Advances in Mathematics: Scientific Journal 8 (2019), no.3, 55–61
(Special issue on ICRAPAM)
ISSN 1857-8365 printed version
ISSN 1857-8438 electronic version

A NEW DISTANCE MEASURE BETWEEN INTUITIONISTIC FUZZY MULTISETS AND ITS APPLICATION IN APPOINTMENT PROCESS

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Abstract: Intuitionistic fuzzy set is a generalization of the ordinary fuzzy set that involves membership, non membership and hesitation function and it is very useful in decision making problems such as medical diagnosis, pattern recognition, clustering etc. The decisions are made by using the two important measures: Similarity measure, Distance measure. Distance measure is a tool used to find the difference between intuitionistic fuzzy sets. In this paper, we propose an effective distance measure for intuitionistic fuzzy multisets in which membership, non membership, hesitation function occurs more than once and also we apply this measure in the appointment process and in pattern recognition.
Keywords: Intuitionistic fuzzy sets(IFS), Intuitionistic Fuzzy Multisets(IFMS), Distance measure.
AMS Subject Classification (2010):03E72, 03B20, 03F55.

1. Introduction

In 1965, L.A.Zadeh [29] introduced the notion of a fuzzy subset of a set as a method for representing uncertainty in real physical world. In fuzzy set theory, the membership of an element to a fuzzy set is a single value between 0 and 1. As a generalization of this, intuitionistic fuzzy subset was defined by K.T.Atanassov in 1986 [1,2]. These sets are suited to deal with vagueness or the representation of imperfect knowledge in decision making. In reality, it may not true that the degree of non-membership of an element in an intuitionistic fuzzy set is equal to 1 minus the degree of membership, but there may be some hesitation degree. At first the study of distance measures for IFS was carried out by E.Szmidt and J.Kacprzyk [22,23,24]. Hung and Yang [6] presented a similarity measure based on Hausdroff distance. Various distance measures were given by the authors like Li and Cheng, Liang and Shi, Mitchell [3,4,7,8,9,25,27,28] which was applied in decision making problem and pattern recognition.

Recently, T.K.Shinoj and J.J. Sunil [20,21] introduced intuitionistic fuzzy multisets from the combination of intuitionistic fuzzy sets and fuzzy multisets which was proposed by Yager [26]. In intuitionistic fuzzy multisets, the membership function and non-membership function are allowed to occur more than once. Some of the distance and similarity measures for IFS were extended to IFMS [5,10,11,12,13,14,15,16,17,18].In this paper, we define a new distance measure for intuitionistic fuzzy multisets and prove its efficiency by comparing the measure with the existing distance measures for IFMS. Also we apply this measure in appointment process and in pattern recognition.

2.Preliminaries

Definition 2.1 [1]

Let X be a non-empty set. An intuitionistic fuzzy sets A in X is an object having the form $A = \{\langle x, \mu_A(x), \nu_A(x) \rangle / x \in X\}$ where the functions $\mu_A : X \to [0,1]$ and $\nu_A : X \to [0,1]$ define the degree of membership and non membership of the element $x \in X$.

For each IFS A in X, if $\pi_A = 1 - \mu_A(x) - \nu_A(x)$, $x \in X$, then $\pi_A(x)$ is called intuitionistic index of the element x in A. It is a hesitancy degree of x in A.

Definition 2.2[25]

Let X be a nonempty set. A Fuzzy Multiset(FMS) A drawn from X is characterized by a function, 'count membership' of A denoted by CM_A such that $CM_A : X \to Q$ where Q is the set of all crisp multisets drawn from the unit interval [0,1]. Then for any $x \in X$, the value $CM_A(x)$ is a crisp multiset drawn from [0,1]. For each x in X, the membership sequence is defined as the decreasingly ordered sequence of elements in $CM_A(x)$. It is denoted by $(\mu_A^1(x), \mu_A^2(x), \dots \mu_A^P(x))$where $(\mu_A^1(x) \geq \mu_A^2(x) \geq \cdots \geq \mu_A^P(x))$.

