Modeling the central nervous system control of the cardiovascular system by support vector machines

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Abstract

The control of the cardiovascular system (CS) has been scarcely modeled due, basically, to the complexity of the central nervous system (CNS). The cardiovascular and the central nervous systems are closely related one to each other. Some models based on fuzzy inductive reasoning, genetic fuzzy systems, neural network and quantitative approaches using nonlinear with autoregressive techniques, have been employed for this purpose, resulting in a significant, but still improvable approximation of the expected control response of the CNS. In this research, we used support vector machines for predicting the response of a branch of the CNS, which controls an important part of the cardiovascular system. In this study, five controllers that generate signals that regulate heart rate, myocardial contractility, peripheral resistance, venous tone, and coronary resistance, and that react to variations of the carotid sinus blood pressure (CSBP), are presented. The predictive models were trained using an input signal (i.e., CSBP) and an output signal for each controller; and a set of six input and output signals were employed for testing each controller model. Input signals were processed using an all-pass filter, and the performance of the predictive models were evaluated using the average of the normalized mean square error (MSE) in percentage. The best forecasting performance was obtained for the peripheral resistance controller with a MSE= 1.20e-4 %, and the worst for the heart rate controller with a MSE= 1.80e-3 %. Support vector machines presented a better performance estimating the dynamical behavior of the control of the CNS over the cardiovascular system than other modeling systems previously studied.

Key words: Central nervous system, cardiovascular system**,** modeling, support vector machine, fuzzy inductive reasoning.

1. Introduction

The mechanisms of regulation of visceral organs in the nervous system has been historically a research topic. One of the most important systems of the body is the cardiovascular system and, obviously, it is almost fully controlled by the central nervous system. The CNS generates regulatory signals which are transmitted by bundles of nerves through the autonomic nervous system (sympathetic and parasympathetic) to the heart, blood vessels, kidneys, and other body parts; this allows to maintain an appropriate blood flow, following hemodynamic changes due mainly to variations of the arterial blood pressure. The CNS controls important global functions in the CS such as: cardiac output (modifying the heart rate and myocardial contractility), redistribution of blood flow, and rapid control of the arterial pressure to mention a few [1].

Most of the control generated by the CNS over the CS is carried out in the vasomotor center which manages integral information from: visceral sensors (coming from baroreceptors of cardiac cavities and large vessels, and from chemoreceptors), the bulbar respiratory center, and other suprasegmental structures of the brain [2]. The reflex function of baroreceptors is very important in rapid control of blood pressure, which modulates efferent signals directed to the heart and blood vessels. It is well known that baroreflex action produces rapid changes in renal sympathetic nervous activity, which plays a very important role in the short term control of the blood pressure carrying out a variety of functions like mediating renin secretion, tubular reabsorption of water and sodium, and renal intravascular resistance [3, 4].

The hemodynamic behavior of the CS has been widely studied, and there are many mathematical and computational models that permit fairly and accurately simulate the performance of the hemodynamic variables of this system [5-7]. Moreover, due the high complexity of the CNS, modeling the control response over the components of the hemodynamic system (heart and blood vessels) can represent an important challenge.

A simplified diagram of the cardiovascular system proposed by Valverdú [7] is shown in Fig. 1. In the diagram, hemodynamic system (HS), controlled by the CNS, makes up the cardiovascular system. The branch of the CNS that controls the hemodynamic system is composed of five controllers that produce efferent signals leading changes in the peripheral resistance, the cardiac output and the coronary circulation. The controllers are: heart rate (HR), myocardial contractility (MC), peripheral resistance (PR), venous tone (VT), and coronary resistance (CR). The afferent signal that drives these controllers is represented by the carotid sinus blood pressure, originated from the arterial carotid sinus baroreceptors [7].

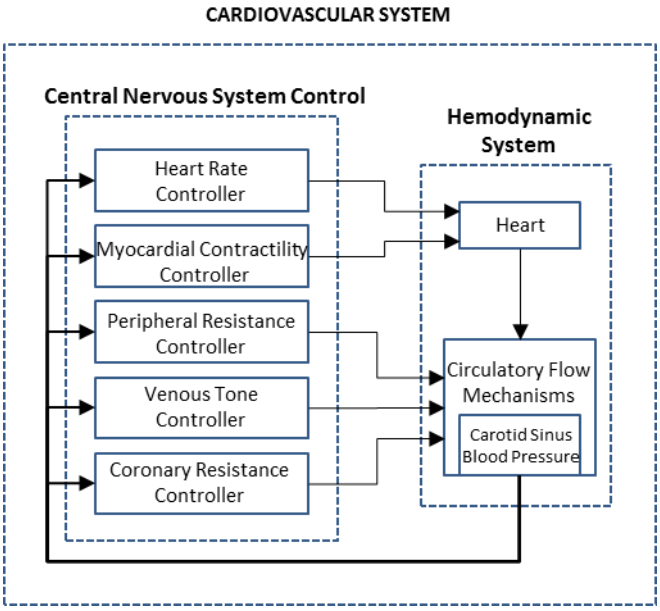

Fig. 1. Simplified diagram of the cardiovascular system model composed of the CNS control and the hemodynamic system [7].

