Ultrasound in Med. & Biol., Vol. 30, No. 5, pp. 647–653, 2004

0301-5629/04/$–see front matter

ELSEVIER

doi:10.1016/j.ultrasmedbio.2004.03.009

● *Original Contribution*

ONLINE AUTOMATED DETECTION OF CEREBRAL EMBOLIC SIGNALS USING A WAVELET-BASED SYSTEM

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(*Received* 6 *October* 2003; *revised* 3 *March* 2004; *in final form* 18 *March* 2004)

Abstract—Transcranial Doppler ultrasound (US) can be used to detect emboli in the cerebral circulation. We have implemented and evaluated the first online wavelet-based automatic embolic signal-detection system, based on a fast discrete wavelet transform algorithm using the Daubechies 8th order wavelet. It was evaluated using a group of middle cerebral artery recordings from 10 carotid stenosis patients, and a 1-h compilation tape from patients with particularly small embolic signals, and compared with the most sensitive commercially available software package (FS-1), which is based on a frequency-filtering approach using the Fourier transform. An optimal combination of a sensitivity of 78.4% with a specificity of 77.5% was obtained. Its overall performance was slightly below that of FS-1 (sensitivity 86.4% with specificity 85.2%), although it was superior to FS-1 for embolic signals of short duration or low energy (sensitivity 75.2% with specificity 50.5%, compared to a sensitivity of 55.6% and specificity of 55.0% for FS-1). The study has demonstrated that the fast wavelet transform can be computed online using a standard personal computer (PC), and used in a practical system to detect embolic signals. It may be particularly good for detecting short-duration low-energy signals, although a frequency filtering-based approach currently offers a higher sensitivity on an unselected data set. (E-mail: h.markus@sghms.ac.uk)

Key Words: **Applied wavelets, Daubechies, Transcranial Doppler ultrasound, Automatic detection, Cerebral embolism.**

INTRODUCTION

Transcranial Doppler ultrasound (US) can be used to detect asymptomatic emboli in the cerebral circulation. Such embolic signals (ES) have been detected in patients with a wide variety of potential embolic sources, including symptomatic and asymptomatic carotid stenosis, prosthetic cardiac valves and atrial fibrillation (Markus 2000). They have also been detected during and after interventional procedures, such as carotid endarterectomy, cardiopulmonary bypass and carotid artery angioplasty and stenting. Increasing evidence suggests that asymptomatic ES have clinical significance, at least in certain situations. For example, in patients with carotid stenosis they have been shown to predict future transient ischaemic attack and stroke risk (Molloy and Markus 1999; Valton et al. 1998). The technique may have a number of clinical applications, including identification of patients at high risk of recurrent stroke for specific treatments, and evaluating the effects of drug therapy. However, in most conditions, ES are relatively infrequent, and prolonged recording periods of 1 h or longer may be required. If the technique is to become clinically useful an essential requirement is a reliable automated system for ES detection.

In the past, the "gold standard" has been the experienced human observer. Early attempts at producing an automated system failed to match the accuracy of the human expert consistently (Van Zuilen et al. 1996). More recent systems, particularly those that have used a frequency-filtering approach, have shown improved performance (Cullinane et al. 2000, 2002), but they are still not at the level of the expert human observer. A promising approach has been a rule-based expert system (Fan et al. 2001), although it was not evaluated online.

The ES appear as short-duration high-intensity signals that have a characteristic frequency distribution, having maximal intensity over a narrow frequency band (Ringelstein et al. 1998). They reach their maximum

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intensity over a very short time period of usually less than 200 ms. They need to be differentiated from both artefacts and random Doppler speckle (high-intensity signals that occur in the normal Doppler waveform). Differentiation from artefacts has proven to be relatively easy by exploiting the fact that the intensity increase due to artefacts is usually bidirectional and at low frequencies. Differentiation of small ES from random Doppler speckle has been more troublesome. Any system that increases the ES-to-background noise ratio (EBR) is likely to improve detection.

