NEURAL-NETWORK BASED CLASSIFICATION OF LASER-DOPPLER FLOWMETRY SIGNALS

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Abstract: Laser Doppler flowmetry is a most advantageous technique for non-invasive patient monitoring. Based on the Doppler principle, signals corresponding to blood flow are generated, and metrics corresponding to healthy vs. patient samples are extracted. A neural-network based classifier for these metrics is proposed. The signals are initially filtered, and transformed into the frequency domain through third-order correlation and bispectrum estimation. The pictorial representation of the correlations is subsequently routed into a neural network based MLP classifier, which is described in detail. Finally, experimental results demonstrating the efficiency of the proposed scheme are presented.

INTRODUCTION

Laser-Doppler flowmetry (LDF) is a noninvasive method for semi-quantitative assessment of microcirculation currently applied in the fields of angiology, cardiology, vascular surgery neurology and physiology [1]. Its easy handling lead to its widespread clinical use in acquiring relevant information on the microcirculation. LDF appears to offer substantial advantages over other methods in the measurement of cutaneous blood flow. Studies have shown that it is not only highly sensitive and responsive to regional blood perfusion,

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but also versatile and easy to use for continuous noninvasive patient monitoring.

In principle, LDF is an optical technique for estimation of micro-circulation, based on the Doppler principle. When the laser beam is directed toward the issue. reflection transmission and absorption occur. Laser light backscattered from moving particles, such as red cells, is shifted in frequency according to the Doppler principle, while radiation backscattered from non-moving structures remains at the same frequency. Even though Laser-Doppler flowmeters are easy to use, sources of variation need to be known and taken into consideration.

An interesting aspect in the processing of LD signals is the extraction of appropriate parameters and the classification of signals to categories, e.g. corresponding to healthy and patient samples. In this paper, we propose a classification scheme with bispectrum analysis for extracting useful features of the LDF signal, and neural networks for classification of the extracted information.

BISPECTRUM ANALYSIS

As an initial step for the LDF biomedical signals are subjected to the following preprocessing :

First, the original signal is decomposed into three components, consisting of the trend ($\leq 20mH$), component 2 ($\approx 20mH - 800mH$) and component 3 ($\geq 800mH$). This step has proved more useful for the preprocessing of the signals and particularly bispectral analysis. A FIR low-pass Hamming filter (25-taps) was used for the detection of the trend, which allows attenuation of the artifacts or abrupt and brief changes in the signals. The second component is obtained through subtraction of the trend from the original signal and additional low-pass filtering. The effect of linear phase delay is subtracted from the resulting signal.

Let $x(t)$ be a real two-dimensional signal with support $S = [0 \ldots N-1] \times [0 \ldots N-1]$. Its triple correlation is defined as ,

$$x_3(\tau_1,\tau_2) = \frac{1}{N^2}\sum_{S} x(t)x(t+\tau_1)x(t+\tau_2)$$

where τ_1,τ_2 are defined in $S' = [-(N-1),...,(N-1)] \times [-(N-1),...,(N-1)]$

In general, we can move indistinguishably from the signal domain to the triple correlation domain without loss of information or, in other words, we can distinguish two signals by comparing their triple correlations.

Third-order signal correlations and their Fourier transforms i.e. the corresponding bispectra are higher-order statistics with two important properties [2].

→ In contrast to second order correlations, triple correlations of *deterministic* signals have a one-to-one correspondence with the original signal (except of a shift ambiguity).

→ Third-order-correlations of zero-mean non-skewed noise (such as Gaussian or linear and symmetrically distributed) are zero in the mean, and furthermore, they tend to zero w.p. 1 as the size of the available data record tends to infinity.

The first property generally yields a complete description of the signal, based on its triple-correlation. On the other hand, the second property can be used under certain conditions, to improve SNR in applications where the signal under consideration is corrupted by non-skewed additive noise. Based on their properties, third-order correlations can be very advantageous for image recognition, leading to invariant representation of the input images with respect to scale, rotation and translation.

