INDEPENDENT NEURO-FUZZY CONTROL SYSTEM

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Abstract: The neuro fuzzy system based on two independent structures is described, the first a neuro-observer system developed by use of dynamical neural networks, and the second as the control system based on fuzzy logic system. These structures are described by independent way and their properties are analyzed. Besides, the neuro-fuzzy system performance is proved by the application to the Bergman th blood Insulin-Glucose interaction model, the simulations show the neuro-fuzzy output as the insulin infusor output (insulin concentration), the glucose concentration estimated state is also described, as well as the inferential rules and the membership functions in the fuzzy.

Keywords: Dynamical neural networks, Neuro-Fuzzy control, Observer, Estimation.

1. INTRODUCTION

The hybrid control designs based on neural networks and fuzzy systems have increased their applications mainly due to their accuracy, adaptability, and stability characteristics among others. These systems have worked using the best properties of both structures. For example Fuzzy inference provides an efficient way of handling imprecision and uncertainty while neural learning permits determining the model parameters using input-output data of the process. The hybrid system combines the capability of fuzzy reasoning in handling uncertain information (Wang 1997), and the capability of artificial Neural Networks in learning from processes (Poznyak et al. 1999); (Narendra and Parthasarathy 1995); (Park et al. 1996); (Poznyak et al. 2001). Thus, the merits of the Fuzzy Neural scheme are faster convergence speed with smaller network size as compared to the general Neural Network (Jang 1992); (Gorrini and Bersini 1994). Recently, considerable research has been devoted toward developing recurrent Neuro-Fuzzy models that are divided into two major classes. The former class includes those models with external feedback (Zhang and Morris 1999); (Mouzouris and Mendel 1997); (Jang 1992), while the later one includes fuzzy models with internal recurrency (Theocharis and Vachtsevanos 1996). However, the designs based on the mixing of the independent neural and fuzzy description have been applied poorly. These kinds of systems are simple because these have a structure compound by two parts: the first part the neural network and the fuzzy system in the second part. These structures are different of the neuro-fuzzy structures mentioned above because in some way the applications consists the connection between the Dynamic Neural Network (DNN) instead of the Static Neural Network like neuro-observer (Cabrera et al. 2003) and the Fuzzy system like a fuzzy control. So this system is not properly a Neuro-fuzzy system but that represents another alternative in this kind of system.

The rest of this paper is organized as follows: section 2 shows the structure of the suggested model for each one of the subsystems. In section 3, we applied the system to the Bergman’s insulin-glucose interaction model in blood while the simulations results are presented in section 4. In section 5 the results are discussed. Finally in the last section the conclusions are shown.

2. INDEPENDENT NEURO-FUZZY STRUCTURE (INFS)

In this section: the Dynamical Neural Network (DNN) (Poznyak et al. 1999), applied as a neuro-observer and the fuzzy controller are described, the neuro-observer estimates the unmeasured states of the plant then the estimate states are applied to the fuzzy system to develop the control output signal.

2.1 Differential Neural Networks

The differential neural network (DNN) structure is proposed as in (Poznyak et al. 2001) to develop the model's state estimate. The structure of this DNN is presented in (Fig. 1) and corresponds to a multilayer ANN of Hopfield's (Catfollis 1994). The DNN-observer dynamics is continuous in time is given by

$$\frac{d}{dt}\hat{x}_t = A\hat{x}_t + W_{1,t}\sigma(V_{1,t}\hat{x}_t) + W_{2,t}\phi(V_{2,t}\hat{x}_t)\gamma(u_t) + K[y - H\hat{x}_t] \quad (1)$$

where:

- $\hat{x}_t \in \Re^n$ is the neural network vector of states,
- $u_t \in \Re^m$ is the input,
- the matrix $A \in \Re^{nxm}$ is a feedback stable matrix , and should be selected a priori,
- the matrices $W_{1,t} \in \Re^{nxm}$, $V_{1,t} \in \Re^{nxm}$ and are $W_{2,t} \in \Re^{nxm}$, $V_{21,t} \in \Re^{nxm}$ the weights matrices describing the connection among the hidden layers and output layer,