In the last few decades, important contributions have been produced, both in theory and in practice, related to the support vector machines (SVM) approach. This approach has led to the development of methodologies useful in the design of efficient algorithms with applications focused to practical problems [8-10]. Linear and non-linear SVM regression for time series prediction have been widely used in many real word applications such as forecasting of financial market, electric utility, weather, traffic, among others [11]; however, there is not much literature that outline approaches to predict biomedical signals. In one of these studies, Shen et al. [12] developed a predictor model based on a wavelet kernel function for a SVM in order to predict multichannel electroencephalogram signals. It has been shown that SVMs is a methodology that captures effectively the dynamism of system processes which are typically nonlinear, non-stationary and not defined a-priori.

The purpose of this study is to predict the output of the five CNS controllers in the cardiovascular system model proposed by Valverdú [7], employing regression models of support vector machines. Previous investigations have employed NARMAX (nonlinear autoregressive moving average with external inputs) models [13], neural networks [14], fuzzy inductive reasoning (FIR) [13, 15], genetic fuzzy systems (GFS) or hybrid techniques such as genetic-FIR algorithm (GA-FIR) [16], and an automatic construction of linguistic rules methodology based on FIR (CARFIR) [17], for the same target. Although some of these models have reported good results, in the present study the authors intend to explore the potentialities of support vector machines in this prediction task, which due to its great complexity, represents a major challenge for any nonlinear regression model. The authors propose a new predictive model derived from SVMs which combines digital signal processing, offering an alternative to build a model that can be as robust and efficient as others already mentioned. The performance of the proposed SVM model is compared with those obtained in previous studies.

2. The Support Vector Machines Methodology

According to the theory of SVMs, instead of minimizing the empirical risk (to optimize the training set performance), which is the target of traditional techniques for pattern recognition, SVMs minimizes an upper bound on the expected risk (structural risk). It supplies SVM with a great ability to generalize any model, the main goal in statistical learning.

There are three important characteristics of the SVMs [18]:

1) With few training data points, the learning technique generalizes the model; and from this training data set, the generalization error limit can be estimated.

2) There is only one variable acting as a regularizing parameter (associated to the penalty for misclassification) [19], which determines a balance between generalization performance and resolution [20].

3) To obtain the best performance with data not included in the training, the algorithm finds a decision surface that maximizes the margin between the classified data in the training.

Support vector machines can be used for both classification and regression tasks. SVMs determinate the output as a linear combination of samples in the training data, in which the data points with nonzero coefficients are called "support vectors".

Given a set of data training composed of l attribute-label pairs (x_i, y_i), $i = 1, \dots, l$; where $x_i \in R^n$ and $y_i \in \{1, -1\}$, for classification purposes, the SVM needs the solution of the optimization problem posed in Equation (1) under the constraints describes in the Equation (2) [21]:

$$min \qquad \Phi_{(w,\xi)} = \frac{1}{2} w^T w + C \sum_{i=1}^{l} \xi_i \qquad 1$$

$$\text{subject to} \qquad \begin{aligned} & y_i(w^T \phi(x_i) + b) \geq 1 - \xi_i \\ & \xi_i \geq 0 \end{aligned} \qquad 2$$

Here, training vectors x_i are mapped by the function ϕ into a higher dimensional space; in this higher dimensional space, SVM finds a linear separating hyperplane with the maximal margin. The vector w determines the generalized optimal separating hyperplane. ξ_i represents a measure of the misclassification errors, and $C > 0$ (a settable parameter) is the cost parameter of the error term.

The solution to the optimization problem of Equation (1) under the constraints of Equation (2) is equivalent to determine the point at which the gradient of the Lagrangian is zero:

$$\Phi_{(\mathrm{w,b,\alpha,\xi,\beta})} = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}\xi_i - \sum_{i=1}^{l}\alpha_i[y_i(w^T\phi(x_i) + b) - 1 + \xi_i]\sum_{i=1}^{l}\beta_i\xi_i \qquad 3$$

where α, β are the Lagrange multipliers. An easy way to solve Equation (3) is to transform the primal problem in a dual problem, by minimizing the Lagrangian with respect to w, b, ξ, and maximizing it with respect to α, β; which is given by,

$$\max_{\alpha} W(\alpha,\beta) = \max_{\alpha,\beta}\left(\min_{w,b,\xi}\Phi(w,b,\alpha,\beta,\xi)\right) \qquad 4$$

Equation (5) represents the minimum of the Lagrangian Φ with respect to w, b and ξ:

$$\frac{\partial \Phi}{\partial b} = 0 \;\; \Rightarrow \sum_{i=1}^{l} \alpha_i y_i = 0$$

$$\frac{\partial \Phi}{\partial w} = 0 \;\; \Rightarrow \; w = \sum_{i=1}^{l} \alpha_i y_i \phi(x_i) = 0 \qquad 5$$

$$\frac{\partial \Phi}{\partial \xi} = 0 \;\; \Rightarrow \alpha_i + \beta_i = C$$

