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TYPE-2 TRIANGULAR FUZZY MATRICES IN MEDICAL DIAGNOSIS

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ABSTRACT

The important and difficult process of medical diagnosis has promoted attempts to model it with the use of type-2 fuzzy numbers. In this paper, the model proposes two types of relations to exist between symptoms and diseases; an occurrence relation and confirmability relation. Also this paper addresses the parametric representation of type-2 triangular fuzzy numbers and arithmetic operations on type-2 triangular fuzzy numbers.

INTRODUCTION

The concept of a type-2 fuzzy set, which is an extension of the concept of an ordinary fuzzy set, was introduced by Zadeh, (1975). A type-2 fuzzy set is characterized by a membership function, i.e., the membership value for each element of this set is a fuzzy set in [0, 1], unlike an ordinary fuzzy set where the membership value is a crisp number in [0, 1]. Hisdal, (1981) discussed the IF THEN ELSE statement and interval-valued fuzzy sets of higher type. Jhon, (1998) studied an appraisal of theory and applications on type-2 fuzzy sets. The fuzzy matrices were introduced first time by Thomason, (1977), who discussed the convergence of powers of fuzzy matrix. Kim, (1988) presented some important results on determinant of square fuzzy matrices. Ragab and Emam, (1995) presented some properties of the min-max composition of fuzzy matrices. Shyamal and Pal, (2007) introduced triangular fuzzy matrices. Recently Stephen Dinagar and Latha introduced type-2 triangular fuzzy matrices. And presented some special types and properties of them (Stephen Dinagar and Latha, 2012 and Stephen Dinagar Latha, 2013). Medicine is one field in which the applicability of fuzzy set theory was recognized quite early in the mid of 1970. The utility of fuzzy set theory in medical diagnosis was first demonstrated by Albin in the year 1975. Within this field, it is the uncertainty found in the process of diagnosis of disease that has most frequently been the focus of applications of fuzzy set theory. With the augmented capacity of information available to physicians from new medical technologies, the process of classifying different sets of symptoms under a single name and determining appropriate therapeutic actions becomes increasingly difficult. A single disease may manifest itself quite differently in different patients and at different stages of malady. Furthermore, a single symptom may be indicative of several different diseases, and the presence of several diseases in a single patient may disrupt the expected symptom pattern of any one of them. The best and most useful descriptions of disease entities often use linguistic terms that are irreducibly fuzzy. Although medical knowledge concerning the symptom-disease relationship constitutes one source of imprecision and uncertainty in the diagnostic process, the knowledge concerning the state of the patient constitutes another. Normally, the physician gathers knowledge about patient from the past history, physical examination, laboratory test results, and other investigative procedures such as X-rays, and ultrasonic diagnosis. The knowledge provided by each of these sources carries with it varying degree of uncertainty.

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Thus, the state of symptoms of the patient can be known by the physician with only limited degree of precision. In the face of uncertainty concerning the observed symptoms of the patient as well as the uncertainty concerning the relation of the symptoms to a disease entity, it is nevertheless crucial that the physician determine the diagnostic labels that will entail the appropriate therapeutic regimen. Adlassing, (1986) introduced a fuzzy relational model for diagnostic process. John *et al*., 2000 presented Neuro-fuzzy clustering of radiographic tibia image data using type-2 fuzzy sets. Innocent and John *et al*., 2000 deals with computer aided fuzzy medical diagnosis. Stephen Dinagar and Anbalagan, (2014) presented type-2 fuzzy numbers in medical diagnosis. In this paper, in section 2 definition of type-2 triangular fuzzy number, new ranking function and arithmetic operations on type-2 triangular fuzzy numbers are reviewed. In section 3 definition of type-2 triangular fuzzy matrix and arithmetic operations on type-2 triangular fuzzy matrices are given. In section 4 medical diagnosis problem using type-2 triangular fuzzy matrices is discussed. Finally in section 5 conclusion is discussed.

2. Type-2 Triangular Fuzzy Numbers

Definition 2.1: Fuzzy set

A fuzzy set A in a universe of discourse X is defined as the set of pairs. A = {(x, $\mu_A(x)$); x ϵ X}, where μ_A: X → [0,1] is a mapping called the (degree of) membership function of the fuzzy set A, while $\mu_A(x)$ is called the membership degree of x ϵ X in the fuzzy set A.

