COMPARISON BETWEEN SVM AND ANN FOR MODELING THE CEREBRAL AUTOREGULATION BLOOD FLOW SYSTEM

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Abstract: The performance of SVMs and ANNs as identifiers of time systems is compared with the purpose of analyzing the Cerebral blood flow Autoregulation System, one of the main systems in the field of cerebral hemodynamics. The main variables of this system are Arterial Blood Pressure (ABP) variations and changes in End-tidal pCO_2 ($EtCO_2$). In this work we show that models that have ABP and $EtCO_2$ as input, trained with the SVM, are superior to ANN models in terms of the fit of an unknown set, and they are also more adequate for measuring the influence of $EtCO_2$ on Cerebral Blood Flow Velocity.

1 INTRODUCTION

Since the introduction of SVMs in the early 1990s, they have been applied to a large number of classification or regression problems, but little work has been done on their use as predictors of temporal series or for identifying systems over time. Among the work that has centered on their application over time, the proposals of J. Suykens' group stand out (Suykens et al., 2000; Espinoza et al., 2007) in the development of LS-SVM, and that of A. Martínez and J.L. Rojo (Rojo-Alvarez et al., 2004; Martínez-Ramón et al., 2006). But these works are centered mainly on forecasting known chaotic series that are used as "benchmarks" of the proposed methods.

In the field of biological signals the use of SVMs has been focused on applications in which the signals' characteristics are extracted from the signals to use them as static classifiers (Acir and Guzelis, 2004).

In this paper we apply SVMs (as multivariate identifiers of systems over time) to one of the main problems of cerebral hemodynamics: identification of the *Cerebral Blood Flow Autoregulation* System (CAS). This method is also compared with the performance of Artificial Neural Networks (ANNs).

The main mechanisms that affect the CAS are autorregulation of *Arterial Blood Presure* (ABP) and the reactivity of cerebral blood vessels to arterial CO_2 pressure ($EtCO_2$) (Widder et al, 1986).

The most common technique for determining reactivity of a subject's blood vessels to CO_2 is to measure the change that occurs in CBF as a consequence of breathing a mixture of air and 5% CO_2 (Panerai et al., 2000), using the measurements made with the *Transcranial Doppler Ultrason* to estimate CBF Velocity (CBFV).

The works of Panerai and Simpson (Panerai et al., 2000; Simpson et al., 2000) has modeled both the $EtCO_2$ signal and *Median Arterial Blood Pressure* (MABP) to predict CBFV, using linear models such as cross-correlation analysis over frequency and auto-regressive models over time. These models have shown that under baseline conditions (spontaneous fluctuations) CO_2 accounts for part of the variability of CBFV, and when changes in CO_2 are introduced it is possible to represent the relation with CBFV by means of a linear model.

The only report on the use of a data-based nonlinear model to study the MABP and $EtCO_2$ variables is that of Mitsis et al. (2004), who use a special Laguerre-Volterra network to analyze the baseline MABP and $EtCO_2$ signals of ten subjects. The conclusions show that the relation between $EtCO_2$ and CBFV are highly nonlinear at low

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frequencies and the time varying system. That paper is centered mainly on the analysis of frequency, it uses a network based on polynomials that approximate efficiently only up to the third order, and the CO_2 signal considers only the baseline state.

In the present paper we use more general tools (SVM and ANN), that allow modeling MABP and CO_2 as input, with CBFV as output for the baseline case and for induced 5% CO_2 changes. With these elements we will evaluate the nonlinear behavior of the SVM and its comparison with ANNs from the standpoint of numerical precision, to predict a previously unknown CBFV signal, and we will subject the models to CO_2 changes to evaluate their ability as a clinical method for obtaining reactivity to CO_2.

2 METHOD AND MATERIALS

2.1 Subjects and Measurements

The data used in this work were obtained from 16 voluntary subjects (aged between 25 and 51 years) who had no history of vascular diseases or neurological problems.

The study was approved by the ethics committee of the Royal Infirmary of Leicester, UK.

CBFV was measured in cm/s in the medial cerebral artery by means of a Scimed QVL-120 Doppler Transcranial system with a 2 MHz transducer. MABP was measured in mmHg on the patient's finger with a noninvasive *Finapres 2300 Ohmeda* monitor. $EtCO_2$ levels were recorded on a Datex Normocap 200 infrared capnograph connected to the subject through a nasal mask.

The three signals were filtered with an order 8 low pass Butterworth filter with a 20-Hz cutoff frequency. The signals were then interpolated linearly and normalized between 1 and -1.