Then, the solution of the optimization problem in the Equation (5) becomes:

$$\alpha^* = \arg\min_{\alpha} \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} \alpha_i \alpha_j y_i y_i K(x_i, x_j) - \sum_{k=1}^{l} \alpha_k \qquad 6$$

$K(x_i, x_j) \equiv \phi(x_i)^T \phi(x_j)$ represents the kernel function, which makes a nonlinear mapping of the input space into a feature space (usually with a higher dimension).The constraints are:

$$0 \leq \alpha_i \leq C \quad i = 1, \dots, l$$

$$\sum_{j=1}^{l} \alpha_j y_j = 0 \qquad 7$$

Solving Equation (6) with constraints in (7) determines the Lagrange multipliers. Equation (8) establishes the classifier for the optimal separating hyperplane in the feature space.

$$f(x) = sgn\left(\sum_{i=1}^{l} \alpha_i y_i K(x_i, x) + b\right) \quad 8$$

The role of the kernel then is to change the representation of the data into another feature space. Popular kernels used for pattern recognition are the followings:

$$K(x, y) = (1 + x \cdot y)^p \quad 9$$

$$K(x, y) = exp\left(-\frac{\|x - y\|^2}{2\sigma^2}\right) \quad 10$$

$$K(x, y) = \tanh(kx \cdot y - \delta) \text{ for some } k \text{ and } \delta \quad 11$$

Equation (9) represents a polynomial kernel. It provides a classifier, which is a "*p*" degree polynomial over the data. Equation (10) gives a classifier based on Gaussian radial basis functions, and Equation (11) provides a kernel that represents a kind of special neural network of a hide layer with sigmoid activation functions. Most of the kernel functions are presented and detailed in [18, 22, 23].

For regression problems, SVM includes an alternative loss function [24], which must be modified to introduce a measure of distance. Four examples of loss function for implementing SVM regression models are presented in [23, 24].

For regression tasks, given a training set of l data points, (x_i, z_i), $i = 1, \dots, l$; where $x_i \in R^n$ is an input and $z_i \in R^1$ is the corresponding output, the optimization problem that needs to be solved [18] is:

$$\min_{w,b,\xi,\xi^*} \quad \frac{1}{2} w^T w + C \sum_{i=1}^{l} \xi_i + C \sum_{i=1}^{l} \xi_i^* \tag{12}$$

$$\text{subject to} \quad \begin{aligned} & (w^T \phi(x_i) + b - z_i) \leq \epsilon - \xi_i \\ & (z_i - w^T \phi(x_i) - b) \leq \epsilon - \xi_i^* \\ & \xi_i, \xi_i^* \geq 0, \qquad i = 1, \dots, l \end{aligned} \tag{13}$$

where C is a pre-specified value (cost parameter of the error term, like in classifier SVMs), and ξ_i, ξ_i^* are looseness variables that set upper and lower limits on the outputs of the system.

When using a ϵ-insensitive loss function [23], the dual problem is expressed by:

$$\min_{\alpha,\alpha^*} \quad \frac{1}{2} (\alpha - \alpha^*)^T Q (\alpha - \alpha^*) + C \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) + \sum_{i=1}^{l} z_i (\alpha_i - \alpha_i^*) \tag{14}$$

$$\text{subject to} \quad \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) = 0, \qquad 0 \leq \alpha_i, \qquad \alpha_i^* \leq C, i = 1, \dots, l \tag{15}$$

where $Q_{ij} = K(x_i, x_j) \equiv \phi(x_i)^T \phi(x_j)$.

Lagrange multipliers, α, α^*, are determined by solving Equation (14) with the constraints of the Equation (15). The regression function is given by:

$$f(x) = \sum_{i=1}^{l} (\overline{\alpha_i} - \overline{\alpha_i^*}) K\,(x_i, x) + \bar{b} \qquad 16$$

where

$$w^T \phi(x_i) = \sum_{i=1}^{l} (\alpha_i, \alpha_i^*)\, K(x_i, x)$$

$$\bar{b} = -\frac{1}{2} \sum_{i=1}^{l} (\alpha_i, \alpha_i^*) \left(K(x_i, x_r) + K(x_i, x_s) \right) \qquad 17$$

The Kernel function could contain a bias term b. In that case, the regression function is given by:

$$f(x) = \sum_{i=1}^{l} (\overline{\alpha_i} - \overline{\alpha_i^*}) K\,(x_i, x) \qquad 18$$

The optimization criteria for the other loss functions are similarly to those ones obtained in [24]. The ϵ-insensitive loss function is attractive because the solution can contain few support vectors, instead, in the quadratic and Huber cost functions, all data points are support vectors.

In this investigation, support vector machine regression models are implemented in Matlab [25] using the LIBSVM tool developed by the Taiwan University [26].