Definition 2.2: Type-2 fuzzy set

A type-2 fuzzy set is a fuzzy set whose membership values are fuzzy sets in [0, 1]. In other words, the type-2 fuzzy sets are defined by functions of the form μ_A: $X \rightarrow \chi$ ([0,1]), where χ ([0,1]) denotes the set of all fuzzy subsets of the interval [0, 1].

Example 2.3 [7]

An example of a membership function of this type is graphically represented in the following figure 1.

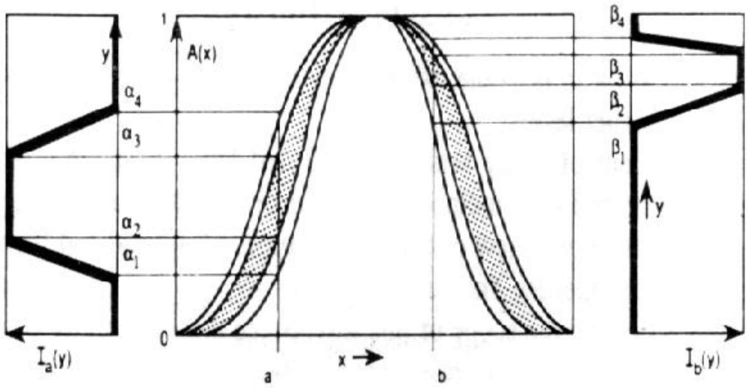

Figure 1. Illustration of the concept of a fuzzy set of type-2

The above figure 1 represents a pictorial representation of a type-2 fuzzy set whose membership function is also a fuzzy set.

Definition 2.4: Type-2 fuzzy number

Let $\tilde{\tilde{A}}$ be a type-2 fuzzy set defined in the universe of discourse R. If the following conditions are satisfied:

- $\tilde{\tilde{A}}$ is normal,
- $\tilde{\tilde{A}}$ is a convex set,
- The support of $\tilde{\tilde{A}}$ is closed and bounded, then $\tilde{\tilde{A}}$ is called a type-2 fuzzy number.

Definition 2.5: Type-2 Triangular Fuzzy Number

A type-2 triangular fuzzy number $\tilde{\tilde{A}}$ on R is given by $\tilde{\tilde{A}}$ = {(x, ($\mu_A^1(x)$, $\mu_A^2(x)$, $\mu_A^3(x)$)); xϵR}
and $\mu_A^1(x) \leq \mu_A^2(x) \leq \mu_A^3(x)$, for all xε R. Denote $\tilde{\tilde{A}} = (\tilde{A}_1, \tilde{A}_2, \tilde{A}_3)$, where $\tilde{A}_1 = (A_1^L, A_1^N, A_1^U)$, $\tilde{A}_2 = (A_2^L, A_2^N, A_2^U)$ and $\tilde{A}_3 = (A_3^L, A_3^N, A_3^U)$ are same type of fuzzy numbers.

2.6. The Proposed Ranking Function

Let F(R) be the set of all type-2 normal triangular fuzzy numbers. One convenient approach for solving numerical valued problem is based on the concept of comparison of fuzzy numbers by use of ranking function. An effective approach for ordering the elements of F(R) is to define a linear ranking function Ř:F(R) → Rwhich maps each fuzzy number into R.

Suppose if $(\tilde{A}_1,\tilde{A}_2,\tilde{A}_3)$,= $((A_1^L,A_1^N,A_1^U),(A_2^L,A_2^N,A_2^U),(A_3^L,A_3^N,A_3^U))$ then we define $\check{R}(\tilde{\tilde{A}})$ = $(A_1^L+A_1^N+A_1^U+A_2^L+A_2^N+A_2^U+A_3^L+A_3^N+A_3^U) / 9$.

Also we define orders on F(R) by

$\check{R}(\tilde{\tilde{A}}) \geq \check{R}(\tilde{\tilde{B}})$ if and only if $\tilde{\tilde{A}} \gtrsim_{\check{R}} \tilde{\tilde{B}}$,
$\check{R}(\tilde{\tilde{A}}) \leq \check{R}(\tilde{\tilde{B}})$ if and only if $\tilde{\tilde{A}} \lesssim_{\check{R}} \tilde{\tilde{B}}$
and $\check{R}(\tilde{\tilde{A}}) = \check{R}(\tilde{\tilde{B}})$ if and only if $\tilde{\tilde{A}} =_{\check{R}} \tilde{\tilde{B}}$.