The most common technique for carrying out the test of reactivity to CO_2 (standard reactivity) is to breathe a mixture of air and CO_2 and determine the changes that it causes in the CBFV. In this work each subject was first allowed to breathe a sample of ambient air for 5 minutes and was then made to breathe a mixture of air and 5% CO_2 for approximately 3 minutes.

2.2 Support Vector Machine

The SVM algorithm adopted was the ν-SVM, introduced by Schölkopf et al. (1998). It is based on the statistical theory of learning which introduced regression as the fitting of a tube of radius ε to the data. The decision boundary for determining the radius of the tube is given by a small subset of training examples called Support Vectors (SV).

Assuming $\vec{x}$ represents the input data vector, the output value $f(\vec{x})$ is given by the SVM regression using a weight vector $\vec{w}$.

$$f(\vec{x}) = (\vec{w} \bullet \vec{x}) + b,\ \vec{w}, \vec{x} \in \mathbf{R}^N, b \in \mathbf{R}, \qquad (1)$$

where b is a constant obtained from $\vec{w}$.

The variation of the ν-SVM introduced by Schölkopf et al. (1998) consists in adding ε to the minimization problem, weighted by a variable ν that adjusts the contribution of ε between 0 and 1.

$$\text{minimize}\ \ \theta(\vec{w}, \xi) = \frac{1}{2}\|\vec{w}\| + C\left(l\nu\varepsilon + \sum_{i=1}^{l}\xi_i\right) \qquad (2)$$

In the above equation, l represents the total dimension of the data (number of cases), C is a model parameter determining the trade-off between the complexity of the model, expressed by $\vec{w}$, and the points that remain outside the tube. Slack variables ξ depend on the distance of the data points from the regression line.

We used ε-insensitive loss function.

The solution of this minimization problem for obtaining the weight vectors $\vec{w}$ is found by the standard optimization procedure for a problem with inequality restrictions when applying the conditions of Kuhn-Tuker to the dual problem. The main advantage of introducing parameter $\nu \in [0\text{-}1]$ is to make it possible to control the error fraction and the number (or fraction) of *SVs* with only one normalized parameter.

To solve a nonlinear regression problem it is sufficient to substitute the inner product between two independent original variables $\vec{x}_i \bullet \vec{x}_j$ (Eq. 1) by a kernel function gaussian radial base function (RBF),

$$k(\vec{x}_i, \vec{x}_j) = \exp(-\left\|\vec{x}_i - \vec{x}_j\right\|^2 / (2\sigma^2)) \qquad (3)$$

2.3 Artificial Neural Networks

Use was made of static neural networks with external recurrence, which correspond to the structure of a multilayer perceptron that can be trained using the classic *Backpropagation* algorithm.

Different learning algorithms were evaluated, such as *One Step Secant*, *Delta Bar Delta*,

Backpropagation through time, and *Levenberg Marquardt,* with the latter delivering the best results. This mixed algorithm combines a descending gradient with one of quasi-Newton type. Eq. 4 shows how the algorithm updates the weight at each iteration.

$$\omega_{k+1} = \omega_k - \left[J^T J + \mu I\right]^{-1} J^T e \quad (4)$$

where ω_{k+1} is the weight vector in iteration $k+1$, ω_k is the weight vector in iteration k, J is the first derivatives Jacobian matrix, and e corresponds to the network error vector. Factor μ is reduced at each successful step, controlling the trade off between a descending gradient and a *quasi-Newton* method.

Early Stopping was used to get a good generalization in the set of tests (Demuth and Beale, 2001).

To implement recurrence in both the SVMs and the ANNs we used external feedback of the delayed outputs ($v(t)$=CBFV), and current inputs ($p(t)$=MABP, $c(t)$=$EtCO_2$) and past time instants are considered. Training is carried out estimating a forward step, as shown in Eq. 5 .

$$\hat{v}(t) = f(v(t-1),...,v(t-n_v), p(t),..., p(t-n_p),...,c(t),...,c(t-n_c)) \quad (5)$$

The prediction is obtained using the estimated values, as shown in Eq. 6.

$$\hat{v}(t) = f(\hat{v}(t-1),...,\hat{v}(t-n_v), p(t),..., p(t-n_p),...,c(t),...,c(t-n_c)) \quad (6)$$

2.4 Evaluation and Statistics

To evaluate the learning of the models (training and evaluation) use is made of the correlation between the model's response ($\hat{v}$) and the real output signal (v).

