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Type-2 Fuzzy Hybrid Expert System For Diagnosis Of Degenerative Disc Diseases

S. Rahimi Damirchi-Darasi [1], M.H. Fazel Zarandi [1,2*], and M. Izadi [3]

1- Department of Industrial Engineering, Amirkabir University of Technology, Tehran, Iran
2- Knowledge Intelligent System Laboratory, University of Toronto, Toronto, Canada
3- Sub-special Neurosurgery, Fayyazbakhsh and Erfan Hospital, Tehran, Iran

ABSTRACT

One-third of the people with an age over twenty have some signs of degenerated discs. However, in most of the patients the mere presence of degenerative discs is not a problem leading to pain, neurological compression, or other symptoms. This paper presents an interval type-2 fuzzy hybrid rule-based system to diagnose the abnormal degenerated discs where pain variables are represented by interval type-2 membership functions. For this purpose, Mamdani interval type-2 fuzzy sets are utilized in the inference engine. The main contribution of this paper is to present the interval type-2 fuzzy hybrid rule-based system, which is the combination of forward and backward chaining approach in its inference engine. Combining forward and backward chaining leads to detect the exact location of degenerated disc that shows some spinal instability. The phase of forward chaining diagnoses the severity of the degeneration based on taking history of the patient. The second phase uses backward chaining approach to find the exact location of the degenerated disc by investigating related clinical examinations. Using parametric operations for the fuzzy calculations increases the robustness of the system. The system is tested for 11 patients and the results are compared with the neurosurgeon's diagnosis. Results indicate that the hybrid of forward and backward chaining approaches provide fast and accurate diagnosis of degenerative disc disease, and determine the necessity of taking MRI. Concluding, the proposed system could be a valuable tool in hand of the physicians in clinics and imaging centers to support diagnosis of the degenerated discs.

KEYWORDS

Type-2 Fuzzy Expert System, Forward-Backward Chaining, Degenerative Disc Diseases, Diagnosis System.

*Corresponding Author, Email: zarandi@aut.ac.ir

1. INTRODUCTION

Low back pain is widely prevalent in the word today and more than 80% of people have experienced it in their life. Neck pain is the other common spinal problem that has increased in recent years as a result of the long-time computer usage. Cervical disc degenerative disorder can be characterized by neck pain, while lumbar disc degenerative disorders can be characterized by low back pain. If these problems are diagnosed earlier, it could decrease the treatment costs and duration. The disc degeneration disease is one of the common spinal disorders, but it should be considered that the degeneration of the discs, particularly in the moving sections of the spine (cervical and lumbar levels), is a natural process of human aging. The dehydration or desiccation of the disc material reduces the flexibility and typically the height of the disc. In most patients, the mere presence of degenerative discs is not a problem leading to pain, neurological compression, or other symptoms. However, in a certain number of patients, the disc degeneration leads to spinal “instability”, the condition in which the spine is unable to bear the patient’s weight or perform its normal functions without disabling pain [1]. Approximately 90% of herniated discs occur in the low back at disc L4/5 and disc L5-S1 and cause pain in the L5 or S1 nerve that radiates down the sciatic nerve [2]. The most common discs in the cervical spine to herniate are disc C5/6 and disc C6/7. The next most common is disc C4/5 and rarely disc C7-T1 may be herniated [3]. Many studies have reported development of new methods for the computer-aided diagnosis system that could identify the degenerative discs successfully based on the MRI, and/or the CT [4-10]. There have been reported many expert systems designed to assist medical diagnosis, but only few expert systems have been found for diagnosis of the low back and neck pain [11]. O.A. Mansour and O.A. Kandil [12] have proposed a Knowledge Based Expert System to diagnose the low back disorders whose knowledge bases were developed using structured questionnaire based on various scenarios. M.A. Kadhim et al. [13] have reported a Fuzzy Expert System to diagnose the back pain disease based on clinical observation symptoms using fuzzy rules. M. Sari et al. [14] have proposed two expert systems (artificial neural network and adaptive neuro-fuzzy inference system) to assess the low back pain level. In addition, the MatheMEDics Company have developed an expert system designed to assist medical diagnosis of the back pain based on the assumption that the back pain is the principal complaint [15]; hence we are motivated to develop a robust and highly accurate expert system to reveal the diagnosis of the disc degeneration disease in the neck or low back quickly before providing the MRI. In order to handle the high uncertainty in this medical expert system, a type-2 fuzzy approach is used. A hybrid model is designed to diagnose the severity and location of the disease as soon as possible. Diagnosing the severity of the back disorder declares the necessity of providing the MRI in order to decrease unnecessary costs of the diagnosis and treatment.

The rest of this paper is organized as follows: in section 2, the reason for using type-2 fuzzy logic is shortly addressed. In section 3, type-2 fuzzy definition is presented and fuzzy logic systems is proposed. Section 4 is dedicated to propose the hybrid model. In section 5, some examples are presented to represent the performance of the proposed model, and section 6 represents the result of comparison between performance of the expert system and a neurosurgeon in type-2 fuzzy logic system and type-1 fuzzy logic system. Finally, conclusions and future works are presented in section 7.