Definition 2.3[20]

Let X be a non-empty set. An Intuitionistic Fuzzy Multiset A denoted by IFMS drawn from X is a characterized by two functions: count membership of $A(CM_A)$ and 'count non membership' of $A(CN_A)$ given respectively by $CM_A : X \to Q$ and $CN_A : X \to Q$ where Q is the set of all crisp multisets drawn from the unit interval [0,1] such that for each $x \in X$, the membership sequence is defined as a decreasingly ordered sequence of elements in $CM_A(x)$ which is denoted by $(\mu_A^1(x), \mu_A^2(x), \dots \mu_A^P(x))$ where $(\mu_A^1(x) \geq \mu_A^2(x) \geq \cdots \geq \mu_A^P(x))$ and the corresponding non membership sequence will be denoted by $(\vartheta_A^1(x), \vartheta_A^2(x), \dots \vartheta_A^P(x))$ such that $0 \leq \mu_A^i(x) + \vartheta_A^i(x) \leq 1$ for every $x \in X$ and i = 1,2,…p.

An IFMS A is denoted by $A = \{\langle x: (\mu_A^1(x), \mu_A^2(x), \dots \mu_A^P(x)), (\vartheta_A^1(x), \vartheta_A^2(x), \dots \vartheta_A^P(x)) \rangle : x \in X\}$.

Definition 2.4[21]

The length of an element x in an IFMS A is defined as the cardinality of $CM_A(x)$ or $CN_A(x)$ for which $0 \leq \mu_A^j(x) + \vartheta_A^j(x) \leq 1$ and it is denoted by L(x : A). That is

$L(x : A) = |CM_A(x)| = |CN_A(x)|$

Definition 2.5[21]

If A and B are IFMS drawn from X then L(x : A,B) = Max{L(x : A), L(x : B)}. Alternatively we use L(x) for L(x : A, B).

Definition 2.6[25]

A function d : IFSs(X) x IFSs(X) $\to$ [0,1] is called distance measure of IFSs if d satisfies the following properties: for any A, B, C $\in$ IFSs(X),

(DP1) $0 \leq d(A,B) \leq 1$;

(DP2) d(A,B) = 0 if and only if A = B;

(DP3) d(A,B) = d(B,A);

(DP4) If A ⊆ B ⊆ C, then d(A,C) ≥ d(A,B) and d(A,C) ≥d(B,C).

Definition 2.7 [14]:

Let A and B be two IFMSs. Then the Normalized Hamming distance between A and B is

$$N_D^*(A,B) = \frac{1}{\eta}\sum_{j=1}^{\eta}\left\{\frac{1}{2n}\sum_{i=1}^{n}\left(\left|\mu_A^j(x_i)-\mu_B^j(x_i)\right|+\left|\vartheta_A^j(x_i)-\vartheta_B^j(x_i)\right|\right)\right\}$$

and with all three degrees, it is

$$N_D^*(A,B) = \frac{1}{\eta}\sum_{j=1}^{\eta}\left\{\frac{1}{2n}\sum_{i=1}^{n}\left(\left|\mu_A^j(x_i)-\mu_B^j(x_i)\right|+\left|\vartheta_A^j(x_i)-\vartheta_B^j(x_i)\right|+\left|\pi_A^j(x_i)-\pi_B^j(x_i)\right|\right)\right\}$$

Definition 2.8 [11]:

In Hamming metrics, the Hausdroff distance of IFMS is defined as

$$d_h(A,B) = \frac{1}{\eta}\sum_{j=1}^{\eta}\left\{\frac{1}{n}\sum_{i=1}^{n}\max[\left(\left|\mu_A^j(x_i)-\mu_B^j(x_i)\right|+\left|\vartheta_A^j(x_i)-\vartheta_B^j(x_i)\right|\right)]\right\}$$

and with all three degrees, it is

$$d_h(A,B) = \frac{1}{\eta}\sum_{j=1}^{\eta}\left\{\frac{1}{n}\sum_{i=1}^{n}\max[\left(\left|\mu_A^j(x_i)-\mu_B^j(x_i)\right|+\left|\vartheta_A^j(x_i)-\vartheta_B^j(x_i)\right|+\left|\pi_A^j(x_i)-\pi_B^j(x_i)\right|\right)]\right\}$$

