EMG and EOG Artifacts in Brain Computer Interface Systems: A Survey

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Abstract

It is widely accepted in the brain computer interface (BCI) research community that neurological phenomena are the only source of control in any BCI system. Artifacts are undesirable signals that can interfere with neurological phenomena. They may change the characteristics of neurological phenomena or even be mistakenly used as the source of control in BCI systems. Electrooculography (EOG) and electromyography (EMG) artifacts are considered among the most important sources of physiological artifacts in BCI systems. Currently, however, there is no comprehensive review of EMG and EOG artifacts in the BCI literature. This paper reviews EOG and EMG artifacts associated with BCI systems and the current methods for dealing with them. More than 250 refereed journal...
and conference papers are reviewed and categorized based on the type of neurological phenomenon used and the methods employed for handling EOG and EMG artifacts.

This study reveals weaknesses in BCI studies related to reporting the methods of handling EMG and EOG artifacts. Most BCI papers do not report whether or not they have considered the presence of EMG and EOG artifacts in the brain signals. Only a small percentage of BCI papers report automated methods for rejection or removal of artifacts in their systems.

As the lack of dealing with artifacts may result in the deterioration of the performance of a particular BCI system during practical applications, it is necessary to develop automatic methods to handle artifacts or to design BCI systems whose performance is robust to the presence of artifacts.

**Keywords**: brain computer interface, electrooculography, electromyography, artifact rejection, artifact removal

1. Introduction

A brain computer interface (BCI) system provides a communication channel between a user’s brain and a device the user intends to control. A successful BCI system enables a person to control some aspects of his or her environment (such as lights in the room, a television, a neural prosthesis or a computer) by analyzing his or her brain signals (see Figure 1). Specific features of the user’s brain activity (or “neurological phenomenon”) that relate to their intent to control a device are measured. These features are then translated to control commands that are used to control the device.

Figure 1 goes here.

Artifacts are undesired signals that can introduce significant changes in brain signals and ultimately affect the neurological phenomenon. Artifacts are attributed either to non-physiological
sources (such as 50/60 Hz power-line noise, changes in electrode impedances, etc.) or physiological sources, such as potentials introduced by eye or body movements. Although BCI researchers usually take necessary precautions for handling non-physiological artifacts, physiological artifacts, especially those generated by eye or body movements, remain a significant problem in the design of BCI systems.

In this paper, artifacts caused by eye movements (electrooculography [EOG] artifacts) or muscle movements (electromyography [EMG] artifacts) are reviewed in the context of BCI systems. The aim of the current study is to find out how the BCI community has addressed EMG and EOG artifacts and what outstanding issues still remain. This review is part of a broader attempt to review the field of BCI systems using the framework proposed in (Mason and Birch, 2003b; Mason and Bashashati et al., 2005).

In Section 2, we briefly address the current neurological phenomena used in the BCI literature and their associated artifacts. In Section 3, we address the existing methods for handling these artifacts, with special focus on EOG and EMG artifacts. In Section 4, we present a review of artifact handling methods in the BCI literature. Discussion and conclusions are presented in Section 5.

2. Current Neurological Phenomena and Associated Artifacts

In this section, we briefly review the current neurological phenomena in BCI systems and their associated artifacts.

2.1. Current Neurological Phenomena

Although several strategies exist for sensing the brain signal used for direct communication between the brain and a computer, not all such strategies have been extensively explored. For example, applications of BCI systems based on functional magnetic resonance imaging (fMRI) and
magnetoencephalography (MEG) are currently limited, as such systems are large, expensive, and require a magnetically shielded environment (Vaughan and Heetderks et al., 2003).

The electrical signals of the brain provide suitable representations of the sources of the control signals used in BCI systems. The technology needed for recording the brain’s electrical signals can be relatively cheap, especially when these signals are recorded from the scalp. Brain signals typically have fast responses and co-vary with cognitive processes (Kubler and Kotchoubey et al., 2001). Hence, the focus of this paper is on the neurological phenomena embedded in the electrical signals of the brain. Our survey showed that artifacts related to direct cortical recording (DCR), which uses microelectrodes that penetrate the brain, have not yet been addressed in the BCI literature. Since this paper is a review study, no critical commentary will be given on artifacts in DCR-based systems. Rather, we focus on BCI systems that use recordings from the surface of the scalp (electroencephalography [EEG]) or from the surface of the brain (electrocorticography [ECoG]) for recording brain activity.

