ADJUSTMENT OF MEMBERSHIP FUNCTIONS, GENERATION AND REDUCTION OF FUZZY RULE BASE FROM NUMERICAL DATA

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ABSTRACT

In this paper we introduce a new approach for adjustment of membership functions, generation, and reduction of fuzzy rule base from data in the same time. The proposed approach consists of five steps: First, generate fuzzy rules from data using Mendel & Wang Method introduced in [1]. Second, calculate the degree of similarity between rules. Third, measure the distance between the numerical values which induces similar rules. Four, if the distance is greater than base value then merge membership functions. Finally, regenerate rules from data with new fuzzy sets. This approach is applied to truck backer-upper control and Liver trauma diagnostic. A comparative study with a simple Mendel Wang method shows the advantages of the developed approach.

Keywords: ***fuzzy inference system, rule base generation and reduction, similarity, numerical data.***

1.0 INTRODUCTION

Fuzzy logic techniques implementing the expert knowledge and experiences have been widely applied to many complex control systems with unknown dynamics [2].

The main issues associated with a fuzzy system are

1. Estimation parameter, which involves determining the parameters of premises and consequences
2. Structure identification, which concerns partitioning the input space and determining the number of fuzzy rules for a specific performance [3].

The first issue can be based on expert knowledge available from human experts. This point of view, which seems natural, was historically the first one to be implemented, as in [4]. However, it soon appeared that for complex partially unknown systems, the interactions are very difficult to grasp and expert rules are not sufficient to yield a satisfactory simulation of the system. For this reason, fuzzy rule induction from sample data has been proposed in the bibliography for the problem of function approximation [1], [5], [6]. Tong [7] was the first to use numerical information to construct fuzzy systems. Using a relation model, a relation matrix was constructed by testing fuzzy propositions about the process against non fuzzy data. An important study in this context was carried out by Wang [1], whose paper proposes a procedure in which the principal characteristic is that each training datum is assigned to a region in the decomposition of the input space formed by the fuzzy partitions of the input domains. The element that has the maximal value within that region is used to create the rule for this one. As consequence of the rule is the fuzzy set in the output domain in which the training instance has maximal value. This is produced in a simple way; as for a datum, it first selects the membership functions that are activated to the greatest degree for each of the variables and then relates them (discarding the remaining linguistic values activated, both in the premise and the conclusion). Naturally, this algorithm produces an enormous number of rules when the total input data is considerable. There also arises the problem of contradictory rules, that is, rules with the same antecedent but different consequences. Furthermore, the determination of the consequence of a rule using a single training example can be adversely affected by noisy data in the training examples [8].

To acquire fuzzy rules, several paradigms have also been developed to generate fuzzy rules from numerical training data. In general, these approaches are simple and fast, i.e., they involve neither time-consuming iterative procedures nor a complicated rule-generation mechanism. The major drawbacks of these methods are that they are heuristic methods, and the membership function and the number of fuzzy rules needs to be predefined [9]. Among these methods are those based on hybrid techniques like methods using genetic algorithms [8-24] and methods using neural networks [25]-[41]. We can also find methods based on Fourier series [42], locality [18] or self organisation [24].

The classical approaches of fuzzy control deal with dense rule bases where the universe of discourse is fully covered by the antecedent fuzzy sets of the rule base in each dimension, thus, for every input there is at least one activated rule. The main problem is the high computational complexity of these traditional approaches. If a fuzzy model contains k variables and maximum T linguistic (or other fuzzy) terms in each dimension, the order of the number of necessary rules is T^k. This expression can be decreased either by decreasing T, or k, or both [43].

Several research efforts have been made in the fuzzy rule base reduction. We distinguish the interpolation approach ([17], [21], [37], [38]), the orthogonal methods based on the singular value decomposition ([44], [45]), and neural networks [15]. In recent years, some research has been undertaken in simplification of fuzzy rule-base using similarity analysis [46]. We consider three kinds of similarity: The first compares two fuzzy sets like in [23]. The second is defined between rule premises [31]. The third is proposed between two fuzzy numbers [47]. Every type of these approaches gives interesting results.

In this paper, a method to generate and reduce a fuzzy rule base and to adjust fuzzy membership functions is introduced. It is based on computing the similarity degree between fuzzy rules and numerical data. In fact, in some cases of similarity we propose to merge two fuzzy sets in the same set, thereby reducing fuzzy rules number. The remainder of this paper is organized as follows. In Section 2, a brief description of the Mendel-Wang Method is reviewed. Section 3 presents similarity method from the literature. The proposed approach is described in Section 4. In Section 5, simulation and experiment results are illustrated to indicate the effectiveness of the proposed method through a comparison with the Mendel Wang method. Finally, Section 6 provides the conclusion.

2.0 MENDEL & WANG METHOD

To design a control system, we first need to see what information is available. We assume that there is no mathematical model, i.e., we consider a model of free design problem. Since there is already a human controller, there are two kinds of information available: 1) the experience of human controller; and, 2) sampled input-output (state-control) pairs that are recorded from successful control by the human controller. The experience of the human controller is usually expressed as some linguistic "IF-THEN" rules that state in what situation(s) which action(s) should be taken. The sampled input-output pairs are some numerical data that give the specific values of the inputs and the corresponding successful outputs [1].

Each of the two kinds of information alone is usually incomplete. Although the system is successfully controlled by a human controller, some information will be lost when human controllers express their experience by linguistic rules. Consequently, linguistic rules alone are usually not enough for designing a successful control system. On the other hand, the information from sampled input-output data pairs is also generally not enough for a successful design because the past operations usually cannot cover all the situations the control system will face [1].

The method developed in [1] by Mendel and Wang generates fuzzy rules from numerical data pairs, collects these fuzzy rules and the linguistic fuzzy rules into a common fuzzy rule base, and finally designs a control or signal processing system based on the combined fuzzy rule base. A five-step procedure for generating fuzzy rule from numerical data pairs is proposed:

Step 1: divide the input and output spaces of the given numerical data into fuzzy regions

Step 2: generate fuzzy rules from the given data. First, determine the degrees of given data in different regions. Second, assign it to the region with a maximum degree. Finally, obtain one rule from one pair of desired input output data

Step 3: assign a degree of each of the generated rules for the purpose of resolving conflicts among the generated rules

Step 4: create a combined fuzzy rule base based on both the generated rules and linguistic rules of human experts

Step 5: determines a mapping from input space to output space based on the combined fuzzy rule base using a deffuzification procedure.

As we have already seen in the introduction, this method can be the origin of an enormous number of rules especially if the fuzzy sets choice is not discriminating enough. The introduction of noisy data can also be the source of erroneous rules. A similarity measure between fuzzy rules and a review of numerical data which generate these rules for alternative merging process can be a solution to these problems.

3.0 SIMILARITY MEASURES

The concept of similarity has been interpreted in different ways depending on the context. The interpretation of similarity in everyday language is "having characteristics in common" or "not different in shape, but in size or position." This interpretation of similarity differs from the one we use [47].

In the literature, we can find several kinds of similarity measure. In the next three sections, we cover three different approaches.

3.1 Similarity measure between two fuzzy sets

Since the theory of fuzzy sets [48] was proposed in 1965, many measures of similarity between fuzzy sets have been developed in the literature [26 - 32], [35].

