# TECHNICAL REPORT

## Novel Intelligent Wavelet Filtering of Embolic Signals from TCD Ultrasound

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### Abstract

Transcranial Doppler ultrasound can be used to detect emboli in blood flow for predicting stroke. Embolic signals have characteristic transient chirps suitable for wavelet analysis. We have implemented and evaluated the first on-line intelligent wavelet filter to amplify embolic signals building on our previous work in detection. Our intelligent wavelet amplifier uses the matching filter properties of the Daubechies $8^{th}$ order wavelet to amplify embolic signals. Even the smallest embolic signal is enhanced without affecting the background blood flow signal. We show an increase of over 2db (on average) in embolic signal strength and an improvement in detection of 10-20%.

### Introduction

Embolic signals need to be differentiated from both artifacts and random Doppler speckle (high intensity signals that occur in the normal Doppler waveform). Previous attempts at improving the embolic to signal noise ratio have used frequency filtering using band-pass filters with a fixed band-width. In contrast, our approach is not based on isolating the embolic frequency segments, but rather enhancing them using the Daubechies discrete wavelet transform. Wavelets are an excellent transform for analyzing embolic signals, because of their resemblance to embolic signals and superior time resolution [Nizam 1999, Krongold 1999]. We use the discrete wavelet transform as a method of finding an instantaneous matching filter for each embolic signal. The better the chosen basis the better the enhancement process works. Our experiments showed that the Daub $8^{th}$ order wavelet provided the best match for the embolic signals from the standard set of discrete wavelets. Figure 1 shows that on the first two scales the wavelet transform acts as a matched filter, although it is not a perfect match.

We have shown that the method is feasible in practice and much more efficient than doing multi band filtering, especially when combined with some intelligence.

**Wavelet Filter process**

Time-Scale and Time Frequency representations are powerful methods for analyzing and processing non-stationary signals with time-varying spectral content. A one-dimensional signal is mapped by a time frequency representation into a two-dimensional (2-D) signal, which is a function of both time and frequency. This joint representation exploits the non-stationary characteristics of a signal and, therefore, can be very useful in detecting non-stationary signals. The simplest and most popular time frequency representation is the short time Fourier transform which is simply an overlapped windowed fast Fourier transform. The problem with this type of analysis is that short duration narrowband signals such as embolic signals can be destroyed because of the time frequency resolution dilemma. With a large overlap, this problem is mitigated but it is still very time consuming to filter and nearly impossible to just amplify without altering the background signal significantly. The squared magnitude of the short time Fourier transform is known as the spectrogram and this is the usual display found on trans-cranial Doppler machines. Various quadratic time frequency representations, such as the Wigner distribution, provide a better potential detection performance. However the problem with these mathematical tools is that they require a concise statistical description of embolic signals.

$$W_s(t,f) \equiv \int s\left(t+\frac{\tau}{2}\right)s^*\left(t-\frac{\tau}{2}\right)e^{-j2\pi f\tau}\,d\tau.$$

[Wigner Transform]

Implementation of the quadratic time-frequency/time-scale detectors requires a statistical model of the emboli centred at some nominal time and frequency/scale. On the other hand simple linear detectors have not been always accurate. In order to use Linear filters as detectors, the underlying assumption is that the signal is known and deterministic. Embolic signals have a characteristic sound, but their sound is not uniform and requires visual confirmation on the spectrogram. As most embolic signals are similar to a Gaussian white noise process (as there intensities peaked at a centre frequency), a filter that most resembles their shape would be considered an optimal detector [Poor(1994)].

Krongold (1999) showed that the scalogram or magnitude square power of the wavelet scales is an optimal basis, using generalised likelihood ratio test statistics, as the exact embolic signal structure is not known before encountering the emboli. We used the discrete wavelet transform and a Daubechies $8^{th}$ order mother wavelet to provide a basis for searching for the scale that is most similar to the matching filter. A matched filter of each embolic signal provides the highest Embolic to background noise ratio possible. The Daubechies $8^{th}$ order wavelet is quite similar to embolic signals and at various dilations it represents an estimate of the matched filter. Higher order Daub filters were too smooth and resulted in the removal of parts of the course embolic signal. Estimates of embolic to background ratio along with intelligence for rejecting artefact and speckle were used to select the best scale. The process is detailed by Marvasti et al (2004).

