Automatic Construction of Fuzzy Rules for Modelling and Prediction of the Central Nervous System

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Abstract. The main goal of this work is to study the performance of CARFIR (Automatic Construction of Rules in Fuzzy Inductive Reasoning) methodology for the modelling and prediction of the human central nervous system (CNS). The CNS controls the hemodynamical system by generating the regulating signals for the blood vessels and the heart. The main idea behind CARFIR is to expand the capacity of the FIR methodology allowing it to work with classical fuzzy rules. CARFIR is able to automatically construct fuzzy rules starting from a set of pattern rules obtained by FIR. The new methodology preserves as much as possible the knowledge of the pattern rules in a compact fuzzy rule base. The prediction results obtained by the fuzzy prediction process of CARFIR methodology are compared with those of other inductive methodologies, i.e. FIR, NARMAX and neural networks.

1 Introduction

The Fuzzy Inductive Reasoning (FIR) methodology emerged from the General Systems Problem Solving (GSPS) developed by Klir [1]. FIR is a data driven methodology based on systems behavior rather than structural knowledge. It is a very useful tool for modelling and simulate those systems from which no previous structural knowledge is available. FIR is composed of four main processes, namely: *fuzzification*, *qualitative model identification*, *fuzzy forecasting*, and *defuzzification*. The *FIR structure* box of figure 1 describes all the processes of FIR methodology.

The fuzzification process converts quantitative data stemming from the system into qualitative data. The qualitative model identification process is able to obtain good qualitative relations between the variables that compose the system, building a pattern rule base that guides the fuzzy forecasting process. Both the fuzzification and the qualitative model identification processes are relevant in the present study and, therefore, are explained in more detail in the next section.

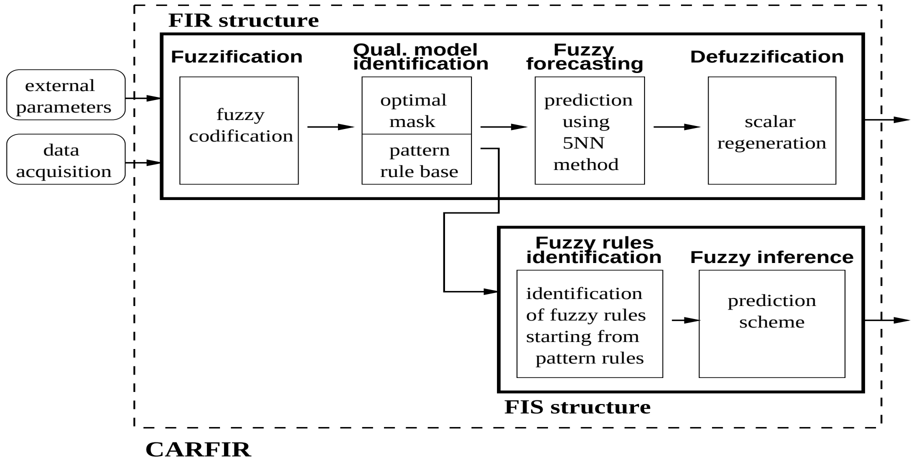

Fig. 1. CARFIR structure

The fuzzy forecasting process predicts systems' behavior. The FIR inference engine is a specialization of the k-nearest neighbor rule, commonly used in the pattern recognition field.

Defuzzification is the inverse process of fuzzification. It makes possible to convert the qualitative predicted output into a quantitative variable that can then be used as input to an external quantitative model. For a deeper insight into FIR methodology the reader is referred to [2, 3].

It has been shown in previous works that FIR methodology is a powerful tool for the identification and prediction of real systems, specially when poor or non structural knowledge is available [4–7]. This is the case of the human central nervous system that controls the hemodynamical system. FIR methodology was used to identify the five controllers that compose the central nervous system obtaining very good results when comparing with other inductive methodologies such as NARMAX models [6] and time delay neural networks [8]. However, FIR methodology has an important drawback. The pattern rule base generated by the qualitative model identification process can be very large if there exists a big amount of data available from the system. As it is explained accurately latter, the number of generated rules is almost as large as the number of observations recorded from the system. Therefore, when a large number of pattern rules exists in the rule base the prediction of a new output value becomes very slow.

