Kidney Diseases Diagnosis by Using Fuzzy Logic

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Abstract

The present study aimed to develop a new method in fuzzy logic which can be used for kidney disease diagnosis. To this aim, across-sectional descriptive study was conducted in Shafa kidney clinic in Tehran, Iran in 2012. The medical diagnosis fuzzy rules were formulated and applied using MATLAB software. We defined a set of symptoms (F) related to the set of considered diseases. The input case to be diagnosed was defined by giving a fuzzy value to each symptom. The fuzzy inference was applied to obtain a decision fuzzy set for each disease, and crisp decision values were attained to tell the certainty of existence for each disease. The results indicated that in the diagnosis of eight cases of kidney diseases through the examination of 21 indicators using fuzzy logic, kidney stone disease with 63% certainty was at the first level and renal tubular with 15% was at the lowest level and the other kidney diseases were at the other levels. The most obvious finding of the current study was that the results of the kidney disease diagnosis (e.g. kidney stone) via fuzzy logic were fully compatible with those of kidney physicians. Therefore, fuzzy logic is a valid, reliable and flexible instrument to diagnose several typical input cases.The developed system decreases the effort of initial physical checking and manual feeding of the input symptoms.

Keywords: Chronic kidney disease, Fuzzy logic, Fuzzy medical diagnosis, Medical diagnosis problems.

1-Introduction

According to global research, by 2015, chronic kidney disease will face the lives of over 36 million people around the world with a serious risk. Among nine seemingly healthy people, one person has some symptoms of chronic kidney diseases[1]. Chronic renal failure is a disease with the severe and irreversible disorder of kidney function that its outcome is the inability of body in balancing fluids, electrolytes and metabolism[2]. The five important causes of more global attention to chronic kidney disease include growing prevalence; the hidden actual outbreak, high cost, high impact on the increase of the cardiovascular diseases and finding solutions effective in preventing from disease progression [3]. Unfortunately, chronic renal failure is usually asymptomatic and the exact number of patients is unclear. Today, 1.5 million people around the world are under hemodialysis or kidney transplantation. If government and people disregard it, this statistic may be doubled within the next few years. Iran has the highest international statistics in the prevalence of kidney diseases so that Iranian statistics is higher than the countries in the region. Kidney diseases indicate 15 to 20% growth in the country. There are over 7 million renal failure patients in the country and other people aren't aware of this possible disease. In 2005, the number of patients with advanced renal failure who were treated with one of ESRD methods (2% paclitaxel dialysis, 50% hemodialysis and 48% kidney transplantation) reached 22376 and during the next five year, it will be doubled, i.e., over 40000 people [4].

The natural development of different diseases, the unclear nature of medical data and the intrinsic vagueness of medical problems lead to a need for a reliable framework that can deal with the ambiguity via permitting variable and multiple class memberships and facilitating approximate reasoning. This unavoidably causes the fuzzy logic to be a valuable tool for describing medical concepts via dealing with them as fuzzy sets [5,6]. The fuzzy logic was applied in medical systems [7], almost 20 years after its introduction by Zadeh [8]; however, it has recently given birth to various interesting implementations [9,10]. Medical diagnosis and prognosis problems are the prime examples of decision making in the face of uncertainty. Dealing with uncertainties is a common problem in pattern recognition and the use of fuzzy set theory has given rise to a lot of new methods of pattern recognition for medical diagnosis [11]. The diagnosis of a disease is a problem in medicine since some patients may have similar symptoms, but the doctor may diagnose different diseases. So, this work will help doctor when he or she has fuzziness in that thinking process [12, 13]. This study introduces a simple and efficient method to create fuzzy expert systems for medical diagnosis. The methodology is general and can be applied in diagnosing a wide range of diseases. However, to demonstrate the concept, in this article, we study kidney infection and kidney stone diseases to create a prototype computer program that can infer accurate diagnosis decisions based on patient's data.

