

HRV and BPV neural network model with wavelet based algorithm calibration

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Abstract – The heart rate and blood pressure power spectrum, especially the power of the low frequency (LF) and high frequency (HF) components, have been widely used in the last decades for quantification of both autonomic function and respiratory activity. Discrete Wavelet Transform (DWT) and the Fast Fourier Transform (FFT) represent important tools in this field. The paper presents a new solution for LF and HF evaluation that combines the Daubechies DWT with neural processing techniques. Several types of neural networks (Radial Basis Function and Multilayer Perceptron) capable of evaluating LF and HF values were designed and implemented. The training values to design the network were obtained after heart rate and blood pressure wavelets processing. The designed neural structures assure a faster evaluation tool of the sympathetic and parasympathetic autonomic nervous system control of cardiovascular function.

I. Introduction

During the last two decades, spectral analysis of heart rate variability (HRV) have been providing important insights into neuronal control of the heart and considerable diagnostic utility in assessing autonomic nervous system function [1][2][3][4][5][6]. A number of studies have suggested that these measurements of variability have important prognostic cardiovascular implications [7][8]. Although not as popular as HRV, blood pressure variability (BPV) also carries important information about cardiovascular and respiratory autonomic control [4][6]. Many studies refer to the Fast Fourier Transform as one of the important method to obtain the low frequency (LF) and high frequency (HF) information [1][2] but time length constrains (not less than 5 minutes) and required stationarity make this method less attractive for short time intervals (5-30s) associated to autonomic nervous system changes. For these situations, digital wavelet transforms proved to be a good solution [9]. Previous works of the authors in the autonomic nervous system assessment were related to the design and implementation of wavelet-based algorithms for the evaluation of heart rate variability and blood pressure variability on rats [9][10]. Taking into account the correlations between the results of wavelet analysis and real physiological evoked response to experimentally induced changes, the present paper proposes a fast evaluation model of cardiovascular autonomous modulation based on neural networks using a DWT *calibration* algorithm.

II. LF-HF wavelet calibration algorithm

Time series were constructed from electrocardiograms (Neurolog) and blood pressures signal of 20 male Wistar rats (400-460g), anesthetized (α -chloralose, 100mg/kg) with spontaneous respiration (n=10) or artificially ventilated and paralysed (pancuronium bromide, 4mg/kg/h) (n=10). The femoral artery and vein were catheterised for pressure measurement (pressure transducer Sensoror 840 driven by a Lectromed Ltd. Amplifier) and the administration of drugs, respectively. Rats were artificially ventilated (Harvard rodent app.) with a mixture of oxygen and small amount of room air. The cycling rate was set as 62 ± 2 cycles/min. The temperature was controlled using a rectal probe in 38.5 - 39.5°C and a Harvard homeothermic blanket. All recorded variables were digitized (Instrutech VR100B, Digitimer Ltd.) and recorded on videotape. Off-line analysis of blood pressure and heart rate was made using a computer-based data acquisition system with data capture and analysis software (PowerLab 8SP, ChartWindow). The electrocardiogram (ECG) and blood pressure signals were acquired for 5 minutes in each rat with a sampling frequency $f_s=2\text{kHz}$ (Neurolog Digitimeter Ltd.). Signals from pharmacological induced inhibition in vagal tone (atropine hydrochloride, 2mg/kg) or cardiac sympathetic blockade (propranolol 1mg/kg) in spontaneously breathing rats were also introduced in the analysis. Thereafter, five episodes of five seconds (one minute between

each one) from each rat with spontaneous or artificially respiration and six episodes of five seconds (baseline, first fifty seconds, two and five minutes after atropine or labetalol) from six rats were transferred to software developed at our institute. The principles of the software for data acquisition and wavelets analysis have been described elsewhere [9]. In summary, a time series of R-R intervals derived from ECG and systolic arterial pressure (SAP) were spline interpolated and re-sampled according to the Shannon theorem to produce 2^n samples (128 samples in this case). Wavelets coefficients for details associated to 0.01 and 3 Hz frequency intervals were calculated and the energy distribution on the frequency axis was investigated. R-R and SAP signals were decomposed with orthonormal Daubechies wavelets of order 12 into seven wavelet scales ($j = 7$). LF and HF components of signals were obtained by merging the detail signals at scale 6 (0.2-0.5 Hz) and at scales 3, 4 and 5 (0.5-3 Hz), respectively. The decomposed VLF signals corresponded to the detail at scale 7. Wavelet-filtered components were obtained by summing wavelet detail coefficients for each scale separately and the instantaneous power for the reconstructed detail signals was calculated as the square of the wavelets details positive values corresponding to low frequency and high frequency signal components. The normalized LF and HF components were obtained by calculating the percentage LF and HF variability with respect to the total power after subtracting the power of the VLF component (detail 7 of decomposition).

