The Brain-Computer Interface: A Review and Some New Concepts

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Abstract -- **Over the past decade, many laboratories have begun to explore brain computer interface (BCI) technology as a new communication option for those with neuromuscular impairments that prevent them from using conventional augmentative communication methods. This work outlines the potential benefits of BCI, summarises a number of developments which have been made in recent years and provides an overview of the fundamental requirements which must be acknowledged for the successful progression of BCI technology. A novel proposal for a unique BCI system is also detailed.**

Keywords – **Brain Computer Interface (BCI), Translation Algorithm, Electroencephalogram (EEG), Signal Analysis, Chaos Theory, Self-Organising Fuzzy Neural Network (SOFNN)**

I INTRODUCTION

The study of EEG-based communication is a very important area of research in the world. Around three million people in the UK [1], approximately thirteen million people in rural America [2] and an estimated 1 in 8 people in Australia [3] alone are affected from neuromuscular disorders. The pathways that control motor neurons in the spinal cord and brainstem are affected and in the worst cases patients have no control over any of their muscles and thus, have no means of communication with other people. A new form of communication is essential to aid these disabled people and especially those with no communication ability whatsoever (i.e. "locked out"). Brain-computer interface technology may help improve the standard of living for these people. An alternative communication channel for those physically impaired people is one of the major advantages of the BCI. There are, however, other advantages, again, from a medical point of view and from a similar medical focus (i.e. neuro disorders).

25% of the world's 50 million people with epilepsy [4] have seizures that can not be controlled by medication or epilepsy surgery. Since the 1970s clinicians, neuroscientists and engineers have proposed technologies for treating seizures, with the ultimate goal of implanting stimulators or drug infusion devices in the brain to abort seizures before clinical onset. Such efforts have received further boosts in recent years due to evidence suggesting that seizures may be predictable [5].

Non-linear time series analysis of the EEG recorded within the seizure generating area of the brain indicate marked changes in non-linear characteristics for up to several minutes prior to other states or recording sites [6]. However, it remains to be established whether different methods of non-linear time-series analysis could furnish additional precursors that allow extending the knowledge about seizure generating mechanisms in humans.

The EEG based BCI technology is aimed at offering a new communication channel to those people who suffer from neuromuscular disorders or in the case of epilepsy a sub-conscious communication channel. This technology provides an alternative communication channel which does not depend on the peripheral nerves or muscles [7]. This method of communication is provided solely by the presence of ElectroEncephaloGraphic (EEG) activity around the brain. The EEG, measured from the scalp, is used to determine what the user is attempting to communicate or what action is intended. A translation algorithm is used to convert or translate the electrophysiological signal, from the user, into an output that can be used to control a computer. Using the same concepts as that of BCI, an epileptic seizure prediction system may also be feasible. In this case it would be a communication channel that the user communicates to a device or computer sub-consciously that he/she is about to have a seizure and the user can then respond with the appropriate action.

The following section describes the EEG signal and how it is measured. Various features of the EEG signal are discussed and an analysis of these characteristics in relation to specific BCI applications is given. The method of measuring the effectiveness of the BCI is shown in section III and section IV provides a review of algorithms used to classify the EEG signals. Detailed in section V are some unfrequented concepts of the EEG signal in relation to chaos theory. Section VI outlines a few novel ideas for future research in BCI technology. A conclusion is given in section VII.

II ELECTROENCEPHALOGRAM (EEG)

EEG is an electrical activity produced by billions of firing neurons within the brain. The neurons carry low voltage (≤100mV) spikes which occur in various cortical areas at different times causing an electrical field of activity all over the surface of the brain. The voltages carried within the neurons are relatively low thus; the resultant EEG activity is nebulous, ranging from 5-100 µV.

The vast amount of neuronal activity causes the EEG signals to be very complex. There are a number of other features which add to this complexity, causing the observed signal to appear chaotic. The Electromyogram (EMG) is an electrical activity associated with muscle movement. It is detectable all over the scalp and is generally much higher in amplitude than the EEG, and overlaps the middle and upper parts of the EEG frequency range; therefore can be difficult to differentiate between the two. The EMG is regarded as a noise source in a BCI system. Other sources of superfluous noise include eyelid and facial muscle movement and EEG signals which are not required for a specific BCI system. The EEG signal is measured from the scalp using electrodes and the signal is usually amplified before being digitised for storage or processing within the computer. A standard sampling frequency of about 128Hz is usually used and the signals can be band-pass filtered between 0.5Hz and 50Hz, as this frequency range contains the most informative components. Figure 2 shows an example of an EEG signal taken from an electrode positioned at C_3, as in the standard electrode positioning nomenclature shown in Figure 1. The signal shown is taken over a four second period and is an imagery of imagined left arm movement.

a) EEG Signal Analysis

The EEG activity recorded at the scalp can be analysed and quantified in the time domain, as voltage versus time, or in the frequency domain, as voltage versus frequency. The time domain is usually used in a system when the user is trying to produce EEG in response to exogenous stimulus such as a directional arrow flashing on a computer monitor.