The current neurological phenomena in EEG/ECoG-based BCI systems are as follows:

1) Changes in the Brain Rhythms such as Mu, Beta and Gamma rhythms related to a movement (CBR): A voluntary movement results in a circumscribed desynchronization in the Mu and lower Beta bands (Jasper and Penfield, 1949; Kozelka and Pedley, 1990; Kubler and Kotchoubey et al., 2001; Niedermeyer and Da Silva, 2004; Pfurtscheller and Aranibar, 1977). This desynchronization starts in the contralateral rolandic region about two seconds prior to the onset of a movement, and becomes bilaterally symmetrical immediately before execution of movement (Pfurtscheller and Lopes da Silva, 1999). After a voluntary movement, the power in the brain rhythms as well as the amplitude of gamma rhythms increases.

2) Movement related potentials (MRPs): MRPs are low-frequency potentials that start about 1-1.5 seconds before a movement. They have bilateral distribution and present maximum amplitude at the vertex (Babiloni and Carducci et al., 1999; Deecke and Grozinger et al., 1976; Hallett, 1994).
3) Other movement related activities (OMRAs): The movement-related activities that do not belong to any of the preceding categories are categorized as OMRA. They are usually not restricted to a particular frequency band or scalp location and usually cover different frequency ranges. They may be a combination of specific and non-specific neurological phenomena.

4) Slow cortical potentials (SCPs): SCPs are slow non-movement potential changes generated by the subject. They reflect changes in the cortical polarization of the EEG, lasting from 300 ms up to several seconds. Functionally, a SCP reflects a threshold regularization mechanism for local excitatory mobilization (Neumann and Kubler et al., 2003; Wolpaw and Birbaumer et al., 2002).

5) Cognitive tasks (CTs): Changes in the brain signals as a result of non-movement mental tasks (e.g., mental counting, solving a multiplication problem) are categorized as CTs (Kubler and Kotchoubey et al., 2001).

6) P300: Infrequent or particularly significant auditory, visual or somatosensory stimuli, when interspersed with frequent or routine stimuli, typically evoke a positive peak at about 300 ms after the stimulus is received. This peak is called P300 (Allison and Pineda, 2003; Kubler and Kotchoubey et al., 2001).

7) Visual evoked potentials (VEP): VEPs are small changes in the brain signal, generated in response to a visual stimulus such as flashing lights. They display properties whose characteristic depends on the type of the visual stimulus (Kubler and Kotchoubey et al., 2001).

8) Steady-State visual evoked potentials (SSVEP): If a visual stimulus is presented repetitively at a rate of 5-6 Hz or greater, a continuous oscillatory electrical response is elicited in the visual pathways. Such a response is termed SSVEP. The distinction between VEP and SSVEP depends on the repetition rate of the stimulation (Gao and Xu et al., 2003).

9) Auditory evoked potentials (AEPs): AEPs are small electrical activity changes that are generated in response to an auditory stimulus (such as clicks or tones).

10) Somatosensory evoked potentials (SSEPs): SSEPs are potentials generated in response to the stimulation of somatic sensation.
11) Multiple neurological phenomena (MNs): BCI systems based on multiple neurological phenomena use a combination of two or more of the above-mentioned neurological phenomena.

Each neurological phenomenon has unique spatiotemporal characteristics. This fact should be taken into consideration when addressing the presence of artifacts, as a particular neurological phenomenon may be more vulnerable to the presence of certain artifacts.

### 2.2. Artifacts in BCI Systems

Artifacts are undesirable potentials that contaminate brain signals, and are mostly of non-cerebral origin. Unfortunately, they can modify the shape of a neurological phenomenon used to drive a BCI system. Thus, even cerebral potentials may sometimes be considered as artifacts. For example, in an MRP-based BCI system, a visual evoked potential (VEP) is considered as an artifact. Visual alpha rhythms can also appear as artifacts in a Mu-based BCI system (McFarland and McCane et al., 1997). One problem with such artifacts is that they could mistakenly result in controlling the device (Vaughan and Heetderks et al., 2003). Therefore, there is a need to avoid, reject or remove artifacts from recordings of brain signals.