We define similarity between fuzzy sets as *the degree to which the fuzzy sets are equal*. This definition is related to the concepts represented by the fuzzy sets. Consider the fuzzy sets A and B in Fig. 1. They have exactly the same shape, but represent clearly distinct concepts, e.g., respectively a low and a high value. They have zero degree of equality and are considered dissimilar. On the other hand, the two fuzzy sets have a high degree of equality in Fig. 2, even though they differ in shape. They represent compatible concepts and are considered similar [47].

Let A and B be two fuzzy sets with membership functions μ_A and μ_B, respectively. The similarity of those fuzzy sets may vary from 0, which means "completely distinct", to 1, which means that the fuzzy sets are similar. The most common similarity measure of fuzzy sets in the literature is based on the intersection and union operations among fuzzy sets and given by:

$$S(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|} \qquad (1)$$

where S is the similarity measured and |.| designates the cardinality or the size of a set, and intersection and union operators are shown by ∩ and ∪, respectively. However, implementation of this measure in a discrete universe is an easy task. In a continuous universe of discourse, it proves computationally intensive, particularly for Gaussian membership functions [49].

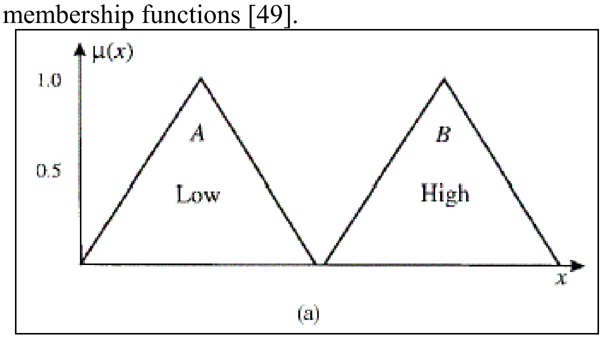

Fig.1: Distinct fuzzy sets with no degree of equality

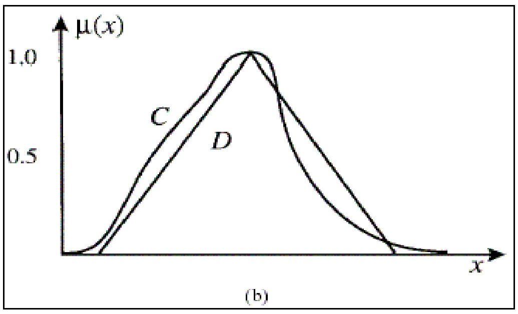

Fig. 2: Overlapping [47]

3.2 Similarity measure between rule premises

In [40] a similarity of rule premise (SRP) is adopted. This kind of similarity has been described first in [39] as follows:

R_i : if x_1 is A_{i1} and ... and x_n is A_{in} then y is B_i
R_k : if x_1 is A_{k1} and... and x_n is A_{kn} then y is B_k

The SRP of the two rules is defined by Equation (2).

$$SRP\ (i,k) = \min_{j=1}^{n}\ S(A_{ij}, A_{kj}) \qquad (2)$$

Where S(A, B) is a fuzzy similarity measure for fuzzy sets A and B, which is defined by Equation (1)

By checking the SRP of the fuzzy rules, redundant and inconsistent rules can be removed. In this way, the rule base can be simplified greatly.

3.3 Similarity measure between generalized fuzzy numbers

The measure of the similarity of fuzzy numbers is very important in the research topic of fuzzy decision [31]. In [29] and [30], Chen represented a generalized trapezoidal fuzzy number $\widetilde{A}$ as $\widetilde{A}$ = (a,b,c,d;w), where 0<w≤1, and a, b, c and d are real numbers [31].

Assume that there are two trapezoidal fuzzy numbers, where $\widetilde{A}$ = (a_1, a_2, a_3, a_4; w) and $\widetilde{B}$ = (b_1, b_2, b_3, b_4; w), then the degree of similarity $S(\widetilde{A}, \widetilde{B})$ between the trapezoidal fuzzy numbers $\widetilde{A}$ and $\widetilde{B}$ can be calculated as follows [28]:

$$S(\widetilde{A}, \widetilde{B}) = 1 - \frac{\sum_{i=1}^{4} |a_i - b_i|}{4} \qquad (3)$$

where $S(\widetilde{A}, \widetilde{B}) \in [0,1]$. If $\widetilde{A}$ and $\widetilde{B}$ are triangular fuzzy numbers, $\widetilde{A}$ = (a_1, a_2, a_3) and $\widetilde{B}$ = (b_1, b_2, b_3), then the degree of similarity between them can be calculated by the same formula when 4 is replaced by 3. There exist others definitions of similarity measure described in [31]. In the following section, similarity measure will be used in order to reduce an over dimensioned fuzzy rules sets.

4.0 PROPOSED METHOD

In the literature we find especially methods of fuzzy rule generation through numerical data [8-10]. The reduction step is generally made when the rule base is more complete. Our main objective in this work is to link reduction and generation process to obtain better benefit from the numerical values. Thus, one gets an adequate rule base with well adjusted membership functions and a necessary and sufficient number of fuzzy sets.

The key ideas of our new approach are to generate fuzzy rules from numerical data according to Mendel and Wang method. Then, the degree of similarity between fuzzy rules is computed. In case of similar rules, we check the distance between input data which permitted the generation of these rules. If the distance is higher than the intersection base between concerned fuzzy sets, then we merge them. So there will be rules deletion and membership function adjustment at the same time. Next, we return to the generation of rules from numerical data. Finally, we obtain fuzzy rules and collect linguistic fuzzy rules into a common fuzzy rule base. We cover these five steps next.

(i) *Step 1*
Generate an initial fuzzy rule base from data using Mendel & Wang Method (see more detail in section III)

(ii) *Step 2*
In this step, we propose a new similarity measure between two fuzzy rules defined by Equation (4).

$$d_s = \frac{\sum_{k \in input \ and \ output \ paameters} S\left(A_{ik}, A_{jk}\right)}{Total \ number \ of \ input \ and \ output \ parameters} \quad (4)$$

Similarity relation $S(A_{ik}, A_{jk})$ is the same as the one defined in Equation (1). For the sake of simplicity, we consider the particular case where similarity is Boolean. This means $S(A_{ik}, A_{jk})$ is equal to zero if the fuzzy sets are different.

The step consists of the computation of the degree of similarity between all rules in the order of apparition.

- Consider these two rules:

R_1: if x_1 is A_1 and x_2 is B_1 and x_3 is C_1 then y is D_1
R_2: if x_1 is A_1 and x_2 is B_1 and x_3 is C_2 then y is D_1

The degree of similarity in this case is computed as follows:
$d_s = 3/4 = 75\ \%$

- Consider these two rules:

R_1 : if x_1 is A_1 and x_2 is B_1 and x_3 is C_1 and x_4 is D_1 then y_1 is E_1 and y_2 is F_1
R_2 : if x_1 is A_1 and x_2 is B_1 and x_3 is C_2 and x_4 is D_1 then y_1 is E_1 and y_2 is F_2

The degree of similarity in this case is computed as follows:
$d_s = 4/6 = 66{,}67\ \%$

(iii) <u>*Step 3*</u>

One can give a minimal value of the degree of similarity between two rules: d_{smin}

if ($d_s > d_{smin}$) then
  Go to step 4
else
  Stop algorithm

In the first example of the last step, we can choose d_{smin} equal to 50%. Since 66.67 > 50 we can go to the next step.