3. Cardiovascular Control of the Central Nervous System

The specific data used in the present study corresponds to the same signal sets used by Vallverdú in [7], where a generic model of the CS was identified and validated. Cardiac catheterization of patients was employed to obtain physiological data in order to validate the model. This led to the simplified cardiovascular system model shown in the diagram of Fig. 1. The branch of the CNS that controls the hemodynamic system is composed of five controllers that produce efferent signals to lead changes in peripheral resistance, cardiac output and coronary circulation; these are: heart rate, myocardial contractility, peripheral resistance, venous tone, and coronary resistance. The afferent signal for driven these controllers is represented by the carotid sinus blood pressure, originated from the arterial carotid sinus baroreceptors [7]. Sensibility analysis of the Valverdú's study showed that the parameters of the baroreceptors having the most influence on the output variables of the model were those of the carotid sinus baroreceptors, so the influence of the baroreceptors of the aortic arch is neglected. It is important to notice that, in this CS model, the regulatory mechanisms of the renal function, in response to changes of the renal sympathetic nerve activity (RSNA) mediated by baroreflex action, is not assessed due to the fact that RSNA data is not available.

The signals were obtained simulating a model of differential equations of the central nervous system [7]. The model of differential equations was tuned in order to represent patients with different percentages of coronary arterial obstruction (between 30 % and 70 %) by making agree the four physiologic variables of the model (heart rate, aortic pressure, right auricular pressure, and coronary blood flow) with measurements taken from the patients. It was used 7279 data samples of the input and output signal of each CNS controller to identify each model (the training data set), from simulations of the differential equation model with a sampling period of Ts=0.12 s [7]. Fig. 2 and Fig. 3 show the training signals of the input variable (CSBP) and the output variables of the controllers.

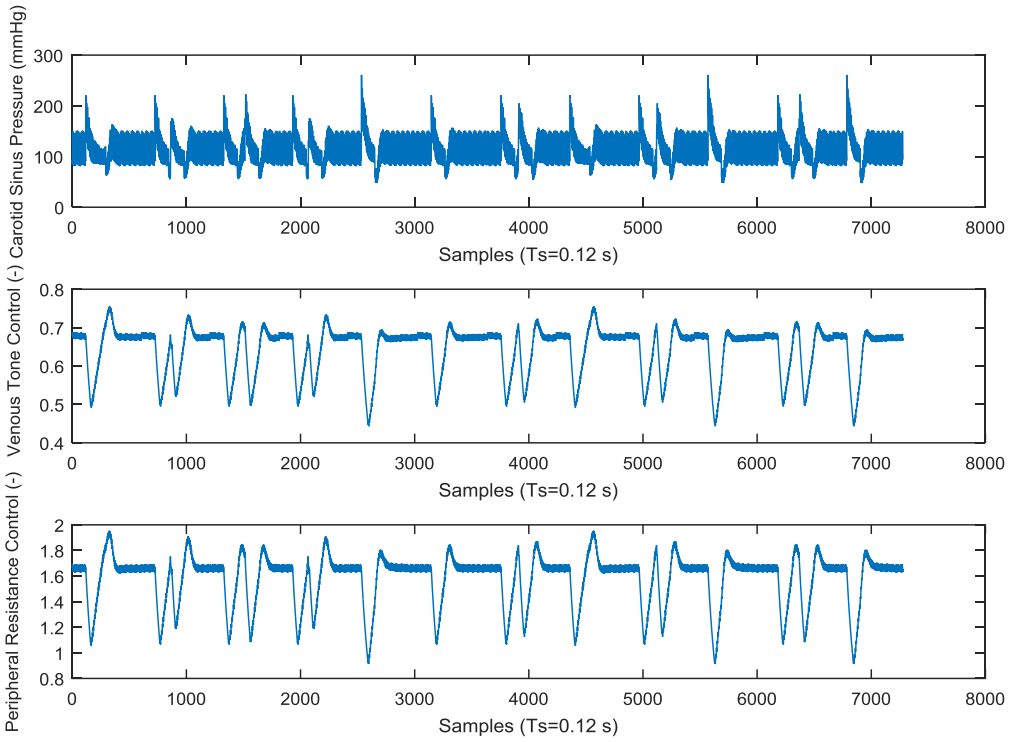

Fig. 2. From top to bottom, the carotid sinus blood pressure (input), and the output signals of the controllers of venous tone and peripheral resistance, used for training the SVM models.

