Gray-box Neural Model for Cerebral Autoregulation Index and Assistive Diagnoses in m-Health

Universidad Central de Chile - Escuela de Computacion e Informatica

Abstract. The cerebral autoregulation system (CAS), is a mechanism which aims to regulate pressure variations occurring in the cerebral circulatory system. At present, there only exist invasive methods and, in turn, they are not used to prevent cerebrovascular accidents. Nowadays, the emergent concept of m-Health allows to use mobile devices to assist the cerebral autoregulation index (ARI). For this, it is necessary to find novel models which allow to approximate the ARI by using the blood pressure value. This work proposes a gray-box neural model to find a relation between the arterial blood pressure (ABP) and the cerebral blood flow velocity (CBFV) in order to obtain the ARI. Preliminary results show a good performance by using a phenomenological model in comparison to the Aaslid-Tiecks model.

1 Introduction

The cerebral autoregulation system (CAS) is one of the fundamental biologic mechanisms. In mammals, the CAS allows the human body to work properly. This system supplies blood to the cerebral region, also providing needed nutrients which are metabolized in the brain.

In general terms, the cerebral autoregulation is affected by physiological and physicochemical variables, e.g. cerebral metabolic rate, posture, or carbon dioxide levels in the arteries; leading to a non-static autoregulation system but to a highly dynamic system able to adapt to sudden changes of blood pressure. Hence, its correct operation it is fundamental to avoid cerebrovascular diseases and keep a healthy brain.

Currently, methods to measure and diagnose cerebrovascular diseases are invasive. The skull makes difficult to take directly brain measures, therefore, it is not possible for patients to determine the brain condition using this kind of exams [1].

Furthermore, cranial trauma and cerebrovascular diseases are the base for some of the most frequent and dangerous neurological disorders currently detected due to the direct impact in the human brain. These diseases may be caused by serious skull injuries as well as an interruption of the cerebral blood flow, the latter, due to the clot generation or intense haemorrhage in a blood vessel preventing the normal blood circulation and the supply of oxygen to the brain. This malfunction may cause a brain disorder or even death, therefore, it is fundamental for the human brain to be optimally regulated.

The cerebral autoregulation index (ARI) is a value fluctuating between 0 and 9, which indicate whether a person is doing the cerebral autoregulation properly. Currently, there are no exams nor models which compute a precise ARI. This index is very hard to obtain by a simple measure, as aforementioned, there are many variables which influence in the CAS.

Therefore, there is an opportunity, on the one hand, to study novel methods to obtain variables difficult to measure, and methods which are not fully developed in the state-of-the- art literature [2]. On the other hand, we take into account the growing use of mobile devices which could lead to an assistive diagnose by using smartphones.

2 The Aaslid-Tiecks model

To better understand how to compute the ARI, we show the Aaslid-Tiecks (A-T) model. The A-T model uses four state equations to represent changes in the blood pressure P(t). The set of equations is able to obtain the cerebral blood flow velocity (CBFV) [3] which is represented by V as follows:

$$dP(t) = \frac{P(t)}{1-CrCP} \tag{1}$$

$$X_1(t) = X_1(t-1) + \frac{dP(t-1)-X_2(t-1)}{f \times T} \tag{2}$$

$$X_2(t) = X_2(t-1) + \frac{X_1(t-1)-2\times D \times -X_2(t-1)}{f \times T} \tag{3}$$

$$V'(t) = 1 + dP(t-1) - K \times X_2(t) \tag{4}$$

where dP(t) normalizes the pressure using a baseline, CrCP is the critical closing pressure, f corresponds to the sampling frequency, K represents a gain parameter in the equation, T is the time constant and D is the damping factor. Furthermore, X1(t) and X2(t) are the state variables of a second-order differential system.

This proposal of A-T shows ten different theoretical responses according to how are combined the parameters K, D, and T, which are associated with a fixed value of ARI as shown in Table 1.

For each measured of P(t), the A-T model produces ten curves representing each ARI based on the velocity $V'(t)$. The curves are compared with the real velocity of the subject and are measured using minimal square error or maximal correlation between the real velocity and the estimated velocity by the model. When the real velocity fits one of the ten estimated curves by either error or correlation, an ARI value is assigned.

K	D	T	ARI
0.00	1.70	2.00	0
0.20	1.60	2.00	1
0.40	1.50	2.00	2
0.60	1.15	2.00	3
0.80	0.90	2.00	4
0.90	0.75	1.90	5
0.94	0.65	1.60	6
0.96	0.55	1.20	7
0.97	0.52	0.87	8
0.98	0.50	0.65	9

Table 1: Association between K, D, T, and ARI.

