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Estimation of time-varying causal connectivity on EEG signals with the use of adaptive autoregressive parameters

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Abstract— **In this paper, we address the problem of time-varying causal connectivity estimators on Electro-encephalographic (EEG) signals by means of Directed Transfer Function (DTF). The DTF method reveals causal information flows between brain areas, while direct DTF (dDTF) is able to distinguish and estimate only direct flows. Since neuro-physiological signals such as EEG and event related potentials (ERP) can be nonstationary, their temporal dynamics cannot be satisfactorily represented. Time-varying dDTF can be estimated using Kalman Filter for adaptive calculation of multivariate autoregressive coefficients. This approach can reveal transient causal relations and model time-dependent flow patterns. This approach was applied to simulated signals and the results indicated that time-varying dDTF can provide efficient estimates of connectivity patterns.**

I. Introduction

An issue of great scientific interest that remains still open in the field of neurosciences is the way different brain areas communicate with each other. Advances in this area have been helped by the evolution of non-invasive brain imaging techniques (such as EEG/ERP, MEG, fMRI). These techniques provide useful information about the functional brain activation and the way human brain responds during different cognitive tasks or pathological states with continuously improving accuracy.

In this perspective, coherence and synchronization analysis are widely used approaches to detect cooperative neuronal activity in electrophysiological signals. Coherence can be considered as the correlation in the frequency domain between two channels. Various studies have been proposed in order to estimate functional synchronization and connectivity on EEG signals. Linear methods usually make use of measures such as cross-correlation coefficient [1] or coherence [2][3]. On the other hand, non linear methods assess the existence of nonlinear interdependences between signals. There are various measures such nonlinear correlation coefficient [4], mutual information [5], generalized synchronization [6]. Such measures are, in principle, able to indicate relation between two signals and also the delay in coupling which is a very useful parameter.

But a question of great interest is not only if there is relation between brain regions but also whether there exists causal relation. So, measures are needed to be established to reveal this directionality and its strength. The traditional coherence analysis has not a directional nature, i.e. it just examines whether a link exists between two structures, by describing instances when they are in synchronous activity, and it does not provide directly the direction of the information flow.

A step in the coherence analysis was given by the introduction of the Directed Coherence, to examine the relation between a pair of data channels described by means of a bivariate autoregressive process [7]. The pair-wise analysis used is defined for only two signals each time and does not account for all the covariance structure information from a multivariate data set [8]. This can lead to erroneous and deceptive results [9].

In order to avoid such problems a multivariate model is more appropriate for the analysis. The Directed Transfer Function (DTF), introduced by Kaminski and Blinowska, is a multivariate approach for the estimation of the intensity of activity flow among brain structures [10]. It relies on the concept of Granger Causality between time series [11] and follows the spectral properties of the initial signals.

DTF was modified to direct DTF (dDTF) [12] so as to distinguish between direct and indirect information flows eliminating the second ones. The DTF estimates are obtained by fitting on a multivariate autoregressive (MVAR) model. MVAR models were among the first methods to investigate signals' spectral characteristics because they are well understood, easily solved by means of linear equations and yield enhanced power spectrum density estimates.

However, the traditional estimation of MVAR model requires stationarity conditions for the signals because fitting the entire time series on a MVAR model may hide dynamic phenomena of transient information flows mainly in non-stationary signals like Event Related Potentials (ERPs). Classical estimation of DTF can not give a complete picture of brain dynamics since these signals' spectra are changing with time. A development that overcomes this problem is the short-time DTF (SDTF) [13], which uses time windows where the signals can be considered as stationary and averages the correlation matrices of multiple trials of the experiment in the calculation of MVAR coefficients.

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The purpose of the present paper is to obtain DTF estimates that characterize the temporal relationship between time series with an adaptive manner without the need to define time windows as SDTF does. This approach is based on an adaptive autoregressive model (AAR) [14][15] or a time-varying multivariate model (TVMVAR) for the case of multivariate analysis. The TVMVAR coefficients can be estimated by the Kalman filter which is an optimal estimator in the mean-square sense. This model produces enhanced resolution in both frequency and time domain, which is of great importance especially in cases of non stationary signals like ERPs.

II. Methods

A. *Time – Varying Multivariate Model*

The Time-Varying Multivariate Model (TVMVAR) has the underlying assumption that the data comes from an MVAR process with time-varying coefficients. The evolution of TVMVAR coefficients along time can be estimated by the use of the Kalman filter algorithm.