III. Autonomous modulation model based on neural networks

Neural Networks (NNs) are efficient function approximators and represents an important solution in dynamic systems modelling [11][12]. In the present case, multi-input, multi-output Multilayer Perceptron (MLP) and a Radial Basis Function (RBF) neural networks architectures were designed in order to model the cardiovascular autonomous modulation based on the HRV and BPV evaluation.

A. General processing scheme

In order to obtain the LF and HF components that express the cardiovascular autonomous modulation a hybrid architecture expressed by a cubic spline interpolation block (C-Spline), a time delay line (TDL) [13], and a multiple input – multiple output neural network (MIMO-NN) is used (Figure 1).

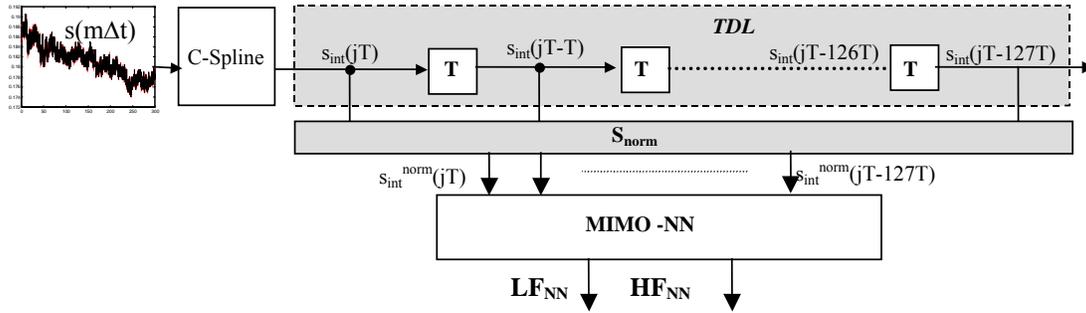


Figure 1. NN processing scheme for the autonomous cardiovascular modulation assessment: TDL- time delay line characterized by 127 T delay cells, C-Spline – cubic spline interpolation of cardiovascular signals, S_{norm} -normalization block, MLP-NN – Multilayer Perceptron neural processing block.

The interpolated signal (s_{int}) is re-sampled at the tape delay line (TDL) level using a set of 127 delay cells characterised by $T=1/f_{RS}$ period. The re-sampling frequency is automatically calculated (included in 17 to 27 Hz) in order to obtain 128 samples for 5s time interval. The signals that had a sampling frequency lower than 16 Hz were not input to the neural network block. The re-sampled and normalized signals (s_{int}^{norm}) are applied to the designed MIMO-NN, which estimates the LF and HF components.

B. NN architecture and training

The neural network architectures designed to materialize the MIMO-NN block were the Multilayer Perceptron [13] and Radial Basis Function [14]. In both cases the input layer is characterized by 128 input elements that receives the RR or SAP samples while the output is expressed by two linear neurons that

deliver the LF_{NN} and HF_{NN} values. The training and test data are the elements of an input matrix including RR or SAP re-sampled signals (e.g. 128×60) and of an output matrix including the LF_{DWT} and HF_{DWT} obtained upon application of a wavelet based processing algorithm considered thus as a *calibration* algorithm. The training input-output set is taken from different experiments (eg. base-line condition, atropine or labetalol injection) associated to autonomous system modulation. Elements of MLP-NN hidden layers and training algorithms are presented next.

MLP-NN case

The MLP-NN includes a hidden layer with 5 to 15 tansigmoid neurons and an output layer with two linear neurons that deliver the HF and LF values characterizing the autonomous modulation for a given experience expressed by fluctuations in the RR or SAP signal. The neural network weights and biases of hidden ($\mathbf{W1}, \mathbf{B1}$) and output layers ($\mathbf{W2}, \mathbf{B2}$) were obtained using Levenberg Marquardt training algorithm [14] and onet 128×60 input matrix and two 2×60 -output matrices. Each column of the input matrix includes 128 sampled values that constitute the 128 NNs input nodes and which were extracted from the RR or SAP signals (Figure 2.a). Referring to the target matrix (output matrix), it is represented by the normalized LF and HF numerical values as results of wavelet processing block that are represented in Figure 2.b.

