Non-Invasive Estimation of Central Aortic Pressure from Radial Artery Tonometry by Neural Networks

M Varanini, M Massoni, P Marraccini, M Kozàkovà, G Djukic,
M Bamoshmoosh, R Testa, F Vittone, C Palombo

CNR Institute of Clinical Physiology, Pisa, Italy
Department of Internal Medicine, University of Pisa, Pisa, Italy

Abstract

This study compares a neural network-based autoregressive exogenous (NNARX) model with a linear autoregressive exogenous (ARX) model in reconstructing central aortic pulse curve from peripheral arterial pulse.

Invasive aortic and radial tonometry pressures were recorded in 20 patients in rest condition. A set of 10 patients (learning) was used to estimate the model parameters, the remaining 10 patients (test set) were used for validation. The estimated waveform of aortic pressure obtained by NNARX results more accurate than that estimated by linear ARX model providing a more fine reconstruction of dicrotic notch and systolic flex. Comparison of Augmentation Index measurement computed from NNARX and ARX reconstructed pressure signals with the reference value derived from invasive aortic waveform showed an improvement in accuracy of the NNARX measure.

1. Introduction

Aortic pressure signal conveys important information about cardiovascular system; valuable clinical features such as augmentation index [1], arterial stiffness, and LV ejection duration can be derived. However the invasive nature of the measure restricts their use. The recent availability of high fidelity non-invasive peripheral pressure signal by applanation tonometry stimulated the research of methods for estimating the aortic pressure waveform for widespread clinical use.

In most studies the central pressure signal is reconstructed from peripheral (femoral, carotid, radial, finger) waveforms using a transfer function estimated by Fourier transform. More recently, an approach based upon linear ARX model estimation has been proposed [2,3]. However the physiological components involved in the propagation of the central aortic pressure wave towards the periphery are intrinsically non linear, and a linear approximation of their characteristics on large variations like that of pressure signal, can result unable to reproduce waveform details. In particular the flex around the systolic peak which is at the base of augmentation index (AI) computation. AI takes into account the augmentation of aortic pressure by the return in systole of the wave reflected from small peripheral arteries, and it is highly predictive of cardiovascular mortality.

The present study estimates a Neuronal Network based non linear model [4,5], and compares the reconstructed central pressure signal with the one obtained by the estimation of a linear ARX model [6]. The accuracy of the reconstructed pressure signals was evaluated using the sum of squares errors respect to true (invasive) central pressure signal. Moreover the augmentation index (AI) values computed on the estimated signals were compared with those extracted from the true signal.

In this work has been used the "Neural network based system identification toolbox" (NNSYSID) of Magnus Nørgaard [4] which can be downloaded free of charge from the address
http://www.iau.dtu.dk/research/control/nnsysid.html.

2. Methods

Aortic invasive and radial tonometric pressure signals were simultaneously acquired in 20 patients undergoing diagnostic left heart catheterization for known or suspected ischemic heart disease. Central pressure was obtained by a fluid-filled catheter placed in aorta. Radial pressure was recorded by applanation tonometry technique using a Millar SPT 301 transducer with an amplifier TCB 500. Signal acquisition was performed at 500 Hz with 16 bits A/D converter continuously for 5 minutes in bed rest condition before undergoing to diagnostic manoeuvres. Both pressure signals were low pass filtered (20Hz), mean value was removed and decimation at 50Hz was performed.

For each recording, a two minute long sequence of signal without artifacts was selected. The set of 20 records was partitioned: 10 patients were used for learning and the other 10 for validation set. Each record was normalized to zero mean and unitary variance, this leads to no lack of information because the amplitude of tonometric pressure signal depends on ability of the operator in performing vessel applanation and, on the other hand, the AI is invariant on scale change.

As we are interested in the reconstruction of the aortic pressure from a peripheral pulse, we try to estimate directly a model from peripheral to central, inverse respect to the physiological one related to the forward wave propagation.

A Neuronal Network AutoRegressive eXogenous (NNARX) model [4,5] was estimated on the learning set using radial pressure as input and aortic pressure as desired output. Similarly, a linear AutoRegressive eXogenous (ARX) model [6] was estimated. The results obtained from validation set were compared together.

