HRV and BPV neural network model with wavelet based algorithm calibration

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1. Introduction

Heart rate and arterial blood pressure are the fundamental physiological parameters for assessment of cardiovascular and hemodynamic functions in basic medical research as well as in clinical practice. During the last two decades, the spectral analysis of heart rate variability (HRV) and blood pressure variability (BPV) have been providing important insights into neuronal control of the heart and blood vessels functions and considerable diagnostic utility in assessing cardiovascular and respiratory autonomic nervous system function [1–7]. A number of studies have suggested that the measurement of variability has important prognostic cardiovascular implications [8,9]. Many studies refer to the Fast Fourier Transform as one of the important methods to obtain the low frequency (LF) and high frequency (HF) information [1,2] but time length constrains (not less than 5 min) and required stationarity make this method less attractive for short time intervals (5–30 s) associated to autonomic nervous system changes. Digital wavelet transforms proved to be a good solution [7,9–13] for time–frequency analysis of heart rate and blood pressure signals allowing time visualization of the contribution of the LF signal component (related with sympathetic outflow), of the HF signal component (related with parasympathetic outflow and respiratory rhythm) and of the LF/HF ratio as an indicator of the balance between sympathetic and parasympathetic outflows. 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 [10,13]. Several correlations between the results of wavelet analysis and real physiological evoked response to experimentally induced changes were underlined based on wavelet analysis. With this approach, relative contributions of the two branches of the autonomic nervous system

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(sympathetic and parasympathetic systems) are assessed. Likewise, information from short-time cardiovascular signal analysis can be inferred on autonomic nervous system outflow.

In this work special attention was granted to the design and implementation of an automatic system for the measurement of physiological parameters on rats that provides estimation of cardiovascular autonomic modulation based on intelligent algorithms. A study related to fast modeling methods of multivariable systems was carried out. In this way design aspects such as the selection of an optimal sampling frequency of the measured signal and the analog-to-digital converter’s resolution were considered. Intelligent algorithms, such as artificial neural networks and fuzzy systems showed to be important candidates for fast estimation of systems’ internal parameters [14,15] particularly for autonomic nervous system control of the cardiovascular function. Different solutions based on neural networks modeling are reported in the literature both for static and dynamic characteristics of different kind of systems including biological systems [16–18]. Artificial Neural Networks (ANN), with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an “expert” in the category of information it has been given to analyze. Thus, considering ANN advantages such as high degree of generalization and parallel computing [19], the present paper proposes a novel solution for fast evaluation of cardiovascular autonomic modulation based on neural networks using a DWT calibration algorithm.

2. LF and HF reference estimator based on wavelets

Time series were constructed from electocardiograms (Neurolog) and blood pressure signals from 20 male Wistar rats (400–460 g), anesthetized (α-chloralose, 100 mg/kg) with spontaneous respiration (10 rats) or artificially ventilated and paralysed (pancuronium bromide, 4 mg/kg/h) (10 rats). The femoral artery and vein were catheterised for pressure measurement (pressure transducer Sensonor 840 driven by a Lectromed Ltd. amplifier) and the admin-
istration of drugs, respectively. Rats were artificially ventilated (Harvard Rodent Ventilator, model 683) 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 at 38.5–39.5 °C using a rectal probe and a Harvard homeothermic blanket. All recorded variables were acquired (Instrutech VR100B, Digitimer Ltd.) and recorded on videotape. On-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 of each rat were acquired for 5 min at sampling frequency $f_s = 2$ kHz using the Neurolog Digitimeter Ltd. card. Signals from pharmacological induced inhibition in vagal tone (atropine hydrochloride, 2 mg/kg) or cardiac sympathetic blockade (labetolol, 2 mg/kg) in spontaneously breathing rats were also introduced in the analysis. Thereafter, signals from five episodes of 5 s (1 min between each one) from each rat with spontaneous or artificially respiration and six episodes of 5 s (baseline, first 50 s, 2 and 5 min after atropine or labetolol) from six rats were processed by the software.

In Fig. 1 are represented a set of five episodes of 5 s R–R interval and systolic arterial pressure (SAP) obtained from rats with spontaneous respiration.

The pattern of variability of cardiovascular signals observed in the rats with spontaneous respiration diminished with sympathetic and parasympathetic blockade, and with artificial respiration (Fig. 2).

The software block diagram of the LF–HF estimation based on wavelets was described elsewhere [10] and synthesized in Fig. 3.

