A New Tool for Detection of Bacteria and Pattern Recognition by Intuitionistic Fuzzy Measure

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Abstract - Here, we proposed new similarity information measure between AIFSs and proved some necessary properties. The direct applications of proposed information measure in (PR) pattern recognition and bacteria detection are studied. Proposed measure is the more reliable compare to other measures for deal Pattern Recognition problems.

Keywords – Intuitionistic fuzzy set, fuzzy information measures, pattern recognition, bacteria detection.

I. Introduction

Firstly, Zadeh introduced the concept of FSs. Atanassov developed the AIFs based on the concepts of FSs [51]. In fuzzy sets theory, an element in the universal set is assigned to a membership degree but in IFSs theory, an element in the universal set is assigned to each element a membership degree, non-membership and hesitant degree. This is one of the main reasons why IFSs has been treated as a more effective and efficient concept FSs.
AIFs have been applied to many fields, such as PR [14, 11, 33], MD [11, 15], decision-making [12, 20, 22, 34]. Li et al. introduced a new axiomatic definition of a similarity measure for IFSs. Later, Mitchell developed a statistical approach as an allowance of Li's similarity measure and introduced some examples. firstly, Gau and Buehrer introduced the concept of vague sets [19]. Baccour et al. reviewed some similarity measures on IFSs. After that Bustince and Burillo have find out that vague sets are IFs. In recent years, many methods [14, 18, 21, 16] have been developed to deal with similarity measures between IFSs.

Beliakov et al. [3] introduced a vector-valued similarity measure for IFSs. Chen and Chang [8] developed a similarity measure on IFSs with applications to PR. Boran and Akay [4] introduced a bi-parametric similarity measure for IFSs. Chen [7] introduced some similarity measures on vague sets and elements. Grzegorzewski [21] developed the Hausdorff distance measure between two IFSs. Hung and Yang [26, 27] generalized the Hausdor distance and proposed three new similarity measure on IFSs. Using the cosine function, Ye proposed a new similarity measure and a weighted similarity measure on IFSs and used in PR and MD. Hwang et al. [28] introduced a new similarity measure by Sugeno integral and used in PR. Li et al.[30] presented the relationship in between similarity measures and the entropy on IFSs. Liang and shi developed the some similerity measures on IFSs. Mitchell introduced a similarity measure on IFSs to overcome the drawback of Dengfeng and Chuntian's similarity measure.

The paper is organized by presenting some mathematical preliminaries and some existing similarity measures of IFSs in Section II and III. In Section IV, we apply the proposed similarity measure of intuitionistic fuzzy sets to PR and bacteria detection. Finally, some concluding remarks are shown in Section V.

II. PRELIMINARIES

In this section, we briefly review some concepts of intuitionistic fuzzy sets and the properties of similarity measures between [26] intuitionistic fuzzy sets.

Definition 1. [1] Let A be an IFS in the universe of discourse X. Where X = $\{x_1, x_2, ..., x_n\}$, X = $\{x_i, \mu_A(x_i), \nu_A(x_i) \mid x_i \in X\}$, $\mu_A : X \rightarrow [0, 1]$, $\nu_A : X \rightarrow [0, 1]$ where, $\mu_A(x_i)$ and $\nu_A(x_i)$ denote the degree of membership and the degree of non-membership of element $x_i \in A$, respectively, $\mu_A(x_i) \in [0, 1]$, $\nu_A(x_i) \in [0, 1]$, $0 \leq \mu_A(x_i) + \nu_A(x_i) \leq 1$, $1 \leq i \leq 1$.

Definition 2. [1] Let A and B be two IFS in the universe of discourse X, where X = $\{x_1, x_2, ..., x_n\}$ and $A \subseteq B$ iff $x_i \in X$, $\mu_A(x_i) \leq \mu_B(x_i)$ and $\nu_A(x_i) \leq \nu_B(x_i)$, where $1 \leq i \leq n$.

