Automatic Recognition and Classification of Cerebral Microemboli in Ultrasound Images

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Abstract—The aim of this work was the definition of a method devoted to the automated recognition of different composition of cerebral microemboli. The developed diagnostic procedure made use of a feature-based analysis of ultrasonographic images containing the characteristic microembolic signals. The images were acquired with a transcranial Doppler and classified using a hierarchical neural network. The proposed procedure was tested on clinical cases selected by expert neurologists for their relevance, and experimental results showed its reliability.

INTRODUCTION

Transcranial Doppler (TCD) detection and monitoring of cerebral microemboli (ME) have provided a new and useful method to diagnose, and potentially to foresee, increased risk of stroke [1–3]. Until now, however, the assessment of this method in routine clinical practice has been limited by the lack of a reliable automatic differentiation between solid and gaseous microemboli. Actually, researchers are still seeking a truly reliable method for characterizing the inner composition of microemboli.

In light of these considerations, we have undertaken a study for automated ME classification based on the characterization of ultrasound images that show the characteristic microembolic signals (MES) [4]. To this purpose, an image analysis procedure has been developed for MES extraction and description by means of a set of densitometric and morphological features. Then, a multilevel artificial neural network (ANN) [5], characterized by improved adaptability and classification capability, has been designed for ME classification [6].

PROBLEM STATEMENT

Circulating cerebral microemboli produce characteristic audible and visible short-duration, unusually high-pitched signals within the TCD frequency spectrum, also called high-intensity transient signals (HITS) [2]. These signals are generally converted into more explicative images in order to help physicians to perform a diagnosis by visually inspecting acquired data. Moreover, current improvement in the TCD technique has allowed a more accurate and detailed visualization of HITS which are shown in appropriate ultrasonographic images at higher temporal resolution and larger dynamic range (Fig. 1), assuring, in this way, an easier detection of microembolic events.

The characterization of ME composition is still an open problem. The physical phenomena that regulate HITS generation and detection make it difficult, if not impossible, to discriminate among different ME categories by only measuring the increase in the echo-signal intensity. According to these considerations, some studies have tried to investigate the validity of other parameters, such as signal duration [7, 8], the peak velocity [9], or the sample volume length [10]. Moreover, other approaches have proposed more elaborate methods of characterization based, for instance, on the wavelet transform [11] or on the multifrequency insonation [12]. However, all of them have at least one drawback that makes difficult their practical application [13].

APPROACH AND TECHNIQUES

The method proposed in this paper is based on the analysis and the interpretation of the high-temporal-resolution ultrasound images of the HITS, as the ones shown in Fig. 1. This approach relies on two main points:

—The possibility of considering HITS as structures, superimposed on Doppler spectra, whose features can be correlated with acoustic and hemodynamic charac-

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1 The text was submitted by the authors in English.

2 This point is motivated by the property of the intensity increase to be frequency-focused, i.e., maximal over a narrow frequency range [2], and, thereby, of the HITS to be visualized as a closed structure focused on a peak intensity value.
characteristics of the generation embolic event and are recognizable and understood from clinicians.

The application of a particular hierarchical ANN [6, 14] that allows for specialization and adaptability at the same time. Actually, each individual level can be finely tuned to the characteristics of the feature set, while the entire architecture can be easily modified, if the problem model changes, by training only those levels involved in the modification.

In particular, the categorization process is performed through the following steps:

1. **Region of interest (ROI) extraction**: the ultrasonographic images are first processed to isolate the structure corresponding to the HITS.
2. **Feature extraction**: each ROI is analyzed by evaluating a set of geometrical and statistical features that describe the embolic event.
3. **Microemboli characterization**: the feature vector is processed by the hierarchical neural network to obtain the classification of embolus composition.

In the following subsections, each step is described in more detail.

### ROI Extraction

HITS segmentation is performed through a thresholding method that consists in evaluating the embolus intensity increase. For a robust, automated choice of the threshold, an error back-propagation (EBP) neural network is used for considering both statistical and spatial information of the intensity distribution of the image: the input to the network is obtained by the concatenation of the image histogram with a matrix formed by the mean intensity values of $n \times m$ image patches. Once trained, the network is able to determine the threshold for the processed image: the most excited neuron corresponds to the binarization gray level. Then, with a line-tracking method and a masking process, the ROI contour and the ROI itself are obtained.

### Feature Extraction

The HITS extracted in the previous phase are represented and described by means of morphological and statistical features chosen for taking into account information regarding, respectively, duration and velocity and backscattered intensity of MES.

