On the Linearity/Non-linearity of Mental Activity EEG for Brain-Computer Interface Design

T. Balli[1], R. Palaniappan[1] and D.P. Mandic[2]

[1]Department of Computer Science, University of Essex, Colchester, United Kingdom
[2]Department of Electrical and Electronic Engineering, Imperial College, London, United Kingdom

Abstract— **In this study, we investigated the linearity/non-linearity of mental activity electroencephalogram (EEG) signals for Brain-Computer Interface (BCI) designs using the recent but well established Delay Vector Variance (DVV) method. EEG data recorded from seven subjects while they were performing five different mental activities were used in the experimental study. Through the use of DVV, it was investigated whether EEG signals would become linear or non-linear when segmented into smaller parts. Concluding, the results of the studies showed that a large percentage of the EEG signals exhibited non-linear behaviour. This is an important result as it shows that the currently used linear modelling methods are mostly unsuitable.**

Keywords— **Brain-Computer Interface, Delay Vector Variance, Electroencephalogram, Non-linearity analysis, Surrogate data**

I. INTRODUCTION

Electroencephalogram (EEG) is a representative signal that contains information about the electrical condition of the brain. These signals can be used to assess brain damage, epilepsy and other disorders. In recent years, there have been many developments in utilising EEG for Brain-Computer Interface (BCI) design as an alternative communication tool between disabled people and their environment [1], [2], [3]. These studies used EEG signals recorded during mental activities and focused on designing BCI systems that can discriminate between these different mental activities. While designing these BCI systems, it is important to verify the presence of linearity or non-linearity in the corresponding signals so that appropriate modelling methods can be used. However, the previous studies assumed that the EEG signals were linear and used linear modelling methods like autoregressive. The use of linear methods simplifies the implementation but it is likely to give erroneous results when the signal is in fact non-linear.

In this study, the aim is to investigate on the linearity (or non-linearity) of the mental activity EEG signals using Delay Vector Variance (DVV) method. DVV is a recently proposed method for assessing the non-linearity [4]. This method works by testing the local unpredictability of the signal. It is hoped that the DVV method would yield a reliable characterisation of the EEG signals, which will move future BCI system design towards minimising the classification error of different mental activities.

II. EEG DATA AND PRE-PROCESSING

A. Data

The EEG data used in this study were obtained from http://www.cs.colostate.edu/eeg/. These data were recorded from seven subjects. Subjects performed five trials on each day. Subjects 2 and 7 performed only one five-trial session, while subject 5 performed three five-trial sessions and the rest of the subjects performed two five-trial sessions. The EEG data were recorded from six positions (channels) C3, C4, P3, P4, O1, and O2. There was an additional EOG channel (for reducing eye blink contamination).

Signals were recorded for 10s during each activity and each activity was repeated for several sessions (subjects 2 and 7 performed only one session). The sampling rate of the signals was 250 Hz, so the length of EEG signals were 2500 sampled points for each channel.

In this study, the EEG signal for each mental activity was segmented into 20 parts with length 0.5s i.e. 125 data points in length. We studied EEG with this segmentation length as it has been used in the previous studies [2, 3].

EEG signals from five different mental activities performed by each subject were used. These mental activities were:

1. Baseline activity: The subjects were asked to relax and think of nothing in particular. This activity was used as a control and baseline measure of the EEG signals.

2. Math activity: The subjects were given a multiplication activity and were asked to perform it without vocalising or making any other physical movements. The numbers were selected such that none of the subjects could complete the activity before the end of 10s recording session.

3. Mental letter composing activity: The subjects were asked to mentally compose a letter to a relative or friend without vocalising. Since the activity was repeated several times, the subjects were told to continue where they left off in the previous activity.

4. Geometric figure rotation activity: The subjects were given 30s study the drawing of a complex 3D object. After that, they were asked to visualise the object being rotated about an axis. The EEG was recorded during the mental rotation.

5. Visual counting activity: The subjects were asked to imagine a blackboard and to visualise the numbers being written on the blackboard sequentially with the previous number being erased before the next number was written. The subjects were asked not to verbally read the numbers but to visualise them and they were told to continue counting where they left off in the previous activity rather than starting again.

Keirn and Aunon [1] specifically chose these mental activities since they involve hemispheric brainwave asymmetry.

B. Pre-processing

The eye blinks occur naturally during the EEG recording process and they cause contamination to the recorded EEG data. In this paper, the original EEG was recovered by subtracting separately recorded EOG (with appropriate weights) from EEG data. The weights were 0.1 for C3 and C4, 0.05 for P3 and P4, and 0.025 for O1 and O2.

