Improved Automated Detection of Embolic Signals Using a Novel Frequency Filtering Approach

Hugh Markus, DM; Marisa Cullinane, BSc; Greg Reid, BSEE

Background and Purpose—Asymptomatic embolic signal detection with the use of Doppler ultrasound has a number of potential clinical applications. However, its more widespread clinical use is severely limited by the lack of a reliable automated detection system. Design of such a system depends on accurate characterization of the unique features of embolic signals, which allow their differentiation from artifact and background Doppler speckle. We used a processing system with high temporal resolution to describe these features. We then used this information to design a new automated detection system.

Methods—We used a signal processing approach based on multiple overlapping band-pass filters to characterize 100 consecutive embolic signals from patients with carotid artery disease as well as both episodes of artifact resulting from probe tapping and facial movement and episodes of Doppler speckle. We then designed an automated detection system based both on these embolic signal characteristics and on the fact that embolic signals have maximum intensity over a narrow frequency range. This system was tested in real time on stored 5-second segments of data.

Results—The value of peak velocity at maximal intensity discriminated best between embolic signals and artifact and allowed differentiation with 100% sensitivity and specificity. Relative intensity increase, intensity volume, area under volume, average rise rate, and average fall rate appeared to discriminate best between embolic signals and Doppler speckle. For the majority of embolic signals, the intensity increase was spread over a narrow frequency or velocity range. The automated system we developed detected 296 of 325 carotid stenosis embolic signals from a new data set (sensitivity, 91.1%). All 200 episodes of artifact from a new data set were differentiated from embolic signals. Only 2 of 100 episodes of speckle were misidentified as embolic signals.

Conclusions—Using a novel system for automated detection, which utilizes the fact that embolic signals have maximum intensity over a narrow frequency range, we have achieved detection with a high sensitivity and high specificity. These results are considerably better than those previously reported. We tested this initial system on short 5-second segments of data played in real time. This approach now needs to be developed for use in a true online system to determine whether it has sufficient sensitivity and specificity for clinical use. (Stroke. 1999;30:1610-1615.)

Key Words: carotid artery diseases ■ cerebral embolism ■ signal processing, computer-assisted ■ ultrasonography

Asymptomatic cerebral emboli can be detected with the use of Doppler ultrasound. Such asymptomatic embolic signals have been reported in patients with a wide variety of potential embolic sources including carotid artery stenosis, cardioembolic sources such as atrial fibrillation, and during interventional procedures including carotid endarterectomy and cardiopulmonary bypass. The technique has a number of important potential clinical applications, including identifying individuals at high risk of stroke, monitoring the effectiveness of therapy, localizing the source of active embolization in patients with more than 1 potential embolic source, and monitoring during interventional procedures. A major current limitation of the technique is the lack of sufficiently specific and sensitive techniques for automated embolic signal detection. In many conditions the frequency of embolic signals is low, often on the order of 1 or 2 per hour, and therefore recordings of at least 1 hour may need to be performed. The current gold standard for data analysis is to record the Doppler signal and analyze it at a later date, blinded to patient identity and diagnosis. This is time-consuming and not clinically applicable.

Interobserver reproducibility studies have demonstrated a high level of agreement in the identification of embolic signals. However, previous systems for automated detected have failed to achieve levels of performance approaching that of the human observer. When analyzed with the use of the
fast Fourier transform (FFT), embolic signals have a characteristic appearance with a short-duration increase in signal intensity, usually contained within the flow spectrum. The intensity increase is usually frequency focused, i.e., the maximum increase is at a specific frequency. Such signals have to be differentiated from artifact, which is usually bidirectional and has an intensity increase that is maximal at low frequency. They also have to be differentiated from random Doppler speckle, and in practice this is a more difficult problem. Early attempts at automated detection used a simple pattern recognition algorithm based on the FFT spectral analysis to detect a transient intensity increase, but intensity measurements were averaged over all frequencies or velocities and did not utilize the frequency focusing of embolic signal intensity increase in their detection. While such systems performed well offline for the relatively intense embolic signals produced in experimental systems and seen in patients with prosthetic cardiac valves, their performance online in the detection of the lower-intensity embolic signals found in patients with carotid stenosis was unsatisfactory. The use of a neural network whose input is the FFT spectral analysis achieved improved specificity but still inadequate sensitivity. Improved automated detection requires both (1) a signal processing approach that will maximize the relative intensity or embolus-to-blood ratio (EBR) for individual signals and (2) an algorithm programmed to detect those features characteristic of embolic signals that allow differentiation from artifact signals and Doppler speckle. Regarding the first point, it is likely that the EBR can be increased by the use of a frequency filtering approach; the relative intensity increase of the embolic signal compared with that of the background will be greater if analysis is restricted to only those frequencies at which the embolic signal occurs. We have previously shown that utilizing this frequency information and applying a band-pass frequency filter to the embolic signal resulted in a 3-dB intensity increase. In this previous study, the frequency range of the filter was chosen offline to suit the particular embolic signal. In practice, the frequency at which the maximal intensity increase will occur cannot be known in advance. Therefore, analysis must be performed concurrently over a number of frequency or velocity bands that cover the range over which an embolic signal may occur. Regarding the second point, before an effective system for automated signal detection is designed, the characteristics of embolic signals must be fully described. A number of features of embolic signals have not been previously studied and may be useful in their detection.

