ANALYSING COUPLING ARCHITECTURE IN THE CORTICAL EEG OF A PATIENT WITH UNILATERAL CEREBRAL PALSY

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ABSTRACT

The detection of coupling presence and direction between cortical areas from the EEG is a popular approach in neuroscience. Granger causality method is promising for this task, since it allows to operate with short time series and to detect nonlinear coupling or coupling between nonlinear systems.

In this study EEG multichannel data from adolescent children, suffering from unilateral cerebral palsy were investigated. Signals, obtained in rest and during motor activity of affected and less affected hand, were analysed. The changes in interhemispheric and intrahemispheric interactions were studied over time with an interval of two months. The obtained results of coupling were tested for significance using surrogate times series. In the present proceeding paper we report the data of one patient. The modified nonlinear Granger causality is indeed able to reveal couplings within the human brain.

Keywords: human EEGs, time series analysis, unilateral cerebral palsy, Granger causality

1. INTRODUCTION

The detection of coupling presence and coupling direction of the ongoing EEG derived from different cortical EEG electrodes is a popular approach in current neuroscience. In this study we apply a modified non-linear Granger causality approach to human EEG data. Data of adolescents with unilateral Cerebral Palsy has previously been recorded. Cerebral palsy (CP) describes a group of permanent disorders of movement and posture that are attributed to non-progressive disturbances that occurred in the developing fetal or infant brain. In unilateral CP predominantly one side of the body is affected, often with the upper extremity being more affected than the lower extremity due to early damage in the motor areas of the contralateral hemisphere.[1] In the current report multi-channel EEG-data from one patient suffering from unilateral CP was analysed.

The Granger causality approach[2] is a promising method for coupling detection when applied to biomedical data. It can operate with short time series,[3] detect non-linear coupling or coupling between non-linear systems[4] using different types of model[5] if these models are well suited.[6] Previously it was applied to different EEG-data. The comparison between different techniques of directed coupling detection was performed.[7,8] For instance, intracranial EEGs (local field potentials) from WAG/Rij rats were analysed with linear[9–11] and non-linear[12] Granger causality.

2. DATA

The data were derived from a 32-channel EEG recording with a sampling frequency of 1000 Hz. All experiment were approved by the Ethical Committee on Animal Experimentation of Radboud University Nijmegen (RU-DEC). Time series is 15000 points length were analysed (see fig. 1). Signals, obtained in rest and during motor activity of the affected and less-affected hand, were investigated during two recording sessions. Three samples of time series from each recording session were further analysed. Since the total number of channels was large

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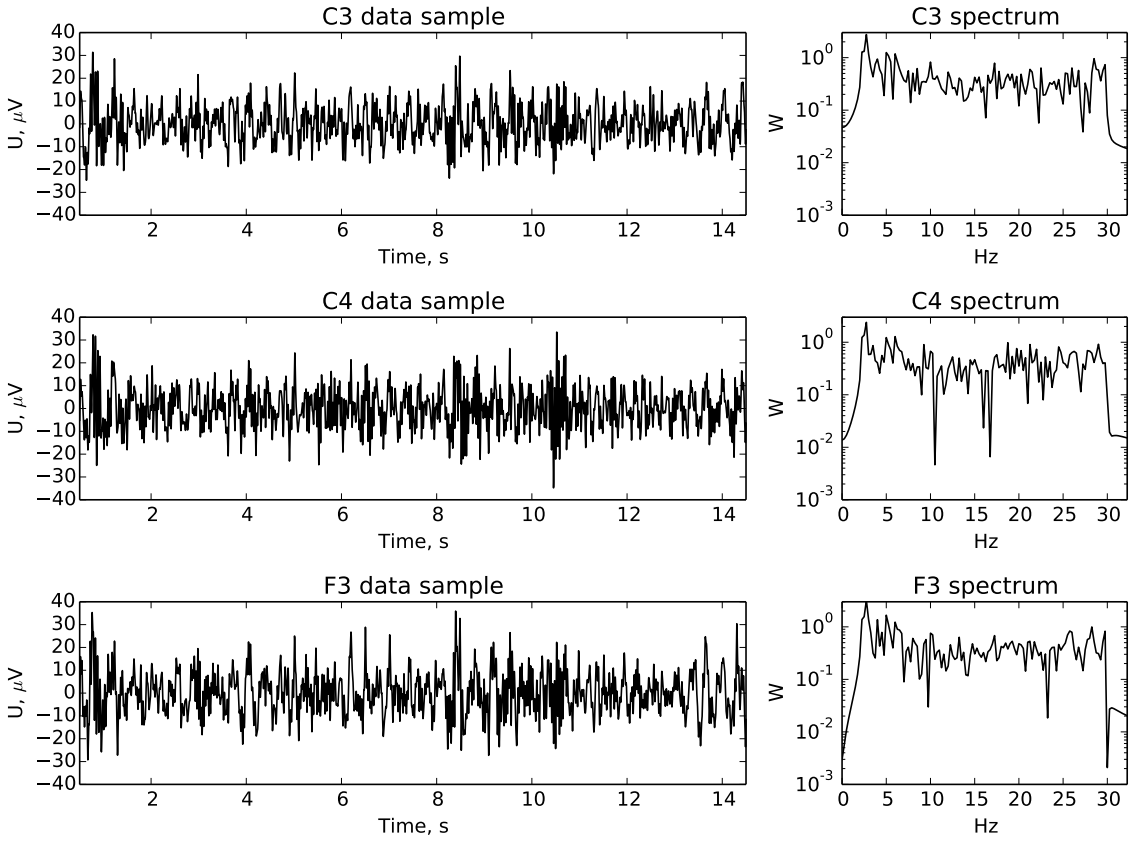

