LINEAR DIGITAL FILTERING AND SPECTRAL ESTIMATE IN PROCESSING EEG TRACES

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RESUME

Ce travail a le but d'introduire des techniques avancées d'élaboration du signal pour le traitement automatique des informations de l'éléctro-encephalogramme (EEG).

En particulier on met en évidence les techniques des filtres linéaires optimums avec la application dans le moment de pré-élaboration de l'EEG. Le problème en question est la réduction du bruit muscolaire qui corrompt le signal dans une bande de fréquence qui est centrée à peu près à 70 Hz et qui arrive jusqu'aux basses composantes de fréquence.

On décrit l'implementation d'un filtre de Kalman qui reduit cette contribution de bruit et on présente à ce propos des resultats expérimentals.

En suite on applique à l'EEG des méthodes d'identification (la méthode des minimums carrés à lots) et on extrait les paramètres du model AR (autoregressif).
Les résultats de l'identification sont presentés dans un diagramme polaire qui réussit à capturer la dynamique du même procès.

A partir des coéfficients de l'identification on réussit à obtenir aussi le spectre de puissance (spectre à maximal entropie) et il vient comparé avec les résultats déduits de l'approche du périodogramme et de la transformation rapide de Fourier (FFT).

Les méthodes d'élaboration introduites sont très efficaces pour les moments de pré-élaboration et d'extraction de paramètres utiles au but dyagnostique.

SUMMARY

The present paper aims at introducing advanced signal processing techniques for the automatic analysis of electroencephalographic traces (EEG). In particular, techniques of optimal linear filtering are emphasized with application in the phase of EEG pre-processing. The problem encountered is the reduction of muscular noise which corrupts the signal in a bandwidth which is centered approximately at 70 Hz and goes as far as the low frequency components. The implementation of a Kalman filter which reduces such noise contribution is described and experimental-results are shown at this regard.

Furthermore, methods of signal identification are carried out on the EEG tracing (batch Least Squares method) and AR model parameters are extracted. The results of the identification are presented in a pole diagram which is able to capture the dynamics of the process itself. Starting from the identification coefficients the power spectrum (maximum entropy spectrum) is also obtained and compared with the results given by the periodogram/FFT approach.

The introduced processing methods are extremely suitable for the phases of signal preprocessing and of parameters extraction useful for diagnostic aims.

INTRODUCTION

A widely diffused technique for the diagnostic evaluation of various pathologies at the level of Central Nervous System (CNS) is constituted by the analysis of electroencephalographic traces (EEG). The EEG is detected via a series of electrodes positioned in various standard sites (the most common lead system is the 10-20 one) on the external surface of the skull. The potentials recorded in this way (unipolar or bipolar leads) are the external signs of the electrical activity inside the CNS and particularly of the cortical neurons of the area in vicinity of the electrode itself.

From the clinical standpoint the EEG tracing carries some information about the patho physiological aspects of CNS: dominant rhythm of the signal (i.e. frequency bandwidth where the major information are concentrated in the power spectrum); presence of possible paroxismal rhythm (either "transient" or "long term"); asymmetries of certain leads (i.e. right vs. left, frontal vs. occipital and so on) which may reveal the presence of tumors, hematoma, bleedings and so on; indicators of clinical status of CNS both in physiological state (i.e.: sleep) and in phase of drug induction (i.e. anesthesia, effects of neurolectic, antiepilectic drugs and so on) and finally for the detection of clinical death. The raw EEG tracings themselves are sometimes very poor of information and the clinical evaluation by the neurologist may be very difficult. The main advantage of EEG automatic treatment is to provide physicians with post-processing methods which are able to enhance the information contained in the tracings. The traditional approaches for EEG automatic processing are in the time domain (zero-crossing, slope descriptors, correlation analysis etc.) and/or in the frequency domain (Fourier or Walsh analysis, polispectra, cepstra etc.). References may be made at (1) (2) (3) at this regard.

In the present paper some results are illustrated which show applications of linear digital filtering (traditional and optimal ones) and of identification methods using AR (autoregressive) models both for an accurate parameters extraction and for a spectral estimate which is compared with the traditional FFT approach.