Almost all approaches to date have relied on the fast Fourier transform (FFT) to process the Doppler signal. This has the disadvantage that there is an intrinsic trade-off between frequency and temporal resolution. An ideal signal-processing approach for ES detection would have both high temporal resolution and allow the EBR to be maximised. The Wigner transform has been used to provide improved temporal resolution (Smith et al. 1994). An alternative is the wavelet transform, which provides high temporal resolution and is, therefore, suited to the analysis of intense short-duration signals. In a previous off-line analysis, the continuous wavelet transform provided better temporal resolution and time localisation of ES than the FFT, without any reduction in EBR (Aydin et al. 1999). The continuous wavelet transform does not have the trade-off problems between block size and overlap ratio apparent with short-time windowed FFT techniques. However, its accurate implementation is computationally demanding due to an exponentially increasing number of scales, and this makes it unsuitable for an online system. The fast wavelet transform (FWT) can compute a discrete wavelet transform (Thuillard 2001) for a small finite number of scales. A wavelet scale is inversely proportional to frequency with a higher scale implying a lower frequency. The FWT can be readily implemented online using a standard personal computer (PC). In this study, we implemented an online ES detection system using the discrete wavelet system, and compared it with a commercially available frequency filter-based system that utilised the FFT for ES detection.

METHODS

System development and design

Our automated embolic detection system (discrete wavelet transform-1, DWT-1) involves four main steps. Initally, raw data are obtained from the Doppler device or other data storage medium (data acquisition). Second, the data are processed to remove as much noise as possible (filtering). At this stage, data preselection can also be incorporated to increase the overall performance. The third step calculates a set of parameters with values that can discriminate between ES and artefacts, including Doppler speckle (characterisation). Finally, a decision is made as to which parts of the data are ES (classification).

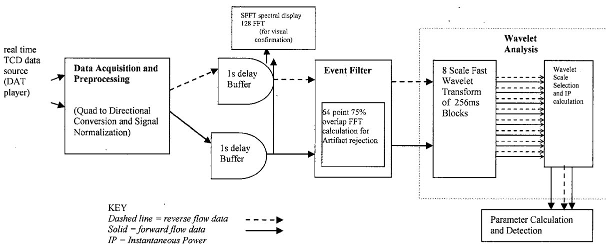

Fig. 1. A schematic diagram of the discrete wavelet transform (DWT-1) detection system.

We used the Daubechie family of discrete wavelets (Daubechies 1992) because they closely resemble embolic signals and, thus, provide the best suppression of noise. The choice is analogous to the use of the continuous Morlet wavelet, which was found to well-describe embolic signals in a previous off-line study of ES (Aydin et al. 1999). The best performance was provided by the 8th order wavelet (daub-8). The majority of the parameters that characterise the ES were calculated directly from the wavelet transform. Additional parameters based on the FFT were used to verify the presence of artefact using the standard bidirectionality criteria (Ringelstein et al. 1998).

The architecture of the wavelet-detection system is shown in Fig. 1. Initially, quadrature-modulated digitised data are converted into a directional signal and buffered (Aydin and Evans 1994). The buffers then feed data to the event detector. The event filter triggers the daub-8 wavelet analysis and detection layer. The wavelet analysis consists of a fast wavelet block filter that converts the data into eight reconstructed scales.

Data acquisition. All recordings were made from the ipsilateral middle cerebral artery with the same TC 4040 transcranial Doppler system (EME/Nicolet, GmbH Kleinostheim, Germany) and a 2-MHz transducer. A standard protocol was used with a sample volume of 5 mm, pulse repetition frequency (PRF) of 7125 Hz, and a depth setting of between 45 and 54 mm. The Doppler audio signal was recorded on digital audio tape (Sony TD 60ES, Osaka, Japan). For identification of ES, the tapes were played back into the same system and the FFT spectra and audio signal were analysed in real-time by an experienced observer using standard consensus criteria (Ringelstein et al. 1998). A second trained observer then reviewed the saved signal and, if both observers agreed, the signal was marked embolic. The training data set was a compilation of segments of recordings containing a total of 3 h of data from patients with symptomatic

