Dynamic Estimation of Non Invasive Intracranial Pressure Using SVM with External Recurrences

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Abstract— **Intracranial Pressure measurements are of great importance for the diagnosis, monitoring and treatment of many vascular brain disturbances. The standard measurement of Intracranial Pressure is performed invasively by perforation of the cranial scalp in the presence of a severe injury. Measuring Intracranial Pressure in a noninvasive way is relevant for a large number of pathologies where the invasive procedure represents a high risk. The method proposed in this study uses the Arterial Blood Pressure and the Cerebral Blood Flow Velocity –which may be obtained by non-invasive methods– to continuously estimate Intracranial Pressure. The results show that it is possible to estimate Intracranial Pressure using a non-linear Support Vector Machine with a correlation coefficient of 0.74 and a maximum deviation below 2 mmHg, which is comparable with (invasive) direct measurement instruments.**

Keywords— **Intracranial Pressure, Non-invasive, Support Vector Machine, cerebral hemodynamics.**

I. Introduction

Currently the only established method for measuring IntraCranial Pressure (ICP) is a direct measurement procedure that gains access to the intracranial space. Although this is an invasive procedure, it is the established protocol for managing patients with severe head injury in intensive care units. The various risks involved in this kind of measurement contrast with the demonstrated benefits that can be obtained in the handling of patients with brain damage. Avoiding such a risky measurement would be a great advance in the treatment of these cases.

Moreover, there is a large variety of other situations in which a non-invasive measurement or monitoring of the ICP is very important, such as the management of patients with coagulopathy, liver failure and liver transplant, as well as in the treatment in other units that require the management of patients with pre-eclampsia, hydrocephalus and others, who would benefit from a non-invasive measurement.

Several attempts to evaluate ICP non-invasively have been examined, and one that has had much attention is the use of Transcranial Doppler Ultrasound (TCD), which measures Cerebral Blood Flow Velocity (CBFV).

At present there have been several attempts to evaluate ICP non-invasively (nICP). The first papers of Aaslied et al. [1] and the variations of Czosnyka et al. [2] and Belfortet al. [3] show a simplified method for getting nICP, based on average values (components of the first harmonic and/or diastolic values) of Arterial Blood Pressure (ABP) and CBFV. On the other hand, there are some mathematical models [4-6] based on electro-mechanical analogies, that allow examining the relation that exists between ABP, CBFV and ICP.

The works of Schmidt et al. [7-9] was the first to attempt a black-box type of model to predict the nICP. They used linear prediction over time methods to estimate ICP as a function of ABP and CBFV. These models have shown good results in different scenarios, both normal and clinical conditions. The serious drawback that they have is that their predictions are for a particular patient or subject, so it is not possible to predict the ICP of a subject who has not undergone an invasive procedure in the past.

The work of Hu et al. [10] presents a Data Mining method that uses a database of patients characterized by different signals obtained non-invasively, which are represented by Auto Regressive models with eXogenous inputs (ARX). These models use linear mapping that allows estimating the nICP values of unknown patients who are not part of the original database. The results show that they improve the results of the conventional indices [1-3].

All the methods described above use linear models to predict the ICP. The work of Shieh et al. [11] shows a non-linear approach to the problem and uses Artificial Neural Networks (ANN) to estimate the nICP. They used a set of only six patients; three for training and three for evaluating, using multivariate models to estimate an indication of the Cerebral Blood Flow using a non-invasive regional oxygenation monitor (rSO_2) by means of near infrared spectroscopy. The temporal resolution of this device is very reduced and the system achieves a sampling rate of 0.25 Hz. The results show that evaluating the worst case exceeds 2.5

A. Braidot and A. Hadad (eds.), *VI Latin American Congress on Biomedical Engineering CLAIB 2014, Paraná, Argentina 29, 30 & 31 October 2014,* IFMBE Proceedings 49, DOI: 10.1007/978-3-319-13117-7 _229

times, which is unacceptable for clinical ICP prediction.

Another non-linear approach is that presented by Xu et al. [12], which uses Support Vector Machines (SVM) and Kernel Spectral Regression (KSR). By means of the leave-one-out strategy and using signals from 23 patients, the authors got an Absolute Mean Error (AME) of 6 mm Hg in the prediction of the ICP. Although the results obtained by means of non-linear approaches are better than those presented by Schmidt using linear methods, the set of patients used is different, so the methods are not directly comparable.