The application of these techniques of EEG signal processing is discussed and the original properties of signal parametrisation which are derived are illustrated in a few cases for the following aims: (i) step of preprocessing (reduction of myoelectric noise superimposed to the tracings); (ii) step of parameters extraction useful for clinical aims (monitoring of the effect induced on the CNS by the delivery of strong ipotensive drug during riskful surgical intervenction).

ADVANCED TECHNIQUES OF EEG AUTOMATIC PROCESSING

It is not the aim of this section to deal extensively with the most common method of EEG automatic processing. See the cited references at this regard.

Here only a few methodologic information are provided of advanced techniques such as optimal linear filtering, identification and spectral estimation which are applied to EEG tracings. The relevant experimental results are reported in the following section.

Optimal Linear filtering

A discrete-time Kalman filter is implemented for the reduction of myoelectric noise superimposed to the EEG tracing. Some a priori assumptions are required: 1) stationarity of the EEG time series (for normal subject tracings this hypothesis is reasonably fulfilled in wide sense (4) (5) for short time data, while ergodicity is implicitally assumed); 2) knowledge of the mechanism of muscular noise influence on the tracing (that is postulated as the generating process of an impulsive Poisson distribution whose transfer function is determined in an experimental way) see (6) (7); 3) estimate of the true signal model: that is fulfilled by means of an identification (via Batch Least Squares method or other alternative approaches) of the EEG tracing generating mechanism in patients in particular relaxing situation in which, by hypothesis, the contribution of muscular noise is negligigle (see also next paragraph).

Fig. 1 shows the block diagram of the filtering procedure with the following input white noises: w_1 refers to the signal model, w_2 refers to the noise model and v to the noise at the level of the measurement process. The filter block is determined by the corresponding matrices evaluated previously in the noise and signal blocks (see points 2 above).

For details see (7) (8). The performance of the filter is tested by evaluating the whiteness of the innovation $\varepsilon(k) = x(k) - \hat{x}(k/k-1)$: if such hypothesis is fulfilled the Kalman filter is optimal in the sense that no other linear filter can do better to remove the noise on the EEG signal with the above mentioned assumptions. It is well known that the starting hypothesis might be quite far from the real case: in this case, the algorithm adapts itself to the new coming data and may converge in such a way as to minimize the prediction error, by adjusting matrix K(k).

Parametric identification

Many situations in biomedical signal processing may be described by the model shown in Fig. 2, where y(k) is the time series constituted by the sampled signal and w(k) is a gaussian white noise $WN\,|\,0, \lambda^2|$ where $E\,|\,w(k)|=0$ and $E\,|\,w(k)\,w(l)| = \lambda^2 \delta_{kl}$ for all k ; $E|.|$ is the expected value and δ_{kl} is the delta of Kronecker.

Generally the model indicated is random, discrete, and wide sense stationary.

Inside the set of parametric models, the ARMA models constitute a particular important family defined by the linear difference equation

$$y(k)=\sum_{n=1}^{N} a_n y(k-n)+\sum_{m=1}^{M} c_m w(k-m)+w(k)$$

where the vector of parameters

$$\theta = |a_1 \ldots a_N \quad c_1 \ldots c_M|'$$

and variance λ^2 define univocally the model.

In the case of pure AR (autoregressive) model, the coefficients c_m are equal to zero. In this case the identification problem calculates the parameters a_n and λ^2 by minimizing the figure of merit $J(\theta)=\frac{1}{N}\sum_{k=1}^{N}|\varepsilon(k)|^2$

where N is the numerosity of the time series and $\varepsilon(k)$ is the prediction error.

The various ways of parametric identification are described in (9).
The goodness of the identification is tested (whiteness of the prediction error) and the optimal number of coefficients (degree of polynomial in a_n) is verified according to criteria already introduced in literature (Akaike's and Rissanen's) (10) (11).

An original visualisation of the identification coefficients is the pole diagram in the complex z-plane: changings in pathophysiological conditions determine movements of the poles (and zeros) of the identification in a dynamic ways.

