Brain-Based Computer Interfaces in Virtual Reality

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***Abstract*—*Virtual Reality* (VR) research is accelerating the development of inexpensive real-time *Brain Computer Interface* (BCI). Hardware improvements that increase the capability of Virtual Reality displays and Brain Computer wearable sensors have made possible several new software framework for developers to use and create applications combining BCI and VR. It also enables multiple sensory pathways for communications with a larger sized data to users' brains. The intersections of these two research paths are accelerating both fields and will drive the needs for an energy-aware infrastructure to support the wider local bandwidth demands in the mobile cloud. In this paper, we complete a survey on BCI in VR from various perspectives, including *Electroencephalogram* (EEG)-based BCI models, machine learning, and current active platforms. Based on our investigations, the main findings of this survey highlights three major development trends of BCI, which are entertainment, VR, and cloud computing.**

***Index Terms*—Virtual reality, electroencephalogram, brain computer interface, brain machine interface, cloud computing**

I. Introduction

Computer technologies are at the edge of a huge leap forward with direct interface to the brain combined with *Virtual Reality* (VR). The increasing capabilities, processing speed and maturity of the hardware has made VR software and devices more useful, affordable and responsive. Concurrently, machine learning is quickly advancing innovations in *Brain-based Computer Interface* (BCI), which is already moving quickly to become widely available as the sensor technology is becoming more economical. The intersection of the two, VR and BCI, is the topic of this survey paper.

Natural human interaction is experienced in real behavior of user, senses and thoughts as they react in vast whole body awareness to the VR experience. This immersion can increase the cognitive ability of people to process information [1]. More information can be communicated between the human and the machine in a shorter amount of time when using all the senses, such as audition, haptic feedback, vision, and somatosensation, than the old communication bottleneck of keyboard input with display output.

In the VR interaction between the user and the computer, the human user receives rich output that is felt through multiple senses inputting data into the brain. The BCI delivers faster input into the computer program. The fingers, voice, eye gaze, skin, head and body position are concurrent channels of interactive communication between human and computer [2]. Numerous studies [3]–[6] show that humans can use brain *Electroencephalogram* (EEG) signals to convey their intentions to computers using BCI, a pathway between an enhanced, sensor-equipped or wired brain and an external computing device. BCI enables user interaction through "thought".

Recent advances in machine learning in BCI research combined with the development of inexpensive sensor wearable devices has made practical the interaction of users with computers and mobiles through brain EEG signals [7]. In the *Virtual Environment* (VE), the human perception of immersion has become a measurable factor [8], [9]. While the physical movement of the human body responds to the VE, its brain waves are active in dealing with environmental information, decision-making in space, and motor movement [10]. Through real-time detection, EEG communications data is sent to the computer containing these variations and changes in brain activity. The significant features of this brain activity is measured and translated into control signals that can drive an output, with meaningful content feedback. The pattern classification or machine learning or artificial intelligence analysis of the EEG signals to find control signals in those patterns, in real-time, is the cutting edge of the VR-BCI research field.

Our contributions of this work are twofold:

1) We investigate the existing BCI VR researches from three crucial aspects that are EEG-based BCI models, machine learning, and platforms. The findings can be used as reference for future relevant researches.
2) We present three main development trends of BCI research in VR field, which include entertainment, VR-based applications, and cloud computing.

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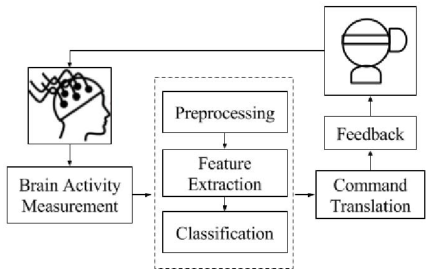

Fig. 1: Model of the on-line BCI

The rest of this paper is organized as follows: Section II lists the computationally complex machine learning algorithms in use. Section III shows the EEG-based BCI model. Section IV compares the new software frameworks of BCI VR. Section V highlights important recent accomplishments in BCI VR. Section VI contains our conclusions and future work.

