Review of Brain Computer Interface Components and Corresponding Research Topics

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Abstract—This paper conducts a research on the literature of Brain Computer Interface(BCI) in recent years, inducing the four components of BCI and the research topics respectively, and providing a guide to newcomers for exploring BCI. BCI is divided into four parts including signal collection, feature extraction, feature classification and practical application. Papers of above four parts are retrieved respectively from the SCI database. Topics of all papers are concluded, based on which the research topics of BCI are assigned to the four parts of BCI. In topics of each part of BCI, similar topics are summarized to the unique topic. Finally some research topics may cover dozens of papers while some topics may cover only several papers. In each of the four BCI components, there are several topics attracting most of the attention. BCI still has a great research value and good prospects for study.

Keywords-Brain Computer Interface(BCI); signal collection; feature extraction; feature classification; practical application;

I. INTRODUCTION

Brain computer interface(BCI) is a system that translate the brain activity that reflects user's intention to a control instruction without the help of brain's normal output pathways of peripheral nerves and muscles. The control instruction is then transferred to hardware or software systems for helping the users to interact with surroundings. For users with problems in nerve and muscle systems, the BCI system may improve the quality of life in the remained long life of the users for helping them with moving, speaking, etc. For normal users, equipped with a BCI system may bring convenience to daily life and provide recreational activities. The research of BCI started in USA and Europe from the 1970s, and associated conferences began to be held for exchange of relevant development of BCI. In recent years, BCI began to attract more attention from the researchers in China. This paper mainly summarizes the four main aspects of BCI and the research topics respectively, aiming at giving some inspiration for exploration of BCI by providing the development and current status of BCI research.

II. THE COMPOSITION OF BCI

The main components of BCI include the sampling of brain activity signals, feature extraction, feature classification, and practical application. Introduction of feedback into the BCI may improve the control effect of the latter.

BCI relies on the information provided by different brain activities. The information can be collected by Magnetoencephalogram(MEG), Near Infrared Spectrum Instrument(NIRS), Electroencephalogram(EEG), Electrocorticography(ECoG), or some other ways. The above methods differ in the signal media and the locations of signal source. The signal media may include magnetic, light, electric and so on. The locations may include the scalp surface, the surface of cerebral cortex, or inside the neurons. The most commonly used signal acquisition method is EEG for it collecting information on the surface of scalp safely and quickly. For EEG signal, according to different incentives, EEG may be divided to several distinct types. Three types named as P300 potential, Motor Imagery(MI), and Steady-State Visual Evoked

Potential(SSVEP) cover most of the BCI associated papers. P300 potential happens after 300ms when the subject observes a small probability event. When subject stares at a light block which flickers at a fixed frequency, the SSVEP of the same frequency or frequency multiplication can be detected in the occipital region of the brain. When subject imagines the movement of their arms or other parts of the body, the activity of the contralateral half brain becomes weak, while activity of the ipsilateral half brain become stronger.

The purpose of feature extraction is to get vectors which can represent specific states of brain. Feature extraction algorithms can be divided according to the time domain, frequency domain, or spatial domain. There are several common methods and many variants based on them working well for the feature extraction process. Integration of a variety of method is an acceptable way to do the feature extraction for it integrating the advantages of various methods and extracting the information from more than one domains. We can see from the papers of recent years that the method called Common Spatial Patterns(CSP) are more frequently used.

The purpose of feature classification is to classify the vectors into a category which represents one state of brain activities. According the results of feature classification, we translate an extracted vector to a control instruction to control the external equipment. Integration of several classification methods is a good way to optimize the accuracy and robustness of BCI. In recent years, Artificial Neural Network(ANN) and Support Vector Machine(SVM) are mostly used for the classification of BCI.

Practical application is the implementation for BCI controlling the external world. In 1988 the P300 BCI based character spelling system was developed, from then BCI based implementation including cursor control, robot arm control, etc. began to appear in labs around the world. The nature of BCI is to map the brain signal which is modulated by the subjects' intention to a series of control instructions. Then we can design the control instructions to control a external device like a wheelchair to make it go ahead or back off.

III. THE DEVELOPMENT OF BCI

In 1973, UCLA professor Vidal conducted a research on the communication between the brain and computer, which can be seen as the emerge of BCI. In 1996 the 1th BCI Meeting was held by Wolpaw in America. In 2001, the 1th International Brain Computer Interface Conference was held by Gert Pfurtscheller in Austria.