2-Medical diagnosis problems

Diagnosis and prognosis are the tasks of medical science. The most important problems in medical diagnosis and prognosis are [14]:

i. The limited observation and subjectivity of the specialist,

ii. Uncertainties and incompleteness in medical knowledge

iii. Poor time effect in diagnosis.

These difficulties have to be recognized during medical decision. A patient can have a set of symptoms which can be attributed to several diseases and these symptoms need not be strictly numerical. In observing these symptoms, different doctors with different professional levels and clinical experience may diagnose differently, resulting in misdiagnosis. Also, due to the unknown noise in acquisition process, the use of computers in medical diagnosis and prognosis has become necessary, especially with the increasing size and number of medical data.

3-Fuzzy Logic Medical Diagnosis

Medical diagnosis and prognosis problems are the prime examples of decision making in the face of uncertainty. In this study, a fuzzy expert system is developed that rather than applying Boolean logic for reasoning about data, employs a set of fuzzy membership functions and rules. Leung, Lau and Kwong defined a general structure of the fuzzy system as the main section of a fuzzy use [15]. The structure can be encapsulated in the succeeding four stages, carried out in order:

1) **Fuzzy Functions:** the membership functions defined on the input variables are applied to their actual values, to determine the degree of truth for each rule premise.
2) **Deduction:** the truth value for the premise of each rule is computed and applied to the conclusion part of each rule. This results in one fuzzy subset to be assigned to each output variable for each rule.
3) **Combination:** all of the fuzzy subsets assigned to each output variable are combined together to form a single fuzzy subset for each output variable.
4) **Deffuzification:** is an optional step which is used when it is useful to convert the fuzzy output set to a crisp number.

4-Materials & Methods

Often medical diagnosis entails the careful examination of a patient to test the existence and strength of some symptoms related to a suspected illness in order to make a decision whether the patient suffers from that illness or not [11]. A feature, such as a Hematuria for example, may be very strong for one patient; however, it can be moderate or even very weak for another. How to bring together a set of symptoms (features and their strengths) to learn the accurate diagnostic decision is determined by the experience of the physician.

A kidney infection is a painful unpleasant illness that usually happens when bacteria travel up from your bladder into one or both of your kidneys. Kidney infection, if not treated promptly, can lead to serious complications, including kidney damage and sepsis (blood poisoning). According to the researches' statements, it has been found that each year 135 people out of every one hundred thousand people are on the kidney stone patient list. Women are more commonly affected by kidney infection, as are pregnant mothers, children under two years of age, as well as individuals over 60 [16].

Kidneys stones (renal lithiasis), formed inside the kidneys, are small hard deposits composed of mineral and acid salts. They have many causes and can influence any part of urinary tract from kidneys to bladder. Passing kidney stones can be extremely painful; however, the stones usually cause no lasting damage[17].

In the current study, we are to utilize the physician's experience and save it in a set of fuzzy tables. Fuzzy deduction is applied to create a computer program that can automatically realize the certainty whether a patient having some identified symptoms suffers from any one of a set of suspected sicknesses. This certainty for every suspected disease is specified via a crisp percentage value.

We assume a set of m diseases S, and define a collective set of n features I relevant to these diseases. Let:

$$S = \{s1 , s2 , s3 , \ldots , sm \}$$

$$I = \{ i1 , i2 , i3 , \ldots , in \}$$

In order to identify the symptoms of a patient, he would be tested against all symptoms in the set I and a fuzzy value would be allocated to each symptom. The fuzzy values are chosen from the set:

{Very Low, Low, Moderate, High, Very High}

For instance, a single feature can be determined as < Hematuria, Moderate >. By checking the ill person for all n features of the set I and ascribing a suitable fuzzy value for each feature, the set of patient's symptoms S will be obtained as follows:

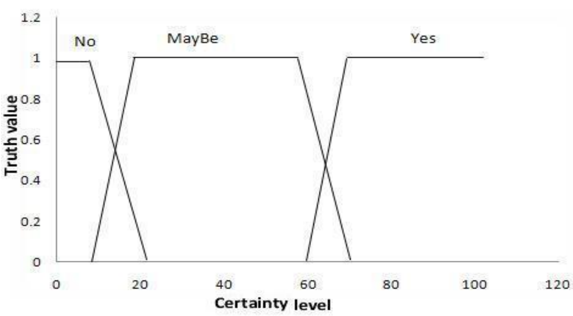
$$M = \{ \langle i1 , v1\rangle , \langle i2 , v2\rangle , \langle i3 , v3\rangle , \ldots , \langle in , vn\rangle \}$$

Where v_i is the fuzzy value allocated to the feature i_i when testing the patient, i=1, … ,n.

5-Adaptation of Fuzzy Model

Considering the set of considered diseases S, the expert physician's experience is obtained in a set of fuzzy tables, each of which determines the profile for one illness. To denote the assurance of sickness presence, three fuzzy sets including Yes, May Be, and No as shown in fig.1 were considered. Entries in the disease profile tables would be chosen from these fuzzy sets.

Fig (1) The fuzzy sets for the certainty of disease presence



For a given disease there will be a set R of $k \leq n$ related features which is a subset of the collective features set I. Table 1 indicates an empty fuzzy table for the disease profile. It illustrates five fuzzy values for each related feature ri , i=1, … , k.

Table (1) The fuzzy table for the disease profile

Relevant Features	***Fuzzy Value of the Symptom***				
	Very Low	***Low***	***Moderate***	***High***	***Very High***
r_1					
r_2					
…					
r_k					

It is the responsibility of the skillful physician to offer suitable values for each and every entry in the disease profile table based on his experience. This should be carried out for every disease in the set of considered diseases ***S***. Table 2 demonstrates the profile tables for two of the considered upper respiratory infections according to an expert physician consultation. Similar profile tables are also obtained for the rest of the considered diseases.

Table (2) The profile for kidney stone

Properties Features	***Very Low***	***Low***	***Moderate***	***High***	***Very High***
Flank pain bilateral	NO	Yes	Yes	Maybe	Yes
Flank pain unilateral	NO	Maybe	Maybe	Yes	Yes
Hematuria	Yes	Maybe	Maybe	Yes	Yes
Chill and fever	Yes	Yes	Maybe	Maybe	Maybe
Nausea & vomiting	Yes	Yes	Yes	NO	NO
Bad smell urine	Maybe	Maybe	Yes	Maybe	Maybe
Frequency &urgency	NO	Maybe	Maybe	Yes	Yes
Urine pus	Maybe	Maybe	Maybe	Maybe	Maybe
Dysuria	NO	Maybe	Yes	Yes	Yes

Table (3) profile for kidney infection

Properties Features	***Very Low***	***Low***	***Moderate***	***High***	***Very High***
Dysuria	Maybe	Maybe	Yes	Yes	Yes
Urinary frequency	Maybe	Yes	Yes	Yes	Yes
Cloudy urine	Maybe	Yes	Yes	Yes	Yes
Purulent urine	Maybe	Maybe	Yes	Yes	Yes
Hematuria or leukocyturia	NO	Maybe	Yes	Yes	Yes
Nucturia	Maybe	Maybe	Maybe	Yes	Yes
Hesitency	Yes	Yes	Yes	Yes	Yes
Suprapubic	Yes	Yes	Yes	Maybe	Maybe
Abrupt fever and chill	NO	Maybe	Yes	Yes	Mayb
Unilateral or bilateral flank pain	NO	Maybe	Maybe	Yes	Yes
Nausea & vomiting	Yes	Yes	Maybe	NO	NO
Spumy urine	Yes	Yes	Maybe	Yes	Maybe

6-Fuzzy Pattern Recognition for Medical Diagnosis

When a patient is examined for diagnosis, his/ her disease symptoms set M would be obtained. A typical example for the set of symptoms is given in table 3 which shows the fuzzy values for all features in the collective set **I**. It is totally natural to determine the strength of a non-measurable feature by a fuzzy value. However, there are other measurable features such as proteinuria, hypertension, and blood sugar, etc. that can be identified by numbers. The next subsection reveals how such fuzzy features are showed.