In this paper the methodology of the automatic construction of fuzzy rules (CARFIR) is used to solve the drawback of FIR methodology. CARFIR proposes an alternative for the last two processes of FIR methodology (fuzzy forecasting and deffuzification) that consists on a fuzzy inference system (FIS) that allows to compact the pattern rule base in a classical fuzzy rule base and to define a inference scheme that affords the prediction of the future behavior of the system. This is shown in the *FIS structure* box of figure 1. The additional structure does not pretend to substitute the fuzzy prediction and deffuzification processes but to increase the efficiency of FIR methodology.

The extended methodology obtains a fuzzy rule base by means of the *fuzzy rules identification* process that preserve as much information as possible contained in the pattern rule base. Therefore, the former can be considered a generalization of the latter. In other words, the fuzzy rule base is a set of compacted rules that contains the knowledge of the pattern rule base. In this process some precision is lost but the robustness is considerably increased.

The *fuzzy inference* process of CARFIR methodology allows the prediction of systems behavior by means of two different schemes. The first scheme corresponds to the classical forecasting process of FIR methodology, i.e. *pattern prediction scheme*. The second correspond to purely Sugeno fuzzy inference system, i.e.*Sugeno prediction scheme*.

In this paper CARFIR performance is studied in the context of a biomedical application, i.e. the human central nervous system. The central nervous system is part of the cardiovascular system and controls the hemodynamical system, by generating the regulating signals for the blood vessels and the heart. These signals are transmitted through bundles of sympathetic and parasympathetic nerves, producing stimuli in the corresponding organs and other body parts. A simplified diagram of the cardiovascular system is shown in figure 2.

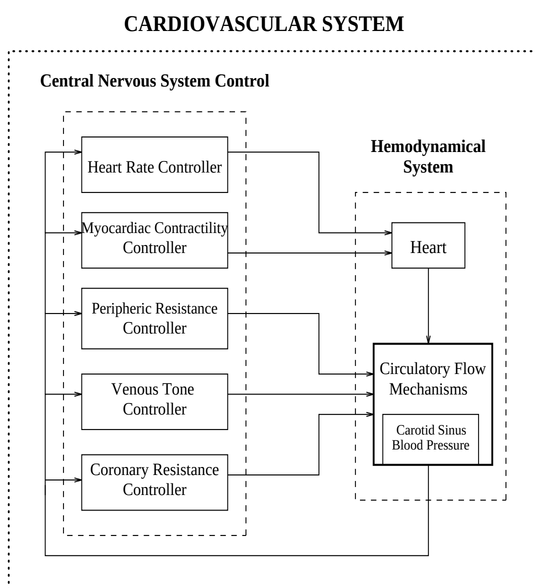

Fig. 2. Simplified diagram of the cardiovascular system model

The CNS control model is composed of five separate controllers: the *heart rate controller (HRC)*, the *peripheric resistance controller (PRC)*, the *myocardiac* *contractility controller (MCC)*, the *venous tone controller (VTC)*, and the *coronary resistance controller (CRC)*. All five controller models are single–input/single–output (SISO) models driven by the same input variable, namely the *Carotid Sinus Pressure* (see figure 2). The five output variables of the controller models are not even amenable to a physiological interpretation, except for the *Heart Rate Controller* variable, which is the inverse heart rate, measured in seconds between beats.

The functioning of the central nervous system is of high complexity and not yet fully understood. However, individual differential equation models for each of the hypothesized control mechanisms have been postulated by various authors [9, 10]. These models offer a considerably low degree of internal validity. The use of inductive modelling techniques with their reduced explanatory power but enhanced flexibility for properly reflecting the input/output behavior of a system may offer an attractive alternative to these differential equation models.

In previous works [6, 11], the FIR methodology was used to find a qualitative model of the CNS control that accurately represents the input/output behavioral patterns of the CNS control that are available from observations. However, the pattern rule base obtained was quite large, increasing considerably the time needed in the prediction process. It is the aim of this paper to use CARFIR methodology to identify a set of Sugeno fuzzy rules from the pattern rule base obtained initially by FIR but preserving, as much as possible, their prediction capability.

CARFIR methodology is introduced in section 2. In section 3, CARFIR is used to infer a Sugeno rule base for the central nervous system control. CARFIR prediction results (pattern and Sugeno prediction schemes) are presented and discussed from the perspective of the prediction performance and the size of the rule base. CARFIR results are compared with those of other inductive modelling methodologies, i.e. NARMAX and time delay neural networks. Finally, the conclusions of this research are given.

