2014 International Joint Conference on Neural Networks (IJCNN)
July 6-11, 2014, Beijing, China

Using EEG Artifacts for BCI Applications

Wanli Ma, Dat Tran, Trung Le, Hong Lin, and Shang-Ming Zhou

***Abstract*: Brain computer interface (BCI) is about the communication channel between the brain of a human subject and a computerized device. Electroencephalography (EEG) signals are the primary choice as the sources of interpreting the intention of the human subject. EEG signals have a long history of being used in human health for the purposes of studying brain activities and medical diagnosis. EEG signals are very weak and are subject to the contamination from many artifact signals. For the applications in human health, true EEG signals, without the contamination, is highly desirable. However, for the purposes of BCI, where stable patterns from the source signals are critical, the origins of the signals are of less concern. In this paper, we propose a BCI, which is simple to implement and easy to use, by taking the advantage of EEG artifacts, generated by a number of purposely designed voluntary facial muscle movements.**

I. Introduction

Human electroencephalography (EEG) signals were discovered in early 1900. Gradually, they found their applications in medical diagnosis and human brain activity studies. The former focuses on abnormal EEG patterns, or the lack of certain patterns, in diagnosing, for example, epilepsy, dementia, and mental disorder etc. The later studies brain activities: EEG signals with focal cerebral disturbance, EEG patterns associated with certain mental or physical activities (evoked potentials or EPs), health monitoring, e.g., the depth of sleep and the level of alertness etc., and so on. In this paper, we call these applications *medical applications*.

Brain computer interface (BCI) was first experimented by Vidal [1, 2] in 1970s. Last decade witnessed a fast growing interest in BCI research. In [3], Wolpaw et al stated that BCI is about "*sending messages and commands to the external world*" from human brains. The primary purpose of BCI was envisaged as a means for people with disabilities to communicate with computerized systems, and possibly through a computer to other human beings. BCI can also be used by these without disabilities as an extra means to interact with computer systems.

EEG signals are the primary choice for BCI as the carrier of human intention. In an EEG based BCI system, an EEG headset with electrodes collects EEG signals from the scalp of a human subject. After being processed, the EEG signals are converted into a sequence of control commands for the intended object, being it a cursor on a computer screen, a robot, a wheelchair, or an artificial limb. We call this type of applications *BCI applications*.

EEG signals are very weak and subject to the contamination of many artifact signals, which are the "*signals that are non-cerebral in origin*" [4, Chapter 6]. Chief of them are from electrooculography (EOG), electrocardiography (ECG), electromyography (EMG), and the environments. Recorded EEG signals are always the mixture of the true EEG signals and the artifact signals of the time. There are solutions to separate the true EEG signals from the artifact interfaces; however, in general, the operation is very difficult, and sometimes impossible.

The 2 different types of applications of EEG, medical and BCI, have different requirements, and therefore different demands, from the signals. The primary focus of the former is the activities and the functions of a brain, which is where the true EEG signals originated. For these applications, the artifact signals, which are from other origins, distort the true EEG signals. They make the measurements of the true EEG signals less accurate, and thus whatever conclusion drawn less genuine. Therefore, artifacts are undesirable, and they should be removed, as much as possible. However, for BCI applications, from the signal processing point of view, the primary focus is actually neither the origins nor the purity of signals, but the accurate, stable, and repeatable patterns of the signals. Therefore, EEG artifact signals may not be as undesirable. To the contrary, if indeed EEG artifact signals have the characteristics of being accurate, stable, and repeatable, they may very well contribute positively to BCI. Interesting enough, in their extensive survey paper on the removal of artifacts from EEG signals, Fatourechi et al reported that "*Most BCI papers do not report whether or not they have considered the presence of EMG and EOG artifacts in the brain signals*" [5]. The fact is also positively confirmed by the authors of this paper when conducting their own literature survey in the field. It seems that the role of EEG artifacts in BCI is not yet fully understood.

On the other hand, from the point of view of human computer interaction (HCI) [6], any system for a human being to use should be easy to use and natural to operate, with respect to human nature and limits. Humans have very short attention span, yet the focuses of attention shift all the time [7]. A good HCI system must try to adapt the

Manuscript received April 15, 2014.
Wanli Ma is with the Faculty of Education, Science, Technology and Maths, University of Canberra, Australia (phone: +61-2-62012838; e-mail: Wanli.Ma@canberra.edu.au).
Dat Tran is with the Faculty of Education, Science, Technology and Maths, University of Canberra, Australia (phone: +61-2-62012394; e-mail: Dat.Tran@canberra.edu.au).
Trung Le is with the Faculty of Information Technology, the HCMc University of Pedagogy, Hochiminh city, Vietnam
Hong Lin is with Department of Computer Science, University of Houston, USA.
Shang-Ming Zhou is with Health Information Research Unit, College of Medicine, Swansea University, UK.

intrinsic cognitive load, to reduce extraneous cognitive load, and to foster germane cognitive load of human users [8]. An extraneous cognitive load is caused by requiring the users to perform unnatural or irrelative activities. In [9], Turk proposed the same ideas through perceptual user interface, which promises "*natural, intuitive, adaptive, and unobtrusive*" HCI. Lenman et al [10] also suggested "*natural and intuitive*" HCI. In short, BCI has to follow the same standards.