In summary, a time series of R–R intervals derived from ECG and systolic blood pressure (SBP) is 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 are calculated and the energy distribution on the frequency axis investigated. R–R and SBP signals are decomposed with orthonormal Daubechies wavelets of order 12 into seven wavelet scales ($j = 7$). LF and HF components of signals are obtained by merging the detail signals at scale 6 (0.1–0.4 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 are obtained by summing wavelet detail coefficients for each scale separately and the instantaneous power for the reconstructed detail signals is calculated as the square of the positive values of the wavelets details corresponding to low frequency and high frequency signal components.
An example of LF and HF value obtained from cardiac and blood pressure signal after DWT decomposition is represented in Fig. 4a and b.

The normalized LF and HF components were obtained by calculating the ratio of LF and HF variability with respect to the total power after subtracting the power of the VLF component (detail 7 of decomposition). Low frequency component (d6 detail of decomposition) from blood pressure and cardiac signal reflects tonus of the sympathetic control of the vessels and heart. Parasympathetic autonomic control of the heart is highly correlated with high frequency component of the cardiac signal (d5, d4, d3). High frequency oscillation in systolic blood pressure signal is mechanically induced by respiratory function.

A reference result of LF, HF estimation based on DWT (reference algorithm) is presented in Fig. 5.

Acting on both sympathetic control of the heart and vessels, labetolol injection produced higher variability on rats' cardiac signal. Great variation on parasympathetic tonus (HFn-RR) was produced to physiological changes induced by artificially ventilation, atropine and labetolol injection, revealing an imbalance on autonomic outflow to the heart. Decreased blood pressure produced by labetolol administration was correlated with a higher decreased in sympathetic outflow to the vessels (LFn-SAP). The normalized LF and HF components obtained by the DWT algorithm was used for neural network design.

3. Autonomic modulation estimator based on neural networks

Neural Networks (NNs) are efficient function approximators and represent an important solution in dynamic systems modeling [20,21]. In the present case, multi-input, multi-output Multilayer Perceptron (MLP) and a Radial Basis Function (RBF) neural network architectures were designed in order to materialize the cardiovascular autonomic modulation fast estimator based on the HRV and BPV evaluation.

3.1. General processing scheme

To obtain the LF and HF components that reflect the cardiovascular autonomic modulation a hybrid architecture expressed by a cubic spline interpolation block (C-Spline), a time delay line (TDL) [22], and a multiple input – multiple output neural network (MIMO-NN) is proposed (Fig. 6).
The interpolated signal ($s_{int}$) is re-sampled at a $T_{RS}$ period by the tape delay line (TDL) using a set of 127 delay cells. The re-sampling frequency is automatically calculated (included in 16–28 Hz) in order to obtain 128 samples for 5 s time interval. The signals with sampling frequency lower than 15 Hz were not input to the neural network block. The re-sampled and normalized signals ($s_{norm}$) are applied to the designed MIMO-NN that estimates the LF and HF components.
3.2. NN architecture and training

The neural network architectures designed to materialize the MIMO-NN block were the Multilayer Perceptron and Radial Basis Function [19,23]. In both cases, the input layer is characterized by 128 input elements and receives the RR or SBP samples while the output is expressed by two linear neurons that deliver the LFNN and HFNN values. The training and test data are the elements of an input matrix including RR or SBP re-sampled signals (e.g., $128 \times 60$) and of an output matrix including the LF$_{DWT}$ and HF$_{DWT}$ obtained upon application of the wavelet-based processing algorithm considered as a calibration or reference algorithm. The input-output training set is taken from different experiments (e.g., base-line condition, atropine or labetolol injection) associated to autonomic nervous system modulation. Elements of MLP-NN hidden layers and training algorithms are presented next.

Fig. 5. The normalized LFn-SAP and HFn-RR components obtained using wavelets coefficients from DWT decomposition of signals from rats with spontaneous respiration (R-sp), atropine (A) and labetolol (L) injection and artificial respiration (R-art).
is the vector of neuron center coordinates and

where vector $u$ weights and biases of hidden (fluctuations in the RR or SBP signals. The neural network nomic modulation for a given experience expressed by that deliver the HF and LF values characterizing the auto-

noid neurons and an output layer with two linear neurons (output matrix) is represented by the normalized LF and HF numerical values as results of wavelet processing block, (Fig. 4), applied to RR or SAP signals.

A study concerning the dependence of the number of hidden neurons ($n_{\text{hidden}} = 5 \div 15$) and LF and HF components estimation was performed and presented in the results section.

3.2.1. MLP-NN case

The MLP-NN includes a hidden layer with 5–15 tan-sig-
noid neurons and an output layer with two linear neurons that deliver the HF and LF values characterizing the auto-
nomic modulation for a given experience expressed by fluctuations in the RR or SBP signals. The neural network weights and biases of hidden ($W_1,B_1$) and output layers ($W_2,B_2$) were obtained using Levenberg Marquardt training algorithm [19] and a training set expressed by $128 \times 60$ input matrix and $2 \times 60$ target 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. The target matrices (output matrix) is represented by the normalized LF and HF numerical values as results of wavelet processing block, (Fig. 4), applied to RR or SAP signals.