Table 1. The parameters used in embolic signal detection

Parameter (ratio dB)	Embolic signal Mean	SD	Relative contribution	Speckle Mean	SD	Relative contribution
EBR (dB)	11.54	6.11	0.08	6.02	2.09	0.15
EPDFF (ms)	3.24	6.38	0.10	6.10	2.56	0.10
I_{vs} (s^{-1})	90.36	23.73	0.20	19.15	24.52	0.18
FRWPR (peak dB)	6.00	1.44	0.10	3.8	3.4	0.10
pknE (ratio)	3.27	4.10	0.11	2.18	2.14	0.07
BScP (ratio)	0.90	1.93	0.10	1.06	1.91	0.02
RiR (dB)	2.20	1.50	0.02	1.25	1.54	0.02
RSPR (ratio)	5.70	2.47	0.12	1.85	1.20	0.15
ASEBR (dB)	10	3.1	0.17	7.00	1.71	0.10

For each parameter, the mean and SD values for embolic signals and Doppler speckle are given. The third column represents the relative contribution or ranking of each parameter to the characterisation of embolic signals and speckle, where the sum of rankings equals one. Full details of each parameter are given in Appendix 1.

carotid stenosis and 3 h from patients postcarotid endarterectomy. Artefacts were obtained by tapping and moving the transducer, as well as through patient movements such as talking and chewing; therefore, replicating those occurring during standard recordings. Episodes of Doppler speckle from normal recordings were identified from the FFT spectrum. The digital audio tapes were then played into our PC-based detection system at a sampling rate of 8 kHz with 16-bit resolution on each quadrature channel. The recording volume was set to be 50% of maximum volume.

Filtering. Previous work has shown that most artefacts can be efficiently identified using features of the Fourier spectrum (Markus et al. 1999). We, therefore, included an initial event filter, using the FFT spectrum, to identify and reject some artefacts, and pass on candidate ES to the wavelet analysis module. This improved the accuracy of the FWT layer (Fig. 1). Only 64-point FFT blocks, with 75% time window overlap, were used to calculate the moving average of the frequencies to estimate the signal background. The criteria for artefact rejection previously developed were then applied. Only waveforms that had a peak forward signal with intensity 6-dB higher than the reverse signal, were selected as nonartefacts. To ensure that the initial event detector did not miss ES, we tested it on more than 300 signals from patients and demonstrated a sensitivity of 99.6% of all ES. The only false rejection by the event detector was a small ES that coincided with a strong artefact. Without this event selector, the specificity of detection was reduced by 5 to 10%. Hence, it is not a crucial component of the detection algorithm; however, it makes the system faster than real-time when used off-line.

The event filter selects blocks based on the following parameters (Table 1):

1. Background frequency intensity: The value of the background is calculated by ignoring extremes and finding a moving average of the frequencies, which is then used to judge if there is a possible ES. This is a Boolean variable with a time duration that triggers the detection logic. Our threshold was a rise of 3 dB in any frequency (velocity) band.
2. Distance to centre frequency: The distance between the centre frequency and the frequency with the maximum intensity is computed. If it is less than 0.25 *fs* Hz, where *fs* is the sampling frequency, the signal is passed on for wavelet analysis.
3. Forward-to-reverse intensity ratio (FRI): The power of the forward channel is divided by the power of the reverse channel at the point of a suspected ES. If the result is < 6, the signal is classified as artefact; otherwise, the signal is passed on for wavelet analysis.
4. Intensity ratio in one frequency block-(TOP2AVG): The maximum intensity of one FFT time window, relative to the average of that window, is measured. If it is greater than 2.3 dB the signal is passed on for wavelet analysis.
5. Average frequency intensity area (AFIA): The AFIA is measured over the extent of a suspected embolic signal. It is integral of the intensity rise above the background, and is computed by summing the intensity rise above the background in each frequency band and dividing by the number of frequency bands multiplied by the time. If it is greater than 4 dB/ms, the signal is passed on for wavelet analysis.