In this study we used a novel form of signal processing based on a number of parallel frequency filters to analyze embolic signals with a high degree of temporal resolution. We determined which features most accurately differentiated embolic signals from speckle and artifact. In the second half of the study, we used this information to design a computer algorithm for embolic signal detection that also utilized the frequency focusing of the embolic signal intensity increase.

Subjects and Methods

Transcranial Doppler Recordings

Transcranial Doppler recordings were performed with the use of a commercially available transcranial Doppler system (Pioneer 4040, Nicolet-EME GmbH). This system is based on a 75-MHz processor. Recordings were made from the ipsilateral middle cerebral artery in patients with symptomatic carotid stenosis. The Doppler signals were recorded onto digital audiotape and subsequently played back through the same machine, at which time a 128-point FFT was performed. Segments containing embolic signals were saved with the use of proprietary SoundTrak software; this software allows the audio time domain data to be saved to the disk along with the spectral FFT information for each spectral record. Successive embolic signals were identified subjectively by recognized criteria, including both the audible and visible characteristics on the spectral display, and were saved to the disk. Embolic signals were identified as short-duration, high-intensity, frequency-focused signals accompanied by a characteristic audible click. In addition, an intensity threshold of 7 dB was used because this has been found to improve specificity without an excessive loss of sensitivity. All embolic signals were reviewed by a second experienced observer, and only those that both observers agreed were definite embolic signals were used in further analysis. One hundred successive embolic signals recorded from 3 individuals with carotid stenosis were used for the initial study. Two hundred episodes of artifact produced by probe tapping (n=100) or facial movement (n=100) were also studied. A second independent data set of 325 embolic signals recorded from an additional 8 patients with symptomatic carotid stenosis was used for evaluation of the software; these were identified by the same criteria by the same observers.

Doppler Signal Analysis Using Frequency Filters

An array of band-pass filters was applied to the time domain data. Band-pass filters are defined by their ability to discriminate in favor of or against particular frequency bands. The frequencies to be filtered were selected by sizing a box around the section of the signal to be analyzed, i.e., an embolic signal, artifact, or random Doppler speckle, as identified on the FFT spectra. The frequencies selected from the box were divided into 256 subbands, each of equal frequency range. For each subband, a separate set of finite impulse response band-pass filter coefficients was calculated. The filter coefficients were then applied to the time domain data selected, with application of a Hanning windowing function centered at each time value. This resulted in a sequence of filtered time domain data values representing the time domain signal within each of the 256 frequency subbands. Each of these time domain data values consisted of an in-phase and quadrature value. These were converted to signal intensity in decibels. The filtered time domain intensity values for each individual frequency filter output were displayed as a single horizontal row, representing one subband of time domain data. The software was programmed to determine specific characteristics for individual embolic signals. Relative intensity increase was determined from peak intensity minus background intensity. Intensity volume was determined from intensity summed over the area of the event. The time of onset of the intensity of increase and the time at peak intensity were determined, and from these values the average intensity rise rate was determined. Similarly, the average intensity fall rate was determined. The peak velocity at peak intensity was determined. Peak sample length was derived from peak velocity multiplied by the time width of the embolus. The degree of frequency focusing of the embolic signals was determined from the ratio of the frequency range of the embolic signal at its time point of maximum intensity to the frequency range of the flow velocity envelope curve at that time.

The portion of the embolic signal that was analyzed for these calculations was determined by the region over which intensity was above a running background threshold intensity. This was calculated over the previous 1.5 seconds of data. All samples of negative flow or those within 1/8 of the pulse repetition frequency were excluded. The highest 1/32 of samples were then excluded, and the next 1/32 of samples were averaged and converted to decibels to determine the background threshold. An example is shown in the Figure.
Automated Embolic Signal Algorithm