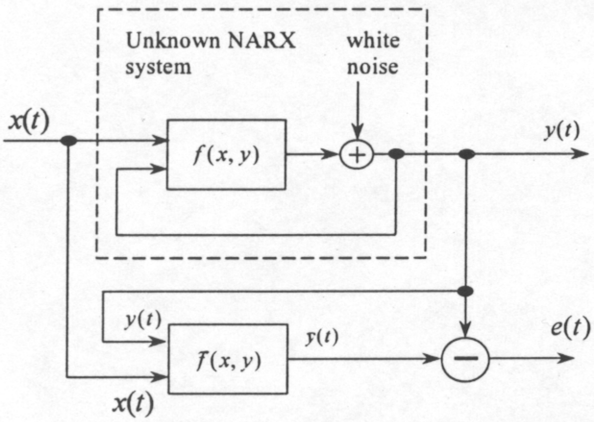


Figure 1. The system model (in the dashed box) and the scheme for its identification.

An ARX model structure was selected for its simplicity in estimation of the parameters respect to the more general AutoRegressive Moving Average eXogenous (ARMAX).

A general Non linear AutoRegressive eXogenous (NARX) model is expressed by the equation

$$y(t)=f(y(t-1),\ldots\ldots,y(t-n_a),x(t-d),\ldots\ldots,x(t-d-n_b+1))+\varepsilon(t)$$

where t denotes discrete time, *y(t)* is the output (aortic pressure signal), *x(t)* is the input (radial signal), $\varepsilon(t)$ is white noise and $f(.)$ is a general non linear function. The constant n_a is the number of autoregressive terms (past output values *y(t-k)*), n_b is the number of moving average terms (past input values *x(t-k)*), *d* represents the delay between the input and its effect on the output. It should be noted that there is no moving average (MA) terms on $\varepsilon(t)$. The figure 1 shows the NARX system and the prediction error scheme used for model identification. Introducing the regression vector

$$\varphi(t)=[y(t-1),\ldots,y(t-n_a),x(t-d),\ldots,x(t-d-n_b+1)]^T$$

we can write:

$$y(t)=f(\varphi(t))+\varepsilon(t)$$

where the predictor is $\hat{y}(t)=f(\varphi(t))$.

The problem consists in the estimation of the unknown function $f(\varphi(t))$ using the training set $Z^N=\{[x(t),y(t)]\,|\,t=1,\ldots,N\}$ so that the predictor $\hat{y}(t)$ is "close" to the actual value $y(t)$.

The most used criterion of "closeness" is the least squares which minimizes the sum of squared residual errors:

$$\xi=\frac{1}{N}\sum_{n=1}^{N}|e(n)|^2$$

where $e(n)=y(n)-\hat{y}(n)$

The general function $f(\varphi(t))$ can be restricted to belong to a class of parametric functions $f(\varphi(t),\theta)$, the problem is so reduced to determine the unknown vector of parameters θ which minimizes ξ.

$$\hat{\theta}=\arg\min_{\theta}\{\xi(Z^N,\theta)\}$$

In this work are considered two classes of parametric functions: a) the linear function; b) the forward multilayer perceptron neural network.

Linear ARX model.

The model is expressed by the equation

$$y(t)=\theta^T\varphi(t)+\varepsilon(t)$$

where $\theta=[a_1,\ldots,a_{n_a},b_1,\ldots,b_{n_b}]^T$ and the predictor is $\hat{y}(t)=\theta^T\varphi(t)$

For a set of N data the previous equation yields the matrix formulation

$$\mathbf{y}=\Phi\theta+\varepsilon$$

The measure ξ results a quadratic function of θ, it follows that the minimum is unique and it can be determined analytically (if the following matrix inversion is possible).

$$\hat{\theta}=\left[\Phi^T\Phi\right]^{-1}\Phi^T\mathbf{y}$$

If $\varepsilon(n)$ is white i.i.d. the estimate $\hat{\theta}$ results unbiased, consistent and of minimum variance.

NNARX model.

The predictor $\hat{y}(t)$ is a nonlinear function of the class neuronal network functions.

$$\hat{y}(t)=f(\varphi(t),\theta)$$

Now the measure ξ is not a quadratic function of θ, then the minimization problem must be solved with iterative procedures and local minima can occur. The selection of a NNARX structure leads to a not recurrent NN (network inputs does not depend from previous network outputs, i.e. the term $\hat{y}(t)$ is not argument of the function $f(\varphi(t),\theta)$) and this reduces convergence and instability problems.