II. EEG-Based BCI Model

The data signals of BCI are developed in three stages: (1) the personal training stage for the human users learning to consciously control their brain signals in a BCI system, usually through reinforcement learning games; (2) the data training stage of machine learning, recognizing and classifying the significant patterns of the brainwave signals, and (3) the on-line testing stage for controlling the BCI in the system used for applications. In this last stage, the architecture of an on-line BCI system flows through six processes as shown in the model in Figure 1.

a) Brain Activity Measurement: step is where positive contact of the sensor electrodes on the scalp of the user's head is made, bringing in the users's EEG signals, for input into the BCI. The sensors need to be adjusted gently until their signals meet the necessary threshold for measurement.

b) Preliminary Processing (Preprocess): step is to dampen the noise of brain signals and to amplify the relevant information from inside the data. This stage uses filtering, segmentation, and detrend methods. Detrend subtracts the mean or best-fit line from the data so that the fluctuations are easier to observe, to accommodate for sensor drift [11], [12]. Filtering and segmentation methods identify and maximize, in order to reveal the data of brain activity changes that are characteristic for a specific time interval.

For noise reduction filtering, as typical EEG cognitive activity is in the range of 0.2-40 Hz, the electrical signals outside of that scope are ignored. After filtering, the data is separated where the brain waves overlap, and labeled into a stimulus or response class.

c) Feature Extraction: is differentiating the signal of a few relevant, command-related values known as "features". Features that describe the signal in as few components as possible and that are resilient to noise are identified. Identifying and extracting good features from signals is the most important step in the design of BCI systems [13]. Research [14], [15] shows that the choice of preprocessing and feature extraction method has more impact on the final performance than the choice of classification algorithm [16].

d) Classification: is accomplished with simple linear models or complex nonlinear neural network classifiers. This step is where the correct class label is assigned to a previously extracted feature vector. The class, when purposefully thought by the user in order to send a control signal, represents an intention of the BCI user. In involuntary thoughts, the class can represent an emotion or a mental state. The vital step for identifying neurophysiological signals in a BCI used for controlling VR applications is translating the features into commands [17]. In order to achieve this translation step, one can use either regression algorithms or classification algorithms, the classification algorithms being by far the most used in the BCI community [18].

e) Translation: is performed by issuing commands for a specific action.

f) Feedback: step provides the user with information about their own mental state, using text, image or voice prompts. This step helps the user to learn to control their brain activity to clarify their EEG signals to increase accurate performance.

III. Machine Learning

Selection of the classification algorithms used in BCI with VR is made so that the pattern recognition machine learning method chosen delivers results quickly in order to deliver a real-time, real-life experience.

Pattern classification techniques used to drive BCI use specific time interval variations of EEG input data [19] and are divided loosely into three categories: the Generative Model, the Linear Classifiers, and the Non-Linear Classifiers, listed in Table I.

A. Generative Model

The Bayesian statistical classifiers are pattern classifiers which aim with high probability to assign an observed feature vector w from its class x. Bayesian statistical classifiers are not popular in the BCI community.

B. Linear Classifiers

Linear classifiers are discriminant algorithms that distinguish classes with linear functions.

1) Linear Discriminant Analysis (LDA): The most popular classification algorithm for BCI applications is LDA. The aim of LDA is to use hyperplanes to separate different classes of data, then transform the data from a high dimensional space to a low dimensional space, and then make the classification decision in the low dimensional space. This provides acceptable accuracy without requiring high computational capability which makes it useful for online

TABLE I: Summary of Classification Methods of BCI

Classification	Approach	Properties
Generative Model	Bayesian Analysis	Assigned the observed feature vector to a labled class with the highest attribution probability; usually generated by non-linear decision boundaries; researched between 1990-2004, not popular in current BCI.
Linear Classifiers	Linear Discriminant Analysis(LDA, FLDA, BLDA, RFLDA)	An acceptable accuracy simple classifier with low computation requirements; usually for separates two classes, and the extended versions of multi-class method exists; fails in the presence of outliers or strong noise.
Non-Linear Classifiers	Support Vector Machine(SVM) Linear & RBF	A Speedy classifier; perform linear and nonlinear (Gaussian) modes; support binary or multi-class method; Maximum-margin hyperplane and distance between the nearest training samples.
	k-nearest neighbors algorithm (k-NN)	Support Multi-class; efficient with low dimensional feature vectors; use the metric distance to classify new cases based on similarity measures; sensitive to the local structure of the feature vectors.
	Neural Networks(NN)	flexible classifier(usually unstable); support multi-class method. Multiple architectures (MLP, PNN, BLRNN, ALN-NN, TDNN, GDNN, Gaussian, LVQ-NN, RBFNN, Fuzzy-ARTMAP-ANN, FIRNN, PeGNC).