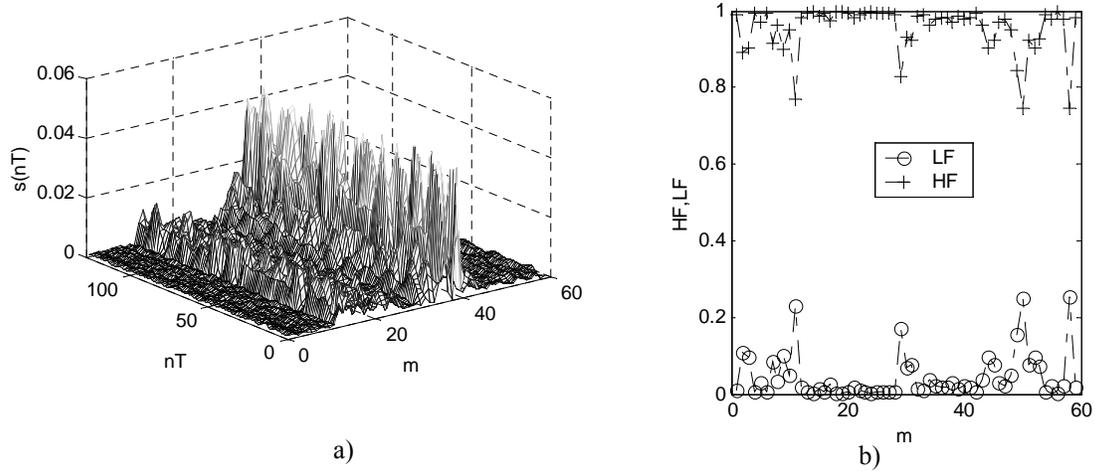


Figure.2. The neural network training set a) input matrix (128×60) b) target matrix (2×60).

A study concerning the dependence of the number of hidden neurons on NN ($n_{\text{hidden}}=5 \div 15$) and model accuracy was performed and presented on the results section.

RBF-NN case

The radial basis function ANN (RBF-NN) is also a fully connected feedforward artificial neural network architecture. It includes only 3 layers: input, hidden and output layer. The input and output layer are similar to the MLP-NN case, 128 input neurons, 2 linear output neurons, while the hidden layer includes a variable number of neurons with gaussian activation functions [14] [15].

The individual activation function of each hidden layer neuron is given by:

$$\varphi(\mathbf{x}) = e^{-\|\mathbf{x}-\mathbf{C}\|^2/2\sigma^2} \quad (1)$$

where vector \mathbf{X} represents the input values of the neuron, \mathbf{C} is the vector of neuron center coordinates and σ the width of the radial function.

This type of networks creates a local approximation of a non-linear input-output function. The local approximation, instead of the global approximation performed by MLP-ANN, implies the utilization of higher number of hidden neurons (more than 60 neurons in our case) for the same degree of accuracy. Otherwise, the RBF-NN requires reduced design times for a good modeling performance when a large number of training vectors are available.

Referring the training, it consists of 2 separate phases. During the first phase the parameters of the radial basis functions, centers and widths, are set using an unsupervised training mode until their values are stabilized. In a second phase the weights of the connections between hidden and output neurons are established using a supervised training mode (backpropagation type) that minimizes the errors between NN outputs (LF_{NNi} and HF_{NNi} values) and correspondent targets, (LF_{DWTi} and L_{DWTi}) for a given set of input training vectors, $\mathbf{RR}_{i..}$, $i=1\dots 60$ in our case.

IV. NN processing results

The performances of the designed MLP-NNs and RBF-NNs depend on the internal architectures chosen (number of neurons, transfer functions), data training, and training algorithm. After training, the designed networks were tested using the validation input matrix and corresponding LF-HF output matrix whose elements were obtained using the mentioned wavelet algorithm. The absolute and relative approximation errors are calculated for different network types (MLP and RBF) and for different internal parameters (number of neurons, spread values etc) in order indicate the optimal solution for LF-HF neural network model.

The absolute and relative approximation errors for LF and HF were calculated using the following relations:

$$e_{aa}|_{LF} = LF_{NN} - LF_{DWT}, e_{ar}|_{LF} = \frac{e_{aa}|_{LF}}{LF_{DWT}} \cdot 100[\%] \quad (2)$$

$$e_{aa}|_{HF} = HF_{NN} - HF_{DWT}, e_{ar}|_{HF} = \frac{e_{aa}|_{HF}}{HF_{DWT}} \cdot 100[\%] \quad (3)$$

Thus, for the particular case of RR-interval signals associated with sympathetic/parasympathetic variations , the MLP-NN approximation performance is expressed by the $e_{aa}|_{LF}$ and $e_{aa}|_{HF}$ (Figure 3).

