Automatic Embolus Detection by a Neural Network

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Background and Purpose—Embolus detection using transcranial Doppler ultrasound is a useful method for the identification of active embolic sources in cerebrovascular diseases. Automated embolus detection systems have been developed to reduce the time of evaluation in long-term recordings and to provide more “objective” criteria. The purpose of this study was to evaluate the critical conditions of automated embolus detection by means of a trained neural network (EMBotec V5.1 One, STAC GmbH, Germany).

Methods—In 11 normal volunteers and in 11 patients with arterial or cardiac embolic sources, we performed simultaneous recordings from both middle or both posterior cerebral arteries. In the normal subjects, we produced 1342 additional artifacts to use the latter as false-positives. Detection of microembolic signals (MES) was done offline from digital audiotapes (1) by an experienced blinded investigator used as a reference and (2) by a trained 3-layer–feed-forward neural network.

Results—From the 1342 provoked artifacts the neural network labeled 216 events as microemboli, yielding an artifact rejection of 85%. In microembolus-positive patients the neural network detected 282 events as emboli, among these 122 signals originating from artifacts; 58 “real” events were not detected. This result revealed a sensitivity of 73.4% and a positive predictive value of 56.7. The spectral power of the detected artifact signals was 16.5±5 dB above background signal. MES from patients with artificial heart valves had a spectral power of 6.4±2.1 dB; however, in patients with other sources of emboli, MES had an averaged energy reflection of 2.7±0.9 dB.

Conclusions—The neural network is a promising tool for automated embolus detection, the formal algorithm for signal identification is unknown. However, extreme signal qualities, eg, strong artifacts, lead to misdiagnosis. Similar to other automated embolus detection systems, good signal quality and verification of MES by an experienced investigator is still mandatory. (Stroke. 1999;30:807–810.)

Key Words: cerebral embolism ■ image processing, computer-assisted ■ ultrasonography, Doppler

Cerebral embolism is the main cause of ischemic stroke.1,2 Embolus detection using transcranial Doppler ultrasound (TCD) allows for the identification of active embolic sources in stroke-prone individuals and the selection of high-risk patients for appropriate treatment.3–7 The large number of patients at risk and the time and manpower needed for TCD-based embolus detection led to the development of various systems for automatic microembolic signal (MES) evaluation.6–12 Some presently available settings use the relative intensity increase of the embolic signal as compared with the background spectrum (“noise”) as the criterion for an event to be categorized as “embolus,” others have a more sophisticated approach with computerized embolus detection algorithms.5,7,8 The problem with these methods is that artifacts can produce similar relative intensity increases. At present, the multi-gate TCD technology is the most promising method for an automatic embolus detection. This system traces the moving embolus at two or more different insonation depths and evaluates the time delay between the occurrence of the high intensity signals in the different channels. In contrast to a true embolus, an artifact produces high intensity signals in all channels simultaneously.5–11

The use of a trained neural network is another attractive development for automatic embolus detection. This device uses a pattern recognition procedure to discriminate MES from the physiological/pathological blood velocity spectra and from artifacts caused by, for example, probe motion and signal overload. The neural network is trained by presenting the pattern of a lot of characteristic Doppler signals (emboli, artifacts, normal “background”). After a sufficient learning phase (more than 1 million iterations), the network could generalize its newly learned pattern recognition paradigm to similar signals during novel recordings. Unfortunately, trained networks have the disadvantages of being a “black box,” of bearing the risk to be overtrained (loss of generalization), of perpetuating mistakes introduced by their “teachers” and bearing the risk of misdiagnosis of pathological signals not encountered frequently enough during the learning phase (eg, unusual velocity profiles, strong artifacts).8,12–14
Previous studies showed that microemboli originating from mechanical prosthetic cardiac valves are mainly gaseous.\textsuperscript{15,16} Consequently, they yield more intense signals than solid microemboli derived from thrombotic material or fatty debris.\textsuperscript{15,16} Because of their much higher relative intensity increase, echoes from gaseous microemboli are easy to identify within the normal background noise, i.e., the signal of the normal flowing blood.

The purpose of this study was to assess the limits of the automatic embolus detection technique by means of a neural network. We also wanted to assess positive predictive value and sensitivity separately for gaseous and nongaseous emboli.