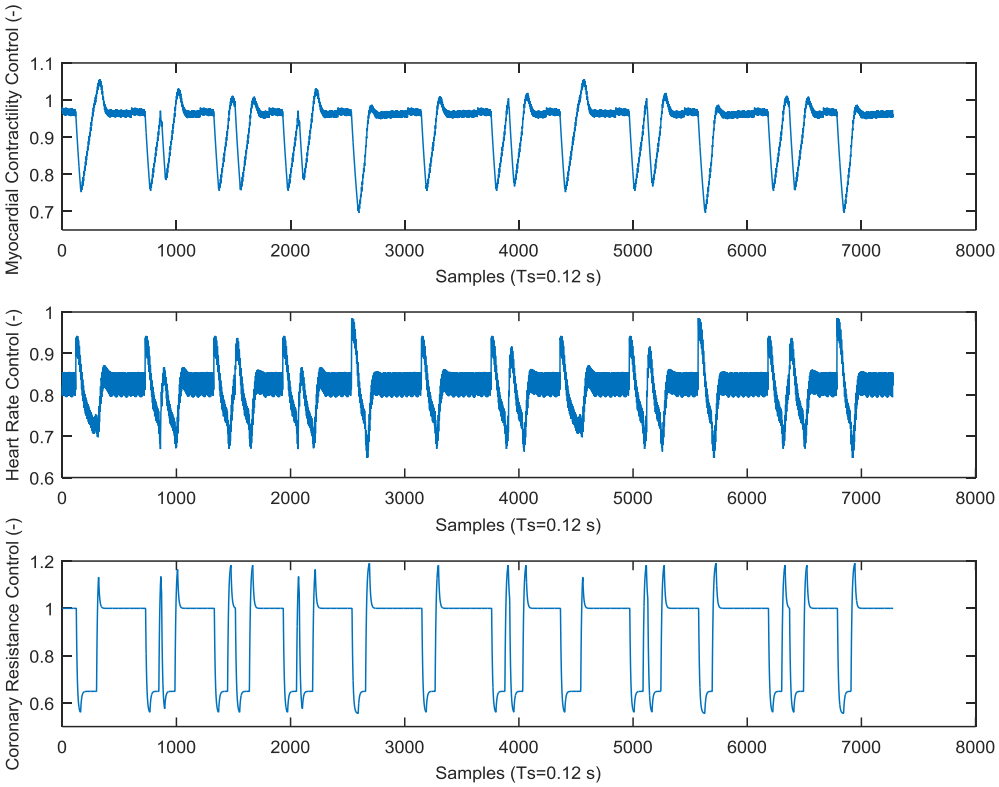

Fig. 3. From top to bottom, the output signals of the controllers of myocardial contractility, heart rate, and coronary resistance, used for training the SVM models.

A set of test data with six signal segments (not employed in training) were used to evaluate the models of each controller. Each test data segments has a size of about 600 samples. These contain signals with specific morphologies, product of performing one standardized Valsalva maneuver and five different exhibitions of this maneuver with different duration and relative

intensity. A detailed explanation of the test data sets can be found in [7, 13, 15]. Fig.4 shows the output signals (test data set) of the heart rate controller.

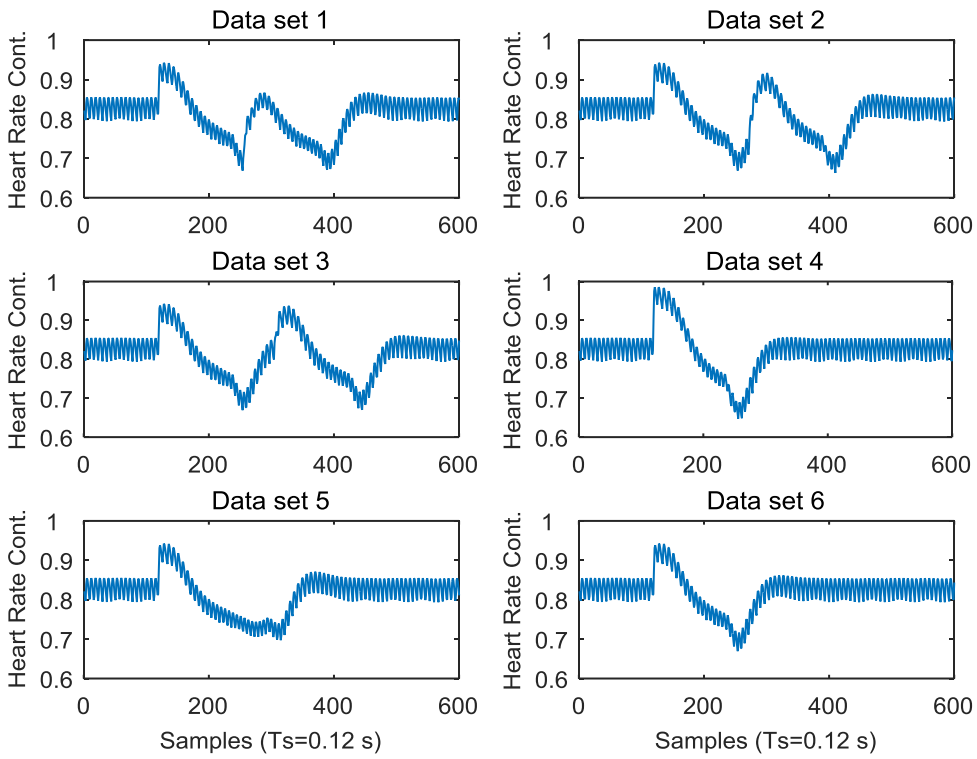

Fig. 4. Heart rate controller test data set.

3.1 Training Process

An all-pass filter (two pole/cero pairs) was used to create a signal with time delay (phase compensation), without affecting its magnitude response, which could be used as a second input signal to the models. Preliminary attempts using only one input signal (and different

processed version of that) for training the SVM model presented a very poor performance in the training process. For this reason, a second input signal for the model had to be chosen.

