Review on EEG-BCI classification techniques advancements

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Abstract: A BCI is a system of hardware and software integrated as an interface between the brain and the computer. A BCI translates the EEG signals, originating from the brain, into computer commands, commands that help the user interact with the external real world in a useful manner. The possibility that EEG signals can be translated into any open-ended computer command opens endless possibility. What a person can do with EEG-based BCI is now just limited by imagination. This paper will discuss advances in the practical aspects of different classifiers for EEG-based BCI, as well as the theoretical advances in signal processing and user relevance of these advances in EEG-based BCI in real-time applications.

Keywords: Brain Computer interface (BCI); Electroencephalogram (EEG); Usability; Amyotrophic Lateral Sclerosis (ALS).

1. Introduction

People throughout history have thought about controlling objects external to their body, moving things with their thoughts was considered to be a great power and people with such abilities were considered superior in some sense. Some called it magic, some called it dark arts and some called it science. Controlling something with one's mind has always been a hot topic in humanity throughout history. A world where people can interact with the external world without physical contact was always dreamed. In the modern world this not just part of a philosophical discussion or part of the dream, but have been made possible, defiantly by using science and not by magic.

EEG came into the light in 1929[1-2], and this provided non-invasive access to brain-related information. What people could accomplish with this EEG information was yet to be discovered. The true potential of EEG was not realized until the computers were invented. Researchers gained more information about the brain with the growing tech technology and research along with it. The success in understanding these EEG signals opened the doors for a new field of non-invasive EEG-based Brain-Computer Interface (BCI).

An EEG-based BCI can be used to write on computer-based windows[3-5], it can be used to control the home appliances Park et al[6-7], it can be used to control a robot[8-10], it can be used to control robotic arms, it can be used to drive a wheelchair it can be used in an exoskeleton, it can be used as browse[11], it can be used to fly a quadcopter[12]. These are not just possibilities but are actual BCI that is extensively researched about and with some form of experimental proof of concept. But as mentioned before BCI is just limited by imagination, BCI has the potential to be so much more than it already is. In a futuristic world, a more complicated task could be done using a BCI, for instance, driving a car, playing video games, surgeries (medical) and much more. BCI is just not the vision of the future but also a helping hand to the people that are differently-able and suffering from neurodegenerative diseases. Human body can be seen as an input-output system, any form of interaction with the outside world is initiated from brain. BCI provides an alternative pathway to interact with the outside world. A person with the severely impaired motor system, individuals with Multiple Sclerosis (MS), Amyotrophic Lateral Sclerosis (ALS) etc, BCI provides a means to interact with the environment in some way (written communication, device control, navigation, robot control,
internet browsing etc). BCI does expand the limits of our mind, the physical world would be an extension of the mind. This would open the limitless potential to how we, humans, understand the world around us.

The current state of BCI is an outcome of more than 3 decades of research in the field of computing hardware, machine learning, signal processing and brain imaging (mostly EEG). Today we have very fast parallel processors and GPUs which can process large amounts of data quicker than ever before, which significantly decreased the latency of the BCI systems making the BCI more practical and not just proof of concept. BCI since 2000 have shifted from using Blind Source Separation (BSS) and Independent Component Analysis (ICA). [13-15] to the newer algorithm such as Linear Discriminant Analysis (LDA). [16] Step-wise-LDA (SWLDA) [17] and then to Machine Learning and Deep learning algorithms such as ANN, CNN , LSTM, which allowed better classification of the signals and hence increase in the accuracy of a BCI system.

In this paper we review the progress of BCI in the last decade, If you lookup the keywords “BCI” OR ”Brain-Computer Interface” on Scopus 15000+ papers till date came up. This shows the extent of work being done in the area. The outcome of this massive interest in BCI research is different BCI technologies such as Spellers, BCI robot, BCI exoskeleton, BCI wheelchair, BCI prosthetic and more. This impossible achievement was possible because of brain imaging technologies more specifically EEG. EEG has been studied extensively since 1970. Using this extensive knowledge of EEG, various non-invasive BCI paradigms were made possible.

It is pivotal for science to grow for the advances to be made by the human race. The BCI research shows a definite upward trajectory in terms of the growth of the field, but has this research helped people. Since BCI is applied science and the ultimate goal is to help the real people (users) out in the real world, the parameters of success of the field must also consider a user view of the BCI systems. The research of EEG based BCI can be broadly divided into two research categories first the BCI exploratory and replication research and the other research which includes review papers [18-21] and comparison works. Review paper on either on BCI or classification techniques [22-23] or different paradigms, it would represent the advances in science over the years, but these advances in science does not necessarily represent advances in actual usable BCI system. In fact, most of these proposed BCI research never went past the proof of concept. Hence even though there are thousands of BCI papers, only a small amount of resulting BCI system might be usable by the intended users. A functional BCI simply doesn't mean being able to control the command signals as accurately as possible, accuracy is just one of the important factors. BCI evaluated using accuracy does not say much about user concerns. If the BCI system does not meet the requirements of the users then they would eventually be useless as they are not fulfilling their intended purpose. Hence this paper review the BCI papers on the scale of possible user’s issues with the current hardware and software, and in the process figure out a possible new direction and motivation the non-invasive BCI research.