2 The CARFIR Methodology

CARFIR methodology is composed of two parts, a FIR structure and a FIS structure (see figure 1). As mentioned earlier CARFIR is an extension of the FIR methodology. Therefore, the first part of CARFIR consists on the generation of the pattern rule base using FIR methodology. To this end, the next steps are required:

- Specification of the external parameters
- Qualitative model identification

The second part of CARFIR methodology consists on the identification of fuzzy rules and on systems' prediction by means of a fuzzy inference system. To this end, it is necessary to follow the next steps:

- Identification of Sugeno fuzzy rules starting from pattern rules
- Prediction by means of two different schemes

These steps are explained in detail next.

External parameters

There is a set of external parameters that need to be specified in CARFIR methodology, mainly in the fuzzification process. FIR fuzzification process converts quantitative values into qualitative triples. The first element of the triple is the class value, the second element is the fuzzy membership value, and the third element is the side value. The side value indicates whether the quantitative value is to the left or to the right of the peak value of the associated membership function.

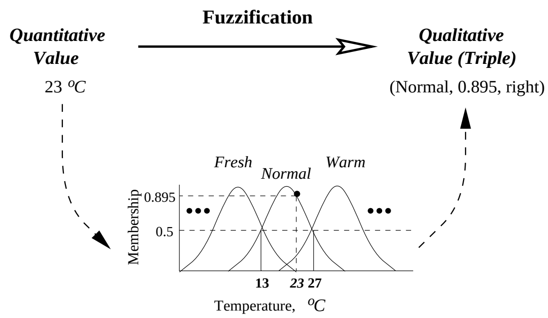

Fig. 3. FIR fuzzification process

Figure 3 shows an example of fuzzification of the variable *Temperature*. For instance, a quantitative temperature value of $23°C$ is discretized into a qualitative class value of *'normal'* with a fuzzy membership function value of 0.895, and a side function value of *'right'* (since 23 is to the right of the maximum of the bell–shaped membership function that characterizes the class 'normal').

In order to convert quantitative values into qualitative ones, it is necessary to provide to the fuzzification function the number of classes into which the space is going to be discretized, the landmarks (limits between classes) and the shape of the membership function for each input and output variable. The default value for the number of classes' parameter is three. The equal frequency partition (EFP) is used as the default method to obtain the landmarks of the classes. Finally, the gaussian shape is used as the default value for the membership function parameter. These default values have been used in different applications obtaining usually very good results [4–7].

Qualitative model identification

The result of the fuzzification process, i.e. the qualitative behavior, is stored in the qualitative data matrices. The first matrix contains the class values, the second stores the membership information, and the third records the side values. Each column represents one of the observed variables, and each row denotes one time point, i.e., a recording of all variables, or a recorded state.

The qualitative model identification process of the CARFIR methodology is responsible of finding spatial and temporal causal relations between variables and, therefore, of obtaining the best qualitative model that represents the system. A FIR model is composed by a so-called *mask* and the *behavior matrix*. The mask represents the structure of the model, whereas the behavior matrix is the associated pattern rule base. An example of mask is shown in equation 1.

$$\begin{array}{l|ccc} {}_t\backslash^x & u_1 & u_2 & y \\ \hline t-2\delta t & & & \\ t-\delta t & & & \\ t & & & \end{array} \quad \begin{pmatrix} 0 & -1 & 0 \\ 0 & 0 & -2 \\ -3 & 0 & +1 \end{pmatrix} \tag{1}$$

The negative elements in the mask are referred to as m–inputs (mask inputs) and denote causal relations with the output. The sequence in which they are enumerated is immaterial. The zero elements are forbidden relations. The single positive value denotes the output. The mask can be described, also, in a position notation, were the m-inputs and the output are numbered from left to right and from top to bottom. The mask of equation 1 corresponds to $(2, 6, 7, 9)$, in position notation.

The qualitative model identification process evaluates the possible masks and concludes which of them offers the highest quality from the point of view of an entropy reduction measure. Once the best mask has been identified, it can be applied to the qualitative data matrices obtained from the system, resulting in a particular pattern rule base called behavior matrix in FIR nomenclature. The process of constructing the pattern rule base from the qualitative data matrices using the best mask obtained is described in figure 4.