The Kalman filter is a real-time processing algorithm in which the state estimates is updated when a new observation is available. It is the best sequential estimator if the Gaussian assumption is valid and it is the best linear estimator whatever the distributions are [16]. The Kalman filtering problem is to find the minimum mean square estimator for state given the observations. The state noise and the observation noise covariances determine the adaptation ability of the Kalman filter through the Kalman gain. Usually their values are set to identity but as the observation noise variance has no relation to the true error variance this would lead to meaningless state estimates [17]. So the observation noise covariance is iteratively estimated at every step of the Kalman filter with the help of an update coefficient c. The update coefficient c relates to the time resolution of an adaptive autoregressive model. However, the variance of the state estimates is inversely proportional to the value of c, so c should be specified in such a way that a desired balance between the filter adaptation and estimate variance is obtained [17].

The Directed Transfer Function (DTF) is a multivariate method that reveals directed information flow among signals. It measures both direct and indirect causal relationships between channels. Nonzero DTF values between two signals do not necessarily come from direct causal influences. However, when various coupled structures communicate with each other along various pathways, the identification of direct activity flow is important.

Using a different normalization procedure (the denominator of the expression calculating DTF does not change with frequency) the full frequency Directed Transfer Function (ffDTF) is calculated. ffDTF shows peaks mostly for frequencies represented in coherences (when there is a net flow) [12]. In addition, partial coherence is a measure that calculates coherence between two signals, removing the (partial) components common to any other signal combination. The multiplication of the ffDTF and partial coherence results dDTF which is a measure that estimates direct causal relations between signals. The dDTF function takes values from 0 to 1. Zero indicates a lack of causal relationship between signals.

In this study, dDTF was calculated in terms of time-varying multivariate model using Kalman filtering. This perspective enables a time-frequency approach for dDTF estimations which is of great importance especially when the signals are nonstationary. In this way, transient information flows among brain regions can be revealed. With $dDTF_{ij}(t,f)>0$ we indicate direct flow of activity from channel j to channel i at frequency f and at time point t.

III. Results

A. *Simulation Study*

In this section, we study the effectiveness of the algorithm on both simulated and real EEG/ERP signals.

We study the time varying DTF with respect to its ability to accurately represent information flow between signals on both time and frequency domain. Also the ability of our model to quickly follow rapid temporal changes is examined. We consider the following signal

$$x(n) = \begin{cases} 10\cos(2\pi 10n/1000), 1 \le n < 400\, m\sec \\ 10\cos(2\pi 30n/1000), 401 \le n < 700\, m\sec \\ 10\cos(2\pi 20n/1000), 701 \le n < 1000\, m\sec \end{cases} \quad (1)$$

consisting of three different frequencies in three time intervals with jump spectral discontinuity. This signal and its time-frequency properties are shown in Fig. 1.

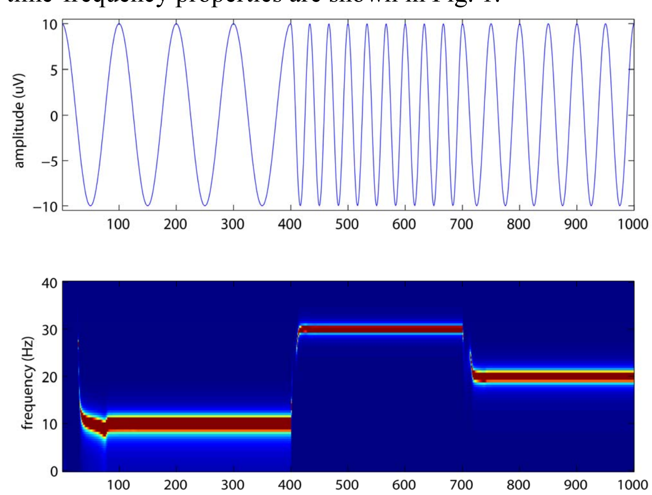
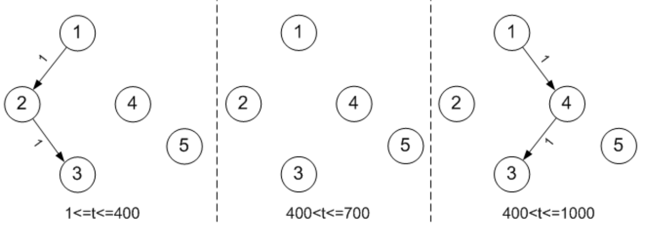


Fig. 1. Simulated signal consisting of three frequencies in three different time intervals and its spectrogram.