One of the most powerful minimization methods is the Gauss-Newton with Hessian approximation of

Levenberg-Marquardt. This method was used for its convergence properties and robustness. The iterative procedure for weight updating is

$$\boldsymbol{\theta}_{n+1} = \boldsymbol{\theta}_n - \eta \cdot \boldsymbol{H}^{-1} \nabla \xi_N \Big|_{\theta=\theta_n}$$

Where $\nabla \xi_N \big|_{\theta=\theta_n}$ is the gradient and $\mathbf{H}$ is the Hessian matrix which is approximated by the outer product of the instantaneous gradient of the output w.r.t. weights:

A regularization term is used in the ξ cost function in order to improve generalization. This term penalizes the cost measure ξ of a value increasing with the square value of each weight.

$$\xi = \frac{1}{N}\sum_{n=1}^{N} |e(n)|^2 + \frac{1}{N}\boldsymbol{\theta}^T \boldsymbol{D}\boldsymbol{\theta}$$

Where $\boldsymbol{D}$ is a diagonal matrix, we use the uniform setting: $\boldsymbol{D} = \alpha \boldsymbol{I}$ with $0 \le \alpha << 1$. The regularization term leads an exponential decay of the weights $\boldsymbol{\theta}$ which are non essential for the fitting. The surface of the cost function $\xi(\boldsymbol{\theta})$ results more smooth and with less local minima, on the other hand the solution results polarized as all the parameters get a value less then the optimal.

Model Estimation

As we are estimating a model inverse respect to the physiological process we need to anticipate the radial signal so that radial pulse (input of the model) occurs before the aortic waveform from which it derives. Different delay time were tested and the one of -240ms provided better results.

Linear ARX estimation: the estimation of linear ARX, which will provide the reference performance for the evaluation of the NNARX, was performed on the 10 patients learning set getting an inter-patient model. As the pressure signals and the cardiovascular system changes from patient to patient, estimation of intra-patient models was performed in order to compare the global inter-patient variability with the intra-patient variability.

A correct order setting is a prerequisite to get good estimates; a too high model order can fit the random structure in each single data sequence producing poor generalization. On the other hand, low order model can be unable to represent the system dynamic distorting the output signal. Different orders, ranging from 5 to 30, were tested by the Akaike Information Criterion (AIC), and by cross validation comparing the obtained ξ measures. The order [8,15] was selected.

Neural Network ARX estimation: The NN structure, we choose, consists of a full connected multilayer perceptron (MLP) with one hidden layer with hyperbolic tangent activation functions and one output layer with linear activation. The lag space was determined by cross validation, it turns out $n_a = 6$, $n_b = 12$ i.e. 18 inputs. Moreover 8 artificial neurones were selected for the internal layer, resulting a total number of 161 weights (including neuron polarization). The regularization factor was set to 1e-5. Parameter setting resulted from the examination of the behaviour of the ξ criterion on the learning and on the test set with the increasing of one parameter and keeping constant the others. As expected, the average value of ξ on the test set, after an initial decrease got a minimum value and returned to increase, however the region of the minimum was flat and quite wide; i.e. different parameter settings led to similar performance. The variance of ξ showed a similar behaviour. The increasing of the regularization term led to translation of this flat region towards high number of weights.

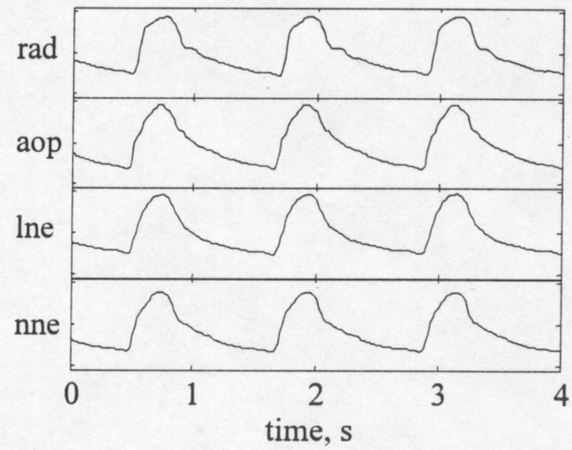


Figure 2. Pressure signals; from top: radial, aortic, linear estimate, NN estimate.

3. Results

The visual inspection of the signals provides the best approach to preliminarily catch the accuracy of the aortic pressure waveform reconstruction by Neural Network modelling respect to the linear one. The figure 2 shows an example extracted from the test set. From top to bottom: tonometric radial pressure, true aortic pressure, linear ARX reconstructed and NNARX reconstructed pressure. The estimated waveform obtained by NNARX mimics more closely the aortic signal than that estimated by linear ARX model. In particular, it results in a more accurate reconstruction of dicrotic notch and systolic flex. A quantification of this improvement can be get examining the global mean square error (mse) obtained on the test set. The mse value for NNARX was 0.059, corresponding to less then 60% of the value of 0.098 obtained by the linear ARX model. The table 1 shows the individual results for the 10 patients of the test set; each row is relative to a patient and on each column are reported, from left to right, the mse resulting from the linear approach, the mse from the NN approach, the AI computed on the aortic signal, the AI computed from the linear estimate and the AI computed from the NN estimate.

Table 1. Results on 10 patients test set.