The bispectrum $X_3(u,v)$ of a signal $x(t)$ is computed as

$$X_3(u,v) = X(u)X(v)X(-u-v)$$

where $X(u,v)$ is the Fourier transform of $x(t)$. As a consequence, $X_3(u,v)$ can be computed as the triple product of FFTs using fast software or hardware implementations.

The final step of pre-processing consists of computing the absolute values of the resulting bispectra. Sample plots of these values are shown in (Figure 1, Figure 2, Figure 3). The first one corresponds to a signal obtained from a healthy volunteer, whereas the other two to signals obtained from patients suffering from arterial occlusion.

The volunteers bispectra appear to have frequency components coupled to a certain pair of frequencies. On the contrary, the patients bispectra do not include such regular structures and tend to have several mutually coupled frequencies. In this paper, we use a neural network architecture to classify the LD-images, based on the aforementioned observations.

PROPOSED NEURAL CLASSIFIER

Multilayer perceptrons have been widely examined in the neural network field, as a tool for signal classification, based on the extraction of appropriate features from signals [4]. Error-feedback supervised learning algorithms, such as backpropagation, are generally used to train a multilayer feed-forward neural network. A crucial aspect concerning the network performance is generalisation i.e. the ability of a network to classify correctly input data which were not included in its training set. Good generalisation is a result of appropriate network design; a small number of interconnection weights (i.e. free parameters during training) should generally be used for this purpose, and any a-priori knowledge about the problem should be included in the network architecture. Consequently, structured networks of small size are likely to have better generalisation. Our architecture consists of a multilayer feed-forward perceptron, whose inputs are described below.

The LD signals bi-spectra are processed as grayscale images. Since the size of the images is quite large, we chose to decompose them into images of lower size, using a multiresolution decomposition scheme described below.

Let x_0 denote an $N \times N$ image representation. Using appropriate reconstruction FIR filters $h_l(n)$ and $h_h(n)$, where $h_l(n)$ generally is a low-pass and $h_h(n)$ a high-pass filter, we can split the image into four $(N/2 \times N/2)$ images. Applying for example the low-pass filter $h_l(n)$ in the horizontal and then vertical direction of the original image (we consider the separable case for simplicity) we get the *approximation* image at the lower resolution level $j = -1$ denoted as

$$x_{-1}^{LL}(m,n) = \sum_{k=1}^{N}\sum_{l=1}^{N} h_l(2m-k) h_l(2n-l) x_0(k,l)$$

By applying all other possible combinations of the above FIR filters, we get three lower resolution *detail* images, denoted as $x_{-1}^{LH}, x_{-1}^{HL}, x_{-1}^{HH}$. Moreover, if the above procedure is successively applied to the approximation images, we have a *multiresolution approximation* of the original image, providing images of continuously decreasing size.

The resulting low-resolution (LR) approximation image is used as input to the classifier. Furthermore, in order to exploit useful information included in the detail images, we extract from them several features, especially the number of pixels with non-zero values at each detail level. These pixels generally correspond to non-zero frequency couples in the original image content.

The LR images are fed to the first hidden layer MLP, which is of a receptive field type, while the extracted features as well as the output of the first layer are subsequently fed to a second hidden layer. The output of the second layer is fed to the final layer, the output of which constitutes the result of our classifier.

After training with data obtained both from signals corresponding to healthy persons and patients, our classifier was fed with bispectra obtained by LD-signals. The results were most satisfactory,including a correct classification rate of 93%. Sample bispectra that were successfully classified are shown in (Figure 4, Figure 5).

Further research and experiments are currently performed using extended data sets, as well as refinements to the pre-processing methodology and fine-tuning of the proposed neural network classifier architecture.

