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A Survey on EEG Signal Classification with Neural Network for Brain Computer Interface Applications

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Abstract: - Recent advances in computer hardware and signal processing have made possible the use of EEG signals or "brain waves" for communication between humans and computers. Locked-in patients have now a way to communicate with the outside world, but even with the last modern techniques, such systems still suffer communication rates on the order of 2-3 tasks/minute. In addition, existing systems are not likely to be designed with flexibility in mind, leading to slow systems that are difficult to improve. This article explores the effectiveness of Time Frequency Analysis as a technique of classifying different mental tasks through the use of the electroencephalogram (EEG). EEG signals from several subjects through 6 channels (electrodes) have been studied during the performance of five mental tasks (a baseline resting task, mental multiplication, geometric figure rotation, mental letter composition, and counting). Improved off-line classification of two of them ("geometric figure rotation" and "mental letter composition"), for which poor results had been obtained with autoregressive models before, were the principal objective of this project. Different methods based on Time Frequency Representations have been considered for the classification between the two tasks mentioned above. A non-iterative method based on the Ambiguity Function was finally selected. The results indicate that this method is able to extract in half-second, distinguishing features from the data that could be classified as belonging to one of the two tasks with an average percentage accuracy which tends to zero. The same results were found when the method was exported for five tasks EEG signal classification.

Keywords: *EEG, Signal Processing, Classification, Time Frequency, Brain Waves, Signal Processing.*

1. Introduction

A brain-computer interface (BCI) is a communication system that relies on the brain rather than the body for control and feedback. Ideally, it should run in a servo mode, allowing the subjects to initiate the communication anytime and anywhere without resorting to external stimuli or triggers. Such an interface not only offers a promising prosthetic device for those severely paralyzed but also signifies a radically new technology for the general public. Current BCI research is still in its early stage and the emphasis is placed on the design of algorithms to decode a pre-specified set of brain states. This involves three main aspects:

Brain states. Only brain states consciously controllable by the subjects are suitable for BCI. Besides, these states should generate distinct, repeatable and measurable patterns whenever accessed. Among the most commonly used brain states are imaginations of body movements (motor imaginations). Motor imaginations can reliably change the neural activities over sensorimotor cortices. Depending on the part of the body imagined moving, these changes exhibit distinct spatial distributions [4]. Recognition of these patterns can then be translated into control signals, as is the case in this study. Recording devices. Motor imaginations can be recorded by both electroencephalography (EEG) and magneto encephalography (MEG). EEG remains the most popular way to record BCI signals, and will be the focus of this study. It measures scalp electrical activities diffused from the cortex. Compared to MEG, it is portable and inexpensive. However, EEG can only measure blurred cortical activities due to the diffusion of the skull and the skin. Thus EEG is normally used for studying cortical patches in the centimeter scale. Furthermore, EEG signals are contaminated by noise from various sources, such as muscle activities and power line interference. Spatial and temporal filters are commonly applied before any further analysis [3]. Decoding algorithms. Pre-filtered EEG signals still contain considerable noise, which poses a challenge for its decoding. Statistical machine learning (ML) techniques have been introduced into BCI to combat these variations. Techniques like Artificial Neural Networks, Support Vector Machine (SVM) and Linear Discriminant Analysis [4], have been employed to learn patterns from training EEG signals and then classify new EEG signals. This strategy often results in increased decoding success and significant shortening of subject training time. Artificial neural networks (ANNs) are computational framework inspired by our expanding knowledge of the activity of networks of biological neurons in the brain. ANNs cannot hope to reproduce all the still not well-understood complexities of actual brain networks. Rather, most ANNs are implemented as sets of nonlinear summing elements interconnected by weighted links, forming a highly simplified model of brain connectivity. The basic operation of such artificial neurons is to pass a weighted sum of their inputs through a nonlinear hard-limiting or soft "squashing" function. To form an ANN, these basic calculating elements (artificial neurons) are most often arranged in interconnected layers. Some neurons, usually those in the layer furthest from the input, are designated as output neurons. The initial weight values of the interconnections are usually assigned randomly. The operation of most ANNs proceeds in two stages. Rules used in the first stage, training (or learning), can be categorized as supervised, unsupervised, or reinforced. During training, the weight values for each interconnection in the network are adjusted either to minimize the error between desired and computed outputs (supervised learning) else to maximize differences (or to minimize similarities) between the output categories (unsupervised or competitive learning). In reinforced learning, an input-output mapping is learned during continued interaction with the environment so as to maximize a scalar index of performance [5]. The second stage is recall, in which the ANN generates output for the problem the ANN is designed to solve, based on new input data without (or sometimes with) further training signals. Because of their multifactorial character, ANNs have proven suitable for practical use in many medical applications. Since most medical signals of interest are usually not produced by variations in a single variable or factor, many medical problems, particularly those involving decision-making, must involve a multifactorial decision process. In these cases, changing one variable at a time to find the best solution may never reach the desired objective [6], whereas multifactorial ANN approaches may be more successful. In this chapter, we review recent applications of ANNs to brain signal processing, organized according to the nature of brain signals to be analyzed and the role that ANNs play in the applications [7]