3 The Simpson′s model

Currently, the optimized Simpson′s model [4] to compute the ARI establishes that the relation between the CBFV and the arterial blood pressure (ABP) is represented by the equation (5).

$$V(i) = h(0)p(i) + h(1)p(i-1) + h(2)p(i-2) + ... + h(6)p(i-6) \tag{5}$$

where i is the sampling index, V is the CBFV, p is the ABP, and h is the is the resulting coefficient to a filter impulse response (FIR). The filter uses as input and output the CBFV and the APB to get a numeric relation. For ABP, it is posed that exists a set of common coefficients to the subjects. Therefore, having only the pressure values is possible to obtain the estimated flow velocity and thus to compute the ARI based on the model A-T using the equations (1-4).

The proposed model in this work aims to find a better relationship between the CBFV and the ABP, hence, we propose to replace the coefficients from equation (5) to coefficients estimated by a gray-box neural model.

4 Proposed model

We hypothesize that an artificial neural network combined with the phenomenological model described in equation (5), to represent a gray-box model, may lead to a better association between the CBFV and the ABP and, therefore, to better results when computing the ARI.

The proposed model comprises a neural gray-box model within a hybrid model as shown in Fig. 1. The gray-box model is based on an artificial neural network (black box) and a phenomenological part (white box). Furthermore, the hybrid model consists of the gray-box model and the A-T model which uses the variables ABP and CBFV estimated by the neural network to obtain the estimated ARI for a test subject.

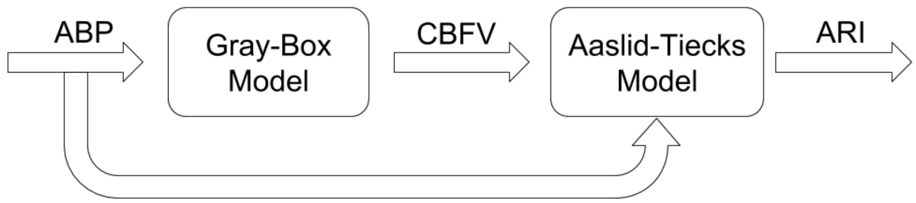

Fig. 1: Proposed hybrid model to obtain the ARI.

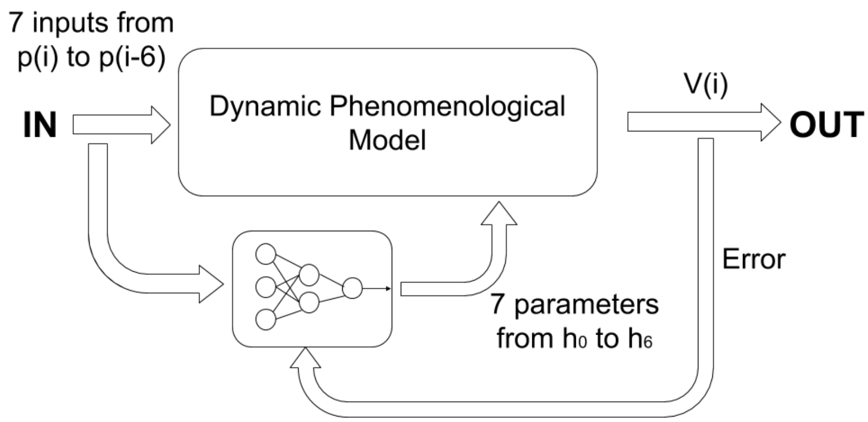

Fig. 2: Proposed hybrid model to obtain the ARI.

In the model shown in Fig. 1, it is observed that the hybrid model input is the ABP represented as 7 values which are associated to a flow velocity inside the gray-box model, thereafter it is evaluated in the A-T model to obtain the ARI.

In the hybrid model, the pressures work as a double input, in terms of they are given to the neural network as well as to the proposed A-T model with different aims in each subsystem.

The gray-box model used in the work has been designed to work in a serial manner. This means that the obtained results by the empirical part of the model are sent directly to the phenomenological model [5] as shown in Fig. 2.

The inputs of the neural network are the ABP of the subjects and, as stated above, they have a direct relationship with a single velocity, therefore, the output is defined as the CBFV.

The training of the gray-box model is performed using indirect training, i.e. the error is computed at the output of the phenomenological model of the gray box [6]. We are interested to know the performance of the whole model and not particularly in the neural part of the model, therefore, we compute the error at the output of the gray-box model using the CBFV.

