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ARTIFICIAL NEURAL NETWORK BASED CLASSIFICATION OF CEREBRAL BLOOD FLOW SIGNALS

Péter SOMOGYI

Department of Control Engineering and Information Technology
Budapest University of Technology and Economics
H–1117 Budapest, Magyar Tudósok krt. 2, Hungary
e-mail: psomogyi@bio.iit.bme.hu

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Abstract

Oscillation of the cerebral blood flow (CBF) is a common feature in several physiological or pathophysiological states of the brain. It is promising to identify the disorders of the cerebral circulation based on the classification of CBF signals. In order to distinguish between different physiological states, an artificial neural network classification model has been developed using spectral matrix based feature vectors describing the temporal blood flow patterns. The efficiency of the classification is evaluated and compared to the results obtained by wavelet subband analysis.

Keywords: biomedical systems, classification of time series, neural-network models, radial base function networks.

1. Introduction

This study is an attempt to classify cerebral blood flow (CBF) oscillations using spectral analysis for feature extraction and an unsupervised artificial neural network (ANN) using a radial based function (RBF) for classification. Low frequency spontaneous oscillations in cerebral hemodynamics have been observed – and linked to certain physiological and patophysiological states [1], such as epilepsy [2]. Therefore it is worthwhile to investigate the possibilities of classification of the temporal patterns of this vasomotion. Three classes of CBF signals have been distinguished experimentally [3], [4] and [5] in relation to consecutive administration of two different drugs:

1. Normal blood flow signals before applying any drugs, that do not exhibit low frequency oscillations (LFO-s), referenced as class A;
2. Slight oscillation after the administration of L-NAME, a NO synthase inhibitor reportedly evoking CBF oscillations, referenced as class B;
3. More pronounced oscillation observed after the administration of U-46619 for stimulating thromboxane receptors, having the effect of also inducing LFO, referenced as class C.

The separation of the first class from the two latter has been carried out successfully using two feature vector elements derived from the measured signal, as done in [3].

With the use of amplitudes given by the Fourier Transform, the second and third classes cannot be effectively distinguished [6] due to the highly overlapping regions (stars and squares), as seen on the feature map *Fig. 1*. Hence the discrimination of the two LFO classes, or cerebral blood flow states, is the subject of this paper. The result of the spectral analysis based feature extraction with ANN classification is compared to a feature extraction using wavelet subband analysis processed by a support vector machine (SVM) classifier as presented by [7].

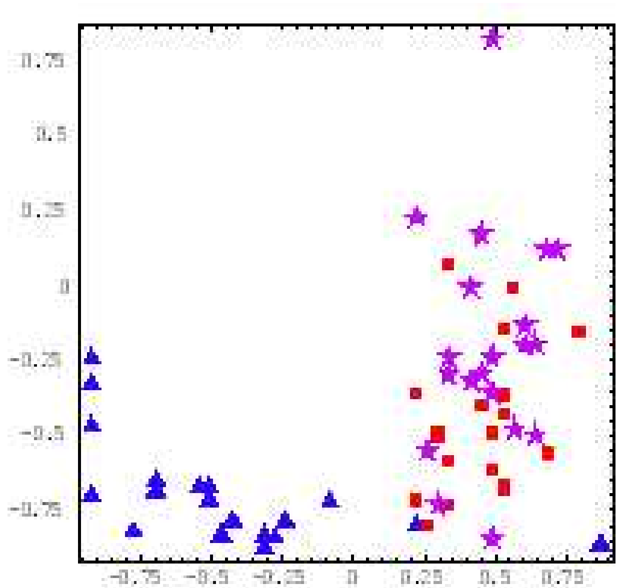

Fig. 1. Normalized dimensionless feature map of cerebral blood flow: normal blood flow, class A (triangle), before administration of U-46619, class B (box) and after administration of U-46619, class C (star) from [6].

2. Feature Extraction Using Spectral Analysis

According to [6], the two greatest components of a wavelet decomposition do not represent adequately the signals derived from drug induced oscillations. A different approach is an eigenvalue based characterization [8]. In order to obtain the singular values being characteristic of the different states, a matrix has to be derived from the time signal. This is obtained by creating a spectral matrix. Given the time series of data d_i, where $i = 1 \dots 70.000$ are the sample points, we pick a window size of $n << 70.000$ and form $70.000 - n$ window vectors, which we apply to a given range of data points:

$$\begin{aligned}
\mathbf{u}_1 &= (d_1, d_2, d_3, d_4, d_5, d_6, \ldots, d_n)\\
\mathbf{u}_2 &= (d_2, d_3, d_4, d_5, d_6, d_7, \ldots, d_n)\\
&\vdots\\
\mathbf{u}_j &= (d_j, d_{j+1}, d_{j+2}, \ldots, d_{j+n-1})
\end{aligned} \tag{1}$$

The matrix is built from these window vectors as columns:

$$\mathbf{A} = \ \mathbf{u}_1^T \mathbf{u}_2^T \cdots \mathbf{u}_j^T \tag{2}$$

and our spectral matrix is $\mathbf{A}^T\mathbf{A}$.

In order to find the optimal window size and range, a series of decompositions have been completed, and the reconstructed signals have been compared to the originals recordings. A window size of about 150 samples with a corresponding 4000 sample window range proved to have around 10% average approximation error while resulting in a 27% maximal approximation error. A sample of the maximal reconstruction errors can be seen in *Fig. 2*, showing the local minimum and maximum.