Definition 3. [2] Let A, B and C be a three IFS in X = $\{x_1, x_2, ..., x_n\}$. A similarity measures between IFS satisfies the following properties:

(i) $0 \leq S(A, B) \leq 1$,

(ii) S (A, B) = 0 iff A = B,

(iii) S (A, B) = S (B, A)

(iv) If $A \subseteq B \subseteq C$, then $S (A, C) \leq S (A, B)$ and $S (A, C) \leq S (B, C)$

III. SOME EXISTING MEASURES FOR IFSs

In this section, we review some similarity measures [18, 19] on IFS. And let A and B be two IFS in X = $\{x_1, x_2, ..., x_n\}$, where A = $\{x_i, \mu_A(x_i), \nu_A(x_i) / 1 \leq i \leq n\}$, and B = $\{x_i, \mu_B(x_i), \nu_B(x_i) / 1 \leq i \leq n\}$. The similarity measures on IFS A and B are defined as: Here $\mu_A(x_i)$ and $\nu_A(x_i)$ denoted by μ_{Ai} and ν_{Ai}.

(i) (Chen, 1995):

$$S_E(A;B) = 1 - \left[\frac{\sum_{i=1}^{n} |(\mu_{A_i} - \nu_{A_i}) - (\mu_{B_i} - \nu_{B_i})|}{2n} \right], \quad (1)$$

(ii) (Hong, Kim,1999):

$$S_K(A;B) = 1 - \left[\frac{\sum_{i=1}^{n} |(\mu_{A_i} - \mu_{B_i})| - |(\nu_{A_i} - \nu_{B_i})|}{2n} \right], \quad (2)$$

(iii) (Li, Xu,2001):

$$S_R(A, B) = 1 - \left[\frac{\sum_{i=1}^{n} |(\mu_{A_i} - \nu_{A_i})| - |(\mu_{B_i} - \nu_{B_i})|}{4n} \right] + \left[\frac{\sum_{i=1}^{n} |(\mu_{A_i} - \mu_{B_i})| - |(\nu_{A_i} - \nu_{B_i})|}{4n} \right], \quad (3)$$

(iv) (Dengfeng, Chuntian,2002):

$$S_t(A;B) = 1 - \sqrt[t]{\left[\frac{\sum_{i=1}^{n} \left| \frac{\mu_{A_i} + 1 - \nu_{A_i}}{2} - \frac{\mu_{B_i} + 1 - \nu_{B_i}}{2} \right|^t}{n} \right]}, \quad (4)$$

(v) (Mitchell,2003):

$$S_N\left(A;\ B\right) \ = \frac{1}{2}\left(1-\sqrt[t]{\frac{\sum_{i=1}^{n}|\ \mu_{A_i}-\mu_{B_i}\ |^t}{n}} \ + \ 1-\sqrt[t]{\frac{\sum_{i=1}^{n}|\ \nu_{A_i}-\nu_{B_i}\ |^t}{n}}\right) \ , \tag{5}$$

(vi) (Liang, Shi,2003):

$$S_e^t(A,\ B)=1-\sqrt[t]{\frac{\sum_{i=1}^{n}\left|\frac{\mu_{A_i}-\mu_{B_i}}{2}\right|^t+\sum_{i=1}^{n}\left|\frac{\nu_{A_i}-\nu_{B_i}}{2}\right|^t}{n}}\ , \tag{6}$$

(vii) (Hung, Yang,2004):

$$S^1_{YH}\left(A;B\right)\ =1-\frac{\sum_{i=1}^{n}\max(|\ \mu_{A_i}-\mu_{B_i}\ |,|\ \nu_{A_i}-\nu_{B_i}\ |)}{n} \tag{7}$$

(viii) (Ye,2011):

$$C_{FIS}(A,B)=\frac{1}{n}\sum_{i=1}^{n}\left[\frac{\mu_{A_i}\mu_{B_i}+\nu_{A_i}\nu_{B_i}}{\sqrt{(\mu_{A_i})^2+(\nu_{A_i})^2}+\sqrt{(\mu_{B_i})^2+(\nu_{B_i})^2}}\right]\ , \tag{8}$$

(ix) (Song, Wang, Lei, Xue,2015):

$$C_Z(A,B)=\frac{1}{2n}\sum_{i=1}^{n}\left(\sqrt{\mu_{A_i}\mu_{B_i}}+2\sqrt{\nu_{A_i}\nu_{B_i}}+\sqrt{\pi_{A_i}\pi_{B_i}}+\sqrt{(1-\nu_{A_i})(1-\nu_{B_i})}\right)\ , \tag{9}$$