Finally, it is of interest to consider the review of invasive and non-invasive methods presented by Raboel et al. [13]. In relation to non-invasive methods it shows several types such as the TCD, measurement at the tympanic membrane, measurement of the diameter of the optic nerve, magnetic resonance, and tomography. The methods that use TCD shown there, which are based mainly on the calculation of the pulsatility index, can achieve deviations of 4.2 mm Hg, when the ICP is limited to low magnitudes.

We used directly the signals of CBFV (obtained by TCD) and ABP as inputs of a dynamic model that uses SVMs with external recurrences (ARX) to estimate the nICP.

II. Materials and Methods

A. Subjects and measurements

The CBFV, ABP and ICP signals were obtained from 36 patients who suffered severe head injury, admitted in the *Adult Intensive Care Unit, Queen's Medical Centre*, Nottingham, England (work approved by the institution's ethics committee). Multiple recordings were made of each patient. Attempts were made to get a continuous recording with an approximate duration of 10 minutes, during periods of physiological stability. The CBFV signal was measured using a *Scimed Transcranial Doppler* with a 2 Mhz ultrasonic transducer, attached with elastic bands to the head of the patients and making measurements of the Middle Cerebral Artery. The ABP was measured with an intravascular catheter in the Middle Radial Artery (*Baxter PX-600F*). The ICP was measured with a subdural transducer (*Codman MicroSensor)*. To get the maximum signal frequency of the CBFV the fast Fourier transform was used, with a temporal resolution of 5 ms. The ABP and ICP signals were digitized and sampled at 200 samples per second.

To calculate the mean values of the ABP, the ICP and the CBFV, each cardiac cycle was identified and the operation was performed on each one, then applying a third degree polynomial interpolation to get continuous signals sampled every 5 Hz. Finally, the signals were re-sampled at 1.67 Hz and normalized in amplitude between the values -1 and 1, to be entered in the models.

B. The Models

The algorithm that is used in this work is the ν-SVM, presented in Scholkopf et al. [14] and created originally by Valpnik [15].

In the models with SVM the present and past CBFV *v(t)* and ABP *p(t)* samples are used as inputs, as well as the external feedbacks of the delayed outputs of the ICP *i(t)*. This is an ARX model, which can have linear (ARX) characteristics for a linear kernel as well as non-linear (NARX) for an RBF (*Radial Basis Function*) kernel.

The training of the ARX and NARX models is done estimating one-step-ahead (OSA), i.e.:

$$\hat{i}(t) = f(i(t-1),...,i(t-n_i),v(t-1),...,v(t-n_v), \\ p(t-1),...,p(t-n_p)) \quad (1)$$

while the prediction is made based on the estimated values:

$$\hat{i}(t) = f(\hat{i}(t-1),...,\hat{i}(t-n_i),v(t-1),...,v(t-n_v), \\ p(t-1),...,p(t-n_p)) \quad (2)$$

The linear models use the linear kernel tion $K(\vec{x},\vec{y}) = \vec{x}\cdot\vec{y}$, while the non-linear models use the Gaussian kernel function (RBF)

$$k(\vec{x}_i,\vec{y}_i) = exp(\frac{-\|\vec{x}_i - \vec{y}_i\|}{2\sigma^2}) .$$

C. Application of the models

What is important for an SVM training is the choice of the parameters. In the case of a non-linear regression the hyper-parameters to be adjusted are: *v*, which is the support vector proportion; *C*, the degree of adjustment to the training data; and σ, the problem's non-linearity. When external recurrences are used to estimate the dynamic systems, then the input delays must also be entered: n_v, $n_{a,}$, as well as those of the output (ARX models) n_i, where the latter would correspond to the model's order or complexity.

In general, this parameter search is very time demanding because it has to evaluate all the combinations of these six parameters. To avoid this great disadvantage of the SVMs, it is possible to use some heuristic that allows reducing the computational costs. In this paper use is made of Vasconcelos' genetic algorithm [16] to limit the range of the values of the parameters of the SVMs.

Each of the subjects is characterized by 10 min of signals, of which 2.5 min of 15 subjects (chosen randomly) are used for training and 7.5 min of the remaining subjects for evaluating.

D. Evaluation of the results

The statistical comparison to analyze the performance among the models is made using the correlation coefficient (r) in the model evaluation stage. Furthermore, hypothesis tests were made, specifically Wilcoxon's contrast for paired samples, with which the correlations of the models are compared. A probability $p<0.05$ is considered to be a significant difference between the models.