BCI systems that need a rapid real-time response, but that are restricted to using limited computational resources, such as mobile devices.

The LDA decision plane can be represented mathematically as:

$$f(x) = w_x^T + b \tag{1}$$

w is the linear model coefficient or weight vector, x is the input feature vector and b as the bias. The weight vector w could be calculated as:

$$w = \Sigma_k^{-1}(\mu_2 - \mu_1) \tag{2}$$

Where μ is the estimated mean of class i, and Σ is the covariance matrix. The estimators of the mean and of the covariance matrix are calculated as:

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{3}$$

$$\Sigma_k = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \mu)(x_i - \mu)^T \tag{4}$$

x is a matrix containing n feature vectors. x_1, x_2, ..., $x_n \in \mathbb{R}^d$.

2) Support Vector Machine (SVM): Support Vector Machine (SVM) is a discriminative classifier, similar to LDA, defined by finding a hyperplane in order to separate the feature vectors into several classes. What differs, in the theory of SVM, is that it optimally selects hyperplanes by finding the maximums of the margins of training data, which may increase the generalization errors for real-time online classifications of EEG data, in contrast to the LDA classifiers.

SVM supports using both linear and non-linear decision boundaries. The linear analysis classifier version, *linear SVM*, uses regularization, in order to prevent the classifier from being distracted by noisy datasets in large amounts of BCI data [20].

C. Non-Linear Classifiers

1) Support Vector Machine (SVM): It is possible to create nonlinear decision boundaries by using the "kernel trick" $K(x, x')$. This nonlinear SVM leads to a more flexible decision boundary in the data space, which can increase classification accuracy. The kernel function used in BCI research is the Gaussian or Radial Basis Function (RBF) kernel:

$$K(x, x') = exp(\frac{-\gamma||x - x'||^2}{2\sigma^2}) \tag{5}$$

Thus, the decision function will be calculated as.

$$f(x) = \sum_{i=1}^{n} \alpha_i exp(\frac{-\gamma||x - x'||^2}{2\sigma^2}) + b \tag{6}$$

The corresponding nonlinear SVM is known as Gaussian SVM or RBF-SVM. The RBF-SVM have given good results for BCI synchronous applications, fast enough for real-time BCI.

2) k-Nearest Neighbors (k-NN): The k-NN works by distinguishing the features corresponding to the different classes to form separate clusters in the feature space, when the closest neighbors belong to the same class. In classifying the test feature vectors, k-NN distances that are similar between the test vector and each class are considered between the clusters of the test sample and the most recent class.

The advantage of using the k-NN approach in classification is that the error probability, in the decision of which cluster class the data point belongs to, is decreased. Some training samples may be affected by noise and artifacts, which can influence the classification results. If decisions are made involving several neighbors, it is less likely that errors will occur because the probability of several simultaneous errors in the data is much lower. On the other hand, if several k-NN closest classes are considered, then a voting scheme is then required to decide between the competing choices. This k-NN with a weighting function (aka WKNN) is defined by the following equation (7) [21] :

$$w_i^k = \begin{cases} \frac{d_k - d_i}{d_k - d_1} & \text{if } d_k \neq d_1 \\ 1 & \text{if } d_k = d_1 \end{cases} \tag{7}$$

where d_i denotes the distance of the i-th nearest neighbor from a test example. So d_1 corresponds to the nearest neighbor and d_k to the furthest neighbor. The decision rule of k-NNC assigns the unknown examples to the class with the greatest sum of weights among its k nearest neighbors.

3) Mahalanobis Distance: Mahalanobis Distance is a *Neural Network (NN)* classifier which assumes a Gaussian distribution $N(\mu_c, M_c)$ for each class c. A feature vector x is assigned to this class that corresponds to the nearest prototype:

$$D_c(x) = \sqrt{(x-\mu)M^{-1}(x-\mu)^T} \tag{8}$$

D. Neural Network Classifiers

Neural Networks working with linear classifiers are common in BCI research. They can universally approximate any continuous function. Their structure of multiple neurons and layers simulate brain shape-shifting pattern recognition in *Artificial Neural Networks (ANN)*.