III. A NEW INFORMATION MEASURES FOR IFSs

In this section, we propose a new similarity measure based on the other measures on IFSs, which satisfies all properties of IFSs.

$$\Delta_{\text{VS}}(A,B)=\sum_{i=1}^{n}\frac{(\mu_{A_i}-\mu_{B_i})^2}{\mu_{A_i}+\mu_{B_i}}+\sum_{i=1}^{n}\frac{(\nu_{A_i}-\nu_{B_i})^2}{\nu_{A_i}+\nu_{B_i}} \tag{10}$$

Theorem 1. Let A, B and C be a three IFS in X = $\{x_1, x_2,...,x_n\}$. The proposed knowledge measure Δ_{VS}(A, B) on IFSs from Definition (3) satisfies the following properties: $\forall\ x_i \in X$,

(i) $0 \leq \Delta_{VS}(A, B) \leq 1$,

(ii) $\Delta_{VS}(A, B) = 0$ iff A = B

(iii) $\Delta_{VS}(A, B) = \Delta_{VS}(B, A)$

(iii) $\Delta_{VS}(A, B) \leq \Delta_{VS}(A, C)$ and $\Delta_{VS}(B, C) \leq \Delta_{VS}(A, C)$

Proof. It is clearly to see that Δ_{VS}(A, B) satisfies (i)-(iii).

(iv) For A, B, C $\in$ IFS(X),

$\|A - B\| \leq \|A - C\|$,

and $\|B - C\| \leq \|A - C\|$,

Thus,

$\Delta_{VS}(A, B) \leq \Delta_{VS}(A, C)$ and $\Delta_{VS}(B, C) \leq \Delta_{VS}(A, C)$

IV. APPLICATIONS

In this section, we apply the similarity measure on PR and bacteria problem with IFSs. Suppose, $\exists$ m patterns which are defined by IFSs $A_k = \{x_i, \mu_{A_k}, / x_i \in X\}$ (k= 1, 2, .., m) in the finite universe of discourse $X = \{x_1, x_2,...,x_n\}$ and that there is a sample to be recognized which is defined by an IFS $B = \{x_i, \mu_B(x_i), \nu_B(x_i) / x_i \in X\}$.

Step 1. Calculate the similarity measures $\Delta_{VS}(A_k, B)$ Between A_k and B by eq. (10)
Step 2. Select the largest one $\Delta_{VS}(A_{k0}, B)$ from $\Delta_{VS}(A_k, B)$:

Example 6.1 Consider a problem having four known patterns R_1, R_2 and R_3 which have classifications D_1, D_2 and D_3 respectively. These are rep-resented by the following fuzzy sets in $K = \{k_1, k_2, k_3\}$.

$R_1 = \{\langle k_1, 1, 0\rangle, \langle k_2, .8, 0\rangle, \langle k_3, .7, .1\rangle\}$
$R_2 = \{\langle k_1, .35, .15\rangle, \langle k_2, .45, .25\rangle, \langle k_3, .55, .35\rangle\}$
$R_3 = \{\langle k_1, .25, .25\rangle, \langle k_2, ..35, .35\rangle, \langle k_3, .45, .45\rangle\}$

Given an unknown pattern S, defined by the fuzzy set
$B = \{\langle k_1, .3, .2\rangle, \langle k_2, .4, .3\rangle, \langle k_3, .5, .4\rangle\}$

Table 1 shows a comparison of the outcomes the proposed similarity mea-sure Δ_{VS} with the other measures.

Similarity measures	$S(R_1, B)$	$S(R_2, B)$	$S(R_3, B)$	Outcomes
S_E	.650	**.950**	**.950**	Can not be find out
S_K	.650	**.950**	**.950**	Can not be find out
S_R	.650	**.950**	**.950**	Can not be find out
S_T	.650	**.950**	**.950**	Can not be find out
S_N	0.650	**.950**	**.950**	Can not be find out
S^t_e	.650	**.950**	**.950**	Can not be find out
S^1_{YH}	.533	**.950**	**.950**	Can not be find out
C_{FIS}	.831	.989	.998	R_2
S_Z	.826	**.998**	**.998**	Can not be find out
Δ_{VS}	1.2235	.7733	.772	R_1

Table 1: A comparison of the outcomes of the proposed similarity measure Δ_{VS} with the other similarity measures (t = 1 in S_T, S_N, S^t_e).

