DETECTION AND ESTIMATION OF EMBOLIC DOPPLER SIGNALS USING DISCRETE WAVELET TRANSFORM

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ABSTRACT

Almost any system for the detection of asymptomatic circulating emboli by Doppler ultrasound employs the fast Fourier Transform (FFT). However, the FFT is not ideally suited to study short-lived embolic signals. The wavelet transform (WT) is an optimized way of analyzing short-lived signals and performs better than the FFT in some respect. We propose a detection method based on the discrete wavelet transform (DWT) and study some parameters, which might be useful for describing embolic signals. We used 2 independent data sets, comprising 100 low intensity embolic signals, 100 various type of artifacts and 100 Doppler speckle. After applying the DWT to the data, several parameters were evaluated. The threshold values used for both data sets were optimized using the first data set. 98 out of 100 embolic signals were detected as embolic signals for the first data set. 95 out of 100 embolic signals were detected for the second data set when the same threshold values were used.

1. INTRODUCTION

Asymptomatic circulating cerebral emboli, which are particles larger than red blood cells, can be detected by transcranial Doppler ultrasound [1]. In certain conditions, such as carotid artery stenosis, asymptomatic embolic signals appear to be markers of increased stroke risk and may be useful in patient management [2]. A major problem with clinical implementation of the technique is the lack of a reliable automated system of embolic signal detection. Recordings in patients may need to be one or more hours in duration and analyzing the spectra visually is time consuming and subject to observer fatigue and error. While inter-observer reproducibility studies have demonstrated that there is an overall high level of agreement in identifying embolic signals, this is poorest for embolic signals of low relative intensity [3]. Agreement would be improved by any method of signal analysis, which improves the embolic signal to background signal ratio. Embolic signals reflected by an embolus, has some distinctive characteristics when compared to the Doppler signals from normal blood flow and artifacts. They have usually larger amplitude than the signals from normal blood flow and show a transient characteristic because of their reflectivity and size compared to the blood cells. They are also frequency focused. So they can be considered as narrow-band signals. They are finite oscillating signals and resemble wavelets. Therefore, the wavelet transform appears to be a natural method for analysis and detection of such signals [4]. Fig. 1 shows some examples of embolic signals seen in-vivo. Unlike many artifacts such as caused by probe movement or speech, embolic signals are unidirectional and usually contained within the flow spectrum. Embolic signals corrupted by large artifacts are shown in Figs. 1(c), 1(d), and 1(g). In this study we use the DWT to decompose an embolic signal into different frequency bands and attempt to determine which features most accurately describe embolic signals over the scales. Then we investigate how to utilize these features in an online system.

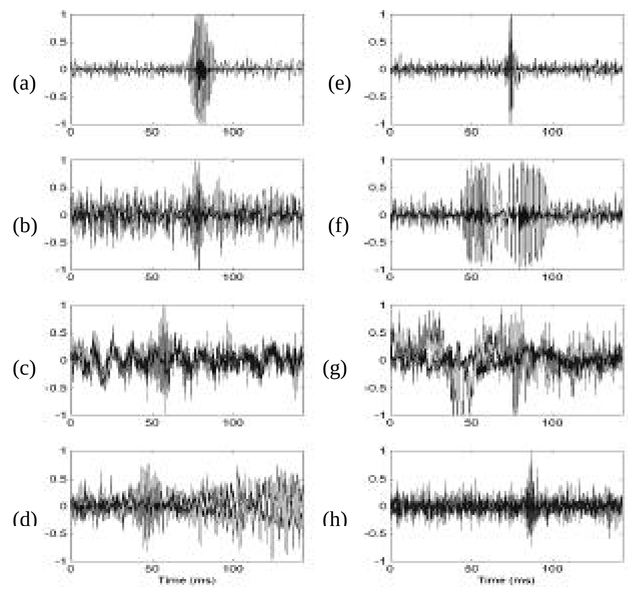

Figure 1. Examples of embolic signals seen in-vivo. For clarity, forward (ligth) and reverse (dark) flow components are shown. Note that the signals in (c), (d), and (g) are corrupted by large artifacts.