Research centers and labs of universities in China began to put attention on BCI in recent year and have obtained some achievement. Professor Gao Shangkai from institutes of biomedicine, Tsinghua University has researched BCI for many years and majors in brain signals collection, feature extraction and practical application. Lab of Shanghai University majors in the feature extraction method named optimal wavelet packet decomposition. National Defense Scientific and Technical University majors in brain signal collection and achieved BCI based control on NAO robot and cars in 2015. South China University of Technology gains some achievement about feature classification and practical application. Professor Song Aiguo from Southeast University majors in the feature extraction algorithms based on wavelet transform and AutoRegression(AR) model. Professor Zheng Xiaoxiang from Zhejiang University majors in practical application of BCI and achieved the outcome that help a monkey control a robot arm by decoding its brain signals in 2012. Third Military Medical University majors in brain signal collection and practical application. Tianjin University and South-central University for Nationalities both work on all four components of BCI and achieved some outcomes. Northeastern University majors in feature extraction and practical application. In general, though research on BCI in China labs is in development stage, there are more and more outcomes about BCI appearing. News that Shanghai Jiaotong University used BCI to control a cockroach and Nankai University developed a car controlled by a BCI system began to enter the public eye. Currently the papers about BCI in China mainly concentrate on signal processing algorithms and few papers can establish a working BCI system . Especially some BCI systems may be invasive, which need operations on subjects or some animals. Most of labs in China have no ability to carry out such a BCI system. There is still a large gap between China and USA or some European countries in the BCI area.

The research on BCI started as early in 1973 in America. Now there are hundreds of BCI research groups around the world. Several groups made huge contribution to the development of BCI. Graz University of Technology in Austria majors in practical application including character communication system, robot arm control, and the introduction of virtual reality. The lab of this university realize two BCI systems named Graz I and Graz II, and provide datasets of EEG to researchers around the world as a standard for test of their signal processing algorithms. Professor Pfurtscheller of the university hold the 1th International Brain Computer Interface Conference. Wadsworth Center of America majors in practical application including character communication system, cursor control, audition based BCI, robot arm control, and BCI for home application. The object of Wadsworth Center is to develop BCI for home use or disabled person. The center developed the BCI2000 system which is an open source software platform for studying and research BCI. University of Tubingen majors in practical application including character communication system and audition based BCI. The lab of Tubingen University also have some work on hybrid BCI, wheelchair control, and BCI with a feedback component. Duke University developed a BCI based exoskeleton system to help a boy with paralysis kick off for the 2014 FIFA World Cup. Brown University developed an invasive BCI based robot arm control system, and make patient with tetraplegia feeding herself coffee come true.

The development of BCI in USA and European countries begins to slow down at present, while the development in China just starts. No matter for the better life of the disabled persons or people with neuromuscular diseases, or for the convenience and entertainment of normal people, BCI is still a valuable topic.

IV. COMPONENTS OF BCI AND CORRESPONDING TOPICS

A. *Signal acquisition*

In the beginning, the research object of BCI is to provide a way for helping people with neuromuscular diseases communicate with the external world. Most of the BCI research groups don't emphasize whether the final objects of their BCI systems are normal people or people with neuromuscular diseases. When considering people affected by Amyotrophic Lateral Sclerosis(ALS), brainstem stroke or spinal cord injury, whether the above patients could use the BCI as well as a normal person is still a topic demanding attention. For some severely disabled users who can't do the gaze shifting, SSVEP based BCI [1] and P300 based BCI [2] may all fail because they rely on eye movement to work. For these patients, compared with BCI based on vision, the BCI systems based on audition may work better [3]. There is no difference in terms of ability controlling BCI for patients in different stages of ALS, but for the patients in the Complete Locked In State(CLIS), the patients can absolutely not use any BCI system [4]. Moreover, for stroke patients [5], paralytics [6] and epilepsy patients [7], whether the above patients can use BCI to control one-dimensional cursor movement was also studied. Reference [8] do a further research on that how the nerve disorder degree of stroke patients influence the performance of they controlling BCI.