The intelligent wavelet amplification software utilizes both the scale number(s) and the location of the potential embolic signal in time. At first glance it might appear that the filter is needlessly complicated, but this is because the interpretation of the discrete wavelet transform is not very intuitive. After taking the wavelet transform, only detail coefficients and one set of approximation coefficient are left. In order to reconstruct the original signal, each level of the approximation coefficients c(m,n) must be constructed from decomposed high pass d(m-1,n) and c(m-1, n) coefficients. The synthesis and analysis (g, h) filters are the same in an orthogonal wavelet basis such as Daubechies. The multiplication is in fact a sparse matrix.

$$C_{m,n} = \Sigma g_{n-2k} . c_{m-1,k} + h_{n-2k} . d_{m-1,k}$$

where $C_{m,n}$ and $d_{m-1,k}$ are approximation and detail coefficients at decomposition scale level $m$ - $log_2(n)$. A variable Hanning window is used to amplify the time scale-position denoted by $(m,n)$. Ultimately, no original data is eliminated unlike most wavelet de-noising applications. Within each wavelet transform block (Figure 2 S2), the selected scale wavelet coefficients are replaced with the new amplified wavelet coefficients. A scale (scale 2 in the example) is selected from all the detailed coefficients and copied to a new buffer (S3) where all the other coefficients are set to zero. It is reconstructed in the time domain by using the inverse discrete wavelet transform. The reconstructed scale (S4) is amplified by multiplying by a scaled Hanning Window. The amplified wavelet coefficients (S5) are then created using the forward discrete wavelet transform. The amplification window causes some distortion in the other scales (similar to Gibb's phenomenon in fast Fourier transform), but the effect is not significant because only the selected scale coefficients are used in the replacement stage.

The process shown in Figure 2 is repeated for both scales where the embolic signal is present. The intelligent wavelet amplification process evaluated in this paper operates on two scales, but does not always amplify both. The second scale is only amplified if there is a potential embolic signal also appearing on it. The peak on the second scale must be as high as 60% of the first scale. The second scale is ignored if it is at a high frequency as scales greater than 5 are mainly composed of artefacts.

The following parameters were found to provide optimal amplification with least distortion: Wavelet block size 1.024 seconds or 8192 data points; search window 150ms or 1200 data points; amplification multiples 2.1 and 1.5 for best and second best scales respectively, and amplification window size 64 ms or 512 data points. The amplification multiples represent a maximum gain of approximately 3 dB and 1.7 dB for the best and second best scale respectively. This is the limit before significant signal distortion occurs (due to clipping). The search window ensures that the peak of the embolic signal is aligned with the amplification window. The amplification window size is 512 data points or 1/16 of the total data on the selected scales, so only 1/16 of the selected scale is amplified using the variable Hanning Window. All the scale coefficients are calculated and a raw quadrature audio signal is reconstructed ready for passage through a commercial software package, called FS-1, for final embolic signal detection and decibel calculation.

## Results

The system was trained on 2 hours of recordings made from various patients. The testing was done on 1 hour of recordings from a combination of nine patients with symptomatic carotid stenosis. The raw Doppler audio was sampled at 8khz.

Table 1

| | Increase in Embolic Signal Strength | | | | |
|---|---|---|---|---|---|
| Std-dev | Average intensity (dB) | Number of Emboli | Average increase (dB) | False Positives | Extra |
| 2.99 | 9.00 | 96 | 2.0 | 1 | 2 |

On average there was an increase of 2db in signal intensity when comparing the filtered and non-filtered signals. Our intensity measurements used a fast Fourier transform spectrogram that is standard in blood flow measurements.

There was only one case in the compilation tape where a non embolic signal that was filtered created a false emboli. This false detection occurred on the first and second scales, which have a higher bandwidth. The larger bandwidth means more noise components (speckle and artifact) are present and thus the signal to noise ratio can be reduced. The higher frequency emboli are more sensitive to amplification. Sensitivity was also increase by 20% in the compiled data, and 10% in the online data from carotid stenosis patients. Specificity was mainly unchanged or slightly reduced in the online data. We plan to address this minor problem in the near future using better intelligence and packet filtering.