Applications in EEG signal processing are found in (12) (13) (14).

Spectral estimate

The identification allows to obtain an estimate of the power spectral density $S_y(f)$ given by

$$S_y(f) = \frac{\lambda^2 \Delta t}{\left|1 - \sum_{k=1}^{M} a(k)e^{-j2\pi fk\Delta t}\right|^2}$$

where Δt is the sampling period, a(k) and λ^2 are determined via identification.

It is possible to demonstrate (15) that such spectrum, is a Maximum Entropy one (ME) in case of gaussian models. Such method has some advantages in respect to the more traditional FFT techniques carried out on the periodogram (fewer coefficients to obtain useful clinical information - even for short time data - resolution which is not dependent on N, no errors induced by the windowing procedure, no rigid assumption on how is the signal outside the considered time lenght etc.) and some disadvantages as well (very smooth spectra with little information in case of few coefficients, the scale of amplitude is not maintained in the spectrum, an overestimate may induce spurious peaks in the spectrum, further studies have to be done for the choosing of optimal number of coefficients etc.).

For detailed comparison between AR spectral estimation and FFT see (16).

EXPERIMENTAL RESULTS

Application of linear digital filtering

The original EEG signal, Fig. 3a, is processed applying three methods :

i) low-pass digital filtering procedure with 35Hz as -3dB point (FIR filter, Weber-Cappellini window, 299 coefficients).
The filtered signal is shown in Fig. 3b.
There is a satisfactory removal of high frequency noise but the low-frequency components (under 35 Hz) of myoelectric noise are not obviously reduced.

ii) Kalman filtering procedure: sixth order filter described by the models reported in Fig. 1 (Fig. 3c).
It is possible to note that a good removal of the low frequency myoelectric noise is also fulfilled. The models of the noise generation mechanism and the EEG signal generation have proved a satisfactory behaviour on the basis of the introduced figures of merit (whiteness of the prediction error and fulfilling of Akaike and Rissanen criteria in the identification block and whiteness of the residual in the Kalman filter). For further details see the cited references.

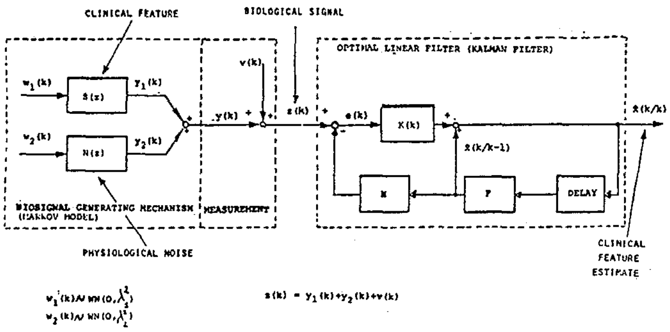

Fig. 1 - General block diagram of the whole Kalman filtering procedure. z(k) is the EEG time series corrupted by v(k) and $y_2(k)$ (see text).

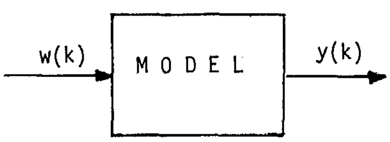

Fig. 2 - Schematization of identification model.

iii) the third method comprises method i) and ii) (Fig. 3d).
Here the behaviour is very satisfactory, as the FIR filter is able to remove in