Artifacts originate from non-physiological as well as physiological sources. Non-physiological artifacts originate from outside the human body (such as 50/60 Hz power-line noise or changes in electrode impedances), and are usually avoided by proper filtering, shielding, etc. For reviews of non-physiological artifacts and the methods of avoiding, rejecting or removing them, the reader can refer to biomedical books (Fisch, 2000; Moore and Zouridakis, 2004; Niedermeyer and Da Silva, 2004).

Physiological artifacts arise from a variety of bodily activities. Electrocardiography (ECG) artifacts are caused by heart beats and may introduce a rhythmic activity into the EEG signal. Respiration can also cause artifacts by introducing a rhythmic activity that is synchronized with the body’s respiratory movements. Skin responses such as sweating may alter the impedance of
electrodes and cause artifacts in the EEG signals (Barlow, 1986). The two physiological artifacts that have been most examined in BCI studies, however, are ocular (EOG) and muscle (EMG) artifacts.

EOG artifacts are generally high-amplitude patterns in the brain signal caused by blinking of the eyes, or low-frequency patterns caused by movements (such as rolling) of the eyes (Anderer and Roberts et al., 1999). EOG activity has a wide frequency range, being maximal at frequencies below 4 Hz, and is most prominent over the anterior head regions (McFarland and McCane et al., 1997).

EMG activity (movement of the head, body, jaw or tongue) can cause large disturbances in the brain signal. EMG activity has a wide frequency range, being maximal at frequencies higher than 30 Hz (Anderer and Roberts et al., 1999; McFarland and McCane et al., 1997). Difficult tasks may cause an increase in EMG activity related to the movement of facial muscles (Cohen and Davidson et al., 1992; Waterink and van Boxtel, 1994).

A number of studies have shown that EOG and EMG activities may generate artifacts that affect the neurological phenomena used in a BCI system (Goncharova and McFarland et al., 2003; McFarland and Sarnacki et al., 2005). For example, (McFarland and Sarnacki et al., 2005) demonstrated that brain rhythms are contaminated with EMG artifacts during the early training sessions of a BCI system that used Mu and Beta rhythms as sources of control.

Physiological artifacts such as EOG and EMG artifacts are much more challenging to handle than non-physiological ones. Moreover, controlling them during signal acquisition is not easy. There are different ways of handling artifacts in BCI systems. In Section 3, we examine the reported methods for handling EOG and EMG artifacts, as they are among the most important sources of contamination in BCI systems.

3. Methods of Handling Artifacts

In this section, we briefly address methods of handling artifacts. Our focus throughout this section will be on EOG and EMG artifacts.
3.1 Artifact Avoidance

The first step in handling artifacts is to avoid their occurrence by issuing proper instructions to subjects. For example, subjects are instructed to avoid blinking or moving their body during the experiments.

Instructing subjects to avoid generating artifacts during data collection has the advantage of being the least computationally demanding among the artifact handling methods, since it is assumed that no artifact is present in the signal (or that the presence of artifacts is minimal). However, it has several drawbacks. First, since many physiological signals, such as the heart beats, are involuntary, artifacts will always be present in brain signals. Even in the case of EOG and EMG activities, it is not easy to control eye and other movement activities during the process of data recording. Second, the occurrence of ocular and muscle activity during an online operation of any BCI system is not avoidable. Third, the collection of a sufficient amount of data without artifacts may be difficult, especially in cases where a subject has a neurological disability (Vigario, 1997/9). Finally, avoiding artifacts may introduce an additional cognitive task for the subject. For example, it has been shown that refraining from eye blinking results in changes in the amplitude of some evoked potentials (Ochoa and Polich, 2000; Verleger, 1991).

3.2 Artifact Rejection

Artifact rejection refers to the process of rejecting the trials affected by artifacts. It is perhaps the simplest way of dealing with brain signals contaminated with artifacts. It has some important advantages over the “artifact avoidance” approach. For example, it would be easier for subjects to participate in the experiments and perform the required tasks, especially those subjects with motor disabilities. Also, the “secondary” cognitive task, resulting from a subject trying to avoid generating a particular artifact, will not be present in the EEG signal.
"Artifact rejection" is usually done by visually inspecting the EEG or the artifact signals, or by using an automatic detection method (Gratton, 1998).