Primarily, start and end frequencies of the pole/cero pair spacing of the all-pass filter were determined. It was used a coarse (0.1 π step) grained searching in the frequency plane [0 – π], followed by a fine (0.01 π step) grained searching around the frequency pair with the best performance found previously. Pole magnitude was set to $1/\sqrt{2}$. It was used a Gaussian radial basis function (RBF) kernel, described in Equation (10), for many advantages over other kernel functions as recommended by Hsu et al. [27]. Preliminary tests were made with different kernels, and RBF approach showed the best performance on the prediction task over polynomial and sigmoid functions, and it was also faster during the training than others. In this case, we used C=10 and σ=10 for the SVM model, and the performance of each iteration employing the whole training data for each controller was analyzed.

The model performance of each iteration was determined by computing the normalized mean square error (MSE), in percentage, between the predicted output of the model ($\hat{y}_{(n)}$) and the expected system output ($y_{(n)}$). The error was computed by the Equation (19):

$$MSE = \frac{E\left[\left(y_{(n)} - \hat{y}_{(n)}\right)^2\right]}{y_{var}} \cdot 100\% \qquad 19$$

where y_{var} is the variance of $y_{(n)}$, given by:

$$y_{var} = E\left[y_{(n)}^2\right] - \{E[y_n]\}^2 \qquad 20$$

A cross validation process was employed in order to adjust the parameters of the SVM models. To do this, training dataset of each controller was segmented in subsets of 4279 data samples, in which 3679 samples (about 50.5 % of the total training dataset) were used for training the model, and the other 600 samples were used for testing proposes. Only continuous segments of the data were considered for training and testing (to avoid discontinuousness in the signal processing). In total, six subsets of data were formed sliding the 4279 samples window from the beginning to the end of the data with 3679 overlapped samples in each case. Twelve iterations of cross validation were performed; in six cases the test data was located at the end of the data subsets (testing data subsets “a”), and in the others, it was at the beginning of the data subsets (testing data subsets “b”). This process is shown in Fig. 5. In this figure the subplot a) contains 4279 data samples of the subset 1, where the training data represent the first 3679 samples, and the remaining 600 ones were used to test the model (subset “a” in this case); subplot b) represents the data window of 4279 samples which is moved to the right to incorporate 600 new samples (overlapping 3679 samples of the subset 1) forming the subset 2; subplot c) presents the last data window by sliding step by step to the end of the training data set in order to conform a total of 6 data subsets; and subplot d) represents the version “b” of the data subset 1; the first 600 samples represent the data for testing and the following 3679 samples were used for training the model.

Fig. 5. Data segmentation for cross validation process.

The MSE average of the 12 iterations in the cross validation process was computed to find the best parameters C and σ of the SVM regression model by using the grid-search procedure as suggested in [27].

3.2 Validation Process

Only the parameters that produce models with the best performance obtained in the cross validation process were employed in the evaluation phase. Once all parameters of signal processing and SVM models were found, a final model was built including the whole training data set (7279 samples) for each controller. Set parameters of the all-pass filter (start and stop frequency) and the SVM models (C and σ), for each controller are shown in Table 1.

Table 1. Parameters used in the all past filter and SVM for each controller

		HR	PR	MC	VT	CR
All-pass filter	Start - stop frequency [π rad]	.01 - .11	.01 - .13	.01 - .13	.01 - .11	.01 - .13
SVM	C	10	10	10	5	5
	σ	10	53	60	58	60

Support vector machine regression models of each CNS controller were then evaluated using the testing data set. The MSE obtained when evaluating the models with the six test data sets and their average were reported in the results section.

3.3 Results

Table 2 shows the MSE of the predictions obtained by the five controller SVM models. Looking closer to Table 2 it can be seen that the largest average error was 1.8e-3 % (for the HR controller).

Table 2. Prediction MSE for the validation data sets of each controller model using SVM

	HR (%)	PR (%)	MC (%)	VT (%)	CR (%)
Training data	1.7e-3	1.14e-4	6.38e-4	7.05e-4	1.36e-4
Data set 1	1.7e-3	1.10e-4	5.34e-4	6.06e-4	1.05e-4
Data set 2	1.5e-3	1.10e-4	4.61e-4	5.81e-4	0.99e-4
Data set 3	1.5e-3	0.89e-4	4.97e-4	4.55e-4	1.08e-4
Data set 4	1.6e-3	1.03e-4	5.32e-4	5.98e-4	1.39e-4
Data set 5	2.0e-3	1.31e-4	7.44e-4	7.55e-4	1.57e-4
Data set 6	2.8e-3	1.83e-4	9.42e-4	1.10e-3	1.80e-4
Average Error	1.8e-3	1.20e-4	6.18e-4	6.81e-4	1.36e-4

Fig. 6 shows the results of the prediction for the test data set 3 of the peripheral resistance controller. It presents the best prediction results obtained, with a MSE= 0.89e-4 %. In the upper plot of this figure, the expected and predicted output signals are presented in the same frame. Differences between these signals cannot be appreciated, demonstrating the excellent performance of the predictions of our models. The prediction errors (real minus predicted values) is shown in the lower plot of this figure.

The worst case is shown in Fig. 7, which corresponds to the prediction of the test data set 6 of the heart rate controller. Even in this case, differences between expected and predicted signals are not distinguishable, which means a great precision of our model.

