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Parametric methods of dynamic spectral analysis of non-stationary biological signals

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ABSTRACT

The complex and non-stationary character of multichannel biological signals like the EMG and the EEG requires dynamic methods for multidimensional processes in the spectral domain. The paper presents an adaptive algorithm of fitting bivariate time-dependent ARMA models. On this basis it is possible to calculate both univariate and bivariate spectral parameters with high temporal and spectral resolution in a parametric way. Further, the application of mapping procedures allows a topographic dynamic analysis of multidimensional non-stationary processes. The possibility of complex dynamic spectral analysis in this way is exemplarily shown for surface EMG signals of movements with fast changes and for EEG signals of finger movement.

1 Introduction

In addition to multivariate spectral analysis methods based on Fourier transforms, the fit of linear multivariate models and the parametric calculation of the spectral density matrix and other spectral parameters are widely used because of the advantage of an immense data reduction. Owing to the non-stationarity of real biological signals, linear modelling is often rejected. Isaksson [2] recommended the transition to non-linear models or the use of linear models with time-dependent parameters for the investigation of non-stationary EEGs. For this purpose an adaptive fitting algorithm of bivariate ARMA models with time-varying parameters is constructed which combines the LMS algorithm and general adaptive estimation procedures. On the basis of this adaptive model, the dynamic estimation of the spectral density matrix enables the adaptation of spectral parameter estimations to structural changes and allows the continuous investigation of univariate and bivariate spectral functions with an arbitrarily high frequency resolution at every sample point. Using mapping procedures a dynamic topographic power and coherence analysis of multidimensional signals is possible. The application of these dynamic methods and the ability for single-trial analysis are demonstrated for surface EMG analysis of fast movements and for the examination of EEG signals during planning a finger movement.

2 Method

Let $\mathbf{x} = \left\{\left(x_i^1\ x_i^2\right)^T\right\}_{i=0,1,2,\ldots}$ be the sample values of a two-dimensional signal. This signal will be fitted by a two-dimensional linear model which is able to react on structure changes of the signal. This condition is fulfilled by an autoregressive moving average model (ARMA model) with time-varying parameters:

$$\mathbf{y}_n + \sum_{k=1}^{p} \mathbf{A}^k(n)\mathbf{y}_{n-k} = \mathbf{z}_n - \sum_{l=1}^{q} \mathbf{B}^l(n)\mathbf{z}_{n-l} \quad ,$$

where p and q are the orders of the model, $\mathbf{z}$ is a two-dimensional noise process, $\mathbf{y}$ is the two-dimensional model process, and $\mathbf{A}^k(n)$ and $\mathbf{B}^l(n)$ are 2*2- matrices of the autoregressive and moving average parameters. The parameter matrices are changed at every sample point in a manner minimizing the prediction error of the model. The fit of the parameter matrices will be realized by the following adaptive estimation procedure

$$\begin{aligned} \tilde{\mathbf{A}}^k(n) &= \tilde{\mathbf{A}}^k(n-1) - c_n \mathbf{e}_n \mathbf{x}_{n-k}^T \;;\; k = 1,\ldots,p \\ \tilde{\mathbf{B}}^l(n) &= \tilde{\mathbf{B}}^l(n-1) - c_n \mathbf{e}_n \mathbf{e}_{n-l}^T \;;\; l = 1,\ldots,q \end{aligned} \quad ,$$

where $\{\mathbf{e}_n\}_{n=1,2,\ldots}$ is the estimated vector sequence of the prediction error and $\{c_n\}_{n=1,2,\ldots}$ is a control sequence determining the speed of adaptation (see [4], [5]. The orders p and q are determined before using well-known estimation methods of model order. The momentary transfer function $\mathbf{H}_n(\lambda)$ of the fitted ARMA model may be calculated by the formula $\mathbf{H}_n(\lambda) = \mathbf{A}_n^{-1}(\lambda) * \mathbf{B}_n(\lambda)$, with the momentary matrices $\mathbf{A}_n(\lambda) = \mathbf{I} + \sum_{k=1}^{p} \tilde{\mathbf{A}}^k(n) e^{-ik\lambda}$ and $\mathbf{B}_n(\lambda) = \mathbf{I} - \sum_{l=1}^{q} \tilde{\mathbf{B}}^l(n) e^{-il\lambda}$. The momentary covariance matrix $\mathbf{S}_n$ of the bivariate prediction error $\{\mathbf{e}_n\}_{n=1,2,\ldots}$ may be estimated adaptively (see [5]). Now it is possible to calculate the spectral density matrix at every sample point n by $\mathbf{f}_n(\lambda) = \mathbf{H}_n(\lambda) * \mathbf{S}_n * \mathbf{H}_n^{*T}(\lambda)$, where $\mathbf{H}_n^{*T}(\lambda)$ denotes the complex conjugate and transpose of $\mathbf{H}_n(\lambda)$. That means that this adaptively estimated spectral density matrix