3.2.1. Manual Rejection

Manual rejection of epochs contaminated with artifacts is a common practice in the BCI field. Trials are visually checked by an expert, and those that are contaminated with artifacts are removed from the analysis.

Similar to “artifact avoidance”, manual rejection also has the advantage of not being computationally demanding, as it is assumed that a human expert has identified all the artifact-contaminated epochs and removed them from the analysis. On the other hand, there are many disadvantages in using “manual rejection”. First, “manual rejection” comes at the cost of intensive human labor, especially if the study involves a large number of subjects or a large amount of recorded data. Second, the process of selecting the artifact-free trials may become subjective. It has been argued that because of the selection bias, the sample trials that are artifact-free may not be representative of the entire population of the trials (Gratton, 1998). Third, in the case of offline analysis, the rejection of artifact-contaminated trials, may lead to a substantial loss of data. This may become a huge drawback, especially in the case of subjects with motor disabilities, where offline data recording is not as convenient as it is for able-bodied subjects.

3.2.2 Automatic Rejection

In the “automatic rejection”, the BCI system automatically discards the epochs of brain signals that are contaminated with particular artifacts. This procedure is commonly carried out in offline investigations.

Automatic rejection of epochs can be done in the following two ways:

Rejection using the EOG (EMG) signal: When one of the characteristics of the EOG (EMG) signal in an epoch exceeds a pre-determined threshold, the epoch is considered as artifact-contaminated and is automatically rejected.
Rejection using the EEG signal: This rejection methodology is similar to the above; only the EEG signal is used instead of the EOG (EMG) signal. This approach has the advantage of being independent of the EOG (EMG) signal, and is useful if the EOG (EMG) signal is not recorded during data collection.

An advantage of the “automatic rejection” approach over that of “manual rejection” is that it is less labor intensive. However, automatic rejection still suffers from sampling bias and loss of valuable data (Millan and Franze et al., 2002; Ramoser and Muller-Gerking et al., 2000). In the case of EOG artifacts, the automatic rejection approach also does not allow the rejection of contaminated trials when EOG amplitude is small (Croft and Barry, 2000; Rowland, 1968).

Two issues need to be addressed for the BCI systems that reject artifacts:

1) Because of the vast number of artifacts that exist in BCI systems (eye blinking, eye movements, movements of different parts of the body, breathing, etc.), not all the artifact-contaminated trials can be rejected. Usually only the epochs with a strong presence of artifacts are excluded from the analysis. Therefore, the so-called “clean” data are unfortunately not free of artifacts.

2) The rejection of artifact-contaminated data during an offline analysis may generate “cleaner” data, however for online real-time applications of a BCI system, this may pose a huge drawback. In online applications, artifacts are unavoidable. If artifacts are rejected during the offline analysis, the same rejection mechanism can be used to reject them during the online analysis. The only problem is that during the specific time periods when artifact-contaminated signals are rejected, the system is unreachable and cannot be used for controlling the device. On the other hand, if artifacts are rejected during the offline analysis and the design of the BCI system is not robust to artifacts, false responses may occur in an online application due to the presence of artifacts.
3.3 Artifact Removal

Artifact removal is the process of identifying and removing artifacts from brain signals. An artifact-removal method should be able to remove the artifacts as well as keep the related neurological phenomenon intact. Common methods for removing the artifacts in EEG signals are as follows.

3.3.1 Linear Filtering

Linear filtering is useful for removing artifacts located in certain frequency bands that do not overlap with those of the neurological phenomena of interest (Barlow, 1984; Ives and Schomer, 1988). For example, low-pass filtering can be used to remove EMG artifacts and high-pass filtering can be used to remove EOG artifacts. Linear filtering was commonly used in early clinical studies to remove artifacts in EEG signals (Gotman and Skuce et al., 1973; Zhou and Gotman, 2005).