## Conclusion and Future Work

During this study we managed to show that a simple detection algorithm matched to a wavelet based amplifying filter can improve the S/N ratio and performance of manual and automated embolic detection systems. The commercial FS-1 software used in the EME Nicollete TCD Doppler had an improved performance after filtering. We had an average increase of 2db and a detection rate improvement of 10 – 20% after filtering. Two extra embolic signals were found after enhancement and were verified as embolic signals that had an original intensity of 5 db. The clear indication here is that while using the wavelets alone for detection wasn't necessarily better than frequency filtering, discrete wavelet transform amplification is useful as a preprocessing mechanism.

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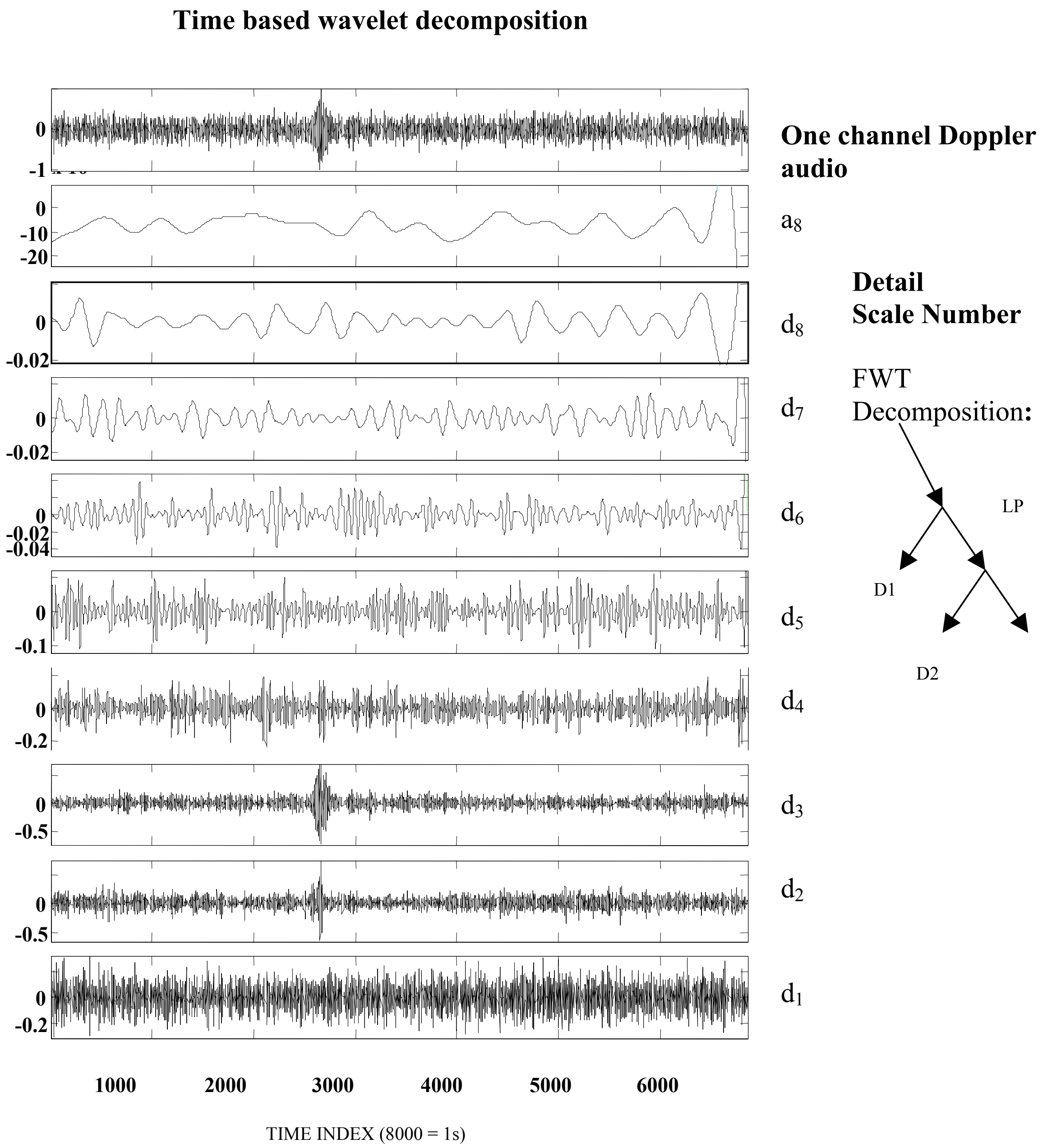


**Figure 1** 8 detail scales and one approximation scale using Daub 8 DWT. Each Scale is reconstructed to the full data width.