2. WHY TYPE-2 FUZZY LOGIC

There are (at least) four sources of uncertainties in type-1 FLSs: (1) The meanings of the words that are used in the antecedents and consequents of rules can be uncertain (words mean different things to different people). (2) Consequents may have a histogram of values associated with them, especially when knowledge is extracted from a group of experts who do not all agree. (3) Measurements that activate a type-1 FLS may be noisy and therefore uncertain. (4) The data that are used to tune the parameters of a type-1 FLS may also be noisy. All of these uncertainties translate into uncertainties about fuzzy set membership functions. Type-1 fuzzy sets are not able to directly model such uncertainties because their membership functions are totally crisp. On the other hand, type-2 fuzzy sets are able to model such uncertainties because their membership functions are themselves fuzzy. Membership functions of type-1 fuzzy sets are two-dimensional, whereas membership functions of type-2 fuzzy sets are three-dimensional. It is the new third-dimension of type-2 fuzzy sets that provides additional degrees of freedom that make it possible to directly model uncertainties [16]. Even in the face of the difficulties of the understanding and using, type-2 fuzzy sets and FLSs have already been used for (this list is in alphabetical order by application):

classification of coded video streams, co-channel interference elimination from nonlinear time-varying communication channels, connection admission control, control of mobile robots, decision making, equalization of nonlinear fading channels, extracting knowledge from questionnaire surveys, forecasting of time-series, function approximation,, learning linguistic member-ship grades, pre-processing radiographic images, relational databases, solving fuzzy relation equations, and transport scheduling [16].

They seem to be applicable when: (1) the data-generating system is known to be time-varying but the mathematical description of the time-variability is unknown (e.g., as in mobile communications); (2) measurement noise is non-stationary and the mathematical description of the non-stationarity is unknown (e.g., as in a time-varying SNR); (3) features in a pattern recognition application have statistical attributes that are non-stationary and the mathematical descriptions of the non-stationarities are unknown; (4) knowledge is mined from a group of experts using questionnaires that involve uncertain words; and (5) linguistic terms are used that have a non-measurable domain [16].

3. TYPE-2 FUZZY LOGIC SYSTEMS [18]

In this section, we briefly review some characteristics and definitions of Type-2 Fuzzy Sets and systems which will be extensively used in other sections of the paper.

A. Type-2 Fuzzy Sets (T2 Fss)

A T2 FS, $\tilde{A}$ is characterized by a type-2 MF $\mu_{A^{\sim}}(x,u)$, where $x \in X$ and $u \in J_x \subseteq [0,1]$ [16,20] given in (1).

$$\tilde{A} = \{((x,u), \mu_{A^{\sim}}(x,u)) \mid \forall x \in X,\ \forall u \in J_x \subseteq [0,1]\} \quad (1)$$

where $0 \le \mu_{A^{\sim}}(x,u) \le 1$. $\tilde{A}$ can also be expressed in (2) as

$$\tilde{A} = \int_{x\in X} \int_{u\in J_x} \mu_{A^{\sim}}(x,u)/(x,u),\ J_x \subseteq [0,1] \quad (2)$$

in which $\iint$ denotes union over all admissible x and u. When the universe of discourse is discrete, then $\int$ is replaced by $\sum$. Here J_x is called the primary membership function and $\mu_{A^{\sim}}(x,u)$ is the secondary membership function. In fact, secondary membership functions are the membership function values for each point of the primary membership function.

When all $\mu_{A^{\sim}}(x,u) = 1$, then the type-2 fuzzy set is called interval type-2 fuzzy set (ITS FS). In this kind of T2 FSs, the third dimension of the general T2 FS is not needed anymore since it represents no new information about the IT2 FS, but IT2 FSs can still be expressed as a special case of the General T2 FS (GT2 FSs) in (3) as

$$\tilde{A} = \int_{x\in X} \int_{u\in J_x} 1/(x,u),\ J_x \subseteq [0,1]. \quad (3)$$

The Upper Membership Function (UMF) and Lower Membership Function (LMF) of $\tilde{A}$ are two T1 membership functions that bound the FOU (Fig. 1). The UMF of $\tilde{A}$ is the upper bound of the $FOU\ (\tilde{A})$ and denoted $\bar{\mu}_{\tilde{A}}(x)\ \forall x \in X$, and the LMF is lower bound of the $FOU\ (\tilde{A})$ and denoted $\underline{\mu}_{\tilde{A}}(x)\ \forall x \in X$. The UMF and LMF can be characterized in (4-5) as below

$$\bar{\mu}_{\tilde{A}}(x) \equiv \mathrm{FO\bar{U}}(\tilde{A})\ \forall x \in X \quad (4)$$

$$\underline{\mu}_{\tilde{A}}(x) \equiv \mathrm{FO\underline{U}}(\tilde{A})\ \forall x \in X. \quad (5)$$

B. Type-2 Fuzzy Systems (T2 Flss)

In conventional fuzzy rule-based structures, type-1 FSs are used as antecedents and/or consequent of rules. Meanwhile, recent researches demonstrate that T2 FSs can increase the performance quality of fuzzy rule-based systems.