The mostly used brain signal EEG is sampled from the surface of scalp, and the collection relys on the contact between the scalp and the electrodes. As the electrodes can be see as the source of the whole BCI system, how to choose and allocate the electrodes is of great importance for subsequent obtaining effective brain signal and optimizing the effect of feature extraction and classification. Adopting capacitive electrodes [9], multiple channel detection [10], or active electrodes [11] will all improve the effect of the signal collection. Besides, through some way to choose the optimal electrode configuration is also an import method to enhance the spatial resolution of EEG signal [12, 13].

Another fundamental problem about signal collection is the stimulus presentation. The standard row/column paradigm is used for P300 potential induction, and several light blocks flickering at different frequencies are used to induce SSVEP potentials. Some new or modified stimulus presentation patterns may enhance the information transfer rate or reduce the fatigue of users to achieve a better performance of the whole BCI system. Checkerboard paradigm [14] and auditory spatial BCI concept [15] are developed to enhance the performance. Reference [16] researches how stimulus flash patterns and number of elements in P300 stimulus presentation influence the information output performance of BCI. Some papers do a comparison of different stimulus presentations in performance [17-19], that giving a guide for the design of further BCI system. Moreover, from the aspect of users, reference [20] introduce a frequency modulation method form the auditory field, which is used to induce SSVEP and is not so easy to cause user fatigue, so the method is more like to be used in a long-time working BCI.

Human body always generates EOG, EMG and other interfering signals, besides that 50hz or 60hz signal in power supply will also have an impact on the collected EEG signal. EEG signal denoising and improving the signal to noise ratio can effectively benefit the classification of EEG signal, avoiding the EEG signal that reflects user's intention drowned in unwanted noise. Reference [21] shows several EEG denoising methods. Reference [22] uses two independent component analysis methods, InformaxICA and FastICA, to eliminate the EMG noise. Reference [23] uses pearson correlation coefficient to identify the source and interfering signals.

Most brain computer interfaces require users training for a long period of time, but reducing or eliminating this training process is required in order to make BCI practical. Some research results show that, for motor imagery based BCI, using machine learning and signal processing method can reduce the upfront training time [24].

EEG signal instability happens in many scenes including from offline to online [26], from trials to trials [27], within trials, or the change of users [25]. In the above scenes, statistical properties of the EEG signal are likely to change leading to failure of some original system parameters affecting system performance. Introduction of a series of adaptive algorithms [26, 27, 28] or dynamic algorithms can effectively eliminate the instability of the system. Reference [29] shows that continuous update is better than the effect of non-continuous adaptive update, and gives out a reference for evaluation of adaptive classification algorithms.

Currently, most BCIs are called synchronous BCI, which means that users can only give out control instructions in a period of time after the computer giving a hint. What we need is the asynchronous BCI that is able to respond to the control requirement of users at any time. Reference [30] proposed a SSVEP based asynchronous self-pacing prosthetics control system. Furthermore some papers use MI signal to establish self-pacing BCI [31-33], and some introduce the concept of brain switch.

The feedback signal is a component of BCI, not only reflecting the results of tasks performed by the users, but also having relationship with the signal generation and the overall performance of system. Many scholars consider the virtual environment [34-36] as a feedback in BCI and study the influence of feedback on the performance of the system [37, 38]. Reference [37] studies how the feedback influences the strength of the generated signal. Reference [38] shows that auditory feedback and visual feedback have little effect on system performance if users are adequately trained.

Traditional BCI is usually based on a single kind of brain signal, such as P300 based character spelling system, SSVEP based BCI, MI based wheelchair control system, etc. In order to improve system performance, make robustness of system stronger, and make the classification results more accurate, combining two or more kinds of EEG signals [40] and integrating EMG [41] or EOG [39] which is regarded as interference in the past can be considered as an effective way to use the brain signal.

Most current BCI systems are based on visual stimulation, but for patients who lose their vision or can't control eye movement, such as patients with advanced ALS, visual stimulation based BCI does not meet the requirement or even can't work. For this type of patients, we need to induce effective EEG by other ways. Most

practical BCIs for the above patients concentrate on the use of auditory stimulation [42-45]. Reference [42] uses auditory P300 potentials and Reference [43] uses auditory ECoG signal. Besides, BCI based on dichotic listening paradigm is also studied [44, 45].

