NEURAL NETWORK CLASSIFICATION OF CEREBRAL EMBOLIC SIGNALS

S. Matos[1], M. G. Ruano[1], A. E. Ruano[1], D. H. Evans[2]

[1]ADEEC, FCT, University of Algarve, Faro, Portugal
[2]Department of Medical Physics, University of Leicester, Leicester, UK

Abstract-**The presence of circulating cerebral emboli represents an increased risk of stroke. The detection of such emboli is possible with the use of a transcranial Doppler ultrasound (TCD) system. When a gaseous or particulate embolus passes through the TCD sample volume, it produces high intensity transient signals that are normally relatively easily detected. However, because most current TCD systems rely on human experts for the detection and classification of candidate events, this technique is not widely used.**
The appearance of a reliable automatic system, able to detect these signals and to classify them as originating from either a gaseous or solid source, would encourage the widespread utilization of this technique.
This paper reports the application of new signal processing techniques to the analysis and classification of embolic signals. We applied a Wavelet Neural Network algorithm to approximate the embolic signals, with the parameters of the wavelet nodes being used to train a Neural Network to classify these signals as resulting from normal flow, or from gaseous or solid emboli.
***Keywords* – Embolic signals, Transcranial Doppler ultrasound Wavelets, Neural Networks**

I. INTRODUCTION

Transcranial Doppler (TCD) ultrasound has become the accepted method for detecting emboli in the cerebral circulation. The application of this technique in clinical practice is still limited because it usually relies on human experts to detect and classify events in the generated signals.

A reliable automatic system to detect and also classify events occurring in these signals could increase the application of TCD in the monitoring of high-risk patients. This system should be able to detect true embolic events, rejecting artifacts from sources like patient movements or talking, and to differentiate between gaseous and solid emboli. This classification feature has been limited by the poor time resolution of the signal processing techniques usually used to analyse these signals [1-3].

In previous studies the application of the Wigner distribution produced better estimates of the signal characteristics, allowing a better differentiation between gaseous and particulate emboli [3-4]. In these studies, the measure of the sample volume length (SVL), given by the product of embolic duration and velocity and representing the physical length over which the signal could be detected, was used to separate the two kinds of embolic signals.

Krongold et al. [5] reported the application of time-frequency and time-scale based matched-filters to automatically detect embolic signals. Their results showed that time-scale analysis, like the Wavelet Transform (WT), is better suited for processing these signals.

Devuyst et al. [6] analysed embolic signals using the matching pursuit (MP) method. MP is related to the WT because the analysed signal is approximated by a linear combination of time-frequency atoms obtained from a wavelet function. Results in that paper showed that embolic signals are well approximated by wavelet functions, but the classification of the signals based on the parameters of the wavelet atoms was not reported.

Siebler et al. [7] and Kemény et al. [8] reported the detection and classification of cerebral embolic signals from TCD systems using Neural Networks (NNs). In both studies, pre-processing of the signals was done with the use of the Fourier Transform.

The application of the WT for feature extraction in the analysis and classification of biomedical signals by NNs is reported in [9-10]. These studies show that the combination of the non-linear analysis by the WT, and the classification capability of the NN, can result in a powerful method for the analysis of this kind of signal.

In this paper we report the application of Wavelet Neural Networks (WNNs) and NNs for analysing and classifying embolic signals. The WNN is used to approximate the signals, and the parameters of the wavelet nodes are used as features to train a NN for classifying the signals as originating from gaseous or solid emboli or from normal blood flow.

II. MATERIAL AND METHODS

A. Embolic signals

The embolic signals used were recorded from a TCD system with two output channels. These two channels have a 40dB attenuation between them to accommodate the great dynamic range of gaseous embolic signals [2]. Because these signals present high amplitudes they overload the non-attenuated channel and are always taken from the attenuated channel. Signals from solid emboli, on the other hand, are normally of lower magnitude and can be taken from the first channel.

We used 200 files, each containing 30000 samples, corresponding to 2.4 s of Doppler signal, and each containing at least one gaseous or solid embolic event, previously classified by a group of experts. These events were manually selected and recorded as 1000-sample signals (corresponding to 80 ms).

Signals from 137 gaseous emboli, 119 solid emboli, and 150 from normal flow formed the data set used. For the classification part of the study, this set was divided into a training set with 270 signals (gaseous=90; solid=80; normal=100) and a test set with 136 signals (gaseous=47; solid=39; normal=50).