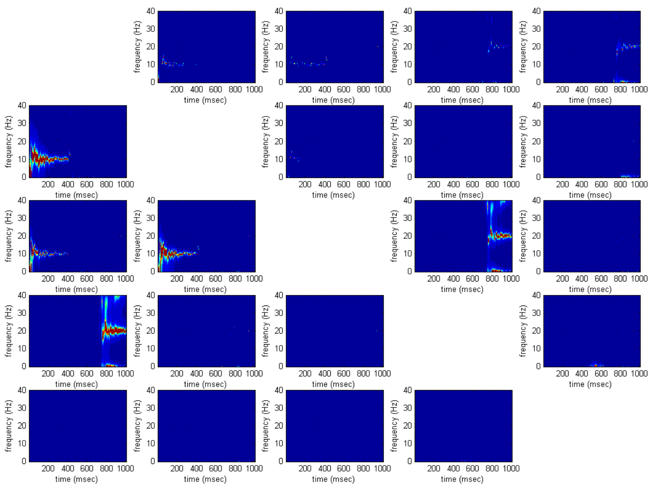
In simulating the connectivity pattern of Fig. 2(a), the signal of Fig.1 is considered to be the signal in channel 1. The other channels are produced from this signal by applying successive 10 msec delays in each step and the time series is transmitted from one channel to another with a specific weight shown with a number on the corresponding arrow. When there is no arrow, no information flow takes place. A white Gaussian noise with amplitude equal to 10%

of the initial signals' amplitude was added to all signals.

In the case under study, the signals were simulated in such a way that the flows 1→2 and 2→3 of weight 1 exist during the first 400 msec. From 400 msec to 700 msec, no flow (no causal relations) between channels is present. During the next 300 msec, flows 1→4 and 4→3 of weight 1 appear. The signal in channel 1 is identical with that of Fig. 1.



(a)



(b)

Fig. 2. (a) Scheme of simulated connectivity. (b) Time-frequency representations of dDTF. Horizontal axis: time (0÷1000msec range). Vertical axis: frequency (0÷40Hz range). Red are values near 1 whereas blue are values near 0. In this map matrix, columns denote the channels from which information flow starts and rows denote where it ends.

As shown in Fig. 2(b) the connectivity pattern is very well described by the time-frequency maps. For the first 400 msec there is activity (red color) in $dDTF_{21}$ (second row, first column) and $dDTF_{32}$, for time period 400-700msec no activity is observed (only blue color) and for time period (700-1000msec) there is activity in $dDTF_{41}$ and $dDTF_{34}$. It is worthy to note that activity is observed in the proper simulated frequency. This property is quite informative especially when the connectivity path between brain regions changes over time.

B. EEG/ERP signals during auditory Wechsler Test

In this section the dDTF function is applied to real EEG/ERP signals induced by the auditory Wechsler test [18]. For each trial of the experiment, rest EEG signal is recorded for 100 msec. A single sound tone of either high (3000 Hz) or low frequency (500 Hz) is presented to the subjects through earphones, followed by a set of numbers which have to be memorized. At the start of this tone, ERP signal is recorded for 900msec. At the end of the number sequence presentation, the same auditory tone is repeated. The EEG/ERP signals are recorded at 11 electrodes (F3, C5, C3, F4, C6, C4, P4, P3, Pz, Cz, Fz) according to the 10–20 international system, referred to both earlobes. Eye movements are recorded through electro-oculogram (EOG) and recordings with EOG higher than 75 μV are rejected. A sampling frequency of 1 kHz is used. The total task consisted of 52 trials and it lasted about 45 min. For more details about experiment procedure, see [19].

Firstly, the baseline of the signals is determined by the grand average of the rest EEG (before stimulus) for each channel separately. As noise (signals that are not EEG/ERP) is considered to be random process with zero mean value, the EEG/ERP signal's SNR is improved by averaging across the 52 trials of the experiment. The determination of rest EEG baseline and the averaging process tends to decrease the influence of random activity (i.e., the background or non-event related EEG) while maintaining the consistent event-related activity. The signal of a control subject for the electrode Cz is shown in Fig. 3.