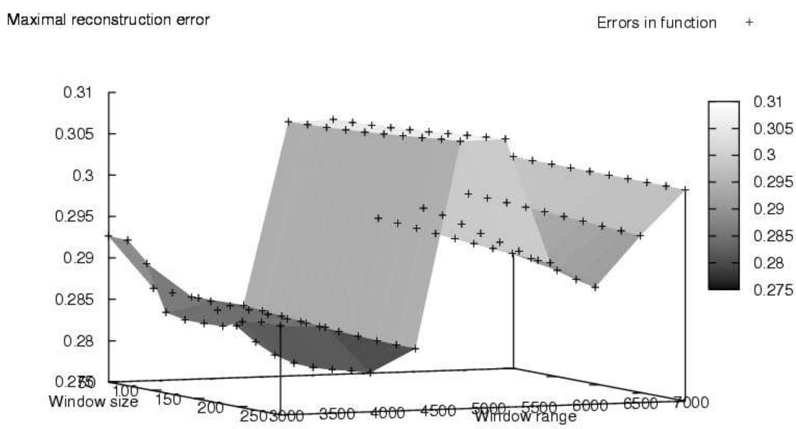

Fig. 2. Approximation error in function of window size and range.

As it can be seen on *Fig. 3*, approximately the first five eigenvalues of the spectral matrix obtained dominate in the case of a class C signal; therefore the first few values are good candidates to be elements of the feature vector describing a given signal.

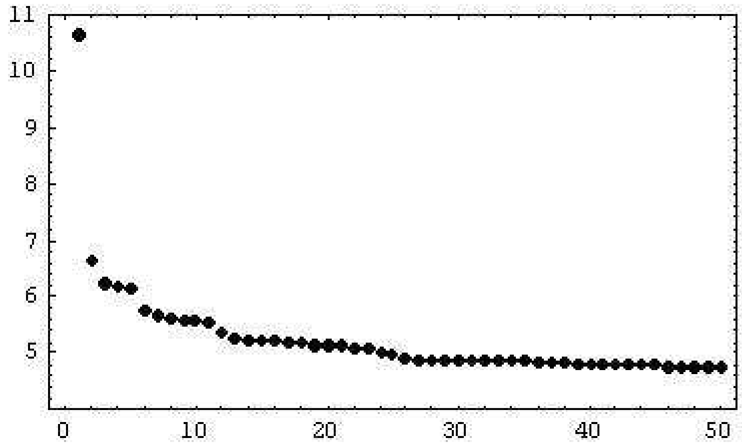

Fig. 3. Eigenvalues of the spectral matrix of a class C signal, on a logarithmic scale.

3. Classification with RBF ANN

The goal of the classification problem is to assign new, previously unseen patterns to their respective classes based on previously known examples: in our case to assign input signals to class B or class C. Therefore the output of our unsupervised learning algorithm is a set of discrete class labels corresponding to the different CBF states. Considering N patterns of measured CBF signals representing three different states of blood flow, we have $\mathbf{x}_i \in R^n$ feature vectors derived from time series samples, where $i = 1 \dots N$ are the samples, and n is the dimension of the feature vector, consisting of several dominant eigenvalues. In our case the number of the measurements were $N = 40$. In order to obtain the minimum size of the feature vector required to produce reliable results, up to six eigenvalues were used in the feature vector. The labelled patterns $\{\mathbf{x}_i, \mathbf{y}_i\}$, $\mathbf{y}_i \in 2, 3$ corresponding to classes B and C, were to be classified. This means, that we are looking for a decision function; the output of this estimating function is interpreted as being proportional to the probability that the input belongs to the corresponding class.

To carry out the systematic classification of CBF signals, an RBF was used. Radial functions have the characteristic feature that their response increases or decreases monotonically according to the distance from a central point. The Gaussian function is used in a single layer network, consisting of two input nodes in the input layer, seven nodes in the hidden layer, and two nodes in the output layer. Several lengths of feature vectors have been fed to the classifier – producing fewer misclassifications as the number of components of the input feature vector increased. The output of the classifier was accepted, if the rounded value of the output nodes corresponded to the proper class, correctly classifying the input pattern, otherwise the classification of that particular input signal was registered as a misclassification.

4. Results

A comparison of different feature extraction methods and classification algorithms can be seen in *Table 1*. Although wavelet decomposition produces coefficients in pairs, the results can be still compared to a spectral decomposition. For the sake of robustness, the spectral matrix was produced at a poor window size/range ratio (50/5000), leading to approximation errors while producing the spectral matrix. Taking different numbers of eigenvalues as feature vectors, the results are very close to that obtained when using wavelet decomposition. In any case, it is clear, that a merely two element feature vector is insufficient for reliable results; a five element feature vector was needed to differentiate class B from class C.

The misclassification rate was steadily decreasing when using longer feature vectors (i.e. more eigenvalues).

The classification method presented, based on an artificial neural network using a radial based function, combined with a spectral matrix based feature extraction can successfully differentiate cerebral blood flow classes B and C. Based on this procedure, we have the opportunity to develop a systematic diagnostic method identifying the actual physiological state of the brain.

Table 1. Misclassification rate

Wavelet coefficient (subband level)	Number of eigenvalues	Wavelet feature extraction & SVM classification, misclassification number	Eigenvalue feature extraction & ANN classification, misclassification number
16 (5)	6	0	0
8 (4)	5	0	0
4 (3)	4	0	3
-	3	-	3
2 (2)	2	4	6

Acknowledgements

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