Synchronous Detection of Emboli by wavelet packet decomposition

Jean-Marc Girault, *Member*, *IEEE*, Denis Kouamé, *Member*, *IEEE*, and François Tranquart*

Abstract— **We showed in a previous study that the detection of micro-emboli can be markedly improved by taking into account the quasi-cyclostationary properties of the blood Doppler signal. However, in order to detect still smaller events, we propose to combine the use of synchronous detectors and sub-band decomposition. We evaluated and compared the detector's performance to existing methods by using both numerical modeling of the Doppler signal and ROC curves.**

Keywords— **Doppler, ultrasound, detection of micro-emboli , wavelet packet decomposition, cyclostationarity.**

I. INTRODUCTION

CE rebral vascular accidents, like cerebral embolisms, represent more than two-thirds of all ischemic strokes. Indeed, several insoluble bodies foreign to blood composition (fat, red cell aggregation, clots ...) known as emboli, can move into intracranial arteries and can even block them. Transcranial Doppler ultrasound (TCD) systems are commonly used to detect these micro-events (micro-emboli signals). Detection of micro-emboli [1], [2], [3] (small size emboli) is important for reasons such as preventing cerebrovascular accidents, finding the cause of embolism and validating the effectiveness of treatment. The underlying phenomenon of the embolism explains why the embolic Doppler signature is an unpredicted high intensity transient signal (HITS) superimposed on the Doppler signal backscattered by the blood. The information on which embolus detection must be based can therefore be the energy of the signal. This involves the combined use of an energy estimator and an energy detector. The standard techniques implemented in TCD systems seem to be sufficient to detect most micro-embolic events. Nevertheless, sometimes a medical expert observes micro-embolic signatures during clinical examinations that are not detected by the system and this has led our team to analyze the signals with another approach. By assuming that the Doppler signal is cyclostationary [4], we hypothesized that energy is statistically periodic. If we periodically take and compare the values of energy at different time points in the cardiac cycle, we should detect the presence of non-periodic events such as micro-emboli. In a previous study [5] we showed that detection of micro-embolus can be considerably improved by using a synchronous detector. We combined the use of a standard synchronous detector with sub-band decomposition like that obtained by wavelet packet analysis [6], the underlying idea being that by using an energy detector in each sub-band of the spectrum, we improve the energy contrast between the background Doppler energy and the embolus Doppler energy. Such synchronous detection based on sub-band decomposition should improve the detection of micro-emboli.

The authors work at François Rabelais University, LUSSI FRE CNRS, Tours, France. * INSERM U619, Bretonneau Hospital, Tours, France. E-mail: jean-marc.girault@univ-tours.fr.

II. DOPPLER EMBOLUS SIGNAL MODELING

In order to test the different detectors, we decided to use numerical simulations. The Doppler embolus signal was modeled by using the method proposed by Girault et al. [3]. This numerical method is equivalent to simulating a narrow band signal modulated both in amplitude and frequency. The main advantage of this numerical model is that the embolus signature does not show any abrupt phase change, as an abrupt phase change can be identified as a micro-embolus signature, the latter have to be removed to reduce the false alarm rate. An illustration of a simulated Doppler signal with one micro-embolus is given in Fig.(1). The instantaneous energy of each embolus was chosen in order to be lower than the highest level of the background Doppler signal. As our main objective was to detect very small embolus signatures.

From an analytical point of view, the Doppler embolus signal $y(t)$ can be expressed by four terms [4]:

$$y(t) = A(t)B(t)C(t)D(t). \tag{1}$$

The first component $A(t)$, known as the "carrier", is a mono-frequency signal which corresponds to the instantaneous frequency of the Doppler signal:

$$A(t) = e^{j\omega_d t}, \tag{2}$$

where ω_d is the mean Doppler frequency.

The second term $B(t)$, which modulates the amplitude of the first component, corresponds to the cyclic time varying bandwidth or energy. This amplitude modulation term is periodic (cardiac cycle) and can be expressed as a Fourier series:

$$B(t) = \sum_{k=0}^{\infty} a_k e^{jk\omega_c t}, \tag{3}$$

where ω_c is the fundamental cyclic frequency and where a_k are the amplitudes of the different harmonics, $a_0 = 1$. These amplitude coefficients serve as amplitude modulation indices.