The advantage of using filtering is its simplicity. Also the information from the EOG signal is not needed to remove the artifacts. This method, however, fails when the neurological phenomenon of interest and the EMG or EOG artifacts overlap or lie in the same frequency band (de Beer and van de Velde et al., 1995). A look at the frequency range of neurological phenomena used in BCI systems unfortunately shows that this is usually the case. As a result, a simple filtering approach cannot remove EMG or EOG artifacts without removing a portion of the neurological phenomenon. More specifically, since EOG artifacts generally consist of low-frequency components, using a high-pass filter will remove most of the artifacts. Such methods are successful to some extent in BCI systems that use features extracted from high-frequency components of the EEG (e.g., Mu and Beta rhythm). However, for BCI systems that depend on low-frequency neurological phenomena (such as MRPs), these methods are not as desirable, since these neurological phenomena may lie in the same frequency range as that of the EOG artifacts.

In the case of removing EMG artifacts from EEG signals, filtering specific frequency bands of the EEG can be used to reduce the EMG activity. Since artifacts generated by EMG activity generally consist of high-frequency components, using a low-pass filter may remove most of these artifacts.
Again, such methods may be successful to some extent for BCI systems that rely on low-frequency components (e.g., MRPs), but they cannot be effective for BCI systems that use neurological phenomena with high-frequency content (such as Beta rhythms).

### 3.3.2. Linear Combination and Regression

Using a linear combination of the EOG-contaminated EEG signal and the EOG signal is the most common technique for removing ocular artifacts from EEG signals (Croft and Barry, 2000). The linear combination technique is based on the following model (Gratton, 1998):

\[
EEG_{nc}^i(t) = EEG_{ac}^i(t) - K.EOG(t)
\]

where \( EEG_{ac}^i(t) \) is the EOG-contaminated EEG signal of channel \( i \), \( EEG_{nc}^i(t) \) is the non-contaminated EEG signal of channel \( i \), \( EOG(t) \) is the EOG signal and \( K \) is an unknown constant.

Based on the model in Eqn.1, a fraction of the EOG signal(s) should be subtracted from \( EEG_{ac}^i(t) \) to generate \( EEG_{nc}^i(t) \). The question then is how to estimate the value of \( K \). A popular method that aims at minimizing the effect of noise on the estimates employ linear regression using least square criterion to estimate the value of \( K \) (Croft and Chandler et al., 2005).

A question as arises as to whether the value of \( K \) should be calculated separately for each type of EOG artifact (Gratton, 1998) and for the different frequencies of a particular EOG artifact (Gasser and Sroka et al., 1985). Both cases have been discussed extensively in the literature, but some papers have shown that similar results are obtained by the standard linear regression method (Croft and Barry, 2000).

One problem with using the above linear combination and regression approach is that the EOG signal to be subtracted from the EEG signal is also contaminated with the EEG signal. However, subtracting the EOG signal may also remove part of the EEG signal. Nevertheless, (Croft and Barry, 2002) arguein favor of using correction methods over rejection methods.
This problem becomes more challenging for EMG artifacts, since they have no reference channels (Barlow, 1986) and applying regression using signals from multiple muscle groups requires multiple reference channels (Jung and Humphries et al., 1998). The papers use regression techniques for the removal of head-movement artifacts (Bayliss and Ballard, 1999; Bayliss and Ballard, 2000a; Bayliss and Ballard, 2000b), but they do not explain how this was done. The validity of the results is also not verified.

### 3.3.3 Blind Source Separation (BSS)

BSS techniques separate the EEG signals into components that “build” the EEG signals. They identify the components that are attributed to artifacts and reconstruct the EEG signal without these components (for a review, see Choi and Cichocki et al., 2005). Among the BSS methods, Independent Component Analysis (ICA) is more widely used. ICA is a method that blindly separates mixtures of independent source signals, forcing the components to be independent. It has been widely applied to remove ocular artifacts from EEG signals (Jung and Makeig et al., 2000; Jung and Makeig et al., 2001; Vigario and Sarela et al., 2000). Preliminary studies have shown that ICA increases the strength of motor-related signal components in the Mu rhythms, and is thus useful for removing artifacts in BCI systems (Makeig and Enghoff et al., 2000b).

Although BSS methods have been used to remove EOG artifacts in EEG clinical studies, only a few studies have used BSS methods to remove EMG artifacts (De Clercq and Vergult et al., 2005; Iriarte and Urrestarazu et al., 2003; Jung and Humphries et al., 1998).