The thresholds for the parameters were estimated statistically using human identification of artefacts and ES as the "gold standard."

Characterisation. The characterisation stage is dependent on the wavelet analysis module and comprises three main processes. The first is to estimate normal background signal due to blood flow. The second is to identify the wavelet scales in which ES are best characterised, and the third is to compute the parameters used to characterise the ES. The wavelet analysis module operates on 256-ms blocks of data read from the two buffers. The data are transformed into two banks of eight scales using a zero-centred daub-8 filter (Daubechies 1992).

The intensity of the background signal in the wavelet domain is calculated using a median filter on the absolute value of the signal to remove the effect of ES and artefacts. When it identifies a candidate ES, the system selects the best scales for parameter calculation by using three parameters; the scale with maximum power (maxP), the scale with maximum peak to threshold ratio (maxP-TR), and the scale with maximum variance (maxV). The wavelet scale selection algorithm looks for the scale with the largest value of each parameter. If all three parameters refer to the same scale, then the classification is done on this scale. If these parameters refer to different scales, then the scale with highest maxP-TR and maxP is considered. If there is no agreement between maxP-TR and maxP then maxP-TR is used. Having selected the best scale, the second-best scale is identified based on the maxP-TR of all the other scales. Finally, the wavelet parameters are calculated on the instantaneous power of the two selected scales. The fuzzy classifier based on the determined thresholds for each parameter makes the final classification decision. A 75% and 25% weight is given to the best and second-best scale, respectively. A typical example is shown in Fig. 2; here, the second and third scales have been selected. Having selected the correct scales, 10 parameters are then calculated. These are described in Appendix 1. Our choice of parameters was based on a review of previous published data (Markus et al. 1999; Aydin et al. 1999) and off-line analysis of ES using the daub-8 wavelet. The parameters were weighted in terms of importance, and used in the classifier to calculate an overall probability of speckle and ES.

Classification. The classification layer is the final process in detection and determines the system accuracy. The first stage rejects signals that are clearly not embolic by using statistical rules from the data analysis. Then, possible embolic or speckle signals are processed using Gaussian fuzzy logic. The training set of data were used to build multidimensional Gaussian models to calculate the probability that a given point is embolic or speckle. We used two Gaussian models for each parameter set, one to estimate the probability that a signal is embolic and one to estimate the probability that it is speckle. To ensure fast computation, the continuous Gaussian models were quantised into a discrete set of ranges associated with a particular probability. The various models for the different parameters were then combined using fuzzy logic. Each parameter is combined with the other parameters with which it is least correlated. The contribution of each model toward the final probability is based on the relative importance of the parameters. The choice of combinations was made both using heuristic rules and some expectation-maximisation iterative techniques. Finally, the best probability thresholds were determined for a simple "defuzzification" stage that decides between the embolic and speckle classes.