The third component, which corresponds to the cyclic variations in the instantaneous frequency, modulates the frequency of the last two terms. This frequency modulation term is periodic (cardiac cycle) and can be expressed as a Fourier series:

$$C(t) = e^{j\sum_{k=1}^{\infty} a_k sin(k\omega_c t)}, \tag{4}$$

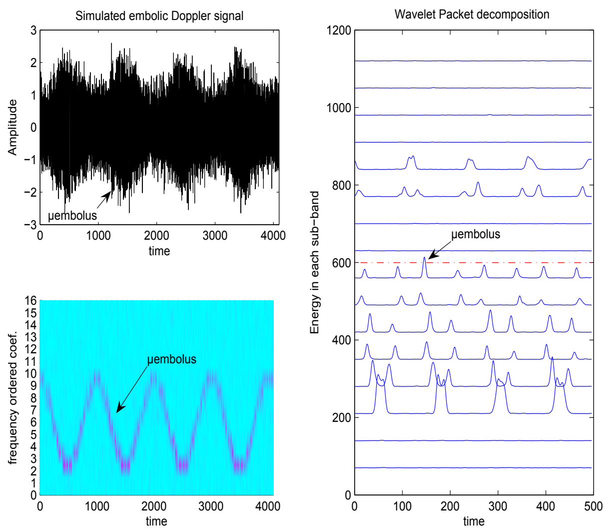

Fig. 1.
Wavelet packet analysis of a Doppler embolus signal corrupted by a white noise ($SNR = 10dB$ and $ESR_2 = 1.4dB$).

where ω_c is the fundamental cyclic frequency and where a_k are the amplitudes of the different harmonics, $a_0 = 1$. These amplitude coefficients serve as modulation frequency indices.

The fourth component corresponds to the embolus signature. A simple way to take into account the presence of an embolus is to superimpose a higher amplitude of limited duration on the blood Doppler signal:

$$D(t) = 1 + \gamma E(t), \tag{5}$$

where $E(t)$ is a function of limited duration, as for example a rectangular signal or a Hamming function. γ is a weighted coefficient indicating over-intensity.

Note that the energy level of the micro-embolus signal compared to the background Doppler signal is denoted ESR embolic energy to signal ratio. Here two ESR will be used: $ESR_1 = 1.2dB$ and $ESR_2 = 1.4dB$

III. SYNCHRONOUS DETECTION BY SUB-BAND DECOMPOSITION

Micro-embolus signals are usually detected by a binary test. If the decision information $DI(t)$ is greater than the threshold λ then an embolus is detected (hypothesis H_1), otherwise no embolus is detected (hypothesis H_0). This formulation can be expressed as follows:

$$DI(t) \quad \underset{H_0}{\overset{H_1}{\gtrless}} \quad \lambda \tag{6}$$

Such detection is then performed on decision information $DI(t)$ which, in our case, is the instantaneous energy $E(t)$.

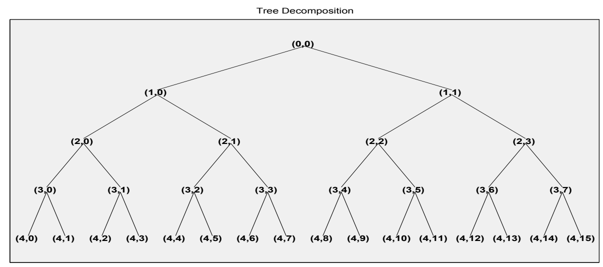

Fig. 2.
Tree decomposition of uniformed sub-bands.

Two types of energy estimators can be used, i.e. temporal or frequential estimators. Only temporal techniques were taken into account, with a view to implementing our detector/estimator in real time,.