2. DISCRETE WAVELET TRANSFORM OF EMBOLIC SIGNALS

A DWT yields a countable set of coefficients, which correspond to points on a two dimensional grid of discrete points in the time-scale domain. The DWT is defined with respect to a mother wavelet and maps finite energy signals to a two dimensional grid of coefficients. When a discrete time finite energy signal $s(k)$ with length N is considered, its DWT is a discrete inner product with wavelet function ψ, which can be written as a circular convolution:

$$W_s(m,n) = \frac{1}{\sqrt{a_0^m}} \sum_{k=0}^{N-1} s(k)\psi\left(\frac{k-nb_0a_0^m}{a_0^m}\right) = s(k) \otimes \psi_{m,n} \quad (1)$$

where m and n are discrete scale and translation steps. The process implemented at each stage can be simplified as low-pass filtering (averaging) of the signal for the approximations and high-pass filtering (differencing) of the signal for the details, and then decimating (downsampling) of the coefficients to reduce sampling rate by half. The WT coefficients can be interpreted as the resemblance indexes between the signal and the wavelet, so the WT of a signal is not unique and very much depends on the choice of the wavelet. Under certain conditions [5], reconstructing a signal from its wavelet coefficients is also possible. The process is called inverse discrete wavelet transform (IDWT) and involves upsampling (interpolation) and filtering. Upsampling is the process of lengthening a signal by inserting zeros between samples.

Prior to study of Doppler speckle, embolic signals, and artifact, it is important to understand the DWT of the Gaussian white noise. If a Gaussian white noise is decomposed by using the DWT, variance decreases approximately two-fold between one level and next. So the signals reconstructed at each scales are no longer white noise as the filters introduce color. Approximations and details of a Gaussian white noise are Gaussian colored noises and that these signals are increasingly interdependent as the resolution increases. If the analyzed signal $s(t)$ is stationary, zero mean, white noise, the wavelet coefficients are uncorrelated. If $s(t)$ is Gaussian, coefficients are independent and Gaussian. If $s(t)$ is colored, stationary, zero mean Gaussian sequence, the coefficients remain Gaussian.

Audio Doppler signals can be considered as band-limited signals as they are caused by many small scatterers (red blood cells) within the ultrasonic sample volume. Since the speed of the red blood cells is not uniformly distributed within the sample volume, backscattered Doppler ultrasonic signals form a range of frequencies. Actual distribution of the Doppler ultrasound signal is influenced by many other factors as well, such as tissue interface, transducer characteristics, filters etc. The DWT coefficients resulting from normal blood flow concentrates mostly in the lower scales. Embolic signals differ from normal Doppler signals in some respect. Although they are much shorter in time, have higher amplitudes and narrower frequency bands, it is obvious that there is an overlap between embolic signals and normal Doppler signals. Therefore it is impossible to isolate an embolic event totally from the normal Doppler signal. However a certain degree of improvement on detecting embolic signals is achievable by using the wavelet decomposition. The movements of some components of a complete examination system, which are supposed to be stationary during the examination procedure, produce artifacts. These include probe movement, tapping, breathing, speaking, coughing, etc. They contribute some unwanted components to the Doppler signals. However, unlike the normal Doppler signal, most of them are bi-directional and have lower frequency spectrum. Identifying and eventually suppressing the low frequency bi-directional artifacts using the DWT are quite straightforward. Artifacts usually dominate the higher scales, as they are mostly low frequency signals.

Table 1 Some parameters for embolic signals, artifacts and Doppler speckle. Values are mean (standart deviation)

	Embolic Signal	Artifact	Speckle
SMI	2.45(0.83)	5.96(0.77)	3.27(0.72)
TP2TR(dB)	25.13(3.17)	34.57(6.62)	18.32(3.13)
PI2TR(dB)	12.1(3.01)	14.16(6.77)	6.29(1.82)
F2RRM(dB)	25.44(7.01)	9.4(11.15)	23.18(7.59)
F2RR8(dB)	1.29(7.13)	1.79(11.25)	-0.58(6.18)
RR(ms/dB)	3.88(2.53)	0.95(0.59)	3.52(2.05)
FR(ms/dB)	4.65(3.15)	0.97(0.63)	4.00(2.12)

3. METHOD

The embolic signals used for this study were recorded using a commercially available transcranial Doppler system (EME Pioneer TC4040) with a 2MHz transducer. The recordings were made from the ipsilateral middle cerebral artery of patients with symptomatic carotid stenosis. The quadrature audio Doppler signals containing embolic signals were exported to a PC for signal analysis. The sampling frequency of these signals was 7150 Hz. In order to evaluate feasibility of the DWT of embolic signals, 2 independent data sets, comprising 100 low intensity embolic signals, 100 various type of artifacts and 100 Doppler speckle, were used. After applying the DWT to the data, several parameters were evaluated. The threshold values used in the both data sets were optimized using the first data set. An eight order Daubechies wavelet filter was used for the both data sets. Number of scales was eight. Main difference between two data sets was number of data considered for processing. Only one cardiac cycle (approximately 1 second) was considered for the 1st data set. For the 2nd data set, several cardiac cycles (approximately 5 seconds) were considered. The following parameters were derived from the reconstructed wavelet coefficients;