The phenomenological part of the gray-box neural model contains the equation (5) which is represented along with the neural network using fixed neurons and weights. In this regard, the training algorithm does not modify these connections to keep unaltered its mathematical meaning of the equation.

In parallel, the empirical model is represented by neurons and weights inside the same network. In contrast with the phenomenological part, these weights are adapted over the training.

To complete the hybrid model, the output of the gray-box model is used to compute the ARI based on equations (1), (2), (3) y (4) according to the A-T model. The experimental set-up is coded in Matlab.

5 Subjects and measurements

The data used in this work was measured in the University of Leicester, England and approved by the etic committee of the Royal Infirmary Hospital of Leicester. The data comprise the ABP and the CBFV divided in two phases for 16 healthy volunteer patients between 24 and 47 years old. The first phase is carried out with patients in normocapnia state obtaining measures of ABP and CBFV. Afterwards, in the second phase, the subjects are induced to inhale CO2, which leads them to a hypercapnia state (see Fig.3). This state reduces the oxygen amount in the blood, hence, the subject is not fully healthy as in the first phase. These phases allow to observe differences through obtained data between the normo- and hypercapnia. The obtained samples were supervised by a doctor to assure that the data represent actual information for each subject.

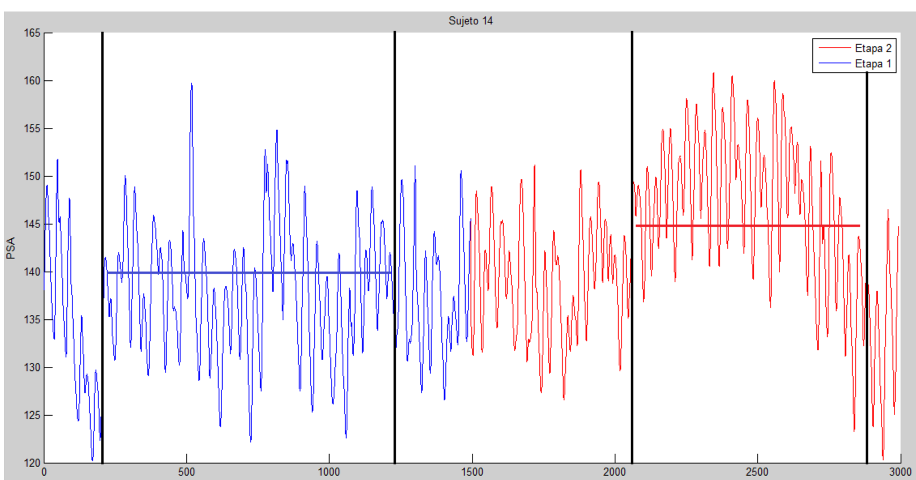

Fig. 3: Muestra de PSA del sujeto 14. Azul-Normocapnia (primera etapa), Rojo-Hipercapnia (segunda etapa)

Sujeto	Normocapnia	Hipercapnia
1	8	8
2	8	8
3	8	6
4	8	8
5	7	7
6	8	8
7	7	6
8	8	7
9	9	8
10	8	8
11	7	6
12	7	6
13	7	7
14	6	7
15	8	8
16	8	8

Table 2: Resultados de cÃ¡lculo de ARI de cada sujeto en estados de normo e hipercapnia con valores estimados por la caja gris.

6 Experimental Results

En la Tabla 2 se puede observar el ARI resultante del modelo hibrido en base a la velocidad estimada por el modelo neuronal de caja gris. Por otra parte la diferencia entre cambios de estados que debe tener cada sujeto no debe superar 2 valores, por lo tanto, como se senala en la Tabla 2, la mayorÃa de los sujetos no presenta una amplÃa diferencia entre los valores del ARI cuando pasan de un estado al otro, sin embargo el sujeto 14 posee un cambio anormal entre normo e hipercapnia.

7 Conclusions and Future Work

Even though the Simpon′s model obtained a good ROC value, it is expected to improve it by using the proposed grey-box neural model. Due to the mixing of the Simson′s model (phenomenological part) with an artificial neural network (empirical part) would boost the data learning taking into consideration the states of normo- and hypercapnia to validate the analysis (healthy state versus deteriorated state of health induced by CO2 inhalation.

As future work, we are planning to develop a mobile app to assist people to obtain easier diagnoses by mean of an m-Health application.