(iv) <u>*Step 4*</u>

Compute the absolute value of the distance between the numerical data which gives different fuzzy sets in the concerned rules (d_{num})

If d_{num} is greater than the base intersection distance of the membership function (d_b), then the two concerned fuzzy sets is merged. The same process is applicable for premise and conclusion parts.

Example:

Consider these two rules R_i and R_j (with i<j precedence at the generation process):

R_i: if x_1 is A_{i1} and x_2 is A_{i2} and x_3 is A_{i3} and x_4 is A_{i4} then y is A_{i5}
R_i: if x_1 is A_{j1} and x_2 is A_{j2} and x_3 is A_{j3} and x_4 is A_{j4} then y is A_{j5}

We suppose: $A_{i1} = A_{j1}$, $A_{i2} = A_{j2}$ and $A_{i4} = A_{j4}$
The degree of similarity is $d_s = 3/5 = 60\%$
We suppose: $d_{smin} = 50\%$, so we go from Step 3 to 4. Data pairs which permit the two rules R_i and R_j generation are respectively:

$$D_i = \{(X_{i1}^1, X_{i2}^1, X_{i3}^1, X_{i4}^1, Y_{i1}^1), (X_{i1}^2, X_{i2}^2, X_{i3}^2, X_{i4}^2, Y_{i1}^2), (X_{i1}^3, X_{i2}^3, X_{i3}^3, X_{i4}^3, Y_{i1}^3)\}$$
$$D_j = \{(X_{j1}^1, X_{j2}^1, X_{j3}^1, X_{j4}^1, Y_{j1}^1), (X_{j1}^2, X_{j2}^2, X_{j3}^2, X_{j4}^2, Y_{j1}^2)\}$$

with

$$X_{ab}^c \begin{cases} a & \text{Rule number} \\ b & \text{Parameter number in the rule} \\ c & \text{Data pair number} \end{cases}$$

This step consists of the validation of the possibility of adjustment of the fuzzy sets relative to the first rule through numerical data. This can be achieved by verification of the following assumption:

$$\forall X_{ib}^c, d_{num}(X_{ib}^c, R_j) > d_b(A_{ib}, A_{jb}) \quad (5)$$

This relation must be verified for each data pairs of D_1. It justifies the merging process. In fact, if the numerical data pairs exist in an intersection zone, then the similarity value computed in the third step is a logic consequence.

Consider the same example with the following data pairs:

$$D1 = \begin{bmatrix} X_1 & X_2 & X_3 & X_4 & Y \\ 10 & 22 & 2.25 & 3 & 0.8 \\ 12 & 24 & 2.5 & 3.5 & 0.7 \\ 15 & 25 & 2.75 & 4 & 0.6 \end{bmatrix}$$

With the stated equalities, rules R_i and R_j are written as:

R_i: *if* x_1 *is A and* x_2 *is B and* x_3 *is* C_i *and* x_4 *is D then y is* E_i
R_j: *if* x_1 *is A and* x_2 *is B and* x_3 *is* C_j *and* x_4 *is D then y is* E_j

Graphically these points are located in Fig. 3.

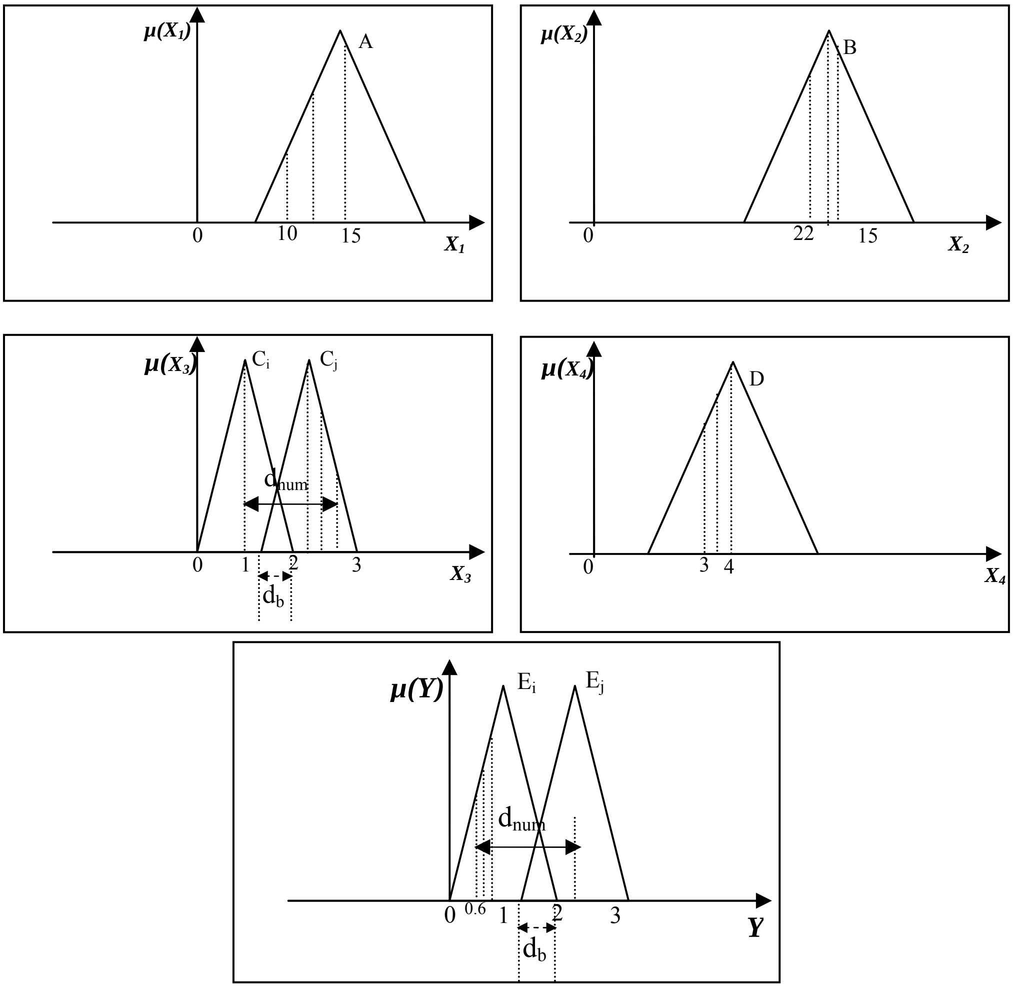

Fig. 3: Graphically representation of R_i and R_j rules

Thus C_i and C_j must be merged by generating a new fuzzy set. In the same way E_i and E_j are merged. Only one rule is therefore obtained:

$$R_i': \textit{Si } x_1 \textit{ est } A \textit{ et } x_2 \textit{ est } B \textit{ et } x_3 \textit{ est } C' \textit{ et } x_4 \textit{ est } D \textit{ alors } y \textit{ est } E'$$

The merging process is represented in Fig. 4. A conflict problem does not arise. Indeed, if we have three similar rules R_i, R_j, and R_k which can be subjected to merging operations we treat its rules according to their generation order.

(v) *Step 5*

Regenerate fuzzy sets from initial numerical data with new fuzzy sets.