2.7. Arithmetic Operations on Type-2 Triangular Fuzzy Numbers

Let $\tilde{\tilde{a}} = (\tilde{a}_1, \tilde{a}_2, \tilde{a}_3)$ = $((a_1^L,a_1^N,a_1^U),(a_2^L,a_2^N,a_2^U),(a_3^L,a_3^N,a_3^U))$ and $\tilde{\tilde{b}} = (\tilde{b}_1, \tilde{b}_2, \tilde{b}_3)$ = $((b_1^L,b_1^N,b_1^U),(b_2^L,b_2^N,b_2^U),(b_3^L,b_3^N,b_3^U))$ be two type-2 triangular fuzzy numbers. Then we define,

(i) Addition

$\tilde{\tilde{a}} + \tilde{\tilde{b}}$ = Max{ $\tilde{\tilde{a}}$, $\tilde{\tilde{b}}$}

(ii)Subtraction

$\tilde{\tilde{a}} - \tilde{\tilde{b}}$= $((a_1^L-b_3^U,a_1^N-b_3^N,a_1^U-b_3^L),(a_2^L-b_2^U,a_2^N-b_2^N,a_2^U-b_2^L),(a_3^L-b_1^U,a_3^N-b_1^N, a_3^U-b_1^L))$

(iii)Multiplication

$\tilde{\tilde{a}} \times \tilde{\tilde{b}}$ = Min {$\tilde{\tilde{a}}$, $\tilde{\tilde{b}}$}

3. Type-2 Triangular Fuzzy Matrices (T2TFMS)

Definition 3.1: Type-2 Triangular Fuzzy Matrix (T2TFM)

A type-2 triangular fuzzy matrix (T2TFM) of order m×n is defined as A = $(\tilde{\tilde{a}}_{ij})_{mxn}$ where the ij[th] element $\tilde{\tilde{a}}_{ij}$ of A is the type-2 triangular fuzzy number.

3.2. Operations onT2TFMs

As for classical matrices we define the following operations on T2TFMs. Let A = $(\tilde{\tilde{a}}_{ij})$ and B = $(\tilde{\tilde{b}}_{ij})$ be two T2TFMs of same order. Then we have the following:

(i) A+B = $(\tilde{\tilde{a}}_{ij} + \tilde{\tilde{b}}_{ij})$
(ii) A−B = $(\tilde{\tilde{a}}_{ij} - \tilde{\tilde{b}}_{ij})$
(iii) For A = $(\tilde{\tilde{a}}_{ij})_{mxn}$ and B = $(\tilde{\tilde{b}}_{ij})_{nxk}$ then AB = $(\tilde{\tilde{c}}_{ij})_{mxk}$ where $\tilde{\tilde{c}}_{ij} = \sum_{p=1}^{n} \tilde{\tilde{a}}_{ip} . \tilde{\tilde{b}}_{pj}$, i=1,2,…..,m and j=1,2,…..,k.
(iv) A^Tor A′= $(\tilde{\tilde{a}}_{ji})$
(v) kA = $(k\tilde{\tilde{a}}_{ij})$, where k is a scalar.

