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Automatic classification of brain emboli using transcranial Doppler and convolutional neural networks

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Abstract

Stroke prevention is a major societal issue. Given that 80% of strokes are of ischemic origin, i.e. caused by emboli that can clog brain blood vessels, it is essential to monitor Doppler blood flows in main brain arteries to identify these high intensity transient signals (HITS) and provide a reliable and efficient diagnosis tool to prevent strokes and improve patient care. One area for improvement to help physicians identify the cause of stroke is to assess the nature of the emboli. This study proposes the in-vivo HITS classification from time-frequency images using a convolutional network. The major contributions of this study are the following: (i) the construction of a database of 1500 HITS issued from 39 patients, (ii) an end-to-end classification of artifacts, solid and gaseous time-frequency in-vivo emboli images using CNN. All Doppler data were acquired with a TCD-X Holter device, a miniaturized, mono-gate and portable device equipped with a robotized probe to maximize alignment between the ultrasound beam and the mean cerebral artery (MCA) throughout the recording period. We studied the performance of HITS classification using the proposed database and different CNN configurations. Additionally, we did dimensionality reduction on the learnt features of the CNN and use the results to improve HITS classification up to 97% of accuracy.

1. Introduction

Several studies have been carried out over the past 20 years to try to discriminate solid emboli from gaseous emboli, using for example several probe frequencies [1][2] and new approaches have been tried in vitro [3] particularly for the problem of replacing aortic valves which is a very emboligenic procedure [4]. In [5], machine learning methods combined to a signal detection algorithm were used to separate artifacts and emboli.

In this paper, we studied the performance of end-to-end high-intensity transient signals (HITS) classification using the proposed database and different CNN configurations. After training the networks, we evaluated their performance as a number of input data, network size and parameters using metrics associated to confusion matrices. Additionally, we did dimensionality reduction on the learnt features of the CNN and we analyzed the results to deepen our understanding of this tool. The major contributions of this paper with respect to the previous ones [6] [7] [8] are the following:

- the construction of a database of 1500 HITS from 39 patients,
- an end-to-end classification of artifacts, solid and gaseous time-frequency in-vivo emboli images using CNN,

2. Materials and methods

The classification was made from 3 categories: artifacts, gaseous emboli and solid emboli. We monitored more than 39 patients for a total of 2400 minutes of TCD recording with the parameters given in Table 1. The shortest recording was 30 minutes and the longest 180 minutes. The Doppler data was then processed with Atys' software based on the paper of Guépié et al. [5] to detect HITS of 7 dB minimum higher than the spectral background, with a duration of 250 ms.

The supervised learning method used for the emboli classification was a convolutional neural network [7][8]. To determine what CNN architecture best suited our data, we defined several models, ranging from 1 to 6, where one is the lightest tested model (4,367 parameters) and 6 is the deepest (91,427 parameters). They were all built following the same configuration pattern. This pattern consists of a 2D convolutional layer, with 3 x 3 filters, stride 1 and 'same' padding. The number of filters is increased after each pattern. A batch normalization [layer with momentum 0.99, where and are respectively initialized to 1 and 0. The mini batch size was 32, the activation layer, ReLu. A 2D max pooling layer, with a 2 x 2 pooling. A dropout layer, with a rate set to 0.2. Then a dense layer and softmax output are used for classification. The loss function computed on all mini-batch training examples is the categorical cross-entropy loss.

3. Results

The data set we made for the classification contains 500 HITS per category (artifacts, gaseous emboli, solid emboli). It was divided in 400 HITS for training, and 100 HITS per category in the test set. We performed five-fold cross-validation on the training set with model 5 (64,251 parameters). Each fold contained 240 RGB Doppler spectrogram images of size 214 x 100 in pixels. We achieved 97.3% accuracy on the three classes. The artifact class got the highest score for each metrics. It implies that the solid / gaseous confusion is more probable than confusing artifacts with other classes. Indeed, their signature is very different from the 2 other classes, with the total symmetry.

4. Conclusion

This paper proposes a classification method based on CNN for transcranial Doppler emboli signals. It is capable of very fast learning and can separate solid, gaseous emboli and artifacts with great accuracy (97%). This work will allow further study on the origins and characterization of solid and gaseous emboli.

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