So one can note that this new algorithm gives the possibility to generate and reduce fuzzy rules with membership function adjustment from numerical data in the same process. Note that different fuzzy sets (having no common region) are not concerned with the merging process and the linguistic significance of fuzzy sets should be respected in the merging operation to preserve the interpretability of obtained fuzzy rules.

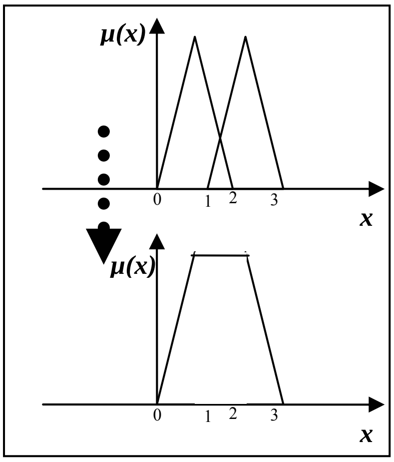

Fig. 4: Merging operation

5.0 ILLUSTRATIONS

In this section, the proposed method will be tested on two examples. The first is the same as that described in [1]; only parameter values are different. It is about truck backer upper control. The second is a medical application. It is about treatment of liver trauma.

5.1 Truck backer-upper control

Backing a truck to a loading dock is a difficult exercise. It is a non linear control problem for which no traditional control system design methods exist [1].

The truck position is exactly determined by three state variables Φ, x, and y, where Φ is the angle of the truck with the horizontal as shown in Fig. 5. The manipulated variable to control the truck is the angle θ. Only backing up is considered. The truck moves backward by a fixed unit distance every stage. For simplicity, we assume enough clearance between the truck and the loading dock such that y does not have to be considered as an input [1].

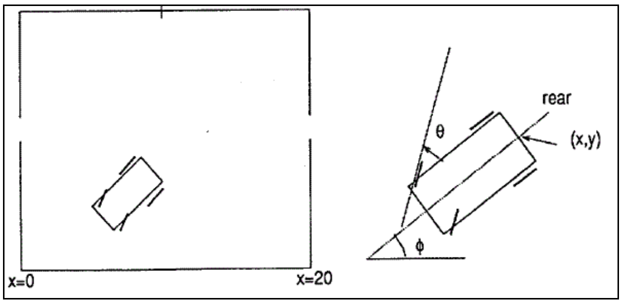

Fig. 5: Diagram of simulated truck and loading zone

The following kinematics approximation is used (see [50] for details):

$$x(t+1) = x(t) + \cos[\Phi(t)+ \theta(t)] + \sin[\theta(t)] \sin[\Phi(t)] \quad (6)$$
$$y(t+1) = y(t) + \sin[\Phi(t)+ \theta(t)] - \sin[\theta(t)] \cos[\Phi(t)] \quad (7)$$
$$\Phi(t+1) = \Phi(t) - \sin^{-1} [2 \sin(\theta(t)) / b] \quad (8)$$

where b is the length of the truck. We assume $b = 4$ in the simulation of this paper [1].

The task here is to design a control system, whose inputs are Φ Є [-90°, 270°] (see Fig. 6) and x Є [0, 20] (see Fig. 7), and whose output is θ Є [-40°, 40°] (see Fig. 8), such that the final states will be (xf, Φf) = (9,90).

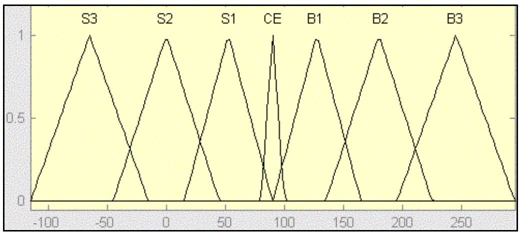

Fig. 6: Φ membership function

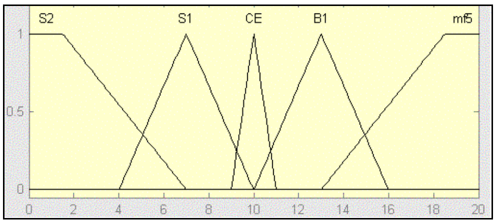

Fig. 7: x membership function

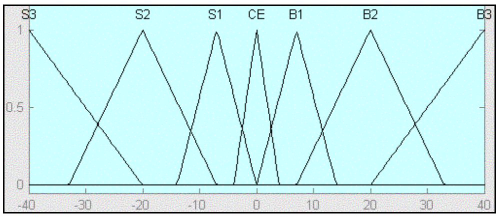

Fig. 8: θ membership function

Numerical data for simulation are the same as that defined in [1] (see Table 2)

Table 1: Truck backer-upper (Numerical data)

X	Φ	θ
1.00	0.00	-19.00
1.95	9.37	-17.95
2.88	18.23	-16.90
3.79	26.59	-15.85
4.65	34.44	-14.80
5.45	41.78	-13.75
6.18	48.6	-12.70
7.48	54.91	-11.65
7.99	60.71	-10.60
8.72	65.99	-9.55
9.01	70.75	-8.50
9.28	74.98	-7.45
9.46	78.7	-6.40
9.59	81.9	-5.34
9.72	84.57	-4.30
9.81	86.72	-3.25
9.88	88.34	-2.20
9.91	89.44	0.00

Table 2: Truck backer-upper (Fuzzy rules generated from numerical data) and degree of truth Step 1 to 3 of MW method

X	Φ	Θ	Degree of truth
S2	S2	S2	0,925
S2	S2	S2	0,793
S2	S2	S2	0,598
S2	S2	S2	0,415
S2	S1	S2	0,426
S1	S1	S2	0,481
S1	S1	S2	0,439
S1	S1	S2	0,359
S1	S1	S1	0,484
S1	S1	S1	0,429
S1	S1	S1	0,332
CE	S1	S1	0,28
CE	S1	S1	0,2751
CE	CE	S1	0,19
CE	CE	S1	0,457
CE	CE	S1	0,464
CE	CE	CE	0,45
CE	CE	CE	0,91

The fuzzy rules obtained after the application of the first to third steps of Mendel-Wang method are regrouped in Table 3. After the application of fourth and fifth steps of Mendel-Wang algorithm, five fuzzy rules have been obtained (See table 4).

Let;s measure similarity between these two following rules:

R1 : if x is S2 and Φ is S2 then θ is S2
R2 : if x is S2 and Φ is S1 then θ is S2

d_s = 2/3 = 66.66 % , and suppose that d_{min_s} = 50 %

These two rules are obtained from the first and the fifth numerical data. One can calculate d_{num} as:

$d_{num} = 34.44 - 0 = 34.44 > d_b = 45 – 15 = 30$

So we merge the S_1 and S_2 fuzzy sets. After this, we apply Mendel-Wang algorithm for the numerical data with the new fuzzy sets. Obtained rules are regrouped in Table 5.