In this paper, we propose a BCI system, which is simple to implement, easy to use, yet is ubiquitous and can be used at any time and in anywhere. The system can be used by people with disabilities to issue simple commands to devices, such as wheelchairs and electronic appliances, and exchange simple messages with other human beings via a computerized device. It can also be used by these without disabilities as an extra communication means, for example, when the 2 hands of a person are fully engaged, and other communication means, e.g., voice or foot operation, are not feasible.

The system is based on voluntary facial muscle movements. A set of easy-performing facial muscle movement actions is purposely designed to carry the human intention. For example, blinking left eyes means turning left, and blinking right eyes means turning right. To refine further, when blinking, by keeping the eye closed for a longer time, it can be interpreted as the degree of turning left or right, just like the operation of the steering wheel of a car. EEG signals of these actions, with the presence of strong artifact signals, are recorded, processed, and then recognized by machine learning algorithms. The patterns of the EEG signals corresponding to the facial muscle movement actions, being taken as states, can be regarded as the alphabets to code the messages through the channel between the human subject and a computer. Furthermore, so long we have more than 2 stable patterns, i.e., states, we can code any text, in binary form, Morse code, or any other specially designed coding system.

Preliminary experiments have been conducted. The outcomes are encouraging, yet also expose more questions to be further studied. The EEG signals were collected from 3 male subjects, performing a number of common voluntary facial muscle movements in a few different occasions. No training or practicing was administered before the data collection, and some data collection sessions were interrupted by unexpected events. The interruption was not planned, but just wasn't purposely prevented. In the experiments, no special consideration was given to the fact that the true EEG signals are heavily influenced by the artifact signals. We treat them as the normally collected EEG signals. We use autoregressive model and power spectra density for feature extraction and Support Vector Machines and AdaBoost for classification. The results confirm that voluntary facial muscle movements based BCI is indeed feasible. However, we are at the very early stage of implementing the system. Our preliminary results are more of concept proof. Nevertheless, the experiments conducted offered the opportunity for us to learn some lessons and also lead to a number of open questions.

There are also a few approaches which do take EEG artifacts into consideration, but they are different from ours. In [11], Chin et al studied the patterns of recorded EEG signals under the influence of voluntary facial emotion expressions. They recorded EEG signals with the subjects purposely making smile, wince, and frown etc. emotion expressions. The best recognition rates of these facial emotion expressions range from 66.71% to 97.42%. Heger et al conducted similar experiments on recognizing facial actions through recorded EEG signals [12]. The facial actions are: neutral, smile, sad, surprise, angry, speak, and blink. They reported an average recognition rate of 81.1%. The lowest recognition rate is for "sad", which we consider not actually a pure facial action. Barreto et al [13] proposed a HCI by utilizing the EMG from cranial muscle movements and EEG for "*two-dimensional (2-D) cursor movement, the left-click (Enter) command, and an ON/OFF switch for the cursor-control functions*". The involved facial muscle movements are: *eyebrows up, left jaw movement, right jaw movement,* and *full jaw clench*. In our proposal, the focus is to study the patterns of all possible facial muscle movements and find out these which produce the most stable signal patterns.

The rest of the paper is organized as follows. In Section II, we briefly discuss EEG signals, artifacts, and their applications, with the reflection on the roles played by true EEG signals and artifacts. In Section III, we examine EEG based BCI on the basic principles developed from the discipline of human computer interaction (HCI). Section IV provides the details of the voluntary facial muscle movements based BCI, including the list of facial muscle movements, and Section V reports our experiment results with a discussion. We conclude the paper with a summary, a few open questions, and our near future tasks in Section VI.

II. EEG Signals, Artifacts, and Application

EEG signals are the electric current measured on the scalp of a human subject. The electric current is originated from the ion movements inside the brain cells, caused by the activities and functions performed by the brain. However, the movement of the ions, which generates the electric current of the very EEG signals, is not the only sources of the electricity. Many others, inside and on the human body and of the surrounding environment, also generate electricity. The signals from these origins are called artifacts, which are not a part of the true EEG signals. The artifacts are also captured by the EEG device, when recording. Therefore, the recorded EEG signals have 2 parts: originated from the brain and artifacts:

$$S_R = S_T + S_{AF}$$

where S_R represents the recorded signals, S_T represents the true EEG signals, and S_{AF} represents the artifacts.