Subjects and Methods

All normal subjects and patients received a full color-coded duplex investigation of the extracranial brain-supplying arteries and a continuous-wave Doppler investigation of the periorbital arteries. They were also examined by transcranial Doppler sonography (TCD). For embolus detection, both middle cerebral arteries (MCA) or both posterior cerebral arteries (PCA) were insonated simultaneously through the temporal bone window. The MCAs or PCAs were investigated in patients with carotid territory or vertebral artery pathology, respectively. Two 2-MHz probes were secured in a special bilateral probe-holder. The same ultrasound device (NeuroGuard CDS/Medasonics) was used in all studies. The device’s setting was given by the software with a high sweep speed and automatic gain. Power was 100%, the pulse repetition frequency was 3 kHz, sample volume was set to 7 mm in axial width, and the high-pass filter was at 150 Hz. The color-coded power spectra of the audible Doppler shift were visualized on screen after calculation of a 128-point fast Fourier transform (FFT), using an overlap of 75%. The audible Doppler signal was recorded on digital audiotapes (DAT-recorder: Tascam DA-30 MU II, Teac Corp.) with normal speed. The tapes (DV10 RA, Sony) were given numbers for blinded offline analysis. The neural network software EMBotec V5.1 One (STAC GmbH) was used for automatic embolus detection. The experienced observer’s offline analysis of embolic signals was taken as standard reference. It consisted of listening to the signals and watching them on the screen. The following acoustic and visual criteria for embolic signals were used: (1) typical visible and (2) audible (click, chirp, bloop) (3) short-duration (4) high-intensity signal (5) within the Doppler flow spectrum and (6) occurrence at random within the cardiac cycle. The actual point in time of each single MES was recorded and identified on the DAT tape instead of only counted as absolute numbers of MES.\textsuperscript{8,17,18}

The energy distribution of the reflected Doppler signal and the power of the artifacts were calculated offline using the following algorithm: \( e^{-20 \log (\text{signal of interest/background power})} \) [dB], where the “signal of interest” was the power averaged over 4 neighboring FFT lines, and the background power was the average from the FFT of the 2 seconds without the signal of interest (Figure 1).

Normal Subjects

Eleven young coworkers of our laboratory and medical students, aged between 20 and 36 years, 9 men and 2 women with normal color-coded duplex findings of their cervical and intracranial arteries and without any cardiovascular or cerebrovascular disease in their history participated in the study. These subjects were on no medication. The recordings were made bilaterally from both MCAs at a depth of 46 to 56 mm. Insonation time was 20 minutes. After 10 minutes of recording, the normal persons underwent a series of provoked artifacts. First, the subjects opened their mouths 11 times, then, in the second minute, they coughed 10 times, in the third minute they clicked their teeth together 10 times, in the fourth minute they swallowed 10 times, in the fifth minute they moved their jaw 10 times horizontally, and in the sixth minute the investigator tapped 10 times against the probes. In the seventh minute the subjects read a text aloud. That means a total of 671 artifacts were produced, i.e., 1342 artifacts considering both probes of the bilateral recording (plus a 1-minute continuous reading-period).

Patients

Subgroup I, Patients With Thromboembolic Disease

We investigated 2 women and 4 men, aged 40 to 83 years, with potential active arterial sources of embolism. Microembolus detection lasted 60 minutes in every patient. One patient had a dissection of the left extracranial internal carotid artery (ICA) that had become symptomatic with a right-sided hemiparesis 18 days before the investigation. Two patients had an ICA occlusion with stenosis of the contralateral ICA, one of them was asymptomatic, the other patient had a transient ischemic attack (TIA) 6 months before. One patient had an asymptomatic high-grade stenosis of the right intracranial ICA. One patient had stenoses of both ICAs with a symptomatic infarct in the right carotid territory. One patient had high-grade stenosis at the origin of the left vertebral artery with a TIA in the vertebrobasilar territory. Two patients were on intravenous heparin, 2 on ticlopidine treatment, and 1 on aspirin. One patient was on no medication. One 53-year-old patient was investigated with an intracardiac shunt. He had a history of TIA’s in the territory of 1 ICA. He was on no antiaggregant treatment.

Subgroup II, Patients With Mechanical Prosthetic Cardiac Valves

Three men and 1 woman with mechanical prosthetic aortic valves, aged 20 to 68 years, were investigated 105 to 1338 days after cardiac surgery. One patient had an additional asymptomatic low-grade carotid stenosis, and 3 had normal ultrasound findings of their
Data Analysis

In the group of normal subjects the artifact rejection rate of the network was calculated; in all the patients together and in the 2 patient subgroups considered separately, sensitivity and positive predictive values for MES detection by the network in comparison to the investigator’s decisions were assessed.

Results

Normal Subjects

During offline analysis, the blinded investigator detected no embolic signal. The software detected 238 events during the entire investigation period. During the period of the produced artifacts, 216 events were recorded by the software, yielding an artifact rejection of 85%. It detected 48 events in the mouth-opening period, 33 during coughing, 26 during teeth clicking, 1 event in the swallowing period, 33 during jaw moving, 64 during tapping of probes. In the reading period, 11 events were detected. Most of the artifacts, detected by the software as “emboli,” had an energy increase of more than 10 dB above background (16.5±5 dB, cf. Figure 2). During the remaining periods, 22 normal signal epochs were labeled as embolic events. Their reflected energy spectra showed no intensity increase compared with the background signal.