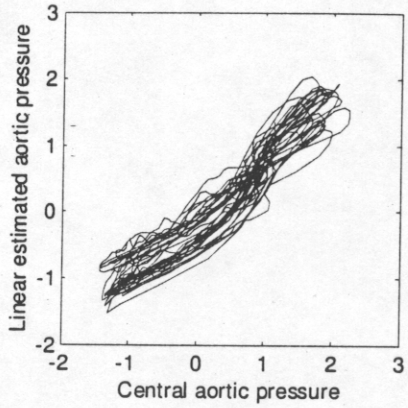
	mse_ln	mse_nn	AI	AI_ln	AI_nn
1	0.108	0.109	0.510	0.658	0.549
2	0.107	0.082	0.605	0.643	0.584
3	0.238	0.076	0.729	0.631	0.633
4	0.053	0.084	0.653	0.661	0.600
5	0.014	0.022	0.584	0.685	0.597
6	0.017	0.041	0.582	0.724	0.682
7	0.086	0.017	0.544	0.728	0.541
8	0.149	0.040	0.669	0.711	0.592
9	0.139	0.067	0.678	0.574	0.611
10	0.066	0.050	0.524	0.714	0.566

The more accurate reconstruction of the waveform details (appreciable in x-y plot example of figure 3) leads to a more incisive difference in estimating AI diagnostic measure. The comparison of Augmentation Index measurements computed on NNARX and on ARX reconstructed pressure signal with the true value derived on invasive aortic waveform was performed. The standard deviation of the difference from linear estimated AI and true AI resulted 0.11, while the one relative to NN estimate was 0.06, yielding a confidence interval for the NN measure corresponding to about the half of the linear estimated measure. The variance ratio F-test rejected the hypothesis of equal variance at a significance level of 0.05.

4. Discussion and conclusions

Neural network approach improves the accuracy of the reconstructed aortic pressure waveform from noninvasive recording of radial artery pressure signal. In particular the improvement concerns waveform details with high frequency content allowing a better estimation of AI and thus opening promising perspectives for clinical use, namely in the cardiovascular prevention field.

However, some pitfalls still affect the results. The residual of the estimated aortic pressure obtained by the NNARX model using only the radial pressure as input got a power greater than expected and resulted autocorrelated. It may be at least partly explained by the quite wide variability of the radial pressure waveform observed from patient to patient, which is due to both intrinsic variability, i.e. different cardiovascular conditions, and the amplitude instability of the applanation tonometry measurement. Nonetheless, the shape of the estimated signal resulted close to the aortic pressure wave, which appeared better reconstructed than by ARX. The overall performance of the NNARX model may be further improved by expanding the learning set, as well as by using an operator-independent. tonometric device.



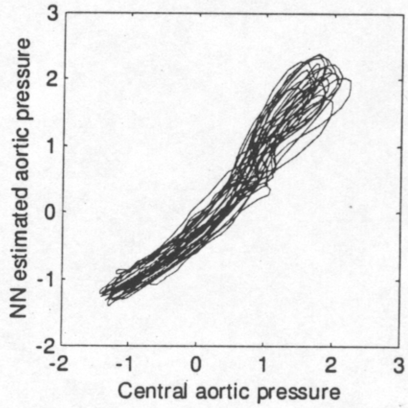


Figure 3. Example: linear estimated pressure versus aortic (top), NN estimated pressure versus aortic (bottom).

References

[1] Murgo JP, Westerhof N,, Giolma JP, Altobelli SA. Aortic input inpedence in normal man: relationship to pressure waveform. Circulation 1980;62:105-16.

[2] Chen C-H, Nevo E, Fetics B, Pak PH, Yin FCP, Maughan L, and Kass DA. Estimation of central aortic pressure waveform by mathematical transformation of radial tonometry pressure: validation of generalized transfer function. Circulation 1997;95: 1827-36.

[3] Fetics B, Nevo E, Chen CH, and Kass DA. Parametric model derivation of transfer function for non-invasive estimation of aortic pressure by radial tonometry. IEEE Trans Biomed Eng 1999;46:698-706.

[4] M. Nørgaard. Neural network based system identification toolbox. Tech. Report. 00-E-891, Department of Automation, Technical University of Denmark, 2000.

[5] Haykin S. Neural Networks: a Comprehensive Foundation. 2nd ed. Englewood Cliffs, NJ: Prentice Hall, 1999.

[6] Lennart Ljung: System Identification: Theory for the User. Englewood Cliffs, NJ: Prentice Hall, 1987.

Address for correspondence.

Maurizio Varanini
Institute of Clinical Physiology, CNR
via Trieste, 41 - 56126 - PISA, Italy
E-mail: varanini@ifc.cnr.it