

Transmission of information during Continuous Attention Test

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The Short-Time Directed Transfer Function (SDTF) is an estimator based on a multivariate autoregressive model which has proved to be successful in ERP experiments, e.g. those connected with motor action and its imagination. The aim of this study is the evaluation of the performance of SDTF in the cognitive experiment. We have applied SDTF for the estimation of the pattern of EEG signal transmissions during a Continuous Attention Test (CAT). Time-frequency patterns of propagation were estimated for two experimental conditions. Statistical procedures based on thin-plate spline model were used for estimation of significant changes in respect to the reference epoch. The repeatability of the results for a subject and across the subjects were investigated. The effect of prolonged transmission in the gamma band from the prefrontal electrodes found in all subjects was explained by the active inhibition in the case when a subject had to sustain from performing the action.

Key words: EEG, multivariate AR model, SDTF, CAT, gamma activity, cognitive test, motor action

Modern imaging techniques, especially functional magnetic resonance (fMRI) provide information on the localization of active sites in brain under different experimental conditions. However, their limitations are connected with low time resolution, a not well known connection between hemodynamic response and brain activity and, finally, a lack of information on spectral properties of brain activity. EEG provides, despite its lower topographic resolution, information on time-variable brain rhythms and is at the same time a relatively cheap technique broadly available in clinics. Another advantage of the EEG technique is the possibility of estimating the transmission of brain activity which may reflect the interactions within and among networks synchronized at multiple different frequencies.

The method which allows for estimation of propagation of brain activity is Directed Transfer Function introduced by Kaminski and Blinowska (1993). It has

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been applied for localization of epileptic foci (Franaszczuk and Bergey 1998), transmission of brain activity during locomotion in animals (Korzeniewska et al. 1997), for propagation of EEG during sleep (Kaminski et al. 1997, 1995), for investigation of epileptogenesis (Medvedev and Willoughby 1999), for estimation of brain connectivity (Astolfi et al. 2005, Babiloni et al. 2005).

The dynamical propagation of brain activity can be estimated by means of the Short-time Directed Transfer Function (SDTF) (Ginter et al. 2001, Kaminski et al. 2001). A comparison of different methods estimating directionality of signal flow was made by Kus and coauthors (2004) and Blinowska and others (2004), which demonstrated that only the multivariate (not bivariate) approach allows for correct estimation of directionality of flows. SDTF has been applied in the investigations concerning motor related tasks. A very good performance of the method was demonstrated – among others, similarities and differences between EEG propagation during real and imagined movement were found (Ginter et al. 2001, 2005, Kus et al. 2006).

Here we shall apply the SDTF function to the EEG recorded during a Continuous Attention Test (CAT). This kind of brain activity is much more difficult to analyze, since several processes, such as cognition, decision making and motor reaction, are involved.

The CAT test was proposed by Tiplady (1992) for psychopharmacology research. It is a modification of the continuous performance test-identical pairs (CPT-IP) which is considered as the most accurate and sensitive test in investigations of attention deficits (Cornblatt and Erlenmeyer-Kimling 1985). The advantage of CAT is the use of abstractive visual patterns (instead of digits or pictures), hence only visual attention and working memory is involved and the role of possible semantic or emotional associations is ruled out.

Topographic features of event-related potentials registered during the CAT test were investigated by means of low resolution electromagnetic tomography (LORE-TA) (Basinska-Starzycka and Pascual-Marqui 2001). The strictly cognitive activity, reflected by inter-condition differences, was found mainly in the prefrontal cortex structures, corresponding with surface early P3 component identified at the midline frontal derivation Fz. Here we shall consider propagation of oscillatory brain activity in the beta and gamma bands with the aim of testing the performance of the SDTF function for investigation of cognitive phenomena.