A. Synchronous detectors

Unlike standard detection that is already implemented in commercial devices, synchronous detection allows detection synchronized with the cardiac cycle. This synchronization is very important because it detects low energy events during the cardiac cycle. Indeed, by synchronizing detection to the cardiac cycle, we compare the energy at a fixed time position t_0 in the cycle to a threshold $\lambda(t_0)$. This threshold is set to a statistical value obtained for example by $\lambda(t_0) = \mu(t_0) + 5\sigma(t_0)$. $\mu(t_0)$ and $\sigma(t_0)$ are the mean and the standard deviation taken at the time position t_0 of the cyclic energy, respectively. Note that this synchronous detection is equivalent to detection based on an adaptive threshold.

As our objective was to enhance the energy contrast between the embolus signature and the background Doppler signal, we decided to reduce the bandwidth. Note that in our study the background Doppler signal was considered as a non-desirable signal (as noise) and the information to be considered was the embolic signature. Therefore, to reduce the bandwidth and hence the energy, we decided to compute the energy of a signal $y(t)$ decomposed in N-sub-bands. In order to do this, we decided to assess the energy $E_n(\tau)$ in each channel n. In this case the binary case is given by:

$$E_n(t) \quad \underset{H_0}{\overset{H_1}{\gtrless}} \quad \lambda(t) \tag{7}$$

Note that the threshold $\lambda(t)$ is a function of time in the cardiac cycle, as mentioned above.

B. Energy estimator based upon Wavelet packet decomposition

There is a wide range of techniques proposing uniform decomposition in the M-channel including modified discrete cosinus transform filter banks, M-band pseudo

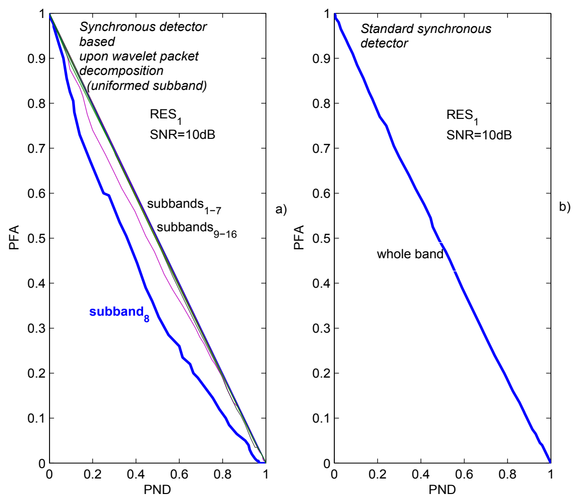

Fig. 3.
ROC curves obtained with $SNR = 10dB$ and $ESR_1 = 1.2dB$. a) Synchronous detector based on wavelet packet decomposition (16 uniformed sub-bands).b) Standard synchronous detector.

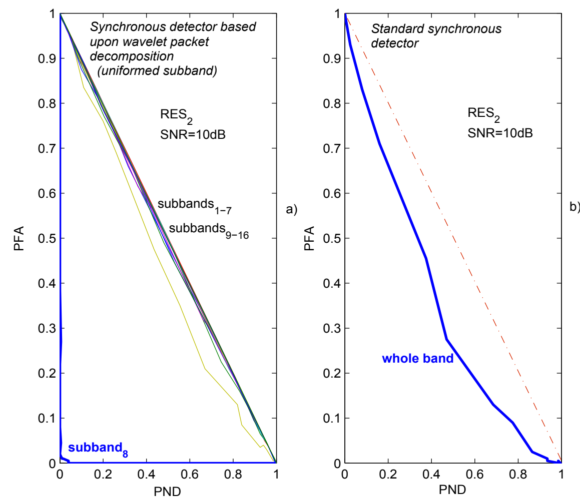

Fig. 4.
ROC curves obtained with $SNR = 10dB$ and $ESR_2 = 1.4dB$. a) Synchronous detector based on wavelet packet decomposition (16 uniformed sub-bands). b) Standard synchronous detector.

quadrature mirror filters, and wavelet packet decomposition. Here we focus only on analysis of wavelet packet decomposition [6].