Table (4) The typical symptoms for a given input case

Features	***Fuzzy Value******
Flank pain bilateral	M
Flank pain unilateral	M
Hematuria	H
Chill and fever	L
Nausea & vomiting	M
Bad smell urine	M
Frequency &urgency	H
Urine pus	VL
Dysuria	VH

Features	***Fuzzy Value******
Dysuria	VH
Urinary frequency	VH
Cloudy urine	H

Purulent urine	L
Hematuria or leukocyturia	H
Nucturia	M
Hesitency	H
Suprapubic	H
Abrupt fever and chill	H
Unilateral or bilateral flank pain	L
Nausea & vomiting	VL
Spumy urine	L

** VH=very high, H=high, M=moderate, L=low, and VL=very low.*

Let:

s[f] = fuzzy value for the feature f of the input case's symptoms.

r_{ij} = j^{th} relevant feature of the i^{th} disease.

$P_{ij}[r_{ij}, v]$ = the certainty of the presence of the i^{th} disease when the relevant feature r_{ij} has a fuzzy value v.

δ_{ij} = the diagnosis decision of the i^{th} disease based on the relevant feature r_{ij} .

k_i = the total number of relevant features for the i^{th} disease.

w_{ij} = the weight of the r_{ij} feature in diagnosing the i^{th} disease.

σ_i = overall diagnosis decision for the i^{th} disease.

The impact of the r_{ij} feature on the diagnosis decision can be directly obtained from the disease profile table $P_{ij}[r_{ij}, v]$. The fuzzy value v is obtained from the patient's symptoms for the feature r_{ij} as $s[r_{ij}]$. The effect δ_{ij} would be one of the fuzzy sets **Yes**, **May Be**, and **No**. It can be denoted in this manner:

$$\delta_{ij} = P_{ij}[r_{ij}, s[r_{ij}]] \quad (1)$$

By summarizing the impact of all k_i related features, the overall diagnosis decision for the i^{th} disease would be acquired like this:

$$\sigma_i = \left(\sum_{j=1}^{j=k_i} w_{ij}\delta_{ij}\right) / \left(\sum_{j=1}^{j=k_i} w_{ij}\right) \quad (2)$$

The weighting factor w_{ij} is introduced here to permit the physician to determine that some features can have more or less importance than others when diagnosing a disease, and he should set appropriate relative values to the weights. If he considers that all features have the same importance, weighting factor will be equal for all features. In this case, equation (2) can be simplified as follows:

$$\sigma_i = \frac{1}{k_i}\sum_{j=1}^{j=k_i} \delta_{ij} \quad (3)$$

The final phase is to acquire crisp values specifying the certainty of existence for every disease in the set ***S***. To show how to find such crisp values, consider the following example.

- Suppose that a given disease si has 10 associated symptoms, all of which has the same weight in the diagnosis. That is:

  ki = 10, wij = 1 for all j = 1, … , 10.

- Suppose that when applying equation (1) to realize the diagnostic decisions (δij , j = 1, … , 10), the result was 7 Yes, 2 May Be, and 1 No.
- The overall diagnostic decision will be: σi = (7 Yes + 2 May Be + 1 No) / 10 This fuzzy set will be as illustrated in fig.2.
- The center of area method will be considered for defuzzification. Let: ci = the centroid of the overall diagnosis decision fuzzy set

  cy = the centroid for the Yes fuzzy set qi = the certainty of the presence of the considered disease si in percent