The CAT test was performed for a group of 16 young healthy males. The experiment consisted of the presentation of 720 consecutively displayed geometrical patterns, 120 of which were identical to a preceding one. The target condition was defined as any immediately repeated pattern. After perception of the target the subject had to press the button with his thumb. The patterns were presented in random time intervals varying from 1.5 to 2.5 seconds. The EEG was recorded from 23 electrodes (10-20 system) referenced to the linked mastoids. The sampling frequency was 250 Hz. The signals were filtered in the 15–45 Hz frequency band, since the frequencies of interest encompassed beta and gamma band.

In order to analyze transmissions between signals, a parametric description of the data was used, namely the autoregressive (AR) model. In this approach we assume that the actual value of the k-channel time series $\mathbf{X}(t)$ depends on a certain number p of its previous values weighted by parameters $\mathbf{A}(j)$:

$$\mathbf{X}(t) = (X_1(t), X_2(t), \dots, X_k(t))^{\mathsf{T}}$$

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

The variable $\mathbf{E}(t) = (E_1(t), E_2(t), ..., E_k(t))^T$ represents the random component of the stochastic time series \mathbf{X} . Model coefficients $\mathbf{A}(j)$ are matrices of size $k \times k$.

This type of model is well-suited to describe stochastic signals containing components in certain frequency ranges. The EEG data are good examples of such signals and EEG can be successfully fitted by AR models. Because we are interested in analyzing the specific frequency components of our signals (rhythms) we must transform the AR model to the frequency domain. By changing the sign of model coefficients **A** and assuming that **A**(0) is the identity matrix we may rewrite (1) in the following form:

$$\sum_{j=0}^{p} \mathbf{A}(j)\mathbf{X}(t-j) = \mathbf{E}(t)$$
 (2)

After applying the Z transform to (2) we obtain:

$$\mathbf{A}(z)\mathbf{X}(z) = \mathbf{E}(z) \tag{3}$$

where A(z), X(z) and E(z) are Z transforms of A(j), X(t) and E(t), respectively. To make them dependent on frequency we apply the substitution: $z = \exp(-2\pi i f \Delta t)$, Δt is the data sampling interval.

$$\mathbf{A}(f)\mathbf{X}(f) = \mathbf{E}(f) \tag{4}$$

There are many methods of estimating model parameters from the data available in the literature. The Yule-Walker method relies on estimating the data covariance matrix. The elements of that matrix are estimated for each realization of the process as:

$$R_{ij}(s) = \frac{1}{N - s} \sum_{t=1}^{N - s} X_i(t) X_j^{\mathrm{T}}(t + s)$$
(5)

where N is the data record length.

The above presented formalism assumes that stationary time series are analyzed. In our case the response for a stimulus is a phenomenon producing nonstationary time series. To solve this problem the data segment can be divided into shorter time windows, where we can assume data stationarity.

However, when a data segment is short, the statistical properties of the fitted parameters deteriorate and the estimate becomes unacceptable. We may improve the fit using information from all the repetitions of the experiment. Assuming that every repetition is a realization of the same stochastic process we may extend the covariance matrix definition (5) to utilize all (N_R) realizations (r in parentheses indexes realizations):

$$R_{ij}(s) = \frac{1}{N_R} \sum_{r=1}^{N_R} \frac{1}{N-s} \sum_{t=1}^{N-s} X_i^{(r)}(t) X_j^{(r)T}(t+s)$$
 (6)

The rule of thumb is to have at least several times (say, 10) more data points than fitted parameters. It implies a practical limitation that a time window cannot be shorter than $10kpN_R$. Moreover, the result is smoother when overlapping windows are used.

From the correlation matrix defined by (6) the model parameters can be found. They can be used to calculate spectral estimates of the signal: power spectrum and coherences. By multiplying both sides of (4) by $A^{-1}(f)$ we get:

$$\mathbf{X}(f) = \mathbf{A}^{-1}(f)\mathbf{E}(f) = \mathbf{H}(f)\mathbf{E}(f)$$
(7)

Then the power spectrum of X is defined as

$$\mathbf{S}(f) = \mathbf{X}(f)\mathbf{X}^{*}(f) = \mathbf{H}(f)\mathbf{V}\mathbf{H}^{*}(f)$$
(8)

The matrix V is the input noise variance. Note that it does not depend on frequency.