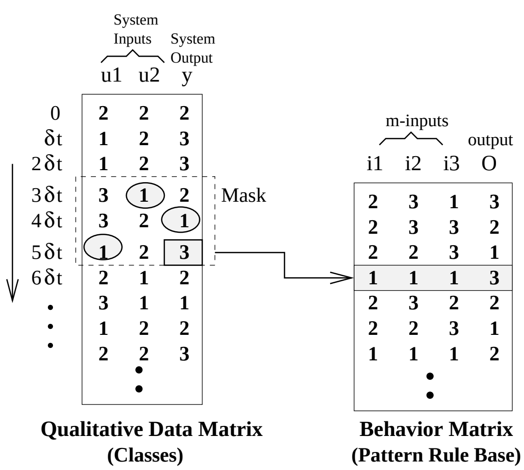

Fig. 4. Pattern rule base construction

The mask can be used to "flatten" dynamic relationships into "pseudo–static" relationships. The left side of figure 4 shows an excerpt of the class qualitative data matrix, one of the three matrices belonging to the qualitative data model. In the example shown in this figure, the second variables, u_2, was discretized into two classes, whereas the remaining variables, u_1 and y, have been discretized into three classes each. The dashed box symbolizes the mask that is shifted downwards along the class qualitative data matrix. The round shaded "holes" in the mask denote the positions of the m–inputs, whereas the square shaded "hole" indicates the position of the output. The class values are read out from the class qualitative data matrix through the "holes" of the mask, and are placed next to each other in the behavior matrix (pattern rule base) that is shown on the right side of figure 4. Each row of the behavior matrix represents one pseudo–static qualitative state or qualitative rule. For example, the shaded rule of this figure can be read as follows: "If the first m–input, i_1, has a value of '1' (corresponding to 'low'), and the second and third m–inputs, i_2 and i_3, have also a value of '1' (corresponding to 'low') then the output, o, assumes a value of '3' (corresponding to 'high').

Identification of Sugeno fuzzy rules

At this point the pattern rule base representing the system behavior is already available. The next step is the generation of fuzzy rules starting from the pattern rules by adjusting automatically the parameters of the fuzzy system. Traditionally, the development of a fuzzy system requires the collaboration of a human expert that is the responsible of calibrating and tuning all its parameters manually. It is well known that this is not an easy task and requires a good knowledge of the system.

The CARFIR methodology allows the automatic construction of a fuzzy rule base as a generalization of the previously obtained pattern rule base by means of the *fuzzy rules identification* process (refer to figure 1). The idea behind the obtaining of fuzzy rules starting from pattern rules is based on the spatial representation of both kind of rules. The pattern rule base can be represented graphically on the input-output space. If the model identified by FIR is of high quality then the pattern rules form a uniform thin surface in the input-output space. However, if the model obtained is not so good the spatial representation looks as a surface where the thickness of some parts is more significant than that of others. The thickness of the surface means that for a given input pattern (or a set of antecedents) the output variable (or consequent) can take different class values, i.e. the pattern rule base is not deterministic. As mentioned before, the quality of the model is computed by means of an entropy measure that reflects the level of determinism of the state transition matrix associated to the mask and the behavior matrix. A good model is obtained when it has a high level of determinism associated in its rules and all the physical behavior patterns are represented in the model. The spatial representation of such a situation would be a uniform thin surface.

A fuzzy inference system generates a unique output value (consequent) for a set of antecedents. Therefore, the graphical representation looks always as a totally uniform surface or mesh in the input-output space. The tuning process consists on automatically adjusting the mesh built by the fuzzy inference system to the surface obtained from the pattern rules.

Figure 5 shows an example of the tuning process. This figure presents a three dimensional view of the graphic representation of the pattern rule base (circles) and the fuzzy rule base (squares) of the heart rate controller of the CNS. The pattern rule base was constructed by using the best mask inferred by FIR. The consequent of a Sugeno fuzzy rule is obtained from the values of the antecedents using equation 2.