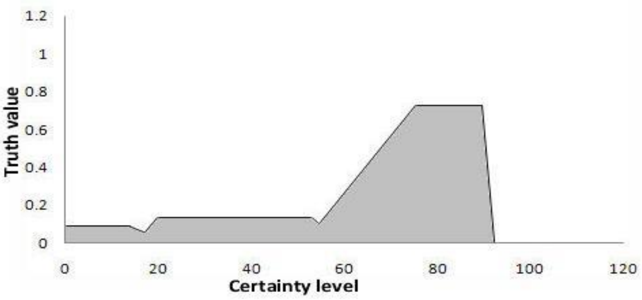
Accordingly, the crisp decision value for the disease di will be calculated as demonstrated below. It should be mentioned that if the results were yes for all related symptoms of di, the decision would be 100%.

$$Qi = (ci / CY) \times 100\% \quad (4)$$

- For the current instance, the values of ci and CY are 0.55and 0.87, respectively. This shows that the certainty of the presence of the considered disease is 89% as shown in Fig.2.

  $c_i = 0.55$ $c_y = 0.87$ $q_i = 90$ %

Fig (2) Fuzzy set representing the overall diagnosis decision for the example case

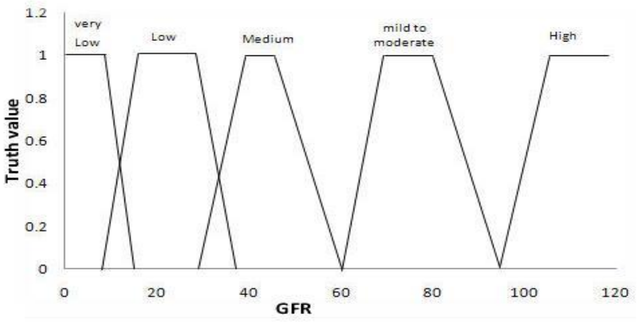


7-Displacement of Measurement Attributes

The signs for quantifiable features such as Hypertension, edema, etc. will be determined as a numeric value. For the sake of simplicity, one may employ fixed tables arranged by the physician to map these numeric values into fuzzy values from the set {Very Low, Low, Moderate, High, Very High}. This solution may be sufficient in some cases. However, in the following part, we indicate a better solution that is more precise and avoids sudden (unexpected) changes. Here, we consider GFR for illustration. Glomerular filtration rate (GFR) is a test used to check how well the kidneys are working. Specifically, it estimates how much blood passes through the tiny filters in the kidneys, called glomeruli, each minute [18].

Fig.3 demonstrates five fuzzy sets that map percentage values of GFR. GFR levels are respectively very low (0-15), low (15-38), medium (30-60), mild to moderate (60-90), and high (90 and above).

Fig (3) Fuzzy sets for the GFR% values



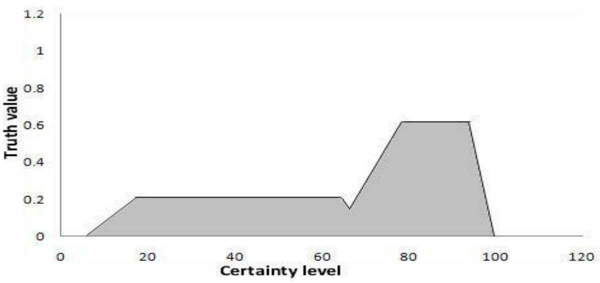
Suppose that the following information is saved in the profile table of some disease di.

If the GFR is Medium, the certainty of the existence of di will be May Be.

If the GFR is High, the certainty of the existence of di will be Yes.

Hence, the diagnosis decision δij for the disease di according to the GFR value of 8% will be the upper envelop of two fuzzy sets: 0.3 May Be, and 0.6Yes as illustrated in fig.4. This will be included in equation (2) to offer the overall decision.

Fig (4) The fuzzy set of the diagnosis decision for a GFR of 8%



The above solution can be generalized to contain features that are identified by two numeric values such as the blood pressure. In this case, a given measurement may lead to four possible fuzzy sets, and the minimum rule [11] should be employed to combine the pairs of fuzzy sets by the AND operator.