Eq. 7 shows that the AR model can be considered as a linear filter of transfer matrix $\mathbf{H}(f)$, input $\mathbf{E}(f)$, and output $\mathbf{X}(f)$. In terms of linear filter, the element $H_{ij}(f)$ describes the connection between the input j and the output i at frequency f. Based on that property the Directed Transfer Function (DTF) introduced by Kaminski and Blinowska (1993) was defined as:

$$\theta_{ij}^{2}(f) = \frac{\left| H_{ij}(f) \right|^{2}}{\sum_{m=1}^{k} \left| H_{im}(f) \right|^{2}}$$
(9)

This function takes values from the [0, 1] range, the value 0 indicates no causal relation. DTF is a measure of the flow of activity from channel *j* to channel *i* (as a function of frequency) in respect to all inflows to channel *i*.

DTF is a measure derived from the concept of Granger causality, defined in the field of econometrics (Granger

1969) for a two-channel process. The correspondence between Granger causality and DTF was pointed out in Kaminski and coworkers (2001). In the estimation of directional transmissions in the system of mutually dependent channels it is important to use multivariate measures, since it has been shown that bivariate measures of directionality, such as bivariate coherence or twochannel Granger causality, give misleading results when more than two channels of the system are involved in the given process (Granger 1980, Blinowska et al. 2004, Kus et al. 2004). DTF is a multivariate estimate obtained by fitting all channels of the process simultaneously to the model. In order to obtain the time varying estimator of transmission we fit the model to short data epochs and calculate the model parameters from the correlation matrix obtained by ensemble averaging (Eq. 6). From model parameters DTF functions are calculated according to Eq. 9. By applying the moving window technique the time varying estimator of transmission SDTF can be obtained. Here we applied a sliding window of 160 ms length which was moved by 2 points (8 ms).

Short-time DTF (SDTF) is presented as a matrix of time-frequency maps of transmissions between channels. For each pair of channels from a given multichannel set and for each direction of influence we obtain SDTF as a function of time and frequency -y(t, f); its value describes the transmission strength.

The SDTF is a complicated and non-linear function of the data and its statistical properties are difficult to be expressed in an analytical form. Moreover, its value fluctuates due to nonstationarity of the data. In order to assess a statistical testing procedure we utilize the approach introduced in Korzeniewska and colleagues (2007), which we will briefly present here. Let us assume that SDTF value can be expressed as a smooth trend and noise component: y(t, f) = g(t, f) + e(t, f). During the procedure we substitute the SDTF function v(t, f) for each pair of channels by a simplified surface g(t, f), smoothing the variability of the original function while preserving the general trend of changes of the relation. The unknown functions g(t, f) were estimated using the thin-plate spline model (Ruppert et al. 2003), resulting in the estimates $\hat{g}(t, f)$.

Each repetition of the measurement was divided in two parts: a pre-stimulus and a post-stimulus period (the sets of time windows were chosen accordingly; we got 43 time windows in the pre-stimulus and 105 windows in the post-stimulus part). The pre-stimulus part was treated as a baseline and the question was if the

data after the stimulus differ from the baseline value. In practice the null hypothesis of the test was the guestion if a transmission value in the post-stimulus part $g(t_{POST}, f)$ is not significantly different from any of the transmission values g(t, f) in the pre-stimulus period $(t_i = t_{1,PRE}, t_{2,PRE}, ..., t_{max,PRE})$. The g values were considered different if for given t_{POST} and f they are different for every t_i from the pre-stimulus period for the frequency f (separate comparisons with every pre-stimulus time point were made due to nonstationarity of the data). To test such a hypothesis we may consider a difference between the pre- and post-stimulus estimated spline values $\hat{u}(t_{PRE}, t_{POST}, f) = \hat{g}(t_{PRE}, f) - \hat{g}(t_{POST}, f)$ and hypothetical SDTF trend values $u(t_{PRE}, t_{POST}, f) = g(t_{PRE}, f)$ $g(t_{POST}, f)$. Such differences will be compared against zero value. Let $\sigma(t_{PRE}, f)$ and $\sigma(t_{POST}, f)$ be standard errors of the $\hat{g}(t_{PRE}, f)$ and $\hat{g}(t_{POST}, f)$ estimators. Applying the law of large numbers we may assume that the distribution of the normalized difference tends to normal distribution:

$$\frac{\hat{u}(t_{\text{PRE}}, t_{\text{POST}}, f) - u(t_{\text{PRE}}, t_{\text{POST}}, f)}{\sqrt{\sigma^2(t_{\text{PRE}}, f) + \sigma^2(t_{\text{POST}}, f)}} \sim N(0, 1)$$
(10)

Based on that assumption the t-test can be used to compare the estimated transmissions difference $\hat{u}(t_{\text{PRE}}, t_{\text{POST}}, f)$ against a zero value. The corridor of confidence can be calculated for that difference at a given significance level as

$$\hat{g}(t_{\text{PRE}}, f) - \hat{g}(t_{\text{POST}}, f) \pm \alpha \sqrt{\sigma^2(t_{\text{PRE}}, f) + \sigma^2(t_{\text{POST}}, f)}$$

(11)

If such a corridor contains zero value within its range (for at least one pair t_{PRE} and t_{POST} for the frequency f), the hypothesis about lack of change in transmission holds. The α coefficient is a quantile of the distribution corrected for multiple comparisons, corresponding to the chosen significance level. It is a conservative approach, so we may miss some flows, but rather we will not observe nonsignificant connections.

In the first step of the analysis the artifacts were thoroughly eliminated by visual inspection. In some subjects the performance of the test was accompanied by eye blinking or muscle artifacts. The data epochs with artifacts were eliminated, for subjects with high occurrence of artifacts whole data records were eliminated. After the procedure 10 subjects were left for further analysis.

Since the number of parameters of the model has to be higher than the number of data points and the number of parameters increases as a square of the number of channels, we had to limit the number of signals simultaneously fitted to the signal to twelve. We chose to consider the electrodes overlying the areas that were found to be involved in the processing of the CAT test r by (Basinska-Starzycka and Pasqual Marqui 2001).

The trials were synchronized in respect to the onset of the visual CAT items. Records of 1.5 seconds length were analyzed. The first 0.5 second before pattern presentation were used as a reference period to assess the significant changes in the brain activity during the test.

The inspection of SDTF function revealed that in all subjects there were three channels which were active during the whole experiment namely F3, Fz and Cz. They were sources of activity before and after the pattern presentation and they sent the signals to almost all other channels. The temporal pattern of the transmissions from these electrodes was complicated. Since we are mainly concerned with the processes of decision making, the most interesting is the period after the pattern presentation and the relative changes in transmission in respect to the pre-stimulus epoch.

The examples of significant changes in flows of EEG activity in respect to the reference period assessed according to the procedure described above are shown in Fig. 1 for the target and non-target conditions. Both conditions correspond to the correct responses, namely: target – pressing of the switch in case the shown pattern was equal to the previous one, and non-target (true negatives) - not pressing the switch when the pattern was different from the previous one. The number of false reactions was too small to statistically estimate the SDTF functions by ensemble averaging. In each panel in Fig. 1 the transmission from the electrode marked above the column to the electrode marked at the left of the picture is shown as a function of time and frequency. By the vertical lines the presentation of the CAT pattern and the beginning of the motor reaction are marked. The reaction times varied between subjects, so at the bottom of the pictures histograms of the reaction times are shown. The scatter of the reaction times has influence on the time evolution of the functions. The results were characterized by a large inter subject variability, therefore establishing of a universal pattern of information transfer during the test is difficult.