$$y = \frac{\sum_{i=1}^{n}(\mu_i \cdot w_i)}{\sum_{i=1}^{n}\mu_i} \tag{2}$$

In equation 2, μ_i is the fire of the ith rule, w_i is the weight of the ith rule and n is the total number of rules of the system. The product is the fuzzy operator used to obtain the fire of each rule. The tuning process consists on adjusting the rules weight, w_i, by iterating through the data set using the gradient descent method [12]. The tuning of the ith rule weight is obtained by calculating the derivative of the cost function E with respect to w_i. The cost function is described in equation 3 (quadratic error addition), where ND is the total number of data points, y is the value given by the fuzzy system and y^r is the real value.

$$E = \frac{1}{2}\sum_{k=1}^{ND}(y - y^r)^2 \tag{3}$$

Prediction schemes

Once the rule base (pattern and/or fuzzy) is available, system prediction can take place. CARFIR includes the option of using the FIR fuzzy forecasting process that use exclusively the pattern rule base. This option is desirable when the computational resources allow to keep the pattern rule base or when the Sugeno fuzzy scheme is not able to obtain an accurate representation of the pattern rules. The Sugeno fuzzy inference system makes use of the fuzzy rules obtained starting from the pattern rule base as explained in the previous section. The prediction process is done by means of the classical Sugeno inference system that have been already mentioned before.

3 CNS controller models

In this work the five CNS control models presented in figure 2, namely, *heart rate*, *peripheric resistance*, *myocardiac contractility*, *venous tone* and *coronary resistance*, are inferred for a specific patient by means of CARFIR methodology.

As has been mentioned earlier, all the controllers are SISO models driven by the same input variable, the *carotid sinus pressure*. The input and output signals of the CNS controllers were recorded with a sampling rate of of 0.12 seconds from simulations of the purely differential equation model. The model had been tuned to represent a specific patient suffering a coronary arterial obstruction, by making the four different physiological variables (right auricular pressure, aortic pressure, coronary blood flow, and heart rate) of the simulation model agree with the measurement data taken from the real patient. The CNS control models obtained were validated by using them to forecast six data sets not employed in the training process. Each one of these six test data sets, with a size of about 600 data points each, contains signals representing specific morphologies, allowing the validation of the model for different system behaviors.

In the modelling process, the normalized mean square error (in percentage) between the simulated output, $\hat{y}(t)$, and the system output, $y(t)$, is used to determine the validity of each of the control models. The error equation is given in equation 4.

$$MSE = \frac{E[(y(t) - \hat{y}(t))^2]}{y_{\mathrm{var}}} \cdot 100\% \tag{4}$$

where y_{var} denotes the variance of $y(t)$.

The quantitative data obtained from the system is converted into qualitative data by means of the fuzzification process of CARFIR methodology. Several experiments were done with different partitions of the data for the five controllers. Both the input and output variables were classified into 3, 5, 7 and 9 classes using the equal frequency partition (EFP) method. The identification of the models was carried out using 4200 samples. The best masks obtained for the coronary resistance (CR) and heart rate (HR) controllers are presented in equation 5.

$$\begin{array}{l} t \backslash^{x} \\ t-2\delta t \\ t-\delta t \\ t \end{array} \begin{array}{c} CSP\ CRC \\ \begin{pmatrix} 0 & 0 \\ -1 & -2 \\ 0 & +1 \end{pmatrix} \end{array} \qquad \begin{array}{l} t \backslash^{x} \\ t-2\delta t \\ t-\delta t \\ t \end{array} \begin{array}{c} CSP\ HRC \\ \begin{pmatrix} -1 & -2 \\ 0 & 0 \\ 0 & +1 \end{pmatrix} \end{array} \tag{5}$$

The best mask inferred for the myocardiac contractility, venous tone and peripheric resistance controllers is shown in in equation 6.

$$\begin{array}{l} {}_{t}\backslash^{x} \\ t-2\delta t \\ t-\delta t \\ t \end{array} \begin{array}{c} CSP \quad MC/VT/PR \\ \begin{pmatrix} -1 & 0 \\ 0 & -2 \\ 0 & +1 \end{pmatrix} \end{array} \tag{6}$$

Applying these masks to the qualitative data, a pattern rule base (behavior matrix) with 4198 rules was obtained for each one of the five controllers. Once the pattern rules are available the fuzzy rules identification procedure can take place. From the experiments performed with different number of classes, it was concluded that the best matching between pattern and fuzzy rules is obtained when the input and output variables were discretized into 9 classes, and, therefore, the Sugeno fuzzy rule base of each controller contain 81 rules. The reduction of the number of rules is significant (from 4198 to 81). Figure 5 shows a three dimensional view of the graphic representation of the pattern rule base (circles) and the fuzzy rule base (squares) of the heart rate controller of the CNS, obtained after the tuning process. The tuning process has been performed during 50 epochs for all the five controllers.