Figure 1. The sample of filtered times series data from EEGs channels: C3, C4, F3; and its power spectra from the recoding session with the active affected left hand.

and studying all possible combinations could be misleading and very time consuming, the coupling analysis was performed on a-priori selected channel pairs (see table 2).

First, time series from multi-channel EEG data had to be preprocessed. Second, moving average subtraction with 1 s window length was implemented in order to remove slow trends, which are the results of breathing, slow movements and other activities. Then a band-pass filter (2.2–30 Hz) was applied. Therefore the 50 Hz artefacts went away automatically.

Spectrum and autocorrelation function were plotted for all considered time series fragments. The analysis of spectrum showed the stable peak at approximately 10 Hz (high α band). For many channels the raise also was observed in β range near the 20 Hz. These findings were used in order to chose the method parameters.

3. METHOD

Let us remind the key point of Granger causality. Supposing that we have time series of two systems — a series $\{x_n\}_{n=1}^N$ from the system X and a series $\{y_n\}_{n=1}^N$ from the system Y, where $n = 1, 2, ..., N$ is discrete time, N is the series length. The task is to determine whether the system Y drives the system X or not.

First, an individual model (dynamical system) is constructed:

$$x'_{n+\tau} = f(x_n, x_{n-l}, \ldots, x_{n-(D_s-1)l}, \mathbf{c}^s), \tag{1}$$

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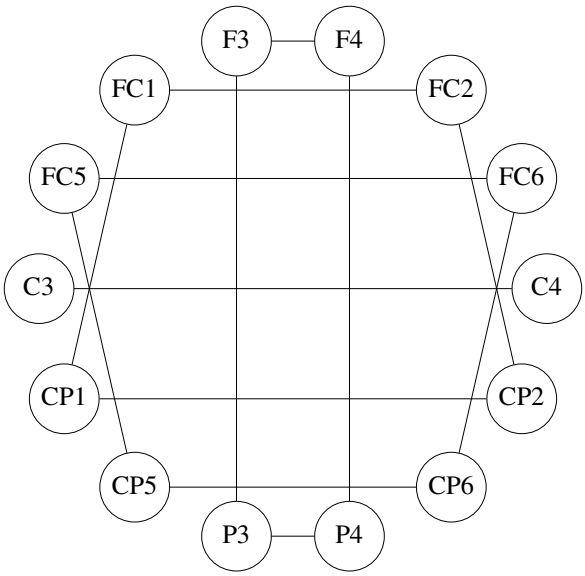

Figure 2. The investigated couplings between the EEGs channel.

where x'_n is a predicted value at the time moment n and it may differ from the measured value x_n, f is an approximating function (if it is non-linear, method is called a non-linear Granger causality), l — lag of the model, i. e. the number of discrete time points between the the two subsequent values from $\{x_n\}_{n=1}^N$, forming D_s-dimensional state vector of the model $\mathbf{x}_n = (x_n, x_{n-1}, ..., x_{n-(D_s-1)l}$, τ is a prediction time — the distance in time between the predicted point and the closest point forming the state vector, D_s is a dimension of the individual model (the number of points included into the state vector[13,14]), $\mathbf{c}^s$ is an unknown vector of coefficients which is chosen using least squares fit to minimise the standard error of approximation (1):

$$\varepsilon_s^2 = \frac{1}{N} \sum_{n=\tau+(D_s-1)l+1}^{N} (x'_n - x_n)^2 \tag{2}$$