Report Documentation Page

Report Date	Report Type	Dates Covered (from... to)
25OCT2001	N/A	-

Title and Subtitle Neural Network Classification of Cerebral Embolic Signals	**Contract Number**
	Grant Number
	Program Element Number
Author(s)	**Project Number**
	Task Number
	Work Unit Number
Performing Organization Name(s) and Address(es) ADEEC, FCT, University of Algarve, Faro, Portugal	**Performing Organization Report Number**
Sponsoring/Monitoring Agency Name(s) and Address(es) US Army Research Development & Standardization Group (UK) PSC 802 Box 15 FPO AE 09499-1500	**Sponsor/Monitor's Acronym(s)**
	Sponsor/Monitor's Report Number(s)

Distribution/Availability Statement
Approved for public release, distribution unlimited

Supplementary Notes
Papers from the 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, October 25-28, 2001, held in Istanbul, Turkey. See also ADM001351 for entire conference on CD-ROM.

Abstract

Subject Terms

Report Classification unclassified	**Classification of this page** unclassified
Classification of Abstract unclassified	**Limitation of Abstract** UU

Number of Pages
4

B. Wavelet Neural Network

The first part of the study was the approximation of all the signals from the data set by means of a WNN, using a Morlet wavelet in the network nodes. Fig. 1 shows the Wavelet Network structure used.

The WNN was composed of 10 wavelet nodes, each described by three parameters: the dilation of the wavelet function (d), the translation (t) and the linear weight (w). The output of the network is given by [11]

$$g(x) = \sum_{i=1}^{10} w_i \cdot \psi\left(d_i\left(x - t_i\right)\right) \tag{1}$$

where x represents time and ψ is the wavelet function used in the WNN, defined by (2):

$$\psi(x) = \cos(2\pi x) \cdot \exp\left(-x^2/2\right) \tag{2}$$

The Morlet wavelet was chosen because of its resemblance to an embolic signal. Fig. 2 shows the Morlet wavelet and an example of an embolic signal.

The WNN can be viewed as an adaptive discretization of the continuous inverse wavelet transform [11, 12]. The initialization of the WNN is done in two steps: first a wavelet library is constructed as a subset of all the possible dilations and translations of the wavelet function; then the “best” regressors are chosen from this library by some regressor selection method [12].

For the first step of the initialization, the wavelet functions with the desired resolution levels (dilations) and whose support contains any sample point of the data set are selected from a regular wavelet lattice.

In the second step, the desired number of wavelets is selected from this library using the algorithm of stepwise selection by orthogonalization, as described in [12].

The training of the WNN is based on a set of input/output pairs {x, $f(x)$} where $f(x)$ is the function to be approximated. After the initialization, the network is trained by a Gauss-Newton procedure [12].

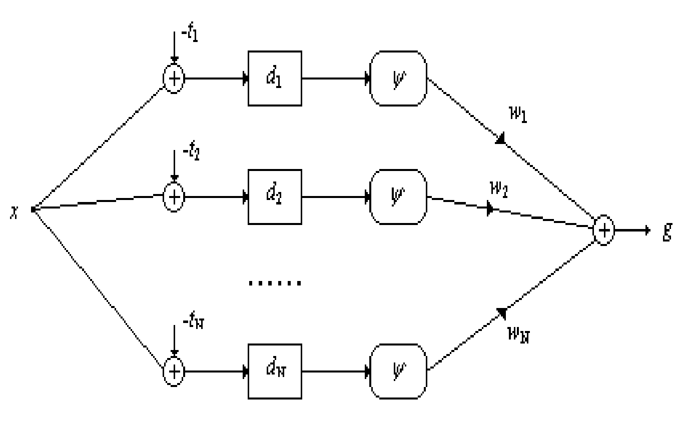

Fig. 1. Wavelet Neural Network.