Los resultados del ARI obtenidos por el modelo planteado dejan en evidencia que la caja gris no es capaz de crear una mejor relacion entre la PSA y la VFSC comparado con los modelos existentes. Aun asi, se logra ver que la caja gris es capaz de aprender ciertos patrones de comportamientos de velocidad y presion, puesto que se observo que sigue la logica de disminucion o mantencion del ARI cuando se somete al sujeto a hipercapnia, por lo que se puede concluir que si bien no es mejor que los modelos actuales, el modelo propuesto es capaz de asociar y distinguir el cambio de normo a hipercapnia en los sujetos.

En base a los resultados obtenidos, se estima que el modelo planteado no logra ser eficaz debido a que el modelo fenomenologico utilizado limita el aprendizaje de la red neuronal, sumergiendola en un contexto en el que esta debe asimilarse con el modelo mas basico para el calculo de la VFSC. Lo anterior implica que la RNA se entreno y aprendio en base a que sus resultados debian ser similar o mejor que el modelo basico, por lo que las probabilidades de que el modelo expuesto en este trabajo resultara mejor que el basico eran bajas, mas aun, cuando se esperaba comparar con el mejor modelo actual. Por lo que se puede concluir que para este estudio seria mas eficaz utilizar una ecuacion cuyo resultado no este limitado por el valor de la VFSC, sino que el resultado esperado sea predicho en base al tiempo y variables de estados predichas anteriormente por el mismo modelo, la cual se podria expresar como una ecuacion diferencial. En cuanto a los datos, se estima que la cantidad de estos luego de ser limpiados, se redujo considerablemente, lo que dificulto el libre aprendizaje de la red neuronal. Lo anterior se basa en que mas datos sin ruido aportan informacion mas precisa para el proceso de aprendizaje en redes neuronales.

Finalmente una gran limitante que presento en este trabajo fue la seleccion de la arquitectura y configuracion de la red neuronal, debido a que no hay forma de saber la arquitectura optima para la solucion de un determinado problema. Es por esto, que en este trabajo se utilizo una arquitectura base para la red neuronal, que evitara problemas de sobre-aprendizaje y poca capacidad de generalizacion de datos, de esta forma, la arquitectura primaria o base evolucionaba en cantidad de capas y neuronas a la vez que se estudiaban sus resultados, por lo que se estima que la arquitectura de la caja gris de la red neuronal se encuentra en un punto estable entre la cantidad de capas ocultas y neuronas, ya que no presenta una arquitectura grande y compleja. Esto se respalda con los resultados obtenidos en la fase de simulacion, en la cual se demostro que la red no memoriza los datos y es capaz de generalizar, lo que provoca que el modelo de caja gris propuesto pueda estimar valores de salida, en este caso VFSC estimada.

Se concluye que los objetivos planteados al comienzo del trabajo fueron realizados en su totalidad, obteniendo un modelo que logra asociar de buena forma la VFSC y la PSA para el calculo del ARI en sujetos sometidos al estado de normocapnia e hipercapnia.

References

[1] Chacon, M., Nunez, N., Henriquez, C., and Panerai, R. B. Unconstrained parameter estimation for assessment of dynamic cerebral autoregulation.Â In Physiological measurement,Â Vol. 29, Nr. 10, pp. 1179-1193, 2008.

[2] Illodo Hernandez, D. L., Cruz Toran, D., Gutierrez Gutierrez, D., Martinez Herrer, D., & Luejes Garcia, D. Estudio de la autorregulacion cerebral en el traumatismo crane-

oencefÃ¡lico. Utilizacion del test de respuesta hiperemica transitoria. In Revista Cubana de Medicina Intensiva y Emergencias, Vol. 5, Nr. 1, pp. 1-5, 2005.

[3] Aaslid, R., Lindegaard, K. F., Sorteberg, W., and Nornes, H. Cerebral autoregulation dynamics in humans.Â In Stroke,Â Vol. 20, Nr. 1, pp. 45-52, 1989.

[4] Simpson, D., Berroeta, C. H., Katsogridakis, E., and Panerai, R. Quantifying autoregulation from estimated model parameters: An optimization approach.Â In The FASEB Journal,Â Vol. 28, Nr. 1, pp. 1184-1184, 2014.

[5] Cruz, F., Acuna, G., Cubillos, F., Moreno, V., and Bassi, D. Indirect training of grey-box models: Application to a bioprocess. InÂ Proceedings of the International Symposium on Neural Networks, pp. 391-397, 2007.

[6] Cruz, F. and Acuna, G. Indirect training with error backpropagation in gray-box neural model: Application to a chemical process. InÂ Proceedings of the IEEE International Conference of the Chilean Computer Science Society (SCCC), pp. 265-269, 2010.