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Methods for localization of time-frequency specific activity and estimation of information transfer in brain.

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Abstract. The methods of signal analysis in time-frequency space are described. The method of adaptive approximations by matching pursuit decomposes the signal into waveforms characterized by: amplitude, frequency, time occurrence and time span. High resolution time-frequency distributions can be constructed and at the same time parametric description of the signal structures allows for extraction from the data the phenomena of concrete physiological meaning e.g.: sleep spindles, slow waves, epileptic spikes, evoked potentials, etc. These data structures can be used as the input values for inverse solutions. The Directed Transfer Function allows for determination of causal relations between channels of multivariate process. The fully multivariate treatment of the signals (contrary to bivariate approach) allows for the determination of transmission patterns of the brain activity. Short-time Directed Transfer Function makes possible to determine the propagation of brain signals as a function of time and frequency. The applications of both methods to the evaluation of EEG connected with motor and cognitive functions are described.

Keywords: multichannel autoregressive model, Directed Transfer Function, Granger causality, information transfer in brain, adaptive approximations, matching pursuit, time-frequency distributions, voluntary movements, Continuous Attention Test.

1.Introduction.

Mechanisms governing transitions between neural pools during information processing are reflected in the oscillatory activity of brain, which can be recorded as Local Field Potentials (LFP), Electrocorticograms (ECoG) or electroencephalograms (EEG). In the last years brain imaging techniques, especially such as PET and fMRI provided the information on the localization of the active sites in brain under different experimental conditions. These techniques are characterized by a high spatial resolution, however they have two limitations. First is connected with low (in comparison to EEG) time resolution, second concerns the lack of spectral information. In the information processing by brain, different rhythms have their specific role and quite often during certain task the decrease of one rhythm is connected with the increase of activity in another frequency band. As an example may serve the motor action when the decrease in the alpha and beta band is accompanied by the increase of gamma activity [Pfurtscheller and Lopez da Silva, 1999; Ginter et al., 2005].

A problem that can be hardly solved by the imaging techniques is the estimate of the dynamic communication between brain structures in a short time scale. The solution may be provided by means of EEG analysis under the condition that proper estimators will be used.

In this paper the methods will be described which allow for the time-frequency analysis of EEG signals. The method that provides highest time-frequency resolution among currently available methods is matching pursuit (MP) approach based on adaptive approximations. It describes signal structures in terms of parameters of a clear meaning: frequency, amplitude, time occurrence and time span. This kind of parameterization allows for solving the inverse problem for specific phenomenon manifested in EEG as particular signal structure e.g. sleep spindle or event related potential, since the algorithm makes possible to extract given component from the overall background signal.

Adaptive approximations by Matching Pursuit method was introduced by [Mallat and Zhang, 1993]. The first application to the physiological signals concerned EEG sleep: [Blinowska and Durka, 1994]. The original algorithm was improved by the introduction of stochastic dictionaries [Durka et al. 2001a] removing the bias due to the dyadic structure. MP has been used for sleep studies [Zygierewicz et al.,1999], high resolution study of Event Related Desynchronisation/Synchronisation (ERD/ERS) phenomena [Durka et al., 2001b] and in its multichannel form to the solution of inverse problem [Durka et al., 2005a].

The method that is based on the phase relations between signals and describes their multivariate structure is Directed Transfer Function (DTF) introduced by [Kaminski and Blinowska, 1991]. By means of DTF the frequency dependent pattern of transmissions between brain structures may be found. With the aim of distinguishing direct from indirect flows, an aspect important in case of implanted electrodes, Direct Directed Transfer Function (dDTF) was devised [Korzeniewska et al., 2003]. A version of DTF based on ensemble averaging –Short time Directed Transfer Function (SDTF) allows for description of the EEG propagation as a function of frequency and time providing a dynamic pattern of the activity transmission.

Below the basic formalism of MP and DTF methods will be described and some applications will be presented. Comparison with other methods will be made, discussion concerning advantages and drawbacks of the methods will follow.

2. Matching Pursuit Method.

The MP method relies on adaptive decomposition of the signal into waveforms from a large and redundant dictionary of functions. A dictionary of basic waveforms can be generated e.g. by scaling, translating and, unlike in wavelet transform (WT), *modulating* window function *g(t)*:

$$g_I(t) = \frac{1}{\sqrt{s}} g\left(\frac{t-u}{s}\right) e^{i\xi t} \tag{1}$$

$s>0$ - scale, ξ - frequency modulation, u - translation.
Index $I = (\xi, s, u)$ describes the set of parameters. The window function $g(t)$ is usually even and its energy in time domain is mostly concentrated around u with variance proportional to s. In frequency domain, the energy is mostly concentrated around ξ with a spread proportional to $1/s$. The minimum of time-frequency variance is obtained when $g(t)$ is Gaussian. The dictionaries of windowed Fourier transform and wavelet transform can be derived as subsets of this dictionary, defined by certain restrictions on the choice of parameters. In case of the windowed Fourier transform, the scale s is constant - equal to the window length - and the parameters ξ and u are uniformly sampled. In the case of WT the frequency modulation is limited by the restriction on the frequency parameter $\xi = \xi_0/s$, $\xi_0 = const$.

Finding an optimal approximation of signal by functions from such a large family is a NP-hard problem (computationally intractable). Therefore, a suboptimal iterative procedure is applied. In the first step of the iterative procedure we choose the vector g_{I_0} which gives the largest product with the signal $f(t)$:

$$f = \langle f, g_{Io} \rangle g_{Io} + R^1 f \tag{2}$$

Then the residual vector R^1 obtained after approximating f in the direction g_{I_0} is decomposed in a similar way. The iterative procedure is repeated on the following obtained residues:

$$R^n f = \langle R^n f, g_{I_n} \rangle g_{I_n} + R^{n+1} f \tag{3}$$

In this way, the signal f is decomposed into a sum of time-frequency waveforms, chosen to match optimally the signal's residues:

$$f = \sum_{n=0}^{m} \langle R^n f, g_{I_n} \rangle g_{I_n} + R^{n+1} f \tag{4}$$

The point at which we should stop the iterations, or, equivalently, the number of waveforms in expansion (4), can be chosen individually for each signal based upon mathematical criteria or set arbitrary e.g. as a percentage of energy accounted for. It was proven (Mallat and Zhang, 1993) that the procedure converges to f. Energy of representation is conserved:

$$\|f\|^2 = \sum_{n=0}^{\infty} \left|\left\langle R^{nf}, g_{I_n} \right\rangle\right|^2 \tag{5}$$

The highest time-frequency resolution is obtained for functions g_I from Gabor family. In our studies, we used Gabor functions, sinusoids and delta functions. An example of the iterative decomposition procedure is shown in Fig.1.