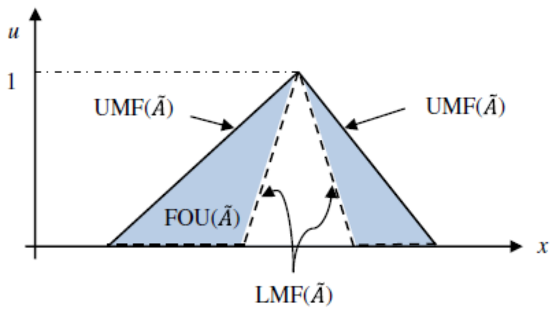

Fig. 1. FOU, UMF, and LMF for an IT2 FS $(\tilde{A})$ [17]

A fuzzy rule-based system contains four major components: rules, fuzzifier, inference engine, and output processor. A general T2 FLS is depicted in Fig. 2. If the antecedent and consequent sets in rules are type-2; the FLS is type-2. It is very similar to a T1 FLS, both type-1 and IT2 FLSs contain the four mentioned major components but the only difference between their structures is in the output processing part. In type-1 FLSs, output processing consists of a defuzzifier which transforms the fuzzy output of the system into a crisp value. However, output processing component in an IT2 FLS has two parts: Type reducer and defuzzifier. As noted before, antecedents and consequents in an IT2 FLS are IT2 FSs and the result of the system is in higher order. So before defuzzifying the output, it should be transformed from type-2 to type-1. After type reduction, the output becomes a type-1 FS and then we can implement various defuzzification methods to obtain the crisp output [18].

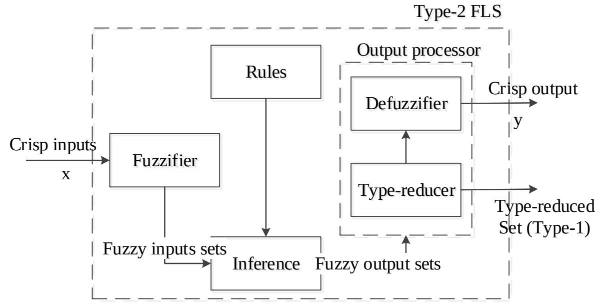

Fig. 2. Type-2 FLS [18]

There are essentially two types of fuzziness: Interval valued type-2 and generalized type-2 fuzzy. Interval-valued type-2 fuzzy is a special type-2 fuzzy, where the upper and lower bounds of membership are crisp and the spread of membership distribution is ignored with the assumption that membership values between upper and lower values are uniformly distributed or scattered with a membership value of 1 on the $\mu(\mu(x))$ axis (Fig. 3.a). For generalized type-2 fuzzy, the upper and lower membership values as well as the spread of the membership values between these bounds (either probabilistically or fuzzily) are defined. That is, there is a probabilistic distribution of the membership values that are between upper and lower bound of the membership values in the $\mu(\mu(x))$ axis (Fig. 3.b) [19].

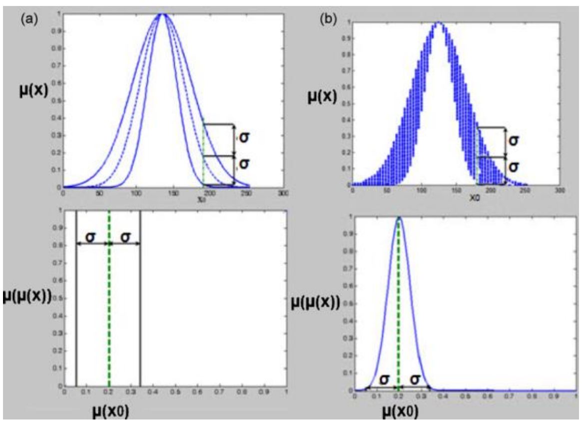

Fig. 3. (a) Interval-valued Type-2 and (b) generalized Type-2 [19]

As mentioned above, the type-2 membership function provides additional degree of freedom in the fuzzy logic system, which can handle the high uncertainty. As there are many uncertainties about the symptoms of the degeneration disc disease and other spinal cord disorders, caused by description of the symptoms in linguistic words, type-2 fuzzy logic could provide a powerful tool for diagnosing the degenerated discs. We use Interval-valued type-2 fuzzy sets in the proposed system.

Generally, there are two different approaches in designing an IT2 FLS: partially dependent approach and independent approach. In the former approach, first, a best possible type-1 FLS is designed and then it is used to initialize the parameters of the IT2FLS. The latter approach is entirely independent from initial type-1 FLS. Its parameters are determined and tuned independently from scratch [20]. Because of inefficient patients' records, our proposed approach is based on partially dependent approach. First, we design a type-1 FLS and then for increasing the robustness of the system, we create a type-2 fuzzy rule-based with certain mean and interval secondary membership functions. The rules of the system, one of the contribution of this study, and the means of the functions are defined by negotiating with the neurosurgeon.