Advances in BCI in the current scenario would one down two separate paths:

a. The solution that the BCI system offer
b. The signal processing tools used to find the required solution

The former question entails the current state of BCI assistive technologies and the latter would include the current state of the signal processing and AI methods for the current BCI solutions will discuss each in detail in the following paragraph.

2. Theoretical advances in BCI
Building a BCI is not a simple task; it is not all hardware or software of a link between the two. It does not rely simply on signal processing, nor on the paradigm used and even with both the tools, much work is needed to bring it all together. A perfect BCI would not just be scientifically perfect but also usable by the user. However it is no doubt without the advances in the theoretical and the experimental advance a good BCI cannot be imagined. Advances in BCI’s theory are manifold, the steps after the experimental paradigms are the signal processing which provides required information about the brain states and makes the BCI work. The signal processing pipeline has 3 important stations, filtration, feature extraction and classification of the signal. To some it might seem like these stations do not play much of a roles in making BCI user-centric, as they are integral algorithms that run on the hardware
but this is what makes them most important. We will review the filtering and classification in the following subsections as they directly impact real time performance and are also common to all BCI. The field of filtration has grown over time but it’s seemed that use of the new filtration techniques is confined to researchers who invented them. It almost seems like pre-processing is thought to be not as relevant as the feature selection and classification techniques.

3. Advances in classification techniques

The aim of BCI is to translate brain activity to a command for computer, for that purpose BCI can be viewed as a pattern recognizer. To make such a system one would need a clean signal, now some identifying features need to be established in order to compare two signals for similarities, now from a new signal these features are extracted and then a classification algorithm recognizes the signal and puts it in its class of similar featured signals. It is not a simple process, a classification algorithm cannot simply tell one signal from another especially with increasing dimensionality. After the signal to noise ratio is reduced and the next step of extracting the features from the data, a classification algorithm is used to classify the selected features, this classification would not be possible without first training classifiers. Hence there are usually two parts to the working of any BCI, offline training, and online testing. In offline training after the feature is extracted, it is used to train the classifier. This trained classifier is then used in online classification. This was needed to be done for almost all the BCI before 2017 but with the growing field of AI and ML and DL efforts are being made to remove this offline calibration [24-25]. The most part of the decade went into improving the performance of BCI systems by improving and inventing new feature extraction and classification techniques.

Linear classifiers use linear differentiators that are linear algorithms to distinguish any two or more classes. LDA puts features into classes by assuming hyper plane, these hyper plane separate the data. If there were only two classes then we will need one hyper plane. New data will fall into one of the classes depending on which side of the hyper plane the data is. LDA assumes normal distribution of data with equal covariance of all the classes. Now the question is how to select this hyper plane for maximum accuracy. The hyper plane is such that distance between classes mean is maximum and minimum interclass variance. To solve N-class problem many hyper plane will be needed. LDA have low computation requirement and hence is suitable for online BCI. SVM also uses hyper planes as discriminant for class identification. This hyper plane is selected based on margin value; margin is nothing but distance of plane from training points. The idea behind SVM classifier is to maximize the margin. Neural networks classifiers are also type of classifiers that are heavily used in BCI research. As the name suggests these classifiers consist of artificial networks, the do not have liner decision boundaries like the liner classifiers. MLP is one of the most used NN classifier

As the name suggests a Multilayer perception is made up to many layers of artificial neurons. The first layer is the input layer the final layer is the output layer and layers in between are called the hidden layers. The input to any layer is output of the previous layer and the output of the last layer (the output layer) is the class separation of the input feature vectors to the first layer (the input layer). The power of hidden layers is such that the MLP can approximate any function which allows for flexible non-linear decision boundaries, which in turn makes MLP a very flexible classifier that can classify any number of classes. However all NN classifiers including the MLP are sensitive of over training when data is non-stationary as is the case with EEG data.