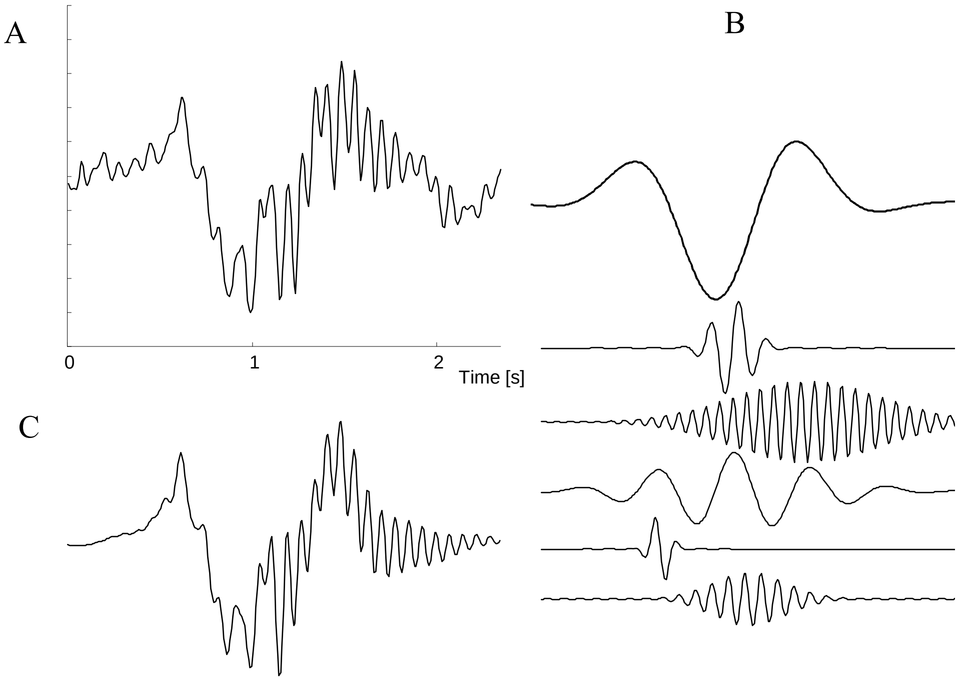

Fig. 1. Decomposition of EEG signal (A) into basic waveforms from Gabor dictionary. At the right (B) the components of the signal (in order decreasing with energy) found by the MP algorithm. At the bottom left (C) the signal reconstructed from the waveforms shown on the right of the picture.

One of the problems encountered in the procedure of the adaptive approximations is sampling of the time-frequency space in respect of fitting atom's positions. In the original algorithm (Mallat and Zhang, 1993) the dyadic sampling was applied, therefore some positions of atoms were privileged. We observed this effect, for averaged distributions of atom's parameters and on time-frequency plots. In order to avoid the effects of dictionary structure a new algorithm based on stochastic dictionaries was introduced (Durka et al. 2001a).

We can visualize the results of MP decomposition in time-frequency plane by adding the Wigner distributions of each of the selected waveforms.

Calculating the Wigner distribution from the whole decomposition, we get:

$$W[f,f](t,\omega) = \sum_{n=0}^{\infty} \left|\left\langle R^n f, g_{I_n} \right\rangle\right|^2 W\left[g_{I_n}, g_{I_n}\right](t,\omega) + \\ \sum_{n=0}^{\infty} \sum_{m=0, m\neq n}^{\infty} \left\langle R^n f, g_{I_n} \right\rangle \overline{\left\langle R^m f, g_{I_m} \right\rangle} W\left[g_{I_n}, g_{I_m}\right](t,\omega) \tag{6}$$

where the double sum in eq. 6, containing cross distributions of different waveforms, corresponds to the cross terms generally present in Wigner distribution. These terms one usually tries to remove in order to obtain a clear picture of the energy distribution in the time-frequency plane. Removing these terms from eq. 6 is straightforward - we keep only the first sum. The energy density in time-frequency plane of signal's representation obtained by means of MP is given by the expression *Ef(t,ω)*:

$$Ef(t,\omega)=\sum_{n=0}^{\infty}\left|\left\langle R^n f, g_{I_n}\right\rangle\right|^2 W\left[g_{I_n}, g_{I_n}\right](t,\omega) \tag{7}$$

The distribution conserves the signal energy in the time-frequency space

$$\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} E\ f(\ t,\omega\ )\ dt\ dw=\|f\|^2 \tag{8}$$

This justifies the interpretation of *Ef(t,ω)* as the energy density of signal *f(t)* in the time-frequency plane.

3. Application of MP method.

The comparisons of time-frequency distributions obtained by different methods of signal analysis: windowed Fourier Transform, wavelets, Choi-Williams distribution and MP can be found in: [Blinowska et al., 2004a and Jedrzejczak et al., 2004], where the superior time-frequency resolution of MP was demonstrated. A good illustration of the performance of MP is the study of sleep EEG, since in this case EEG trace is composed of signal structures with different time-frequency characteristics - transients as well as periodic components. The time-frequency distribution of EEG sleep stage 2 is shown in Fig. 2. Characteristic structures of the EEG signal: K complexes in the low frequency band, sleep spindles in the frequency range 11÷15 Hz are easily distinguished in the background of rhythmic activity.