Definition 2.9 [14]:

The Geometric distance of the intuitionistic fuzzy multi set is defined as

$$D_g(A,B) = \frac{1}{\eta}\sum_{j=1}^{\eta}\left\{\frac{1}{n}\sum_{i=1}^{n}\sqrt{(\mu_A^j(x_i)-\mu_B^j(x_i))^2+(\vartheta_A^j(x_i)-\vartheta_B^j(x_i))^2}\right\}$$

and with all the three degrees, it is

$$D_g(A,B) = \frac{1}{\eta}\sum_{j=1}^{\eta}\left\{\frac{1}{n}\sum_{i=1}^{n}\sqrt{(\mu_A^j(x_i)-\mu_B^j(x_i))^2+(\vartheta_A^j(x_i)-\vartheta_B^j(x_i))^2+(\pi_A^j(x_i)-\pi_B^j(x_i))^2}\right\}$$

Normalized Geometric distance is $D_G(A,B) = \frac{1}{\sqrt{2}} D_g(A,B)$.

3. New Distance Measure Between Intuitionistic Fuzzy Multisets

In this section, a new distance measure between intuitionistic fuzzy multisets is defined and its efficiency is proved by comparing with existing distance measures.

Definition 3.1:

Let A and B be two intuitionistic fuzzy multisets in X. Then the new distance measure between A and B is defined as:

$$D(A,B) = \frac{1}{\eta}\sum_{j=1}^{\eta}\left\{\frac{1}{4(n+1)}\sum_{i=1}^{n}[\left|\mu_A^j(x_i)-\mu_B^j(x_i)\right|+\left|F_A^j(x_i)-F_B^j(x_i)\right|+\left|G_A^j(x_i)-G_B^j(x_i)\right|+\right.$$
$$\left. 2\max\left\{\sum_{i=1}^{n}[\left|\mu_A^j(x_i)-\mu_B^j(x_i)\right|,\left|F_A^j(x_i)-F_B^j(x_i)\right|,\left|G_A^j(x_i)-G_B^j(x_i)\right|]\right\}\right\},$$

$where F_A^j(x_i) = \left(\mu_A^j(x_i)-\vartheta_A^j(x_i)\right), F_B^j(x_i) = \left(\mu_B^j(x_i)-\vartheta_B^j(x_i)\right), G_A^j(x_i) = \left(\mu_A^j(x_i)-\pi_A^j(x_i)\right), G_B^j(x_i) = \left(\mu_B^j(x_i)-\pi_B^j(x_i)\right)$.

Preposition 3.2:

The proposed new distance measure between IFMSs A and B satisfies the following properties:

i) 0 ≤ D(A,B) ≤ 1
ii) D(A,B) = 0 if and only if A = B
iii) D(A,B) = D(B,A)
iv) If A ⊆ B ⊆ C, then D(A,C) ≥ D(A,B) and D(A,C) ≥ D(B,C).

Significance of proposed distance measure

Example 3.3: Let $X = \{A_1,A_2,A_3,A_4,A_5,A_6,A_7,A_8,A_9\}$ with the IFMSs $A = \{A_1,A_2,A_3\}$, $B = \{A_4,A_5,A_6\}$, $C = \{A_1,A_2,A_6\}$ and $Y = \{A_7,A_8,A_9\}$ be defined as

$A = \{\langle A_1:(0.7,0.1,0.2)\rangle, \langle A_2: (0.4,0.5,0.1)\rangle, \langle A_3: (0.3,0.3,0.4)\rangle\}$,

$B = \{\langle A_4:(0.7,0.1,0.2)\rangle, \langle A_5: (0.5,0.4,0.1)\rangle , \langle A_6:(0.4,0.3,0.3)\rangle\}$,

$C = \{ \langle A_1:(0.7,0.1,0.2)\rangle, \langle A_2: (0.4,0.5,0.1)\rangle, A_6:(0.4,0.3,0.3)\rangle\}$ and

$Y = \{\langle A_7:(1,0,0)\rangle, \langle A_8: (0.1,0.1,0.8)\rangle, \langle A_9: (0,1,0)\rangle\}$

Here the cardinality $\eta = 3$ as $|CM_A| = |CN_A| = 3$, $|CM_B| = |CN_B| = 3$, $|CM_C| = |CN_C| = 3$.