One advantage of using BSS methods such as ICA is that they do not rely on the availability of reference artifacts for separating the artifacts from the EOG signals (Zhou and Gotman, 2005). One disadvantage of ICA, along with other BSS techniques, is that they usually need prior visual inspection to identify artifact components (Jung and Makeig et al., 2000; Jung and Makeig et al., 2001). However, some automatic methods have been proposed (James and Gibson, 2003; Joyce and Gorodnitsky et al., 2004; Makeig and Enghoff et al., 2000a).
3.3.4 Principle Component Analysis (PCA)

PCA uses the eigenvectors of the covariance matrix of the signal to transform the data to a new coordinate system and to find the projection of the input data with greater variances. The components of the signal are then extracted by projecting the signal onto the eigenvectors. PCA has been shown to be an effective method for removing ocular artifacts from EEG signals (Lagerlund and Sharbrough et al., 1997; Lins and Picton et al., 1993a; Lins and Picton et al., 1993b).

One disadvantage of PCA is the requirement that artifacts are uncorrelated with the EEG signal. This is a stronger requirement than the independency requirement of ICA. It has been shown that PCA cannot completely separate eye-movement artifacts from the EEG signal, especially when they have comparable amplitudes (Lagerlund and Sharbrough et al., 1997). PCA also does not necessarily decompose similar EEG features into the same components when applied to different epochs (Lagerlund and Sharbrough et al., 1997).

3.3.5. Other Methods

Other methods have also been proposed for removing artifacts from EEG signals in clinical studies with varying degrees of success. Examples include the wavelet transform (Browne and Cutmore, 2002; Zikov and Bibian et al., 2002), nonlinear adaptive filtering (He and Wilson et al., 2004; Selvan and Srinivasan, 1999) and source dipole analysis (SDA) (Berg and Scherg, 1994). However, their application in BCI systems has so far been limited.

4. Literature Survey

In this section, we review how artifacts are addressed in the BCI literature. Since it is expected that proper measures for avoiding non-physiological artifacts were taken during the BCI experiments, the focus in this section will be on EMG and EOG artifacts. These are the physiological artifacts that have been addressed in detail in the BCI literature.
The following criteria were used for selecting the papers reviewed in this study:

1. Since the focus of this paper concerns the design and evaluation of BCI systems, a study that does not include a BCI transducer (i.e., a BCI transducer with the general structure depicted in Figure 1) is not considered. In searching the literature, the keywords “brain interface”, “brain-computer interface”, “brain-machine interface”, “direct brain interface”, “direct brain connection”, “direct neural control” and “brain-actuated control” were used.

2. Only papers published in English in refereed international journals or conference proceedings prior to January 2006 were considered for the analysis.

3. Only BCI systems that use neurological phenomena embedded in the EEG or ECoG signals were chosen for this study (approximately 250 papers).

For each neurological phenomenon, we grouped the artifacts into one of five categories: “Not Mentioned”, “No Rejection/Removal”, “Manual Rejection”, “Automatic Rejection” and “Automatic Removal”. The “Not Mentioned” category signifies cases where the authors did not explicitly mention whether or not they dealt with EMG or EOG artifacts in their BCI designs. “No Rejection/Removal” refers to cases where the authors acknowledged the presence of artifacts in their data, but did not apply any method to handle them.

Table 1 lists the methods of handling EOG and EMG artifacts. Each neurological phenomenon is highlighted by a gray color. The white rows below each neurological phenomenon show the artifacts, methods of handling them and the bibliography. For each of the artifact handling categories and for each of the neurological phenomena (or groups of them), Figures 2 and 3 show the number of published papers on how EMG and EOG artifacts were handled, respectively. Tables 2 and 3 identify the methods used for the automatic rejection of EOG and EMG artifacts (along with references). Tables 4 and 5 list the methods used for the automatic removal of EOG and EMG artifacts (along with references).

Figures 2 and 3 go here.
Based on the results presented in Tables 1 to 5 and Figures 2 and 3, the following observations about the methods of handling artifacts in BCI systems were made:

**4.1. EOG Artifacts**

1. More than half (53.7%) of the BCI studies considered, do not mention whether or not they handle EOG artifacts, 10.0% do not remove EOG artifacts, 10.4% manually reject them, 13.5% use an automatic rejection method and 12.4% use an automatic removal method to handle EOG artifacts.

