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EEG PAROXYSTIC ACTIVITY DETECTED BY NEURAL NETWORKS AFTER WAVELET TRANSFORM ANALYSIS.

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Abstract. The recent development of micro-computers in association with the improvement of data acquisition techniques and signal treatment has made easier the analysis of cerebral electrical activity (EEG).

But the methods based on classical harmonic analysis have been proved to be ineffective in detecting some activities such as epileptiform spike-and-waves of paroxystic origin.

In order to detect these spike-and-waves, we developped a signal treatment based on Morlet's wavelets. This treatment generates a 2D representation including the time/frequency componants of the EEG signal split into 5-second epochs. In these figures, the spike-and-waves are detected by neural networks. The result is then stored into a file, for delayed use.

1. Introduction

The most commonly used treatment methods of biological signals are based on frequency analysis and power density spectrum (FFT), but unfortunately this frequency representation is not suited to the study of transient events. For example, in EEG analysis, many methods have been developed for detection and quantification of paroxystic activities using spike and seizure recognition programs, but the analyses based on morphological aspect of these paroxystic events are strictly localized in the time domain. So it is tempting to speculate whether time-frequency analysis would be useful for detection and quantification of paroxystic EEG activities.

The wavelet transform analysis deserves some attention for it allows such time-frequency representation of the signal. It has been used in applied signal processing, and first in geophysics [7]. This method was recently introduced in biological domains [3, 8, 9] and in the case of EEG [4] we obtained characteristic shapes on analyzing experimental spikes-and-waves.

In these conditions, image analysis can be carried out by comparing expected patterns to given templates [1]. Another way would possibly consist in using neural networks.

As a matter of fact, one of the aims of wavelet transform is to provide an easily interpretable visual representation of signals. This is a prerequisite for further applications, such as pattern recognition [5].

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In this way, a neural networks processes the whole time–frequency representation of the recording every 5–second epochs. The network recognizes the typical representative patterns of epileptiform phases occuring during the totality of the experiment and then records the temporal occurences of the detected events. The recording file allows a delayed reconstitution of the unfolding of the signal paroxystic phase.

2. Material and Method

Paroxystic epileptiform events are induced by intra–peritoneal injection of a GABA antagonist (picrotoxine $2mg.kg^{-1}$) to chronically implanted rats, with cortical electrodes for EEG recording. The EEG signal is amplified and directed to a PC 386 computer. A 12 bits ADC card samples and numerizes the signal at 200 Hz.

We may now formally define the problem of wavelet detection. This operation is carried out in delayed time, from the stored signal.

The chosen wavelet was the same as that written by Morlet. The Morlet's wavelets are complex functions, concentrated in time and frequency, each presenting the same shape and are mainly function of two parameters namely *a* and *b*, but unlike Gabor's wavelet, the *a* parameter quantifies the dilatation (or compression) of the time scale rather than an actual frequency change.

The basic wavelet expression is:

$$w_k(t) = e^{ikt} \left(e^{-t^2/2} - \sqrt{2}\; e^{-k^2/4} . e^{-t^2}\right) \qquad (1)$$

k is an arbitrary constant.

According to the value of the constant *k*, we can obtain several shapes of basic wavelets within the same gaussian envelope.

We can generate other analyzing wavelets by dilatation (or compression) in frequency domain using the parameter *a*. Thus, we obtain a class of wavelets (namely a wavelet family) the elements of which all have the same shape and are spread in frequency domain:

$$w_k(t/a) = e^{ikt/a} \left(e^{-t^2/2a^2} - \sqrt{2}\; e^{-k^2/4} . e^{-t^2/a^2}\right) \qquad (2)$$

Moreover, the energy of these wavelets ($\int [wk(t/a)]^2\, dt$) has to be constant whatever the value of *a*. This is obtained by multiplying $w_k(t/a)$ by $1/\sqrt{a}$. Thus:

$$w_{k,a}(t) = 1 / \sqrt{a}\; [w_k(t/a)] \qquad (3)$$

For application of the wavelet transform method to EEG time–frequency analysis, we have to choose an adequate frequency of the basic analysing wavelet of the family, which is called the "mother"; in practice, we fixed this frequency at 10 Hz. This 10 Hz mother wavelet was obtained using the formula (3) where the compression parameter *a* is the ratio (0.08) of the period of the mother wavelet (0.1 sec.) by the period of the basic wavelet $w_k(t)$ (1.25 sec.).

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Let us condider a wavelet S(n). The (n) index denotes that the wavelet may appear according to many variations. We denote by S the wavelet which has the general shape of a paroxystic spike and by S(i) the particular, exact, shape of the *ith* paroxystic spike in the given EEG signal. The wavelet S(i) is a function of time. Since we work with digital computers, we have to use the sampled wavelet, namely the string of D_i equally spaced samples of the wavelet.