The brain copying algorithms of ANN separate non-linear data into classes as researchers think the human brain recognizes patterns. ANN use hidden layers (at least one hidden layer) between the layer of input and the layer of output. Computer scientists are not sure how ANN works between the hidden layers.

1) Multilayer Perceptron (MLP): A MLP is composed of multiple layers of neurons called Perceptrons. It is used when the data is linearly separable, and is composed of a minimum of three layers: one layer of input, one or several hidden layers, and one layer of output, shown in Figure 2. Each input of a neuron is connected with the output of neurons in the previous layer, where the output layer determines the class of the input vector.

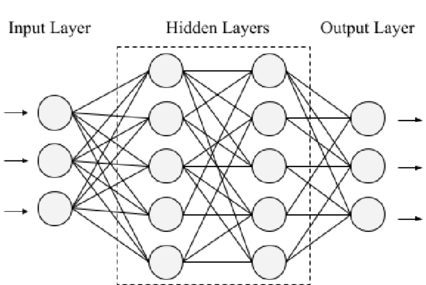

Fig. 2: Diagram using MLP in ANN.

An exciting idea in the machine learning algorithms of BCI research is that using the non-linear ANN to process the input data from BCI can help the computer learn how the human brain it is interfaced to works, resulting in a deep learning enhanced ANN, where as fast as the user trains their thoughts to become control signals, the computer learns how to anticipate those signals in a better and more careful way, most likely by using fewer attributes to get a faster, more brain-equivalent result.

IV. VR Capable BCI Software

Researchers interested in this area find a wealth of software frameworks available to work on BCI with VR. Current BCI software platforms are: BCI2000 [22] , OpenViBE [23], BCILAB [24], BioSig [25], and FieldTrip [26] of the MATLAB software toolbox, a real-time processing VR solution by g.tec, and the OpenBCI platform. These software platforms, built for BCIs, and all VR capable, offer packages for data acquisition, feature extraction, classification, and feedback presentation.

a) BCI2000: The BCI2000 is a general-purpose software system [22] for diverse areas of real-time bio-signal processing in addition to EEG. It is not an open-source but it is free for non-profit research and education.

b) BCI++: BCI++ of Laboratory Sensibilab is a tool for fast prototyping of BCI systems. The BCI++ framework consists of two main modules: Hardware Interface Module(HIM) and Graphical User Interface (GUI), that communicate with each other over TCP/IP. This architecture is designed to divide real-time BCI/BMI system development into two parts: (1) signal processing algorithms and (2) a specific 2D/3D Graphic Engine GUI by AEnima.

c) BioSig: BioSig [25] is an open-source software library. It was designed for biomedical signal processing for BCI research. It works with Matlab and has data import/export, artifact processing, quality control, feature extraction algorithms and classification methods. The rtsBCI package is available for rapid prototyping.

d) BCILAB: BCILAB is an open source toolkit also based on MATLAB for advanced BCI research that offers a graphical and scripting user interface.A. Based on the MATLAB environment, the main advantages of the BCILAB toolbox are rapid prototyping, real-time testing, and comparative evaluations.

BCILAB was built to support the mobile brain/body imaging (MoBI) study [27], BCILAB can classify multiple simultaneous data modalities, including eye gaze, body motion capture and EEG, as well as other biological signals such as those used in the DataRiver framework in ERICA [24].

e) OpenViBE: OpenViBE is a free and open-source software platform for the design, test and use of BCI [23]. This independent platform can be run on Windows and Linux systems without dependence on other software and hardware. The OpenViBE platform is designed for non-programmers. It features an easy-to-use graphical user interface for authors and operators of the BCI applications.

TABLE II: Platform Comparisions

Platform	**Requirements**	**3D Visual-ization**	**Open Source**
BCI2000	Independent System	-	-
BCI++	Independent System	-	-
BioSig	Matlab/Simulink library	-	✓
BCILAB	Matlab toolkit	-	✓
OpenViBE	Independent System	✓	✓

- means not support
✓means support

In a comparison with other platforms, as shown in Table II, OpenViBE is superior to VR BCI application research. It provides third-party embedded tools to design and expand virtualized display and feedback, as well as real-time 3D visualization of brain activities, compared to other reviewed platforms. In addition, OpenViBE can be used for building cloud-supported mobile computing devices to run the VR applications of BCI.