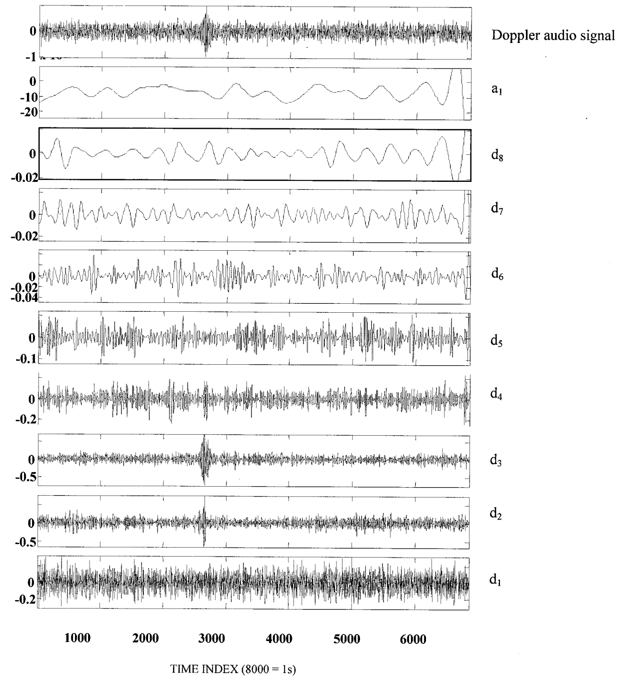

Fig. 2. The plot shows the wavelet decomposition of a typical embolic signal using the daub-8 filter. The upper trace shows the original audio signal. The lower scales show decomposition of the embolic signal into eight detail wavelet scales (d1–d8) and one approximation scale (a1). The detail scales, d1–d8, are the high-pass residues of the daub-8 high/low pass filters applied recursively on the low-pass residues. In this particular case, an embolic signal can be seen in scales d2 and d3. In other cases, embolic signals can appear in other scales.

System evaluation

The final system was evaluated on new data sets. It was compared both against the human expert, who used the detection criteria described earlier, and against the commercially available automated system (FS-1, Nicolet/EME Ltd.) that has, to date, the best published sensitivity and specificity for online ES detection (Cullinane et al. 2000, 2002). FS-1 analyses the output from the individual frequency bins of the FFT in parallel, thereby operating as a frequency-filtering system, and exploiting the fact that embolic signals have an intensity increase over a narrow frequency band to increase signal-to-noise ratio (SNR) (Markus and Reid 1999) We used two data

Table 2. Sensitivity and specificity results for the DWT software in detecting embolic signals

Embolic signal probability setting	Speckle probability setting	Sensitivity (%)	Specificity (%)
0.4	0.4	97.7	29.2
0.65	0.5	81.3	60.6
0.65	0.65	78.4	77.5
0.8	0.7	51.0	92.3

These were obtained at a number of software settings. The embolic and speckle probability settings represent the probability threshold that a signal is embolic or speckle, respectively. A signal is classified as embolic if it exceeds the embolic probability threshold and it does not reach the speckle probability threshold.

Table 3. The proportion of embolic signals of different intensity detected by the DWT compared with FS-1 for analysis of the 10-h evaluation data set from patients with carotid stenosis

Embolic signal intensity (dB)	Number of embolic signals	DWT-1	FS-1
5–7	32	21	16
7.1–8	25	21	19
8.1–10	35	27	31
10.1–12	20	16	19
>12	8	7	7

sets. The first was 10 h of unedited data from 9 patients with $>$ 70% symptomatic carotid artery stenosis (1 h from 8 subjects, and 2 h from 1). In this data set, the human experts identified 88 ES with an intensity $>$ 7 dB. Previous studies have shown that agreement between human experts is much higher for ES above this intensity threshold (Markus et al. 1997), and signals above this threshold have been shown to predict stroke and transient ischemic attacks (TIA) risk in patients with carotid stenosis (Molloy and Markus 1999). An additional 32 signals $<$ 7 dB were also identified. Performance was evaluated for signals both above and below the 7-dB threshold.

To evaluate the performance of the system on less intense and short-duration ES, tests were made on a second data set consisting of a 1-h compilation tape of selected segments from patients with carotid artery disease identified to have an over-representation of short duration and low-intensity ES. In this set, there was a total of 198 ES, of which 138 were below 7 dB.

The DWT software was evaluated at four different ES and speckle-sensitivity settings. For each setting, the sensitivity and specificity in detecting ES was determined. The FS-1 software was run on this system at the manufacturer-recommended sensitivity setting of 60%.

EXPERIMENTAL RESULTS

Determination of best classification threshold

The performance of the DWT on the 10-h data set, at various settings, can be seen in Table 2. A sensitivity as high as 97.7% could be obtained at a corresponding low specificity (29.2%). At an ES threshold probability setting of 65% and a speckle threshold probability setting of 50%, a clinically optimal compromise was obtained with an ES detection sensitivity of 78.4% and specificity of 77.5%.