These will be denoted by :

$$S_k \ (i): \ (k=k_i,k_i+1,\ldots,k_i+D_i-1) \qquad (4)$$

Equation (4) has to be understood as follows : the ith sampled wavelet starts at sample number k_i and ends at sample number k_i+D_i-1 (i.e: its duration is D_i samples). We assume that outside the D_i samples the wavelet is zero namely $S_k(i) = 0$ for all $k>k_i+D_i-1$. The signal we are monitoring consists of many wavelets, each of them having a different "gain", G(i). We may therefore write the signal, S_i as the summation of all wavelets:

$$S_k= \Sigma_i \ G(i)S_k(i); \quad (i=1,2\ldots) \qquad (5)$$

The signal S_k (represented by its *kth* sample) is therefore the collection of the wavelets as they appear along the time axis.

The root wavelet is determined at 10Hz. The six root–derived wavelets are spread over 3 octaves distributed on both sides of this central frequency (i.e.: 1.25Hz, 2.5Hz, 5Hz, 20Hz, 40Hz and 80Hz). Ten bands per octave give an adequate frequency resolution to the form recognition executed by the neural networks.

3. Image Preprossessing

The wavelet transform enables a time/ frequency image (Fig. 1) of the signal which is analysed in this way. A region of interest is defined between 30 Hz to 80 Hz. Indeed, the variations in frequency caused by wave points create an increase of the high frequencies in comparison to a normal recording.

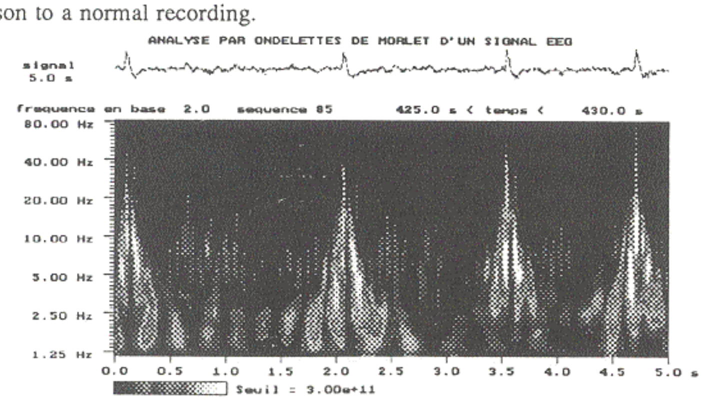

Fig. 1. Time/frequency wavelet transform

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3.1 Threshold Image

We carry out a threshold of the image in the region of interest (Fig. 2), in order to eliminate any possible low amplitude frequency which would not be generated by spikes.

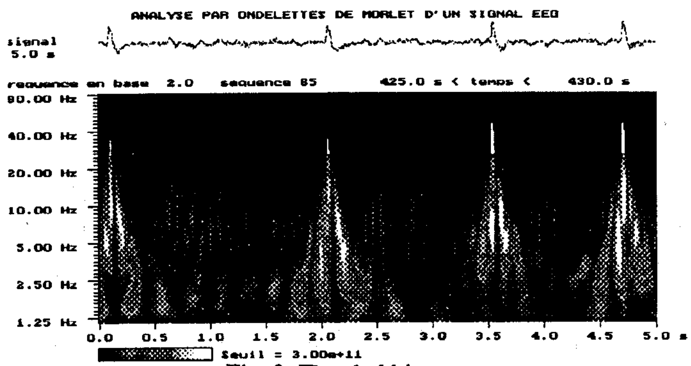

Fig. 2. Threshold image

3.2 Extractions of Parameters

A mean pixel number of 30–80 Hz is calculated using the threshold image. This provides a representation of the time/frequency information between 0 and 1, as well as a lower output of data.

$$X_t = \frac{1}{N} \sum_{i=30Hz}^{80\,Hz} Pixel(t,i) \,. \qquad N = \text{number of pixels.} \qquad (6)$$

4. Neural Networks

4.1 The task

The construction of neural networks is done automatically by localizing the learning for each neuron. This method consists in taking a neuron, carrying out the learning process on the whole data base containing 2 forms to be classified (form *A* and form *B*). If there is no convergence after N iterations (N=50), the 2 forms are not geometrically separable. The unfiled data is sorted so as to keep the 'well filed' data only. A new learning session is carried out from this data which enables us to obtain a pre–classification for a neuron. The system then creates a new neuron, and ensures the learning process of the data form *A* which was badly filed in comparison to the data of form *B* as a whole. It carries out the same operation as previously (sorting of badly filed data and relearning) to obtain a convergence. The system repeats this once more, recreates a neuron until all the vectors of the form *A* are filed with regards to the form *B*.

