INVESTIGATION OF SPECIFIC LEARNING DIFFICULTIES BASED ON THE INFORMATION FLOW IN MULTICHANNEL EEG SIGNALS

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Abstract –The main purpose of this paper is to study the information flow in multi-channel Electroencephalogram (EEG) recordings of δ, θ, α, β rhythms in the case of Specific Learning Difficulties (SLD) and to compare the findings with healthy subjects. The Directed Transfer Function (DTF) was used in order to determine the directional flow in the frequency domain between any given pair of channels. EEG recordings corresponding to 19 healthy subjects and 38 SLD subjects, were used to estimate the directional influences. The Bootstrap technique was used to compare the mean values of the influences extracted from the two investigated groups and to determine the confidence interval of the influences for each group. It has been found that the mean DTF of SLD subjects was significantly lower than that of healthy controls, for the δ and θ frequency bands. These findings seem to suggest that SLDs are associated with limitations in the speed of information processing, concerning the orienting a coordinated response (θ band) and/or the signal detection-evaluation and decision making (δ band).

Introduction

The term Specific Learning Difficulties (SLD) has been used to describe individuals having reading related difficulties despite normal intelligence, adequate training and satisfactory educational opportunities. Approximately 10-15% of the population have SLD. The supposed pathogenetic mechanisms underlying SLD are referred to genetic, neurobiological and cognitive variables. Despite extensive research in this field, the nature of what constitute the core deficits in SLD has remained poorly understood and heavily debated. In general, the functional significance of varying brain activity can be seen in the vicinity of the underlying neural circuits. For instance, it is assumed that alpha band activity reflects an increased excitability level of neurons in certain cortical areas, which may be related to an enhanced information transfer in thalamocortical circuits and is strongly correlated with working memory as well as with long-term memory.

Beta bursts being related to cortico-cortical interactions, shift the system to an attention state that consequently allows for gamma synchronization and perception. Theta EEG activity being associated with cortico-hippocampal interactions, is interpreted as being correlated with 'orienting' a coordinated response indicating alertness, arousal. Delta EEG activity, being observed in the sleeping brain and in epilepsy, is associated with the signal detection-evaluation and decision making and is linked to the cortical-subcorical interactions [1].

It is believed that the way different regions of brain communicate to each other can give useful information about learning difficulties [2]. The Directed Transfer Function (DTF) [3][4] has been introduced as an estimator of the intensity of activity flow between brain structures, depending on the frequency correlation of any given pair of channels in a multivariate dataset. For the analysis of relations between brain structures, a multichannel model is more appropriate as it takes into account all signals simultaneously and not pair-wise. This overcomes the general disadvantage of pair-wise analysis, which in certain cases can lead to incorrect conclusions especially when some channels are fed from common signal sources [5]. Additionally, the multichannel model creates a common base with regard to the whole system providing an absolute scale for comparison of quantitative results. The DTF function is also sensitive to the time delay of signals and it expresses both direct and indirect causal influences between structures.

The DTF has been applied recently in order to examine the differences between the pattern of activity flow in patients before and after the evolution of an epileptic seizure [6]. Moreover, the main centers from which EEG activity is spreading during sleep and wakefulness and differences in coherence patterns between sleep stages have been investigated by means of the DTF [7].

The purpose of the present paper was to study the EEG patterns of information flow in two groups of children, healthy subjects and SLD subjects, and to determine the possible frequency bands and the EEG channels for which the information flow patterns are significantly different between the two groups. The whole analysis of information flow has been focused on EEG rhythms δ, θ, α, β.

Methods

The Directed Transfer Function

Let $X(t) = [X_1(t), X_2(t), \ldots, X_k(t)]$ be the k-channel EEG measurements at time point t as shown in Figure 1.

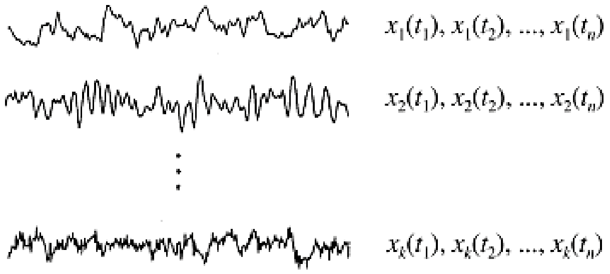


Figure 1. k-channel EEG signal

The signal matrix X(t) can be described by the Multivariate Autoregressive (MVAR) process [8] as

$$X(t) = -\sum_{i=1}^{p} A(i)X(t-i) + E(t) \qquad (1)$$

where $A(i)$ are the autoregressive coefficients of p order, and $E(t)$ is the error between real and estimated from the model values.

