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The Correlation between EEG Signals as Measured in Different Positions on Scalp Varying with Distance

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Abstract

Biomedical signals such as electroencephalogram (EEG) are the time varying signal, and different position of electrodes give different time varying signals. There might be a correlation between these signals. It is likely that the correlation is related to the actual position of electrodes. In this paper, we show that correlation is related to the physical distance between electrodes as measured. This finding is independent of participants and brain hemisphere. Our results indicate that the EEG signal is not transmitted via neurons but through white matter in a brain.

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Keywords: EEG, Biomedical signal processing, Time Series Data Analysis, Cross-Correlation.

1 Introduction

Electroencephalogram (EEG) signals provide a measure of brain nerve cell electro-physiological activity that is accessible on the surface of the scalp (EEG indices of G-induced loss of consciousness (G-LOC), 1988), thus provide information about different types of brain activity. The electrical activity in the brain is recorded via measurement electrodes attached to the surface of the scalp. The EEG signals detected will vary, depending on the location of the electrodes on the scalp. Identifying changes in EEG signals has improved our understanding of the relationship of these signals to people's moods, and behavior (Han, 2012).

Research (Niedermeyer, 2005) suggests that various characteristics of EEG signals are representative of distinct states of brain activity. These distinct states can be quantified using linear or non-linear measures. Previous research has demonstrated a correlation between EEG signals (or brain activity) from different part of the brain (Na, 2002), (Bob, 2010), (Jeong, 2015). A high correlation between the signals from different electrodes indicates similar brain activity, and a low correlation indicates that the brain activity at the different measurement sites is relatively independent.

Researchers (Na, 2002), (Li, 2013) have demonstrated that brain activities within the same (local) region might be similar, but that they might be different among non-identical regions (globally). One question that we address here is whether the activities of the two brain hemispheres are similar.

White matter, which modulates the distribution of action potentials, is brain tissue that is composed of bundles of axons. It acts to coordinate communication between different brain regions (Fields, 2008). One issue we address here is how electrical activity can be communicated across the surface of the brain. We believe that white matter makes a significant contribution to this communication. Our research focuses on evaluating the correlation of EEG signals between different brain regions. The aim of this

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study is to determine the relationship between EEG signals and electrode location on the scalp, and to check whether this relationship differs in the two brain hemispheres.

2 Related Work

A series of data points in time order, or time series, provides the view of a signal as it evolves over time, i.e. in the Time domain (TD). TD analysis is used to analyse the signal in its actual state, which is the earliest and direct way of analysing EEG signals - it is utilised to analyse changes in EEG signals, such as power (or amplitude) over time. In addition, the frequencies present in the signal are open to investigation (for example, by using the Fast Fourier Transform (FFT)). Such an analysis is said to take place in the Frequency domain (FD). FD analysis is used to identify frequencies present in the signals. Furthermore, it can be utilized to establish the relationship between EEG frequency and its corresponding power (amplitude), and so the energy distributions in EEG signals.

In recent research, the correlation between EEG signals has been analysed in FD using various methods, such as Mutual information, Coherence analysis, Wavelet coherence, Correlation coefficient, Auto-correlation and Cross-correlation. Mutual information has been utilized to examine information transmission between different cortical areas in both patients with schizophrenia and Alzheimer's disease (Na, 2002). This research found lower mutual information between EEG signals of patients with these conditions when compared to normal controls. Coherence analysis has been applied to study brain interactions between EEG signals (Nolte, 2004), indicating significant correlation in EEG Beta (β) frequency range between the left and right motor areas of the human brain. Wavelet coherence has been applied to distinguish the EEG signals of normal controls and patients with conditions, such as Parkinson's related dementia and Alzheimer's disease (Jeong, 2015). Correlation coefficient has been utilized to discover changes in EEG signals and autonomic nervous activity, and the association of these with personality traits (Takahashi, 2005), with an increase in EEG theta (θ) power and EEG alpha (α) power predominantly in the frontal area. Cross-correlation has been utilized to study the degree of association between activities in symmetrical (left and right) parts of the brain (Li, 2013), and results indicated that there is a stronger correlation in the delta (δ) frequency range on the right side of a brain than the left. To our knowledge, limited research has been conducted to analyse EEG signals in the TD. Therefore it is important to perform a comparative analysis and an interpretation of EEG signals in the TD, not just the FD.