Example 6.2 Consider a problem having four known patterns R_1, R_2 and R_3 which have classifications D_1, D_2 and D_3 respectively. These are rep-resented by the following fuzzy sets in $K = \{k_1, k_2, k_3\}$.

$R_1 = \{\langle k_1, 1, 0\rangle, \langle k_2, .8, 0\rangle, \langle k_3, .7, .1\rangle\}$
$R_2 = \{\langle k_1, .3, .5\rangle, \langle k_2, .4, .4\rangle, \langle k_3, .2, .6\rangle\}$
$R_3 = \{\langle k_1, .4, .4\rangle, \langle k_2, .3, .5\rangle, \langle k_3, .2, .6\rangle\}$
Given an unknown pattern S, defined by the fuzzy set
$B = \{\langle k_1, .3, .3\rangle, \langle k_2, .4, .4\rangle, \langle k_3, .5, .5\rangle\}$

Table 2 shows a comparison of the outcomes of the proposed similarity measure Δ_{VS} with the other similarity measures.

Similarity measures	S(R_1 , B)	S(R_2, B)	S(R_3, B)	Outcomes
S_E	.600	.900	.900	R_2, R_3
S_K	.600	**.900**	**.867**	Unreasonable case
S_R	.600	**.900**	**.883**	Unreasonable case
S_T	.600	.900	.900	R_2, R_3
S_N	.600	**.900**	**.867**	Unreasonable case
S^t_e	.900	**.867**	**.950**	Unreasonable case
S^1_{YH}	.833	.833	.950	R_2, A_3
$^C{}_{FIS}$	.738	.955	.955	R_2, R_3
S_z	.600	**.900**	**.889**	Unreasonable case
Δ_{VS}	1.5102	.1877	.1917	R_1

Table 2: A comparison of the outcomes of the proposed similarity measure Δ_{VS} with the other measures (t = 1 in S_T , S_N , S^t_e).

Example 6.3 Consider a problem having four known patterns R_1, R_2 and R_3 which have classifications D_1, D_2 and D_3 respectively. These are rep-resented by the following fuzzy sets in K = {k_1, k_2, k_3}.

$R_1 = \{\langle k_1, .5, .4\rangle, \langle k_2, .8, 0\rangle, \langle k_3, .3, .7\rangle\}$

$R_2 = \{\langle k_1, .6, .3\rangle, \langle k_2, .9, .1\rangle, \langle k_3, .6, .4\rangle\}$

$R_3 = \{\langle k_1, .6, .3\rangle, \langle k_2, .9, .1\rangle, \langle k_3, .7, .3\rangle\}$

Given an unknown pattern S, defined by the fuzzy set

$B = \{\langle k_1, 0, 0\rangle, \langle k_2, 0, 0\rangle, \langle k_3, 0, .1\rangle\}$

Table 3 shows a comparison of the outcomes of the proposed similarity measure Δ_{VS} with the other measures.

Similarity measures	S(R_1 , B)	S(R_2, B)	S(R_3, B)	Outcomes
$^S{}_E$	**.800**	.767	**.800**	Can not be find out
$^S{}_K$	.567	.533	.533	$^R{}_1$
S_R	.683	.650	.667	R_1
S_T	**.800**	.767	**.800**	Can not be find out
S_N	.567	.533	.533	R_1
S^t_e	.533	.533	.950	R_1
S^1_{YH}	.300	.333	.950	R_1
$^C{}_{FIS}$	N/A	N/A	N/A	Can not be find out
$^S{}_Z$	**.767**	**.767**	**.767**	Can not be find out
Δ_{VS}	2.45	2.68	2.67	R_2

Table 3: A comparison of the outcomes of the proposed similarity measure Δ_{VS} with the other measures (t = 1 in S_T , S_N , S^t_e)

Example 6.4 Consider a problem having four known patterns R_1, R_2 and R_3 which have classifications D_1, D_2 and D_3 respectively. These are rep-resented by the following fuzzy sets in K = {k_1, k_2, k_3}.