A study concerning the dependence of the number of hidden neurons ($n_{\text{hidden}} = 5 \div 15$) and LF and HF components estimation was performed and presented in the results section.

3.2.2. 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. The hidden layer includes a variable number of neurons with gaussian activation functions [19,23].

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

$$\phi(x) = e^{-(x-c)^2/2\sigma^2}$$  \hspace{1cm} (1)

where vector $x$ represents the input values of the neuron, $c$ is the vector of neuron center coordinates and $\sigma$ 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 to 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 unsu-

ervised 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 super-

vised training mode (backpropagation type) that mini-

mizes the errors between NN outputs ($LF_{NN}$ and $HF_{NN}$ values) and correspondent targets, ($LF_{DWT}$ and $HF_{DWT}$) for a given set of input training vectors, $R_{\text{in}}, i = 1 \ldots 60$ in our case.

4. NN processing results

The performance of the designed MLP-NNs and RBF-

NNs depends 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 net-

work types (MLP and RBF) and for different internal parameters (number of neurons, spread values etc).

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

$$e_{a1}_{LF} = LF_{NN} - LF_{DWT}, e_{a1}_{LF} = \frac{e_{a1}_{LF}}{LF_{DWT}} \cdot 100[\%]$$  \hspace{1cm} (2)

$$e_{a1}_{HF} = HF_{NN} - HF_{DWT}, e_{a1}_{HF} = \frac{e_{a1}_{HF}}{HF_{DWT}} \cdot 100[\%]$$  \hspace{1cm} (3)

Thus, for the particular case of RR-interval signals associated with sympathetic/parasympathetic variations, the MLP-NN approximation performance is expressed by $e_{a1}_{LF}$ and $e_{a1}_{HF}$ (Fig. 7).

Analyzing Fig. 7, one can notice that an MLP-NN with 5 hidden neurons represents in our case a good solution considering the modeling accuracy and the computational load. The maximum of the 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 the relative approximation error lower than 1% for new different real situations (baseline individual variations and induced
changes in autonomic nervous system control), the MLP-NN requires new training for larger training sets (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. However, the generalization performance depends strongly on the spread parameter (sf) used in the RBF-NN training phase. Several results concerning the LF and HF estimation based on RBF-NN are shown in Figs. 8 and 9.

As shown in Fig. 8, using a testing set (128×21 – Mtest) provided also by the DWT based reference algorithm, the RBF-NN estimator of the cardiac autonomic nervous system control with a limited number of neurons (up to 15 neurons) performs the estimation of the LF and HF components with low accuracy when compared to MLP-NN. However, increasing the number of neurons to 60, the RBF-NN estimation accuracy increases and is better than MLP-NN (Fig. 9), the accuracy depending also on the spread factor (sf) used in the network training phase. To obtain an RBF-NN with high generalization capabilities, sf needs to be maintained high (sf > 10).

In order to perform the LF and HF estimation for BPV signals, different types of MLP-NN and RBF-NN were designed and tested. Several results concerning the LF and HF estimation error (eaa|LF and eaa|HF) obtained for the best designed neural network (MLP-NN and RBF-NN case)

![Fig. 7. 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.](image1)

![Fig. 8. The distribution of absolute errors calculated for the NN model validation set (128×21) and for different RBF-NN architecture (1) RBF-NN with 5 hidden neurons, (2) RBF-NN with 10 hidden neurons (3) RBF-NN with 15 hidden neurons.](image2)
are presented in Fig. 10. The results indicate that the RBF-NN is a usefully solution considering the accuracy of RBF-NN estimator and the training times (shorter than in the MLP-NN cases).

5. Conclusion

A fast solution for the HRV and BPV evaluation based on MLP or RBF neural networks is proposed and tested. For optimal results special attention was also granted to the signal conditioning and acquisition of physiological signals that provide accurate samples to input the artificial neural network processing architecture.

It should be emphasized that the work reported here can be seen as a step towards a fast and low computational on-line HRV and BPV dynamics assessment. The following conclusions may be drawn:

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 considering that the scaled and time-shifted wavelets are a better representation of local phenomena in the original signal.

Using MLP-NN or RBF-NN a short time (5 s on rats) assessment of the two branches of the autonomic nervous system (expressed by LF and HF numerical values) can be on-line achieved.

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 types of the designed neural networks, MLP-NN and RBF-NN. Better results can be obtained extending the training set and optimising the MLP-NN architectures.

Compared to 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.

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