Cross-correlation can be performed to analyse the time delay between two related processes. In the present context, it offers a valuable and sensitive method for investigating EEG signals that are recorded at the same time from different electrodes that is independent of their amplitudes. To analyse EEG signals in the time domain, Cross-correlation stands out as the most appropriate correlation method, because of its ability to assess signal similarity at all possible time delays. Cross-correlation has been successfully applied in analysing EEG signals in the FD (Li, 2013) , as well as TD (Bob, 2010). This method can be used to determine the relationship between activity in global and local areas, and also among the different local areas of the human brain.

It has been found that the numbers of electrodes and combinations of electrode pairs used to analyse EEG signals is different. Usually, the combination of electrode pairs depends on the total number of electrodes. For example, if there are 19 electrodes then the number of unique potential electrode pair is 171. According to recent research on EEG signal analysis, electrodes from the central part of the brain deserve the best consideration, possibly because minimum noise is found in the recorded signals (Klein, 2006). This was one of the reasons we explored papers in which EEG signals were analysed using limited numbers of electrodes and combinations of electrode pairs. For example, Na et al. (Na, 2002), examined 16 electrodes with 38 pairs of electrodes within the right hemisphere and within the left hemisphere. Their results showed less complex EEG activity in the left temporal regions. Bob et al. (Bob, 2010), inspected 8 electrodes and 16 electrodes pairs to examine the relation between EEG activity at the Dissociative Experiences Scale (DES) in paranoid schizophrenia patients. Their results explored a significant correlation of DES in 9 EEG electrode pairs. Similar electrode pair effects have been found by Cuevas et al. (Cuevas, 2011), who studied 8 electrodes and 16 electrode pairs in their investigation of patterns of EEG signals in developing children's brains. Their results suggested an age-related increase in EEG power for 9 electrode pairs. Li et al. (Li, 2013), examined 16 electrodes and 4 electrode pairs, and proposed more significant changes in the EEG signals of electrodes from the right-side of the brain when compared to those of the left-side.

This brief review of research on the correlation of EEG signals indicates that investigations have been focused on the FD. Furthermore, limited information was found on the correlation of EEG signals in the TD. Additionally, the numbers of paired electrodes investigated, the number of datasets used, and use of Cross-correlation for analysing EEG signals are limited. Instead, researchers focus has been primarily on electrode combinations within the left and right brain hemispheres. The summary of research work reported in this paper to be replicated can be found at https://ronak2.wixsite.com/mysite/research-blog.

To our knowledge, very limited work has been done on the correlation of EEG signals using multiple electrode. This paper investigates the correlation of EEG signals in the TD using Cross-correlation. Three datasets have been used and are named as Data-set 1, Data-set 2 and Data-set 3. Each dataset involves a different number of electrodes. Therefore, the number of unique electrode pairs to perform Cross-correlation is different. From Data-sets 1, 2 and 3 we have 171 pairs, 45 pairs, and 105 pairs, respectively.

3 Data Collection

Three different datasets were obtained with each of them containing different numbers of participants and electrodes. All of these datasets follow the 10-20 electrode placement system shown in Fig 1. The 10-20 system is the recognized method to describe the location of electrodes (Klem, 1999). The values of 10% and 20% shown in Fig. 1 refer to the distances between adjacent electrodes: either 10% or 20% of the total front-to-back or right-to-left distance over the skull - front-to-back distance is based on the measurement from Nasion (point between forehead and nose) to Inion (lowest point of the skull from the back of the head indicated by a prominent bump), and right-to-left distance is based on the measurement between the left and right preauricular ear points.