Comparison of the DWT with FS-1 software

For comparison with FS-1, an ES probability setting of 65% and a speckle threshold probability setting of 50% were selected. For the 10 h of data in the first evaluation set, FS-1 had a slightly higher sensitivity (86.4% vs. 78.4%), and specificity (85.2% vs. 77.5%) compared to the DWT system. However, the DWT performed better for shorter-duration lower-intensity signals. This difference is illustrated in Table 3, where the proportion of ES detected is shown for ES of different intensities. The improved performance of the DWT for short-duration signals was also demonstrated in the second test data set of predominantly short-duration low-intensity signals. Here, it had a better sensitivity than FS-1 (DWT 75.2%, FS-1 55.6%), and a similar specificity (DWT 50.5%, FS-1 55.0%). The differences between the two systems resulted in the DWT system performing better for tapes from some, although not all, carotid stenosis patients, as illustrated for individual patient data in Fig. 3.

The signals missed by both systems were reviewed. Both systems missed some ES that appeared at the same time as an artefact; the presence of the artefact increased the background intensity level, reducing the calculated relative intensity increase associated with the nearby ES. Occasionally, an ES and artefact occurred simultaneously and the signal was rejected as an artefact. Other cases of missed ES were caused by the signal appearing to have some mirroring effect, probably due to overloading of the preamplifier and, therefore, being miscoded as artefact due to the bidirectional nature of the signal. The only other clear case where both systems performed poorly (patient 3) was when the recorded signal was poor quality with flow from a nearby artery superimposed on the middle cerebral artery flow spectrum. The DWT system missed some ES detected by FS-1. One problem arose from the sudden change in background volume due to patient movement within the 256-ms wavelet block. This skewed the wavelet instantaneous power spectrum and adversely influenced some wavelet parameters.

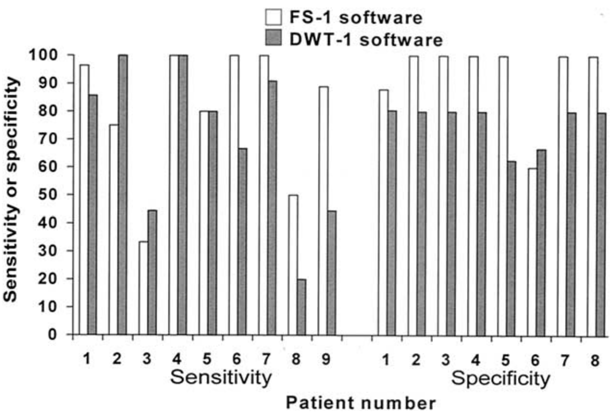

Fig. 3. Relative sensitivity (left half of the x-axis) and specificity (right half of the x-axis) of the wavelet-based system compared to FS-1 software for the individual recordings from 9 patients (numbered 1 to 9) with carotid stenosis. This demonstrates that, on some recordings, FS-1 performed better (*e.g.,* patient 9) and, on others, the DWT-1 software had higher sensitivity (*e.g.,* patient 2).

DISCUSSION

Using a wavelet-based online detection system, we were able to obtain a reasonable sensitivity and specificity of 78.4% and 77.5%, respectively, for the detection of ES in patients with symptomatic carotid stenosis. This is better than older online systems (Van Zuilen et al. 1996). However, performance was not quite at the level of the recently released commercial system (FS-1) that is based on a frequency-filtering approach and utilises the FFT. Despite this slightly worse performance, our wavelet-based system did have some advantages and was more sensitive for short-duration low-intensity ES. This resulted in it performing better than FS-1 on a second data set selected to contain a higher proportion of low-intensity ES.