$\gamma(u_t)$ is the control vector field, $\sigma(\cdot) \in \Re^m$ they are functions of the sigmoidal type and are diagonal:

$$\sigma(\cdot) = diag\lfloor \sigma_1(V_{2,t}\hat{x}_t)_1, \cdots, \sigma_K(V_{2,t}\hat{x}_t)_{\min\{p,m\}}, \rfloor$$

$$\phi(\cdot) = diag\lfloor \phi_1(V_{2,t}\hat{x}_t)_1, \cdots, \phi_K(V_{2,t}\hat{x}_t)_{\min\{r,k\}}, \rfloor \quad (2)$$

with the elements as the sigmoidal functions

$$\sigma_i(x) = \frac{a_i}{1 + e^{-b_i^T x}} - c_i \quad (3)$$

$$\phi_i(x) = \frac{\hat{a}_i}{1 + e^{-\hat{b}_i^T x}} - \hat{C}_i \quad (4)$$

The learning laws for the weights of the DNN are given by a system of differential equations defining the matrix evolutions for $W_{1,t} \in \Re^{nxm}$, $V_{1,t} \in \Re^{mxn}$, $W_{2,t} \in \Re^{nxk}$ and $V_{2,t} \in \Re^{kxn}$

$$\dot{W}_1 = -k_1 P N_\delta^{-1}\left[\Psi_1 - H^T(y_i - H\hat{x}_t)\right]\sigma(V_{1,t}\hat{x}_t)^T$$
$$\dot{W}_2 = -k_2 P N_\delta^{-1}\left[\Psi_2 - H^T(y_i - H\hat{x}_t)\right]\sigma(\hat{x}_t)$$
$$\dot{V}_1 = -k_3 L_\sigma^2 (V_{1,t} - V_1^*)\hat{x}_t \overline{W}_1 \hat{x}_t^T$$
$$\dot{V}_2 = -k_4 \|\gamma(u_t)\| L_\phi^2 \overline{W}_2 (V_{2,t} - V_2^*)\hat{x}_t \hat{x}_t^T$$
$$\tilde{\sigma}(\hat{x}_t) = \gamma(u_t)\phi_t^T(V_{2,t}\hat{x}_t)$$
$$\Psi_1 = \frac{1}{2}(\hat{H}_1)^T N_\delta^{-1} P\left[W_{1,t} - W_1^*\right]\sigma(V_{1,t}\hat{x}_t)$$
$$\Psi_2 = \frac{1}{2}(\hat{H}_2)^T N_\delta^{-1} P\left[W_{2,t} - W_1^*\right]\phi(V_{2,t}\hat{x}_t)\gamma(u_t)$$
$$\hat{H}_1 = H^T \Lambda_\xi^{-1} H + \delta\Lambda_{W1}$$
$$\hat{H}_2 = H^T \Lambda_\xi^{-1} H + \delta\Lambda_{W2}$$
$$W_{1,0} = W_1^*,\ W_{2,0} = W_2^*,\ V_{1,0} = V_1^*,\ V_{2,0} = V_2^* \quad (5)$$

where $k_i\ (i = \overline{1,...,4})$ are positive constants, and P is the positive solution of the following Riccati equation given by

$$A^T P + PA + PRP + Q = 0$$
$$Q = \delta(\Lambda_{W1}^{-1} + \Lambda_{W2}^{-1}) + 2\gamma^2 L_\phi^2 V_2^{*T}\overline{W}_2 V_2^* + 2L_\sigma^2 tr\{\overline{W}_1\}V_1^{*T}V_1^* + Q_0 - H\Lambda_\xi H^T \quad (6)$$
$$R = \Lambda_{W1}^{-1} + \Lambda_{W2}^{-1},\ \overline{W}_i = W_i^{*T}$$

Here *A* is a Hurwitz (stable) matrix providing the existence of a positive solution for (6) and

$$N_\delta := \lfloor H^T + \delta I \rfloor,\ \delta > 0 \quad (7)$$

The function $\gamma(\cdot): \Re^s \to \Re^k$ is assumed to be bounded within a working zone, that is, $\|\gamma(u)\| \le \overline{u}$. Below we select $\gamma(u) = u$. The gain-matrix is $K = P^{-1}H\Lambda_\xi \in \Re^{mxn}$. The constant matrices Λ_{W1}^{-1}, Λ_{W2}^{-1}, Λ_ξ^{-1}, Λ_{Wi} are the procedure parameters that should be selected by the "try-to-test method".