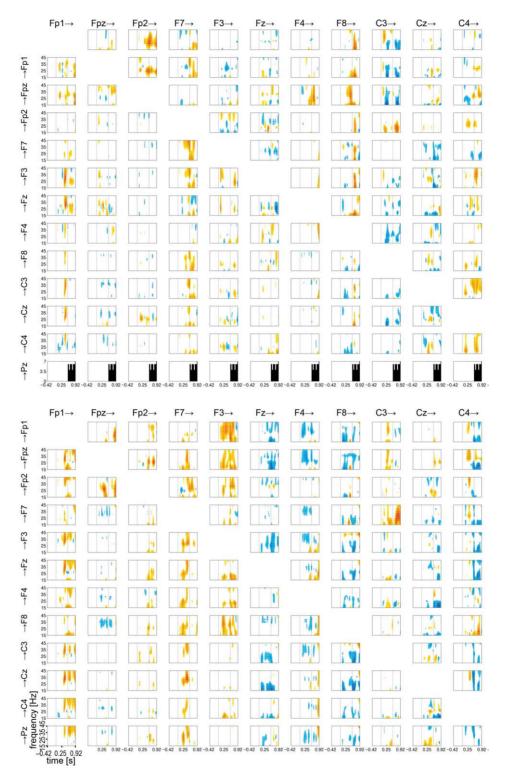


Fig. 1. Example of significant changes in flows of EEG activity in respect to reference period for the target (upper panel) and non-target (lower panel) conditions for the same subject. In each panel the change of transmission from the electrode marked above the column to the electrode marked at the left of the row is shown as a function of time and frequency. Time on horizontal axes in seconds, frequency on vertical axes in Hz as shown on an example at the bottom-left panel. Yellow-red colors indicate increase and blue colors indicate decrease of propagation. Black vertical lines mark the presentation of the CAT pattern and the beginning of the motor reaction. At the bottom of each column a histogram of the reaction times is shown.

In order to test the repeatability of our results we have performed a bootstrap test (Efron and Tibshirani 1993). The alternative approach – dividing the pool of data in two parts to perform calculations – would diminish seriously the number of trials and would decrease the statistical significance too much. In the bootstrap procedure for one of the subjects we have drawn different combinations of single responses with repetitions, so each time we have the

same number of records equal to the original number of trials. This procedure was performed several times for the target and the non-target condition. Some typical examples of results obtained from the data prepared by the above procedure are shown in Fig. 2. We can observe that although the patterns of flows for concrete conditions are not identical, the general tendencies are repeatable. Especially visible is the tendency showing the more prolonged propagation from



Fig. 2. Significant changes of flows obtained for target (right panels) and non-target (left panels) conditions. Bottom panels correspond to original data, upper panels to the data subjected to two different bootstrap procedures. For better visibility only part of the matrix representing flows is shown. In each small box the change of transmission from the electrode marked below the column to the electrode marked at the left of the row is shown as a function of time and frequency. Time on horizontal axes in seconds, frequency on vertical axes in Hz, as presented in an example for the bottom left panel. Yellow-red colors indicate increase and blue colors indicate decrease of propagation.

Fp1 in non-target condition in comparison to target condition.

In all subjects the earliest changes in propagation were observed after about 0.2 s after the stimulus presentation. In those electrodes which were the strongest sources of activity in absolute sense, mainly decrease of propagation was observed. In non-target condition the decrease of propagation was noted in the beta band for electrode Fz (7 subjects) or F3 (5 subjects) or F7 (4 subjects) and also sometimes F4 or F8 or Cz. In five subjects this effect was present for more than one electrode. The increases of propagation in the beta band were usually shorter than the decreases and the pattern was not concise across the subjects. There were no distinct differences in propagation in the beta band for target and non-target conditions.

In almost all subjects, transmissions from prefrontal electrodes were observed in gamma and beta bands during the epoch preceding the motor reaction.

