes with high accuracy.

In this study, a reviews for BCI signal processing based on BSS algorithms. Also provides the recent trends and discusses some of the new ideas for BSS techniques in BCI architecture for artifact rejection and separation. Most of current BCI studies are still at the stage of laboratory demonstrations.

The future may be producing a high technical BCI systems and speed up the effectiveness of determine the relevant task, more workable and more affordable. It is vision that one day the BCI systems can be applicable for all users. By the rapid development in artificial intelligence and computer science nowadays we expected new invention of smart BCI system that can be able to determine the relevant tasks, with very high accuracy.

Finally can be conclude from this study, that the world is heading to merge BCI system with the intelligent soft-computing techniques such as (Fuzzy logic, Genetic algorithms, partial swarm optimization) to improve the performance of the entire system and this is what we saw from the direction of the research in recent years.

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