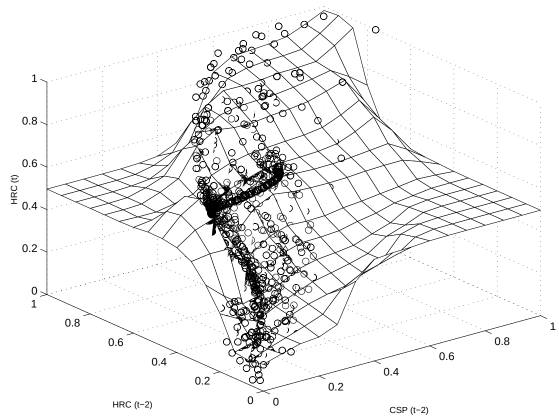

Fig. 5. Pattern and fuzzy rules surfaces for the heart rate controller

As can be seen from figure 5, the mesh that represents the fuzzy rules has been adapted quite accurately to the pattern rules surface. This is due to the fact that the thickness of the pattern rules surface is considerably small making it possible the approximation by means of a fuzzy rules surface (mesh).

Once the Sugeno fuzzy rule base is available for each controller, the Sugeno prediction scheme is performed for each of the 6 test data sets. The MSE errors of the five controller models for each of the test data sets are presented in table 1. The columns of table 1 contain the mean square errors obtained when the 6 test data sets were predicted using each of the five CNS controllers. The last row of the table shows the average error of the 6 tests for each controller.

Table 1. MSE prediction errors of the HR, PR, MC, VT, and CR controller models obtanied using the Sugeno fuzzy prediction scheme of CARFIR methodology

	HRC	**PRC**	**MCC**	**VTC**	**CRC**
Data Set 1	10.89%	11.00%	5.62%	5.65%	2.13%
Data Set 2	10.81%	9.79%	4.43%	4.45%	2.34%
Data Set 3	9.8%	7.67%	3.76%	3.76%	2.11%
Data Set 4	6.41%	6.66%	1.61%	1.60%	3.09%
Data Set 5	14.38%	9.73%	8.97%	8.96%	2.59%
Data Set 6	13.83%	14.98%	5.64%	5.64%	3.62%
Ave. Error	**11.02%**	**9.97%**	**5.00%**	**5.01%**	**2.64%**

From table 1 it can be seen that the coronary resistance (CR) model captures in a reliably way the behavior of this controller, achieving an average error of 2.64% for the 6 test data sets. The largest average error is 11.02% obtained with the heart rate (HR) model. Therefore, the HR model is the one that captures less accurately the behavior of the controller. Figures 6, 7, 8, 9 and 10 show the best and worst prediction results obtained for the heart rate, peripheric resistance, myocardiac contractility, venous tone and coronary resistance controllers, respectively. The solid line correspond to the prediction performed by the Sugeno fuzzy inference model, whereas the dashed line is the true measured output.

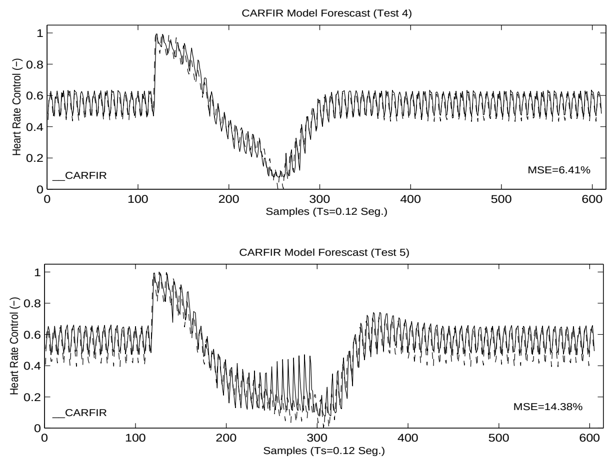

Fig. 6. Heart rate control: best (data set #4) and worst (data set #5) prediction results

From the plots of figure 10 it can be seen that the predictions obtained by the Sugeno fuzzy inference system of CARFIR methodology are fairly accurate, although the forecast signals present high-frequencies that do not appear in the real data.