It is important to notice that the processing time to execute 416 iterations to find the frequencies of the all pass filter is about 4992 seconds (in the worst case), and to find the

parameters C and σ of the SVM model is 44256 seconds. Therefore, in order to perform all the iterations of the cross validation process the total time needed is 5532 seconds. The final training of the SVM model, with the complete training data of each controller, takes 12 seconds at the most. All Matlab simulations were made with a Core 2 Duo computer with a 2.1 GHz processor.

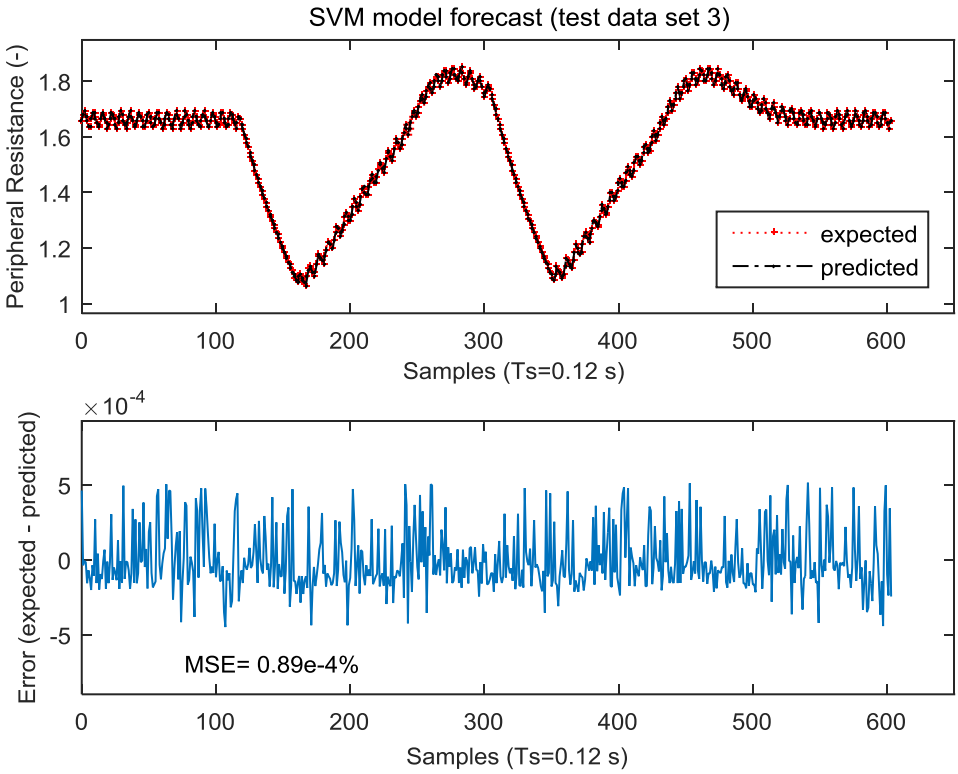

Fig.6. Peripheral resistance controller: Prediction of the test data set 3.

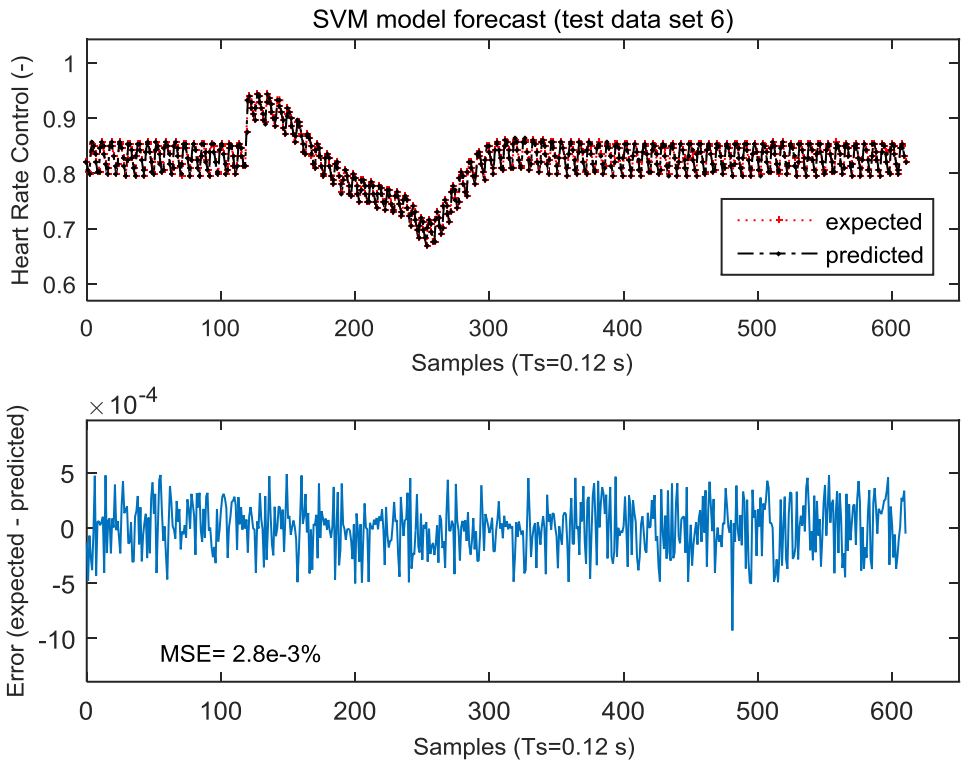

Fig 7. Heart rate controller: Prediction of the test data set 6.