- Scale with maximum intensity (SMI)
- Total power to threshold ratio for the embolic signal duration (TP2TR)
- Peak intensity to threshold ratio (PI2TR)
- Forward to reverse intensity ratio at the scale with maximum intensity (F2RRM)
- Forward to reverse intensity ratio at the scale 8 (F2RR8)
- Rise rate of embolic signal power (RR)
- Fall rate of embolic signal power (FR)

Additional to these parameters, averaged time center (t_s), averaged normalized frequency center (f_s), time spreading (T_s^2), and frequency spreading (B_s^2) of embolic signals were considered. These parameters are defined as

$$t_s = \frac{1}{E_s}\int_{-\infty}^{+\infty} t\left|s(t)\right|^2 dt \quad (2)$$

$$f_s = \frac{1}{E_s}\int_{-\infty}^{+\infty} f\left|S(f)\right|^2 df \quad (3)$$

$$T_s^2 = \frac{4\pi}{E_s}\int_{-\infty}^{+\infty} (t-t_s)^2\left|s(t)\right|^2 dt \quad (4)$$

$$B_s^2 = \frac{4p}{E_s}\int_{-\infty}^{+\infty}(f - f_s)^2 |S(f)|^2 df \qquad (5)$$

where $E_s = \int_{-\infty}^{+\infty}|s(t)|^2 dt \qquad < +\infty$

A narrow-band signal then can be characterized in the time-frequency plane by its mean position (t_s, f_s) and a domain of main energy localization whose area is proportional to the time-bandwidth product $T_s \times B_s$. Another way to describe a signal simultaneously in time and frequency is to consider its instantaneous amplitude (*ie*) and instantaneous frequency (*if*).

ie is defined as $a(t) = |s_a(t)|$

if is defined as $f(t) = \frac{1}{2p}\frac{d \arg s_a(t)}{dt}$

where $s_a(t) = s(t) + jH\{s(t)\}$ and H stands for Hilbert transform. Standard deviation of *ie* and standard deviation of *if* were also used as detection parameters.

Processing steps for the detection of embolic signals can be summarized as following:

- Obtain directional Doppler signals by applying phasing filter technique [6] to quadrature Doppler signals.
- Apply 8 scales DWT to each channel in order to obtain directional DWT coefficients. An 8th order Daubechies wavelet filter was used.
- Reconstruct individual wavelet coefficients using the IDWT.
- Find instantaneous envelopes of each scales.
- Derive a threshold value from the signal for each scale to be used in detection.
- Evaluate certain parameters for each scale.
- Apply detection logic.

4. RESULTS AND DISCUSSION

Mean values (standard deviations) of the various signal characteristics for embolic signals, Doppler speckle, and artifact are shown in Table 1. The mean SMI for embolic signals implies that, embolic signals mainly appear at lower scales. 13 out of 100 embolic signals in the 1st data set had maximum intensity at the 1st scale. 9 embolic signals had maximum intensity at the 4th scale. Some of these embolic signals had some components at lower or higher scales because of the chirping characteristic. The mean SMI for artifacts shows that they appear at the higher scales (centered at 6th scale). The mean SMI for Doppler speckle suggests that the Doppler speckle, which might be detected as embolus, occupy mainly 3rd scale spanning from 2nd to 4th scales. Although they were significantly different (p=<0.0001), there is a certain overlap between the SMI for embolic signals and speckles. One practical conclusion, which can be derived from the SMI values, is that restricting the DWT analysis to the first 4 scales can eliminate most of the artifacts. The mean TP2TR for embolic signal is greater than the mean TP2TR for speckle and less than the mean TP2TR for artifacts. The mean PI2TR value for embolic signals is greater than the mean PI2TR value for speckle and less than artifact. The mean F2RRM value, which reveals the directionality of a signal, suggests that embolic signals and Doppler speckle are unidirectional when compared to the mean value of the F2RRM for artifacts. This parameter is directly influenced by the ability of directional signal separation of the Doppler system used for the recordings. The mean F2RR8 values suggest that there is no useful information at higher scales. These scales are mainly dominated by bi-directional slowly varying signals resulting from artifacts such as tissue movement etc. A practical conclusion from this observation is that a simple WT process can be employed to enhance any Doppler signal or an ultrasonic image by simply canceling out related wavelet coefficient during reconstruction. Embolic signals result from an object passing through an ultrasonic sample volume causing a gradual intensity increase and then gradual decrease with a chirping effect. The mean RR and FR for embolic signals are suggesting that emboli and normal red blood cells have certain behavioral similarities. This can only be justified when both a red blood cell and an embolus are considered as a single scatterer. In practice, the size of the red blood cell is extremely small to be considered as single scatterer and beyond the detection resolution of any Doppler ultrasonic system. Instead red blood cell aggregates are scatterers producing a wide band signal when compared to a signal resulting from an embolus. Frequency band of an embolic signal is much narrower. This is because the size of an embolus, which validates the assumption of an embolus as a single scatterer, is much bigger than that of red blood cells. When the parameters defined above used to classify embolic signals, sensitivity and specificity achieved are give in Table 2. These results are as good or better than the other methods reported in [7].