The heart rate, peripheric resistance, myocardiac contractility and venous tone controller data (see figures 6, 7, 8 and 9), exhibit high frequency oscillations modulated by a low frequency signal. The CARFIR models are capable to properly forecast the low-frequencies but do not predict accurately the high-frequencies behavior of this signals. However, in this biomedical application the important information for the doctors are the one contained in the low-frequencies signals. Therefore, in spite of the relatively large MSE errors obtained, the models are able to capture quite reliably the relevant behavior of the controllers.

The first row of table 2 contains the predictions achieved when the pattern prediction scheme of CARFIR methodology is used for the five controllers. The columns of the table specify the average error of the 6 test sets for each controller. In this case the inference is performed by using exclusively the pattern rule bases. As can be seen, the results obtained are very good, with MSE errors lower than

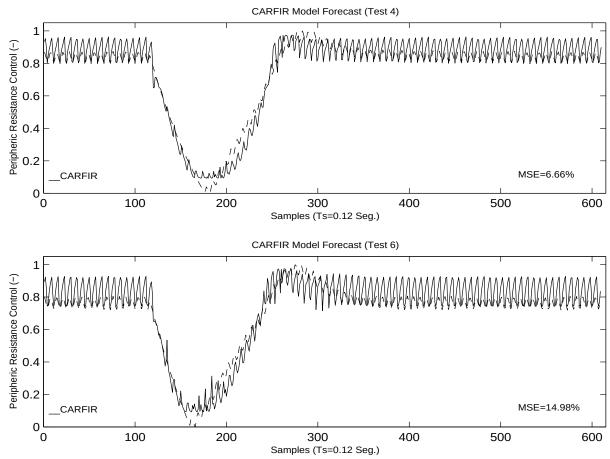

Fig. 7. Peripheric resistance control: best (data set #4) and worst (data set #6) prediction results

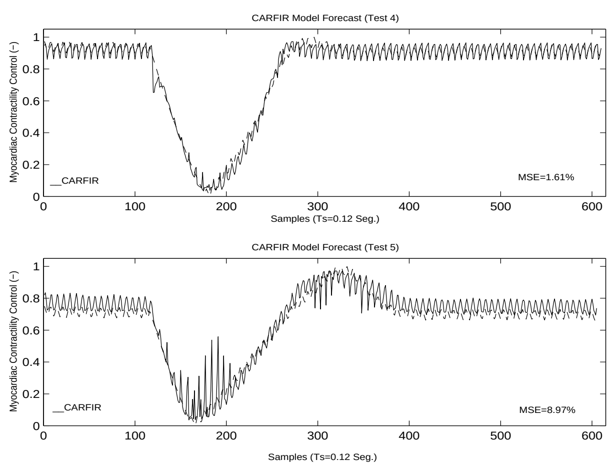

Fig. 8. Myocardiac contractility control: best (data set #4) and worst (data set #5) prediction results

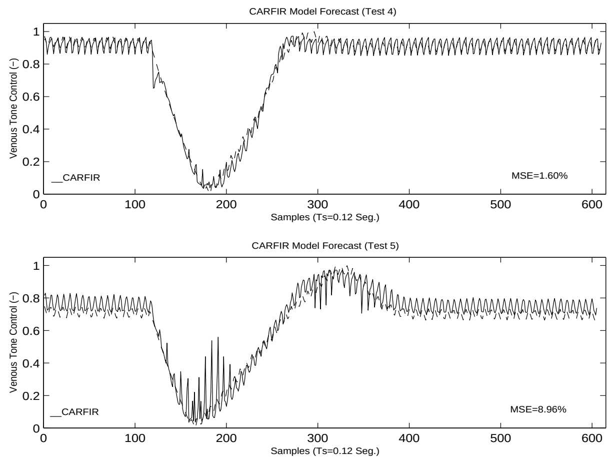

Fig. 9. Venous tone control: best (data set #4) and worst (data set #5) prediction results