Because of the processing constraints of an online band-pass filtering system, analysis was based on a 64-point FFT, with each point of the FFT used as a “frequency filter.” The data from each individual frequency bin of the FFT were analyzed to determine the presence or absence of any potential embolic signal. FFTs were performed every 1 ms with the use of a Hanning windowing function. For each FFT there were 32 bins of positive frequencies and 32 bins of negative frequencies. For each FFT computed, 64 independent thresholds were set by averaging the data for each bin over 6.10 cm/s in the frequency or velocity domain and 6.50 ms in the time domain. Extremely sharp transitions were ignored, and specific minimum and maximum values were used to ensure reasonable thresholds. This resulted in a “bed” of thresholds that “floats” slightly above the median intensity level of physiological blood flow. Any part of the signal that rose above this threshold was considered an event candidate, and this was then analyzed further to determine whether it was likely to be an embolic signal, an artifact, or speckle. The information from the first part of the study was applied for this analysis. Artifact probabilities were summed from measurements of the following: (1) intensity volume, ie, the intensity of the signal above the threshold intensity integrated over the time and frequency range of the event; (2) intensity area, ie, the frequency range of the signal integrated over its time duration; (3) duration of the event in time; and (4) orderliness of the signal over time. This utilized the finding that a gradual rise and then fall in intensity were found for embolic signals, in contrast to a fluctuating rise and fall in intensity for speckle.

After independent embolic signal and artifact probabilities had been computed, an embolic signal probability score and an artifact signal probability score were generated. If the probability score of the embolic signal was >60%, the event was labeled as an embolic signal, unless the artifact score was also >60%.

Results

Embolic Signal Characteristics

Differentiation of Embolic Signals From Artifact

The value of peak velocity at maximal intensity discriminated best between embolic signals and artifact. Velocity at peak intensity was significantly higher for embolic signals (mean, 33.67; SD, 17.45; range, 9.16 to 71.63 cm/s) than for either tapping artifact (mean, 1.94; SD, 2.64; range, –3.95 to 5.27 cm/s; P<0.0001) or facial movement artifact (mean, 0.01; SD, 2.41; range, –5.74 to 6.34 cm/s; P<0.0001). Using a
threshold of $>7$ cm/s achieved 100% specificity and sensitivity in detecting embolic signals and differentiating them from artifact.

### Differentiation of Embolic Signals From Speckle

Mean values of the various signal characteristics for embolic signals, speckle, and artifact are shown in Table 1. Relative intensity increase, intensity volume, and area under volume were all significantly greater for embolic signals than for Doppler speckle. Average rise rate was significantly faster and average fall rate was significantly slower for embolic signals than for Doppler speckle.

The important issue is how well individual parameters discriminate embolic signals from both Doppler speckle and artifact. Relative intensity increase, intensity volume, area under volume, average rise rate, and average fall rate appeared to discriminate best between embolic signals and Doppler speckle. The sensitivity of each parameter for detecting embolic signals, at a threshold at which 100% specificity was achieved in differentiating speckle from embolic signals, is shown in Table 2.

For the majority of embolic signals, the intensity increase was spread over only a proportion of velocities occupied by the flow spectrum. The mean (SD) proportion of the flow spectrum that was taken up by the intensity increase of the embolic signal was 0.57 (0.15) (range, 0.35 to 1.00).
Resolution. However, this requires considerable computing power, making it more difficult to apply online. Therefore, we adapted the approach to use an FFT processing approach. The FFT analyzes the signal at a number of different frequencies or frequency bins, and the output of each bin can be considered equivalent to that of a band-pass filter. By concurrently monitoring signal changes over time in the output from each FFT frequency bin, we have been able to improve the sensitivity and specificity by which we can detect embolic signals. It is possible to run such a processing approach on currently available transcranial Doppler equipment.

In addition to optimizing the signal-to-noise ratio, detection of embolic signals requires an algorithm that can differentiate embolic signals from speckle and artifact. We have demonstrated the characteristics of embolic signals that may be most useful in developing such an algorithm. Intensity volume differentiates embolic signals from speckle better than relative intensity alone, and therefore we used this parameter in our algorithm. The rate of rise of the intensity increase of an embolic signal, as well as the rate of fall, also allowed differentiation of embolic signals from speckle. In contrast, these parameters are poor in differentiating embolic signals from artifact, but this can be performed by analysis of the velocity at peak signal intensity. Artifacts have an intensity that is maximal at low velocity, and using a threshold of 9 cm/s, we differentiated between embolic signals and artifact with 100% sensitivity and specificity.

This semiautomated detection system allows considerable improvement in automated embolic signal detection. Using previous much simpler algorithms in which the intensity increase was measured over the total frequency range, we and others were able to only obtain sensitivities of approximately 60% for similar embolic signals. The embolic signals from patients with carotid artery stenosis and atrial fibrillation tend to be less intense and are therefore more difficult to detect than the more intense embolic signals in patients with prosthetic heart valves or undergoing cardiopulmonary bypass. This emphasizes the importance of developing and testing detection devices for the data set on which they will be used.

