CHOICE OF WAVELET FUNCTION IN DETECTION OF EMBOLIC SIGNALS USING DISCRETE WAVELET TRANSFORM

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ABSTRACT

Wavelet transform is increasingly being used in analysis and detection of biomedical signals. One interesting application is detection and identification of embolic Doppler ultrasound signals caused by very small asymptomatic emboli circulating within blood flow. Since the wavelet transform involves correlating the signal being analyzed and a prototype wavelet function, the choice of the wavelet function may influence the performance of wavelet based detection system. In this paper, an investigation on the effect of the wavelet function on detection of embolic signals is presented.

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 (ES) appear to be markers of increased stroke risk and may be useful in patient management [2]. Therefore detection of ES constitutes an important part in preventing stroke. Fig. 1 illustrates some ES seen in-vivo.

Wavelet transform is increasingly being used in ES detection and identification [3-6]. However importance of the choice of the wavelet function is usually underestimated. In this study, we employ a number of wavelet functions within an on-line ES detection system based on discrete wavelet transform (DWT) [6] and try to determine how the detection result is influenced by the choice of the wavelet function.

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:

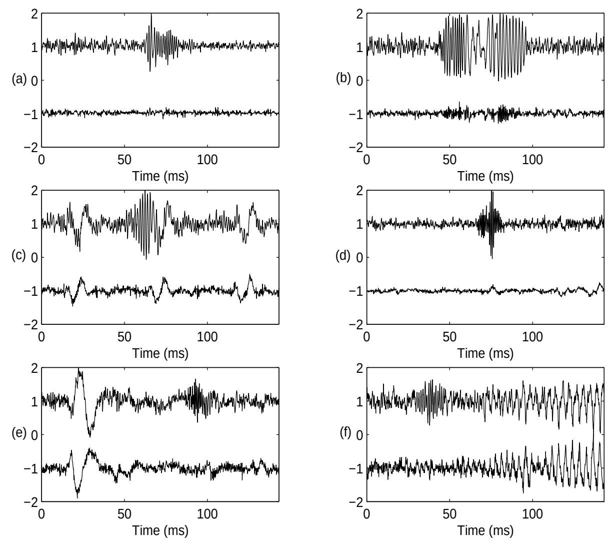

Fig. 1. Examples of ES seen in-vivo. For clarity, forward and reverse flow components are scaled by 1 and -1 respectively.

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

where m and n are discrete scale and translation steps. The process implemented at each stage can be simplified as low-pass filtering of the signal for the approximations and high-pass filtering of the signal for the details, and then decimating of the coefficients to reduce sampling rate by half. The DWT coefficients can be interpreted as the resemblance indexes between the signal and the wavelet, so the DWT of a signal is not unique and very much depends

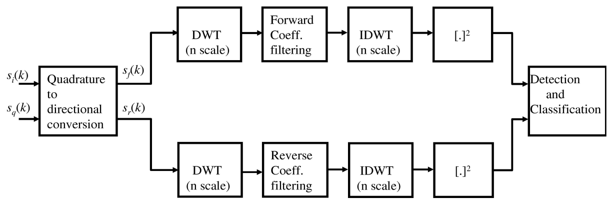

Fig. 2. Block diagram of the automated emboli detection system

on the choice of the wavelet. Under certain conditions [7], reconstructing a signal from its wavelet coefficients is also possible. The process is called inverse discrete wavelet transform and involves interpolation and filtering [8].

2. METHODOLOGY

Two different data sets each containing 100 previously known ES were used for this study. The ES were recorded using a commercially available transcranial Doppler system (EME Pioneer TC4040) with a 2 MHz transducer. The recordings were made preoperatively from patients presented with 50% or more symptomatic internal carotid artery stenosis, and from the patients underwent carotid endarterectomy. Recordings had been made onto digital audiotape. ES were identified subjectively by two experienced observers from both the FFT spectral display and the audio signal using conventional criteria [9]. The quadrature audio Doppler signals containing ES were exported to a PC for signal analysis. The sampling frequency of these signals was 7150 Hz. From this recorded signals, only extracts of 5 seconds of each signal containing ES were used.

An automated detection system based on the DWT and fuzzy logic was used [10]. Block diagram of the system is illustrated in Fig. 2. ES in two data sets were detected by this automated detection system by using each wavelet function considered for this study. Wavelet functions used for this study were standard DWT functions available in Matlab Wavelet toolbox [11], namely Biorthogonal (1.1, 1.3, 1.5, 2.2, 2.4, 2.6, 2.8, 3.1, 3.3, 3.5, 3.7, 3.9, 4.4, 5.5, 6,8), Coiflet (1 to 5), Daubechies (1 to 32), and Symlet (2 to 8). However, Matlab wavelet toolbox was not used in the detection. Instead, these functions were integrated into the automatic detection system.