$R_1 = \{\langle k_1, .34, .34\rangle, \langle k_2, .19, .48\rangle, \langle k_3, .22, .12\rangle\}$

$R_2 = \{\langle k_1, .35, .33\rangle, \langle k_2, .20, .47\rangle, \langle k_3, .0, .14\rangle\}$

$R_3 = \{\langle k_1, .33, .35\rangle, \langle k_2, .21, .46\rangle, \langle k_3, .01, .13\rangle\}$

Given an unknown pattern S, defined by the fuzzy set

$B = \{\langle k_1, .37, .31\rangle, \langle k_2, .23, .44\rangle, \langle k_3, .04, .01\rangle\}$

Table 4 shows a comparison of the outcomes of the proposed similarity measure Δ_{VS} with the other measures.

Similarity measures	S(R₁ , B)	S(R₂, B)	S(R₃, B)	Outcomes
S_E	**.9700**	**.9700**	**.9700**	Can not be fi nd out
S_K	**.9700**	**.9700**	**.9700**	Can not be find out
S_R	**.9700**	**.9700**	**.9700**	Can not be find out
S_T	**.9700**	**.9700**	**.9700**	Can not be find out
S_N	**.9700**	**.9700**	**.9700**	Can not be find out
S^t_e	**.9700**	**.9700**	**.9700**	Can not be find out
S^t_{YH}	**.9700**	**.9700**	**.9700**	Can not be find out
C_{FIS}	.9892	.9745	.9820	R_1
S_Z	**.9700**	**.9700**	**.9700**	Can not be find out
Δ_{VS}	.1346	.0529	.0279	R_1

Table 4: A comparison of the outcomes of the proposed similarity measure Δ_{VS} with the other measures (t = 1 in S_T , S_N , S^t_e).

Example 6.5 Consider a problem having four known patterns R_1, R_2 and R_3 which have classifications D_1, D_2 and D_3 respectively. These are rep-resented by the following fuzzy sets in K = {k_1, k_2, k_3}.

$R_1 = \{\langle k_1, 1, 0\rangle, \langle k_2, .8, 0\rangle, \langle k_3, .7, .1\rangle\}$

$R_2 = \{\langle k_1, .8, .1\rangle, \langle k_2, 1, .0\rangle, \langle k_3, .9, .0\rangle\}$

$R_3 = \{\langle k_1, .6, .2\rangle, \langle k_2, .8, .0\rangle, \langle k_3, 1, 0\rangle\}$

Given an unknown pattern S, defined by the fuzzy set

$B = \{\langle k_1, .5, .3\rangle, \langle k_2, .6, .2\rangle, \langle k_3, .8, .1\rangle\}$

Table 4 shows a comparison of the outcomes of the proposed similarity measure Δ_{VS} with the other measures.

Similarity measures	S(R₁ , B)	S(R₂, B)	S(R₃, B)	Outcomes
S_E	**.9700**	**.9700**	**.9700**	Can not be fi nd out
S_K	**.9700**	**.9700**	**.9700**	Can not be find out
S_R	**.9700**	**.9700**	**.9700**	Can not be find out
S_T	**.9700**	**.9700**	**.9700**	Can not be find out
S_N	**.9700**	**.9700**	**.9700**	Can not be find out
S^t_e	**.9700**	**.9700**	**.9700**	Can not be find out
S^t_{YH}	**.9700**	**.9700**	**.9700**	Can not be find out
C_{FIS}	.9892	.9745	.9820	R_1
S_Z	**.9700**	**.9700**	**.9700**	Can not be find out
Δ_{VS}	.1346	.0529	.0279	R_1

Table 4: A comparison of the outcomes of the proposed similarity measure Δ_{VS} with the other measures (t = 1 in S_T , S_N , S^t_e).

Example 6.5 Consider a problem having four known patterns R_1, R_2 and R_3 which have classifications D_1, D_2 and D_3 respectively. These are represented by the following fuzzy sets in K = {k_1, k_2, k_3}.