Alternatively, equation (1) can be expressed as

$$\sum_{i=0}^{p} A(i)X(t-i) = E(t) \qquad (1')$$

where $A(0) = I$

Transforming equation (1') into the frequency domain

$$A(f)X(f) = E(f) \qquad (2)$$

$$\text{or } X(f) = A^{-1}(f)E(f) = H(f)E(f) \qquad (2')$$

where $$A(f) = \sum_{j=0}^{p} A(j)e^{-i2\pi fj}$$

From equation (2'), it can be assumed that *H(f)* is the transfer matrix of a system with inputs the model errors (noise) and outputs the real signals, as shown in Figure 2. The transfer matrix *H(f)* contains all the information for the frequency properties and the internal relations between channels.

The normalized DTF [3] is defined as

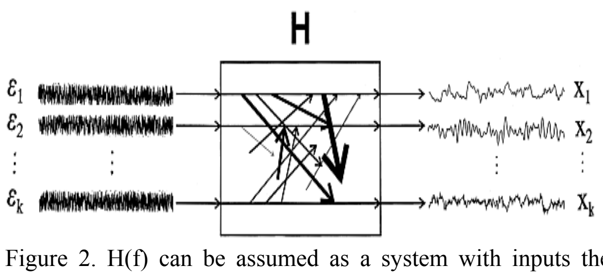


Figure 2. H(f) can be assumed as a system with inputs the model errors (noise) and outputs the real signals.

$$\gamma_{ij}^{2}(f) = \frac{\left|H_{ij}(f)\right|^2}{\sum_{m=1}^{k}\left|H_{im}(f)\right|^2} \qquad (3)$$

and takes values between 0 and 1.

Statistical Analysis using Bootstrap

The bootstrap technique was introduced as an approach to estimate confidence intervals for parameters in circumstances where standard statistical methods cannot be applied [9]. This technique can be used for the estimation of statistical measures without making assumptions about the distribution of the original data and is extremely valuable in situations where the original data size is small.

In the present study, the bootstrap method was used to compare the mean of the DTF values and to determine the frequencies and the channels for which the DTF values are significantly different between the two investigated groups. In particular, bootstrap values of a statistic were generated under the null hypothesis and the achieved significance level were estimated as the proportion of the bootstrap values of the test statistic which are greater than or equal to the observed value of the statistic from the original data. To compare the distribution of sample data into independent groups, we utilized a bootstrap statistic that uses the assumption of equal mean, under the null hypothesis. A total of 5000 bootstrap samples were generated from the original data and the difference in the mean value of the two groups in each sample was used as the statistic to compare the two investigated groups. The statistic was estimated for all the samples and its distribution was determined. The proportion of the samples with a statistic greater than the actual observed value of the statistic was used to determine the P-value of the bootstrap statistic test.

Estimation of the confidence interval for the mean value of DTF

To determine a confidence interval (CI) for the mean values of DTF, in the case of controls and SLD subjects, the bootstrap principle was used. More specifically, the DTF values corresponding to EEG channels and frequencies that were found to be significantly different between the two investigated groups, were used to estimate the CI of the DTF mean values. Briefly, for each frequency the CI of DTF can be found by determining the distribution of the mean value (μ) over the bootstrap samples, and finding values $\hat{\mu}_L, \hat{\mu}_U$ [10] such that $P(\hat{\mu}_L \leq \mu \leq \hat{\mu}_U) = 1 - \alpha$ where $\hat{\mu}_L, \hat{\mu}_U$ are the lower and upper limitσ of the CI, respectively, and *a* is the significance level of the statistical test (*a* = 0.05). In this study, the computation of the CI for each pair of channels and for each frequency was based on 5000 bootstrap replications.