3. RESULTS

Detection results for two data sets with each of the wavelet functions used in the detection algorithm are summarized in Tables 1, 2, 3, and 4. The results in the tables show how many of the previously known 100 ES were detected for

TABLE I

DETECTION WITH BIORTHOGONAL-WAVELET FUNCTIONS

Wavelet type	ES Detection (%)	
	Data set 1	Data set 2
Biorthogonal 1.1	66	86
Biorthogonal 1.3	72	86
Biorthogonal 1.5	72	85
Biorthogonal 2.2	67	89
Biorthogonal 2.4	75	97
Biorthogonal 2.6	78	96
Biorthogonal 2.8	80	97
Biorthogonal 3.1	55	67
Biorthogonal 3.3	67	92
Biorthogonal 3.5	81	95
Biorthogonal 3.7	81	97
Biorthogonal 3.9	86	94
Biorthogonal 4.4	79	97
Biorthogonal 5.5	80	95
Biorthogonal 6.8	83	99

TABLE II

DETECTION WITH COIFLET-WAVELET FUNCTIONS

Wavelet type	ES Detection (%)	
	Data set 1	Data set 2
Coiflet 1	71	93
Coiflet 2	81	96
Coiflet 3	82	98
Coiflet 4	87	97
Coiflet 5	85	98

two data sets. Obviously some ES were missed by the detection system. Since no detection parameters other than the wavelet filter type changed, the results give a good indication on the suitability of the wavelet function for the particular data set. In Table 1, detection results are given for different Biorthogonal types of the wavelet function. Best detection was achieved by Biorthogonal3.9 for the data set 1 and Biorthogonal6.8 for the dataset 2. For the Coiflet type wavelet, Coiflet4 for the dataset 1, Coiflet3 and Coiflet 5 for the dataset 2 achieved the best results (Table 2). For the Symlet type wavelet, the best result was obtained by Symlet8 for the first dataset, Symlet7 for the second dataset (Table 3). For the Daubechies type wavelet, the best result was obtained by Daubechies11 and Daubechies26 for the first dataset and Daubechies13 for the second dataset (Table 4).

4. CONCLUSION AND DISUSSION

From the tables, it is easy to say that ES to background Doppler signal ratio for the first data set was less then the second data set. Detection results for the wavelet functions given in the tables indicate that there is no analytical justification for the choice of a particular wavelet function for a particular signal. Overall, higher order wavelet

TABLE III
DETECTION WITH SYMLET-WAVELET FUNCTIONS

Wavelet type	ES Detection (%)	
	Data set 1	Data set 2
Symlet 2	70	92
Symlet 3	77	95
Symlet 4	83	97
Symlet 5	83	95
Symlet 6	86	97
Symlet 7	82	100
Symlet 8	89	98

functions (or filters) yield better detection results. However, utilization of higher order wavelet filters leads to more computation. It is desirable to obtain the best result by using the least number of coefficients. For the first data set the best detection were obtained for Daubechies11 and Daubechies27 wavelet filters (93% detection). However, when the number of coefficients considered, obvious choice is Daubechies 11 filter. It is also apparent from the table that a wavelet function giving the best detection result for a certain dataset may not give the best result for another

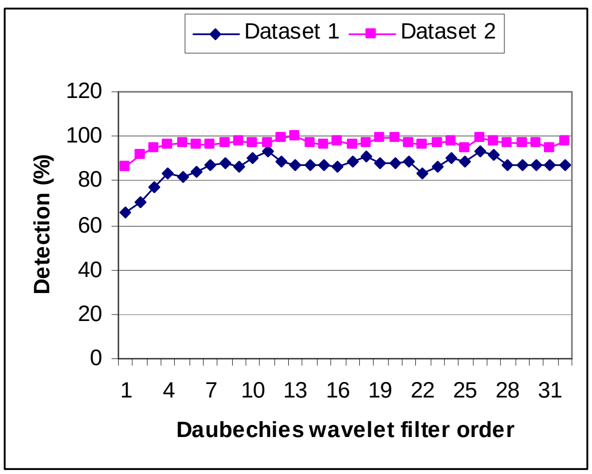

Fig. 3. Detection rates for two data sets with Daubechies wavelet filters.

dataset as also seen in Fig. 3, which illustrates comparative detection rates for the two datasets.

Overall, detection rate consistently increases for the filter lengths 5 and more. However, increase in detection rate is insignificant after a certain filter length. Therefore minimum length wavelet filter should be used. Since there is no analytical method determining the best wavelet filter for a particular data type, the required wavelet filter should be determined experimentally.

TABLE IV
DETECTION WITH DAUBECHIES-WAVELET FUNCTIONS

Wavelet type	ES Detection (%)	
	Data set 1	Data set 2
Daubechies 1	66	86
Daubechies 2	70	92
Daubechies 3	77	95
Daubechies 4	83	96
Daubechies 5	82	97
Daubechies 6	84	96
Daubechies 7	87	96
Daubechies 8	88	97
Daubechies 9	86	98
Daubechies 10	90	97
Daubechies 11	93	97
Daubechies 12	89	99
Daubechies 13	87	100
Daubechies 14	87	97
Daubechies 15	87	96
Daubechies 16	86	98
Daubechies 17	89	96
Daubechies 18	91	97
Daubechies 19	88	99
Daubechies 20	88	99
Daubechies 21	89	97
Daubechies 22	83	96
Daubechies 23	86	97
Daubechies 24	90	98
Daubechies 25	89	95
Daubechies 26	93	99
Daubechies 27	92	98
Daubechies 28	87	97
Daubechies 29	87	97
Daubechies 30	87	97
Daubechies 31	87	95
Daubechies 32	87	98

Experimental results also show that one wavelet filter giving a good result for a data set may not give the same good result for another data set. This is main disadvantage of using wavelet transform in detection and identification of nonlinear signals. There is no universal wavelet function which suits all type of signals. A good choice of the wavelet type for a particular application requires a certain degree of knowledge of the signal of interest. Therefore it is advisable that suitable wavelet for a particular application should be determined experimentally.

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