In wavelet analysis, a signal is split into an approximation and a detail. The approximation is then itself split into a second-level approximation and detail, and the process is repeated. Different ways can be selected to encode the signal. This processing can be viewed as a wavelet packet decomposition tree (Fig.(2)).

Each frequency sub-band corresponds to the decomposition coefficients from each stage. Wavelet packet analysis thus decomposes the signal being studied $y(t)$ into an orthonormal basis as follows:

$$y(t) = x(t) + \epsilon(t) = \sum_j \sum_k C_{j,k}\psi_{j,k} + \epsilon(t),$$

where ϵ represents an error. As in the wavelet framework, k can be interpreted as a time-localization parameter and j as a scale parameter. $\psi_{j,k}$ is the wavelet family and $C_{j,k}$ are coefficients given by:

$$C_{j,k} = \int x(t)\psi_{j,k}dt.$$

The wavelet family (Meyer wavelet for example) can be expressed on different scales by:

$$\psi_{j,k}(x) = 2^{-j/2}\psi(2^{-j}x - k).$$

By introducing a new function W and using an orthogonal wavelet, the computation scheme for wavelet packet generation is easy. Note that W is a function of two filters: a scaling filter h_k and a wavelet filter g_k, given by the following relationship [6]:

$$W_{2n}(x) = \sqrt{2}\sum_{k=0}^{2N-1} h_k W_n(2x - k),$$

$$W_{2n+1}(x) = \sqrt{2}\sum_{k=0}^{2N-1} g_k W_n(2x - k),$$

where $W_0(x) = \phi(x)$ is the scaling function and $W_1(x) = \psi(x)$ is the wavelet function. As for $\psi(x)$, the function $W(x)$ can be expressed by:

$$W_{j,k,n}(x) = 2^{-j/2}W_n(2^{-j}x - k).$$

The basic idea of wavelet packets is that for fixed values of j and k, $W_{j,k,n}(x)$ analyzes the fluctuations of the signal roughly around the position $k2^j$ on the scale 2^j and at various frequencies for the different admissible values of the last parameter n.

After such sub-band decomposition, the Doppler embolus signal can be expressed as follows:

$$x(t) = \sum_{n=1}^{N_{sb}} x_n(t),$$

where N_{sb} is the total number of channels and $x_n(t)$ is the signal in the nth sub-band. The instantaneous energy in the nth sub-band is evaluated by a sliding window approach described as follows:

$$E_n(t) = \int_t^{t+T} x_n(\tau)^2 d\tau.$$

To validate our new synchronous estimator, we compared it to a standard synchronous detector. The decision information corresponds to the energy evaluated in the whole spectral band. This instantaneous energy can be obtained by summing the contributions of all channels:

$$E(t) = \sum_{n=1}^{N_{sb}} E_n(t).$$

IV. COMPARISON AND DISCUSSION

Before discussing the statistical analysis, note that we tested many wavelet functions such as Haar, Daubechies, Coifman, Meyer functions. The best results were obtained from the Meyer wavelet. These results are in part explained by the fact that the Meyer wavelet looks like the embolic signature. Furthermore, the best trade-off between the total number of channels for the $ESR_1 = 1.2dB$ and $ESR_2 = 1.4dB$ tested and the best detection was for $N_{sb} = 16$. Note also that the length of the sliding window is equal to 128 samples.

In order to compare the different synchronous detectors, we estimated the received operating curve (ROC). The statistical study was performed on a simulated embolic signal (only one embolus in the Doppler signal) corrupted by white noise ($SNR = 10dB$) see Fig.(1). The embolus was incorporated in a cyclic position of the Doppler signal whose mean frequency was in the 8th channel. The computation of the probability of false alarm (PFA) and the probability of non-detection (PND) were evaluated over 200 experiments. The ROC curves for two different ESR are illustrated in Figs.(3) and (4): $ESR_1 = 1.2dB$ and $ESR_2 = 1.4dB$. Computation of the ESR was performed with a sliding window of 128 samples.