To analyze the physiological behavior the responses to an MABP step and an $EtCO_2$ step are examined in terms of their dynamics. To evaluate the clinical potential of the models the reactivity index is obtained, extracted from the models after applying to them a CO_2 step, and it is compared with the calculation of the standard reactivity test, which is obtained when the subject inhales 5% CO_2.

The statistical significance was evaluated using Wilcoxon's paired test considering that there are differences if $p<0.05$.

3 RESULTS

Figure 1 shows the three signals after pre-processing them.

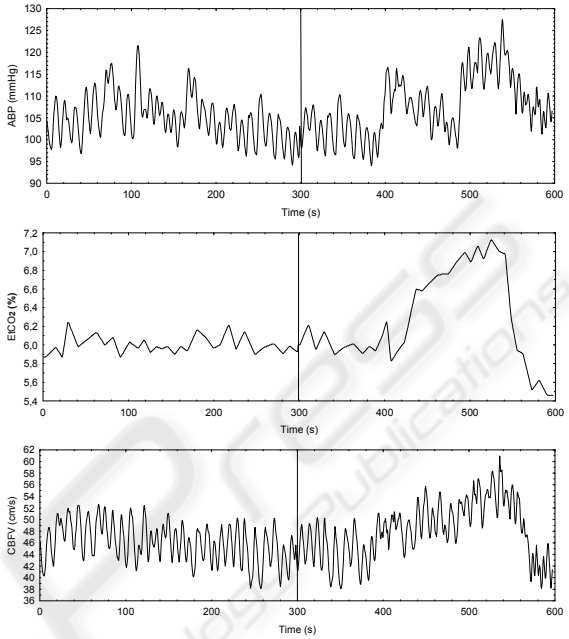

Figure 1: Representative time-series of MABP, $EtCO_2$, and CBFV showing spontaneous fluctuations during baseline (left) and breathing of 5% CO_2 in air (right).

The averages and modes of the best parameters for the 16 SVM models are shown in Table 1.

Table 1: Model parameters for SVM structures tested.

Parameters	*Baseline*	*5% CO_2*
n_p	*4 [4-8]*	*5 [3-6]*
n_v	*3 [1-3]*	*1 [1-3]*
n_c	*3 [2-4]*	*2 [2-4]*
C	*395.0±404.4*	*343.1±416.6*
ν	*0.32 ± 0.28*	*0.43 ± 0.30*
σ	*3.72 ± 4.98*	*19.75 ± 13.24*

The modes of the parameters for the ANNs are equal for the baseline and the 5% CO_2 cases, with $n_p=n_c=n_v=2$ and 8 neurons in the hidden layer.

Table 2: Correlations of the models for the set of tests.

SVM		ANN	
Baseline	5% CO_2	Baseline	5% CO_2
0.76 ±0.1	0.95±0.03	0.77±0.16	0.82±0.11

The results of the correlations in the set of tests appear in Table 2. In the baseline case it is seen that there are no significant differences between SVM and ANN ($p=0.71$), but when compared with the

changes in CO_2, the test shows that the SVMs are significantly better than the ANNs (*p=0.0004*).

The reactivity curves for both types of models show an acceptable physiological response, with those obtained from training with changes in 5% CO_2 always better.

The average results of the standard reactivity test of the 16 subjects was 4.05±1.38%/mmHg, (average±SD).

Entering a normalized step response between [0-1] into the $EtCO_2$ input it is possible to measure each subject's reactivity. The average values of each model are shown in Table 3.

Table 3: Reactivity of the models (%/mmHg).

SVM		ANN	
Baseline	5% CO_2	Baseline	5% CO_2
4.32 ±4.2	4.44 ±1.9	2.22 ±3.0	3.13±1.4

When conducting a hypothesis test between the standard reactivity test and the reactivities obtained by the models, it is seen that there are no differences with the reactivities extracted from the SVMs in both cases. Compared to ANNs, the test is significantly different in the baseline case (*p=0.002*) and has values very close to the limit for CO_2 changes (*p=0.07*)

4 CONCLUSIONS

The results not only show the superiority of SVMs in terms of precision and calculation of reactivity, but it is also seen that they show a smaller variance, particularly in the case of CO_2 changes.

The baseline mean square error of the SVM model is 3%, which is much better than the 20% reached in the work of Mitsis et al. (2004).

We believe that both the global optimization and the slack-variable properties of SVMs are responsible for the better results in comparison with the Artificial Neural Networks.

The main future challenges involve new studies in the field of biomedical signals that may allow the evaluation of the other properties of the SVM, such as the ability to represent time varying phenomena.

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