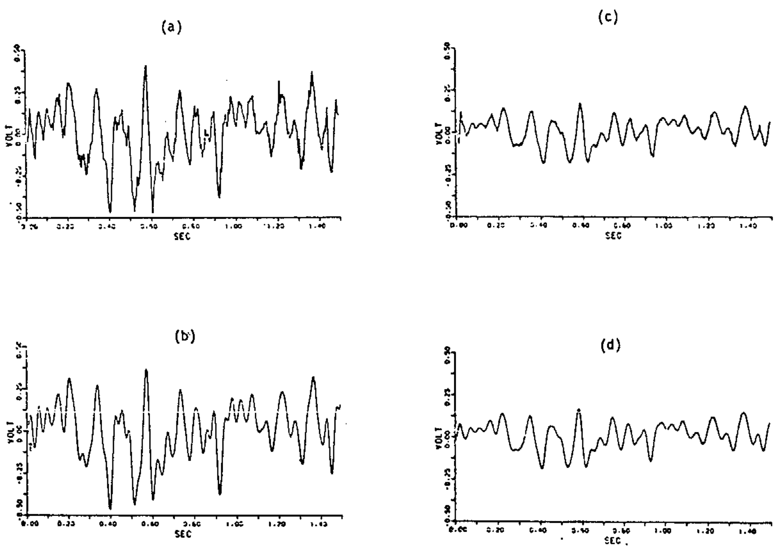

Fig. 3 - Pattern of EEG original signal a).
b) The same signal after low-pass digital filter;
c) After the Kalman filtering;
d) After the operations (b) and (c);
From (8).

a deterministic sense even the high frequency noise components which are still present in method ii . The useful clinical information of the signal in (a) is maintained in (d) and the method was greatly appreciated by the neurologists who cooperated in the present research.

Other results were obtained via traditional band-pass digital filtering (the bandwidths are the classical δ, θ, α, β bands). These results are not discussed in the present paper.

Application of identification techniques

The identification techniques previously described are applied to the EEG signal. The aim is to identify the model of the EEG generating mechanism which satisfies the starting hypothesis of an AR model (all-pole model). The method of batch Least Squares is applied and the goodness of the model is tested under the form of the whiteness of the prediction error (Portmanteau test or other similar ones); the order of the model is determined by optimizing the already introduced figures of merit (Akaike's and Rissanen's).

The method is applied to the EEG signal recorded during riskful surgical intervenction (cerebral aneurysm clipping under controlled ipotension) in order to detect the changes of EEG pattern during the induction of ipotensive drug (sodium nitroprussiate:SNP). Fig. 4 reports as examples the EEG signal together with the relevant pole diagram determined after the identification in two events of the operation: (a) before induction of anaesthesia, (b) during the peak of the induction phase of SNP.

The pole diagram (8 coefficients) is extremely sensitive to the various introduced changes in EEG pattern during the different epochs of the intervenction in about 15 considered patients. The introduced method is believed a very promising techniques of EEG parameters extraction.

Spectral estimate

Another advantage bound to the identification method previously described is the possibility to make an accurate spectral estimate of the EEG signal starting from the AR coefficients.

Fig. 5 reports the spectra determined in this way referred to the cases illustrated in Fig. 4 using 8 and 20 coefficients respectively. In the figure the power spectra calculated via the traditional algorithm of FFT carried out on 256 points are also shown as a reference.

The comparison demonstrates how almost all the information contained in the FFT (256 coefficients) are enhanced in the AR spectra (using only 8 or 20 coefficients); furthermore the information in the latter case is without the redundancies of the former which is also corrupted due to the windowing procedure and the shortness of data segment which was chosen as a starting hypothesis. More detailed information about these problems and the relevant advantages and disadvantages may be found in (16) (17).