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SAMPLE LD-plots

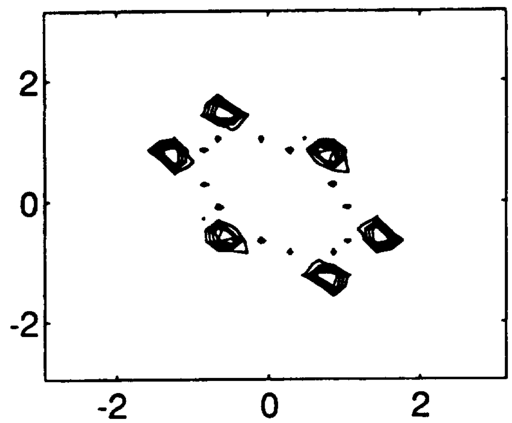

Figure 1 (Volunteer/Healthy)

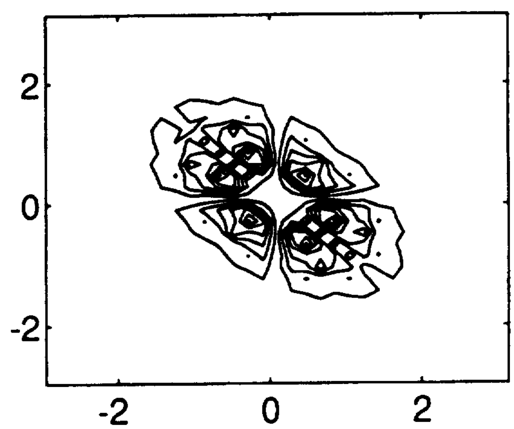

Figure 2 (Volunteer/Patient)

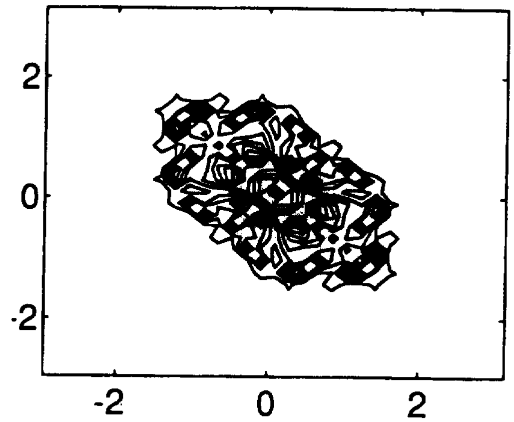

Figure 3 (Volunteer/Patient)

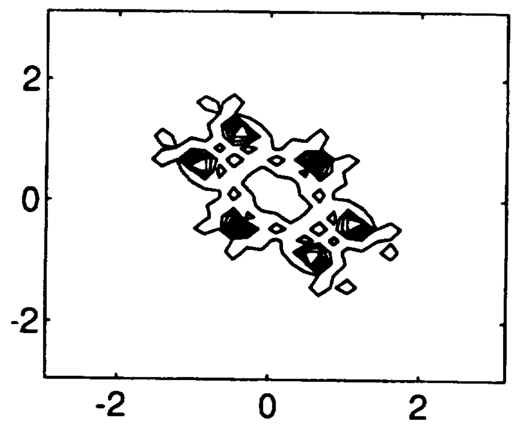

Figure 4

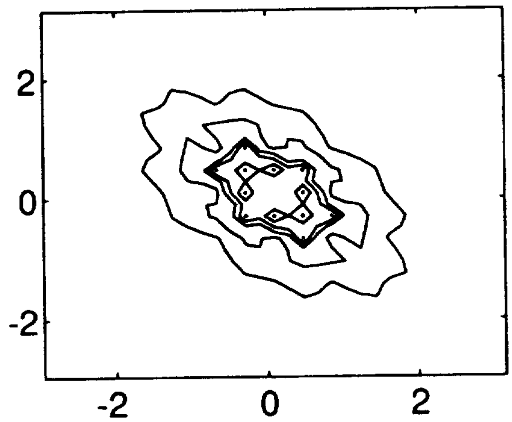

Figure 5