Fig.(3) shows that the best detector for $SNR = 10dB$, $ESR_1 = 1.2dB$ was the synchronous sub-band detector. The embolic signature was detected in the 8th sub-band while all the other channels were insensitive, except perhaps the 7th channel. The ROC curve of the 8th sub-band showed the best performance in terms of PFA and PND because its curve was closer to the ideal point ($PFA = 0$, $PND = 0$) compared to the others. No detections were taken into account for the standard detector, the ROC curves being superimposed on the diagonal.

Fig.(4) confirms the superiority of the new detector compared to the standard detector for $SNR = 10dB$, $ESR_2 = 1.4dB$.The ROC curve of the 8th sub-band showed the best performance in terms of PFA and PND because its curve was quasi superimposed to the ideal point ($PFA = 0$, $PND = 0$) compared to the others. Some detections were taken into account for the standard detector, however the ROC curve was closer to the diagonal.

In order to test the sensitivity of our new detector, we tested it with real embolic signals. An illustration is given in Fig.(5). Although the ESR was high, the proposed detector appeared to be very sensitive. Indeed, channels 3 and 4 showed very high intensities compared to other channels. We did not take into account here the hypothesis that there is time-frequency variability of the cardiac cycle. Research studies are in progress to test this.

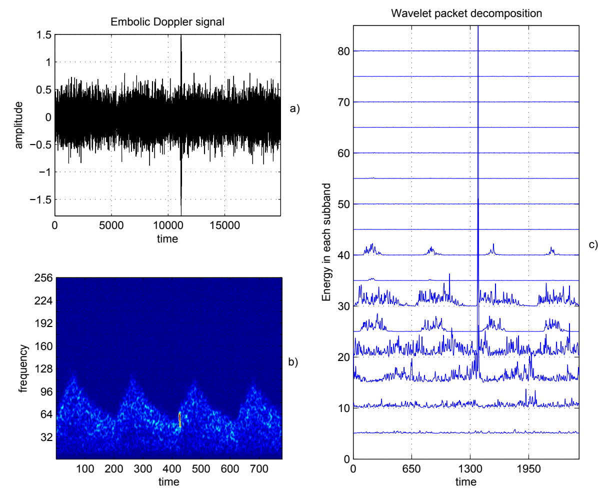

Fig. 5.
In vivo Doppler embolic signal. a) Amplitude of the Doppler signal. b) Spectrogram. c) Energy in each sub-band (Wavelet packet decomposition).

V. CONCLUSION

In this study we report a new detector that combines a synchronous detector and sub-band decomposition. We tested this new detector on simulated embolic Doppler signals and we discuss its performance with ROC curves. This detector seems very appropriate to detect small embolic signatures compared to standard detectors. Its real time implementation and a study to take into account time-frequency variability of the cardiac cycle are in progress.

References

[1] M.P. Spencer, G.I. Thomas, S.C. Nicholls and L.R. Sauvage *Detection of middle cerebral artery emboli during carotid endarterectomy using transcranial Doppler ultrasonography.* Stroke, 21, 415–423, 1990.

[2] J. Smith, D. Evans, and R. Naylor, *Analysis of the frequency modulation present in doppler ultrasound signal may allow differentiation between partiulate and gaseous cerebral emboli,* Ultrasound in medecine and biology, 23, pp. 727–734, 1997.

[3] J.M. Girault, D. Kouamé, A. Ouahabi and F.Patat. *Microembolic detection: an ultrasound Doppler signal processing view point.* Ieee Trans. Biomed. Eng., 47, 1431–1439, 2000.

[4] J.M. Girault, M. Biard, D. Kouamé, A. Bleuzen, and F. Tranquart. *Spectral Correlation of the embolic blood Doppler signal.* ICASSP, Toulouse, 2006.

[5] J.M. Girault, M. Biard, D. Kouamé, G. Souchon, A. Bleuzen and F. Tranquart. *Etude de la cyclostationnarité du signal Doppler sanguin pour la détection de micro-emboles : étude préliminaire.* Gretsi, Louvain, 2005.

[6] R.R. Coifman. *Wavelet Analysis and signal processing*in Signal Processing Part I: Signal Processing theory. L. Auslander et al., eds IMA Springer, vol.22, New York, 1990.