Next, EEG signals were high pass filtered to reduce baseline noise. A forward and reverse Elliptic digital filter with cut off frequency at 1 Hz and minimum 20 dB attenuation in stop band below 1 Hz were used. The ripples in the pass band were kept below 0.1 dB.

A further pre-processing step was to low pass filter the signals to remove 60 Hz powerline interference. For low pass filtering, the same specifications were used but with cut-off at 59 Hz and minimum 20 dB attenuation beyond 60 Hz.

III. Data analysis

In this section, surrogate data and DVV methods will be introduced. Besides these the concept of null hypothesis will be covered briefly.

A. Null Hypothesis

In this study the aim is to test the non-linearity of EEG data. In order to test the non-linearity, a hypothesis is generated that the time series is linear. As it is not possible to test the properties of non-linearity directly, this null hypothesis of linearity is generated. The main idea is to compare the test statistics of original time series against surrogate time series. Surrogate time series are the realisation of null hypothesis. The test statistics of time series will be obtained by DVV method, which will be introduced later in this section.

B. Surrogate Time Series

The surrogate time series are artificially generated time series that retain some statistical properties of original time series (such as mean, variance and Fourier magnitude spectra) in order to have the same linear properties with original data set. They are used for testing non-linearity [5].

There are several methods for generating surrogate time series. In this paper iterative Amplitude Adjusted Fourier Transform (iAAFT) [6] is used for generating surrogate time series, which is an improvement of Amplitude Adjusted Fourier Transform Method (AAFT).

The iAAFT algorithm produces surrogate time series that follow the same distribution and have identical magnitude spectra with the original time series [6].

In order to produce iAAFT based surrogate time series, the following steps must be followed:

- Initially, we have original time series x(t) in which t=1...N;
- Next, apply Fast Fourier Transform to original time series and save the magnitudes in α;
- In the iterative process, we have two time series; r(t) which have the same distribution with original time series and s(t) which have same magnitude spectrum with original time series;
- r(0) is the shuffled sequence of original time series.

- In every iteration:

1. Compute the phase spectrum of r(t-1) and save it to Ø;
2. Calculate the Inverse Fourier Transform of (|α| exp(i Ø)) and save the results to s(t);
3. r(t) is obtained by rank ordering of s(t) so as to match the sorted version of original time series.

C. Delay Vector Variance Method

For obtaining the test statistics of the original and surrogate time series, many methods have been proposed in the literature [7]. In this paper, a relatively recent method for obtaining test statistics will be used. This method is the DVV method [7]. The idea behind DVV is testing the local predictability of time series. Using this method the target variances are computed, σ^{*2}, which are the inverse measure of local predictability of time series for a given embedding dimension, *m*.

The DVV method is based on time delay embedding method, in which original time series X={x(k) | k=1…N} will be represented by a set of delay vectors where each delay vector contains *m* consecutive time samples, denoted by $x(k)=[x_{k-m\tau},\ldots,x_{k-\tau}]$. Every delay vector has a corresponding target, namely next sample x_k. Note that τ is time lag which is set to unity for all of the simulations here.

In order to represent time series in phase space accurately and get the best predictability, the optimal embedding dimension must be determined before performing DVV analysis. The optimal embedding dimension can be determined by trial and error method, in which a number of DVV analyses are performed for different values of *m*. The *m* value which yields the lowest target variance, σ^{*2}, will be selected. For the simulations performed for this paper, the target variances were computed for *m* values between 2 and 40.

Using the selected optimal embedding dimension *m*, the DVV method can be performed as follows:

- Initially, we have original time series x(t) in which t=1...N;

1. Generate the target vector depending on the embedding dimension *m*, in which the target vector is Y={ x(k) | k=m...N};
2. Calculate the variance of the target vector, σ^2_x;
3. Determine delay vectors using the number of delay vectors parameter, Nn, such that Nn delay vectors are obtained from original time series;
4. Calculate the Euclidean distance between Nn delay vectors and N-m delay vectors that is generated from original time series (i.e: DV(1)=x(1)..x(m), DV(2)=x(2)..x(m+1),...,DV(N-m)=x(N-m)..x(m));
5. Calculate mean, μ_d, and standard deviation, σ_d, of all pairwise distances obtained in step 4;
6. Generate the sets $\Omega_k(r_d)$ by grouping DVs that are closer to x(k) than a certain distance r_d such that; $\Omega_k(r_d)=\{x(i) \mid \lVert x(k)-x(i) \rVert < r_d \}$.