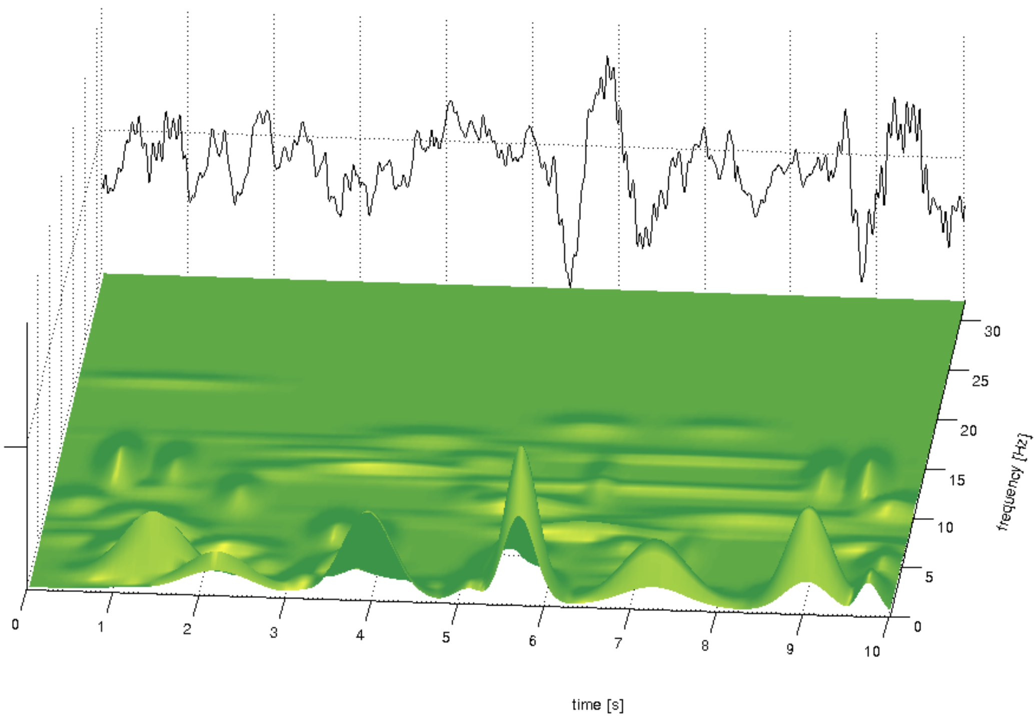

Fig. 2. Energy density in time-frequency coordinates (Wigner maps) obtained from MP decomposition of EEG, sleep stage2. Above EEG signal is shown.

The parametric description of the signal is very convenient for the further statistical analysis and makes possible construction of different kinds of distributions. By setting appropriate constraints on waveforms extracted from a signal, we can choose desired structures and inspect their time-frequency characteristics [Zygierewicz et al., 1999; Durka et al., 2005a].

The example of the application of MP algorithm to the high-resolution study of EEG activity during finger movement and its imagination is shown in Fig. 3. Several components in alpha and beta bands can be distinguished. One can observe high similarity of time-frequency maps for both tasks, however in case of imagination the beta activity is more pronounced, as might have been expected. The methods for estimation of statistical significance of time-frequency-energy density distributions (obtained by MP or spectrograms) of ERD/ERS (event related desynchronisation/synchronisation) including choice of resampling statistics and correction for multiplicity (false discovery rate) was elaborated in [Durka et al., 2004].

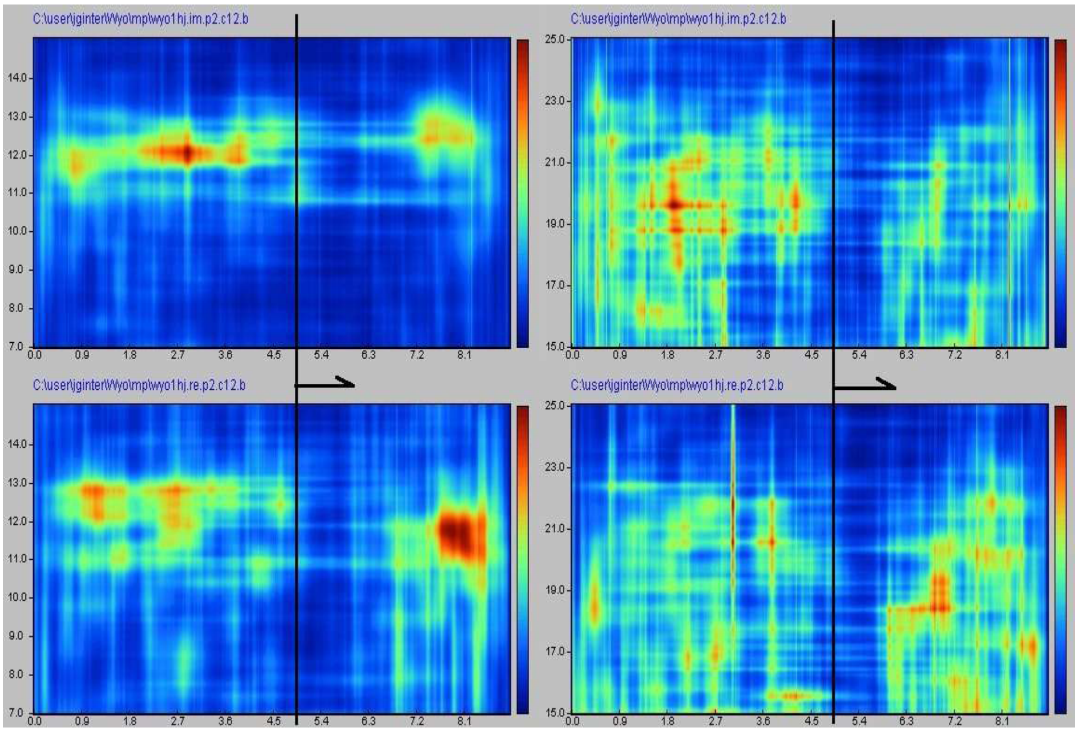

Fig. 3. Energy density distributions in μ (left) and β (right) EEG bands (electrode C1) for the right finger movement (bottom) and its imagination (top). Horizontal scale - time in seconds, vertical scale-frequency in Hz. The black mark indicates the time epoch during which the cue (arrow) indicating left or right finger movement /imagination was displayed.

High resolution of MP allowed for elucidation of the role of different closely spaced rhythms in the voluntary movement experiments Durka et al. 2001b, Ginter Jr. et al. 2001. Other applications of MP algorithm concerned: event related responses to weak vibrational stimuli [Zygierewicz et al. 1998], investigation of the evolution of epileptic seizure [Franaszczuk et al. 1998], analysis of otoelectric emissions [Jedrzejczak et al. 2004]. In the application to the epileptic EEG matching pursuit allowed for analysis of entire seizures without requiring segmentation or restrictions to stationary epochs. This made possible clear distinction of the periods of different dynamics during seizure development.

MP method offers a new approach for source localization of single structures with definite spatial-time-frequency properties. Inverse problem solutions have been mostly applied to instantaneous data (i.e. time points of multichannel EEG trace). An alternative approach, also used as an input to inverse solutions - spectral integrals, contains activity of different origins. MP allows for extraction of particular structure from the background of other activities. As a first step, EEG recordings are decomposed into sums of waveforms by the Multichannel Maching Pursuit (MMP) algorithm, which is a generalization of the matching pursuit for the multidimensional data. The second step consists of using topographic signatures of waveforms of interest as input for obtaining 3D localization of cerebral sources.