4. Confirmation of the Diagnoses using Type-2 Fuzzy Relational Matrices

In this example, let $\tilde{\tilde{S}}$ = { $\tilde{\tilde{s}}_1, \tilde{\tilde{s}}_2, \ldots, \tilde{\tilde{s}}_m$} denote the set of all symptoms, $\tilde{\tilde{D}}$ = { $\tilde{\tilde{d}}_1, \tilde{\tilde{d}}_2, \ldots,\tilde{\tilde{d}}_n$} be the set of all diseases or diagnoses, $\tilde{\tilde{P}}$ = { $\tilde{\tilde{p}}_1, \tilde{\tilde{p}}_2, \ldots, \tilde{\tilde{p}}_q$} be the set of all patients, all $\tilde{\tilde{s}}_i$, $\tilde{\tilde{d}}_j$ and $\tilde{\tilde{p}}_k$ are type-2 fuzzy numbers. Let us define a type-2 fuzzy relation $\tilde{\tilde{R}}_S$ on the set $\tilde{\tilde{P}} \times \tilde{\tilde{S}}$ in which type-2 fuzzy numbers $\tilde{\tilde{R}}_S$ $(\tilde{\tilde{p}}, \tilde{\tilde{s}})$ (where $\tilde{\tilde{p}} \in \tilde{\tilde{P}}$, $\tilde{\tilde{s}} \in \tilde{\tilde{S}}$) indicate the degree to which the symptom $\tilde{\tilde{s}}$ present in patient $\tilde{\tilde{p}}$. Let us further define a type-2 fuzzy relation $\tilde{\tilde{R}}_O$ on the set $\tilde{\tilde{S}} \times \tilde{\tilde{D}}$ where $\tilde{\tilde{R}}_O(\tilde{\tilde{s}}, \tilde{\tilde{d}})$ indicates the frequency of occurrence of symptoms $\tilde{\tilde{s}}$ with disease $\tilde{\tilde{d}}$. Let $\tilde{\tilde{R}}_C$ also be a type-2 fuzzy relation on $\tilde{\tilde{S}} \times \tilde{\tilde{D}}$ where $\tilde{\tilde{R}}_C(\tilde{\tilde{s}}, \tilde{\tilde{d}})$ corresponds to the degree to which symptoms $\tilde{\tilde{s}}$ confirms the presence of disease $\tilde{\tilde{d}}$.

The fuzzy occurrence relation $\tilde{\tilde{R}}_O$ and confirmability relation $\tilde{\tilde{R}}_C$ are determined from expert medical documentation. Since this documentation usually takes the form of statements such as "symptom $\tilde{\tilde{s}}$ seldom occurs in disease $\tilde{\tilde{d}}$" or "symptom $\tilde{\tilde{s}}$ always indicates disease $\tilde{\tilde{d}}$", we assign type-2 fuzzy numbers for the linguistic terms always, almost, often, unspecific, seldom and never. The assignment is given in the following Table.

Table 1. A five member type-2 linguistic term set

Linguistic terms	Type-2 fuzzy numbers
Never	((0,0,0),(0,0,0),(0,0,0))
Seldom	((26,27,31),(27,28,32),(31,32,36))
Unspecific	((45,46,50), (46,47,51), (50,51,55))
Often	((70,71,75), (71,72,76), (75,76,80))
Always	((100,100,100), (100,100,100), (100,100,100))

Four different fuzzy indications are calculated by means of fuzzy relation compositions. Let $\tilde{\tilde{C}}$ be the constant T2TFM of order 3 with all the entries as ((100,100,100), (100,100,100), (100,100,100))

- Occurrence indication $\tilde{\tilde{R}}_1 = (\tilde{\tilde{R}}_S \circ \tilde{\tilde{R}}_O)$.
- Confirmability indication $\tilde{\tilde{R}}_2 = (\tilde{\tilde{R}}_S \circ \tilde{\tilde{R}}_C)$.
- Non-occurrence indication $\tilde{\tilde{R}}_3 = \tilde{\tilde{R}}_S \circ (\tilde{\tilde{C}} - \tilde{\tilde{R}}_O)$.
- Non-symptom indication $\tilde{\tilde{R}}_4 = (\tilde{\tilde{C}} - \tilde{\tilde{R}}_S) \circ \tilde{\tilde{R}}_O$.

Similar indications are determined for symptom/disease relationships, arriving at 12 fuzzy relationships $\tilde{\tilde{R}}$.
Three categories of diagnostic relationships are distinguished:

- Confirmed diagnoses.
- Excluded diagnoses.
- Diagnostic hypotheses.

Diagnoses are considered confirmed if the rank of $\tilde{\tilde{R}}_2(\tilde{\tilde{p}}_k, \tilde{\tilde{d}}_j) = 100$.
We may make an excluded diagnosis for a disease $\tilde{\tilde{d}}$ in patient $\tilde{\tilde{p}}$ if the rank of $\tilde{\tilde{R}}_3(\tilde{\tilde{p}}, \tilde{\tilde{d}}) = 100$ or $\tilde{\tilde{R}}_4(\tilde{\tilde{p}}, \tilde{\tilde{d}}) = 100$.