The better performance for short-duration signals is a consequence of the excellent time resolution of the wavelet transform. However, the lower-frequency resolution of the wavelet transform can explain why it does not outperform the windowed FFT. This reflects the importance of frequency information in the detection of ES. A characteristic feature of ES is that the intensity increase is “focused” or maximal at a particular frequency. Exploiting this feature resulted in a marked improvement in an FFT-based system (Markus et al. 1999). The DWT system only resolves the frequency information into eight scales, compared with the 64 FFT frequency bins utilised by FS-1. Another problem with the DWT was caused by sudden changes in background volume at random time positions caused by patient movement, which skews the wavelet instantaneous power spectrum. This sudden change in power causes fewer problems in FS-1 because the windowed FFT is less dependent on prior time; time does not exist within an FFT block. The larger block size required for effective wavelet analysis is less resilient to sudden background volume change, but more adept to detecting and identifying short-duration artefacts.

This is the first online automated ES-detection system based on the wavelet-transform approach. This study has demonstrated that the fast wavelet transform can be computed online using just a standard PC, and used in a practical system to detect ES. Previous off-line evaluation had suggested that the wavelet transform described ES well, and might allow accurate differentiation form speckle and artefact. In the online environment, the limitations of the fast wavelet transform are clearer. Nevertheless, it does offer advantages for particular types of signals that are less well detected by FFT-based systems, and a combined system exploiting this advantage of the wavelet transform may improve detection further. We used the daub-8 wavelet that approximates the shape of the embolic signal and is ideal for a fast online system. Previous work has demonstrated that the Gabor wavelet also describes embolic signals well (Devuyst et al. 2000). It is possible that further optimisation of the choice of wavelet could improve wavelet detection of embolic signals further.

Acknowledgments—This work was supported by a project grant from the British Heart Foundation (PG 99064). The authors are grateful to Sheila Reihill and Zoltan Kapozsta for help in recording the ES.

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APPENDIX 1

WAVELET SCALE PARAMETER DEFINITIONS

Embolic position difference (EPDIFF).

The difference between two methods of calculating the position of the ES within an FWT block. The first method calculates the position that contains 50% of peak power, searching from time 0 to 256 ms. Method two is the same, except that the search does not start from the beginning, but from 50 ms before the peak event index, in the left to right direction. If the difference is greater than 50 ms, then the probability of it being embolic is less due to the fact that ES generally only have one symmetrical high power peak.

Cutoff values: > 50 ms ES, < 50 ms speckle.

Intensity volume below scales (I_{VS}).

The area under the ES intensity volume distribution.

Cutoff values: < 42 dB/ms speckle, > 42 dB/ms or < 110 dB/ms embolic signal.

Embolic to background noise ratio (EBR).

The ratio of peak ES intensity to background intensity.

Cutoff values: > 7.4 ES, < 7.0 speckle.

Across scale EBR (ASEBR).

A measure of EBR using the wavelet scale.

Cutoff values: ratio < 20 speckle, ratio > 20 ES or speckle.

Peak number evaluation (pknE).

The instantaneous power of the eight scales must contain a limited number of peaks (currently five) that have magnitudes higher than 10% of the maximum magnitude.

Cutoff values: < 5 peaks ES, > 5 peaks speckle.

Average instantaneous power amplitude (AIPA).

The instantaneous amplitude averaged over event duration.

Cutoff values: > 0.5 normalised instantaneous power, ES; 0.3 to 0.4 speckle, < 0.3 ES or speckle.

Best scale position (BScP).

The scale, which is likely to consist ES, is determined by using three parameters; the scale with maximum power (maxP), the scale with maximum peak to threshold ratio (maxP-TR), and the scale with maximum variance (maxV).

Cutoff values: If BSP > 4 it is more likely to be to be speckle, 2 to 4 ES or speckle and 1 ES.

Average rise rate (RiR).

The average rate rise in dB/s of the intensity increase.

Cutoff velues: < 1.8 dB/ms speckle, > 1.8 dB/ms embolic.

Relative scale peak onset rise (RSPR).

The intensity of the ES peak compared with the previous 8 ms of Doppler signal.

Cutoff values: > 1.4 dB/8 ms ES or speckle, otherwise speckle.

Wavelet forward-to-reverse power ratio (FRWPR).

The peak power in the first five wavelet scales divided by the peak power in the reverse flow.

Cutoff values: > 7 embolic, < 3 speckle.