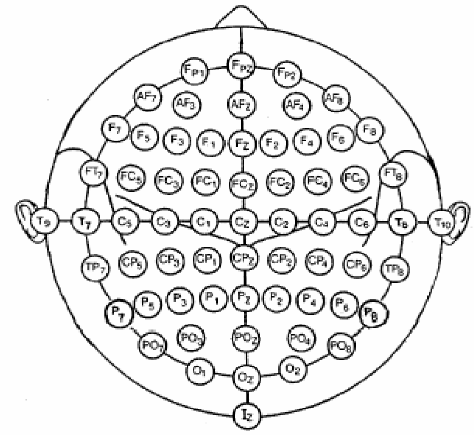

Figure 1: The standard (10/20 system) 64 scalp electrodes, their index reference and position [8].

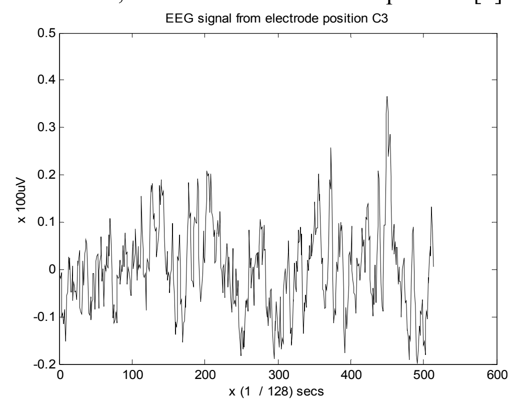

Figure 2: An example of an EEG signal taken from electrode positioned at C3.

Visual Evoked Potentials (VEPs) are the potentials produced in the EEG signals in response to brief visual stimuli and these signals can be recorded from the posterior scalp over the visual cortex. There are number of types of VEPs such as the short latency VEP which is a frequency change that occurs approximately 100ms preceding a stimulus. Other potentials have a longer latency component, which is a positive peak that reaches a maximum approximately 300ms after a stimulus, known as the P300 potential. When a person is presented with a stimulus series composed of several different types, and P300 potentials are measured for each type, amplitude is found to be larger for stimuli that are presented only rarely [8,9]. Using the P300 potential it has been reported in [10] that users can communicate up to 12 bits/min with accuracy rates reaching 95%. The Steady State VEP (SSVEP) constitutes response signals that change amplitude depending on the frequency of a blinking stimulus, such as a light flashing.

EEG signal responses to exogenous stimuli are referred to as Event Related Potentials (ERP). The main advantages of using the evoked response stimuli are that the EEG activity occurring at a specific time, amplitude or frequency can be analysed or focused on thus, the exogenous BCI may not require extensive training but does require an environment where the desired EEG patterns have to be evoked or stimulated.

Other BCI systems use the frequency domain features to analyse spontaneous EEG activity. This EEG activity is referred to as spontaneous because it is not related to an evoking stimulus. These BCI systems usually work on the μ (8-12.5Hz) or β (13-32Hz) ranges (rhythms) of the EEG activity occurring in specific areas of the cortex, largely limited to the sensorimotor cortex. The advantages of spontaneous EEG based methodologies are that this method does not require an evoking stimulus or the constant requirement of any sensory modalities, such as the eyes or ears. Endogenous BCIs provide a better fit to a control model because the trained user exercises direct control over the environment [7] but in many cases this method has the disadvantage of requiring extensive training.

III Speed and Accuracy

The capacity of a communication system is given by its information transfer rate, normally measured in bits/min [12]. With systems which rely on accuracy and speed, the main objective is to maximise the number of bits that can be communicated with high accuracy in a discrete message. In the present BCI systems the speed is of less concern than the accuracy. For example, the BCI systems in [11], [12], [13], and [14] must be able to accurately decipher the EEG signals and respond correctly to its interpretation of the user's command. If the response is to select an option from a menu, the first objective is to ensure that the correct option has been recognised in response to the user's desire, with a real-time response being the next priority. Considering this, the BCI success is dependent on both speed and accuracy being developed simultaneously.