In this study we have used a signal-processing algorithm based on the DWT to characterize embolic signals, Doppler speckle, and artifacts. Results show that the detection parameters derived from the DWT coefficients is likely to improve the sensitivity of an automated system. In an automated embolic signal detection system, there are several important aspects. First, the algorithm must emphasize embolic signals and preferably suppress Doppler speckle and artifacts. Such a feature will lead to an improvement in embolic signal intensity to background signal intensity ratio. As an example, Fig. 2 illustrates an embolic signal corrupted by a large artifact caused by speech or cough and reconstructed wavelet coefficients at each scale (five scales only). Here, the embolic signal is much smaller than the artifact. But after the DWT, it is easy to detect it at the second scale. This problem can be considered as the detection and estimation of signals in noise. Embolic signals can be defined within the context of wavelet theory. In fact, they are 'wavelets' resulting from a single scatterer passing through an ultrasonic sample volume. They satisfy the basic properties of wavelets: embolic signals oscillate and decay rapidly as wavelets do. Therefore they were described as 'frequency focused' as well as 'short duration' high intensity transients [8]. The results prove that the DWT is an effective tool for the detection and estimation of embolic Doppler ultrasound signals. An online embolic signal detection and estimation system, which utilizes some parameters derived from the reconstructed DWT coefficients of Doppler ultrasound signals as described here, is under development.

Table 2 Detection performance of the algorithm based on the DWT.

1st data set	2nd data set
100 embolic signals	100 embolic signals
98% as embolic signal	95% as embolic signal
1% as artifact	3% as artifact
1% disputed	2% disputed
100 artifacts	100 artifacts
96% as artifact	98% as artifact
4% disputed	2% as embolic signal
100 Doppler speckle	100 Doppler speckle
93% as speckle	95% as speckle
6% as embolic signal	1% as artefact
1% disputed	4% disputed

5. REFERENCES

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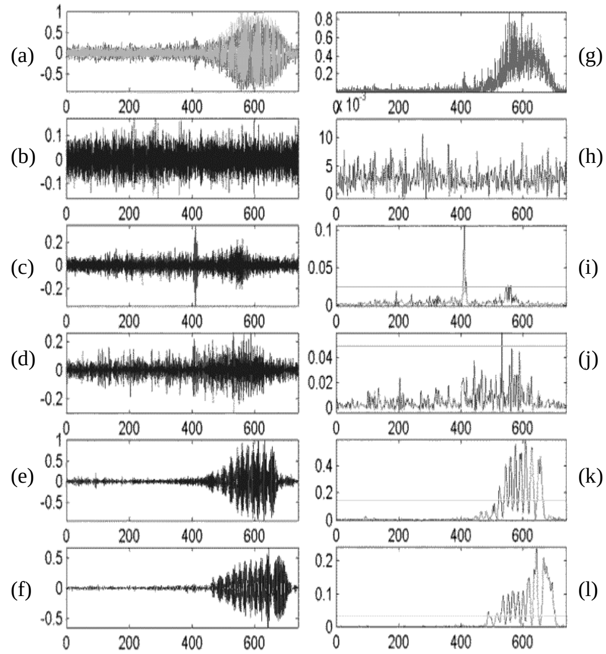

Figure 2. (a) An embolic signal corrupted with an artifact, and (g) corresponding instantaneous envelope. (b, c, d, e, f) Reconstructed wavelet coefficients from scale 1 to 5, and (h, i, j, k, l) corresponding instantaneous envelopes (only for forward signal).

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