Table 4: Truck backer-upper (Initial rule base)

		X						
		S3	S2	S1	CE	B1	B2	B3
Φ	S3							
	S2		S2					
	S1		S2	S1	S1			
	CE				CE			
	B1							
	B2							
	B3							

Table 5: Truck backer-upper (Final rule base)

		X					
		S3	S2	CE	B1	B2	B3
FI	S3						
	S1		S2	S1			
	CE			CE			
	B1						
	B2						
	B3						

One can calculate the degree of similarity between the rules:

R_1 : *if* x is S_1 *and* Φ is S_1 *then* θ is S1
R_2 : *if* x is CE *and* Φ is S_1 *then* θ is S1

A new merge solution can be proposed. The final rule base is proposed in Table 6:

Table 6: Truck backer-upper
(Rules after first fuzzy sets merge and similar rules)

X	**Φ**	**θ**	**Degree of truth**
S2	S1	S2	0,925
S2	S1	S2	0,793
S2	S1	S2	0,598
S2	S1	S2	0,415
S2	S1	S2	0,426
S1	S1	S2	0,481
S1	S1	S2	0,439
S1	S1	S2	0,359
S1	S1	S1	0,484
S1	S1	S1	0,429
S1	S1	S1	0,332
CE	S1	S1	0,28
CE	S1	S1	0,2751
CE	CE	S1	0,19
CE	CE	S1	0,457
CE	CE	S1	0,464
CE	CE	CE	0,45
CE	CE	CE	0,91

In the following we compare simulation results obtained with each of these two methods:

- The evolution of Φ shows a similar behaviour with a faster response for the Mendel-Wang method (see Fig. 9).
- The compared methods present the same evolution for the variables Φ, x, and y (see Fig. 9, 10 and 11 respectively).
- The evolution of θ shows a similar evolution toward the solution in the beginning. Then, we observe an alternation of behaviour (see Fig. 12)

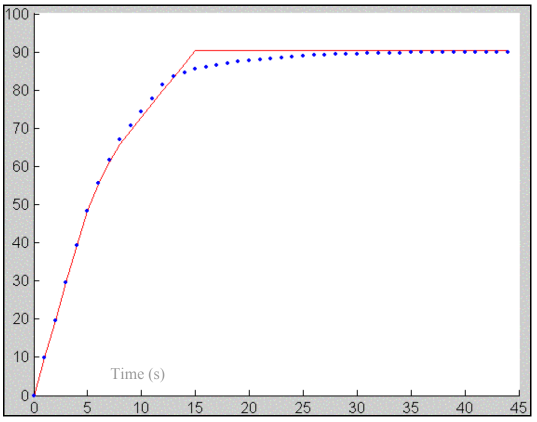

Fig. 9: Φ evolution

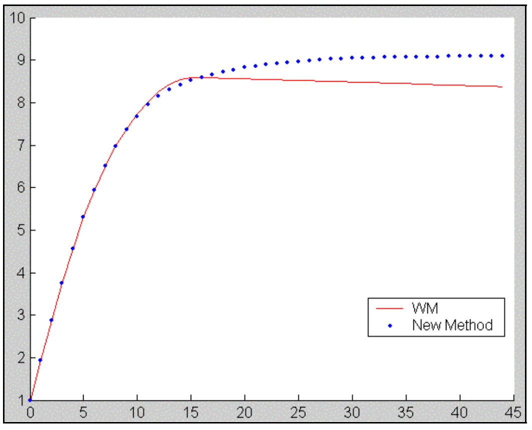

Fig. 10: x evolution

Through these results, we can conclude that these two methods give the same solution in the end with a small rapid convergence for the initial Wang and Mendel method.

However, with the first solution, we obtain 5 rules. In the second method, only three rules are obtained with the best cover of universe.

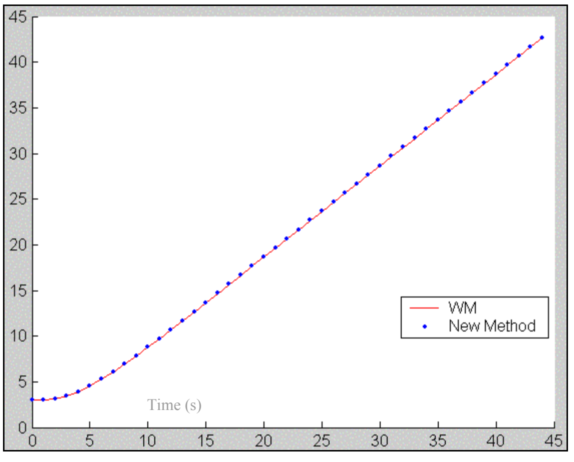

Fig. 11: y evolution

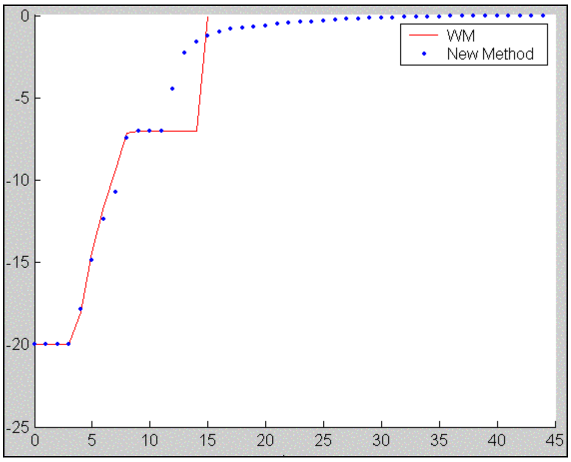

Fig. 12: θ evolution

5.2 Liver trauma

The liver is the largest solid abdominal organ with a relatively fixed position, which makes it prone to injury (See Fig.13). The liver is the second most commonly injured organ in abdominal trauma, but damage to the liver is the most common cause of death after abdominal injury. The most common cause of liver injury is blunt abdominal trauma, which is secondary to motor vehicle accidents in most instances.

Most liver injuries (>85%) involve segments 6, 7, and 8 of the liver [12]. This type of injury is believed to result from simple compression against the fixed ribs, spine, or posterior abdominal wall. Pressure through the right hemi thorax may propagate through the diaphragm, causing a contusion of the dome of the right lobe of the liver. The liver's ligamentous attachment to the diaphragm and the posterior abdominal wall can act as sites of shear forces during deceleration injury.

Different types of treatment have been recommended over the past decades such as no operative treatment, aggressive surgery, and conservative surgery [36]. However, surgical literature confirms that as many as 86% of liver injuries have stopped bleeding by the time surgical exploration is performed, and 67% of operations performed for blunt abdominal trauma are no therapeutic[12].

Several systems have been devised to classify liver injuries; however, the lack of consistency of scoring severity in organ injury is a problem. To rectify the problem, the American Association for the Surgery of Trauma (AAST) developed a system based on the amount of anatomic disruption of an individual organ. Currently, the scoring system which includes grades 1-6 is used routinely in the United States. A CT scan classification of liver injuries based on the AAST liver injury criteria has been devised by Mirvis et al [12]. This classification has been found to be valuable in predicting prognosis and treatment needs in adult patients with liver trauma.