2. Roles Of Ann In Brain Signal Process

Todays, ANNs have been applied to brain data for the following purposes:

- **Feature Extraction, Classification, and Pattern Recognition:** ANNs here serve mainly as non-linear classifiers. The inputs are preprocessed so as to form a feature space. ANNs are used to categorize the collected data into distinct classes. In other cases, inputs are not subjected to preprocessing but are given directly to an ANN to extract features of interest from the data.

- **Adaptive Filtering and Control**: ANNs here operate within closed loop systems to process changing inputs, adapting their weights "on the fly" to filter out unwanted parts of the input (adaptive filtering), or mapping their outputs to parameters used in online control (adaptive control).
- **Linear or Nonlinear Mapping**: Here ANNs are used to transform inputs to outputs of a desired form. For example, an ANN might remap its rectangular input data coordinates to circular or more general coordinate systems.
- **Modeling**: ANNs can be thought of as function generators that generate an output data series based on a learned function or data model. ANNs with two layers of trainable weights have been proven capable of approximating any nonlinear function.
- **Signal Separation and DE Convolution**: These ANNs separate their input signals into the weighted sum or convolution of a number of underlying sources using assumptions about the nature of the sources or of their interrelationships (e.g., their independence).
- **Texture Analysis and Image Segmentation**: Image texture analysis is becoming increasingly important in image segmentation, recognition and understanding. ANNs are being used to learn spatial or spatial-frequency texture features and, accordingly, to categorize images or to separate an image into sub images (image segmentation).
- **Edge Detection**: In an image, an edge or boundary between two objects can be mapped to a dark band between two lighter areas (objects). By using the properties of intensity discontinuity, ANNs can be trained to "recognize" these dark bands as edges, or can learn to "draw" such edges based on contrast and other information [8].