According to Fisch, there are 2 types of artifacts: *physiological* and *non-physiological* [4, Chapter 6]. The former is from the human body: body movements, bioelectrical potentials, and skin resistance change etc. Chief of them are from electrooculography (EOG), electrocardiography (ECG), and electromyography (EMG). The latter is from the external environment and the EEG recording device itself.

For the purpose of medical applications, S_{AF} should be removed or minimized so that as much as possible of S_T is presented. Therefore, accurate measurements can be maintained, and consequently truthful conclusion can be drawn. There is a variety of approaches to remove the artifacts or reject the signals all together, but no solution is perfect. There is no guarantee neither that the true EEG signals and the artifact signals of recorded signals can be accurately separated. We refer the readers to a comprehensive survey on EMG and EOG artifacts in EEG signals by Fatourechi et al [5],. In [4, Chapter 6], Fisch also discussed the recognition of the patterns caused by artifacts and their removals, in the domain of medical applications.

However, on the other hand, in BCI applications, S_{AF} is not always removed [5], yet good results have been reported. This is due to the nature of the application, where the primary requirement is the accurate, stable, and repeatable patterns for a machine learning algorithm. In general, a machine learning process involves 2 steps: training and testing. In the training step, a set of sample data are used to train a machine learning engine (algorithm). Afterwards, in the testing step, another set of sample data is used to test the performance of the trained engine. The performance of the engine is estimated by the outcomes of this testing step.

There are a few possible roles which S_T and S_{AF} can play in a machine learning process.

- If the intention is carried by S_T only: S_{AF} may or may not have any impact on the outcomes. If S_{AF} is consistent with a predictable distribution, say, Gaussian, S_{AF} cancels each other when calculating the differences, i.e., the distances, among different classes. Otherwise, S_{AF} becomes random interference. Depending on the severity, the outcomes will be degradated accordingly.
- If the intention is carried by S_{AF} only: hopefully, S_{AF} follows the same and consistent patterns, the outcomes will then be accurately decided by S_{AF} alone. Because the signal strength of S_{AF} is far stronger than S_T, accurate results can be easily obtained, as the recorded EEG signals are predominated by S_{AF}.
- If the intention is carried by both S_T and S_{AF}: accurate outcomes will be difficult to obtain and explain, as we only know that the signal strength of S_{AF} is far stronger than S_T, but not know their roles in carrying the intention. Ideally, S_T and S_{AF} can be separated and then re-weighted before being further processed for the machine learning process.

Regardless the possibilities, without fully understanding the roles of S_T and S_{AF}, we cannot confidently explain how the outcomes are achieved. Currently, the results reported by BCI research communities very often emphasize on the aspects of feature extraction, the choices of machine learning algorithms, and the classification rates. Although there are some studies on the roles of S_T and S_{AF}, e.g., the EOG artifacts and EEG studied by Bobrov [14], we believe that more research work is still needed.

III. HCI AND BCI

With the development of computers and computerized systems, a new discipline, called human computer interaction (HCI), has emerged [6, 15, 16]. The discipline is a melting pot of computer science, applied physiology, behavioral sciences, and design etc. Its goal is to improve human-computer interaction by designing user-friendly human-computer interface. At the very beginning, human-computer interaction is through simple keyboards and computer screens. Gradually, the interaction moves towards to graphic user interfaces (GUI), so called WIMP (windows, icons, menus, pointer) [17]. Although WIMP still dominates, new natural user interface (NUI) [18] is strongly emerging. NUI promises more natural and intuitive user interfaces. From keyboards with line commands to NUI, it indeed is a process of pursuing more and more natural and intuitive user interfaces.

After all, the interaction between a person and a computer system is through the interface, or more abstractly, the communication channel, between them. Regardless what actions the person is taking to instruct the computer, essentially, the actions, pressing the keys on a keyboard, moving a mouse, touching certain locations on a screen, and making body gestures etc., are coded into the commands or command sequences the computer understands. The format of the commands concerns no human users. From a user's point of view, the actions should be easy, natural, and intuitive to perform. For example, the actions of pointing-left to move the cursor to the left and pointing-right to move the cursor to the right are easy, natural, and intuitive. However, pointing-up to move the cursor to the left is neither natural nor intuitive. This arrangement of course can be achieved by training, but it increases the cognitive load of the users. Thus, the system is neither easy nor pleasant to use, yet the users tend to forget the training received on how to use the system.