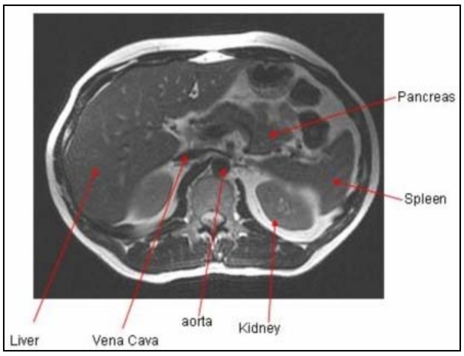

Fig. 13: Axial fast scan breaths hold [51]

A retrospective study about 77 consecutive patients admitted at general surgery service of Habib Bourguiba Hospital of Sfax for hepatic injury was developed in [52]. Among objectives of this survey is the precision of selection criteria's to adopt a CT. Then different parameters have been considered which include:

- Age
- pulse
- Blood pressure - Systolic
- Blood pressure - Diastolic
- Hemoglobin (HGB)
- Hematocrit (HCT)
- White Blood Cell Count (WBC)
- Serum Glutamic-Pyruvic Transaminase - ALT (SGPT)
- Serum Glutamic-Oxalocetic Transaminase – AST (SGOT)
- Prothombin time
- Hemoperitoneum
- Contusion
- Number of Segments

In the following, we briefly define the retained parameters to develop the desired fuzzy system. Usually, in medicine we differentiate the fuzzy sets for men, women, and the children as their normal values are not the same. In this study, we will only treat the men case.

- ***Age***

'Young', 'Middle Age', 'Adult' and 'Aged' are retained fuzzy sets for 'Age'. Fig. 14 shows the MF corresponding to its.

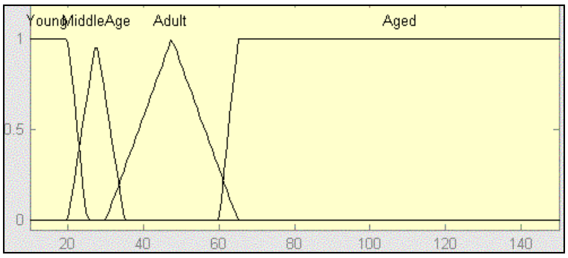

Fig. 14: Age MFs

- ***Pulse***

Many factors affect normal heart rate, including age, activity level, and the time of day. Table 7 shows the normal range of a resting heart rate (pulse rate after resting 10 minutes) in beats per minute, according to age [8].

Table 7: Normal range of a resting heart rate

Age or fitness level	*Beats per minute (bpm)*
Babies to age 1:	100–160
Children ages 1 to 10:	60–140
Children age 10+ and adults:	60–100
Well-conditioned athletes:	40–60

'Very Low', 'Low', 'Normal', 'High', and 'Very High' are retained Fuzzy sets for 'Pulse'. Fig. 15 shows the retained corresponding MFs.

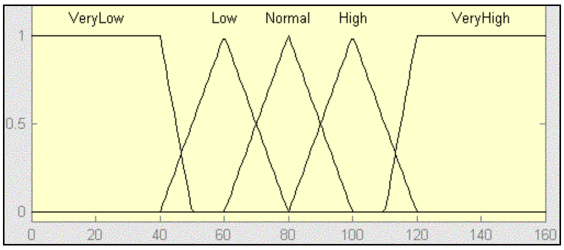

Fig. 15: Pulse MFs

- Blood pressure (**Systolic** / ***Diastolic***): Blood is carried from the heart to all parts of body in vessels called arteries. Blood pressure is the force of the blood pushing against the walls of the arteries. Each time as the heart beats (about 60-70 times a minute at rest), it pumps out blood into the arteries. Blood pressure is at its highest when the heart beats, pumping it. This is called systolic pressure. When the heart is at rest, between beats, blood pressure falls. This is the diastolic pressure [45]. 'Very Low', 'Low', 'Normal', 'High', and 'Very High' are retained Fuzzy sets for 'Systolic' (see Fig. 16). Fig. 17 shows the retained corresponding MF for 'Diastolic'.

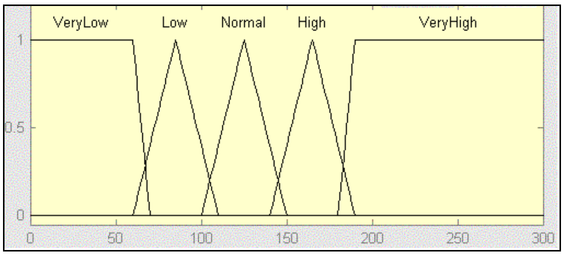

Fig. 16: Systolic MFs

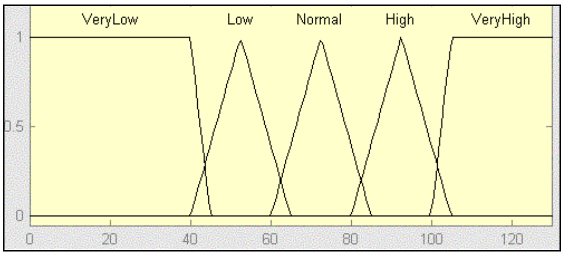

Fig. 17: Diastolic MFs

- Hemoglobin (***HGB***) is the iron-containing protein (pigment) found in red blood cells. Hemoglobin transports oxygen from the lungs to the body's tissues. [3]. 'Very Low', 'Low', 'Normal', 'High', and 'Very High' are retained Fuzzy sets for 'HGB'. Fig. 18 shows the retained corresponding MFs.

- Hematocrit (***HCT***) is the percentage, by volume, of red cells in blood. Normal range for males is about 40-54 and for females 37-47 (values may vary slightly between laboratories)[3]. 'Very Low', 'Low', 'Normal', 'High', and 'Very High' are retained Fuzzy sets for 'HCT'. Fig. 19 shows the retained corresponding MFs.

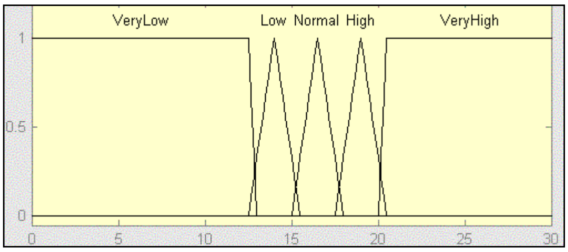

Fig. 18: HGB MFs

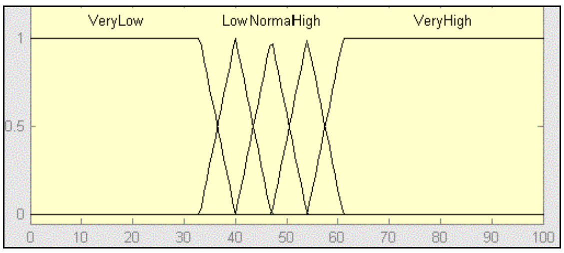

Fig. 19: HCT MFs

- White Blood Cell Count (***W.B.C.***) : blood cells that engulf and digest bacteria and fungi; an important part of the body's defence system [3]. 'Very Low', 'Low', 'Normal', 'High', and 'Very High' are retained Fuzzy sets for 'WBC'. Fig. 20 shows the retained corresponding MFs.

- <u>Serum Glutamic-Pyruvic Transaminase - ***ALT*** (***SGPT***) :</u> Alanine aminotransferase (commonly abbreviated ALT) is a type of enzyme. An enzyme is a type of protein that helps produce chemical reactions in the body. The normal range of ALT on blood work tests is less than 35 units per liter (U/L) or 5 to 35 International Units per liter (IU/L) [27]. 'Low', 'Normal', and 'High' are retained Fuzzy sets for 'ALT'. Fig. 21 shows the retained corresponding MFs.