Second, the joint model is constructed, in which D_a points from the series $\{y_n\}_{n=1}^N$ are used:

$$x''_{n+\tau} = g(x_n, x_{n-l}, \ldots, x_{n-(D_s-1)l}, y_n, y_{n-l}, \ldots, y_{n-(D_a-1)l}, \mathbf{c}^j), \tag{3}$$

where x''_n is a value predicted with the model, $\mathbf{c}^j$are the joint model coefficients. The standard prediction error of the joint model similarly to (2) has the form:

$$\varepsilon_j^2 = \frac{1}{N} \sum_{n=\tau+(\max(D_s,D_a)-1)l+1}^{N} (x''_n - x_n)^2 . \tag{4}$$

If $\varepsilon_j^2 < \varepsilon_S^2$, the system Y is considered to drive the system X (systems are coupled). *Prediction improvement* index is typically used as a measure of coupling:

$$PI = 1 - \frac{\varepsilon_j^2}{\varepsilon_S^2}. \tag{5}$$

If $PI = 0$ (considering the signal $\{y_n\}_{n=1}^N$ did not help in predicting $\{x_n\}_{n=1}^N$), it is considered that Y has no effect on X. If the $PI \to 1$ (considering the signal $\{y_n\}_{n=1}^N$ has significantly improved the prediction of $\{x_n\}_{n=1}^N$), it should be regarded as Y drives X.

Practice shows that the choice of the parameters of the described procedure (lag l, prediction time τ, dimensions D_s and D_a, type of nonlinear functions f and g) significantly determines the efficiency of the method. For example, the use of too small or too large τ may cause a large number of errors: positive conclusions about the coupling, that in fact does not exist.[15,16] Neglecting the nonlinearity in the modelling often leads to a situation, when really existing links are not detected.[4,17] The problem seems to be major since most coupling analysis techniques are very model-dependent.[18] The parameters for this investigation were chosen according to the paper: polinoms degree is equal 3, $D_s = 2$, $D_a = 1$, $l = 25$, $\tau = 25$.

In additional, obtained results were tested for significance using surrogate time series, which were build with randomisation phase Fourier transform method with p-value = 0.05.

4. RESULTS AND DISCUSSION

Applying this method to human EEG data revealed a number of significant couplings. The results of the methods application are shown in the fig. 3. Since analysis for each channel pair was performed on three samples of time series, the following notification was used: if significant coupling was observed in one of the time series this was plotted with grey arrows, if significant coupling was observed in two of the time series this was plotted with black dashed lines, and if significant coupling was observed in all three time series this was plotted with black solid. Only couplings significant on the level $\leqslant 0.5$ were plotted.

In order to make the presentation of coupling information more compact, the summary coupling coefficient was calculated for 4 different cases: for cross-hemispheric coupling in both directions: $C_{L\to R}$ (from left to right) and $C_{R\to L}$ (from right to left), and for intra-hemispheric coupling separately in the left C_{intraL} and right C_{intraR} hemisphere. These coefficients can be used to characterise the coupling asymmetry.

The maximal values of coupling coefficients in the network was found for "active affected left hand" condition as for intra-lateral as for cross-lateral coupling. I. e. the whole network becomes more involved when the patient starts to use the affected hand. This can be interpreted as a mechanism of plasticity in the brain. In contrast, the number of interactions for the "active non-affected right hand" condition is minimal. I. e. the activity of the non-affected hand can be performed mainly without involvement of the affected hemisphere.

Four "rest" conditions may be considered approximately similar with some variation in coupling. Most differences can be seen in $C_{R\to L}$, i. e. in the direction from normal to affected hemisphere.

Two different time moments demonstrate the similar results for the affected hand, but very different for the non-affected one, especially in the "rest" condition. This can be interpreted by the following hypothesis. When the affected hand is used, the whole brain takes part in this process due to plasticity mechanism. This mechanism may involve different parts of the brain in order to compensate different activities of the affected part. when the non-affected hand is used, the plasticity mechanism is not necessary. For the time moment "T1" (before the treatment) larger involvement of the brain is the result of increased interactions due to non stable substitution of activities which corresponded previously to the damaged part. But after the treatment, the replacement becomes more stable, and therefore the overall brain interaction decreased.