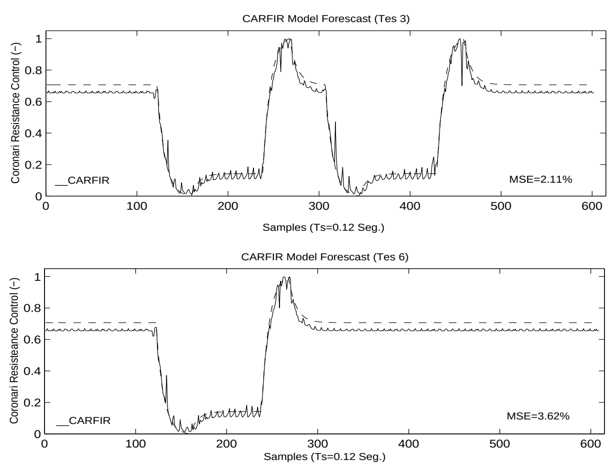

Fig. 10. Coronary resistance control: best (data set #3) and worst (data set #6) prediction results

1.5% for all the controllers [6]. The average error obtained for all the controllers is 1.16% much lower than the 6.72% obtained with the Sugeno fuzzy prediction scheme. Clearly, the prediction capability of the fuzzy rule base is inferior than the pattern rule base. However, the forecasting power of the fuzzy rule base is still acceptable from the medical point of view. It is important to notice that the size of the rule base has been extremely reduced, i.e. from 4198 pattern rules to 81 fuzzy rules. This is a relevant aspect that should be taken into account in the context of the CARFIR methodology.

Table 2. MSE prediction errors of the HR, PR, MC, VT, and CR controller models obtained using the pattern prediction scheme of CARFIR (FIR), NARMAX and TDNN methodologies

	HRC	**PRC**	**MCC**	**VTC**	**CRC**
FIR	1.37%	1.49%	1.41%	1.47%	0.09%
NARMAX	9.80%	14.89%	17.21%	16.89%	31.69%
TDNN	74.80%	21.10%	12.20%	9.20%	5.50%

The second and third rows of table 2 present the prediction results obtained when NARMAX and time delay neural networks are used for the same problem. Both methodologies used the same training and test data sets described previously. The errors obtained for all the controllers using NARMAX models are larger than the ones obtained by the fuzzy prediction scheme of CARFIR methodology (see table 1). The average error for all the controllers is 18.09% in front of the 6.72% accomplished by CARFIR (fuzzy rules). However, NARMAX models are much precise than time delay neural networks. As can be seen in the last row of table 2, the average prediction error computed by TDNNs for the five controllers is 24.56%, bigger than the 18.09% obtained by NARMAX models. In [6] the results obtained by NARMAX models were considered acceptable from the medical point of view. In extension also pattern and fuzzy models of CARFIR methodology should be acceptable, due to their higher prediction performance.

4 Conclusions and Future Work

In this paper a methodology for the automatic construction of rules in fuzzy inductive reasoning (CARFIR) is presented. FIR methodology is a powerful tool for systems identification and prediction. However, it has an important drawback, the size of the pattern rule base can be extremely large.

In this paper CARFIR performance is studied in the context of a biomedical application, i.e. the human central nervous system (CNS). The CNS is composed of five controllers, the *heart rate* , the *peripheric resistance* , the *myocardiac contractility* , the *venous tone*, and the *coronary resistance*. For each one of them a Sugeno fuzzy model has been identified starting form its corresponding pattern rule base. The fuzzy prediction scheme of the CARFIR methodology has been used to predict the 6 test data sets associated to each controller. The results show that the fuzzy models are capable of capturing the dynamic behavior of the system under study more accurately than NARMAX and NN approaches.

A main result of this research is that although the prediction capability of the fuzzy models is lower than that of the pattern models, the forecasting power of the fuzzy rule base is still acceptable from the medical point of view. Moreover, the size of the rule base has been extremely reduced, i.e. from 4198 pattern rules to 81 fuzzy rules. This is an important goal in the context of the CARFIR methodology.

The next step in CARFIR methodology will be the design of a mixed prediction scheme that will allow to obtain a better compromise between prediction performance and size of the rule base. The mixed scheme should be a combination of the Sugeno fuzzy rules and a reduced set of pattern rules. The advantage of the pattern rules is that they are more accurate than the fuzzy rules in those areas where a large degree of uncertainty exist. In order to take advantage of this fact, the mixed scheme will keep a percentage of pattern rules that will allow the prediction of those system states with a high degree of uncertainty. A first attempt of this idea has been postulated in [13], however it should be defined more accurately.

Acknowledgments

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