The method was applied to the localization of the sleep spindles. Single sleep spindles features (MP parameters) extracted by MMP from multichannel EEG data served as an input to the LORETA (Low Resolution Electromagnetic Tomography). The results of the study showed that low frequency spindles come from frontal and high frequency spindles from more posterior areas of brain. In Fig. 4 the localizations obtained for two spindles of different frequencies are shown. The localizations obtained for single structures were coherent with the ones obtained by averaging the results coming from 20 overnight EEG recordings [Durka et al., 2005b]. The above study showed that application of selective and high-resolution estimates of EEG activity significantly improves the robustness of inverse solutions and allows for a repeatable localization of single structures, based upon their time-frequency signatures. Another application of the above method concerned localization of the epileptic foci [Matysiak et al., 2005]. The MMP is by no means limited to particular method of solving inverse problem; any method of the solution may be used together with multichannel matching pursuit.

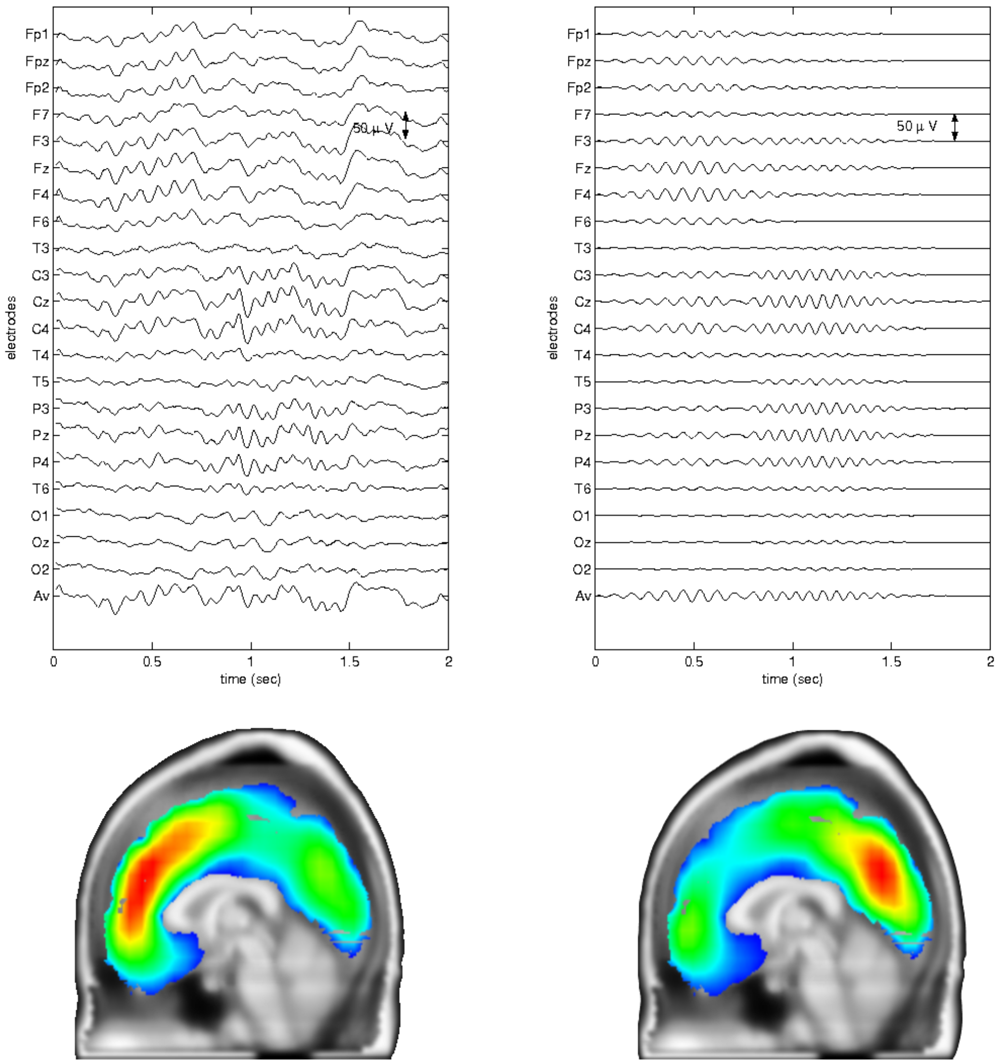

Fig.4. *Inverse problem solution for sleep spindles by means of MP and LORETA. Upper left – EEG signal, upper right sleep spindles extracted from EEG by means of MP. Bottom left - localization of source obtained for low frequency spindle; bottom right - localization of source for high frequency spindle. (The localization of sources obtained as averages for spindles from 20 overnight EEG recordings coincide very well with the results for single spindles).*

4. Multivariate AR model and Directed Transfer Function.

The SDTF method is based on a multivariate autoregressive model (MVAR) fitted to the EEG signal. For a k-channel signal a vector of k EEG values at every time point t can be represented as $X(t)=(X_1(t), X_2(t), ..., X_k(t))$. The MVAR model can be expressed as:

$$X(t) = \sum_{i=1}^{p} A(i)X(t-i) + E(t) \tag{9}$$

where $\mathbf{X}(t)$ is the data vector in the time t, $\mathbf{E}(t)$ is the vector of white noise values, $\mathbf{A}(i)$ are the model coefficients and p is the model order. After transforming the model equation to a frequency domain we get:

$$X(f) = A^{-1}(f)E(f) = H(f)E(f) \tag{10}$$

The $\mathbf{H}(f)$ matrix is called a transfer matrix of the system. $\mathbf{H}(f)$ is asymmetric and contains information about the phase and frequency dependencies between signals.
Directed Transfer Function (DTF) which describes causal influence of channel j on channel i at frequency f [Kaminski and Blinowska, 1991] is defined as:

$$\gamma_{ij}^2(f) = \frac{\left|H_{ij}(f)\right|^2}{\sum_{m=1}^{k}\left|H_{im}(f)\right|^2} \tag{11}$$

The above equation defines a normalized version of DTF, which takes values from 0 to 1 producing a ratio between the inflow from channel j to channel i to all the inflows to channel i. Value of DTF shows whether the signal component of given frequency in channel i is shifted in time in respect to signal component of the same frequency in channel j. The estimate shows only the direction, not the value of the delay. However this information is unambiguous, contrary to Fourier estimate, which gives phase modulo 2π, so the direction of the transmission cannot be determined.

Sometimes it is easier to abandon the normalization property and use values of elements of transfer matrix which are related to causal connection strength. The non-normalized DTF can be defined as:

$$\theta_{ji}^2(f) = |H_{ji}(f)|^2 \tag{12}$$

It has been shown that DTF function defined above may be considered as a multivariate extension of Granger causality measure [Kamiński et al., 2001]. In a strict sense it is equivalent to Granger causality in case of two channels system, since Granger causality was defined for two channels only [Granger 1969]. In both approaches the variance in one channel is explained using past samples from another channel of the set. Namely: if a series $X_2(t)$ contains information in past terms that helps in the prediction of $X_1(t)$ and this information is contained in no other series used in the predictor, then $X_2(t)$ is said to cause $X_1(t)$. The problem of bivariate versus multivariate measures of causality will be discussed below.