2.2 Fuzzy System

The fuzzy interference method suggested by Takagi, Sugeno and Kang, known as the fuzzy model (Takagi *et al.* 1992) and (Takagi and Hayashi 1991), follows a multi-model approach and usually implement using neuro-fuzzy networks, based on process knowledge and input-output data. A Fuzzy model is composed of fuzzy rules that can be written in the following general form:

$R^{(l)}$: IF $u_1(k)$ is A_1^l and $u_2(k)$ is a A_2^l AND …. AND $u_m(k)$ is A_m^l THEN $\hat{y}_l(k) = g_l(u(k))$ (8)

$l = 1,...,r$

where $R^{(l)}$ denotes the fuzzy rule, r is the number of rules, and $u(k)=[u_1(k),u_2(k),\dots,u_m(k)]^T$ is the input vector to the model at time k with. $u_i(k)\in\aleph_i\subset\Re(i=1,...,m)$. $g_l(u(k))$ is a function describing the consequent part of $R^{(l)}$ which provides the rule output $\hat{y}_l(k)$ at time k for a given input $u(k)$, and $A_i^l\ (l=1,...,r)$ are labels of fuzzy sets defined in the universe of discourse $\aleph_i$.

Defining the number and the locations of the membership functions leads to partition of the premise space $\aleph^m=\aleph_1\times\cdots\times\aleph_m$. The collection of fuzzy sets $A^{(l)}=\{A_1^l,....,A_m^l\}$ pertaining to the premise part of $R^{(l)}$ formulates a fuzzy region in $\aleph_i$ that can be regarded as a multi-dimensional fuzzy set whose membership function is determined by

$$\mu_A=(u(k))=\mu_l(k)=\prod_{i=1}^{m}\mu_{A_i}(u_i(k)) \qquad (9)$$

The above equation provides the degree to which a particular input vector *u(k)* belongs to the fuzzy region $A^{(l)}$. From a different point of view, $\mu_l(k)$ represents the firing strength of the *lth* rule, $R^{(l)}$ .The output of the model at time *k*, $\hat{y}(k)$, is determined using the weighted average defuzzification method:

$$\hat{y}(k)=\frac{\sum_{l=1}^{r}\mu_l(k)\cdot\hat{y}_l(k)}{\sum_{l=1}^{r}\mu_l(k)} \qquad (10)$$

The equation above indicates that the Fuzzy model follows a local modelling approach. The input space is first decomposed into r fuzzy regions. In each fuzzy region $A_i^l\ (l=1,...,r)$, the behaviour of the system is locally described by the rule submodel $\hat{y}(k)=g_l(u_k)$ and the overall model output is derived as a fuzzy blending of the local sub-models.

The INFS system structure in a block diagram is shown in the figure

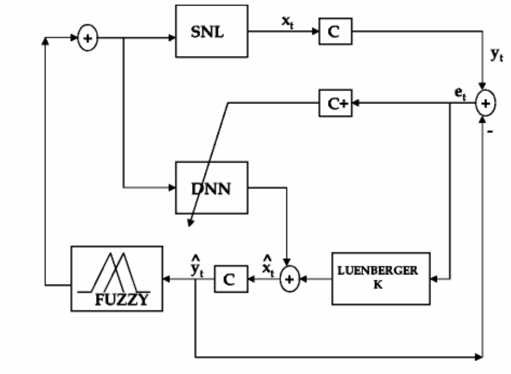

Fig. 1 Independent Neuro Fuzzy Structure.