The inference engine of the system is presented in the next section.

4. Proposed Model

In this section we propose the inference engine of the system. Fazel Zarandi et al. [21] categorized the patients with spinal cord disorder in five groups: Mechanical pain, Herniated disc, Spinal Stenosis, spinal deformity like Scoliosis, Lordosis or Kyphosis and Red Flag. There are two steps in diagnosing spinal cord disorder without MR image processing: taking history and clinical examination. The first step, taking the history of the patient, helps the physician identify the chief complaint of the patient and recognize some factors, called risk factors, which ignoring them may lead him/her to wrong diagnosis. In the second step, investigating the clinical examination results, the final diagnosis and the necessity of providing the MRI are declared. Fig. 4 represents the steps of the neurosurgeon schematically that is the fundamental of the proposed model.

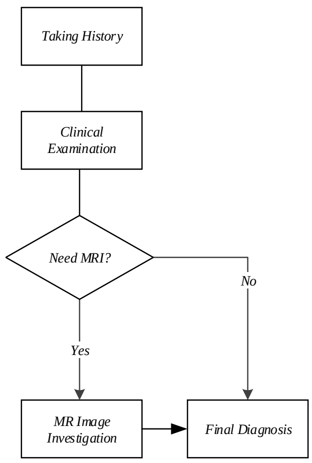

Fig. 4. Schematic view of diagnosing by the neurosurgeon

The design of the proposed model is represented in Figs. 5-6. The modules of Risk Factors and Identifying the Severity of Disease are in the phase of the history taking. They will be explained in subsection Taking History. If the chief complaint of the patient is the pain in his/her arm or leg, some clinical examination should be done. It is explained completely in subsection Clinical Examination.

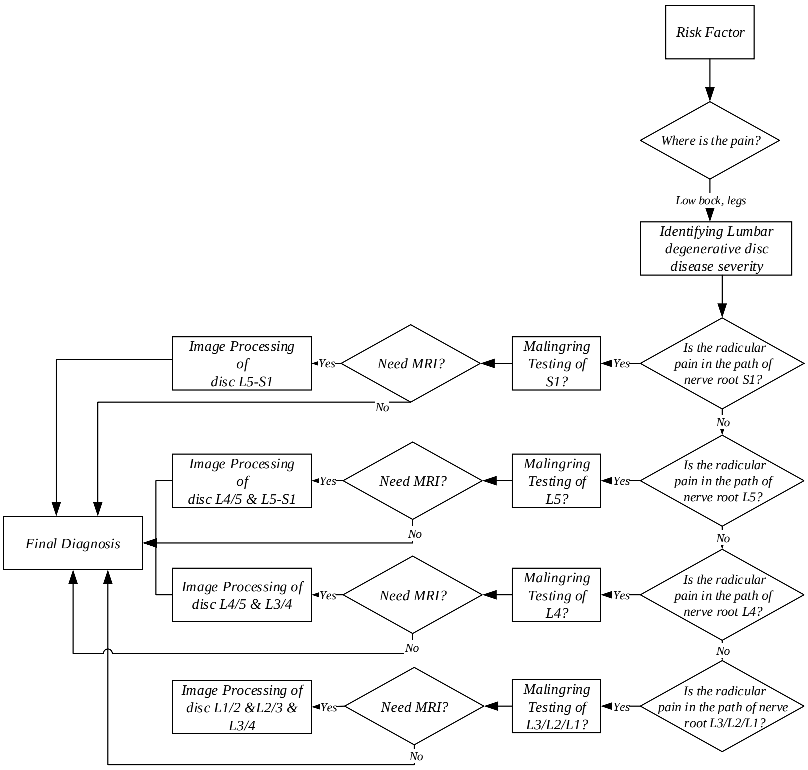

Fig. 5. The proposed algorithm to diagnosis the location of lumbar degenerative discs