Subjects and Procedures for Signal Acquisition

Fifty seven (57) children participated in the experiment. Thirty eight (26 boys and 12 girls) of them were outpatient cases who had been diagnosed as suffering from specific developmental disorder of scholastic skills (learning disorders) according to the 10th edition of the International Classification of Diseases (ICD-10) and the rest 19 children (7 boys and 12 girls) were their healthy siblings. The mean ages for the SLD children and for the controls were 11.47±2.12 and 12.21±2.25 years, respectively.

The children's EEG signals were recorded at 15 electrodes (Fp1, F3, C5, C3, Fp2, F4, C6, C4, O1, O2, P4, P3, Pz, Cz, Fz) according to the 10–20 international system [11], referred to both earlobes. For more experimental details see Papageorgiou et al [12]. The Ag/AgCl electrodes were attached to the scalp with adhesive cream in order keep the electrode resistance below 5 kΩ. An electrode placed on the subject's forehead served as ground. The bandwidth of the amplifiers was set at 0.05 Hz to 45Hz. During the recordings the subjects had their eyes closed in order to minimize eye movements and blinks. Eye movements were recorded through electro-oculogram (EOG) and recordings with EOG higher than 75 μV were rejected.

Raw EEG was sampled for 500msec with sampling frequency 1 kHz, thus oversatisfying the Shannon theorem. In order to remove the EEG noise, the total procedure consisted of 52 repetitions and the finally taken signal was the average of these repetitions.

Results

The DTF method was applied to the EEG recordings of the 57 children participating in the experiment. For each subject, a DTF matrix 15x15x30 (electrode destination x electrode source x frequency) was produced. Plots of asymptotic Akaike Information Criterion (AIC) [13] were made in order to determine the optimum autoregressive model order, which was set to 4.

A hypothesis test based on 5000 bootstrap replications was performed to compare the mean DTF values for each pair of electrodes and frequency between the two investigated groups. The study of the differences between the DTF values of the two groups was splitted in the frequency bands of EEG (δ: 1-4Hz, θ: 4-7Hz, α: 8-13Hz, β:14-30Hz). The results are shown in Figure 3, where arrows represent directed causal relation statistical difference ($p<0.05$) between the two groups of children for at least one frequency within a frequency band.

From Figure 3, it can be observed that there are dominant channels in each EEG rhythm which influence many other channels, while there are channels that appear to be completely inactive. More specifically, such dominant channels are channel P4 in δ rhythm, channels P4, F3, C6 in θ and α rhythms, and channel FP1 in β rhythm. It is important to note that the influences that were significantly different between the two groups of children appeared to have the highest DTF values. For these channel influences that were found to be significantly different, the upper and lower bounds of the 95% CI for the DTF mean value were studied.