3. APPLICATION EXAMPLE

To improved the INFS network it is necessary a model that has the observable property. The Bergman's model (Bergmann 2002); (Khoo 2000), fulfills this condition and it is described by

$$\begin{aligned}
\dot{x}_1 &= -n(x_1+\mathrm{I}_1)+(u(t)/V_1)\\
\dot{x}_2 &= -p_1x_2-x_3(x_2+G_B)+\mathrm{P}(t)\\
\dot{x}_3 &= -p_2x_3+p_3x_1\\
y &= x_2
\end{aligned} \qquad (11)$$

where the states are insulin concentration (x_1); glucose concentration (x_2); insulin concentration in the remote compartment (x_3). Due to the necessity of developing observer's system in the model, the observability study was done in a previous study with successful results see (Cabrera *et al.* 2003), and in this paper the Bergman's is considered observable in a sense of non lineal system theory (Giccarela and Mora 1993).

3.1 DNN parameters

The Neuro-observer parameters was selected by several experiments and these are described below, first the Hurwitz matrix

$$A=\begin{bmatrix}-2 & 0 & 0\\ 0 & -4 & 0\\ 0 & 0 & -9\end{bmatrix}$$

then the Riccati matrix and the another matrices in the DNN algorithm described above

$$P=\begin{bmatrix}0.3238 & 0 & 0\\ 0 & 0.1713 & 0\\ 0 & 0 & 0.0774\end{bmatrix};\ Q=\begin{bmatrix}2 & 1 & 2\\ 1 & 2 & 1\\ 2 & 1 & 2\end{bmatrix}$$

the initial conditions for the weight matrices in the external layer

$$W_{1,0}=\begin{bmatrix}0.5 & 0.1 & 2.0\\ 0.2 & 0.5 & 0.6\\ 0.3 & 1.4 & 0.8\end{bmatrix};$$

$$W_{2,0}=\begin{bmatrix}0.005 & 0.001 & 0.002\\ 0.003 & 0.005 & 0.002\\ 0.004 & 0.006 & 0.001\end{bmatrix}$$

the initial conditions for the weight matrices in the internal layer

$$V_{1,0}=\begin{bmatrix}1.0 & 0.5 & 0.6\\ 0.3 & 1.3 & 0.4\\ 0.5 & 1.0 & 0.9\end{bmatrix};V_{2,0}=\begin{bmatrix}1.0 & 0.1 & 0.4\\ 0.1 & 0.2 & 0.2\\ 1.0 & 0.3 & 0.6\end{bmatrix}$$

The initials weight matrix values was determined by trial and error tests.

3.2 The inferential rules and membership functions

The inferential rules were proposed to the Bergman's model thinking in the performance of the insulin commercial infusion system (Medfusion, 1994), these are described by thirteen statements in table 1

<u>Table 1 Inferential rules</u>

Rule	*Statement*
1	*IF [glucosa] is muy alto AND [insulina] is muy bajo THEN [Suministro] is pasado*
2	*IF [glucosa] is muy alto AND [insulina] is bajo THEN [Suministro] is su f iciente*
3	*IF [glucosa] is muy alto AND [insulina] is normal THEN [Suministro] is escaso*
4	*IF [glucosa] is muy alto AND [insulina] is alto THEN [Suministro] is muy escaso*
5	*IF [glucosa] is muy alto AND [insulina] is muy alto THEN [Suministro] is nulo*
6	*IF [glucosa] is alto AND [insulina] is muy bajo THEN [Suministro] is suficiente*
7	*IF [glucosa] is alto AND [insulina] is bajo THEN [Suministro] is escaso*
8	*IF [glucosa] is alto AND [insulina] is normal THEN [Suministro] is muy escaso*
9	*IF [glucosa] is alto AND [insulina] is altol THEN [Suministro] is nulo*
10	*IF [glucosa] is normal AND [insulina] is muy bajo THEN [Suministro] is escaso*
11	*IF [glucosa] is normal AND [insulina] is bajo THEN [Suministro] is muy escaso*
12	*IF [glucosa] is normal AND [insulina] is normal THEN [Suministro] is nulo*
13	*IF [glucosa] is bajo AND [insulina] is bajo THEN [Suministro] is muy escaso*