To get an evaluation in absolute terms of the predicted variable (using the maximum and minimum values of the normalization), it is possible to get the value of the models' predicted ICP in mm Hg, and then perform the difference and get the Absolute Mean Error, in terms of mm Hg when comparing with the real signal.

III. Results

A. Pre-processing

The 36 patients were analyzed to find 10 min of continuous physiological stability, for each of the three signals. Only 30 patients were selected that fulfilled these conditions.

Good results were obtained in the pre-processing of the signals. First a median filter is applied, a Butterworth order 8 filter, followed by the detection of every heartbeat to average the signal. Finally, an interpolation is made to get a uniform sampling until a sampling interval of 0.6 s is reached. The three signals for a typical patient are shown in Figure 1.

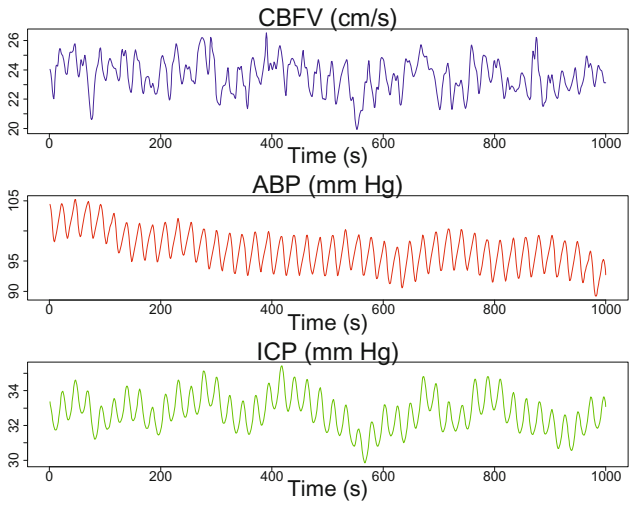

Fig 1: Signals after pre-processing to be entered in the models.

B. Results of parameter selection

Vasconcelos' algorithm [16] receives the previous population as input, and the result of the evaluation of the fitness function (mean of the coefficient of correlation) with a percentage of elitism of 10% and a mutation probability of 0.02. As a stopping criterion, a correlation equal to or better than 0.75 is required.

The size of the population is 30 subjects (chromosomes) and 100 populations (iterations) will be generated. These values were selected due to the time taken to calculate the fitness function (approximately 2 h), a time that is used mainly to train the v-SVR models. The parameters obtained for each model are shown in Table1.

C. Learning

The data are presented by entering the 2.5 min ABP and CBFV signals at the input and the presented ICP signal at the output, for each of the 15 training patients (37.5 min).

The prediction is made by entering only the ABP and CBFV signals over the7.5 min intervals of each of the other 15 test patients, getting the predicted ICP signal (making a total prediction of 1 h and 52.5 min).

The average correlations between the predicted signal and the real test patients are shown in Table 1 for the linear and non-linear models. It is important to note that in spite of the small correlation difference between these two models, those differences are statistically significant.

Table1. Parameters and correlation in validation set for the linear and non-linear models.

Model	n_v	n_p	n_i	C	ν	σ	Correlation
Linear	3	1	4	32768	0.8	-	0.72 ± 0.18†
Non-linear	9	9	2	32	0.1	16	0.74 ± 0.18†

† Wilcoxon test for correlation of validation ($p=0.022$)

Figure 2 shows the prediction of the ICP signal for one of the patients of the validation set.

IV. Conclusions

The results show that with correlations of 0.74 it is possible to predict the nICP and that the non-linear models represent a significant improvement with respect to the linear models.

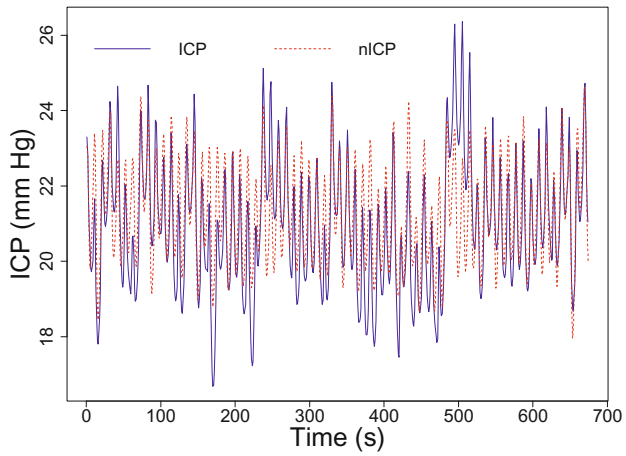

Fig 2: ICP signals predicted by the non-linear model (dotted line), and real signal (solid line) for a characteristic subject.

