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Applications of Transforming Vague Sets into Fuzzy Sets for Knowledge Management

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Abstract - Determining the proper knowledge management strategies is important to make sure that the alignment of organizational Procedures and the knowledge management-related Information produces effective creation, sharing and utilization of knowledge. Data sets in the form of vague values sometimes make the decision process very complicated and unstructured. Besides the fuzzy sets theory, vague sets theory is one of the methods used to deal with uncertain information and vague sets can provide more information than fuzzy sets. The purpose of this research is determining the knowledge management strategy of transforming vague values into fuzzy values using various techniques proposed in the literature and to propose a new method to calculate the correlation coefficient between vague sets. Numerical illustrations are given to support the proposed theory.

Key words: Vague set, Intuitionistic fuzzy set Correlation coefficient of vague set.

I. INTRODUCTION

Since fuzzy set (FSs) theory was introduced, several new concepts of higher-order FSs have been proposed. Among them, intuitionistic fuzzy sets (IFSs), proposed by Atanassov (1986; 1989), provide a flexible mathematical framework to cope, besides the presence of vagueness, with the hesitancy originating from imperfect or imprecise information. A Vague Set (VS), as well as an Intuitionistic Fuzzy Set (IFS), is a further generalization of a FS. Instead of using point-based membership as in FSs, interval-based membership is used in a VS. The interval-based membership in VSs is more expressive in capturing vagueness of data. In the literature, the notions of IFSs and VSs are regarded as equivalent, in the sense that an IFS is isomorphic to a VS(Bustince&Burillo, 1996). Furthermore, due to such equivalence and IFSs being earlier known as a tradition, the interesting features for handling vague data that are unique to VSs are largely ignored. The fuzzy set A in the universe of discourse U, $U=\{u_1,u_2,...,u_n\}$, is a set of ordered pairs $\{(u_1,\mu_A(u_1)),(u_2, \mu_A(u_2)),...,(u_n,\mu_A(u_n))\}$, where μ_A is the membership function of the fuzzy set A,μ_A:U→[0, 1], and μ_A (u_i) indicates the grade of membership of u_i in A. It is obvious that for all $u_i$in U, the membership value $\mu_A(u_i)$ is a single value between zero and one. Gau&Buehrer, (1994) pointed out that this single value combines the evidence for $u_i$in U and the evidence against $u_i$in U, without indicating how much there is of each. They also pointed out that the single number tells us nothing about its accuracy. Thus Gau&Buehrer, (1994) presented the concepts of vague sets. They used a truth-membership function t_A and false-membership function f_A to characterize the lower bound on μ_A. These lower bounds are used to create a subinterval on [0, 1], namely $[t_A(u_i), 1-f_A(u_i)]$, to generalize the μ_A (u_i) of fuzzy sets, where $t_A(u_i) \leq \mu_A(u_i) \leq 1-f_A(u_i)$. For example, let A be a vague set with truth-membership function t_A and false-membership function f_A, respectively. If $[t_A(u_i), 1-f_A(u_i)]$ = [0.5, 0.8], then we can see that $t_A(u_i)=0.5$; $1 - f_A(u_i)=0.8$; $f_A(u_i)=0.2$. It can be interpreted as,the vote for resolution is 5 in favor, 2 against, and 3 abstentions.

The main contributions of this paper are fourfold. First, we examine in more diversified ways, the notions of VSs and IFSs, which has so far been done in the literature only by few authors(Gau&Buehrer, 1994,Bustince&Burillo, 1995; 1996), which leads to the undermining of the development of VSs. Second, the transformation of vague sets into Fuzzy sets using diverse techniques (Liu et al.,2008).Third, numerical illustration for transforming vague sets into fuzzy sets and fourth, proposing a new method for correlation coefficient for vague sets.

II. VAGUE SETS AND INTUITIONISTIC FUZZY SETS

In this section, we introduce some basic concepts related to vague sets (VSs) and Intuitionistic fuzzy sets (IFSs). We illustrate that the graphical representation of VSs is more intuitive in perceiving vague values. Let U be a classical set of objects, called the universe of discourse, where an element of U is denoted by u.