$R_1 = \{\langle k_1, 1, 0\rangle, \langle k_2, .8, 0\rangle, \langle k_3, .7, .1\rangle\}$

$R_2 = \{\langle k_1, .8, .1\rangle, \langle k_2, 1, .0\rangle, \langle k_3, .9, .0\rangle\}$

$R_3 = \{\langle k_1, .6, .2\rangle, \langle k_2, .8, .0\rangle, \langle k_3, 1, 0\rangle\}$

Given an unknown pattern S, defined by the fuzzy set

$B = \{\langle k_1, .5, .3\rangle, \langle k_2, .6, .2\rangle, \langle k_3, .8, .1\rangle\}$

Similarity measures	$S(R_1, B)$	$S(R_2, B)$	$S(R_3, B)$	Outcomes
S_E	.783	.783	.850	R_3
S_K	.783	.783	.850	R_3
S_R	.783	.783	.850	R_3
S_T	.783	.783	.850	R_3
S_N	.783	.783	.850	R_3
S^t_e	.783	.783	.850	R_3
S^1_{YH}	.733	.733	.833	R_3
C_{FIS}	.935	.952	.972	R_3
S_Z	.783	.783	.850	R_3
Δ_{VS}	.702	.0571	.3799	R_1

Table 5: A comparison of the outcomes of the proposed similarity measure Δ_{VS} with the other measures (t = 1 in S_T , S_N , S^t_e).

4.2 . Bacteria Detection

Bacteria are classified broadly by microbiologists according to their shapes. Bacteria come in three shapes rod, sphere and spiral. Rod shaped are called bacilli, spherical shaped are called cocci and spiral shaped are called spirilla. Bacteria can be further classified according to weather they require oxygen and how, they react to a test with grans stain to classify the unknown bacteria. Degrees of membership and non-membership for the features of known bacteria in table 6. The membership and non-membership values for each feature indicate the feature's presence and non-presence degrees in a specific class, respectively. Also the experts provided values of the features for different undiagnosed samples in table 7.

classes	Domial		single micro.		double micro.		egellum	
	μ_1	v_1	μ_2	v_2	μ_3	v_3	μ_4	v_4
Bacillus coli	.85	.05	.87	.01	.02	.97	.92	.06
Shigella	.83	.08	.92	.05	.05	.92	.08	.91
Salmonella	.79	.12	.78	.11	.11	.85	.87	.01
Klebsiella	.82	.15	.72	.15	.22	.75	.12	.85

Table 6: Values of features in classes of bacteria.

Sample	Domical		Single micro.		Double micro.		Flagellum	
	μ_1	v_1	μ_2	v_2	μ_3	v_3	μ_4	v_4
S_1	.837	.133	.718	.159	.064	.897	.021	.806
S_2	.911	.029	.831	.031	.028	.894	.952	0.036
S_3	.929	.037	.812	.033	.021	.926	.054	.922
S_4	.815	.091	.949	.048	.020	.880	.833	.042
S_5	.864	.02	.610	.230	.243	.624	.0004	.964
S_6	.905	.016	.878	.015	.072	.917	.789	.114

Table 7: Values of features in the undiagnosed samples

Sample	Bacillus coli	Shigella	Salmonella	Klebsiella
S_1	1.0584	.0722	**1.5267**	.0132
S_2	.0232	1.2526	.1150	**1.2662**
S_3	1.0373	.0176	**1.8773**	.1379
S_4	.0432	**1.1609**	.0462	1.1274
S_5	1.4680	.0967	**2.0393**	.1090
S_6	.034	.7811	.2853	**.8828**

Table 8: Vector similarity measure values

V. CONCLUSION

The aim of this paper is to developed a new similarity measure for IFSs, which is achieved. We proved the reliability and validity of the proposed similarity measure. The novelty and efficiency has been established by applying the proposed similarity measure in PR and Bacteria detection. Finally compared results of the proposed similarity measure with the existing results. Our aim is to make use of IFSs similarity measures in the bacteria detection to examine their capabilities in encountering uncertainty in the medical pattern recognition.

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