Evaluation indexes of system performance mainly include classification accuracy and information transfer rate, and to optimize the indexes can be started from several aspects. In terms of signal acquisition, there are also several aspects that can be improved [46, 47]. Reference [46] improves classification accuracy and information transfer rate by increasing the number of electrodes, reducing the time interval between incentives, etc. Reference [47] improves system performance from the aspects such as number of channels, channel positioning, data extraction and so on.

B. Feature extraction

Feature is to extract the data vectors that can represent different EEG data patterns. Then these vectors are used as input data of the classifier.

When processing instability of EEG signal, we can use some new or improved algorithms from the feature extraction. Reference [48] uses Common Average Reference(CAR) to filter the offline data, and eliminate the instability of EEG signal to a certain extent. Many feature extraction algorithms based on CSP are used to eliminate the instability. Reference [49] proposed a spatial filtering algorithm called Kullbakc-Leibler(KL) CSP. Reference [50] propose a method which regularizes CSP towards stationary subspace(sCSP) to tackle the non-stationary problem. Reference [51] proposes a discriminative filter bank(FB) CSP algorithm to extract subject-specific FB for MI classification, which can eliminate the instability between users.

Since the sampled EEG data are usually multi-channel, the extracted feature vectors may have a very high dimension which means the vectors may contain a large amount of redundant information, so feature dimension reduction by feature selecting or subspace projecting is quite necessary. Dimension reduction of feature vectors can be considered in two ways, one is spatial projection based dimension reduction [52-55], such as Principle Component Analysis(PCA) [53, 55], Fisher Dicriminant Analysis(FDA) [53], etc., the second is feature based feature reduction [56-62], the most common feature selection method is genetic algorithm [60-62].

Lots of papers are about improving algorithms for extracting features to enhance the classification performance. Reference [63] optimizes spatial spectral features by maximizing the mutual information between spatial spectral features and class labels. In recent years, optimization for feature extraction methods are most focused on CSP [68-79] and wavelet features [64-67].

There are also more articles about innovative algorithms for extraction of features [79-91]. The algorithms such as phase space feature extraction [79-81] generally has improved performance compared with the commonly used feature extraction algorithms. Reference [82] uses dual-tree complex wavelet transform and adaptive model selection to extract features of motor imagery of swallow EEG signal. Reference [83] uses multi-resolution asymmetry ratio to extract features from wavelet data.

C. Feature classification

After feature extraction, feature vectors will be classified and classification results will converted to the corresponding control instructions. Classification accuracy will significantly affect the performance of BCI.

When considering optimizing instability of EEG signals from the classification aspect, introducing adaptability [93, 96, 98, 100] and fuzzy logic [94, 97] will significantly eliminate the adverse effect of signal instability. In terms of instability of EEG signals among users, Reference [99] build a classifier collection based on user-specific spatio-temporal filters and use L1-norm regulated quadratic regression to make the classifier discrete, then the final classifier can be reliably generated to other users. Reference [92] considers that the inter-trial changes are inevitable and it is hard to extract consistent features, so the paper clusters the trials with similar characteristics and uses corresponding adjusted classifiers to eliminate the inert-trial instability. Reference [95] combines several classification methods, such as K Nearest Neighbour, Multilayer Perceptron, etc., for introducing robustness to the classifier.

If we want more complex control functions by using BCI, we must use more than two EEG signal patterns and the the corresponding classifiers must be multi-class. For the classification of multi-class fNIRS signals, we can use multi-class LDA[101], extreme learning machine [102], and SVM [103]. Reference [104] and Reference [107] use improved neural network classifiers to classify three types of EEG signal patterns. Reference [105] uses FisherLDA to classify multi-class feature vectors with feature selection based on mutual information. Reference [106] shows a new classification framework for multiple types of MI signals, whose core is the use of spatial covariance matrix as the EEG signal descriptor. Reference [108] designs test to show the feasibility of multi-class classification in a single trial.

With respect to off-line data processing, only BCIs with online signal classification have practical value. As denoising online can't be done by the average of several past trials, Reference [109] proposes a new method based on variance analysis. Reference [110] significantly improves the online performance of recognition of MI signals by using surface laplace transform. Reference [111] compares the performance of standard Multilayer Perceptron and Finite Impulse Response Multilayer Perceptrons(FIRMLPs) classifying EEG signal patterns in a single trial. Reference [112] uses Hidden Markov Model(HMM) to do the online classification of left and right hand motor imagery signals.