Bit rate is used as the performance measure of the BCI system in many experiments. It depends on both speed and accuracy. If a trial has *N* selections, and the selection accuracy (the probability that the desired selection will actually be selected) is P, then bit rate, or bits/trial (B) is

$$B = \log_2 N + P \log_2 P + (1-P)\log_2[(1-P)/(N-1)]. \quad (1)$$

Equation (1) shown above is derived by Pierce and is described in [15] and is also referred to in [11]. Bit rate calculation, also referred to as information transfer rate, can be affected by the number of targets. If the number of targets (e.g. no. of options in a menu list) does not affect the trial duration, the greatest bit rate will be obtained by choosing the value of *N* for which B is greatest and then using *N* targets in each trial [11]. Depending on the duration of each trial for target selection a corresponding bits/min transfer rate can be calculated.

It is reported that the maximum information transfer rates for EEG based BCI systems used to move a cursor or select an option from a menu range from 5-25 bits/min. Higher information transfer rates have been reported in [16]. The BCI system described uses a SSVEP to allow the user to select from twelve buttons similar to that on a phone. The buttons are virtually displayed on a computer monitor with each button blinking at a different frequency, ranging from 6 – 14 Hz. Using the EEG signals monitored over the occipital lobes, utilising electrodes positioned at O_1 and O_2, the user is able to select a button, using their SSVEP, simply by looking at the button. The translation algorithm decides which button the user is looking at. Depending on the frequency of the blinking button the frequency and amplitude of the EEG signal changes, the computer analyses the EEG signals, and then allocates an evoked potential to each button hence no training of the BCI system is required. Out of five volunteers in this experiment the results were encouraging with two subjects achieving 100% accuracy, selecting 20 numbers ranging from 0-9, with information transfer rates up to 3.32 bits/trial or 44.29 bits/min.

There may be a number of factors affecting the results, compared to other experiments such as the difference in location of the EEG signals analysed. Many of the experiments that report a 5-25 bits/sec use EEG signals analysed from the central regions of the brain such as the sensorimotor cortex and somatosensory areas. EEG in these areas may be heavily contaminated with noise. In this case the information transfer rate may be decreased because of the ratio of correct responses to incorrect responses. Other factors such as the evoking stimulus may have a significant effect on the overall information transfer rate. Selecting a letter from a choice of four by training the μ and β rhythms of the EEG signal may be significantly more difficult to achieve than allowing the algorithm to allocate a button to ten different EEG signals visually evoked by ten different blinking frequencies (stimuli). The practical application of each type of evoked response must also be acknowledged and considered from a medical point of view and the question must be asked, is the evoking stimulus suitable and realistically viable for patients suffering from neuromuscular disorders? In the experiment previously described feedback was not presented to the patient indicating whether he or she had chosen the correct button. Other experiments use feedback as a contributing factor in the method for training the BCI translation algorithm and in some cases [11] accuracy is improved with response verification (i.e. feedback). The following section discusses the importance of the translation algorithm.

IV THE TRANSLATION ALGORITHM

The Translation Algorithm (TA) must have the ability to rapidly analyse the EEG signal and learn patterns or complex sequences to encode the heavily impeded and contaminated EEG signal. Consequently, the TA must be able to recognize patterns contained in the EEG signal and accurately interpret or encode the user's request or thought.

There are a number of types of TA which various research groups have investigated and these involve both classical classification techniques and artificial intelligence processing techniques. Adaptive Autoregression (AAR) is a classical technique used for parametric modelling by which a mathematical model is fitted to a time series. The EEG signal is well fitted with an AAR model. The model is used for feature extraction and is suited to capturing the dominant features in the EEG signal. Linear Discrimanant Analysis (LDA) is commonly used in conjunction with AAR to classify two or more signals. If a number of EEG patterns relating to a thought process (e.g. imagined right or left arm movement) are produced by a subject over a number of trials, this forms a training data set. Each trial is initiated with a directional arrow on a computer monitor pointing either left or right. The AAR is used to model the EEG from each training set and each AAR model produced contains a number of coefficients (usually between 3 and 7). LDA uses the coefficients from all the models to discriminate between the two signals. AAR and LDA have been shown to be more accurate at offline EEG data classification than Neural Networks (NN) (discussed below).