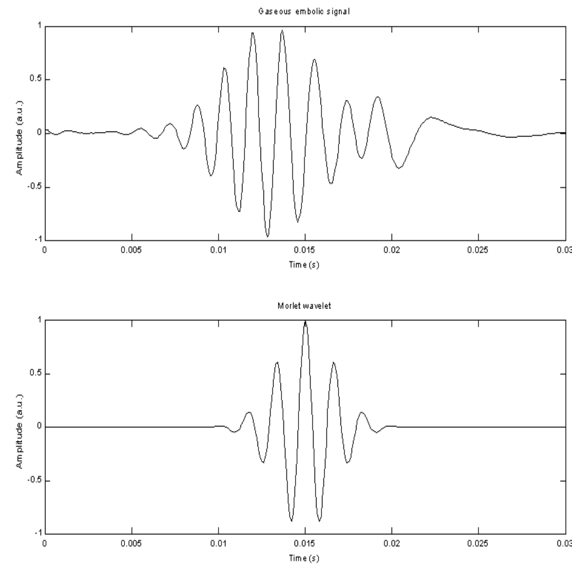

Fig. 2. a) Example embolic signal; b) Morlet wavelet.
(a. u. = arbitrary units)

In this study we used 1000 sample point signals. For each signal, the network parameters were adapted for 10 epochs to minimise the error between the original signal and the output of the WNN, using the Gauss-Newton method. The wavelet parameters that best fitted each signal were saved to be used during the classification stage.

C. Neural Network for classification

The NN used was a Multi-Layer Perceptron (MLP) with 30 inputs, one hidden layer with 3 nodes and one output layer with 2 nodes: MLP(30,3,2). The MLP was implemented in Matlab and trained by a version of the Levenberg-Marquardt algorithm, which explicitly separates the role of the linear and nonlinear network parameters [13].

Two MLPs were trained with the data from the WNN. The first one classified signals as normal flow or embolic, and the second one classified the embolic signals as gaseous or solid.

The training set for the first NN was composed of the 170 examples of embolic signals, gaseous and solid, plus the 100 examples of normal flow signals. The test set was composed of the 86 embolic signals and the 50 normal flow signals from the total test set. For the second NN, the training set was composed of 90 gaseous and 80 solid embolic signals, and the test set by 47 gaseous and 39 solid embolic signals. Each example for the training and test sets was constituted by the 30 parameters of the WNN for the corresponding signal, with the weight values being squared.

For each NN, the training set and the target were presented to the NN, which learned for 100 epochs. Training was repeated 100 times with different initial conditions and the best results chosen. In the test phase, the 136 (86 for the second NN) patterns of the test set were presented to the NN and the outputs compared with the expected ones to verify the generalization capability of the trained network.

III. RESULTS

A. Approximation by WNN

In the approximation part of the study, the normalised square root of the mean square error (NSRMSE), given by (3), was used to verify the quality of the approximation.

$$NSRMSE = \sqrt{mse} \Big/ \sigma_y \tag{3}$$

In (3) above, $mse = \sum_{n=1}^{N} (y-g)^2 \Big/ N$ is the mean square error of the approximation, with y the value of the function, g the approximation, N the dimension of y, and σ_y the standard deviation of y.

The NSRMSE values for the approximation of the analysed signals ranged from 0.07 to 0.73. These higher values appeared mostly because the WNN output is concentrated in the embolic event present in each signal. When the surrounding signal has amplitudes of the order of the event itself, the error of the approximation is increased.

Fig. 3 shows 4 examples of embolic signals used in this study with the approximations obtained with the WNN. The first two signals correspond to gaseous emboli and the other two to solid emboli. The original signals are shown in dotted lines and the output of the WNN in solid.

B. Classification using NNs

Two NNs were trained with the parameters obtained from the approximation part of the study. One network learned to distinguish between normal flow signals and embolic signals while the other learned to separate gaseous from solid embolic signals.

Supervised learning with the same learning algorithm was used in both networks, as explained in section II-C.

The results of the signal classification by the NN were analysed in terms of the correct classification of each kind of signal. From the 100 training sessions of each NN, the one with the best results in the test phase was chosen as the best result.

The results, as percentages of correctly classified signals for the first NN, are shown in Table I. In the training phase the NN learned how to classify signals as embolic or normal, with only 2 embolic signals classified as normal signals and 3 normal signals classified as embolic. In the test phase, the ability of the NN to generalize its knowledge was evaluated using example signals not used in the training set. The classification of the test set signals was done by the trained NN with percentages of correct classification of 92% and 96% for embolic and normal signals respectively, corresponding to 7 of 86 embolic signals being classified as normal signals, and 2 of 50 normal signals being classified as embolic signals.