Transfer function (and hence DTF) is estimated by means of the coefficients of the model (eq. 10). There are several methods described in the literature to estimate the model coefficients $\mathbf{A}(i)$ e.g.: [Marple 1987]. As a first step we must calculate the correlation matrix $\mathbf{R}(t)$. Its elements are defined as:

$$R_{ij}(s) = \frac{1}{n-|s|}\sum_{t=1}^{n-|s|} X_i(t)X_j(t-s) \tag{13}$$

where $X_i(t)$ denotes data point in the i-th channel at the time t, $R_{ij}(s)$ are the elements of correlation matrix $\mathbf{R}(t)$ calculated for time lag t=s, and n is the length of the data record. The correlation matrices calculated for time lags s=0,..., p-1are later used to compute $\mathbf{A}(i)$ coefficients and the transfer matrix $\mathbf{H}(f)$. The above method of calculation of $\mathbf{R}(t)$ estimate is based on an assumption of ergodicity. Statistical properties of the model are connected with the length of the data record — the longer the record the better the estimate. The stationary signal epoch has to be long enough to fulfill that assumption. However, having long stationary epochs in EEG analysis is an exception rather than a rule.
In order to assess dynamical properties of the transmissions another approach may be used, based on ensemble averaging. When multiple repetitions of the experiment are available each realization can be divided into short time epochs and correlation matrix may be calculated according to formula [Ding et al. 2000]:

$$\widetilde{R}_{ij}(s) = \frac{1}{N_T}\sum_{r=1}^{N_T} R_{ij}^{(r)}(s) = \frac{1}{N_T}\sum_{r=1}^{N_T}\frac{1}{n-|s|}\sum_{t=1}^{n-|s|} X_i^{(r)}(t)X_j^{(r)}(t-s), \tag{14}$$

where N_T is the number of the realizations, $R_{ij}^{(r)}(s)$ denotes the elements of $\mathbf{R}^{(r)}(s)$ — correlation matrix calculated for time lag t=s in the realization r, and n is the length of the data window. This approach allows for much shorter data windows in the analysis; short enough to treat the data within the chosen window as stationary (the window cannot be shorter than the model order; the theoretically shortest possible window length is $n_{\min} = p+1$).

From the correlation matrix given by eq. (12) the MVAR parameters and the transfer matrix can be calculated. The data windows can be shifted successively over time to cover the whole length of the investigated epoch. The common model order must be chosen for all the windows. We found the Akaike AIC criterion [Akaike, 1974] to be most stable in the estimation of the model order. Additionally, several preprocessing steps must be performed in order to obtain comparable results for all the data windows. First, the data in every channel should be normalized over time by subtracting the temporal mean and dividing by the temporal variance in that channel. Next the ensemble mean should be subtracted from every data point. We do this to assure data stationarity within each data window. That way, we fulfill the basic assumption that the mean is zero in all the realizations. Finally, each data point should be divided by the ensemble variance to get the data normalized over trials within the same time window.

The bootstrap method [Zaubir and Boashash 1998] can be used to evaluate the error of the estimated functions. The variance of the function value is obtained by repeated calculation of the results for a randomly selected pool of original data trials. Roughly speaking, selecting a random pool of trials corresponds to simulating of another recording session. By repeating this procedure (repeating a "simulation experiment") many times, one can get an estimate of the variance of the chosen function.

5. Simulation studies and properties of DTF function.

Granger causality was defined for two channels only, however Granger in his later work emphasized that the causal relation can be unequivocally determined only, if there are no influences from the other channels of the process [Granger, 1980]. In case of EEG recorded from the set of electrodes all signals are highly related, therefore a multivariate approach have to be used. The simple simulation showed in Fig. 5 illustrates this point. As the input signal experimental EEG (highpass filtered with cutoff frequency 3 Hz) plus random noise was used. The signals in the destination channels were constructed by introducing delays and adding to each delayed channel an extra white noise. The simulation scheme corresponds to the common situation of measurement of signals in different distances from the source. In case of bivariate Granger causality, the false propagations are detected whenever there are phase delays between measurement sites. This observation is true for any bivariate measure as was pointed out in: [Kus et al. 2004; Blinowska et al, 2004b], where different measures of directionality of flows for different simulated patterns of propagation were discussed.

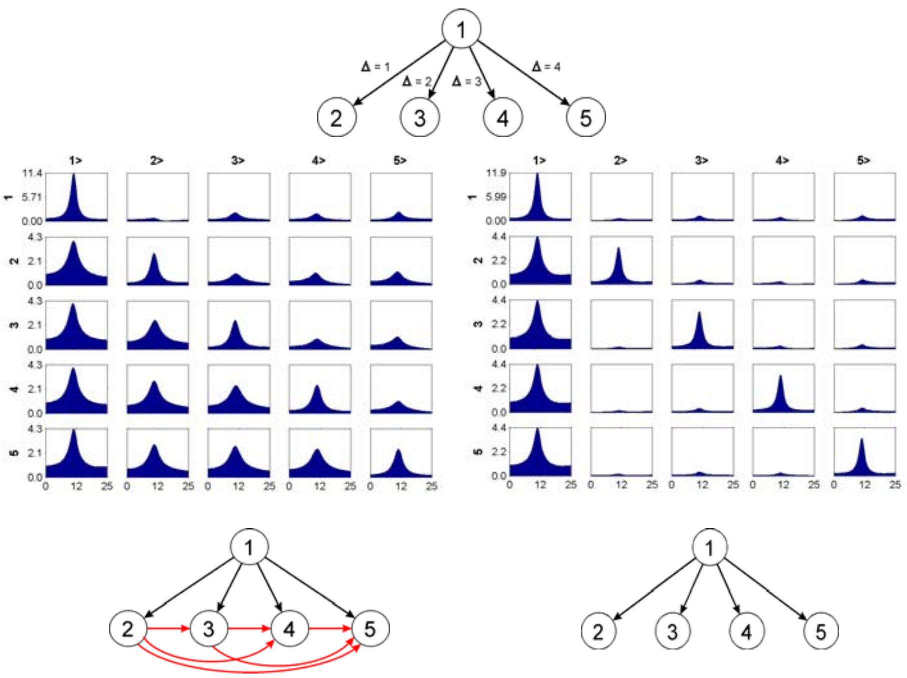

Fig. 5. Simulations showing difference between bi-variate and multi-variate estimates of directionality based on Granger causality. Upper picture – simulation scheme. Middle pictures show Granger causality measures; left bivariate, right multivariate. In each small panel the causality measure is shown as the

function of frequency. The direction of causality relations is from the channel marked above each picture to the channel marked at left. Below the resulting patterns of causality relations (flows).