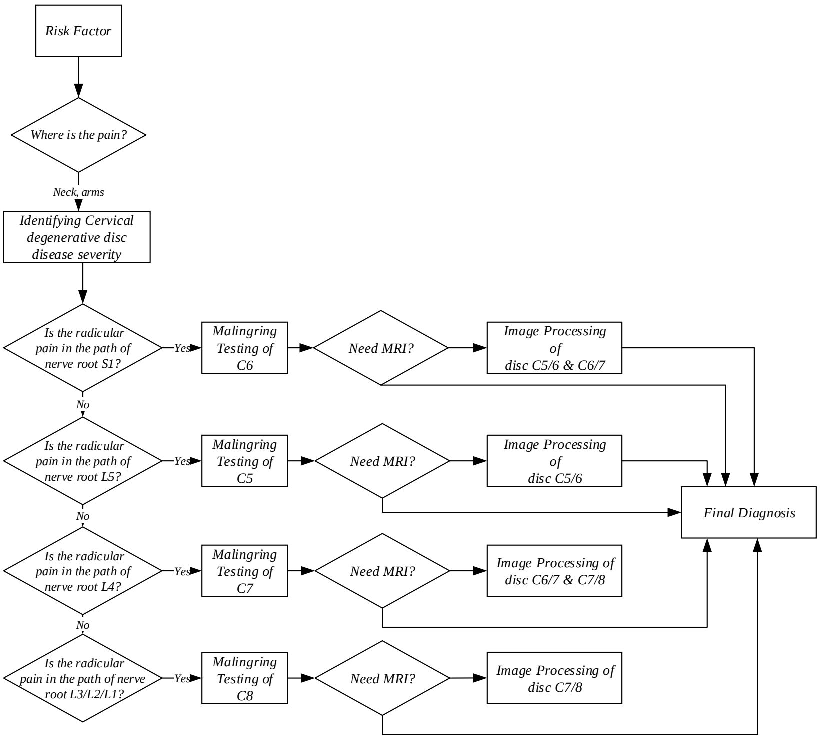

Fig. 6. The proposed algorithm to diagnosis the location of cervical degenerative discs

A. Taking History

Taking History is comprised of two modules: Risk Factors and Identifying Severity of Disease. First of all, the system asks about the risk factor in the module of Risk Factor. Diagnosing these factors could help the patient decrease his/her treatment terms and the pain that he/she feels. We identify them by studying the medical references and negotiating with the neurosurgeon. Table 1 represents these factors and the values assigned to them. The knowledge base of this module is comprised crisp rules. If the input value of any variable is 1, the patient should remove the factor, if possible.

TABLE 1. ANTECEDENTS OF RULES OF MODULE RISK FACTOR

Variables of the Module of Risk Factor	*Variables*	*Values*
Age	*Yes*	*1*
Genetic		
Occupational hazards		
Sedentary lifestyle		
Excess weight	*No*	*2*
Poor posture		
Pregnancy		
Smoking		
Any psychological problem		

The next step is Identifying Severity of Disease that starts by asking about the location of the pain and continues by asking about the quality of the chief complaint. As it presented in Fig. 4, if the pain is in just neck or low back, it could not be a symptom of degenerative disc disease. The main characteristic of this disease is radiating pain in legs or arms. The patient's complaints are investigated in three sub-modules: (i) severity of pain (SOP), (ii) starting time of the pain (STP), and (iii) dependency of the pain to some positions (DOP). The knowledge base of this module is comprised of type-2 fuzzy rules to handle the uncertainty of some linguistic variables. As the patients describe the pain by using different words like numbness, tingling, traveling pain and other symptoms of degenerative disc disease, the class of severity of pain should be comprised of all of these symptoms. The antecedents of rules of pain severity for lumbar and cervical degenerative disc are represented in Table 2 and Table 3. Their linguistic variables are: never or very low, low, medium, high, and very high or insufferable. Membership function of these variables is depicted in Fig. 7. In order to define the variables, intervals, Gaussian membership functions are assigned to antecedents and consequents. Gaussian membership functions are defined by uncertain standard deviation and certain mean.

Consider m_k^j, as a certain means of Gaussian membership function and an uncertain standard deviation that has value in $[\sigma_{k1}^j, \sigma_{k2}^j]$ [19], i.e.

$$\mu_k^j(\mathrm{x}_k) = \exp[-\frac{1}{2}(\frac{x_k - m_k^j}{\sigma_k^j})]^2, \sigma_k^j = [\sigma_{k1}^j, \sigma_{k2}^j]. \qquad (6)$$

This leads to the following definitions

$$\bar{\mu}_k^j(x_k) = N(m_k^j, \sigma_{k2}^j; x_k) \qquad (7)$$

$$\underline{\mu}_k^j(x_k) = N(m_k^j, \sigma_{k1}^j; x_k) \qquad (8)$$

where, $\bar{\mu}_k^j(x_k)$ is the upper membership function, $\underline{\mu}_k^j(x_k)$ is the lower membership function, and for example $N(m_k^j, \sigma_{k1}^j; x_k)$ is defined as follows

$$N(m_k^j, \sigma_{k1}^j; x_k) \triangleq \exp[-\frac{1}{2}(\frac{x_k - m_k^j}{\sigma_k^j})]^2 \qquad (9)$$

where, $k = 1,2,...,p$ and $j = 1,2,...,M$. *p* shows the number of antecedents, *M* indicates the number of rules, and *N* is a Gaussian membership function of m_k^j, σ_k^j, x_k. The outputs of SOP sub-module for lumbar and cervical disease are parametric s-norm of its input variables. This output, and the variables of STP and DOP sub-modules make input variables of assessment of severity of degenerative disc disease severity. Table 4 represents the antecedents of rules of module of degenerative disc disease; and Fig. 8 presents the rules of this module. Membership functions of STP and DOP sub-modules are presented in Figs. 9-10. The linguistic variables of STP sub-module are: less than 3 months, less than 5 years, less than 7 years, less than 10 years, and more than 10 years. Linguistic variables of DOP sub-module are: independent, so-so and dependent. Because of the difference in degree of uncertainty in variables, type-2 fuzzy intervals are assigned to variables of SOP sub-module and type-1 fuzzy intervals to variables of STP and DOP sub-modules. Aggregating the three input fuzzy sets makes output to be type-2 fuzzy set. Type reduction of this type-2 fuzzy set is a type-1 fuzzy set that should be defuzzified. The type reduction method, which is used in this system, is height, and the defuzzification method is Yager parametric defuzzification. The final output of this module is a real number in the interval (0-10), representing the degree of disease severity. The parameters of the system are optimized in the verification phase of the system by using RMSE. y shows the neurosurgeon's diagnosis and $\hat{y}$ shows the system diagnosis. *p*, *q* and *N* are the parameters of t-norm and s-norm and negation. *α* is the parameter of Yager defuzzifier and n is the number of data. The number of train data is 8. The system is tested by using data of 11 patients. Some of the examples are represented in section 4.