When the Absolute Mean Error is calculated, values of less than 2 mm Hg are obtained. This shows that it is possible to use this estimation in clinical applications, because the error would be comparable to the errors obtained by means of the currently used invasive measurement instruments [13]. However, it is still necessary to carry out more experiments to confirm these good clinical results, evaluating more patients with different degrees of ICP.

Acknowledgements

The authors acknowledge with thanks the financial support of this work through DICYT project 061419CHP of the Universidad de Santiago de Chile and *Proyecto de Aportes Basales por Desempeño MESESUP USA*1298.

Conflict of Interest

The authors declare that they have no conflict of interest to carry out this work.

References

1. Aaslid R, Lundar T, Lindergaard K et al (1985) Estimation of cerebral perfusion pressure from arterial blood pressure and transcranial Doppler recordings. *Proceedings of the Sixth International Symposium on Intracranial Pressure*, Springer-Verlag, Glasgow : 226–229
2. Czosnyka M,Matta B.F, Smielewski P et al (1998) Cerebral perfusion pressure in head-injured patients: a noninvasive assessment using transcranial doppler ultrasonography. J Neurosurg5:802–808
3. Belfort MA, Tooke-Miller C, Varner M, et al (2000) Evaluation of a noninvasive transcranial doppler and blood pressure-based method for the assessment of cerebral perfusion pressure in pregnant women.Hypertens Pregnancy3:331–340
4. Ursino M, Lodi CA (1997) A simple mathematical model of the nteraction between intracranial pressure and cerebral hemodynamics.J Appl Physio.4:1256–1269
5. Ursino M, Di Giammarco P, (1991) A mathematical model of the relationship between cerebral blood volume and intracranial pressure changes: the generation of plateau waves. Ann Biomed Eng 1:15–42
6. Ursino M, Iezzi M, Stocchetti N (1995) Intracranial pressure dynamics in patients with acute brain damage: a critical analysis with the aid of a mathematical model.IEEE Trans Biomed Eng 6:529–540
7. Schmidt B, Klingelho¨fer J, Schwarze JJ, et al (1997) Noninvasive prediction of intracranial pressure curves using transcranial doppler ultrasonography and blood pressure curvesStroke 12:2465-2472
8. B. Schmidt B, M. Czosnyka M, J.J. Schwarze JJ, et al (2000) Evaluation of a method for noninvasive intracranial pressure assessment during infusion studies in patients with hydrocephalus.J Neurosurg 5:793–800
9. B. SchmidtB, M. Czosnyka M, A. Raabe A, et al (2003) Adaptive noninvasive ssessment of intracranial pressure and cerebral autoregulation.Stroke1:84–89
10. Hu X, Nenov V, Bergsneider M(2006) A Data mining framework of noninvasive intracranial pressure assessment," Biomed. Sig. Process .and Cont 1:64-77
11. Shieh J-S, Choua C-F, Huang S-J et al (2004) Intracranial pressure model in intensive care unit using a simple recurrent neural network through time.Neurocomputing 57:239-256
12. Xu P., Kasprowicz M., Bergsneider M. y Hu X. 2010. «Improved noninvasive intracranial pressure assessment with nonlinear kernel regression». *Information Technology in Biomedicine, IEEE Transactions on* 14 (4): 971–978.
13. Raboel PH, Bartek J, Andersen M et al (2012) Intracraneal Pressure Monitoring: Invasive versus Non-Invasive Methods – A Review. Crit Care Res Pract 2012:950393.
14. Schölkopf B, Smola A, Williamson R et al (1998) New support vector algorithm.Neural Computation. 2:1083-1121, 1998.
15. Vapnik V(1995).The Nature of Statistical Learning Theory. Springer-Verlag, New York.
16. Kuri-Morales A (2004) Pattern Recognition via Vasconcelos' Genetic Algorithm. En *Progress in Pattern Recognition, Image Analysis and Applications*, ed. Alberto Sanfeliu, José Francisco Martínez Trinidad, y Jesús Ariel Carrasco Ochoa, 3287:328-335. Springer-Verlag, Berlin.

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