In general, BCI relies on 2 aspects of EEG signals generated by a human brain: event-related or evoke potential [19] and motor imaginary [20-22]. The former relies on visual and audio etc. stimuli. When such a stimulus, such as a picture on a computer screen or a sound played by a speaker, is sensed and then processed by the brain, the reaction among a large number of the participating neurons generates certain EEG patterns. A large positive surge, which can be observed at about 300 ms after the stimulus, is then codenamed as P300. Nijboer et al [23] studied the efficacy of a P300 based BCI in the real world (a home environment), with real patients, rather than in a laboratory environment, and concluded that: "*individuals severely disabled by ALS can use a P300-based BCI for writing text and that performance was stable for many months in terms of the ERP response, and in terms of classification accuracy*". The motor imagery approach does not require external stimuli. It relies only on the imagination of the movements of body parts, say, fingers, arms, legs, and toes etc., without real movements.

BCI was initially conceived for people with disabilities to control prosthetic arms and legs, communicate (such as, spelling and operating computers), and operate wheelchairs etc. It can now also be used for people without disabilities as an extra means of interaction with computers and computerized devices, for examples, games and wearable computers [24, 25]. The focuses of these different applications are very different; so are their operating environments. There is no one-size-fits-all solution. However, if we restrict the applications to issuing simple control and communication commands in real life environments, for example, in a noisy open area with the presence of a large crowd, from the HCI point of view, where easy to use and natural to operate are paramount, there are some specific challenges facing the 2 common BCI approaches.

Although it has been proven by laboratory experiments that P300 requires little or even none training, the system is complicated to set up. Two common types of the stimuli are video and audio. Video stimuli require a display unit, which may not display properly in broad sunlight. Audio stimuli require loud speakers or earphones. Either video or audio stimuli have to be delivered to the right place and at the right time, which is itself a great challenge for a real life application. In addition, both types of stimuli are subject to environment interferences, as light and sound are everywhere in a real life environment. In [19], Fazel-Rezai also listed the prerequisite of external stimuli for an individual to generate the associated EEG signals as one of the challenges for this approach. Furthermore, a great level of concentration from the human subjects is required to perform the tasks. On the other hand, the motor imagery approach has another set of challenges. The chief one is that it is very difficult to train a subject to perform the imagination tasks. The effectiveness of the performance is almost impossible to verify, yet the success of the system depends on good quality performance. Besides, the imagined motor movements may not always be natural, for example, imagining moving an arm up to mean turning an object left. Finally, the imagination of moving the same body part may be performed differently at different time, due to the impact of the environment, the body condition, and the levels of training and practice.

IV. A Voluntary Facial Muscle Movements Based BCI

While, in general, random artifacts are undesirable in BCI, as the random artifact signals skew or mask the underlying patterns of EEG signals. Due to the uncontrolled and random nature of the artifact signals, the patterns of interest are added with a great degree of variances. The artifact signals may even completely mask the patterns. However, on the other hand, the recorded EEG signals with the artifacts signals generated from purposely well designed facial muscle movements may demonstrate stable and repeated patterns. For the purpose of BCI, it doesn't really matter where the origins of the signals are, true EEG signals or artifacts, but the following requirements are critical:

- The actions to be performed by human users for the purpose of giving instructions are intuitive and natural.
- The patterns associated with the actions, from the machine learning point of view, have to be very stable and also repeatable.
- The patterns might be population-wise or individualized. Either way, the enrollment phase must be simple or none; while the verification phase has to be of a high accuracy.
- There is no requirement for any extra means of assistance, say, pictures for the human users to stare at.
- There is no need for a quiet room or any sort of well controlled laboratory-like environments, where the human users have to be confined.
- There is no need to record the time of the beginning and the ending of the actions performed.

The following facial muscle movements are proposed at this stage. It is envisaged that these muscle movements and the brain activities to instruct these activities generate stable and repeatable EEG signal patterns, with perhaps significant portion of artifact signals.

1. Blink the left eye
2. Blink the right eye
3. Raise the eyebrows
4. Move the mouth to left
5. Move the mouth to right
6. Move the tongue to left (inside of the mouth)
7. Move the tongue to right (inside of the mouth)
8. Roll the tongue up (inside of the mouth)
9. No action

In essence, BCI is about the channel for a human subject to communicate with a computerized device, through which further actions, such as controlling objects and relaying the message to other human beings, may follow. The essential part is the messages passed on the channel. At their origins, the messages may take any forms, but will be encoded into the format the computerized devices understand. For example, there are many ways of moving a cursor on the screen of a computer to a location. The task can be performed by using the arrow keys on a keyboard, a joystick, a mouse (mechanic or optical), or a touch screen. The raw signals obtained from these different input devices are all very different, but after being processed, they are all converted to the message (i.e., instruction) the computer understands. Along the same line of reasoning, the abovementioned facial movements can be regarded as the raw signals of an input device. Upon being recognized, a coded message is sent to the computerized system for proper reaction.