The most interesting effect was observed for the prefrontal electrodes in the gamma band. For the target condition, a burst of propagation occurred from prefrontal electrodes to the central electrodes overlying motor cortex. In the case of non-target condition there were several bursts of propagation – usually three. In 5 subjects the source of this kind of activity was at electrode Fp2, in 2 subjects at electrode Fp1, also for 2 subjects at electrode Fpz. For one subject this pattern of propagation was observed for electrode Fz. In Fig. 3 the above-described effects are illustrated. For one subject (left panels) the characteristic patterns of propagation were observed from electrode Fp1, for another subject (right panel) a similar pattern of transmissions was visible for electrode Fp2. This effect may be explained by different lateralization in the subjects.

The pattern of transmissions for target and non-target condition in three different time moments is illustrated in the form of arrows in Fig. 4.

At the very end of the task for the target condition, propagation in the gamma band from C3 was noted for the subjects who had short reaction times. Its presence may be interpreted as a message that the task has been

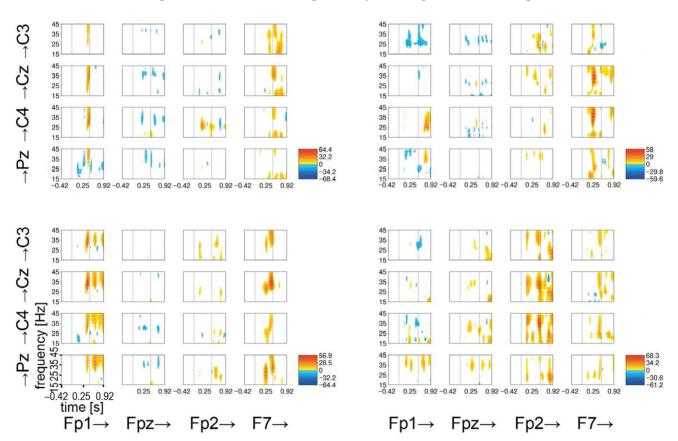


Fig. 3. Significant changes of EEG activity transmissions for two subjects for the target (upper panels) and non-target (lower panels) conditions. Left panels contain results for subject 1, right panels for subject 2. The convention of graphs is similar to the Fig. 2.

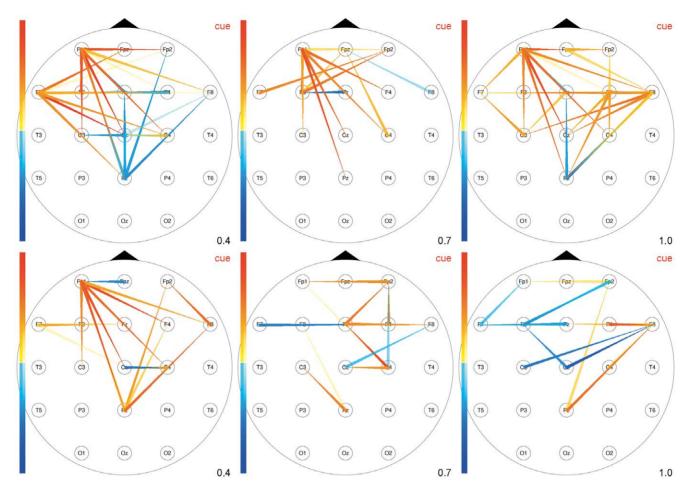


Fig. 4. Snapshots of changes in EEG activity propagations for one of the subjects presented in Fig. 2. Upper row for not-target condition and bottom row for target condition. Color scale corresponds to intensity of the effect indicated in Fig. 2, integrated over the gamma frequency band. Left column for time 0.4 s after the cue presentation, middle column for 0.7 s, and right column for time 1 s.

performed. For those who had longer reaction times this effect probably occurred too late to be observed or the burst is smeared out in the calculations because of variability of reaction times.