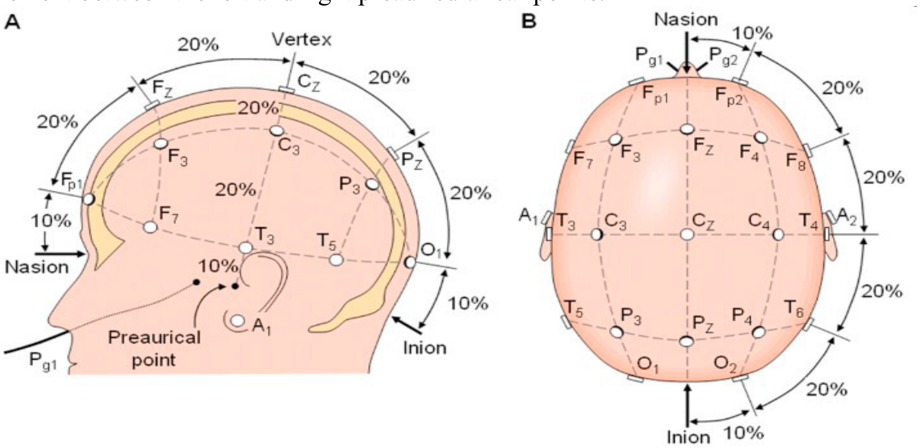

Figure 1: The international 10-20 system seen from **A** (left side of the head) and **B (**above the head). The letter F, T, C, P, O, A, Fp and Pg stands for frontal, temporal, central, parietal, occipital, earlobes, frontal polar, and nasopharyngeal, respectively (Klem, 1999).

Data-set 1 consists scalp EEG recordings of 16 participants obtained over 5 minutes in a relaxed state with eyes opened. 19 electrodes (Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, and O2) were used, following the 10-20 system. The sampling rate used was 250Hz, and the reference was to linked ear electrodes.

Data-set 2 consists of scalp EEG recordings of 20 participants, while they watched a short documentary movie. 10 electrodes (F7, F3, Fz, F4, F8, T5, P3, Pz, P4, and T6) were used following the 10-20 system. The sampling rate used was 500Hz, and the reference was to linked ear electrodes.

Data-set 3 presents a multi-modal dataset for the analysis of human affective states (Koelstra, 2012). 32 participants EEG signals were recorded while the participants watched 40 one-minute long excerpts of music videos. Out of 32 electrodes recorded, 15 electrodes (Fp1, Fp2, F7, F3, Fz, F4, F8, C3, Cz, C4, P3, Pz, P4, O1, and O2) following the 10-20 system were used for this study. The sampling rate used was 512Hz, and the reference was to linked ear electrodes.

4 Methodology

As described in the Related Work section, Cross-correlation measures how closely two different observables are related to each other at the same or different time, taking time lag into consideration. Normalized Cross-correlation (Lewis J. , 1995) is used in this work to find the similarity between two time series signals. The normalized Cross-correlation for time sequence x_t and y_t of signals x and y, respectively, is defined as follows:

$$R_{xy}(\mathcal{T}) = \frac{\frac{1}{N}\sum_{t=1}^{N-\mathcal{T}}[(x_t - \mu_x)(y_{(t+\mathcal{T})} - \mu_y)]}{\sigma_x \sigma_y} \tag{1}$$

$\mathcal{T}$ is the time lag, N is the length of signals x and y, μ_x is the mean of x_t and μ_y is the mean of y_t. σ_x is the standard deviation of x_t and σ_y is the standard deviation of y_t. The values of the normalized Cross-correlation range between 1 (when the matching entities are exactly the same) and −1 (when the matching entities are inverses of each other). A value of zero indicates no relationship existing between the entities. Note that the Cross-correlation can be evaluated for any length of x_t and y_t, and they are not required to be the same (Lewis J. , 1995).

5 Experiments & Results

The EEG signals were processed to remove artefacts, such as eye blinks, eye movements, jaw movements and muscle movements, by using Independent Component Analysis (ICA). Cross-correlation has been calculated on the processed EEG signals for the 171 electrode pairs of Data-set 1, the 45 electrode pairs of Data-set 2 and the 105 electrode pairs of Data-set 3.

In order to obtain the distance in centimeters (cm) between electrodes, a measuring tape was used. For most of our participants the head circumference range was 54-58cm, for which a medium-sized 'electro-cap' is appropriate. According to (Mitsar, 1996), the circumference of the medium-sized EEG cap is ideal for 64% of adults, whether male or female. Therefore, we utilized a medium-sized EEG cap made of an elastic material which stretches according to the participants head circumference, and measured distances using a straight line on the cap - not a curved line over the skull. Note that the distance between electrodes as shown in Fig. 3 is straight line distance between two electrodes, not the distance as measured over the surface of the scalp.