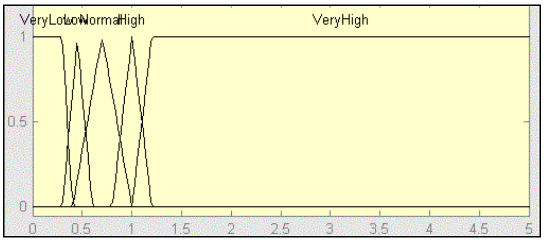

Fig. 20: W.B.C MFs

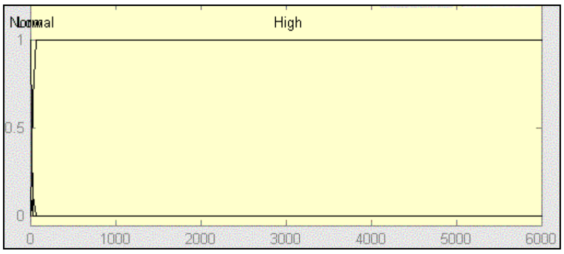

Fig. 21: ALT MFs

- <u>Serum Glutamic-Oxalocetic Transaminase - ***AST*** (***SGOT***)</u> is a type of enzyme. The normal range is 10 to 34 IU/L (Note: IU/L = international units per liter) [27]. 'Low', 'Normal', and 'High' are retained Fuzzy sets for 'AST'. Fig. 22 shows the retained corresponding MFs.

- <u>Prothombin time (***PT***) :</u> The prothrombin time, or PT, test measures the time it takes blood to form a clot. This test is also often called protime. The normal PT range is 11 to 14 seconds. The normal range may vary slightly from lab to lab. 'Low', 'Normal', and 'High' are retained Fuzzy sets for 'PT'. Fig. 23 shows the retained corresponding MFs.

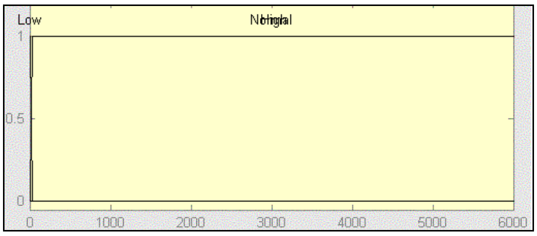

Fig. 22: AST MFs

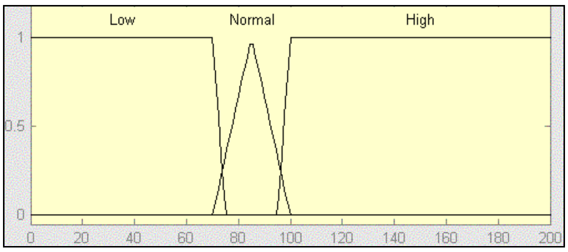

Fig. 23: PT MFs

- <u>Hemoperitoneum</u> is the blood into peritoneal cavity. Four grades are considered: 'Large', 'Medium', 'Small', and 'Not' (see Fig. 24). These grades are attributed by the radiology doctor.
- <u>Contusion</u> or hematoma deep is the direct impact against the abdominal partition engendered by a shock (for example: against the Wheel, a kick, a stroke of clog, a bruising). 'Low', 'Medium', and 'High' are retained Fuzzy sets for 'Contusion'. Fig. 25 shows the retained corresponding MFs.

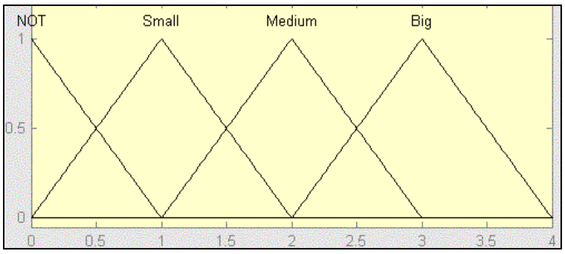

Fig. 24: Hemoperitoneum MFs

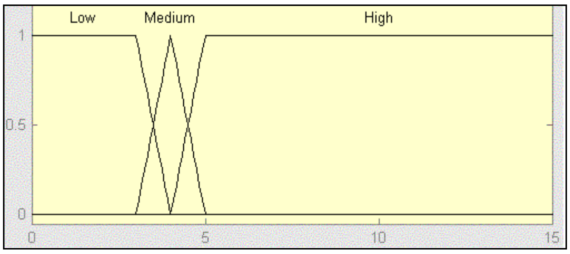

Fig. 25: Contusion MFs

- Number of segments

The liver is generally divided into segments for accurate localization of liver lesion (8 segments) [51]. Four MF are considered 'Small', 'Medium', 'Large', and 'Very Large' (see Fig. 26).

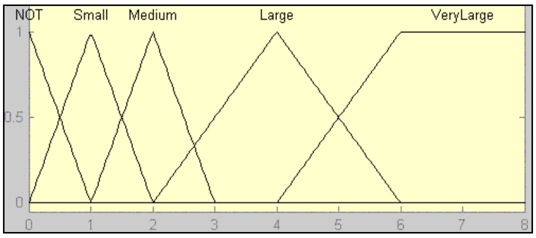

Fig. 26: Nb Segments MFs

In the following, we proceed to the construction of the fuzzy systems. Numerical values were extracted from a retrospective study in [52]; about 77 consecutive patients admitted at general surgery service of Habib Bourguiba Hospital of sfax for hepatic injury. Only men patients (Sex = M and Age > 10 years) were considered in this paper.

Numerical data is presented in Table 8. Rules obtained after application of Mendel Wang method are regrouped in Table 9. There are 19 rules.

In first step, similarity measure can be applied to rules 2 and 4.
$d_s = 11/14 = 78$ % and suppose that $d_{min\_s} = 70$ %

These two rules are obtained from the second and the fourth numerical data. So one can calculate $d_{num(HGB)}$, $d_{num(HCT)}$ and $d_{num(PT)}$ as :

$$d_{num(HGB)} = 15.6 - 13.5 = 2.1 > d_b = 1.5$$
$$d_{num(Contusion)} = 10 - 4 = 6 > d_b = 1$$
$$d_{num(NbSegments)} = 2 - 1 = 1 >= d_b = 1$$

We proceed to the merge of:

- Low and Very Low (HGB)
- Medium and Large (Contusion)
- Small and Medium (NbSegments)

The same procedure can be applied between rule 6 and 10 (see table 9). The final rule base is represented in Table 10.

One can say that the medical domain remains difficult to explore seen the number of parameters and membership functions that are associated to them. Indeed, mathematically the total rule number is about: 101250000. This number is in the order of 43200000 after reduction processes. In reality, this remains to discuss existence of impossible combinations. For our example, the initial number of rules is small compared to these last. The goal for the application of the algorithm is to have a best configuration and definition of the rule base.

6.0 CONCLUSION

In this paper, we propose an idea of using numerical data for generation and reduction fuzzy rules and adjustment of membership function. In our approach, we first generate fuzzy rule base using Mendel & Wang method. Then, we compute the degree of similarity between each rule in the order of apparition. In other words, we select candidate rules. Next, we compute the absolute value of the distance between the numerical data which gives different fuzzy sets in the concerned rules. If this last is greater than the base intersection distance of the membership function, we merge the two concerned fuzzy sets. The same process is applicable for premise and conclusion parts. Finally, we regenerate fuzzy sets from initial numerical data with new fuzzy sets.

The performance of this approach has been evaluated through two examples: a truck backer upper controller and a liver trauma diagnostic. Appreciate results are obtained with both of these applications. In fact, a best cover of universe and definition of the rule base is assured. See the big number of inputs, medical application is still more difficult.