- The $r_d(n)$ is computed as:

$$r_d(n) = (\mu_d - n_d * \sigma_d) + \frac{2 * n_d * \sigma_d * n}{N_{tv} - 1},\ n = 1 \ldots N_{tv}, \tag{1}$$

where n_d is the maximal span parameter which is used to determine the range of standardized distances to consider and N_{tv} is the number of evaluation points for which the target variances are computed such that $N_{tv} = 25*n_d$;

7. For every set, $\Omega_k(r_d)$, compute the variance of corresponding targets, $\sigma_k^2(r_d)$;
8. Normalise the averages of variances by the variance of target vector, σ^2_x, that yields the target variance, σ^{*2}, which is the inverse measure of predictability of the time series,

$$\sigma^{*2} = \sum \frac{\frac{1}{N}\sum_{k=1}^{N} \sigma_k^2}{\sigma_x^2}. \tag{2}$$

- Its worthy to note that the variance estimates will be reliable only if the $\Omega_k(r_d)$ set contains at least 30 delay vectors [7].

The $r_d(n)$ distances are normalised to have zero mean and unit variance. Plotting normalised distances versus target variance, σ^{*2}, will result in DVV plots.

The DVV plots of original and surrogate time series can be combined in a scatter diagram. The target variances are averaged for surrogate time series and are plotted against those of original time series for corresponding normalised distances. This can be obtained by calculating the root mean square error (RMSE) between the degree of unpredictability of original time series and average degree of nonlinearity of surrogate time series. This degree of unpredictability can be computed as

$$t^{DVV} = \sqrt{\left\langle \left(\sigma^{*2}(r_d) - \frac{\sum_{i=1}^{Ns} \sigma_{s,i}^{*2}(r_d)}{N_s} \right)^2 \right\rangle_{,valid\ r_d}}. \tag{3}$$

IV. Results

Figure 1 shows the non-linearity percentages of each channel for different mental activities. The channels stand for positions C3, C4, P3, P4, O1, and O2 respectively defined by 10-20 system. These results were obtained by averaging the non-linearity percentages of seven subjects for each channel. From Figure 1, the highest percentage of non-linearity was detected in channel P4 whereas the lowest percentage of non-linearity was detected in channel O1. It is also obvious that the percentage of non-linearity did not vary significantly for different channels.

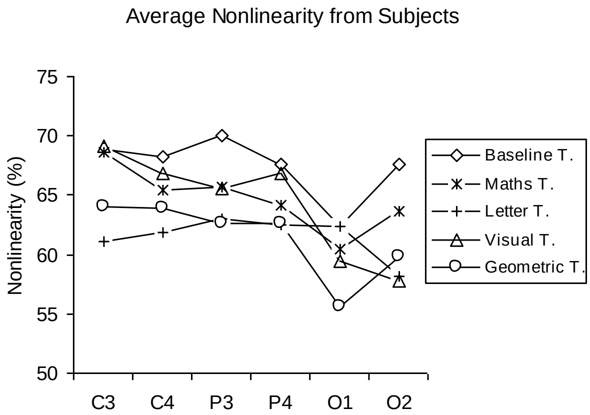

Fig. 1 The average nonlinearity from subjects

Figure 2 shows the non-linearity percentage of each mental activity. These results were obtained by averaging the percentage of non-linearity from six channels for every mental activity. From Figure 2, the highest percentage of non-linearity (68%) was obtained from baseline activity whereas the lowest was obtained from letter composing activity and geometric figure rotation activity.

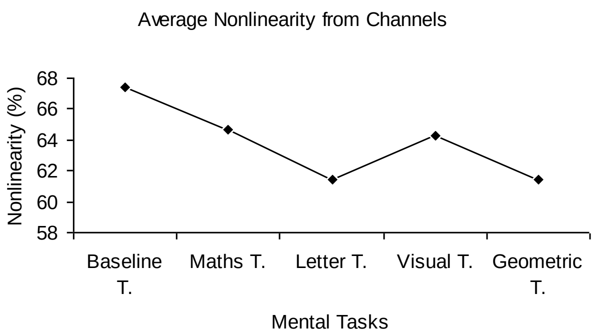

Fig. 2 The average nonlinearity from channels

The overall results show that when the EEG signals were segmented into smaller parts, approximately 65% of them were non-linear. However, changing the length of segments would require a re-analysis of the non-linearity.

V. Conclusion

In this paper, the non-linearity of mental activity EEG signals for BCI designs has been investigated. The EEG data recorded from seven subjects while they were performing mental activities were used in this study. The results indicated that approximately 65% of the segments were non-linear. Accordingly, we conclude that it is more appropriate to use non-linear modelling methods for mental activity based EEG.

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Address of the corresponding author:

Author: Tugce Balli
Institute: Computer Science Dept., University of Essex
Street: Wivenhoe Park
City: Colchester, CO4 3SQ
Country: United Kingdom
Email: tballi@essex.ac.uk