6. Application of DTF and SDTF function.

A comparison of application of bivariate and multivariate measures of directionality to the EEG measured from 21 scalp electrodes in an awake state, eyes closed is shown in Fig. 6. The pattern of flows obtained by means of DTF is in agreement with the known configuration of sources in the above state. In case of the bivariate Granger causality the pattern of propagations is chaotic and for electrode C3 the inversion of propagation is observed in comparison to multivariate measure. In the same figure the transmission pattern obtained by means of another multivariate measure – Partial Directed Coherence (PDC) [Baccala and Sameshima 2001] is shown. PDC is a measure of directionality based on MVAR. Similarly to DTF it operates in the frequency domain, however due to different normalization PDC emphasizes rather sinks and not the sources, therefore it gives less clear picture of the EEG propagation. The above observation concerning DTF versus bivariate measures of directionality holds also for short-time version of DTF – SDTF, since both estimates differ only in respect of the method of computing MVAR coefficients.

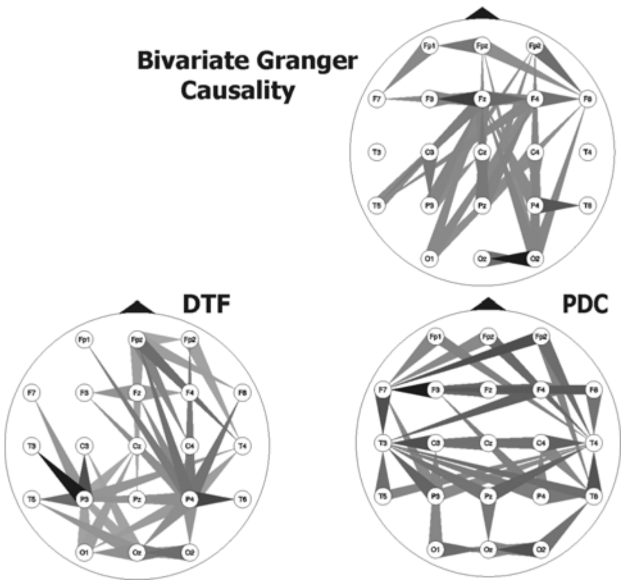

Fig. 6. The patterns of EEG transmissions (awake state, eyes closed) obtained by means of different methods: Bivariate Granger Causality, normalized Directed Transfer Function, Partial Directed Coherence (PDC).

DTF proved to be valuable measure of directionality, which have been confirmed in multiple studies. It has been used e.g.: to the localization of seizure foci Franaszczuk et al., 1994], investigation of epileptogenesis [Medvedev and Willoughby, 1999], identification of the sources of activity in sleep [Kaminski et al., 1997], investigation of propagation of LFP during locomotion [Korzeniewska et al., 1997], the investigation of EEG-MEG coupling mechanisms [Mima et al., 2001]. More recently DTF was applied for the estimation of human functional connectivity [Astolfi et al., 2005; Babiloni et al., 2005].

The investigation of the information processing by brain requires estimation of the dynamical evolution of EEG in the short-time scale, therefore time-varying estimate of causality has to be used. The SDTF is a measure that fulfils this requirement. The performance of SDTF may be illustrated on the example of the data concerning voluntary finger movement, which were already mentioned in the context of time-frequency analysis by MP. MP provides very accurate time-frequency-amplitude distributions; however, SDTF is sensitive also to the phase information, which allows estimating the transmissions patterns of EEG activity.

In series of experiments: the voluntary finger movement [Ginter et al., 2001], imagination of hand movement [Ginter et al., 2005] and finger movement and its imagination for the same subjects [Kus et al., 2006] were investigated. Shortly before and during the movement and imagination the decrease of EEG propagation in the alpha and beta bands from the areas connected with hand sensory/motor areas and increase of EEG outflow from facial and foot sennsory/motor areas were found. The observed EEG flows can be interpreted in connection with focal ERD/surround ERS effect observed by [Pfurtscheller and Neuper, 1994] and modeled by [Suffczynski et al. 1999]. In Fig.7 the matrix of SDTF functions describing time-frequency characteristics of transmissions in case of finger movement is shown. One can observe a gap in propagation in alpha and beta bands, especially for outflows from the electrodes overlying the primary motor areas (C1, C3). In addition, the rebound in propagation after the movement can be observed.

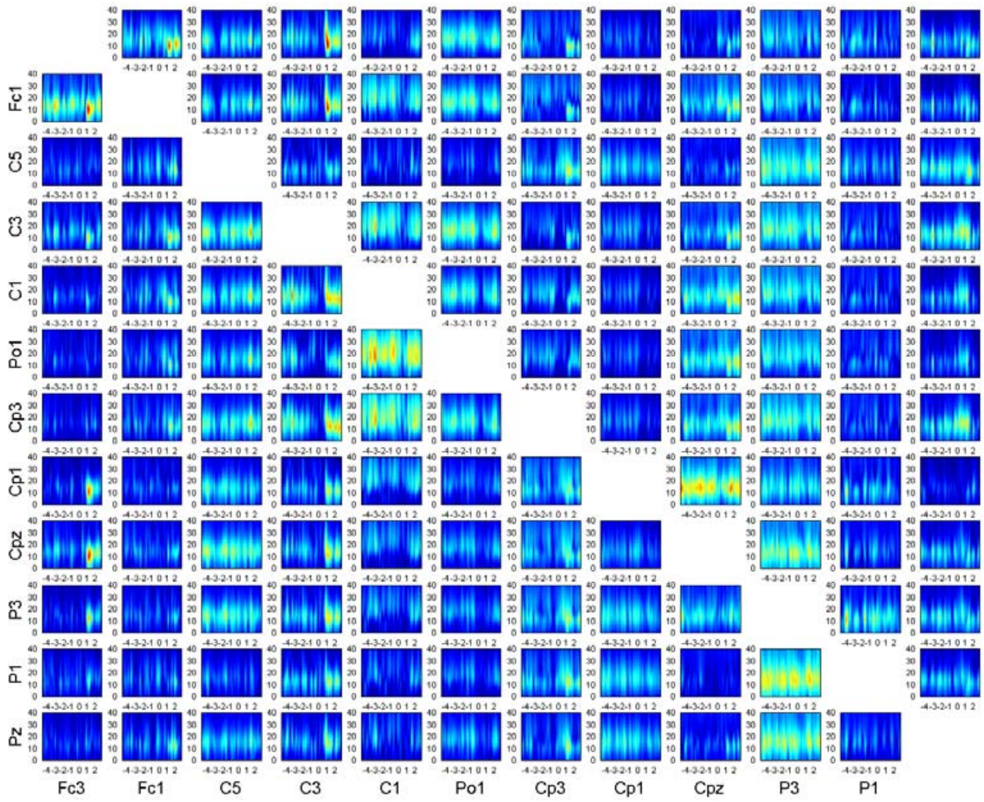

Fig. 7. Propagation of EEG activity in left hemisphere during right finger movement for one subject. In each small panel SDTF as a function of time (horizontal axis) and frequency (vertical axis) is presented. The flow of activity is from the electrode marked under the column to the electrode marked at the relevant row. Red color corresponds to the highest intensity of propagation, blue to the lowest one. (The transmissions in gamma band and to some extent in beta band are much weaker, therefore there are hardly visible in the color scale determined mainly by alpha activity).