V. Experiment Results and Discussion

Emotiv Epoc headsets[1] were used to collect the data. A headset has 14 channels and collects data at 128Hz sampling rate. The data were collected from 3 healthy male subjects. Neither training nor practice was conducted before the data collection. Each of subjects performed the actions listed in Section IV a number of times in different occasions. Subject 1 performed each of the actions 50 times, and each of Subject 2 and 3 performed 28 times. Some of the actions were interrupted by unexpected events. For example, a visitor knocked at the door and came in, and the phone in the office rang. These unexpected events were not deliberately planned for the data collection, but just not purposely prevented. The data was collected by using open source software *experiment-wizard*[2] developed by J. Kools. Therefore, we can obtain the raw data of the signals. Fig. 1 is an EEG signal segments containing 2 artifacts and brain idle, a screen dump from Emotiv TestBench. The figure clearly demonstrates the dominance of the artifact signals at the time of the actions of the facial muscle movements being performed.

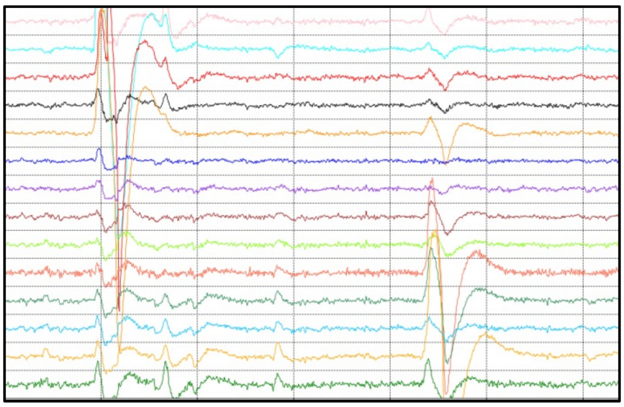

Fig. 1: an EEG signal segment containing 2 artifacts and brain idle, the 2 sets of big spikes suggesting the artifacts, while the flatter waves representing EEG signals without the artifacts

We tried to keep our experiments as simple and as plain as possible so that we can study the baseline recognition rates of these heavily artifacts-influenced EEG signals. The collected EEG signals were cut into segments. Each segment contains an artifact. The data of all 14 channels were kept. Each channel of a segment is modelled by using the popular autoregressive (AR) model and Power Spectral Density.

[1] http://emotiv.com/epoc/
[2] http://code.google.com/p/experiment-wizard/

In an AR model [26, pp 42-45], the signal sample value at time n is the linear combination of k previous sample values, $v(n-1)$, $v(n-2)$, …, and $v(n-k)$, with a random noise sample value $s(n)$. The number k is the order of the model.

$$v(n) = -\sum_{k=1}^{p} a_k v(n-k) + s(n)$$

The coefficients of the linear combination a_1, a_2, …, and a_k are used as the features of this channel of this segment of the EEG signals. For our experiments, we chose 14 order AR model.

A random signal usually has finite average power and can be characterized by average power spectral density, which is simply called power spectral density (PSD) [27, pp 4-7]. Let $\{v(t); t = 0, \pm 1, \pm 2, \ldots\}$ be a discrete time signal, with zero mean, i.e.,

$$E\{v(t)\} = 0, \text{ for all t}$$

where $E\{\cdot\}$ is the expectation operator. The autocovariance sequence (ACS) of $v(t)$ is:

$$r(k) = E\{v(t)v^*(t-k)\}$$

where $(\cdot)^*$ is conjugate transpose of the vector. The PSD of the signal is defined as the discrete time Fourier transform (DTFT) of the covariance sequence:

$$\emptyset(\omega) = \sum_{k=-\infty}^{\infty} r(k) e^{-i\omega k}$$

In our experiments, Welch's method using periodogram was used for estimating the power of a signal at different frequencies. We used both Support Vector Machines (SVMs) [28] and AdaBoost methods [29] to identify the patterns in the EEG signals.