Patients

The automatic embolus detection system detected 282 events in both groups of patients, ranging from 1 to 95 MES per individual. Among these events, 122 signals originated from artifacts. During the offline analysis, the blinded investigator identified a total number of 218 MES. The software did not identify 58 additional MES detected by the investigator (cf. Table 1). The neural network achieved an overall sensitivity of 73.4% and a positive predictive value of 56.7% in comparison to the experienced human investigator.

In the subgroup of patients with thromboembolic sources of emboli, the system detected a total of 174 events. Among these events, 96 signals stemmed from artifacts. Twenty-four additional MES were not identified (cf. Table 2). The sensitivity for identification of true MES in this subgroup of patients was 76.5%, and the positive predictive value was 44.8%.

In the subgroup of prosthetic cardiac valve patients, 108 events were recorded by the software. Among these signals, 26 events originated from artifacts. Thirty-four MES were not identified (cf. Table 3). The sensitivity for identification of true MES in this subgroup of patients was 70.7%, and the positive predictive value was 75.9%.

MES from patients with artificial cardiac valves had averaged energy reflections of 6.4±2.1 dB, and from patients with other sources of emboli of 2.7±0.9 dB.

Discussion

In the past few years the detection of MES by TCD has become a clinically tempting method to identify active embolic sources not otherwise detectable.7,19 The time and manpower needed to evaluate the recordings led to the development of various automatic detection systems. The differentiation of artifacts and MES from the normal spectrum and the differentiation of MES from artifacts are a challenge also for experienced human observers and not just for the automated systems. Although interobserver agreement can be high within centers, a recent study demonstrates that different centers may disagree in the interpretation of MES, especially in MES with small intensity increases.17,20

The present study assessed sensitivity and positive predictive value of automated embolus detection with a trained neural network software. In general, the neural network is capable of classifying patterns in given categories after learning typical examples.12 In a previous study, the neural network had achieved a sensitivity of 93% for the detection of MES in patients with symptomatic and asymptomatic high-grade ICA stenoses13; and in patients with mechanical prosthetic cardiac valves, Georgiadis et al had even found identical performances of the neural network as compared with human observers.14 The latter study, however, had the methodological limitation that only the overall number of detected MES had been compared and not their actual position on the tape on an event-by-event basis. Evaluating the same software (EMBotec), Van Zuilen et al found a network’s overall sensitivity to be 62% in patients with arterial sources of embolism as compared with human observers.8 Again, the reason for the discrepancies in these studies might be that the latter identified individual MES for

![Figure 2](image)
comparison rather than their absolute number. We also chose this signal-by-signal approach to ensure agreement in the corresponding identification of distinct signals. In the present study, the neural network identified a total number of 282 events, which consisted of 160 true MES and 122 artifacts. The true number of MES, however, was 218 according to the experienced investigator. The network’s resultant overall positive predictive value of 56.7% and overall sensitivity of 73.4% for the identification of MES are promising and are particularly good in the group of patients with mechanical prosthetic cardiac valves in which the positive predictive value achieved 75.9%. However, emboli in patients with mechanical prosthetic cardiac valves are mainly gaseous in nature and, presumably, of no harmful clinical relevance.15,16 Their gaseous composition leads to a stronger ultrasound scattering and an enhanced echo. Consequently, embolic signals in the patients with prosthetic cardiac valves are longer in duration and higher in their relative intensity increase than solid emboli from atherosclerotic or thrombotic sources.15,16 This is the reason why the positive predictive value of the software used in this study is higher in patients with prosthetic cardiac valves than in patients with atherosclerotic or thrombotic sources of embolism. The EMBotec software correctly rejected 85% of the provoked artifacts, although this software version was not trained for signals with a >10 dB power (ie, signal-to-noise ratio; Figure 2).

The present study showed that the neural network could not reject all strong artifacts (over 10 dB). On the other hand, a variety of normal spectra in healthy subjects and patients demonstrated patterns similar to embolic signals. This is surprising, but reflects the neural network technique: all patterns for which the network has not yet been trained and those that provide extreme features, pose problems for it. Thus, the network requires a good signal-to-noise ratio and emboli signals between I and 10 dB. The network’s decisions could be improved by a combination of a threshold algorithm and another training set of abnormal and “normal” signals.

Automated embolus detection using a neural network is a promising step forward in the routine assessment of patients at increased stroke risk. However, similar to other automated embolus detection systems, the verification of the signals by an experienced investigator is still mandatory.6,8,9

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References

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