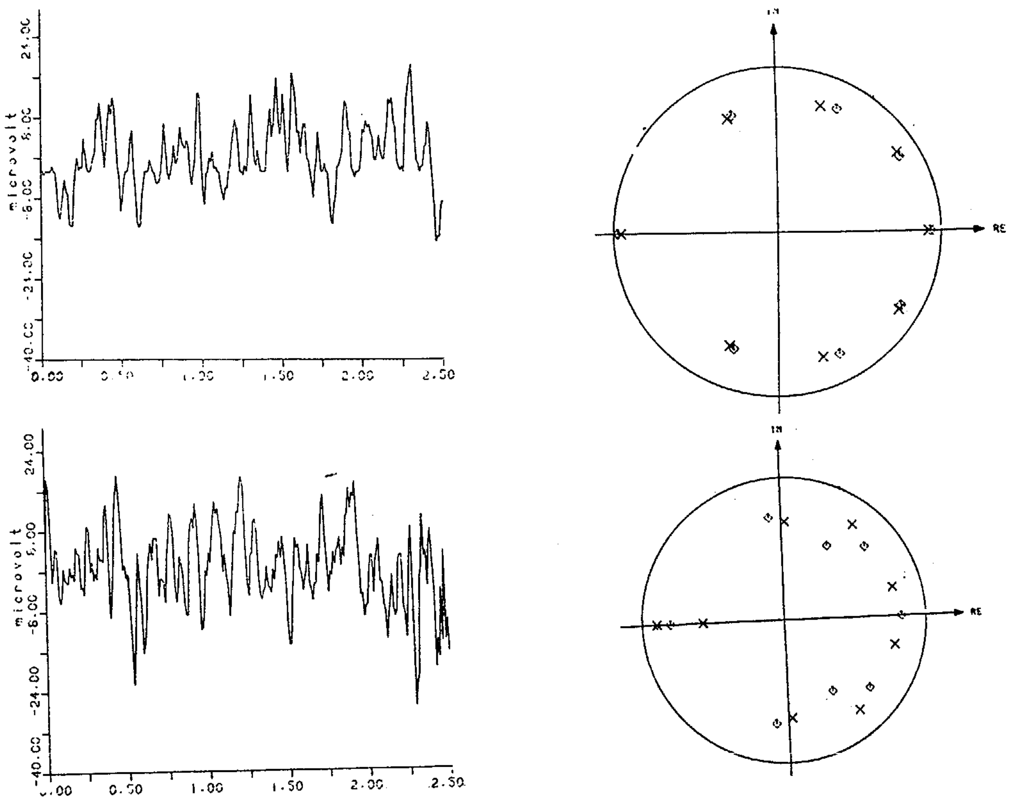

Fig. 4 - EEG signal and pole diagram after the identification. Basal condition (before operation) (upper part). Epoch in which there is a peak of infusion of SNP (lower part). Symbol X identifies the actual pole, while symbol ◊ identifies the pole in the preceding epoch: a dynamic display of the phenomenon is hence possible

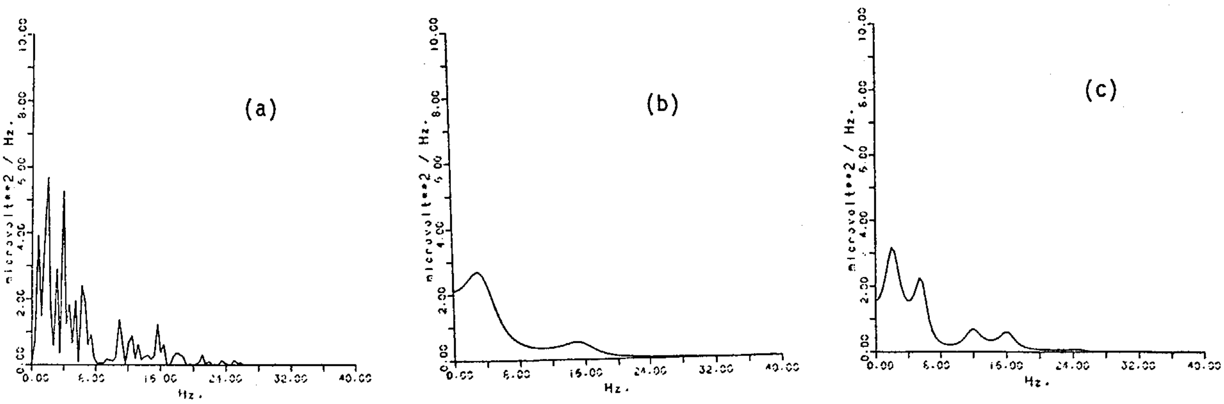

Fig. 5 - Power spectra of the EEG record shown in Fig. 4 (upper part).
a) is calculated via periodogram and FFT,
b) via AR model with 8 coefficients and
c) with 20 coefficients.

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ACKNOWLEDGMENTS

The cooperation of the neurologists of Istituto Neurologico "C.Besta" in Milano for the interpretation of clinical data has been greatly appreciated.

The present paper was partially supported by a grant of the Italian Ministry of Education.