The advantage of our approach is that it can theoretically be applied to any kinds of numerical method. Furthermore, the approach can treat a large data set because the number of candidate rules is decreased by the prescreening procedure.

Finally, different axes from generalization can be discussed. In fact, the study can cover model TSK [53] via similarity study of conclusion coefficient of this last.

Table 8: Liver Trauma (Numerical data about 19 patients)

Case	Age	pulse	Systolic	Diastolic	HGB	HCT	W.B.C	ALT	AST	PT	Hemo	Cont	Nb Seg	TOP
1	37	90	13	8	13.3	40	10400	48	149	52	2	6	2	0
2	18	84	13	8	15.6	43.3	11200	113	116	75	2	4	1	0
3	18	88	9	6	11.3	36	29600	339	243	65	2	4	1	0
4	21	80	12	8	13.5	41.5	24900	1400	835	74	2	10	2	0
5	23	79	10	6	11.6	35	17000	70	46	80	0	8.5	1	0
6	12	100	10	5	9	25	9000	187	75	90	2	5	1	0
7	37	100	14	8	14.2	42.2	17000	1145	1146	90	0	12	3	0
8	19	100	12	5	14.4	40.8	16000	98	119	70	0	2.5	1	0
9	37	100	8	5	9.6	27	13300	800	580	62	4	9	2	0
10	22	100	12	8	14	40	10400	1400	1600	78	2	6	1	0
11	32	130	11	8	17.5	46.3	14700	615	630	45	2	10	1	0
12	15	90	13	7	12	37.8	8900	204	208	58	1	5	1	0
13	34	90	12	7	13.5	39.3	19900	93	106	70	1	4	1	0
14	22	99	14	7	11.6	36.7	12400	150	140	70	2	5	2	0
15	56	140	6	3	12	40	13000	380	442	90	2	10	4	1
16	36	140	8	4	12.7	39.7	14900	116	57	58	2	5	2	1
17	47	76	11	6	13	37	10600	58	135	59	2	3	1	1
18	12	100	10	6	10.9	34.2	11600	440	650	40	1	2	1	1
19	29	75	13	7	11.6	35.3	6500	480	500	36	1	7	2	1

Nb Seg : Number of segments Cont : Contusion

Table 9: Liver Trauma (Rule Base)

Case	Age	pulse	Systolic	Diastolic	HGB	HCT	W,B,C	ALT	AST	PT	Hemo	Contusion	Nb Segments	TOP
1	Adult	High	VLow	VLow	VLow	Low	High	High	High	Low	Medium	Large	Medium	NCT
2	Young	Normal	VLow	VLow	Low	Low	VHigh	High	High	Normal	Medium	Medium	Small	NCT
3	Young	Normal	VLow	VLow	VLow	VLow	VHigh	High	High	Low	Medium	Medium	Small	NCT
4	Young	Normal	VLow	VLow	VLow	Low	VHigh	High	High	Normal	Medium	Large	Medium	NCT
5	Young	Normal	VLow	VLow	VLow	VLow	VHigh	High	High	Normal	NOT	Large	Small	NCT
6	Young	High	VLow	VLow	VLow	VLow	High	High	High	Normal	Medium	Large	Small	NCT
7	Adult	High	VLow	VLow	VLow	Low	VHigh	High	High	Normal	NOT	Large	Large	NCT
8	Young	High	VLow	VLow	Low	Low	VHigh	High	High	Low	NOT	Small	Small	NCT
9	Adult	High	VLow	VLow	VLow	VLow	VHigh	High	High	Low	Large	Large	Medium	NCT
10	Young	High	VLow	VLow	VLow	Low	High	High	High	Normal	Medium	Large	Small	NCT
11	MAge	VHigh	VLow	VLow	Normal	Normal	VHigh	High	High	Low	Medium	Large	Small	NCT
12	Young	High	VLow	VLow	VLow	Low	High	High	High	Low	Small	Large	Small	NCT
13	Adult	High	VLow	VLow	VLow	Low	VHigh	High	High	Low	Small	Medium	Small	NCT
14	Young	High	VLow	VLow	VLow	Low	VHigh	High	High	Low	Medium	Large	Medium	NCT
15	Adult	VHigh	VLow	VLow	VLow	Low	VHigh	High	High	Normal	Medium	Large	Large	CT
16	Adult	VHigh	VLow	VLow	VLow	Low	VHigh	High	High	Low	Medium	Large	Medium	CT
17	Adult	Normal	VLow	VLow	VLow	Low	High	High	High	Low	Medium	Small	Small	CT
18	Young	High	VLow	VLow	VLow	VLow	VHigh	High	High	Low	Small	Small	Small	CT
19	MAge	Normal	VLow	VLow	VLow	VLow	Normal	High	High	Low	Small	Large	Medium	CT

VLow : Very Low VHigh : Very High
Mage : Middle Age VLarge : Very Large
Nb Seg : Number of segments Cont : Contusion

Table 10: Final Liver Trauma Rule Base

Case	Age	pulse	Systolic	Diastolic	HGB	HCT	W,B,C	ALT	AST	PT	Hemo	Contusion	Nb Segments	TOP
1	Adult	High	VLow	VLow	Low	Low	High	High	High	Low	Medium	Large	Medium	NCT
2	Young	Normal	VLow	VLow	Low	Low	VHigh	High	High	Normal	Medium	Large	Medium	NCT
3	Young	Normal	VLow	VLow	Low	Low	VHigh	High	High	Low	Medium	Large	Medium	NCT
5	Young	Normal	VLow	VLow	Low	Low	VHigh	High	High	Normal	NOT	Large	Medium	NCT
6	Adult	High	VLow	VLow	Low	Low	VHigh	High	High	Normal	NOT	Large	Large	NCT
7	Young	High	VLow	VLow	Low	Low	VHigh	High	High	Low	NOT	Medium	Medium	NCT
8	Adult	High	VLow	VLow	Low	Low	VHigh	High	High	Low	Big	Large	Medium	NCT
9	Young	High	VLow	VLow	Low	Low	High	High	High	Normal	Medium	Large	Medium	NCT
10	MAge	VHigh	VLow	VLow	Normal	Normal	VHigh	High	High	Low	Medium	Large	Medium	NCT
11	Young	High	VLow	VLow	Low	Low	High	High	High	Low	Small	Large	Medium	NCT
12	Adult	High	VLow	VLow	Low	Low	VHigh	High	High	Low	Small	Large	Medium	NCT
13	Young	High	VLow	VLow	Low	Low	VHigh	High	High	Low	Medium	Large	Medium	NCT
14	Adult	VHigh	VLow	VLow	Low	Low	VHigh	High	High	Normal	Medium	Large	Large	CT
15	Adult	VHigh	VLow	VLow	Low	Low	VHigh	High	High	Low	Medium	Large	Medium	CT
16	Adult	Normal	VLow	VLow	Low	Low	High	High	High	Low	Medium	Medium	Medium	CT
17	Young	High	VLow	VLow	Low	Low	VHigh	High	High	Low	Small	Medium	Medium	CT
18	MAge	Normal	VLow	VLow	Low	Low	Normal	High	High	Low	Small	Large	Medium	CT

VLow : Very Low VHigh : Very High Mage : Middle Age VLarge : Very Large
Nb Seg : Number of segments Cont : Contusion

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