$$\tilde{\mathbf{f}}_n(\lambda)) = \begin{pmatrix} f_{11,n}(\lambda) & f_{12,n}(\lambda) \\ f_{21,n}(\lambda) & f_{22,n}(\lambda) \end{pmatrix}$$

is a function in frequency and in time. In such a way all spectral functions may be determined for every sample point. Let $\lambda_k = \frac{2\pi k}{N}, k = 0,1,\ldots,\frac{N}{2} - 1$ be discrete frequency points with a resolution determined by the free choosen number N. Further, a fixed frequency band is denoted by $[\lambda_1, \lambda_2]$. Thus, the momentary power of the frequency band $[\lambda_1, \lambda_2]$ may be calculated from

$$\tilde{p}_n = \sum_{\lambda_1 \le \lambda_k < \lambda_2} f_{ii,n}(\lambda_k) \; .$$

The frequency point with the highest power within the fixed frequency band (peak frequency) may be interpreted as the momentary frequency of this frequency band:

$$\text{momfr}_n = \lambda_j \in [\lambda_1, \lambda_2] : f_{ii,n}(\lambda_j) \ge f_{ii,n}(\lambda_k) \forall \lambda_k \in [\lambda_1, \lambda_2] \; .$$

A further useful parameter is the median frequency of a frequency band describing the distribution of the power within the band:

$$\text{medfr}_n = min\{\lambda_j \in [\lambda_1, \lambda_2] : \sum_{k<j, \lambda_k \in [\lambda_1, \lambda_2]} f_{ii,n}(\lambda_k) \ge \frac{1}{2} \sum_{\lambda_k \in [\lambda_1, \lambda_2]} f_{ii,n}(\lambda_k)\} \; .$$

Beside these one-dimensional spectral parameters the instantaneous coherence function may be calculated at every sample point:

$$\tilde{\rho}_n^{\,2}(\lambda) = \frac{|f_{12,n}(\lambda)|^2}{f_{11,n}(\lambda) * f_{22,n}(\lambda)} \; .$$

Therefore, it is possible to observe completely the evolution of the coherence function for the two-dimensional signal and the mean coherence for any arbitrary frequency band.

In the case of multidimensional signals as e.g., the EMG or the EEG mapping procedures for band power and coherences (see [3]) may be applied at every sample point n. The resulting map sequence enables a dynmiac topographic power or coherence analysis.

3 Results

In the first example the complete time evolution of the power of an EMG signal during a fast hand movement is examined. Furthermore, the time courses of the peak frequency and the median frequency are extracted. The task was to turn the hand from pronation into neutral position whereas the arm was flexed in the elbow joint with an angle of 90°. No additional force was applied. Previous experiments showed differences in the median frequency of the biceps muscle performing postures with the described different hand positions. Therefore the aim of this investigation was to verify the differences in frequency parameters analysing the surface EMG continuously while turning the hand from pronation to neutral position.