A SVM is a powerful and popular 2-class classifier. It can be extended to a multiclass classifier by either one-against-all or pairwise method. For a training set of $(\vec{x}_1, y_1)$, $(\vec{x}_2, y_2)$, …, and $(\vec{x}_m, y_m)$, where $\vec{x}_i$ is a l-dimension vector and $\vec{x}_i \in \boldsymbol{X}$ the training samples and $y_i \in \{1, -1\}$ the 2 labels of the two classes, the SVM is aiming at finding the hyperplane with the maximum margin in the kernel space (feature space in SVM term) to separate the samples of the 2 classes. The maximum margin is obtained by solving the optimization problem of:

$$\min\left(\frac{1}{2}\|\vec{w}\|^2 + C\sum_{i=1}^{m}\xi_i\right)$$

subject to

$$y_i(\vec{w}^T\phi(\vec{x}_i) + b) \geq 1 - \xi_i, \qquad i = 1, \ldots, m$$

where C is a constant, $\vec{\xi} = [\xi_i]_{i=1,\dots,m}$ is the vector of the slack variables, and $\phi(\cdot)$ is the kernel transformation from the input space to the feature space. The decision function $f(\vec{x}) = \text{sign}(\vec{w}^T\phi(\vec{x}) + b) = \pm 1$ classifies an unknown data point $\vec{x}$ into either of the 2 classes $\{-1, 1\}$.

AdaBoost (adaptive boosting) [29] is a tactic of improving the classification performance of a weak classifier, which is just better than random guessing, by using multiple instances of the classifier with the training process focusing on misclassification. For a training set of $(\vec{x}_1, y_1)$, $(\vec{x}_2, y_2)$, …, and $(\vec{x}_m, y_m)$, where $\vec{x}_i \in \boldsymbol{X}$ the training samples and $y_i \in \{1, -1\}$ the 2 labels of the two classes, a weight vector $\vec{D}_t$ is associated with the training samples, where t means the t round of the training. Initially, the weight is the same for every sample, $D_1(i) = \frac{1}{m}, i = 1,..m$. In each round, if the sample $\vec{x}_i$ is misclassified, the weight $D_{t+1}(i)$ will be increased; otherwise, decreased. The performance of the classifier at the round t is calculated by its error:

$$\epsilon_t = P[h_t(\vec{x}_i) \neq y_i] = \sum_{i:h_t(\vec{x}_i)\neq y_i} D_t(i)$$

where $h_t(\vec{x})$ can be regarded as the decision function of this round. To calculate $\vec{D}_{t+1}$, the weight vector of the next round, first calculate $\alpha_t = \frac{1}{2}\ln\left(\frac{1-\epsilon_t}{\epsilon_t}\right)$, and then

$$\begin{aligned} D_{t+1}(i) \quad &= \frac{D_t(i)}{Z_t} \times \begin{cases} e^{-\alpha_t}, \text{ if } h_t(\vec{x}_i) = y_i \\ e^{\alpha_t}, \ \text{ if } h_t(\vec{x}_i) \neq y_i \end{cases} \\ &= \frac{D_t(i)e^{-\alpha_t y_i h_t(\vec{x}_i)}}{Z_t} \end{aligned}$$

where Z_t is a normalization factor so that $\vec{D}_{t+1}$ will be a distribution. The iteration of the training will stop when either the error ϵ_t becomes 0 or the number of rounds reaches the predefined limit T. The final decision function is then:

$$H(\vec{x}) = \text{sign}\left(\sum_{t=1}^{T} \alpha_t h_t\,(\vec{x})\right) = \pm 1$$

We randomly chose 70% of the feature vectors for training and 30% for testing purposes. We used LibSVM [30] wrapped in WEKA [31] for our SVM experiments, linear kernel was used. For AdaBoost, we used AdaBoostM1 method with J48 classifier, also in WEKA. Table 1 lists the classification results of SVMs, and Table 2 lists the results of AdaBoost.

TABLE I
THE CLASSIFICATION RATES BY SVMS (%), COLUMN 1-9 REPRESENTING THE 9 ACTIONS LISTED IN SECTION IV

	1	2	3	4	5	6	7	8	9
S1	85.7	92.9	85.7	57.1	57.1	35.7	71.4	85.7	100
S2	85.7	85.7	42.9	57.1	42.9	42.9	28.6	42.9	100
S3	100	100	71.4	42.9	28.6	14.3	85.7	14.3	100

The recognition rates for the actions and the subjects vary greatly. The results reflect the great degrees of freedom in performing some of the actions, due to no training or practicing beforehand. For example, the recognition rates of Action 6 (move the tongue to left), Action 7 (move the tongue to right), and Action 8 (roll the tongue up) differ a lot. These actions actually can be performed with a great degree of freedom, ranging from slightly moving the tongue to as much as possible. It seems that the ambiguity in the action description contributes to these low rates, because the physical actions may not be performed consistently. More accurate descriptions, such as, "move the tongue to left **as much as possible**", will be adapted in the future data collection. Actions 1-3 have consistent good recognition rates, yet more accurate descriptions of the actions, for example, "blinking the left eye **firmly**" etc., can also further decrease the ambiguity of the physical actions, and therefore may increase the recognition rates. Actions 4 and 5 are on the borderline and require further investigation, in addition to more accurate description of the actions. No action, labelled as Action 9, can always be accurately recognized.