$$RMSE(p,q,N,\alpha)=\sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i-y_i)^2}{n}} \tag{10}$$

TABLE 2. ANTECEDENTS OF FUZZY RULES OF SOP IN LEG AND LOW BACK

Fuzzy Variables of Pain in Leg and Low Back	*Linguistic Variable*	*Means of the Fuzzy Intervals*
Local pain in the Low back	*Never or Very low*	*1*
Pain in the legs, feet and toes		
Numbness in the legs, feet and toes	*Low*	*3.25*
Tingling in the legs, feet and toes	*Medium*	*5.5*
Sciatica		
Muscle weakness in the thighs and calves	*High*	*7.75*
Back stiffness or soreness	*Very high or Insufferable*	*10*
Incontinence		

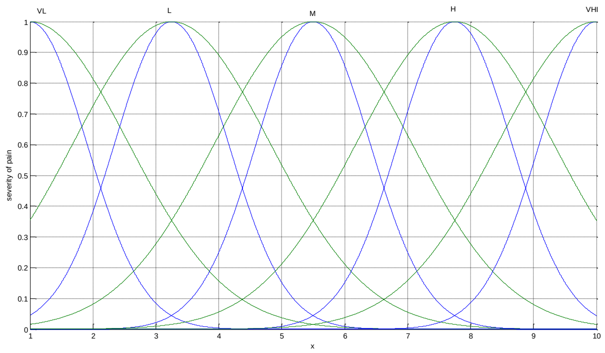

Fig. 7. Membership function of the variables of SOP

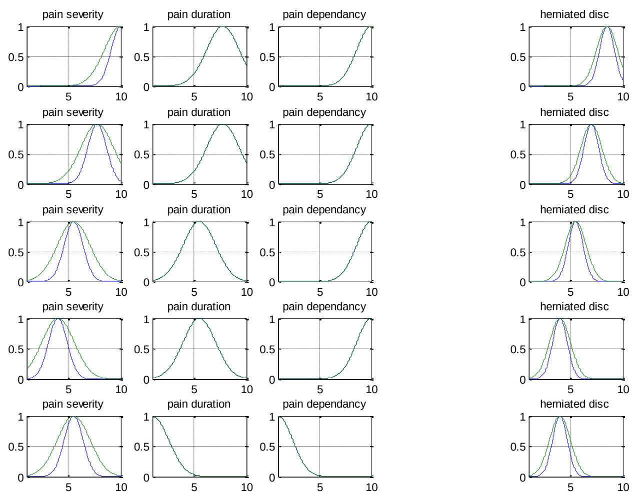

Fig. 8. Schematic view of the rules of the module of Identifying Severity Disease

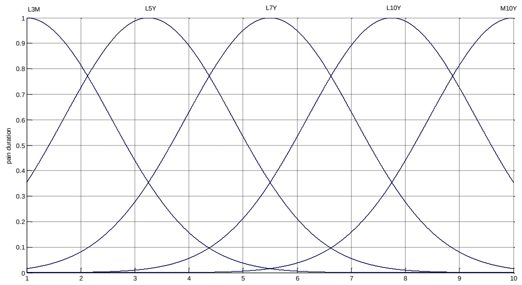

Fig. 9. Membership function of the variables of STP

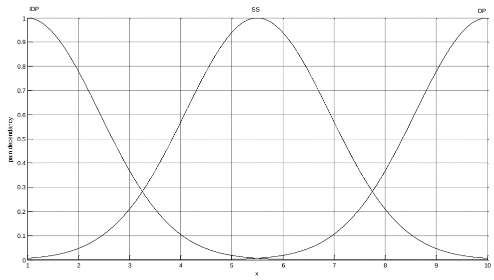

Fig. 10. Membership function of variables of DOP

TABLE 3. ANTECEDENTS OF FUZZY RULES OF SOP IN ARM AND NECK

Fuzzy Variables of Pain in Arm and Neck	*Linguistic Variable*	*Means of the Fuzzy Intervals*
Local pain in the Neck	*Never or Very low*	*1*
Pain in the arm, hands and toes		
Numbness in the arms and hands	*Low*	*3.25*
Tingling in the arms and hands	*Medium*	*5.5*
Neck stiffness or soreness	*High*	*7.75*
Traveling pain radiating along the nerve throughout the arm	*Very high or Insufferable*	*10*
Muscle weakness in the shoulders, arms and elbows		