For excluded diagnosis, the decision rules are more involved; and for diagnostic hypotheses, all diagnoses are used for which the maximum rank of $\tilde{\tilde{R}}_2(\tilde{\tilde{p}}_k, \tilde{\tilde{d}}_j) < 0.50$.
Assume that the following medical documentation exists concerning the relations of symptoms $\tilde{\tilde{s}}_1, \tilde{\tilde{s}}_2$ and $\tilde{\tilde{s}}_3$ to the diseases $\tilde{\tilde{d}}_1, \tilde{\tilde{d}}_2$ and $\tilde{\tilde{d}}_3$:

- Symptom $\tilde{\tilde{s}}_1$ seldom occurs in patients with disease $\tilde{\tilde{d}}_1$ but seldom confirms the presence of disease $\tilde{\tilde{d}}_3$.
- Symptom $\tilde{\tilde{s}}_1$ often occurs in patients with disease $\tilde{\tilde{d}}_2$ but often confirms the presence of disease $\tilde{\tilde{d}}_2$.
- Symptom $\tilde{\tilde{s}}_2$ always occurs in patients with disease $\tilde{\tilde{d}}_1$ but always confirms the presence of disease $\tilde{\tilde{d}}_1$.
- Symptom $\tilde{\tilde{s}}_2$ never occurs in patients with disease $\tilde{\tilde{d}}_3$ but never confirms the presence of disease $\tilde{\tilde{d}}_2$.
- Symptom $\tilde{\tilde{s}}_3$ often occurs in patients with disease $\tilde{\tilde{d}}_2$ but always confirms the presence of disease $\tilde{\tilde{d}}_3$.
- Symptom $\tilde{\tilde{s}}_3$ seldom occurs in patients with disease $\tilde{\tilde{d}}_1$ but seldom confirms the presence of disease $\tilde{\tilde{d}}_1$.
- All missing relational pairs of symptoms and diseases are assumed to be unspecified.

Now assume that we are given the fuzzy relation $\tilde{\tilde{R}}_O$, $\tilde{\tilde{R}}_C$ and $\tilde{\tilde{R}}_S$ specifying the degree of presence of symptoms $\tilde{\tilde{s}}_1, \tilde{\tilde{s}}_2$ and $\tilde{\tilde{s}}_3$ for the three patients $\tilde{\tilde{p}}_1, \tilde{\tilde{p}}_2$ and $\tilde{\tilde{p}}_3$ as follows:

$$\tilde{\tilde{R}}_O = \begin{pmatrix} \text{Seldom} & \text{Often} & \text{Unspecific} \\ \text{Always} & \text{Unspecific} & \text{Never} \\ \text{Seldom} & \text{Often} & \text{Unspecific} \end{pmatrix}$$

$$\tilde{\tilde{R}}_C = \begin{pmatrix} \text{Unspecific} & \text{Often} & \text{Seldom} \\ \text{Always} & \text{Never} & \text{Unspecific} \\ \text{Seldom} & \text{Unspecific} & \text{Always} \end{pmatrix}$$

$$\tilde{\tilde{R}}_S = \begin{pmatrix} \text{Often} & \text{Always} & \text{Seldom} \\ \text{Often} & \text{Seldom} & \text{Never} \\ \text{Seldom} & \text{Never} & \text{Always} \end{pmatrix}$$

From our medical documentation we construct the matrices of relations $\tilde{\tilde{R}}_O$, $\tilde{\tilde{R}}_C$ and $\tilde{\tilde{R}}_S$. Then compute the matrices of relation under the composition (+, ·) where + is maximum and · is minimum.

$$\tilde{\tilde{R}}_O = \begin{pmatrix} ((26,27,31),(27,28,32),(31,32,36)) & ((70,71,75),(71,72,76),(75,76,80)) & ((45,46,50),(46,47,51),(50,51,55)) \\ ((100,100,100),(100,100,100),(100,100,100)) & ((45,46,50),(46,47,51),(50,51,55)) & ((0,0,0),(0,0,0),(0,0,0)) \\ ((26,27,31),(27,28,32),(31,32,36)) & ((70,71,75),(71,72,76),(75,76,80)) & ((45,46,50),(46,47,51),(50,51,55)) \end{pmatrix}$$