3.4 Discussion

In this section, the performance of the SVM regression models of the present work is compared with those obtained in previous studies.

Table 3 contains the prediction results reported for the same problem when using NARMAX, TDNN RNN, FIR, GFS (GA-FIR) and CARFIR models. The table specifies the MSE average of the test data set prediction, for each controller. Row six of this table presents the best performance obtained by Nebot et al. [15]. In that research the FIR methodology was used to

predict the test data sets (which are not employed in the training process), of the five controllers. Nebot and coworkers used a database that includes signals of five different patients. The results presented in Table 3 correspond to the model build for the patient #4, which had the smallest MSE average, when compared with the other patients' results. In the current research, the obtained average error is slightly higher when compared with those obtained by FIR models for patient #4. However, in average, the error obtain using SVMs is lower than the one obtained for the rest of the patients in the Nebot study.

Table 3. MSE obtained when predicting the validation data set by using different methods

	HR (%)	PR (%)	MC (%)	VT (%)	CR (%)
NARMAX [13]	9.8	14.89	17.21	16.89	31.69
FIR [13]	1.37	1.49	1.41	1.47	0.09
TDNN [14]	15.35	33.76	34.02	34.04	55.69
RNN [14]	18.31	31.16	35.16	34.77	57.12
FIR* [15]	7.3e-5	7.0e-4	7.6e-6	7.9e-4	3.0e-4
GFS (GA-FIR) [16]	0.10	0.15	0.30	0.28	9.47e-30
CARFIR [17]	11.02	9.97	5.00	5.01	2.64

*Patient 4

The worst performance reported for our SVM model of the HR controller (MSE average of 1.8e-3 %), corresponds to the test data set #6 with a MSE= 2.8e-3 % (see table 1, sixth row/first column). It is considerably lower than the one reported by Nebot [15] for the HR

controller model of patient #4 (MSE average of 7.3e-5 %), predicting the same test data set with a MSE= 32.1e-3 %. This means that SVM models fit very well to all test data sets for each controller. Therefore, it shows a better performance than other predictive models.

Table 4. Comparison of the best results in the prediction of the output controllers

	HR (%)	PR (%)	MC (%)	VT (%)	CR (%)
SVM (this study)	1.8e-3	1.20e-4	6.18e-4	6.81e-4	1.36e-4
FIR [15]	7.3e-5	7.0e-4	7.6e-6	7.9e-4	3.0e-4
GFS (GA-FIR) [16]	0.10	0.15	0.30	0.28	9.47e-30

In the present study, the MSE average for the MC controller was higher than the one reported by Nebot [15], nevertheless it is probable that the error in some of their validation sets had been worse than the ones obtained by the SVM models for this controller. Moreover, in [15], there are not enough details of the results for each controller in order to make a precise comparison.

It should be also noted, that while the prediction for the CR controller (see Table 4) is better than the one obtained by Nebot [15], it does not exceed the obtained by the GFS technique [16]. However, it should be taken into account the computational cost required to use that hybrid technique. The total execution time for tuning the parameters and training the SVM model of each controller was less than 14 hours. Acosta in [16] reported an average time of more than 357 hour for finding the best parameters of the GFS model, employing a computer

with a 0.6 GHz processor. Although, the computer processor used in our investigation is 3.5 times faster than Acosta's processor, the required lapse to build the SVM model is close to 25.5 times shorter; it means a computational savings near 7.3 times.

4. Conclusions

In this paper support vector machines have been used for modeling a portion of the human central nervous system control, which is in charge of controlling the hemodynamic behavior of the cardiovascular system. The controllers of heart rate, myocardial contractility, peripheral resistance, venous tone and coronary resistance have been modeled in order to predict their responses driven by the same input variable, the carotid sinus blood pressure, under different systems' behaviors.

Methodological considerations were presented for tuning the parameters for processing the input signals and the fitting of the SVM variables. The choice of a second input signal as a group delayed version created from the original signal processing, was a key factor to obtain an excellent performance of the SVM prediction models.

The low computational cost of implementing the training method for these SVM models indicates that it is a very simple and flexible strategy, and it compares very favorably with other optimization techniques implemented in other models with the same purpose.

The purpose of the present study was to predict CNS control responses to transient changes in blood pressure (as caused by Valsalva maneuvers), by means of SVM regression models. Changes in blood pressure cause changes in the afferent baroreceptor signal (which represented the input signal of our model). To close the control loop, the outputs of our model should activate the effector elements of the hemodynamic system (heart and blood vessels), that were modeled in the Vallverdú's study. However, the model of the hemodynamic system was not the focus of the research effort of this paper.

It has been shown that support vector machines represent an efficient and powerful methodology, which is proficient in modeling the dynamical behavior of the control of the CNS over the cardiovascular system.

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