The membership functions due to the above inferential rules are illustrated as follows

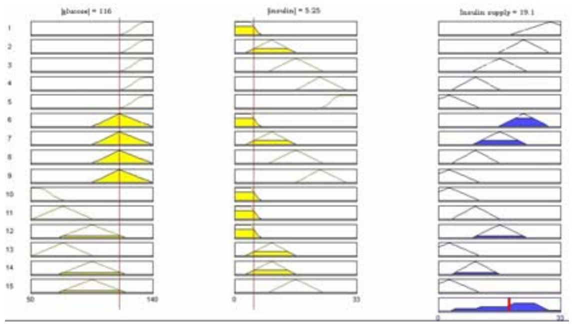

Fig. 2 Specific Membership functions.

for specific numerical values the graphs are shown in the figure

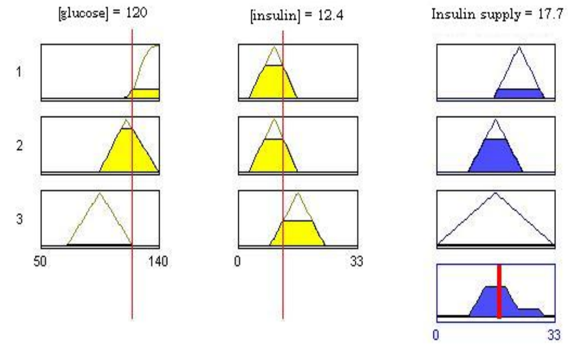

Fig. 3 Specific Membership functions.

We have got to edit membership function to describe fuzzy input as much as output system's states, being mostly triangular functions because of their easy programming and mathematical representation.

4. RESULTS

The Bergman's states model were obtained when applying the INFS technique, these are shown in the next graphics Fig. 4

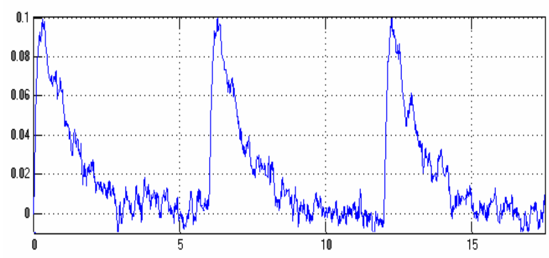

Fig. 4 Glucose concentration evolution.

The glucose concentration is shown in the graph Fig. 5

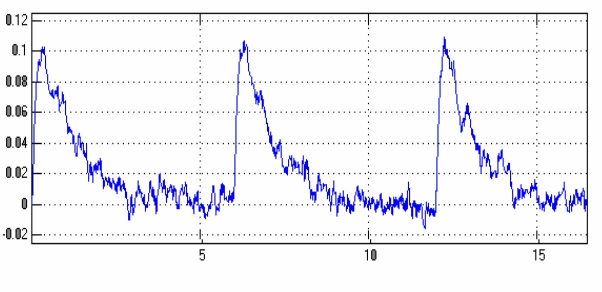

Fig. 5 Glucose concentration obtains by the INFS.

The next graph shows the INFS output signal and the Bergman's model output put together to be compared Fig.4

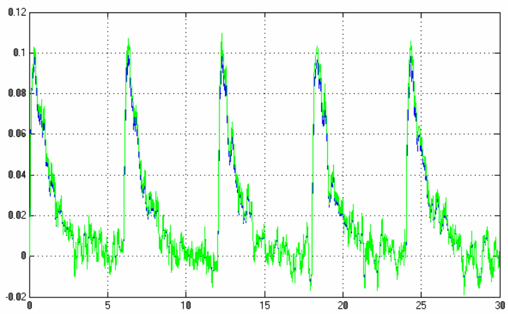

Fig. 6 Glucose concentration.