2. Among the 13.5% of the studies that used automatic EOG artifact rejection methods, nearly half (45.7%) reject trials when the EOG amplitude reaches a certain pre-defined threshold, 14.3% employ this rejection strategy but use the EEG amplitude instead of the EOG amplitude for rejecting the contaminated trials, 22.9% do not mention the rejection method and 17.1% use other EOG rejection methods.

3. Among the 12.4% of the studies that use EOG artifact removal methods, around 69.7% use a linear method of combination of EEG and EOG signals, 9.1% use BSS techniques, 6.1% use PCA, 3.0% use linear filtering methods, 9.1% use other EOG removal methods and one paper does not mention the details of its automatic artifact removal method.

**4.2 EMG Artifacts**

1. Approximately 67.6% of the BCI studies considered, do not mention whether or not they handle EMG artifacts, 12.1% do not remove EMG artifacts, 10.9% manually remove them, 6.2% use automatic rejection methods and 3.2% use an automatic method for removal of EMG artifacts.

2. Among the 6.2% of the papers that use EMG artifact rejection, close to half (43.8%) reject trials when the EEG amplitude reaches a certain pre-defined threshold, 6.2% employ this rejection
strategy but use the EMG amplitude instead of the EEG amplitude, 18.7% reject trials when the EEG power reaches a certain threshold, and the rest (31.2%) do not specify their rejection method.

3. Only seven of all studies reviewed, use an automatic method for removal of EMG artifacts. Two papers use PCA, one uses ICA, one uses linear filtering and three papers use regression.

5. Discussion and Conclusions

In this paper, we have addressed EOG and EMG artifacts associated with neurological phenomena in EEG/ECoG-based BCI systems. We have also discussed the common methods of handling them in BCI systems and we presented a detailed review as to how BCI studies have addressed this issue.

Our survey of the BCI studies (published until January 2006) show that most BCI papers do not report whether or not they considered EMG and/or EOG artifacts in their analysis. The number of studies that do not report these artifacts in their systems is higher for EMG artifacts (65.9%) compared with EOG artifacts (55.6%). This is an important issue, since offline analysis methods that do not account for physiological artifacts may probably face some problems when tested during an online study. As a result, it is important that BCI researchers pay more attention to this very important issue and address the method that they have employed for handling artifacts.

A number of BCI studies state that EMG activity will not be present in the EEG signal when the EEG signal is analyzed before a movement has occurred (Burke and Kelly et al., 2002). This argument may not be valid for BCI systems. This is because peripheral changes such as EMG tension can affect the EEG signal, even though the amount by which the EEG signal is affected remains unclear (Kuebler and Kotchoubey et al., 1998). It is pointed out in (Kuebler and Kotchoubey et al., 1998) that even when the subjects are very restricted, they still preserve motor control over some muscle groups. Although the activities of several muscle groups are monitored in BCI studies, there remain some muscles whose activities are not recorded.
The BCI systems that employ “manual rejection” of EOG and EMG artifacts should also consider the fact that “manual rejection” is only a preliminary step in the design of a BCI system. “Manual rejection” can only be used for offline analysis. In order for a particular BCI system to be able to work in an online fashion, a scheme for handling artifacts should be incorporated. Requesting the subjects to avoid artifacts should be only considered as a temporary solution. In a practical application, EMG and EOG artifacts do happen, so methods of handling these artifacts during an online experiment should be investigated.

One solution for handling artifacts, which is not explored well in the BCI studies, is to design a BCI that is robust in the presence of artifacts. If such a BCI is designed, then the need for having a method of handling artifacts will be minimized. Our literature survey showed that 10.0% of BCI papers reported that they did not remove or reject EOG artifacts, and 12.1% did not reject EMG artifacts. Although one reason for not removing/rejecting these artifacts may be that these BCI designs are robust to them, the performance of such BCI systems when contaminated by artifacts is not well explored in the BCI literature. Future work for such BCI systems should also include the analysis of the robustness of the performance of the method in the presence of artifacts.