NNs have also been used for classification of EEG signals. NNs have proven to be faster at online data classification at the expense of accuracy [17]. In this case the user is told to perform the same thought as before for the first few trials and during this time the NN learns patterns within the signal. The user is then presented with a feedback signal (cursor movement) to indicate whether he/she is producing the correct EEG signal. After further trials the NN adapts further to interpreting the user's thought plus, with the presence of feedback, the user can become more successful at training the NN.

V CHAOS THEORY AND EEG

Signals or patterns, such as that of EEG, are commonly referred to as random or chaotic and even though it is difficult if not impossible to observe repetitive patterns or sequences within these signals there has been methods or theorems developed to attempt the intimidating task of deciphering these multifarious and volatile signals.

The concept of chaos is one of the most exciting and rapidly expanding research topics of recent decades. Ordinarily, chaos is disorder or confusion. In the scientific sense, chaos does involve some disarray and a hallmark in a chaotic system is that even the smallest discrepancy in initial conditions would result in a huge discrepancy at a later time. Chaos involves how something changes over time and, in fact, change and time are the two fundamental subjects that together make up the foundation of chaos [18]. A chaotic time-series can be shown using a simple equation

$$X_{t+1} = 1.9 - X_t^2 \tag{3}$$

Iterating this process approximately thirty times produced a record of widely fluctuating values of Xt_{+1}, as plotted in Figure 3. Analysing the time-series on the graph shown in Figure 3 many of the characteristics of chaos can be shown.

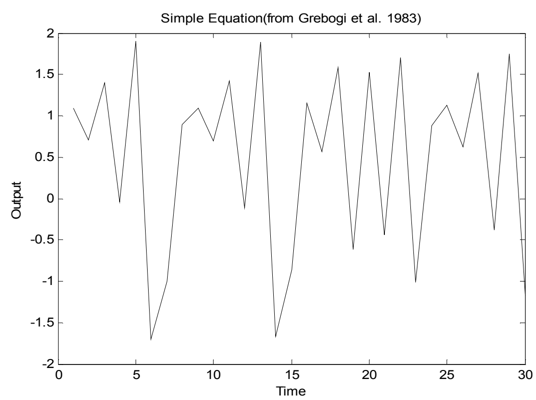

Figure 3: Results plotted from thirty iterations of (3) Graph was reproduced using Matlab.

This simply simulated time series shows several key traits of chaos which are very similar, if not identical, to characteristics observed from the EEG signal. The indiscriminate looking pattern came from a specific equation but even though the chaotic equation looks haphazard it really is deterministic, meaning that it follows a rule. That is, some law, equation or fixed procedure determines or specifies the results [18]. Comparing this to an EEG signal, the EEG signal is essentially a chaotic electrical signal created by billions of neurons firing within the brain. As different neurons fire at different times continuously, the EEG signals are continuously changing. If it was known which neurons were firing and when, then the EEG signals may be deterministic and could be described as deterministic chaos originating at a microscopic level from the large community of firing neurons within the brain. This may be a very strange and crude comparison considering the simplicity of (3) and the complexity of the human brain but none the less it does have a logical or natural association at a macroscopic level. There are other interesting characteristics which can be portrayed through the iteration of (3) which may not be as closely associated with the origins of the EEG signal. The chaotic behaviour was generated by just one variable thus chaos does not have to come from the interaction of many variables. The chaotic EEG signal does originate from a complex origin but chaos can originate from either simple or complex origins and the EEG signal originates from the interaction of many variables (i.e. billions of oscillating neurons).

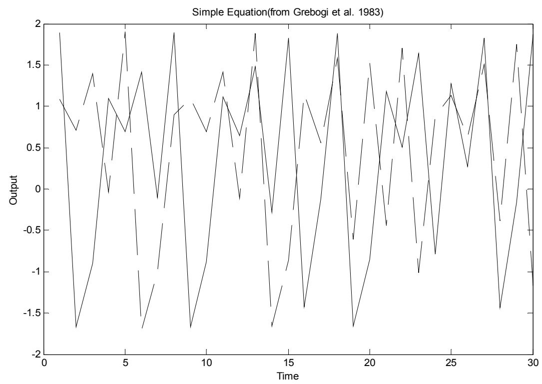

Figure 4: Two graphs with different initial values Xt.
---- $X_0 = 0.9$ ——$X_0 = 0.1$