3. Electro-Encephalogram and Magneto Encephalogram

The electroencephalogram (EEG) is a non-invasive measure of brain electrical activity recorded as changes in the potential difference between two points on the scalp. The magneto encephalogram (MEG) is its magnetic counterpart. In accordance with the assumption that the ongoing EEG can be alternated correspondingly by stimulus or event to form the event-related potential (ERP) or the evoked potential (EP), these changes, though tiny, can be recorded through the scalp [5]. It is possible for researchers to apply pattern recognition algorithms to search for the differences in brain status while the brain is performing different tasks. Thus, applied an autoregressive (AR) model to four-channel EEG potentials to obtain features that were used to train an ANN using a back propagation algorithm to differentiate the subject's intention to move the left or right index finger or right foot. They suggested the framework might be useful for designing a direct brain-computer interface. In the study of [9] ANNs were trained to determine the stage of anesthesia based on features extracted from the middle-latency auditory evoked potential (MLAEP) plus other physiological parameters. By combining power spectral estimation, principal component analysis and ANNs, Jung et al. (1997) demonstrated that continuous, accurate, noninvasive, and near real-time estimation of an operator's global level of alertness is feasible using EEG measures recorded from as few as two scalp site[10]. Results of their ANN-based estimation compare favorably to those using a linear regression model applied to the same PCA-reduced EEG power Spectral data. As a linear mapping device, Sun and Sclabassi (2000) employed an ANN to transform the EEG topography obtained from a forward solution in a simple spherical model to a more realistic spheroidal model whose forward solution was difficult to compute directly. Here, a back propagation learning algorithm was used to train an ANN to convert spatial locations between spherical and spheroid models. Instead of computing the infinite sums of the Legendre functions required in the asymmetric spheroidal model, the calculations were carried out in the spherical model and then converted by the ANN to the more realistic model for display and evaluation. Recently, ANNs have made an important impact on the analysis of EEG and MEG by separating the problem of EEG or MEG source identification from that of source localization, a mathematically underdetermined problem -- any scalp potential distribution can be produced by a limitless number of potential distributions within the head. Because of volume conduction through cerebrospinal fluid, skull and scalp, EEG and MEG data collected from any synchronous but relatively independent neural processes within a large brain volume. This has made it difficult to relate EEG measurements to underlying brain processes and to localize the sources of EEG and MEG signals. Progress has been made by several groups in separating and identifying the distinct brain sources from their mixtures in scalp EEG or MEG recordings assuming only their temporal independence and spatial stationary, using a class of independent component analysis (ICA) or blind source separation (BSS) algorithms [9].

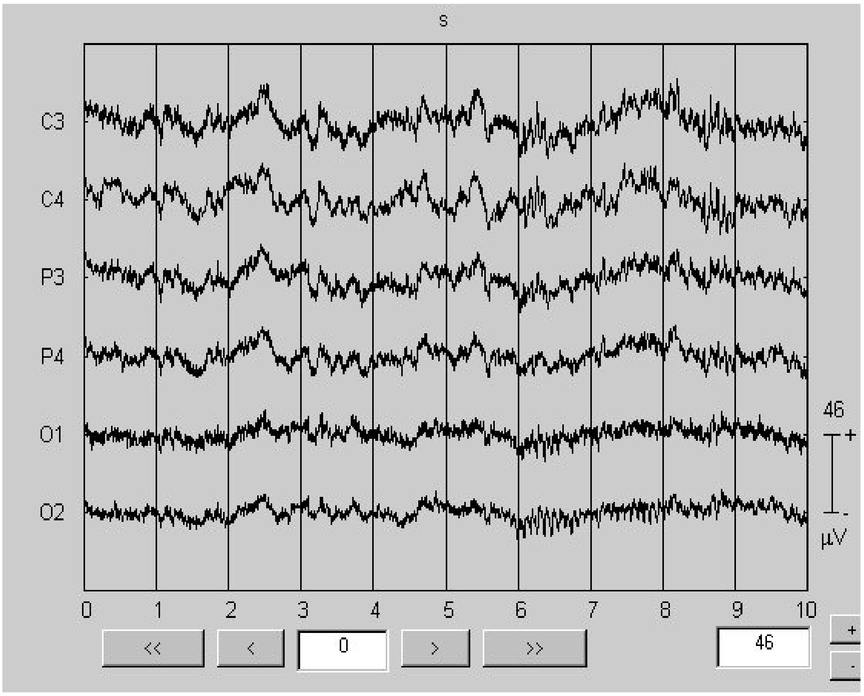

Figure 1: A Segment of a Multichannel EEG of an Adult Subject during a Multiplication Task [10].

4. Mathematical Model OF THE Cortex

Typically, a neuronal cluster will generate electrical oscillations. It has been modeled as an oscillator with phase θ and output s. Its dynamics are governed by a simple phase model:

$$\begin{cases} S = f(\theta) \\ \dot{\theta} = \omega + g(t) \end{cases}$$

Where ω is the intrinsic frequency of the oscillation and f is a function 2π-periodic in θ and g (t) is the input to the oscillator. Further g (t) will accelerate the oscillation if it assumes positive values, and slow it down if negative. The whole cortex can then be modeled as a networked dynamical system D, as shown in Figure 1. Each node in the system represents a neuronal cluster and each link a neural interaction. The input, g (t), to each neuronal cluster now consists of two parts: influence from other clusters and modulation by subcortical structures. Suppose the links of the network are represented as an adjacency matrix G ($G_{ij} = 1$ if node i and j are connected; $G_{ij} = 0$ otherwise). Then the dynamics of a node I take a more specific form [11]:

$$\theta_i = \omega_i + \sum_i \epsilon_{ij} G_{ij}(s_j - s_i) + h_i(t)$$

Where $\sum_j \epsilon_{ij} G_{ij}(s_j - s_i)$ represents the influence from other nodes, and $h_i(t)$ is the subcortical input. Note that there is an added parameter ϵ_{ij} in (2), which controls the strength of the influence from node j to i [12].

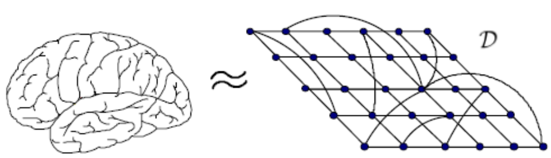

Figure 2: Networked Dynamical System Model of the Cortex [12].

5. Brain Computer Interface Technology

A Brain-Computer Interface (BCI) is a system that acquires and analyzes neural signals with the goal of creating a communication channel directly between the brain and the computer. Such a channel potentially has multiple uses. For example:

- Bioengineering applications: assist devices for disabled people.
- Human subject monitoring: sleep disorders, neurological diseases, attention monitoring, and/or overall "mental state".
- Neuroscience research: real-time methods for correlating observable behavior with recorded neural signals.
- Man – Machine Interaction: Interface devices between human and computers, machines,

For many years, people have speculated that electroencephalographic (EEG) activity or other measures of brain function might provide this new channel. Over the past decade, productive BCI research programs have begun. Facilitated and encouraged by the new understanding of brain functions and by the low-cost computer equipments, these programs have concentrated mainly in developing new communication and control technologies for people with severe neuromuscular disorders. The immediate goal is to provide communication capabilities so that any subject can control the external world without using the brain's normal output pathways of peripheral nerves and muscles. Nowadays, such activities drive their efforts in:

- **Brain (Neural) Signal Acquisition**: development of both invasive and noninvasive techniques for high quality signal acquisition.

- **Algorithms and Processing**: advanced machine learning and signal processing algorithms, which take advantage of cheap/fast computing power (i.e. Moore's Law2) to enable online real-time processing.
- **Underlying Neuroscience**: a better understanding of the neural code, the functional neurons anatomy, the physiology and how these are related to perception and cognition, enabling signals to be interpreted in the context of the neurobiology [13].

Present BCI's use EEG activity recorded at the scalp to control cursor movement, select letters or icons, or operate a neuro-prosthesis. The central element in each BCI is a translation algorithm that converts electrophysiological input from the user into output that controls external devices. BCI operation depends on effective interaction between two adaptive controllers: the user who encodes his or her commands in the electrophysiological input provided to the BCI, and the computer which recognizes the command contained in the input and expresses them in the device control. Current BCI's have maximum information transfer rates of 5-25 bits/min. Achievement of greater speed and accuracy depends on improvements in:

- **Signal Acquisition:** methods for increasing signal-to-noise ratio (SNR), signal-to interference ratio (S/I)) as well as optimally combining spatial and temporal information.
- **Single Trial Analysis:** overcoming noise and interference in order to avoid averaging and maximize bit rate.
- **Co-Learning**: jointly optimizing combined man-machine system and taking advantage of feedback.
- **Experimental Paradigms for Interpretable Readable Signals**: mapping the task to the brain state of the user (or vice versa).
- **Understanding Algorithms and Models within the Context of the Neurobiology:** building predictive models having neuro-physiologically meaningful parameters and incorporating physically and biologically meaningful priors.

The common structure of a Brain Computer Interface is the following Figure3 [14]:

- **Signal Acquisition**: the EEG signals are obtained from the brain through invasive or non-invasive methods (for example, electrodes). After, the signal is amplified and sampled.