The sensitivity of the Directed Transfer Function to the concise phase differences allowed for establishing the patterns of transmissions in the gamma band even in the presence of noise of random or zero phases. In order to see transmissions for different rhythms, DTF functions were integrated in the corresponding frequency bands. One of the forms of presenting the results consisted in movies illustrating the propagation in the different frequency bands. An example of the snapshots of the movie representing propagation in the gamma band during finger movement and its imagination is shown in Fig. 8. (The movies are available at http://brain.fuw.edu.pl/~kjbli/DTF_MOV.html). The performance of the movement is connected with the short burst of gamma activity from the location overlying hand related primary motor area. The imagination involves alternating propagations from primary motor cortex and other motor areas (primarily Supplementary Motor Area).

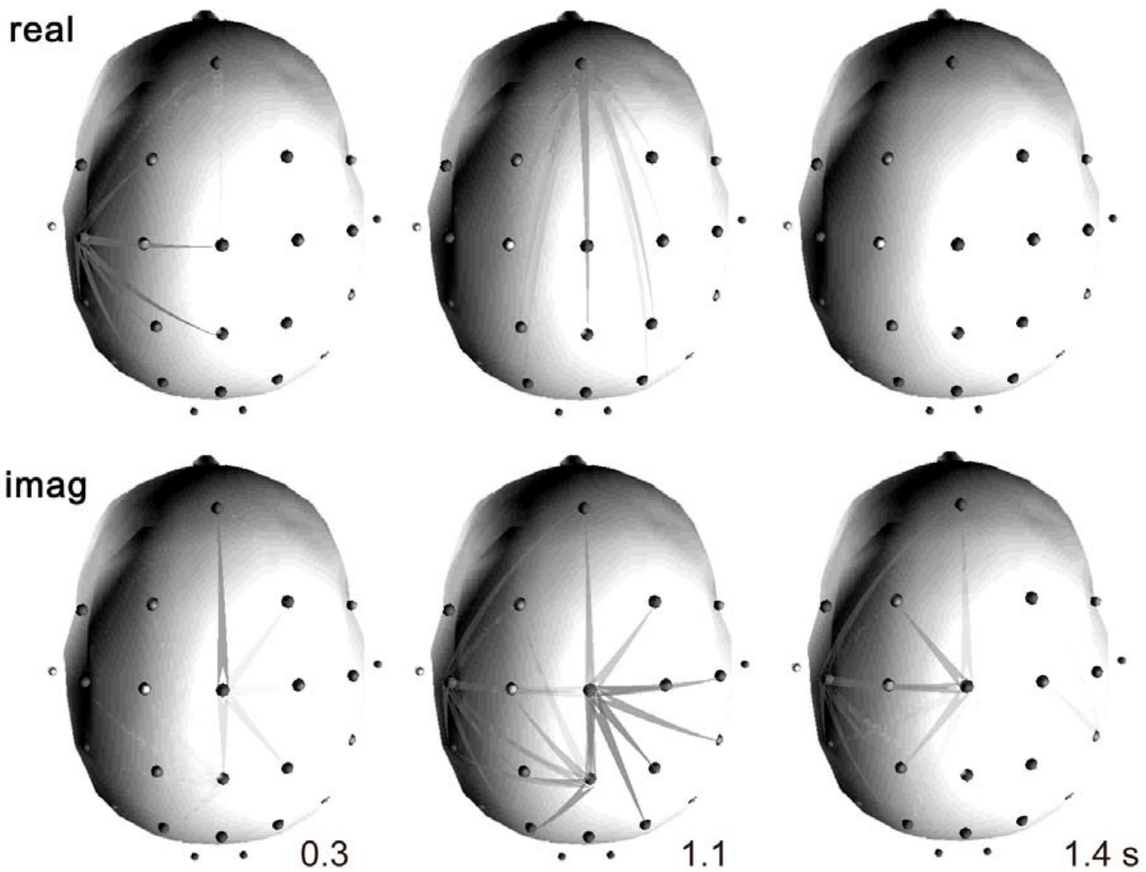

Fig. 8. *Propagation of gamma (35-41 Hz) EEG activity during right hand movement (up) and its imagination (bottomt): 0.3 s, 1.1s and 1.4 s after the cue appearance.*

Another application of SDTF concerned the evaluation of the transmission pattern in the experiment involving cognitive process [Kus et al., 2007]. In the experiment, the EEG from 23 electrodes was recorded during Continuous Attention test (CAT). The CAT test proposed by [Tiplady, 1992] is a modification of continuous performance test-identical pairs. The advantage of CAT is the use of abstractive visual patterns (instead of digits or pictures), therefore only visual attention working memory is involved, and the role of possible semantic or emotional associations is ruled out. The experiment consisted of presentation of consecutively displayed geometrical patterns, some of which were identical as the preceding ones. The person have to press the switch after perception of the pattern identical with the preceding one (target condition). Non-target condition concerned the situation of perception of the different patterns. The CAT test was performed for a group of 16 young healthy males. The data were thoroughly examined in respect of artifacts and the records contaminated by artifacts were eliminated. Special attention was paid to muscle artifacts, which might have disturbed the activity in the gamma band. After this procedure, the records coming from 10 persons were left.

The most interesting result was the finding of the differences in the gamma rhythm propagation for target and non-target condition. Namely for the target condition the burst of propagation from prefrontal electrodes to the central electrodes overlying motor cortex was found. In case of non-target condition, there were more bursts of propagation - usually three. The above effect is illustrated in Fig. 9, where the snapshots from the movie illustrating the transmission patterns in the gamma band are shown (Movies are available at: http://brain.fuw.edu.pl/~rkus/PHD/AVI.). The phenomenon of prolonged transmission from the frontal electrodes in case of non-target condition may be explained by the active inhibition, the mechanism suggested by e.g.: [Aron et al. 2004].