Definition 1: (Vague Set)

A vague set V in a universe of discourse U is characterized by a true membership function, α_v, and a false membership function, β_v, as follows: $\alpha_v : U \to [0,1]$, $\beta_v : U \to [0,1]$, and $\alpha_v(u)+\beta_v(u) \leq 1$ where $\alpha_v(u)$ is a lower bound on the grade of membership of u derived from the evidence for u, and $\beta_v(u)$ is a lower bound on the grade of membership of the negation of u derived from the evidence against u.
Suppose U= $\{u_1, u_2,\ldots, u_n\}$.A vague set V of the universe of discourse U can be represented by

$$V = \sum_{i=1}^{n} [\alpha(u_i), 1-\beta(u_i)] / u_i$$,where

$0 \le \alpha(u_i) \le 1-\beta(u_i) \le 1$ and $1 \le i \le n$ .In other words, the grade of membership of u_i is bounded to a subinterval $[\alpha_v(u_i), 1-\beta_v(u_i)]$ of [0,1]. Thus, VSs are a generalization of FSs
.

Definition 2: (Intuitionistic Fuzzy Sets)

An Intuitionistic Fuzzy Set $A=\{\langle u, \mu_A(u), \gamma_A(u)\rangle | u \in U\}$ in a universe of discourse U is characterized by a membership function, μ_A ,and a non-membership function, γ_A ,as follows: $\mu_A : U \to [0,1]$, $\gamma_A : U \to [0,1]$, and $0 \le \mu_A(u)+\gamma_A(u) \le 1$.

As we can see that the difference between VSs and IFSs is due to the definition of membership intervals (Lu & Ng, 2005;2009). We have $[\alpha_v(u), 1-\beta_v(u)]$ for u in V but $\langle \mu_A(u), \gamma_A(u)\rangle$ for u in A. Here the semantics of μ_A is the same as with α_v and γ_A is the same as with β_v. However, the boundary $(1-\beta_v)$ is able to indicate the possible existence of a data value, as already mentioned. This subtle difference gives rise to a simpler but meaningful graphical view of data sets.

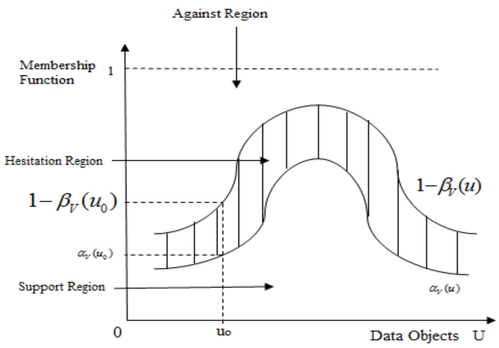

Fig. 1. Membership Functions of a VS

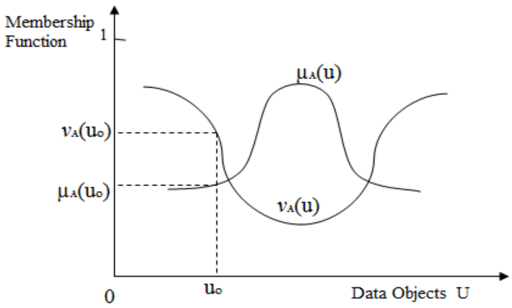

Fig. 2. Membership Function of an IFS

Measurements of Vagueness in Practice:
Example (Lu & Ng, 2005;2009): In a sensor database application, suppose in a testing region we have a set of ten sensor $\{S_1, S_2, \ldots, S_{10}\}$. We then obtain ten corresponding measurements, {20, 22, 20, 21, 20, -, 20, 20, -, 20} at a certain time t. here "-" means that the sensor data is not reachable/accessible at time t. (i.e. we have six 20, one21, one22 and two missing values). Now, we formalize the results to a vague set V_t as follows. There are six occurrences of 20, but two values (21 and 22) are against it. There are also two missing values (neutral), thus the true membership α is 0.6 and the false membership β is 0.2 (i.e. 1-β=0.8). Thus, we obtain the vague membership value [0.6,0.8] for 20. Similarly, we obtain the vague membership value [0.1,0.3] for 21 and [0.1,0.3] for 22. Combining these results, we have the VS, V_t=[0.6,0.8]/20+[0.1,0.3]/21+[0.1,0.3]/22.Equivalently, we have the IFS,

$$A_t = \{\langle 20, 0.6, 0.2\rangle, \langle 21, 0.1, 0.7\rangle, \langle 22, 0.1, 0.7\rangle\}.$$

The above example also indicates that, using a VS is more natural than an IFS for merging fuzzy objects.