8-Results

In the current study, we present the diagnosis decisions acquired by the developed prototype fuzzy expert system, using a typical case study. The prototype system checks for 8 suspected kidney infections and considers a total of 21 features. The input symptoms shown in Table 3 are used in this case study. The symptoms are obtained by physically checking a patient and manually feeding the input to the prototype program. The obtained diagnosis decisions for all suspected diseases are presented in Table 4 and the output fuzzy sets for the overall diagnosis of two diseases having some common symptoms are illustrated in Fig. 5 (refer to table 2).

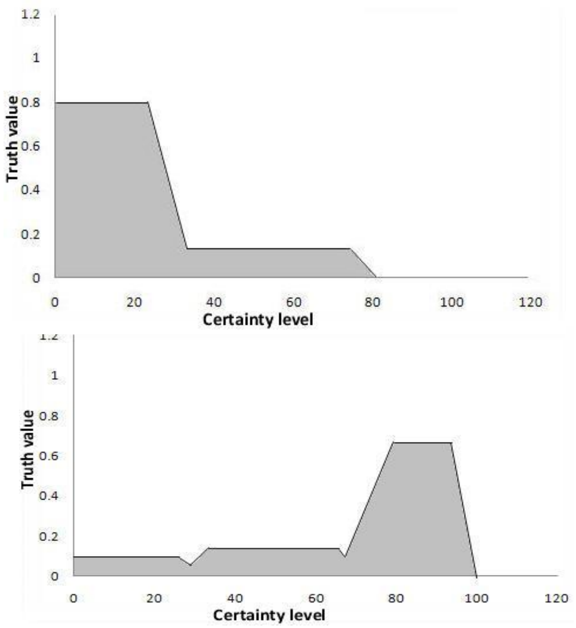
Table (5) The obtained diagnosis decisions for the case study

Certainty Level %	***Disease***
Kidney infection	0.451
Polycystic kidney disease	0.399
Nephroangiosclerosis	0.282
kidney stone	0.633
Chronic renal failure	0.381
Renal Tubular	0.151
Proteinuria	0.302
IgA nephropathy	0.282

Fig (5) The output fuzzy sets for the diagnosis decision of two infections

(a) Kidney stone

(b) Kidney infection



Based on the input symptoms, a high certainty level of 63.3% is given for kidney stone and lower levels are given for all other suspected infections by the prototype expert system. Another significant finding is the fact that the result agrees completely with the diagnosis of human expert physicians. It should be mentioned that the appropriate selection of the membership functions for the three fuzzy sets as 'Yes, Maybe, and No' aids to make better the final results. In the present work, we employed the shapes shown in Fig.1 and tried different parameter values to increase the output certainty level of the most possible disease and decrease that of all others.

9-Discussion

This paper explained how to understand the disease process at its early stage. It is important to perform a quantitative analysis in addition to the qualitative evaluation of the medical data. Applying fuzzy pattern recognition diagnosis methods in medical section can solve the problems in traditional based recognition techniques. The present study aimed to develop a new method in fuzzy logic which could be used for the diagnosis of kidney diseases. We presented in this study a methodology to utilize the experience of skillful physicians and save it in fuzzy tables to indicate disease profiles. The most obvious finding of the study was that the results of the diagnosis of kidney diseases, e.g. kidney stone, via using fuzzy logic instrument were fully compatible with those of kidney physicians. Complete agreement with the diagnosis of human expert physicians has been obtained in many experiments with different input symptoms in each case study. The created system may be augmented to decrease the effort of initial physical checking and manual feeding of the input symptoms.

Although, the empirical findings in this study provide a new understanding of Fuzzy Medical Diagnosis, the study suffers from some limitations. First, the numbers of patients and controls were relatively small. Second, these findings are limited by the use of a cross sectional design. It is suggested that the association of these factors is investigated in future recognition based technique studies. Third, it seems that the efficiency of the existing standard algorithms for analyses in medical diagnoses can be further improved by applying other hybrid soft computing techniques. Further research in this field (regarding the role of fuzzy logic) will be of great help in solving medical diagnosis problems.

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BIOGRAPHY

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