It is not true to say that the more chaotic the origin is the more chaotic the result but one of the main characteristics of chaos is its sensitive dependence on initial conditions. Observing the two graphs shown in Figure 4, which were both generated using (3), it can be seen that both graphs are considerably different. This is due to the fact that the initial value of *Xt* (i.e. the initial condition) was different for each set of iterations of (3). The sensitivity of the EEG signal to initial conditions is also a very important aspect and is probably what makes the EEG signal so complex and difficult to decipher. The EEG is the electrical activity resulting from many neurons firing. The firing neurons can be considered as the initial conditions of the EEG patterns because depending on which neurons are firing the resultant EEG signals acclimatize. For example, if a person thinks one thought and one thought only, such as imagining moving the right arm, then supposedly a specific set or number of neurons would be firing and thus the same EEG pattern would occur. This may be true but it must also be considered that each time a different thought is produced many different neurons are firing and the so called initial conditions are continuously changing which in fact means that the initial condition is only the initial condition for as long as that corresponding initial thought is maintained. If one sequence of EEG is repeated over and over then this chaotic signal can be learned or recognised by the techniques described in previous sections.

As the human brain is an adaptive system, continuously processing rapidly varying inputs from various sensory modalities while constantly learning new things the complexity of the brain and the number of neurons that function is increasing in most humans every day thus, the initial conditions and therefore the chaotic EEG signals are continuously changing. EEG signals may not be well modelled by stationary dynamics over long times therefore, methods that allow measurement of dynamical change that occurs continuously or intermittently may be essential for the BCI.

For reasons which have been made apparent, methods of non-linear dynamics and deterministic chaos theory can be used to analyse the state of the brain and recognize chaotic sequences within the EEG signal. Chaos theory has been used by many research groups for medical applications and not specifically for BCI. Standard quantifiers of chaotic systems such as Lyapunov exponents have been used by some researchers to show that the diminishing chaos in the brain may lead to serious pathology, such as epileptic seizures. Other researchers have experimented with other standard chaotic quantifiers such as time-delay, embedding dimension, pointwise correlation dimension and the largest Lyapunov exponents, for EEG signal analysis to find out if these techniques would be suitable for chemotherapy assessment. However, in [19] it is reported that these methods seem to be unsuitable for that particular application. In [20] it is reported that fractal dimension of EEG-signals in the time domain works as a relative index of the signal's dimensional complexity and may be useful for doctors, e.g. in semi-automatic differentiation of sleep stages.

VI FUTURE DEVELOPMENT

There has not yet been a significant amount of experimentation with Self Organizing Fuzzy Neural Networks (SOFNN) or Adaptive Fuzzy Inference Systems (ANFIS) in the BCI development, therefore these key areas are to be explored as it is possible that these techniques may be more appropriate. It is proposed to develop a novel neural classifier system that classifies the EEG patterns associated with specific thoughts. In order to attain significantly higher classification accuracy, the proposed system would make use of both the time domain and the frequency domain parameters for neural network training. A novel Self-Organising Fuzzy Neural Network (SOFNN) architecture would be used for network design. This hybrid architecture would facilitate the incorporation of fuzzy reasoning capability (in a similar approach to a human EEG expert), in addition to the learning capability of the neural networks. The SOFNN [21] uses an online learning algorithm that makes automatic adaptation in both the number of neurons in the hidden layer and the parameters of the neurons. This adaptive feature may help improve the classification speed as well as creating a BCI system that can be more adaptable to each individual users EEG patterns.

As mentioned above, the EEG signal appears to be chaotic. Chaos theory has been used to find some order within disordered systems or signals. Also, given that previous behaviour of a chaotic system is known, chaos theory has been used to make reasonably accurate predictions about future behaviour of chaotic systems. The fact that ANFIS (a well known neuro-fuzzy architecture) has been used for predicting chaotic time series [22] these techniques appear to be promising. The idea of semi-accurately predicting future EEG signals whilst analysing and classifying current EEG signals could help in progressing towards a faster and more accurate translation algorithm. These techniques may also be the key to developing an advance warning system to predict the onset of epileptic seizure.

VII Conclusion

The anticipated benefits of BCI are definitely inspiring. If BCI technology could provide those patients who have no form of communication whatsoever ("locked out") the ability to answer simply "yes" or "no" or predict an epileptic seizure occurring even a few seconds in advance, then the BCI could be regarded as a great success. Even though BCI is in its early stages of development, initial results prove it has potential. BCI is a revolutionary technology and has been identified by the European Commission proactive initiative in Information Society Technologies (IST) to be addressed as a long term objective in a wide range of interdisciplinary research. The fundamental prerequisites of BCI have been made clear and a number of uncommon approaches to the problem, yet to be explored, have been outlined.

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