The input layer is thus obtained in the same way. This implies that the data which characterizes the 2 classes are separable in an N–dimensional space. For hidden and output layers, it is synthetized by means of logical functions [2, 6]. This method enables a very easy hardware implementation of the system.

4.2 Learning rules

The rule used is the generalized delta rule. Its tranfer function is a sigmoid which guarantees a convergence if data are geometrically separable and places the hyperplane at maximum distance with regards to the marginal points.

Sigmoid function

$$S = f(v) = \frac{e^{\beta v}-1}{e^{\beta v}+1}$$

Sum function

$$v = \sum_{i=1}^{N} x_i c_i \quad (7)$$

Weight adaptation

$$\Delta c = (D-S)\ \delta f(v) / \delta(v) \qquad c_{i+1} = c_i + \mu \Delta c_i \quad (8)$$

v –> decrease with a number of iteration
D –> want output

During the learning period, we used the crossed–validation rule. This rule consists in dividing the data into n sections. The learning is carried out in *n–1* set and is tried out on the last one. This operation is carried out *n* times.
During the test, the transfer function is replaced by a threshold function, and 100% of the learning examples have been correctly classified.

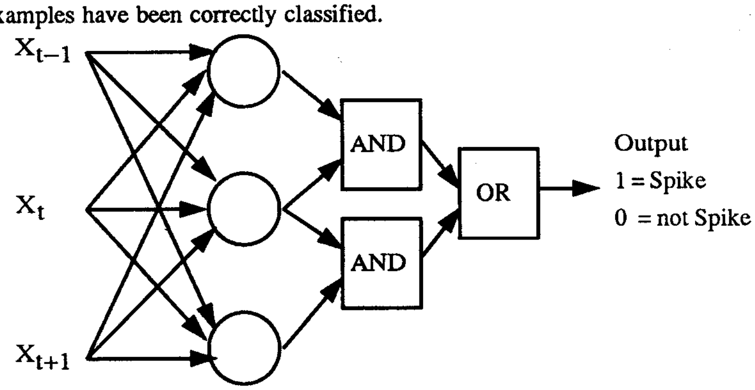

Fig. 3. Neural Networks

5. Results and Conclusion

When only very few data remain to be filled, it is better to duplicate so as to ensure a convergence if the form B contains a large quantity of data.
The classifier is undergoing tests on a larger data base for it to be validated. With this type of network construction we are no longer obliged to resolve the problem of the definition of the number of neurons in a hidden layer.

The results which are obtained in this way are stored in file and the expert analyses the sequences of spikes to discover when they first occurred.

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References

1. R. Caterini, J.L. Vernet, G. Delhomme, A. Dittmar : A sofware for pattern recognition of skin potentiel responses. Innov. Techn. Med., 13, 3, 256–268, (1992).

2. P. Clochon, G. Perchey, C. Couque, H. Rebeyrolle, D. Bloyet, P. Etevenon: Automatized classification by neural networks of EEG signals with artifact rejection. 14th annual international conference of the IEEE Engineering in Medecine and Biology Society, Satellite symposium on neuroscience and technology, 51–55 (1992).

3. J.A. Crowe, N.M. Gibson, M.S. Woolfson, M.G. Somek : Wavelet transform as a potential tool for ECG analysis and compression. J Biomed. Eng., 14, 268–272 (1992).

4. P. Gourmelon, D. Clarençon, H. Vignal, J.M. Brun, E. Macioszczyk et L. Fontenil : Intérêt de la transformée en ondelettes dans l'analyse des activités paroxystiques épileptiformes de l'activité électrique cérébrale. S.S.A. Trav. Scient., 11, 295–296 (1990).

5. A. Grossmann, J. Morlet, T. Paul : Transforms associated to square integrable group representations. J. Math. Phys. 27, 2473–2479 (1985).

6. S. Knerr, L. Personnaz, G. Dreyfus, Senior Member, IEEE: Handwritten digit recognition by neural networks with single–layer training. IEEE Transactions on Neural Networks,1992 , in press.

7. J. Morlet, G. Arens, I. Fourgeau, D. Giard : Wave propagation and sampling theory, Geophysics, 47, 203–206 (1982).

8. A.W. Przybyszewski : An analysis of the oscillatory patterns in the central nervous system with the wavelet method. J. Neurosci. Methods, 38, 247–257 (1991).

9. C. Tismer, M. Jobert : The application of wavelet transformation for sleep EEG analysis, Sleep Research, 20A, 518 (1991).