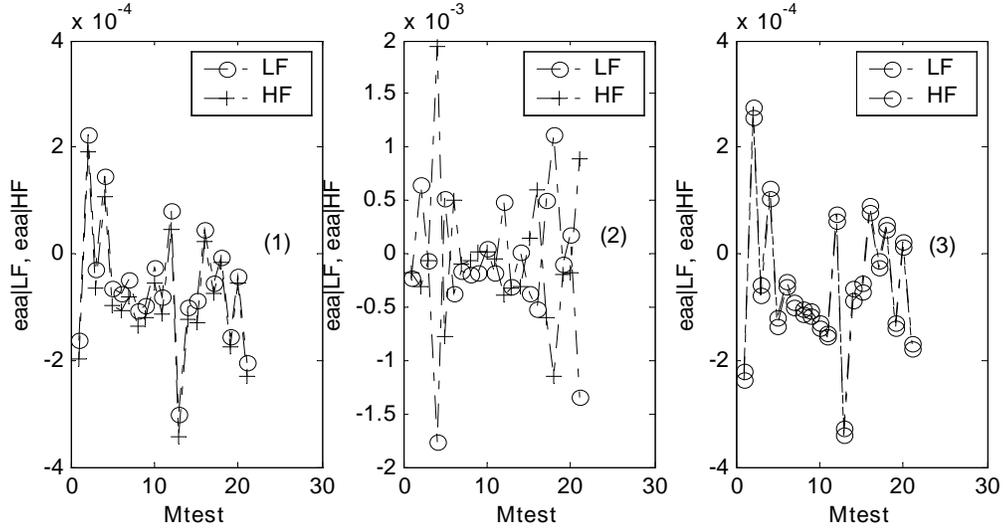


Figure 3. The distribution of absolute errors calculated for the NN model validation set (128×21) and for different MLP-NN architecture (1) MLP-NN with 5 hidden neurons, (2) MLP-NN with 10 hidden neurons (3) MLP-NN with 15 hidden neurons.

Analyzing Figure 3, one notices that an MLP-NN with 5 hidden neurons represents a good solution in our case considering the modelling accuracy and the computational load. The maximum of relative approximation error associated to LF and HF components calculation obtained for the considered testing set was 0.02% and 0.01% respectively. In order to maintain the maximum of relative approximation error lower than 1% for different real situations (baseline individual variations and induced changes in autonomic

nervous system control), the MLP-NN requires new trainings for larger training set (e.g. 128×500) which will conduct to better LF and HF estimation model characterized by high generalization capabilities. The results obtained with the RBF-NN prove the better learning capabilities of this type of network, the generalization performance depending strongly on the spread parameter used in the RBF-NN training phase. Several results concerning the LF and HF estimation based on RBF-NN are represented in Figure 4.

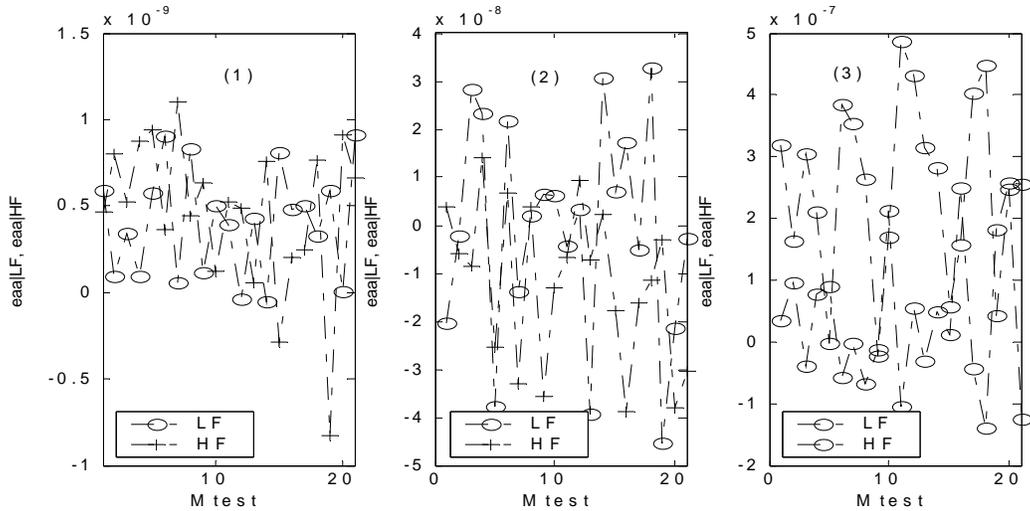


Figure 4. HRV distribution of absolute errors calculated for the RBF-NN model validation set (128×21) and for different values of training spread factor-sf : (1) sf=2; (2) sf=10; (3) sf=20.