Another solution that has not been explored well in the BCI literature, is that of using more than one neurological phenomenon may lead to increasing the robustness to the occurrence of artifacts (Dornhege and Blankertz et al., 2004). Since EOG artifacts mostly affect the low-frequency components of the EEG signals, BCI systems that use low-frequency ERPs, such as MRP and SCP are mostly affected by EOG artifacts. EMG artifacts on the other hand, mainly affect the high-frequency components of the EEG signals, hence BCI systems that use high-frequency ERPs, such as Mu and Beta rhythms are mostly affected. Thus, it can be concluded that a BCI system that uses multiple neurological phenomena from both low and high frequency bands, may become more robust to the presence of artifacts. This promising research area has remained unexplored but it needs attention and further research.
Whatever solution is proposed for handling the artifacts, it is necessary to show that the proposed BCI system can work well in an online manner and it is not the artifacts that are controlling the BCI system. Recently, this issue concerning whether or not a few particular BCI systems, an artifact (and not the neurological phenomenon) is the source of control in the BCI system has been discussed (Bashashati and Fatourechi et al., 2006; McFarland and Sarnacki et al., 2005).

Finally, the comparison between different artifact removal methods is not straightforward because it is generally not clear what a correct EEG waveform should look like. It is therefore important to note that no analytical method for validating artifact removal algorithms is available at this time (Croft and Barry, 2000). This means that to validate a certain artifact removal method, visual inspection of the cleaned signal is used. Development of criteria for validation of artifact removal methods is thus clearly necessary and need to be explored in the future studies.

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# Appendix A. Index of Terms

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Complete Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>AEP</td>
<td>Auditory Evoked Potentials</td>
</tr>
<tr>
<td>ANC</td>
<td>Activity of Neural Cells</td>
</tr>
<tr>
<td>BCI</td>
<td>Brain Computer Interface</td>
</tr>
<tr>
<td>CBR</td>
<td>Changes in the Brain Rhythms</td>
</tr>
<tr>
<td>CT</td>
<td>Cognitive Task</td>
</tr>
<tr>
<td>DCR</td>
<td>Direct Cortical Recording</td>
</tr>
<tr>
<td>ECG</td>
<td>Electrocardiography</td>
</tr>
<tr>
<td>ECoG</td>
<td>Electrocorticography</td>
</tr>
<tr>
<td>EEG</td>
<td>Electroencephalography</td>
</tr>
<tr>
<td>EMG</td>
<td>Electromyography</td>
</tr>
<tr>
<td>EOG</td>
<td>Electrooculography</td>
</tr>
<tr>
<td>ERD</td>
<td>Event Related Desynchronization</td>
</tr>
<tr>
<td>ERP</td>
<td>Event Related Potential</td>
</tr>
<tr>
<td>ERS</td>
<td>Event Related Synchronization</td>
</tr>
<tr>
<td>fMRI</td>
<td>functional Magnetic Resonance Imaging</td>
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<tr>
<td>ICA</td>
<td>Independent Component Analysis</td>
</tr>
<tr>
<td>MEG</td>
<td>Magnetoencephalography</td>
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<tr>
<td>MN</td>
<td>Multiple Neurological phenomena</td>
</tr>
<tr>
<td>MRP</td>
<td>Movement Related Potentials</td>
</tr>
<tr>
<td>NM</td>
<td>Not Mentioned</td>
</tr>
<tr>
<td>OMRA</td>
<td>Other Movement Related Activities</td>
</tr>
<tr>
<td>PCA</td>
<td>Principle Component Analysis</td>
</tr>
<tr>
<td>SCP</td>
<td>Slow Cortical Potentials</td>
</tr>
<tr>
<td>SSEP</td>
<td>Somatosensory Evoked Potentials</td>
</tr>
<tr>
<td>SSVEP</td>
<td>Steady State Visual Evoked Potentials</td>
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<tr>
<td>-----------------</td>
<td>--------------------------------------</td>
</tr>
<tr>
<td>VEP</td>
<td>Visual Evoked Potentials</td>
</tr>
</tbody>
</table>

**Figure Legends**

Figure 1. Functional model of a BCI system depicting its principle functional components (revised from (Mason and Birch ,2003a)).

Figure 2. The number of papers published on different methods of handling EOG artifacts in BCI studies.

Figure 3. The number of papers published on different methods of handling EMG artifacts in BCI studies.