TABLE 2
THE CLASSIFICATION RATES BY ADABOOST (%), COLUMN 1-9 REPRESENTING THE 9 ACTIONS LISTED IN SECTION IV

	1	2	3	4	5	6	7	8	9
S1	92.9	92.9	92.9	64.3	78.6	35.7	64.3	92.9	100
S2	85.7	85.7	57.1	28.6	71.4	71.4	42.9	28.6	100
S3	100	85.7	85.7	42.9	42.9	57.1	85.7	14.3	100

Finally, it is also possible that some of the actions do not have stable patterns, which makes them unsuitable for the BCI application.

VI. SUMMARY AND FUTURE WORK

In this paper, we propose to take the advantage of EEG artifacts, rather than try to remove them, for a BCI system, which is simple to implement and easy to use, yet being ubiquitous without restrictions on the surrounding environments. The preliminary experiments conducted are more on concept proof. Although the results are encouraging, there are still many questions yet to be answered.

Facial muscles are very flexible. Many different types of movements, called actions, are possible. The common ones can be performed in a very similar manner by everybody without the need of special training. Among these actions, which ones can produce stable and repeatable patterns, from the point of view of EEG signal processing and machine learning algorithms? For these actions which can be easily performed, yet produce stable and repeatable patterns, are the patterns only valid for each individual or the whole population? If the former, the system must be calibrated by a training phase before it can be used.

As the EEG signals are heavily influenced by the artifacts, which are caused by the facial muscle movements, do we still need to collect the signals from the scalp of a subject? Can we find other alternative spots on the face, with only a few electrodes? Ideally, the locations are somewhere without hair. The electrodes can then be easily attached, and hopefully, only 2-3 electrodes are needed. The best possible locations are the contacting points of a spectacle frame. If possible, the electrodes can be built into the frame, and attaching electrodes becomes a very simple task, yet with a high level of operation accuracy.

A user interface of any device should always be on stand-by mode, i.e., always being ready to accept user's commands and interrupt the intension. Therefore, it is important to be able to monitor the signals in a real-time manner, and recognize the known patterns on the fly. From Fig. 1, it seems that it is not difficult to identifying the coming artefact signals, out of the others, in real-time. However, we haven't tested it out yet.

The representing features of the raw EEG singals and the machine learning algorithms used in our experiments so far are these of commonly used in processing EEG signals. Are they the best choices for the EEG signals with the strong presence of artifacts? More experiments on a much larger dataset are required.

In the future, our top priority task is to collect more data from more individuals and in many different environments. After conducting more experiments on the data, we can then answer some of the aforementioned questions.

ACKNOWLEDGMENT

The authors sincerely thank Mr Tshering Wangchen and Mr Shuai Fu for conducting some experiments on the data collected in the first round.

REFERENCES

[1] J. J. Vidal, "Toward Direct Brain-Computer Communication," *Annual Review of Biophysics and Bioengineering,* vol. 2, pp. 157-180, 1973.

[2] J. J. Vidal, "Real-time detection of brain events in EEG," *Proceedings of the IEEE,* vol. 65, pp. 633-641, 1977.

[3] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain–computer interfaces for communication and control," *Clinical Neurophysiology,* vol. 113, pp. 767 - 791, 2002.

[4] B. Fisch, *Fisch and Spehlmann's EEG Primer: Basic Principles of Digital and Analog EEG*, 3rd ed.: Elsevier, 1999.

[5] M. Fatourechi, A. Bashashati, R. K. Ward, and G. E. Birch, "EMG and EOG artifacts in brain computer interface systems: A survey," *Clinical neurophysiology,* vol. 118, pp. 480-494, 2007.

[6] A. Dix, "Human–computer interaction: A stable discipline, a nascent science, and the growth of the long tail," *Interacting with Computers,* vol. 22, pp. 13-27, 2010.

[7] T. N. Welsh, S. Chandrasekharan, M. Ray, Heather Neyedli, R. Chua, and D. J. Weeks, "Perceptual-motor interaction: some implications for HCI," in *The Human-Computer Interaction Handbook: Fundamentals, Evolving Technologies, and Emerging Applications*, 3rd ed, 2012.

[8] H. Nina, H. Cristian, D. Michael, and S. Bernhard, "Integrating cognitive load theory and concepts of human–computer interaction," *Computers in Human Behavior,* vol. 26, pp. 1278 - 1288, 2010.