$$\tilde{\tilde{R}}_C = \begin{pmatrix} ((45,46,50),(46,47,51),(50,51,55)) & ((70,71,75),(71,72,76),(75,76,80)) & ((26,27,31),(27,28,32),(31,32,36)) \\ ((100,100,100),(100,100,100),(100,100,100)) & ((0,0,0),(0,0,0),(0,0,0)) & ((45,46,50),(46,47,51),(50,51,55)) \\ ((26,27,31),(27,28,32),(31,32,36)) & ((45,46,50),(46,47,51),(50,51,55)) & ((100,100,100),(100,100,100),(100,100,100)) \end{pmatrix}$$

$$\tilde{\tilde{R}}_S = \begin{pmatrix} ((70,71,75),(71,72,76),(75,76,80)) & ((100,100,100),(100,100,100),(100,100,100)) & ((26,27,31),(27,28,32),(31,32,36)) \\ ((70,71,75),(71,72,76),(75,76,80)) & ((26,27,31),(27,28,32),(31,32,36)) & ((0,0,0),(0,0,0),(0,0,0)) \\ ((26,27,31),(27,28,32),(31,32,36)) & ((0,0,0),(0,0,0),(0,0,0)) & ((100,100,100),(100,100,100),(100,100,100)) \end{pmatrix}$$

Also $\tilde{\tilde{C}} = \begin{pmatrix} ((100,100,100),(100,100,100),(100,100,100)) & ((100,100,100),(100,100,100),(100,100,100)) & ((100,100,100),(100,100,100),(100,100,100)) \\ ((100,100,100),(100,100,100),(100,100,100)) & ((100,100,100),(100,100,100),(100,100,100)) & ((100,100,100),(100,100,100),(100,100,100)) \\ ((100,100,100),(100,100,100),(100,100,100)) & ((100,100,100),(100,100,100),(100,100,100)) & ((100,100,100),(100,100,100),(100,100,100)) \end{pmatrix}$

$$\tilde{\tilde{C}} - \tilde{\tilde{R}}_O = \begin{pmatrix} ((64,68,69),(68,72,73),(69,73,74)) & ((20,24,25),(24,28,29),(25,29,30)) & ((45,49,50),(49,53,54),(50,54,55)) \\ ((0,0,0),(0,0,0),(0,0,0)) & ((45,49,50),(49,53,54),(50,54,55)) & ((100,100,100),(100,100,100),(100,100,100)) \\ ((64,68,69),(68,72,73),(69,73,74)) & ((20,24,25),(24,28,29),(25,29,30)) & ((45,49,50),(49,53,54),(50,54,55)) \end{pmatrix}$$

$$\tilde{\tilde{C}} - \tilde{\tilde{R}}_S = \begin{pmatrix} ((20,24,25),(24,28,29),(25,29,30)) & ((0,0,0),(0,0,0),(0,0,0)) & ((64,68,69),(68,72,73),(69,73,74)) \\ ((20,24,25),(24,28,29),(25,29,30)) & ((64,68,69),(68,72,73),(69,73,74)) & ((100,100,100),(100,100,100),(100,100,100)) \\ ((64,68,69),(68,72,73),(69,73,74)) & ((100,100,100),(100,100,100),(100,100,100)) & ((0,0,0),(0,0,0),(0,0,0)) \end{pmatrix}$$

$$\tilde{\tilde{R}}_1 = (\tilde{\tilde{R}}_S \circ \tilde{\tilde{R}}_O = \begin{pmatrix} ((100,100,100),(100,100,100),(100,100,100)) & ((70,71,75),(71,72,76),(75,76,80)) & ((45,46,50),(46,47,51),(50,51,55)) \\ ((26,27,31),(27,28,32),(31,32,36)) & ((70,71,75),(71,72,76),(75,76,80)) & ((45,46,50),(46,47,51),(50,51,55)) \\ ((26,27,31),(27,28,32),(31,32,36)) & ((26,27,31),(27,28,32),(31,32,36)) & ((45,46,50),(46,47,51),(50,51,55)) \end{pmatrix}$$

$$\tilde{\tilde{R}}_2 = (\tilde{\tilde{R}}_S \circ \tilde{\tilde{R}}_C) = \begin{pmatrix} ((100,100,100),(100,100,100),(100,100,100)) & ((70,71,75),(71,72,76),(75,76,80)) & ((.45,.46,.50),(.46,.47,.51),(.50,.51,.55)) \\ ((45,46,50),(46,47,51),(50,51,55)) & ((70,71,75),(71,72,76),(75,76,80)) & ((26,27,31),(27,28,32),(31,32,36)) \\ ((26,27,31),(27,28,32),(31,32,36)) & ((45,46,50),(46,47,51),(50,51,55)) & ((100,100,100),(100,100,100),(100,100,100)) \end{pmatrix}$$