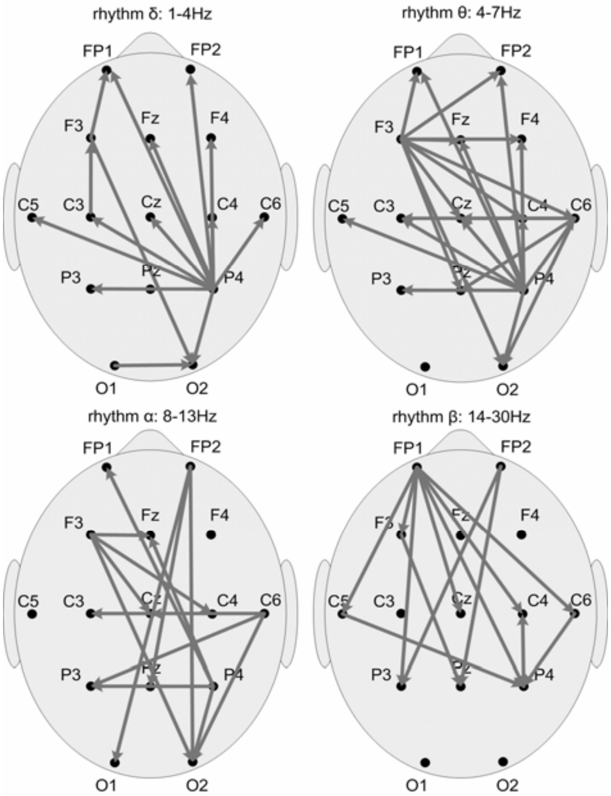


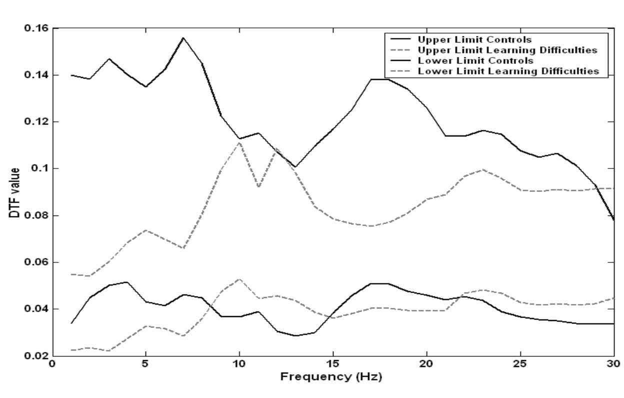
Figure 3. Information flows that were found significantly different (p-value<0.05) between the two investigated groups of children for the EEG rhythms δ, θ, α, β.

In Figure 4, the variation of the upper and lower bounds for the P4→C6 influence for the two groups of children is depicted, as a characteristic one. The selection of the P4→C6 influence was based on the number of consecutive differences between the two groups in rhythms δ, θ, α, where more than 70% of the total EEG energy is concentrated. As someone can see in Figure 4a, in the δ and θ frequency bands, the upper and lower bounds corresponding to healthy subjects are greater than the upper and lower bounds of the SLD subjects.

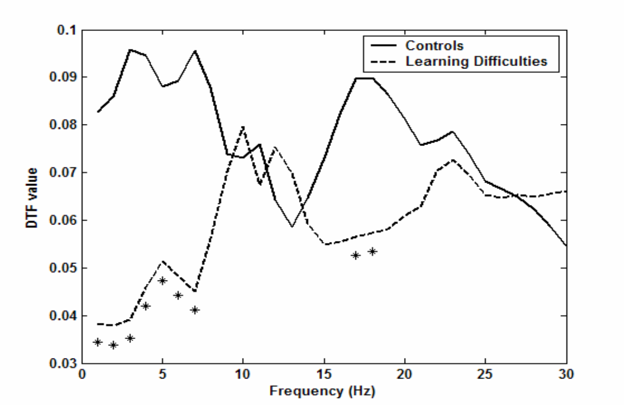
The variation of the mean DTF value of the 5000 bootstrap samples for the influence P4→C6 is shown in Figure 4b. The mean DTF value that corresponds to SLD subjects was found to be significantly lower for the δ and θ frequency bands. This finding indicates that the corresponding information flow seems to be weaker in the case of SLD subjects.

Discussion

The main purpose of this work was to study the EEG information flow between different brain areas in the case of SLD subjects and to compare the findings with healthy subjects. It was shown that there are differences between the two examined groups of children, in the way brain regions interact. These differences change depending on the frequency. What is important to note is that in each frequency band there are dominant channels which seem to disperse information to most of the other channels. These channels had also the highest DTF values, and this fact further enforces our



(a)



(b)

Figure 4. (a) Waveforms showing the upper and lower limits of the 95% confidence interval for the channel influence P4→C6 in the two groups of children (b) mean of the DTF value of the bootstrap samples for the two groups of children. Asterisks denote statistical significance at 0.05 level.

assumption. It is under future investigation if these dominant channels are also related with high brain activity in underlying neurons. It is important to note that the obtained findings appear to be in agreement with other electrophysiological studies providing evidence that the language and cognitive impairments seen in SLD subjects result from limitations in the speed with which information can be processed [14].

The proposed method can provide a quantitative means to assess the connectivity pattern of a subject with respect to the confidence limits of healthy subjects patterns. In a future work, signals from event related potentials can be also investigated. These signals are not stationary as rest state EEG, so Fourier transform cannot produce accurate results. Techniques such as Short Time Fourier Transform can be applied in short segments of signals where stationarity is satisfied.

Conclusions

This study demonstrated that the information flow patterns in multichannel EEG recordings are significantly different in SLD children as compared to healthy subjects, mainly in the δ and θ frequency bands. The application of the bootstrap method allowed the extraction of valuable information about the limits of the DTF values that correspond to healthy subjects and to SLD subjects.

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