V. Development Trends

The BCI VR research field is motivated by the commercial promise of interactive video game technology, mobile applications and medicine. We summarize three major development trends for future research of BCI in VR.

A. Entertainment

BCI VR improves the way games are played by including feedback information from brain activity, providing access to knowledge about the user experience. BCI can report on player's mood and state of mind, including boredom, anxiety or frustration. For example, "Mind Balance" is a video game where the user must assist a frog-like character by helping him keep his balance as he totters across a cosmic tightrope. The data detected and measured in this game is wirelessly collected with a "Cerebus" headset that captures brain activity, and feeds it into a C# signal processing engine, which subsequently analyzes those signals and determines whether the user is looking to the left or right.

A promising real-time BCI gaming system was designed by Martisius and Damasevicius in 2015 [11]. It is a three-class BCI system based on the *State Visually Evoked Potentials Paradigm* (SSVEP) and the Emotiv EPOC headset. Their online target shooting game, implemented OpenViBE, allows the user to mentally explode objects in the air, through controlled focus on visual stimulus as the EEG signals are processed.

This gaming system utilizes wave atom transformation for feature extraction, achieving an average accuracy of 78.2% using the linear discriminant analysis classifier, 79.3% using the SVM classifier with a linear kernel, and 80.5% using another SVM with radial basis function kernel. The reason this game is using multiple methods is that no single method fully met the requirement of the real-time BCI applications.

B. Virtual Reality

A promising design of VR BCI is "Mind-Mirror", designed by Mercier-Ganady at al. [28] in 2014. It enable users to see the real-time changes in the brain's brain waves through their head. This approach uses an optical face-tracking system through a semi-transparent mirror as a screen, to display and automatically follow the user's head movements. The resulting brain activity is extracted and processed in real-time with an EEG device worn by the user. This application is uses a Microsoft Kinect camera for head movement tracking, and uses OpenViBE software as an platform to acquire and analyse the EEG data, then, through a Unity3D-based program, simulates and displays the virtual brain in the mirror back to the user. The real-time EEG signal power over the brain's surface is seen and understood in the resulting brain topography visualization.

In the medical field, Jose and Hugo et al. [6] designed and developed a mixed reality solution, Brain AR/VR, to guide doctors during *Transcranial Magnetic Stimulation* (TMS) procedures. Brain AR/VR was deployed in 2016 on a Samsung Galaxy S4 smart-phone with an Android operating system. The TMS experts are using EEG caps to input their brain wave data into the mobile application.

C. Cloud Computing

The next development is cloud computing [29]–[31] that is an merging technical term for achieving in-demand services by using the Internet-based technologies. The driven force of using cloud computing in BCI is in line with the growing volume of data and the demand of real-time data analytics. Mobile devices do not always have enough capacity to perform all the needed calculations for real-time, which is most useful for control signals. For example, the contradictions between energy and working efficiency are generally considered a tradeoff in system designs.

Moreover, concurrent with the VR and BCI research advances are innovations in mobile cloud computing, spurred on by the desire to save energy [32] with green computing. The feature of data collections for brain waves determines that the process needs to be continuous and synchronous in order to meet the needs of medical analyses or health record tracking [33]. A centralized data center can save on-premises storage [34] and workloads, which can be beneficial for designing complex distributed systems as well as higher-level functions. Therefore, consider distributed computing and different service deployment, future BCI studies aligning with VR can be associated with the field of cloud computing, such as cloud resource management, wireless communications [35], [36], security and privacy [37], and integrated cloud system.

VI. Conclusions

This paper presented a literature review on BCI applications in VR. We found that BCI and VR researches were accelerating and the increase of communications bandwidth between computers and humans was revolutionary. The prediction of the future of BCI and VR research emphasized the improvement of supporting cloud and mobile computing. Reducing extra energy waste with a cloudlet model means battery power in the mobile device was conserved, making the BCI VR mobile device practical. Moreover, dynamic energy-aware small clouds could handle the larger communications channel demands between the VR BCI and its mobile computing device, as well as the mobile device and the cloud resources used for the computationally intensive EEG-signal-to-control-signal pattern classifiers key to making this work. This unique new area of network support, was the next logical step to allow the wide adoption of BCI VR innovations.

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