In the last graph is shown all Bergman's estimate states, for (x_1, x_3) states the error was 7% between the INFS states. Fig. 6

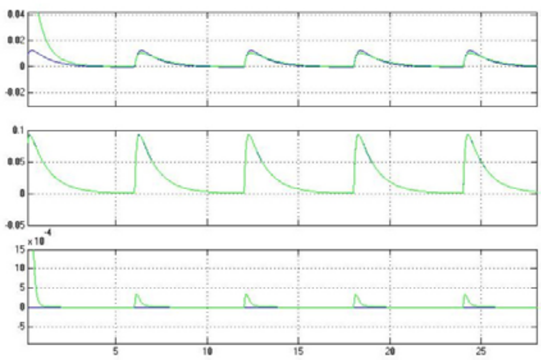

Fig. 7 Bergman's states evolution.

The simulation results show the state evolution in the Bergman's model and the INFS structure, these states are compared with the insulin concentration to normal person Fig. 7, although the evolution of the variables is not the same, the estimate glucose concentration is inside the health normal margins (Guyton 2001).

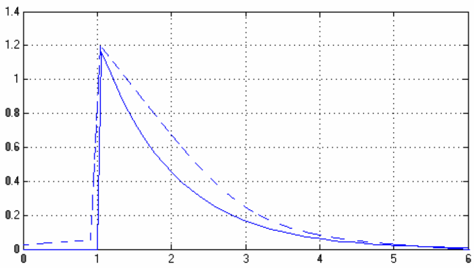

Fig. 8 Glucose concentration in normal conditions.

The insulin-glucose interaction model allows knowing the remote compartment state evolution when the INFS is applied. This model offers good properties like observability and this is the main reason to be selected in this work. The graphs could be used like a tracking trajectory, in the diagnostics for the diabetes illness.

The mentions before are get through fuzzy algorithms development, made in personal computer's platform, that allows at the same time to verify the created system's performance by modifying only input system's states to get a response in real parameters Fig.8

It was possible to get a simulation that shows process input and output evolution Fig. 9 (non lineal in this case).

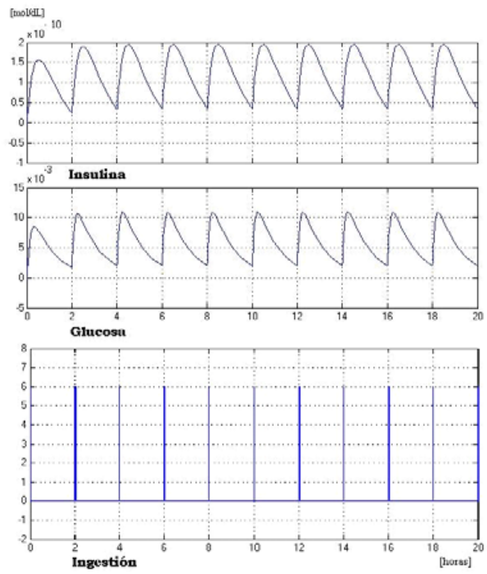

Fig. 9 Insulin and Glucose concentrations.

This evolution is referred to the Bergman's insulin-glucose interaction model (Bergman, 2002), getting this way the possibility for the model's algorithm to become part of the feedback control scheme and making that way the patient's insulin supply analysis, which give us the opportunity to determinate fuzzy control system's efficiency.

5. CONCLUSIONS

The INFS application shows the estimate states are closed to the Bergman's model variables so the neuro-observer works well. The neuro-observer estimated the non measured variables and these could be substitutes by the instrumental measurements in the Fuzzy control input. Input and output evolution parameters in temporal graphs analysis, as much as fuzzy controller response, confirm an efficient behaviour from the designed system about organism insulin requirement, by giving almost immediate insulin supplying when the glucose grows out the normal limit (as it happens in food ingest). This result gives the possibility to design a control system based on the INFS scheme which could determine the variants to control the glucose concentration for the improvement of diabetic patient health.

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