- **Signal Pre-Processing**: once the signals are acquired, it is necessary to clean them.
- **Signal Classification**: once the signals are cleaned, they will be processed and classified to find out which kind of mental task the subject is performing.
- **Computer Interaction**: once the signals are classified, they will be used by an appropriate algorithm for the development of a certain application.

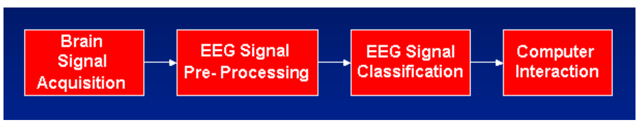

Figure 3: BCI common structure [19]

6. Eeg Signal Classification

Oscillatory states are the most remarkable features of EEG activity, because they reflect not only the synchronization of massive numbers of neurons but also a temporally ordered rhythmicity of activation [26]. Different oscillatory patterns may be indicative of different information processing states, and it has been proposed that the oscillatory patterns play an active role in these states [26], [28.29]. According to this view, the rhythmic synchronization during oscillatory states can serve to enhance perception, learning, and the transmission of neuronal signals between different regions of the brain. Traditional spectral analysis tools are not the best options to quantify the different oscillatory activities in the EEG, since the neural processes that generate the EEG are intrinsically dynamic. Indeed, there are transient changes in the power or peak frequency of EEG waves which can provide information of primary interest. The non-stationary nature of the EEG signals makes it necessary to use methods which are able to quantify their spectral content as a function of time. Time-frequency representation (TFR) methods are well suited as tools for the study of spontaneous and induced changes in oscillatory states, and we will be used here with this purpose in mind [30].

6.1 Signal Processing

A BCI measures brain signals and processes them in real time to detect certain patterns that reflect the user's intent. This signal processing can have three stages: preprocessing, feature extraction, and detection and classification. Preprocessing aims at simplifying subsequent processing operations without losing relevant information. An important goal of preprocessing is to improve signal quality by improving the so-called signal-to-noise ratio (SNR). A bad or small SNR means that the brain patterns are buried in the rest of the signal (e.g. background EEG), which makes relevant patterns hard to detect. A good or large SNR, on the other hand, simplifies the BCI's detection and classification task. Transformations combined with filtering techniques are often employed during preprocessing in a BCI [31]. Scientists use these techniques to transform the signals so unwanted signal components can be eliminated or at least reduced. These techniques can improve the SNR. The brain patterns used in BCIs are characterized by certain features or properties. For instance, amplitudes and frequencies are essential features of sensorimotor rhythms and SSVEPs. The firing rate of individual neurons is an important feature of invasive BCIs using intra-cortical recordings. The feature extraction algorithms of a BCI calculate (extract) these features. Feature extraction can be seen as another step in preparing the signals to facilitate the subsequent and last signal processing stage, detection and classification. Detection and classification of brain patterns is the core signal processing task in BCIs. The user elicits certain brain patterns by performing mental tasks according to mental strategies, and the BCI detects and classifies these patterns and translates them into appropriate commands for BCI applications. This detection and classification process can be simplified when the user communicates with the BCI only in well-defined time frames. Such a time frame is indicated by the BCI by visual or acoustic cues. For example, a beep informs the user that s/he could send a command during the upcoming time frame, which might last 2–6 s. During this time, the user is supposed to perform a specific mental task. The BCI tries to classify the brain signals recorded in this time frame. This type of BCI does not consider the possibility that the user does not wish to communicate anything during one of these time frames, or that s/he wants to communicate outside of a specified time frame. This mode of operation is called synchronous or cue-paced. Correspondingly, a BCI employing this mode of operation is called a synchronous BCI or a cue-paced BCI. Although these BCIs are relatively easy to develop and use, they are impractical in many real-world settings. A cue-passed BCI is somewhat like a keyboard that can only be used at certain times. In an asynchronous or self-paced BCI, users can interact with a BCI at their leisure, without worrying about well-defined time frames [31]. Users may send a signal, or choose not to use a BCI, whenever they want. Therefore, asynchronous BCIs or self-paced BCIs have to analyses the brain signals continuously. This mode of operation is technically more demanding, but it offers a more natural and convenient form of interaction with a BCI. More details about signal processing and the most frequently used algorithms in BCIs can be found in chapters "Digital Signal Processing and Machine Learning" and "Adaptive Methods in BCI Research – An Introductory Tutorial" of this volume. Since the first wave of popularization of back propagation networks, nearly two decades ago, an ever-growing number and variety of ANN models have been devised to tackle an ever-widening variety of problems. The overall insight that ANNs both embody and exemplify is perhaps that our human intelligence is multifactorial and highly adaptable to using whatever forms of information are available to us. In this spirit, we suggest that researchers always attempt to interpret the physiological meaning both of the features of their input data and of the data models that their trained ANNs represent. Too often ANNs have been treated like "black boxes." We believe it is time to open the black boxes and interpret what is happening inside them. Such interpretations might even give new insights into the nature of the biomedical signals, or suggest new or more efficient ways to look at the input data. It is also possible that the ANN models and methods might suggest more efficient methods to collect input data. Such 'model mining' might even prove to be the most rewarding result of applying ANNs. Researchers who simply recount classification accuracy may ignore nuggets of novel information about brain processes hidden in the ANN models that they and the data have jointly constructed.