Part of the articles improve the existing classification algorithms for better results of EEG signal classification. Reference [113] uses the area under ROC curve to find the optimal linear discriminant as the classifier. Reference [114] combines language model with the classifier to optimize the classification of P300 character speller. What's more, there are papers about the optimization of SVM [115-118] and ANN [119-121].

There are more articles about the classification algorithms innovation [122-127]. Reference [125] uses a

semi-supervised training method with cooperation of two kinds of classifiers to build a integrated classifier. Reference [127] proposes a classification method based on hidden conditional random field to classify MI signals.

What's more, some papers apply common classification algorithms on some novel data objects [128-131], such as silent reading syllable [128], Chinese pronunciation imagination [129].

Several papers compare the performance of classifiers to provide a guide for building a BCI system [134-138].

Asynchronous BCI needs always to collect and classify brain signals, so detecting and classifying states of working or idle is the difficulty. Reference [137] distinguishes between idle state and MI state by maximizing sensitivity and minimizing false positive rate.

D. Practical applications

Currently BCI applications are relatively simple, the function is not complicated, and application type concentrated in the following directions.

Cursor control is a kind of relatively easy to implement application, including one-dimensional control [138-141], two-dimensional control [140, 142-147], three-dimensional control [148], etc. One-dimensional control is relatively simple, but two-dimensional and three-dimensional control usually require more than two EEG signal patterns. Based on the cursor control P300 BCI, paper [149] improves BCI2000 and online adjustment to achieve a home BCI prototype.

The initial goal of BCI is to serve the patients with neuromuscular diseases, for this type of patients, movement is a relatively difficult and necessary thing, so BCI based wheelchair control naturally becomes a kind of application given considerable attention. Reference [154] uses an hybrid BCI based on SSVEP and P300 to control a wheelchair. Reference [157] uses a P300 based BCI to choose the destination and combine a route guidance system to control the wheelchair.

For patients with neuromuscular diseases, the prosthetics control [158-173] is also very useful. Reference [159] uses hierarchical control strategy and direction control policy to control manipulator of two degrees of freedom. Reference [173] uses a BCI based on SSVEP and brain switch to control a hand brace.

The most common practical application based on BCI is the character communication system. Currently P300 potential based character communication systems [174-176, 179] are still the majority. Reference [177] and reference [178] use MI based BCI to control a virtual keyboard as input tool.

Combining with part of human body structure or some other biological information, researchers can develop new BCI or improve the performance of BCI. Reference [180] distinguish the smell by detecting the potential of the olfactory bulb of the brain. Reference [181] combines BCI and functional electrical stimulation to control the paralysis muscles. Reference [182] combines BCI with other biological information to build a hybrid BCI as auxiliary equipment.

There are also other ways to combine BCI to build more complex applications [183-186]. Reference [183] combine a semiautomatic explore subsystem to enable BCI to complete more complex tasks.

V. CONCLUSIONS

Currently, BCI still have problems of few control commands, low classification accuracy and low information transfer rate. Study of BCI in USA and European countries started early, but now the heat has weakened and the key technique of BCI has no significant progress. In China, there are not many research institutions studying BCI and most of present achievements concentrate in simple application and theoretical research.

BCI still has much room for development, and the following summarizes several directions of BCI research given focus.

We can consider several topics from the four parts of BCI, such as innovation of EEG signal types or combination of several kinds of EEG signals in the signal collection, combination of multiple extraction algorithms for extracting complementary information from all domains in feature extraction and combination of multiple classification algorithms to enhance the robustness and accuracy of BCI in feature classification.

Semi-supervised BCI, based on a supervised training, uses unlabeled data to do local updates of the classifier, which can eliminate the influence of instability of EEG signals and reduce upfront user training time.

To make BCI practical, implementation of asynchronous BCI is required. Asynchronous BCI frees users from the synchronous control of most BCIs and enables users to control a BCI according to their own wishes by detecting the users' idle and working conditions.

At present applications based on BCI mostly concentrate in the robot arm control, wheelchair control and character interaction. More novel applications are waiting to be found and achieved. At this stage the control capability of BCI is still weak, so how to implement complex efficient BCI based applications or what kind of control strategy to use is also an import research direction.

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