Let *A*, *B* be two VSs in the universe of discourse $U = \{u_1, u_2, \ldots, u_n\}$,

$$A = \sum_{i=1}^{n} \left[t_A(u_i),\ 1-f_A(u_i)\right] / u_i, \text{ and}$$

$$B = \sum_{i=1}^{n} \left[t_B(u_i),\ 1-f_B(u_i)\right] / u_i.$$ Then the operations between VSs are defined as follows.

The intersection of VSs *A* and *B* is defined by

$$A \cap B = \sum_{i=1}^{n} \left\{\left[t_A(u_i),\ 1-f_A(u_i)\right] \wedge \left[t_B(u_i),\ 1-f_B(u_i)\right]\right\} / u_i.$$

The union of vague sets *A* and *B* is defined by

$$A \cup B = \sum_{i=1}^{n} \left\{\left[t_A(u_i),\ 1-f_A(u_i)\right] \vee \left[t_B(u_i),\ 1-f_B(u_i)\right]\right\} / u_i.$$

The complement of vague set *A* is defined by

$$\bar{A} = \sum_{i=1}^{n} \left[f_A(u_i),\ 1-t_A(u_i)\right] / u_i.$$

Definition 3: For the vague value $x = [t_x,\ 1-f_x]$, define the de-fuzzification function to get the precise value as follows:

$$Dfzz\ (x) = \frac{t_x}{(t_x + f_x)}.$$

Relationships of Vague Set Membership Values
In order to compare vague values, the following two derived memberships can be used for discussion. The first is called the Median membership, $Mm = (t + 1 - f)/2$, which represents the overall evidence contained in a vague value and is shown in *Figure 3*. It can be checked that $0 \le (t + 1 - f)/2 \le 1$. In addition, the vague value [1,1]

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has the highest *Mm*, which means the corresponding object totally belongs to the VS (i.e. a crisp value). While the vague value [0,0] has the lowest *Mm*which means that the corresponding object totally does not belong to the VS (i.e. the empty vague value).

The second is called the Imprecision membership, $Mi = (1 - f - t)$, which represents the overall imprecision of a vague value and is shown in *Figure 4*. It can be checked that $0 \leq (1 - f - t) \leq 1$. In addition, the vague value $[a, a]$, $a \in [0,1]$ has the lowest *Mi* which means that the membership of the corresponding object is known exactly (i.e. a fuzzy value). The vague value [0,1] has the highest *Mi* which means that nothing is known about the membership of the corresponding object.

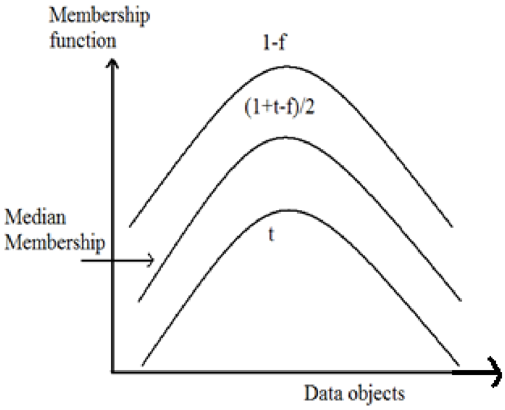

Figure 3: Median membership.

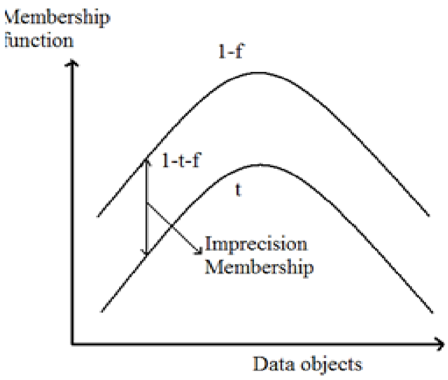

Figure 4:Imprecision membership.