[9] M. Turk and G. Robertson, "Perceptual user interfaces," *Communications of the ACM,* vol. 43, 2000.

[10] S. Lenman, L. Bretzner, and B. Thuresson, "Using marking menus to develop command sets for computer vision based hand gesture interfaces," presented at the Proceedings of the second Nordic conference on Human-computer interaction, Aarhus, Denmark, 2002.

[11] Z. Y. Chin, K. K. Ang, and C. Guan, "Multiclass voluntary facial expression classification based on filter bank common spatial pattern," in *Engineering in Medicine and Biology Society, 2008. EMBS 2008. 30th Annual International Conference of the IEEE*, 2008, pp. 1005-1008.

[12] D. Heger, F. Putze, and T. Schultz, "Online recognition of facial actions for natural EEG-based BCI applications," in *Affective Computing and Intelligent Interaction*, ed: Springer, 2011, pp. 436-446.

[13] A. B. Barreto, S. D. Scargle, and M. Adjouadi, "A practical EMG-based human-computer interface for users with motor disabilities," *Journal of Rehabilitation Research & Development,* vol. 37, 2000.

[14] P. Bobrov, A. Frolov, C. Cantor, I. Fedulova, M. Bakhnyan, and A. Zhavoronkov, "Brain-computer interface based on generation of visual images," *PloS one,* vol. 6, p. e20674, 2011.

[15] A. Dix, *Human computer interaction*: Pearson Education, 2004.

[16] A. Sears and J. A. Jacko, *The human-computer interaction handbook: fundamentals, evolving technologies and emerging applications*: CRC Press, 2007.

[17] Wikipedia. (November). *WIMP (computing)*. Available: http://en.wikipedia.org/wiki/WIMP_%28computing%29

[18] Wikipedia. (November). *Natural user interface*. Available: http://en.wikipedia.org/wiki/Natural_user_interface

[19] R. Fazel-Rezai, B. Z. Allison, C. Guger, E. W. Sellers, S. C. Kleih, and A. Kübler, "P300 brain computer interface: current challenges and emerging trends," *Frontiers in Neuroengineering,* vol. 5, 2012.

[20] W. Tao, D. Jie, and H. Bin, "Classifying EEG-based motor imagery tasks by means of time–frequency synthesized spatial patterns," *Clinical Neurophysiology,* vol. 115, pp. 2744 - 2753, 2004.

[21] L. Qin, L. Ding, and B. He, "Motor imagery classification by means of source analysis for brain–computer interface applications," *Journal of Neural Engineering,* vol. 1, p. 135, 2004.

[22] A. J. Doud, J. P. Lucas, M. T. Pisansky, and B. He, "Continuous three-dimensional control of a virtual helicopter using a motor imagery based brain-computer interface," *PloS one,* vol. 6, p. e26322, 2011.

[23] F. Nijboer, E. Sellers, J. Mellinger, M. Jordan, T. Matuz, A. Furdea*, et al.*, "A P300-based brain–computer interface for people with amyotrophic lateral sclerosis," *Clinical neurophysiology,* vol. 119, pp. 1909-1916, 2008.

[24] B. Blankertz, M. Tangermann, C. Vidaurre, S. Fazli, C. Sannelli, S. Haufe*, et al.*, "The Berlin brain–computer interface: non-medical uses of BCI technology," *Frontiers in neuroscience,* vol. 4, 2010.

[25] A. Nijholt, D. P.-O. Bos, and B. Reuderink, "Turning shortcomings into challenges: Brain–computer interfaces for games," *Entertainment Computing,* vol. 1, pp. 85-94, 2009.

[26] S. Sanei and J. A. Chambers, *EEG signal processing*: Wiley, 2008.

[27] P. Stoica and R. L. Moses, *Spectral analysis of signals*: Pearson/Prentice Hall Upper Saddle River, NJ, 2005.

[28] C. J. Burges, "A tutorial on support vector machines for pattern recognition," *Data mining and knowledge discovery,* vol. 2, pp. 121-167, 1998.

[29] Y. Freund, R. Schapire, and N. Abe, "A short introduction to boosting," *Journal-Japanese Society For Artificial Intelligence,* vol. 14, p. 1612, 1999.

[30] C.-C. Chang and C.-J. Lin, "LIBSVM: a library for support vector machines," *ACM Transactions on Intelligent Systems and Technology (TIST),* vol. 2, p. 27, 2011.

[31] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. H. Witten, "The WEKA data mining software: an update," *ACM SIGKDD Explorations Newsletter,* vol. 11, pp. 10-18, 2009.