The second NN was trained to classify embolic signals in gaseous or solid emboli. Training of this network was done with 170 example signals in the training set and 86 in the test set. Table II shows the percentages of correct classifications obtained.

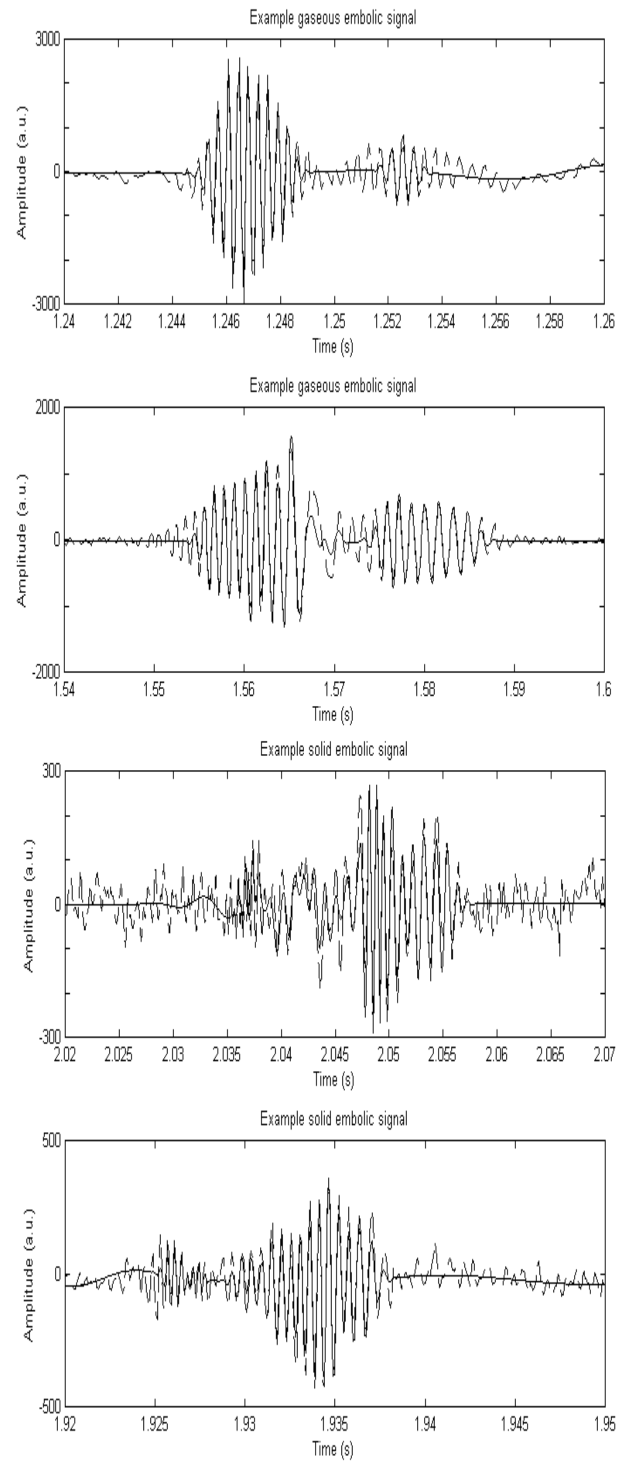

Fig. 3. Example embolic signals: a-b) Gaseous emboli; c-d) Solid emboli. (a. u. = arbitrary units)

In the training phase, percentages of 91% for the classification of gaseous emboli and 99% for the classification of solid emboli were obtained. In the test phase, the NN was able to correctly classify 43 of 47 signals from gaseous emboli and 38 of 39 signals from solid emboli, corresponding to percentages of 92% and 98%, respectively, as shown in Table II.

TABLE I
CLASSIFICATION RESULTS FOR EMBOLIC AND NORMAL SIGNALS

	Training phase	Test phase
Embolic signals	98.8	91.9
Normal signals	97.0	96.0

TABLE II
CLASSIFICATION RESULTS FOR GASEOUS AND SOLID EMBOLI

	Training phase	Test phase
Gaseous emboli	91.1	91.5
Solid emboli	98.8	97.7

The signal examples of Fig. 3 correspond to signals that were not correctly classified by one of the NNs. The gaseous embolic signal from Fig. 3a) and the solid embolic signal from Fig. 3c) were classified as normal flow signals by the first NN, in the test phase.