7. DISCUSSION

Uses of ANNs as classifiers currently dominates their applications to the field of brain signal analysis. This includes classification of brain or related signals as exhibiting normal or abnormal features or processes. Not surprisingly, all published studies report promising results. If the measurements can be modeled as an additive mixture of different sources, including task-related signals and artifacts, applying blind source separation (BSS) prior to the further processing, visualization, or interpretation may better reveal the underlying physical phenomena such as different brain processes) which in the raw data could be contaminated or overwhelmed by other processes of no interest. A survey of relevant papers shows that the most popular architecture for artificial neural network used is the multilayer perceptron (MLP) [32]. The MLP architecture is both simple and straightforward to implement and use. In MLPs, information flows in one direction except during training, when error terms are back-propagated. Back propagation updates network weights in a supervised manner. Although it cannot guarantee a globally minimal solution, back propagation at least arrives at a local minimum through gradient descent. Various techniques have been derived to attempt to avoid over fitting to a local minimum. Once the network weights have been learned and fixed, feed forward networks can be implemented in hardware and made to run in real-time. All these characteristics make the back propagation algorithm most popular in biomedical applications. In some applications, target outputs may not be available or may be too expensive to acquire. In these cases, unsupervised learning algorithms may be used. Among unsupervised learning algorithms, self-organizing maps (SOMs) are the most popular for biomedical applications. During training, SOMs attempt to assign their input patterns to different output regions. Often SOMs may converge after only few learning cycles.

8. Application Issues

Although most published papers have concluded that ANNs are appropriate for their domain of interest, many issues still have to be resolved before ANNs may be claimed to be the general method of choice. Unfortunately, most published studies have not gone beyond demonstrating application to a very limited amount of data. As with any type of method, ANNs have their limitations that should be carefully considered:

- Every study should provide a rationale for the data chosen as input. For example, ANN-based computer-aided-diagnosis (CAD) systems may give misleading results if the ANNs are not given adequately representative features and sufficient naturally occurring data variations in their training data. Using ANNs, any input may yield some sort of output, correct and useful or not ("garbage in, garbage out"). Therefore, keys for success of ANN applications are not only to pick an appropriate architecture or learning algorithm, but also to choose the right data and data features to train the network.
- Although methods of applying ANNs to biomedical signals have already shown great promise and great care must be taken to examine the results obtained. The issue of trust in the outputs of ANNs always deserves informed as well as statistical consideration. Since medical diagnosis is nearly always a multifactorial and multidisciplinary problem, medical experts should always evaluate network outputs in light of other direct or indirect convergent evidence before making final decisions affecting the health of patients.
- Before practical implementation is planned, ANN methods should be compared to more direct ways of obtaining the same answers, as these might sometimes prove more accurate or cost-effective [31].

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