$$\tilde{\tilde{R}}_3 = \tilde{\tilde{R}}_S \text{ o } (\tilde{\tilde{C}} - \tilde{\tilde{R}}_O) = \begin{pmatrix} ((64,68,69),(68,72,73),(69,73,74)) & ((45,49,50),(49,53,54),(50,54,55)) & ((100,100,100),(100,100,100),(100,100,100)) \\ ((64,68,69),(68,72,73),(69,73,74)) & ((26,27,31),(27,28,32),(31,32,36)) & ((45,49,50),(49,53,54),(50,54,55)) \\ ((64,68,69),(68,72,73),(69,73,74)) & ((20,24,25),(24,28,29),(25,29,30)) & ((45,49,50),(49,53,54),(50,54,55)) \end{pmatrix}$$

$$\tilde{\tilde{R}}_4 = (\tilde{\tilde{C}} - \tilde{\tilde{R}}_S) \text{ o } \tilde{\tilde{R}}_O = \begin{pmatrix} ((26,27,31),(27,28,32),(31,32,36)) & ((64,68,69),(68,72,73),(69,73,74)) & ((45,46,50),(46,47,51),(50,51,55)) \\ ((64,68,69),(68,72,73),(69,73,74)) & ((70,71,75),(71,72,76),(75,76,80)) & ((45,46,50),(46,47,51),(50,51,55)) \\ ((100,100,100),(100,100,100),(100,100,100)) & ((64,68,69),(68,72,73),(69,73,74)) & ((45,46,50),(46,47,51),(50,51,55)) \end{pmatrix}$$

Also

Ř[((0,0,0), (0,0,0), (0,0,0))] = 0
Ř[((26,27,31), (27,28,32), (31,32,36))] = 30
Ř[((45,46,50), (46,47,51), (50,51,55))] = 49
Ř[((70,71,75), (71,72,76), (75,76,80))] = 74
Ř[((100,100,100), (100,100,100), (100,100,100))]= 100
Ř[((*20,24,25*), (*24,28,29*), (*25,29,30*)] = 26
Ř[((*45,49,50*), (*49,53,54*), (*50,54,55*))] = 51
Ř[((*64,68,69*), (*68,72,73*), (*69,73,74*))] = 70

From the above four indication relations, we may draw different types of diagnostic conclusions. For instance, we may make a confirmed diagnosis of a disease d for a patient if the rank of $\tilde{\tilde{R}}_2(\tilde{p}, \tilde{\tilde{d}}) = 100$. Since the rank of $\tilde{\tilde{R}}_2(\tilde{p}_3, \tilde{\tilde{d}}_3) = 100$, $\tilde{\tilde{R}}_2(\tilde{p}_1, \tilde{\tilde{d}}_1) = 100$, we may make a confirmed diagnosis of a disease $\tilde{\tilde{d}}_3$ for the patient $\tilde{p}_3$ and a disease $\tilde{\tilde{d}}_1$ for the patient $\tilde{p}_1$. $\tilde{\tilde{R}}_2$ does seem to indicate, for instance, that disease $\tilde{\tilde{d}}_2$ is strongly confirmed for patient $\tilde{p}_2$ and $\tilde{p}_3$. We may make an excluded diagnosis for a disease $\tilde{\tilde{d}}_j$ in patient $\tilde{p}_k$ if the rank of $\tilde{\tilde{R}}_3(\tilde{p}_k, \tilde{\tilde{d}}_j) = 100$ or $\tilde{\tilde{R}}_4(\tilde{p}_k, \tilde{\tilde{d}}_j) = 100$. In our example we may exclude disease $\tilde{\tilde{d}}_1$ as a possible diagnosis for patient $\tilde{p}_3$ and exclude disease $\tilde{\tilde{d}}_3$ as a possible diagnosis for patient $\tilde{p}_1$.

Conclusion

In this paper we have presented a method to perform type-2 fuzzy arithmetic operation using well known arithmetic operations on type-1 fuzzy numbers. We defined a set of terms that describe different normality formations of type-2 triangular fuzzy numbers. Finally we have explained the medical diagnosis problem using type-2 triangular fuzzy matrices.

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