As shown in Figure 4, using the same testing set (128×21 - Mtest) the RBF-NN performance in terms of LF and HF evaluation is better than MLP-NN and depends on the spread factor used in the network training phase. To obtain an RBF-NN characterized by higher generalization capabilities the sf is maintained high (sf>10). The number of hidden neurons is 60, a number that is equal to the number of columns of the input matrix used in the RBF-NN training phase.

In order to perform the LF and HF estimation from BPV signals different types of MLP-NN and RBF-NN were also designed and tested. In Figure 5 the MLP-NN and RBF-NN performances as LF and HF estimators are expressed by absolute errors ($e_{aa}|LF$ and $e_{aa}|HF$). The results indicate that RBF-NN is an usefully solution considering the accuracy of the RBF-NN estimator and the training times (shorter than in the MLP-NN cases)

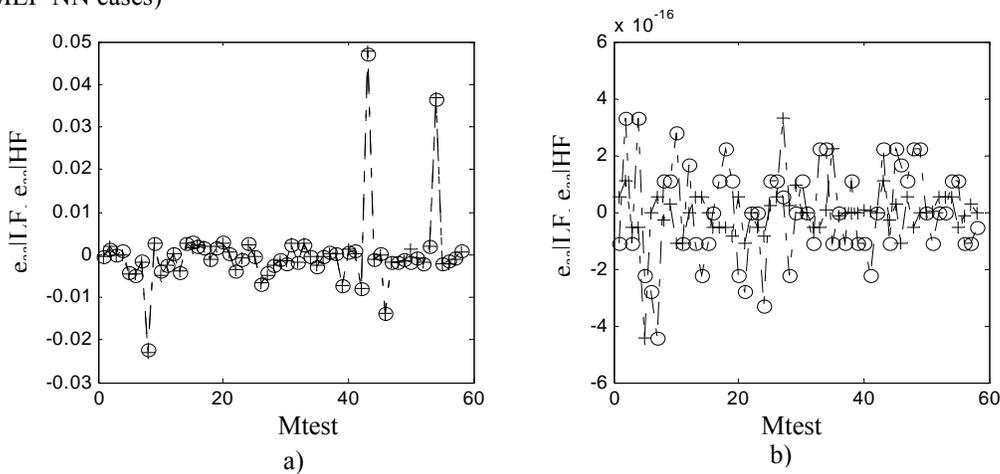


Figure 5. BPV distribution of absolute errors of LF and HF estimation a) MLP-NN (10 hidden neurons) estimator b) RBF-NN, (sf=20) estimator for a validation set Mtest (128×58)

V. Conclusion

A fast solution for the HRV and BPV evaluation based on Multilayer Perceptron Neural Networks is proposed and tested. The following conclusions may be drawn:

- Using the MLP-NN or RBF-NN a short time (5s on rats) assessment of the two branches of the autonomous nervous system (expressed by LF and HF numerical values) can be processed on line.
- The approximation relative errors obtained on neural network testing phase are less than 1% for the LF component and HF components of the RR-interval signal for both type of designed neural networks, MLP-NN and RBF-NN. Better results can be obtained extending the training set and optimising the MLP-NN architectures.
- The use of data obtained from a wavelet algorithm as reference data for neural network training is extremely useful and justifies itself in the present application for two reasons; (a) the scaled and time-shifted wavelets are a better representation of local phenomena in the original signal (b) the signals to analyse and thus their LF and HF components are highly variable.
- Compared with the wavelet algorithm for LF and HF components evaluation, the neural network based method is characterized by less complexity reflected in lower computation load but requires a hard training phase supported on large amount of training data for different physiological situation. As future work the proposed architecture will be better designed increasing the quality of training (128x1000 input matrix) and testing (128x100) to provide a general neural network solution for LF and HF analysis.

It should be emphasized that the work reported here can be seen as a first step towards a low computational on-line HRV and BPV dynamics assessment.

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