Distance measures	d(A,Y)	d(B,Y)	d(C,Y)
Hamming distance for IFMS	0.566	0.566	0.566
Normalized hamming distance for IFMS	0.283	0.283	0.283
Hausdroff distance for IFMS	0.566	0.566	0.566
Geometric distance for IFMS	0.424	0.424	0.424
Normalized Geometric distance for IFMS	0.3	0.3	0.3
Our proposed distance for IFMS	**0.375**	**0.4083**	**0.3916**

From the table, we infer that by using some existing distance measures like hamming distance, normalized hamming distance, Hausdroff distance, geometric distance, normalized geometric distance for IFMS, the sample Y cannot be classified with the sets A,B,C. But the distance measures between the sets (A,Y), (B,Y), (C,Y) can be differentiated by our new distance measure for IFMS. Hence we get the acceptable result that the IFMS Y is closer to the IFMS A since the distance between them is minimum and therefore the sample Y belongs to IFMS A.

4. Appointment Process

An organization has to decide to fill the vacancies of certain posts in various sections in it. So an interview panel of 3 members are formed to select the candidates based on various skills. After the completion of interview, the scores given by panel members are denoted by membership function and each candidate has multi-membership values. In this case, intuitionistic fuzzy multisets is used to make the correct decision.

Let $C = \{C_1,C_2,C_3,C_4,C_5\}$ be the candidates to be appointed, let P = {Sales, Purchase, System, Accounts, Factory}be the departments in which the vacancies to be filled and S = {Communication skill, Experience, Leadership, System skills, Analytical skills} be the parameters for appointing the candidates to the suitable post. Table 1 gives the relation between the sections and the parameters. Table 2 gives the multi membership values of each candidate. Using the proposed distance measure, the distance between the candidates and the sections are found in Table 3. Based on shortest distance, the candidates are appointed in the corresponding sections.

Table 1: Posts and parameters

	Communication skill	**Experience**	**Leadership**	**System skill**	**Analytical skill**
Sales	(0.9,0,0.1)	(0.7,0.2,0.1)	(0.6,0.1,0.3)	(0.5,0.3,0.2)	(0.2,0.6,0.2)
Purchase	(0.7,0.1,0.2)	(0.6,0.1,0.3)	(0.6,0.2,0.2)	(0.4,0.3,0.3)	(0.3,0.5,0.2)
System	(0.6,0.3,0.1)	(0.5,0.4,0.1)	(0.4,0.3,0.3)	(0.9,0.1,0)	(0.3,0.5,0.2)
Accounts	(0.5,0.2,0.3)	(0.6,0.2,0.2)	(0.3,0.4,0.3)	(0.8,0.1,0.1)	(0.9,0,0.1)
Factory	(0.3,0.6,0.1)	(0.8,0.2,0)	(0.8,0.1,0.1)	(0.3,0.6,0.1)	(0.3,0.5,0.2)