The CAT test involves several stages of information processing: perception of the cue, storing the pattern, its rehearsal, decision making and motor action. Communication takes place between different brain structures and therefore we may expect a very complex pattern of transmissions. Another factor which makes the estimation of the activity flows difficult is the time spread of the reaction which deteriorates the time resolution of the results. In case of a motor action the task is much simpler, therefore the results obtained by means of SDTF were more coherent and repeatable across the subjects (Ginter et al. 2001, Kus et al. 2006).

Nevertheless, taking into account the difficulty of the task the applied methodology allowed for observation of several effects repeatable for the given subject and across subjects. The effect which was quite repeatable for all subjects was the sustained propagation from the electrode Fz and neighboring electrodes overlying the supplementary motor area. It can be explained as a constant anticipation of the movement. The observed decrease of propagation from these electrodes was correlated temporally with the decision making.

The identification of propagation connected with the processes of recognition and decision making required evaluation of significance of the flow differences in respect to the reference period, which was a much more complex task than the simple calculation of transmissions. Nevertheless, several effects were consistent across subjects. The most coherent pattern of

flows across subjects was observed between the prefrontal electrodes as well as from the prefrontal electrodes to the motor areas in the gamma band. According to Romo and coauthors (1999) the prefrontal cortex (PFC) is mainly involved in storing the short-time memory, which is in agreement with the increased (relative to the reference period) transmission in the gamma band during the task-solving period as observed by us.

The temporal pattern of these emissions was different for the target and the non-target condition. In the electrodes Fp2, and in some cases in Fp1or Fpz, a prolonged gamma transmission appeared for nontarget condition, contrary to target condition, where only a short burst of gamma propagation was observed. This phenomenon may be possibly explained as an active inhibition required to stop an intended movement. This point requires further investigation, however there is experimental evidence supporting our suggestion. Aron and others (2004) reviewed the role of the inferior frontal cortex (IFC) in the inhibitory processes in the tasks requiring recognition and decision making. They suggest that the right frontal cortex subserves active inhibitory processes (connected with an increase of brain activity) underlying switching. This conjecture is in agreement with our results, since in a large number of subjects we have noted a prolonged propagation in the gamma band from the right hemisphere (although this effect was also visible for Fp1 and Fpz).

In the above quoted publication (Aron et al. 2004) the authors put forward the question whether left IFC interacts with right IFC in inhibitory control or whether either hemisphere can implement inhibition. From our results it follows that indeed there is an interaction between hemispheres manifested by the flows of activity and that the left hemisphere may be involved too.

Some investigators have suggested that non-linear mechanisms may play an important role in the functional connectivity of large-scale neural networks; e.g. Bekisz and Wrobel (1999), Senkowski and coauthors (2007). However, recent investigations have shown that linear measures perform better than non-linear ones in finding the coupling in non-linear processes in the presence of noise (Netoff et al. 2006). Noise is a prominent factor in all biological systems, therefore non-linear methods, which are extremely sensitive to noise (Kantz and Schreiber 2004) are hardly suitable

for the analysis of biological time series. Winterhalder and colleagues (2005) found that the DTF function performed well for non-linear systems, giving correct directions of propagation. Besides the non-linear estimators of transmission it involves only two channels and bivariate measures of directionality are likely to give misleading results in case of multichannel processes (Blinowska et al. 2004b, Kus et al. 2004). The above-mentioned evidence indicates that the application of the DTF function based on the linear MVAR model was fully justified.

The SDTF function revealed the pattern of activity flows which depended on the stage of the task and its performance. In both conditions, target and non-target, the complicated process of storing memory traces, their retrieval and decision making resulted in a complicated but similar for both conditions pattern of flows. The main difference was found in the epoch of decision making, where sustaining from the action of pressing the switch was connected with the active inhibition, manifested by the prolonged increase of flows in the gamma band from the electrodes overlying the prefrontal cortex to motor areas. These results correspond to the active inhibition phenomena taking place under similar conditions in the prefrontal cortex as reported in the literature.

We can conclude that the SDTF method and statistical procedures for evaluation of significant changes in flows as described above are particularly suitable tools for evaluation of information processing in the brain connected with cognitive functions.

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