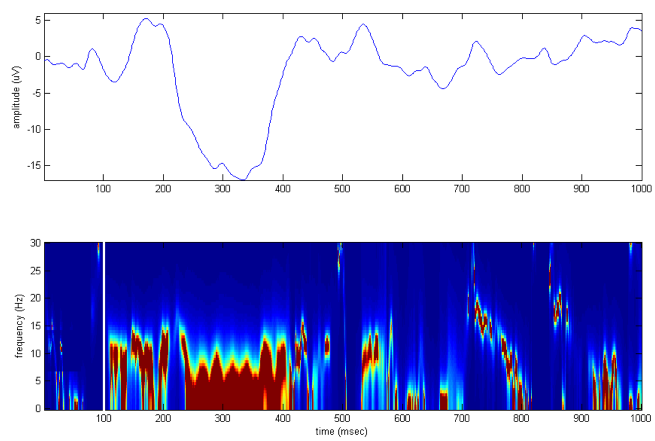


Fig. 3. (a) EEG/ERP signal for a control subject at electrode Cz. (b) Spectrogram of the EEG/ERP signal where the horizontal axis is time (in msec) and the vertical is frequency (in Hz). The white vertical line at 100msec is the stimulus onset.

The stimulus onset takes place at 100 msec. Before this time point, rest EEG is recorded and after this time point someone can see the existence of ERP signal. We used this signal in order to evaluate the effectiveness of dDTF in representing activity flows in a complex signal like ERP in the time-frequency plane. To this end, the propagation scheme of Fig. 4(a) is created.

In the results of Fig. 4(b) it can be observed that activity flows appear to be in accordance with the spectrogram of the signals from which it derived (Fig. 3(b)). The timing of dDTF is also consistent with the expected timing of ERP activations during the auditory test. There is no information flow 2→1 as it is well represented by $dDTF_{12}$. It is known that ERP signals present characteristic peaks that can be identified by the polarity and the latency after the stimulus onset (P50, N100, P200, P300, P600, P or N is for positive or negative peak and numbers is the time in msec).

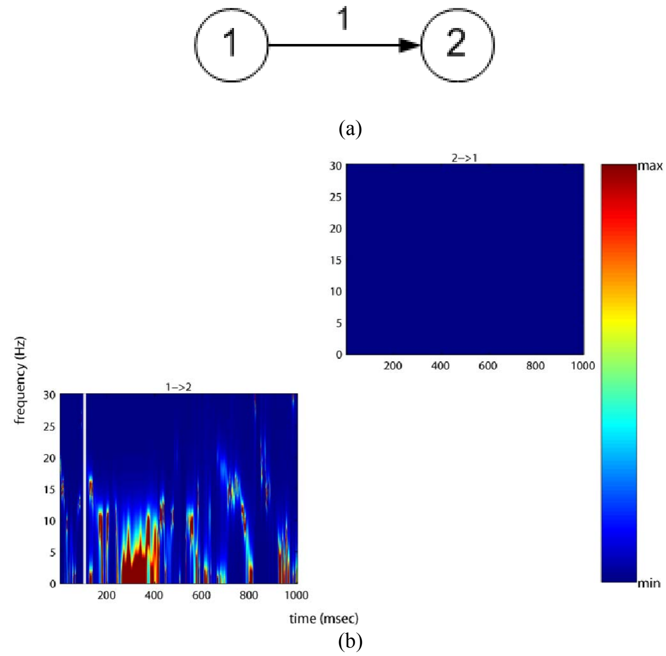


Fig. 4. (a) Scheme of activity flows between channels 1 and 2. (b) Time-frequency representations of dDTF. Horizontal axis: time (0÷1000msec range). Vertical axis: frequency (0÷30Hz range). Colormap is blue for the smaller values and red for the bigger values in arbitrary units.

Some of them can be identified such as the peak between 200 and 400 msec or the small peak between 500 and 600 msec.

IV. Discussion

In this study, we propose the dDTF technique based on a time-varying multivariate autoregressive method through adaptive Kalman Filter, which is quite robust in the analysis of the dynamics of a system. Kalman filter is considered a versatile tool in the analysis of multiple time-series being an optimal adaptive estimator in the mean-square sense and ensuring high performance as regards goodness-of-fit. It concerns a dynamic procedure that does not need to define time windows or the signals to be stationary. The information needed for the model's states is obtained by the previous observations of the signals. The time-varying multivariate model estimates are updated when a new observation takes place so this tool would be ideal for online analysis.

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