TABLE 4. ANTECEDENTS OF FUZZY RULES OF IDENTIFYING SEVERITY OF DISEASE

Fuzzy Variables of Modules of disc Degeneration	*Linguistic Variable*	*Means of the Fuzzy Intervals*
SOP	*Never or Very low*	*1*
	Low	*3.25*
	Meduim	*5.5*
	High	*7.75*
	Very high or Insufferable	*10*
STP	*Less than 3 months*	*1*
	Less than 5 years	*3.25*
	Less than 7 years	*5.5*
	Less than 10 years	*7.75*
	More than 10 years	*10*
DOP	*Independent*	*1*
	So-so	*5.5*
	Dependent	*10*

B. Clinical Examination

After identifying the degree of lumbar or cervical degenerative disc disease, the system tries to find the exact location of the disc. By using the statistic information about the prevalence of degenerative disc, the approach of the algorithm to detect the degenerative disc is backward chaining. Since the degenerative disc leads to compress some nerve roots, we could guess the degenerative discs by finding the compressed nerve root and doing its clinical examination. As it represented in Appendix A, if the chief complaint is pain in the leg and low back, the order of the guess is S1, L5, L4, and L3/L2/L1 nerve root paths. If the pain is in path of S1, disc L5-S1 may be the degenerative disc. If the pain is in path of L5, the degenerative disc may be disc L4/5 or L5-S1. Degenerated L3/4 and L4/5 discs could make the pain in L4 nerve root path. According to Appendix B, if the chief complaint is pain in the arm and neck, the order of the guess is C6, C5, C7, and C8 nerve root paths. The pain in path of C6 is a symptom of degenerated C5/6 or C6/7 discs, and if the pain is in the path of C5, disc C5/6 may be the degenerated disc. So, by detecting the exact location of the degenerated discs, the image processing of the detected discs is sufficient to diagnose accurately and quickly. In order to recognize the malingering of the patients, some clinical examination should be done. If the patient does not malinger, the system assesses the necessity of providing MRI based on severity of degenerative disc disease and psychological risk factor. The necessity of providing MRI is divided into four class: (i) necessary to take MRI, (ii) necessary to take MRI because of mental problems, (iii) necessary to take MRI conditionally, and (iv) not necessary to take MRI. The rules of this assessment have used crisp variables. The performance of the system is tested based on identifying the necessity of providing MRI. It is explained in section 6.

5. Examples

This section presents two different examples of the patients' symptoms that the developed expert system could diagnose the problem successfully.

A. Patient A: Mechanical Pain In Low Back, No Need To Take Mri

Fig. 11 depicts the patient with low back pain for one or two months. He/she feels improvement by resting. The system diagnosed the risk factors of the patient. Since the pain was not in leg or arm, the patient has mechanical pain and do not need to take MRI but he/she could remove some of the factors by doing some exercise. The developed system could diagnose the problem of the patient successfully.

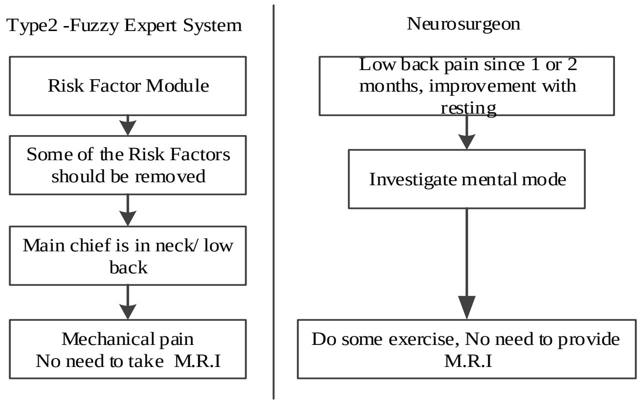

Fig. 11. Comparison between performances of developed type-2 fuzzy expert system and the Neurosurgeon in patient A

B. Patient B: Cervical Degenerative Disc, Necessary To Provide Mri

Fig. 12 depicts the patient with radiating pain in his/her hand, numbness and tingling in his/her fingers. The system diagnosed the risk factors of the patient. Because of existing some pain in neck and arm, the system searches for the exact location of the degenerated disc. In order to feeling pain in C6 nerve root path and the severity of problem, the patient needs to provide MRI and the disc may be C5/6 or C6/7.