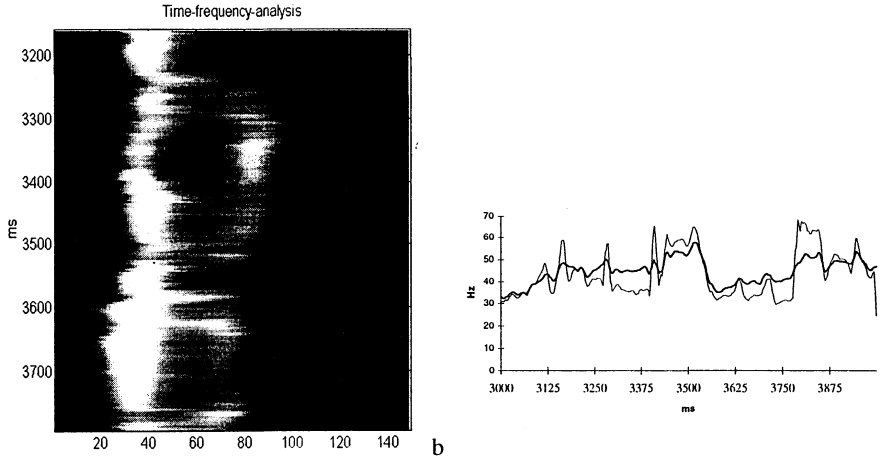

Fig. 1: a) The time evolution of the power of an EMG signal of the biceps muscle during a fast hand movement. (Light colours denote high power, dark colours denote small power.)
b) Time courses of the median frequency (bold curve) and of the peak frequency (thin curve) of the same signal.

The time frequency analysis shows that during the turn there exists a sharp shift in median as well as peak frequency in the sampled surface EMG (figure 1a and 1b). All other functional conditions were constant during the volunteer was performing this exercise. So it can be said that this shift of frequency parameters is caused by intramuscular functional mechanisms. Possible explanations are changes in firing frequency of motoneurons or activation of muscle fibres with different electrical (as well as functional) characteristics.

The application of mapping procedures to the time courses of band powers of a multichannel signal allows a dynamic topographic analysis. The second example shows the topographically oriented distribution of spectral EMG characteristics during natural chewing. In the region of the M. temporalis 16 surface electrodes were localized with respect to morphofunctional conditions of the muscle. While sitting in a dental chair with upright head position a healthy volunteer had to chew hazelnuts, pieces of carrots, bread as well as chewing gum. The surface EMG was recorded monopolarly (reference electrode at the contralateral ear lobe) by means of a 16-channel-EMG-system (sampling rate 1000/s). After checking the original EMG curves for artifacts chewing potentials (EMG during jaw closing / biting) were analyzed by frequency time analysis to characterize the important frequency ranges and its changes in the time course. In figure 2 the topographic distribution of the spectral EMG band power (200-300 Hz) was displayed as a series of maps. During increasing amplitude of the spindle shaped chewing potential the area of higher activation enlarged, expanded in the whole upper-anterior third of the muscle and diminished in the phase of decreasing amplitude. The advantage of the method is the more detailed characterization of highly dynamic muscle activation processes (cyclic movements). It can be expected that it is

possible in this way to show minimal shifts of muscle activation during natural chewing caused by food-consistence as well as by a change of the chewing side, myofascial pain (temporomandibular) dysfunctions, dysgnathia or surgical therapy.

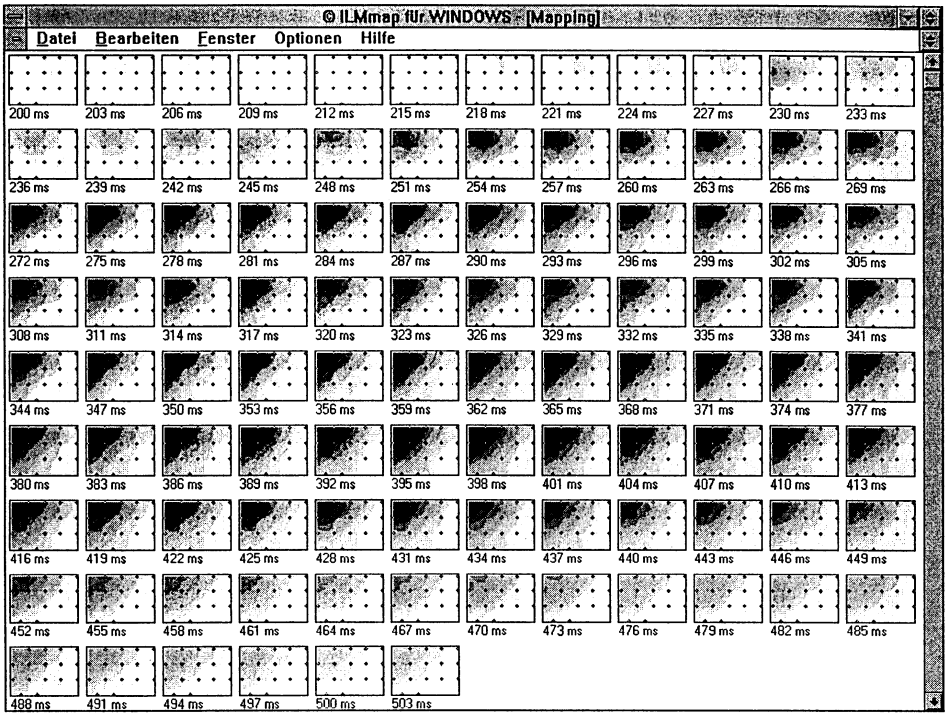

Fig. 2: Map sequence of EMG band power (200-300 Hz) in the region of the M. temporalis during natural chewing of hazelnuts (one chewing potential).