The maximum absolute correlation was found at lag 0. Fig. 2 shows the information for electrode pairs Fp1-Fp2, as an example. The other two datasets show similar results. In Fig. 2, the x-axis (horizontally) denotes the time lag; a lag of 1 corresponds to 4 milliseconds - positive time lags (0 to 1000) and negative time lags (0 to -1000) indicate when one of the signals shifted to the right and left side of the reference signal Fp1, respectively. The y axis (vertically) denotes the cross-correlation value. The blue color line is for an individual participant, and the red is for the average of all participants' correlation performance for each electrode pair.

Electrode F7 from Data-set 2 have been chosen randomly to show the Cross-correlation performance. The other two datasets show similar results. The results show the averages for all participants. Fig. 3 show that there is an inverse relationship between Cross-correlation and distance. The linear regression has been plotted to fit the data with a probability of $p < 0.001$. This indicates that the Cross-correlation value decreases while the distance from F7 increases, irrespective of brain hemisphere.

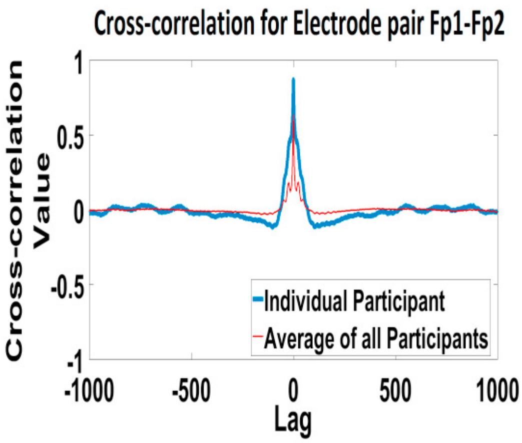

Figure 2: Positive Cross-correlation at Lag 0

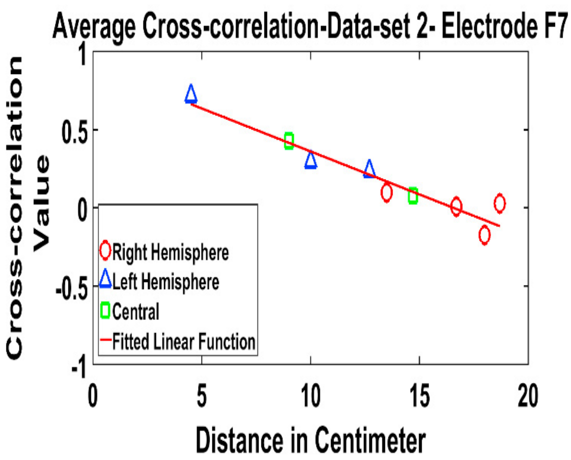

Figure 3: Cross-correlation between electrodes at varying distance on Data-set 2

The results of all other electrodes of all three datasets are similar to the ones shown in Fig. 3. The differences between each Cross-correlation value and the corresponding value on the fitted linear function line were calculated. The results show that the difference between them is very small (about 0.03 98%), which suggests that a close linear dependency does exist.

6 Discussion & Conclusion

One of the main conclusions of this work is that electrical activity correlates linearly with distance within the brain, i.e. when distance increases the correlation decreases. To our knowledge, previous research has not described this linear relationship in TD. Our results cover a gap in the research concerning the correlation of EEG signals in the TD using Cross-correlation and possible combinations of electrodes pairs; and also the linear dependence of Cross-correlation with electrodes location. It is important to consider physical separation as measured directly through the skull, and not over the surface of skull when you position electrodes on the skull.

The second conclusion from this work is that the correlation is independent of brain hemisphere. This suggests that most probably the electrical signals are transmitted through the white matter of the brain. We assume signal transmission is through white matter because of the commissural tracts within the white matter which connect the two hemispheres of the brain. This means in practice it does not matter which side of the medial plane you place the electrodes.

Our work suggests that this white matter in the brain is significant in the transmission of electrical activity. White matter is composed of bundles of axons which connect various grey matter areas (the locations of nerve cell bodies) of the brain to each other and carry nerve impulses between neurons. White matter might actively affect how the brain learns and functions, and modulates the distribution of action potentials, acting as a relay and coordinating communication between different brain regions (Fields, 2008). In summary, regardless of the anatomical substrates involved, our main finding is that the correlation between electrical activities in different parts of the brain is linearly related with the electrode distance between them. At the moment we are extending this work to find the correlation between EEG and Electrocardiogram (ECG) signals.

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