Gaussian classifier is one of the NN classifiers that is specifically designed for the BCI systems. Each unit in the architecture is a Gaussian function that represents a class. It is shown in some cases that a Gaussian classifier can perform better than a MLP. Non-linear Bayesian classifiers are generative non-linear classifiers and are not as popular as liner classifiers. HMM is the most popular of all Bayesian classifiers. Nearest neighbor classifiers are classifiers where a new feature is assigned a class depending on the nearest neighbors. The neighbors can be features themselves which are classified during supervised training or can be a prototype class. kNN is an example of the former type. Here out of k nearest neighbors the most dominant class is selected an assigned to the new unknown feature point. This is usually done using matrix distance; they work well with low dimensional BCI.
Adaptive classifiers are classifiers for which the classification parameters are constantly updated based on the new data. This works well with EEG data because the uncertainty of data is not a problem any longer. All the linear classifiers can be made adaptive and in the past decade adaptive LDA and SVM are being used successfully and more often. Deep learning classifiers are one type of machine learning classifiers which learn about features and classifiers together. It is made of layers of trainable feature extractors and non linear classifiers cascaded together. Restricted Boltzmann machine and CNN are the most popular among deep learning classifiers. Transfer learning classifiers addresses the issues of ever changing feature space as EEG signals are not same for any two people and are different for the same person at two given point. These classifiers learn from the existing datasets and try to solve different but related problems, so more related the problems are better is the performance of the classifiers. Riemannian geometry-based classification these classifiers uses Riemannian geometry for classification. Keeping all that in mind and bringing users into the equation, many concerns again arise. From a scientific eye this seems like a good amount of progress in the field and that is undeniable but this research did not contribute much towards user-centric BCI. In fact, the research might have gone in a totally different direction. According to trends in research, this does not seem to be the best path towards making a BCI that all can use. Making the classifiers better was not the solution to problem of making user-centric BCI and here is why. If one is trying to build a BCI for the users and one should keep in mind that, it does not matter to the user what kind of classifier is running in the system, or how is the system converting its thought into commands. What matters to the user is that, is the system doing what she wants it to do? How accurate is the system? How fast are his intentions becoming reality? The advances in the classifiers only seem to answer one of the questions barely. The classifiers of the past and today only focus on accuracy as the measure of success. Let us consider for a moment that success is the only measure. The classifiers from the past LDA, SVM to the newer deep learning and adaptive classifiers have not managed to improve accuracy by a huge margin. And this optimistic 7-8% more accuracy came at a huge cost of complexity and computational power. This should compel us to ask the question in behalf of the users, Was it worth it? And the answers that one might get are would be up for debate, because the user was never kept in mind while newer classifiers were built. Hence, accuracy is not the only thing that matters, in a system interacting something as complex as the brain and in real time, performance has to be about more than just accuracy. Latency is one of the measures that most BCI try not to address, followed by the computational power, training time, sensitivity and there may be others once we bring user needs into the fold. Table 1 is condensed list of some of the currently existing classifiers:

| Classifier Type                                      | Examples                                      |
|------------------------------------------------------|-----------------------------------------------|
| Linear classifiers                                    | LDA, SVM                                      |
| Neural networks classifiers                           | MLP, Gaussian, Classier, LVQ, FIRNN, TDNN, BLRNN and ALN |
| Non-linear Bayesian classifiers                       | HMM                                           |
| Nearest neighbor classifiers                          | kNN                                           |
| Adaptive classifiers                                  | Adaptive LDA, Adaptive SVM                    |
| Deep learning classifiers                             | Deep ELM, DBN, CNN, CNN+DBN, LSTM, Attention+LSTM |
| EEG matrices and tensors classifiers                  | RMDM, Tangent space + LDA, SVM, Riemannian Kernel |
| Classifiers that can be trained with limited data     | SLDA, RF, RMDM                                |
As discussed before there is no denying that an astonishing amount of work went into the classification techniques in the last two decades. It is shocking to see that there is more number of classifiers than the total number of BCI solutions out there. SWLDA/LDA, SVM, and deep learning classifiers are much more popular than any other classifiers out there. One would think that with such a vast number of classifiers there must be clearly defined parameters on which we can rate the classifiers. Only one paper out of the blue might talk about sensitivity and give a ROC curve, without explaining much about any implications of it. Talking about the complexity, or time required to train the classifier, or the latency are never talked about. These parameters are directly relevant to the classifiers and the users. There is more such parameter which is not talked about and no data was found. Again what is important to understand are the trade-offs between the scientific progress and the user needs.

4. Conclusion

BCI turn our intentions into reality, quite literally. It is a ray of hope for those who have lost some or all motor functions of their body. BCI should be a technology for all, people who need it should get it. Not only they get the technology by also effortlessly be able to use it. Unfortunately, BCI like discussed, is not moving in that direction at moment. Evaluation parameters, in the current scenario accuracy is the parameter on which BCI systems are evaluated on. The last decade majority of the work was done just improve the accuracy of the BCI systems. This is what led to large number of classifiers and caused to focus to shift from the all other signal processing pipeline elements and the experimental paradigms. For BCI to be more user-centric we propose usability parameters must be used to evaluate the BCI systems.

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