Table 2: Candidates and parameters

	Communication skill	Experience	Leadership	System skill	Analytical skill
C_1	(0.4,0.3,0.3) (0.3,0.5,0.2) (0.3,0.4,0.3)	(0.9,0.1,0) (0.8,0.1,0.1) (0.7,0.2,0.1)	(0.7,0.3,0) (0.7,0.1,0.2) (0.6,0.1,0.3)	(0.4,0.6,0) (0.3,0.6,0.1) (0.3,0.5,0.2)	(0.5,0.2,0.3) (0.4,0.4,0.2) (0.4,0.3,0.3)
C_2	(0.8,0.1,0.1) (0.8,0.2,0) (0.7,0.2,0.1)	(0.6,0.2,0.2) (0.7,0.1,0.2) (0.5,0.2,0.3)	(0.5,0.3,0.2) (0.6,0.1,0.3) (0.5,0.2,0.3)	(0.5,0.1,0.4) (0.5,0.2,0.3) (0.4,0.4,0.2)	(0.4,0.3,0.3) (0.5,0.3,0.2) (0.5,0.1,0.4)
C_3	(0.6,0.3,0.1) (0.5,0.3,0.2) (0.6,0.1,0.3)	(0.8,0.2,0) (0.6,0.1,0.3) (0.7,0.1,0.2)	(0.4,0.3,0.3) (0.5,0.2,0.3) (0.3,0.6,0.1)	(0.8,0.1,0.1) (0.8,0.2,0) (0.7,0.3,0)	(0.9,0,0.1) (0.8,0,0.2) (0.9,0.1,0)
C_4	(0.5,0.2,0.3) (0.6,0.1,0.3) (0.7,0.2,0.1)	(0.5,0.3,0.2) (0.6,0.2,0.2) (0.5,0.3,0.2)	(0.6,0.3,0.1) (0.4,0.3,0.3) (0.5,0.3,0.2)	(0.6,0.2,0.2) (0.4,0.2,0.4) (0.4,0.3,0.3)	(0.4,0.2,0.4) (0.5,0.2,0.3) (0.4,0.3,0.3)
C_5	(0.7,0.2,0.1) (0.7,0.1,0.2) (0.6,0.3,0.1)	(0.6,0.2,0.2) (0.5,0.1,0.4) (0.5,0.2,0.3)	(0.5,0.3,0.2) (0.4,0.2,0.4) (0.3,0.4,0.3)	(0.8,0,0.2) (0.7,0.3,0) (0.8,0,0.2)	(0.4,0.2,0.4) (0.5,0.3,0.2) (0.2,0.3,0.5)

Table 3: Distance between the candidates and the sections

	Sales	Purchase	System	Accounts	Factory
C_1	0.3306	0.2861	0.4833	0.5236	**0.1792**
C_2	0.2361	**0.1806**	0.3472	0.4222	0.4444
C_3	0.5055	0.4444	0.3528	**0.15**	0.5653
C_4	0.3139	**0.1889**	0.25	0.3569	0.4291
C_5	0.3667	0.2889	**0.2056**	0.3	0.5708

From the table, the following decisions are made based on shortest distance between the candidates and the sections. The candidate C_1 is appointed in Factory section, candidate C_2 and C_4 are appointed in Purchase section, candidate C_3 is appointed in Accounts section, candidate C_5 is appointed in System section of the organization.

5. Pattern Recognition by using the proposed distance measure

In this section, some testing patterns can be classified by employing the proposed distance measure for IFMS.

Example 5.1

Let Pattern I, Pattern II be the two IFMS's defined as

Pattern I $=\{\langle A_1$: (0.8,0.2,0.2), (0.7,0.1,0.2)$\rangle$, $\langle A_2$: (0.6,0.2,0.2), (0.5,0.5,0) $\rangle$, $\langle A_3$:(0.5,0.3,0.2), (0.4,0.4,0.2) $\rangle$, $\langle A_4$: (0.3,0.1,0.6), (0.4,0.2,0.4)$\rangle$, $\langle A_5$: (0.3,0.2,0.5), (0.2,0.2,0.6) $\rangle\}$,

Pattern II = $\{\langle A_2$: (0.6,0.2,0.2), (0.5,0.5,0) $\rangle$, $\langle$ A_5: (0.3,0.2,0.5), (0.2,0.2,0.6) $\rangle$, $\langle$ A_7: (0.5,0.3,0.2), (0.6,0.2,0.2) $\rangle$, $\langle$ A_8 : (0.7,0.1,0.2), (0.4,0.3,0.3) $\rangle$, $\langle$ A_9: (0.6,0.2,0.2), (0.5,0.2,0.3) $\rangle\}$