Signals from Fig. 3b) (gaseous) and 3d) (solid) were classified as solid and gaseous embolic signals, respectively, by the second NN.

IV. CONCLUSIONS

The purpose of this study was to evaluate the application of Wavelet Neural Networks and Neural Networks in the classification of transcranial Doppler embolic signals. We used signals previously classified by a group of experts as originating from gaseous or solid emboli. Because the detection of these events was not an objective of this study, we manually selected the events from files containing 2.4 s of Doppler signal from the TCD system and recorded these as 1000-sample signals to be approximated by a WNN. The parameters of the WNN were used as inputs for two NNs to classify the corresponding signals as embolic or normal flow signals and as solid or gaseous embolic signals.

Both networks showed good results in training and generalization. For the classification of embolic and normal signals, the NN achieved correct classification rates of 91.9% and 96% respectively in the test phase. For the classification of embolic events as gaseous or solid, the NN achieved correct classification rates of 91.5% and 97.7% respectively, again in the test phase.

The results obtained in this study show that the WNN is a suitable tool for approximating cerebral embolic signals and that the network parameters can be used as features for the classification of the signals, using a NN.

A more detailed study on the signal approximation by WNNs will be performed and the detection of events in TCD signals using these techniques will also be tested.

REFERENCES

[1] D.H. Evans, W.N. McDicken, *Doppler Ultrasound: Physics, Instrumentation and Signal Processing*, John Wiley, 427 p., 2000.

[2] J.L. Smith, D.H. Evans, L. Fan, A.J. Thrush, A.R. Naylor, “Processing Doppler ultrasound signals from blood-borne emboli”, *Ultrasound Med Biol*., vol. 20, pp. 455-462, 1994.

[3] J.L. Smith, D.H. Evans, L. Fan, M.E. Gaunt, N.J.M. London, P.R.F. Bell, A.R. Naylor, “Interpretation of embolic phenomena during carotid endarterectomy”, *Stroke*, vol. 26, pp. 2281-2284, 1995.

[4] L. Fan, D.H. Evans, “Extracting instantaneous mean frequency information from Doppler signals using the Wigner distribution function”, *Ultrasound Med Biol.*, vol. 20, pp. 429-443, 1994.

[5] G. Devuyst, J-M. Vesin, P-A. Despland, J. Bogousslavsky, “The matching pursuit: a new method of characterizing microembolic signals?”, *Ultrasound Med Biol.*, vol. 26, pp. 1051-1056, 2000.

[6] B.S. Krongold, A.M. Sayeed, M.A. Moehring, J.A. Ritcey, M.P. Spencer, D.L. Jones, “Time-scale detection of microemboli in flowing blood with doppler ultrasound”, *IEEE Trans Biomed. Eng.*, vol. 46, pp. 1081-1089, 1999.

[7] M. Siebler, G. Rose, M. Sitzer, A. Bender, H. Steinmetz, “Real-time identification of cerebral microemboli with US feature detection by a neural network”, *Radiology*, vol. 192, pp. 739-742, 1994.

[8] V. Kemény, D.W. Droste, S. Hermes, D.G. Nabavi, G. Schulte-Altedorneburg, M. Siebler, B. Ringelstein, “Automatic embolus detection by a neural network”, *Stroke*, vol. 30, pp. 807-810, 1999.

[9] Y. M. Akay, M. Akay, W. Welkowitz, J. Kostis, “Noninvasive detection of coronary artery disease using wavelet-based fuzzy neural networks”, *IEEE Engineering in Medicine and Biology*, vol. 13, pp. 761-764, 1994.

[10] H. Dickhaus, H. Heinrich, “Classifying biosignals with wavelet networks”, *IEEE Engineering in Medicine and Biology*, vol. 15, pp. 103-111, 1996.

[11] Q. Zhang, A. Benveniste, “Wavelet Networks”, *IEEE Trans Neural Networks*, vol. 3, pp. 889-898, 1992.

[12] Q. Zhang, “Using wavelet network in nonparametric estimation”, *IEEE Trans. Neural Networks*, vol. 8, pp. 227-236, 1997.

[13] A. E. Ruano, D.I. Jones, P. J. Fleming, “A new formulation of the learning problem for a neural network controller”, IEEE Conference on Decision and Control, Brighton, U.K., pp. 865-866, 1991.