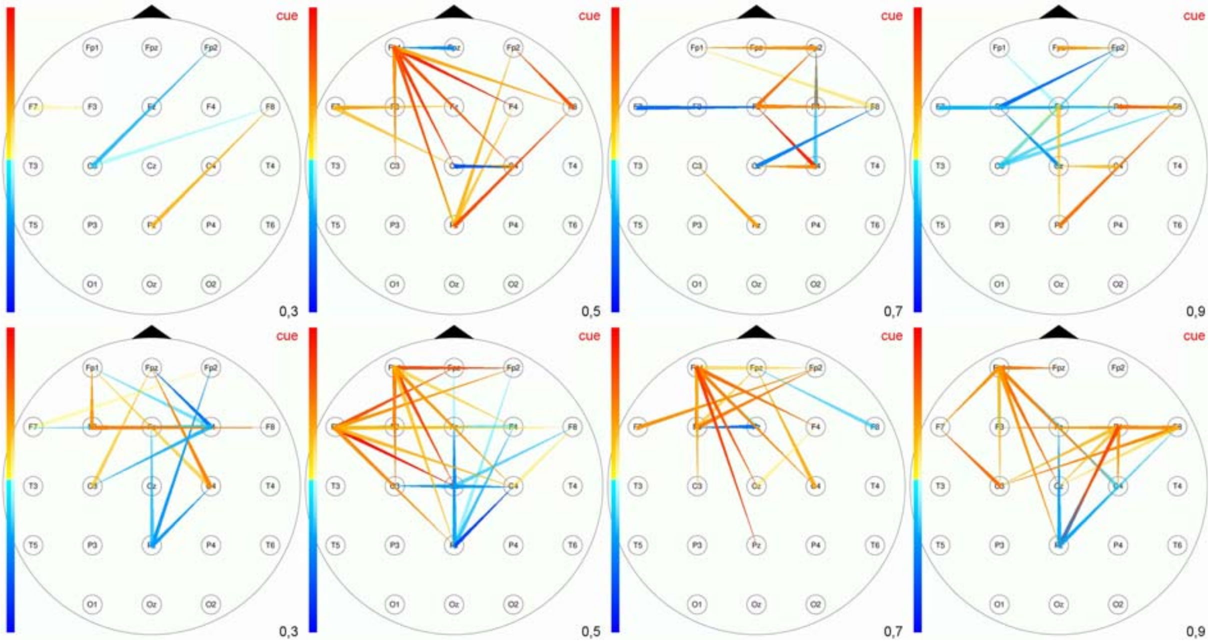

Fig. 9. Propagation of gamma EEG activity in CAT test for target (upper picture) and non-target (lower pictures) conditions. The pictures from left to the right represent propagations in the moments: 0.3s, 0.5 s, 0.7 s, 0.9 s. The arrows correspond to the significant differences in flows before and after the cue.

Discussion and Conclusions

Information processing in brain may be instantiated by different distributed cortical networks and a plausible mechanism for the coupling between them is the formation of dynamic links mediated by synchrony over multiple frequency bands [Varela et al., 2001]. During information processing by brain transitions may occur very rapidly in the process of breaking of functional couplings within one set of areas and establishing new couplings. The identification of the transitions between the stages of information processing requires the methods operating in time-frequency domain. Two such methods MP and SDTF have been presented above.

MP method is characterized by time-frequency resolution close to the limit defined by the "indefinity" principle. It decomposes the signal into the waveforms described by parameters of clear meaning. This makes possible to identify the signal structures corresponding to the ones defined over the years of visual analysis. These structures may serve as an input values to the inverse problem solutions and identification of the sources generating given signal structure – e.g.: sleep spindle, epileptic spike, evoked potential. The MP procedure may be also used for de-noising, namely signal structures of time-frequency signatures corresponding to noise contribution or artifact can be easily identified and eliminated.

SDTF have lower time-frequency resolution, however it accounts for the phase information and therefore allows for estimation of the transmission between brain structures.

Many statistical measures describing coupling in neural system has been devised: linear e.g.: correlation, coherence, Granger causality or non-linear e.g.: mutual information, phase synchronization, generalized synchronization. Some authors e.g.: [Quiroga,2002] claimed higher sensitivity of non-linear methods, however the above investigation concerned one particular application and the results were not unambiguous as admitted by the authors. The systematic study conducted by [Netoff et al., 2006] showed that in the presence of noise linear measures of coupling give better results than non-linear ones, even for highly non-linear systems. The authors conclude:"We have been as guilty as any of our colleagues by being fascinated by the theory and methods of nonlinear dynamics".

Different measures of directionality have been compared by [Winterhalder et al. 2005] The authors report that DTF, as well as PDC estimate correctly the propagation also in case of non-linear processes. Another argument against application of nonlinear methods is the fact that all nonlinear estimators are defined for two channels only and it has been pointed out without the doubt, that in case of mutivariate processes including more than two channels bivariate measures give very misleading results.

The limitations of the DTF and SDTF methods are connected with statistical restrictions concerning all parametric methods. Namely, the number of parameters has to be several times smaller than the number of data points. Number of parameters is proportional to the model order and the square of the number of channels. Therefore, the compromise has to be found between the data window length and the number of channels, which can be simultaneously fitted to the model. In case of SDTF, high number of the repetitions increases the number of the data points and allows for the shorter data window, hence more accurate estimate of time evolution.

In the comparative study of the [Winterhalder et al., 2005] DTF and PDC were found as a most reliable methods, however it was pointed out that DTF detects not only direct but also indirect flows. This feature may be important when estimating transmissions from implanted or subdural electrodes. However in these cases Direct Directed Transfer Function [Korzeniewska et al., 2003] which combines DTF with partial coherence, may be used. The disadvantage of PDC is the fact that it emphasizes rather sinks not sources, which makes the pattern of transitions less clear (Fig. 6). Another unfavorable feature of PDC is its weak dependence on frequency (practically "flat" spectrum), which does not permit to distinguish well the role of different rhythms. In the recent study short-time direct DTF have been successfully used for estimation of the pattern of direct electrocortical flows during the verbal tasks involving words repetition [Korzeniewska et al., 2007].

Concluding one can say that due to the truly multivariate treatment of time series by MVAR model the causal relations between the EEG signals may be established. The DTF function allows for the determination of the correct pattern of transmissions between the brain structures for linear or non-linear processes, including indirect and direct flows. The time-varying version of DTF – SDTF describes pattern of the brain activity transmissions in time-frequency domain providing the information about the dynamic evolution of the functional connectivity.

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