In summary, the number of significant couplings are different for the rest and active condition of the affected left hand and less-affected right hand. Also, the number of significant couplings are different between the two time points. We have to analyse the existing data of more adolescents in order to determine whether these differences are significant. However, this proceeding paper clearly shows that this modified non-linear Granger causality is able to reveal couplings within the human brain.

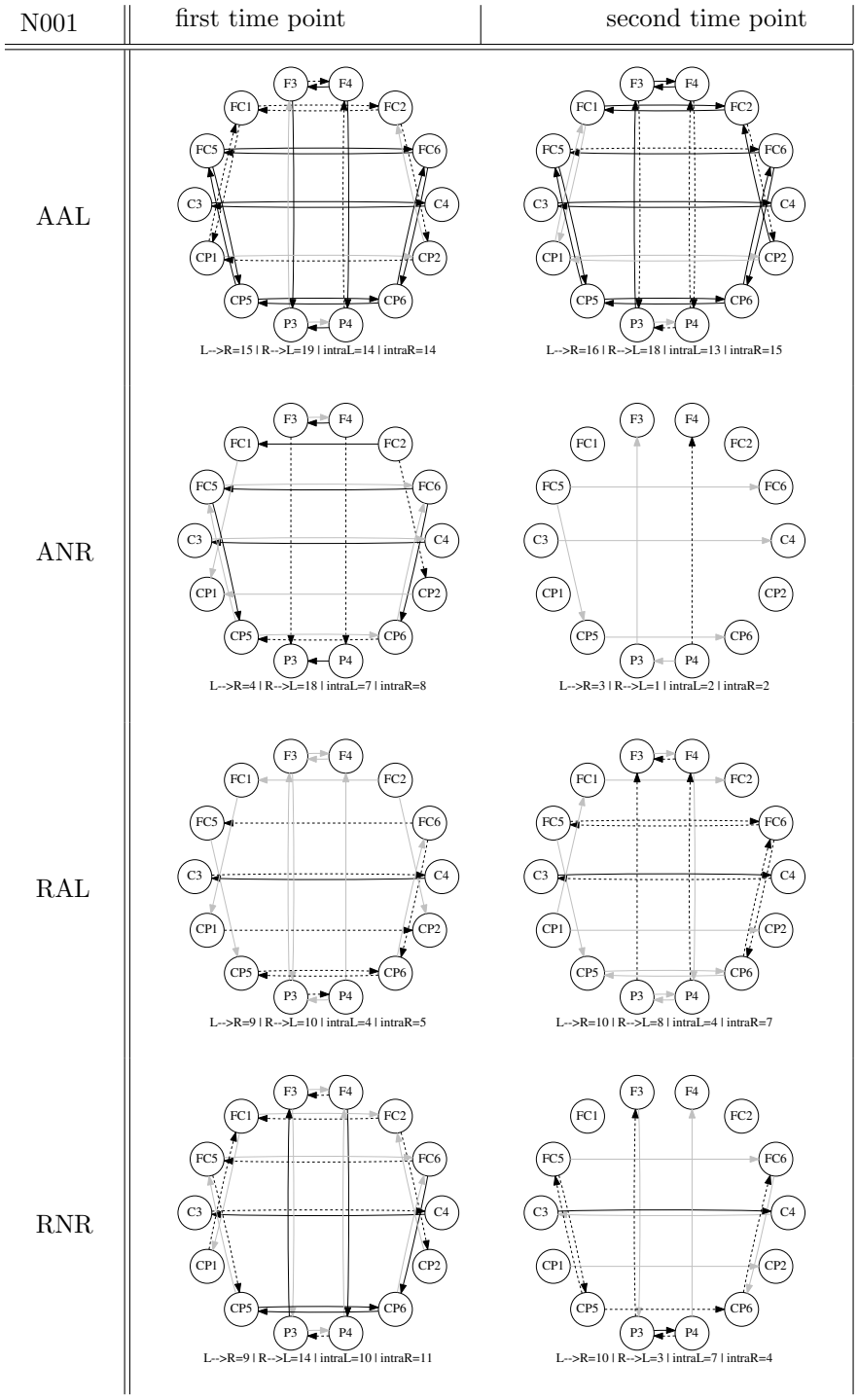

Figure 3. Coupling Architecture shown for the 001 patient. AAL - interaction from active affected left hand; ANR - from active lessaffected right hand; RAL - from rest affected left hand; RNR - from rest less-affected right hand.

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