The testing Pattern III is the IFMS defined as

Pattern III = $\{\langle A_6$: (0.6,0.2,0.2), (0.3,0.4,0.3)$\rangle$, $\langle A_7$: (0.5,0.3,0.2), (0.6,0.2,0.2)$\rangle$, $\langle A_8$: (0.7,0.1,0.2), (0.4,0.3,0.3) $\rangle$, $\langle A_9$: (0.6,0.2,0.2), (0.5,0.2,0.3) $\rangle$, $\langle$ A_{10}: (0.1,0.8,0.1), (0.2,0.7,0.1) $\rangle\}$

Here the cardinality η =5 as ∣CM(Pattern I) ∣ = ∣CN(Pattern I) ∣ = 5, ∣ CM(Pattern II) ∣ = ∣CN(Pattern II) ∣ = 5, ∣CM(Pattern III) ∣ = ∣ CN(Pattern III) ∣ = 5

The proposed distance measure between Pattern I and Pattern III is **0.2733.**

The proposed distance measure between Pattern II and Pattern III is 0.3133.

Hence the testing Pattern III belongs to Pattern I.

Example 5.2

Let X = { $A_1,A_2,\ldots\ldots A_n$} be a non empty set. Let the patterns P={A_1,A_2}, Q ={A_4,A_5}, R = {A_1,A_8}, S = {A_3,A_6}, T = {A_1,A_5} be the IFMSs defined as

P = { ⟨ A_1: (0.1,0.2) ⟩, ⟨ A_2: (0.1,0.3) ⟩ }

Q = { ⟨ A_4: (0.3,0.3) ⟩, ⟨ A_5: (0.2,0.3) ⟩ }

R = { ⟨ A_1: (0.1,0.2) ⟩, ⟨ A_8: (0,0.2) ⟩ }

S = { ⟨ A_3: (0.3,0.2) ⟩, ⟨ A_6: (0.1,0.1) ⟩ }

T = { ⟨ A_1: (0.1,0.2) ⟩, ⟨ A_5: (0.2,0.3) ⟩ }

And the testing pattern Y = {⟨ A_6: (0.1,0.1) ⟩, ⟨ A_8: (0,0.2) ⟩ }

Here the cardinality η =2 .

By the proposed distance measure, D(P,Y) = 0.0875, D(Q,Y) = 0.2375, D(R,Y) = **0.025**, D(S,Y) = 0.1625, D(T,Y) = 0.1375.

Hence the testing Pattern Y belongs to Pattern R.

Example 5.3

Let X = { $A_1,A_2,\ldots\ldots A_n$} be a non empty set. Let the patterns A={A_1,A_2}, B={A_3,A_4}, C = {A_5,A_6} be the IFMS's defined as

Pattern I = { ⟨ A_1: (0.6,0.3,0.1), (0.5,0.3,0.2) ⟩, ⟨ A_2: (0.5,0.3,0.2), (0.4,0.2,0.4) ⟩ }

Pattern II = { ⟨ A_3: (0.7,0.1,0.2), (0.6,0.3,0.1) ⟩, ⟨ A_4: (0.5,0.2,0.3), (0.4,0.3,0.3) ⟩ }

Pattern III = { ⟨ A_5: (0.3,0.6,0.1), (0.2,0.4,0.4) ⟩, ⟨ A_6: (0.7,0.2,0.1), (0.5,0.4,0.1) ⟩ }

The testing pattern IV is ⟨ A_1: (0.6,0.3,0.1), (0.5,0.3,0.2) ⟩, ⟨ A_6: (0.7,0.2,0.1), (0.5,0.4,0.1) ⟩ }

Here the cardinality η = 2 and number of elements n = 2.

The proposed distance measure between Pattern I and Pattern IV is **0.1167.**

The proposed distance measure between Pattern II and Pattern IV is 0.1833.

The proposed distance measure between Pattern III and Pattern IV is 0.1917.

Hence the testing Pattern IV belongs to Pattern I.

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