We evaluated this system using consecutive embolic signals from patients with carotid artery stenosis. We only studied embolic signals with an intensity of >7 dB. This is the standard threshold we use in studies, and embolic signals defined in this way correlate with clinical parameters of increased risk and also with prospective risk of stroke and transient ischemic attack. The present study demonstrates the feasibility of detecting such embolic signals automatically. We have not tested it on very-low-intensity embolic signals, on which its performance may not be as good. However, interobserver agreement for such signals is less good, and the lack of a reliable gold standard for such signals makes evaluation of an automated detection system difficult for such signals. Furthermore, it should be remembered that our gold standard was the subjective identification of embolic signals by 2 experienced observers; this is not ideal, but there is no readily available alternative. While good interobserver agreement has been demonstrated, particularly for signals of >7 dB relative intensity, once a fully automated online system is developed, it should be tested against a number of independent expert observers.

### Evaluation of Automated Detection System

In the analysis of the first data set on which the previous analysis and software development had been performed, 96 of 100 embolic signals were detected. In the second independent data set of 325 embolic signals, 296 were detected (91.1%). All 200 episodes of artifact from a new data set (100 probe tapping, 100 facial movement) were not detected as embolic signals. Two of 100 episodes of speckle were identified as embolic signals.

### Discussion

In this study we used a signal processing approach with a high temporal resolution to describe the characteristics of embolic signals compared with episodes of random Doppler speckle and artifact. We were able to develop a semiautomated detection system that can detect the relatively low-intensity embolic signals occurring in individuals with carotid artery stenosis with a higher sensitivity than previous systems. We have demonstrated its effectiveness in analyzing short segments of stored data played back in real time.

In developing a sensitive and specific automated embolic signal detection system, 2 aspects are of great importance. First, the signal-to-noise ratio or the ratio of embolic signal to background intensity or power (EBR) must be maximized. This increases the conspicuity of the embolic signal and makes it easier to detect and differentiate it from other types of signal. A characteristic feature of an embolic signal is that it is frequency focused, with the maximum intensity greatest over a narrow band of frequencies or velocity. We have confirmed this in our analysis. Consequently, if the intensity increase is calculated over a narrow frequency band, which is centered on the frequency at which the embolic signal has maximum intensity, the EBR will be increased. We have demonstrated this in a previous study and shown that a mean 3-dB increase in EBR can be achieved by a frequency filtering approach. In this previous study the frequency range of the filter was chosen offline to suit the particular embolic signal. In practice, the frequency or velocity at which the maximal intensity increase will occur cannot be known in advance. Therefore, analysis must be performed concurrently over a number of frequency or velocity bands that cover the range over which an embolic signal may occur. Initially we performed this frequency analysis using a band-pass filter approach, which has the advantage of a very high temporal resolution. However, this requires considerable computing

### Table 2. Sensitivity Achieved When Different Parameters Were Used to Differentiate Embolic Signals From Doppler Speckle and the Threshold Was Set at a Value to Allow 100% Specificity

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Threshold to Achieve 100% Specificity</th>
<th>Sensitivity for Embolic Signals, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relative intensity increase, dB</td>
<td>&gt;4.60</td>
<td>93</td>
</tr>
<tr>
<td>Intensity volume</td>
<td>&gt;0.121</td>
<td>95</td>
</tr>
<tr>
<td>Area under volume</td>
<td>&gt;0.0603</td>
<td>94</td>
</tr>
<tr>
<td>Average rate rise</td>
<td>&gt;1.050</td>
<td>94</td>
</tr>
<tr>
<td>Average fall rate</td>
<td>&lt;0.915</td>
<td>92</td>
</tr>
<tr>
<td>Sample volume length</td>
<td>&gt;0.450</td>
<td>80</td>
</tr>
</tbody>
</table>

---

**Note:** The table above presents the sensitivity achieved when different parameters were used to differentiate embolic signals from Doppler speckle, with the threshold set at a value to allow 100% specificity.
Our results demonstrate that by utilizing specific characteristics of embolic signals that allow differentiation from other transient signals and using a novel detection algorithm running concurrently across a number of frequency or velocity bands, considerable improvement in the sensitivity and specificity of embolic signal detection can be achieved. We tested this initial system on short 5-second segments of data played in real time. This approach now needs to be developed for use in a true online system to determine whether it has sufficient sensitivity and specificity for clinical use. It is likely that under conditions in which embolic signals are frequent, such as after carotid endarterectomy, this system will be clinically useful. It remains to be determined whether its specificity is sufficiently good for use in situations in which embolic signals are much less frequent.

Acknowledgment
This study was supported by a grant from the British Heart Foundation (PG 96176).

References
Improved Automated Detection of Embolic Signals Using a Novel Frequency Filtering Approach
Hugh Markus, Marisa Cullinane and Greg Reid

Stroke. 1999;30:1610-1615
doi: 10.1161/01.STR.30.8.1610

The online version of this article, along with updated information and services, is located on the World Wide Web at:
http://stroke.ahajournals.org/content/30/8/1610