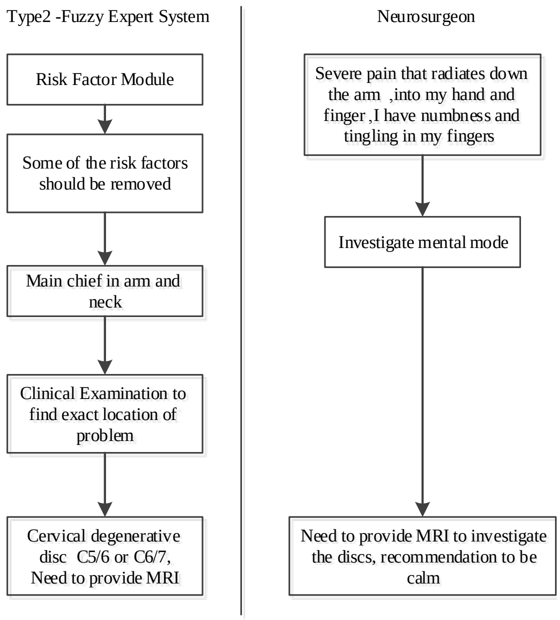

Fig. 12. Comparison between performance of developed type-2 fuzzy expert system and the Neurosurgeon in patient B

6. Results

By the optimization of the parameters of the Yager operators and defuzzifier, the proposed system chooses the best parameters to have the least RMSE in diagnosing the problems. The optimized parameters of the proposed system are given in Table 5.

TABLE 5. OPTIMIZED PARAMETERS EXTRACTED FROM VERIFICATION PHASE

Parameter	*p*	*q*	*N*	*α*
value	*1*	*24*	*351*	*601*

The proposed system was tested for 11 different patients. One of the objective of the system is determining the necessity of providing MRI. Table 6 represents the Comparison of Neurosurgeon diagnosis with expert system, Type-1 Fuzzy expert system and proposed Type-2 Fuzzy expert system in determining it. The first column of the table is Neurosurgeon diagnosis, the second one is compatibility of Crisp expert system diagnosis with Neurosurgeon diagnosis. As shown in Table 6 the Crisp expert system could not diagnose the problem of patients 2, 5, 6, 8, 9, and 10. Some of these patients should provide MRI conditionally, some of them have mental problems, and some of the other patients should not provide MRI, but the crisp expert system asks them to provide MRI. As the high cost of providing the unnecessary MRI (financial cost, time cost, and physiological cost), we could not rely on this system in diagnosing degenerative disc diseases.

The high uncertainty in some of the symptoms made us to develop Fuzzy experts system and compare it with Crisp expert system. The third column of Table 6, shows the performance of the Type-1 Fuzzy Expert System. The Type-1 Fuzzy Expert System could diagnose successfully some of the patients that Crisp expert could not, but the diagnosis of two patients' problem (patients 6 and 8) are not compatible with Neurosurgeon diagnosis. As mentioned in the previous paragraph, providing unnecessary MRI, make an unsuccessful system. Patient 6 should provide MRI conditionally. It means that the problem is not so serious but if he/she could not improve him/herself with some exercises, he/she should provide MRI. Unsuccessful diagnosis in this patient may make unnecessary cost and unnecessary people aggregation in Magnetic Resonance Imaging Centers.

By using type-2 fuzzy rules for some of the more uncertain variables, Type-2 Fuzzy Expert System is developed. The fourth column of Table 6 represents the compatibility of Type-2 Fuzzy Expert System with Neurosurgeon diagnosis. As shown in Table 6, Type-2 Fuzzy Expert System could diagnose all the 11 patients successfully.

TABLE 6. COMPARISON OF NEUROSURGEON DIAGNOSIS WITH CRISP EXPERT SYSTEM, TYPE-1 FUZZY EXPERT SYSTEM AND PROPOSED TYPE-2 FUZZY EXPERT SYSTEM

Patient	*Neurosurgeon Diagnosis*	*Crisp Expert System*	*Type-1 Fuzzy Expert System*	*Type-2 Fuzzy Expert System*
1	*MRI is necessary*	✓	✓	✓
2	*MRI is not necessary*	✗	✓	✓
3	*MRI is necessary*	✓	✓	✓
4	*MRI is necessary*	✓	✓	✓
5	*MRI is not necessary*	✗	✓	✓
6	*MRI is conditionally necessary*	✗	✗	✓
7	*MRI is not necessary*	✓	✓	✓
8	*MRI is not necessary*	✗	✗	✓
9	*MRI is not necessary*	✗	✓	✓
10	*MRI is necessary because of mental problems*	✗	✓	✓
11	*MRI is necessary*	✓	✓	✓

7. Conclusions And Future Work

In order to diagnose lumbar and cervical degenerative disc fast and with low cost, a type-2 fuzzy rule-based expert system was developed. The approach in designing the algorithm of the system was hybrid of forward and backward chaining to investigate history and clinical data before providing MRI. By determining the necessity of providing MRI, providing the unnecessary MRI could be decreased. Guessing the location of lumbar and cervical degenerative discs may decrease the complexity of image processing in computer-aided diagnosis systems and prohibit them to investigate unnecessary discs that are with no radiating pain. The results show that Type-2 Fuzzy Expert System could diagnose more successfully than Type-1 Fuzzy Expert System and Crisp Expert System. Using Fuzzy Expert System can decrease unnecessary cost and unnecessary people aggregation in Magnetic Resonance Imaging Centers. Future work can evaluate the performance of this system by increasing the sample size. In order to improve system accuracy in primary diagnosis, fuzzy rules could be used in knowledge base of clinical examination.

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