First, a set of 20 features has been identified as the most meaningful for the problem and, then, a feature selection algorithm, based on the mutual information [15], has been applied in order to identify the most relevant and nonredundant ones. In so doing, the subset of the following ten features has been obtained: extension along $x$ and $y$ axis, irregularity factor, orientation, minimum and maximum intensity, mean, centroid, skewness, and sample volume length.

### Microemboli Characterization

ME categorization is performed using a two-level hierarchical neural network which has been structured as introduced in a previous experience [6] (Fig. 2) and opportunely studied on the application characteristics.

The lower level consists of a set of eight self-organizing maps (SOMs), one for each feature except min-

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**Fig. 1.** Ultrasound images visualized at higher temporal resolution and larger dynamic range with (a) gaseous and (b) solid microemboli (enclosed in the rectangles). Time is displayed on the $x$ axis of the spectrum on a 2-ms scale, while the $y$ axis shows the blood flow velocity in cm/s. The dynamic range is represented in the color scale on the right side with a width of 70 dB and a 3-dB step.

**Fig. 2.** Hierarchical neural network architecture. $F_i$ represents the $i$th feature.
imum and maximum intensities because of the distinct distribution of these two features. In particular, the SOM corresponding to the centroid is structured as a two-dimensional lattice, while the other modules are monodimensional networks. For each of them, the number of units has been selected during the training phase as a compromise between the number of clusters and the quantization error [16] of each network. Results are shown in Table 1.

The higher level is represented by a single classifier realized as an EBP module, which combines the results of the lower level for the final categorization. This network has no hidden layers and three output units corresponding to the categories solid, gaseous, and unknown. The dimension of the input layer has been experimentally chosen equal to 30.

### RESULTS

The developed procedure was applied to real cases selected by expert physicians: the images obtained by the TCD device Multi Dop X4 by DWL (Germany) have been chosen and supplied by the Department of Neuroscience, Institute of Neurology, Pisa University Medical School. The TCD device used an automated method for detecting HITS based on the criteria of the Ninth International Cerebral Hemodynamics Symposium [53] and on the dual-gated technique [54].

Our study concerned, in particular, a set of 636 examples, relative to 31 patients (21 men and 10 women), 312 of which corresponding to gaseous microemboli and the remaining 324 to solid microemboli. This data set has been divided into two disjoint subsets, of dimensions 400 and 236, used, respectively, for the training and the testing phases of the neural system.

In order to reduce the computational complexity of the application, the ultrasound image were first reduced to the semiplane containing the MES and then the characterization process was applied. Some results of the ROI extracting procedure can be examined in Fig. 3, while the percentage of error in classifying the clinical cases used to test the proposed approach is shown in Table 2.

### DISCUSSION AND CONCLUSION

In this paper, we have presented an approach to microemboli classification based on the analysis and the interpretation of HITS ultrasound images. This approach is based on the use of a hierarchical combination of SOM and EBP networks to classify a set of geometrical and statistical features, selected as very relevant for the classification task and with low interdependence.

The results obtained from the case studies show the reliability and validity of the proposed method. Further analysis of these results shows that the classification system learned to recognize the different typologies of microemboli (zero unknown cases). On the other hand, misclassification cases (5 of 124 for gaseous and 4 of 112 for solid microemboli) correspond to feature vectors very close to each other, and this eventually can be avoided by considering background information of the embolic event (textural features of the Doppler spectrum or patient information like blood velocity, pressure, and so on).

A future extension of our approach will then consider the echo signal acquired during the ultrasound exam. In this way, the hierarchical ANN will be able to supply the final embolus categorization considering both features of the images and the characteristic information extracted from the complementary signal.

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### Table 1. Structures of the SOM modules

<table>
<thead>
<tr>
<th>SOM MODULES</th>
<th>Number of units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extension x</td>
<td>11</td>
</tr>
<tr>
<td>Extension y</td>
<td>12</td>
</tr>
<tr>
<td>Irregularity Factor</td>
<td>12</td>
</tr>
<tr>
<td>Orientation</td>
<td>12</td>
</tr>
<tr>
<td>Skewness</td>
<td>12</td>
</tr>
<tr>
<td>Mean</td>
<td>11</td>
</tr>
<tr>
<td>Centroid</td>
<td>$7 \times 7$</td>
</tr>
<tr>
<td>Sample Volume Length</td>
<td>11</td>
</tr>
</tbody>
</table>

### Table 2. Recognition score of the proposed classifier

<table>
<thead>
<tr>
<th>Class of microemboli</th>
<th>Recognition Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOLID</td>
<td>95.06%</td>
</tr>
<tr>
<td>GASEOUS</td>
<td>94.15%</td>
</tr>
</tbody>
</table>

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That is, the positive one in the case of flow direction towards the probe and the negative one in the opposite case.
REFERENCES