Obviously, the time courses of the peak or median frequencies can be mapped in the same way for detecting areas with frequency shifts of the power.

In EEG analysis the coherence function is used by several authors for the description of the functional relationship between different cortex areals. For the investigation of fast information processing a dynamical coherence analysis is necessary. Florian and Pfurtscheller (1995) examined the planning phase of a finger movement. The electrodes were localized on the post- and precentral cortex. The parametric estimation of the coherence function was executed for a moving window of the length of 0.5s. For each window the mean covariance coefficients of 64 trials were calculated. After that the parameters of an AR(9) model and the coherence function were determined. Figure 3a shows the result for an electrode pair in the central array. The time of a single experiment was 8s. In the planning phase about 5-7s an increase of the coherence within the frequency range of 30-40Hz may be mentioned. This phenomenon could be repeated.

For considering single movements a single-trial analysis is necessary. This may be executed by the introduced above adaptive fitting method of bivariate ARMA models. Figure 3b shows the time-coherence-analysis of a single trial of the same experiment on the basis of adaptive coherence estimation.

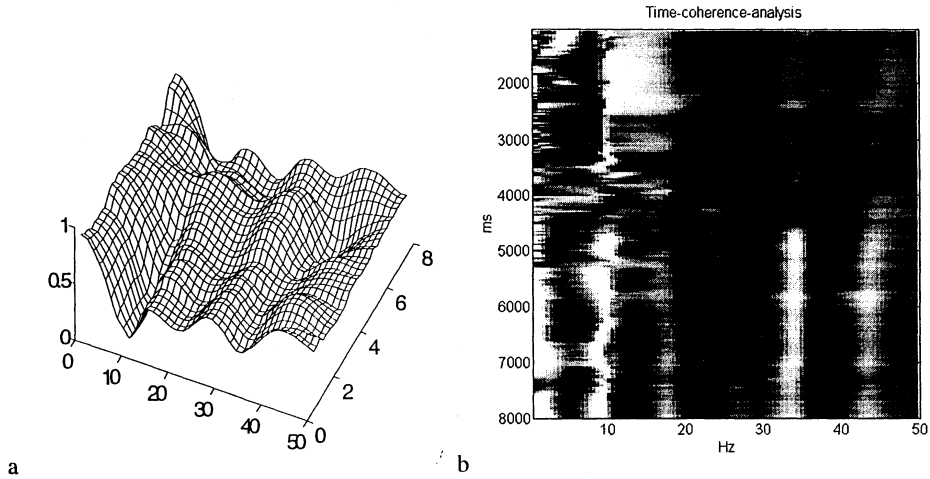

Fig. 3: a) Mean result of a time-coherence analysis during planning a finger movement with a time resolution of 500msec. (x-axis: frequency 0-50Hz, y-axis: time 0-8sec, z-axis: coherence)
b) Time coherence analysis of a single-trial of the same experiment on the basis of adaptive fitting of a bivariate ARMA(15,5) model. (time resolution: 1msec, frequency resolution: 0.5Hz, colour scale as in fig. 1a)

The increase of the coherence within 30-40Hz during the planning phase (5-7s) can be recognized. In such a way the examination of undisturbed planning of movements is possible with a vary high time resolution.

4 Discussion

The spectral analysis of non-stationary signals can be performed by different methods. The introduced adaptive fitting procedure is very simple and may be the basis for on-line calculation due to its recursive algorithms. The possibility of application of this kind of spectral analysis is demonstrated in the one-dimensional case for EMG analysis of fast movements and in the two-dimensional case for EEG analysis of fast information processing during planning a movement. The power and coherence analyses with high time and frequency resolution allow the dynamic observation of the frequency distribution of the signal power, the choice of relevant frequency bands and the changes in the relationship between components of such multidimensional signals as the EMG and EEG.

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5 References

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