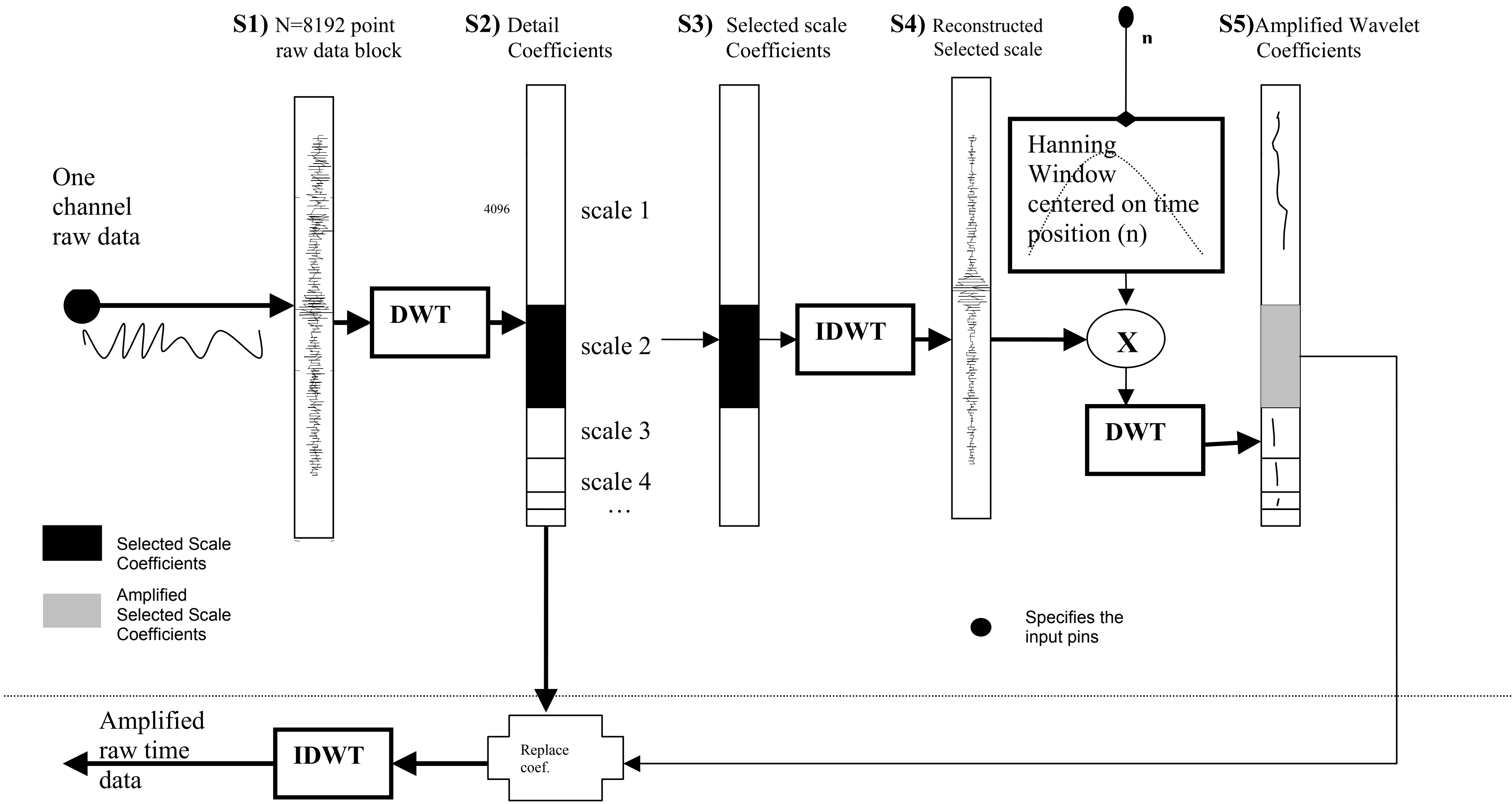


**Figure 2 Embolic Signal Intelligent Wavelet Amplification Process**