Transforming Vague Sets into Fuzzy Sets

There are four methods presented here for transforming vague sets into fuzzy sets.

Method 1: For all $A \in V(u)$ [V(u) is all vague sets of the universe of discourse U] let its vague value is $[t_A(u), 1 - f_A(u)]$ then the membership function of u to A^F (A^F is the fuzzy set corresponding to vague set A) is defined as:

$$\mu_{A^F} = t_A(u) + [1 - t_A(u) - f_A(u)]/2$$
$$\mu_{A^F} = [1 + t_A(u) - f_A(u)]/2$$

Method 2: For all $A \in V(u)$ [*V*(*u*) is all vague sets of the universe of discourse *U*] let $u \in U$ its vague value is $[t_A(u), 1 - f_A(u)]$ then the membership function of u to A^F (A^F is the fuzzy set corresponding to vague set A) is defined as:

$$\mu_{A^F} = t_A(u) + [1 - t_A(u) - f_A(u)]\, t_A(u) / [t_A(u) + f_A(u)] = t_A(u) / [t_A(u) + f_A(u)]$$

There are some unreasonable problems for some cases when we use method two to transform vague sets into fuzzy sets.

Method 3:In a more generalised form, the membership function of u to the set A^F (which is the fuzzy set corresponding to the vague set *A*) is defined as (Lin et al., 2004):

$$\mu_{A^F} = \begin{cases} t_A(u) + [1 - t_A(u) - f_A(u)](1 - f_A(u)) / [t_A(u) + f_A(u)]; & t_A(u) = 0 \\ t_A(u) + [1 - t_A(u) - f_A(u)] t_A(u) / [t_A(u) + f_A(u)]; & 0 < t_A(u) \leq 0.5 \\ t_A(u) + [1 - t_A(u) - f_A(u)] \left[0.5 + \dfrac{t_A(u) - 0.5}{[t_A(u) + f_A(u)]} \right]; & 0.5 < t_A(u) \leq 1 \end{cases}$$

There are 3 cases following this argument.

Case (i): When $t_A(u)=0$ in the voting model, there are 0 votes in favor, the abstention persons favorite voting attitude is $(1 - f_A(u)) \dfrac{(1 - f_A(u))}{(f_A(u))}$.

Case (ii): When $0 < t_A(u) \leq 0.5$ method there is the same is method two.

Case (iii): When $0.5 < t_A(u) \leq 1$ abstentions persons favourite voting attitude is $[1 - t_A(u) - f_A(u)] \times \left(0.5 + \dfrac{t_A(u) - 0.5}{t_A(u) + f_A(u)} \right)$. In this case, the abstentions persons voting attitude tends to vote in favour instead of against, since there are more affirmative votes than negative votes.

Method 4: For all $A \in V(u)$ where *V*(*u*) is all vague sets in the universe of discourse U.

For all $A \in V(u)$ the vague value $[t_A(u), 1 - f_A(u)]$. Let λ be the distance of the line segment as in Lin et al., (2004) and λ>0 the membership function of A^F (A^F is the fuzzy set corresponding to vague set A) is defined as:

$$\mu_{A^F} = t_A(u) + \frac{1}{2}\left[1 + \frac{t_A(u) - f_A(u)}{t_A(u) + f_A(u) + 2\lambda}\right][1 - t_A(u) - f_A(u)]$$

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Table-1: Transforming vague values into fuzzy values

METHOD	μ_{A^F} for vague value [0, 0.9]	μ_{A^F} for vague value [0, 0.3]	μ_{A^F} for vague value [0.9, 1.0]	μ_{A^F} for vague value [0.2, 0.7]
1	0.45	0.15	0.95	(λ=0.5) 0.433
2	0.0	0.0	1.0	(λ=0.8) 0.438
3	8.1	0.129	0.994	(λ=10) 0.449
4	0.429	0.111	0.966	(λ=100) 0.450

Lu & Ng, (2005;2009) presented a similarity measure between two VSs, which is based on the median membership and the imprecision membership. Chen & Tan, (1994), Hong& Choi, (2000) and Li et al., (2007) defined and analysed various score functions to defuzzify vague values. Zhang et al., (2004), Hong & Kim, (1999) and Fan &Zhangyan, (2001) proposed methods to calculate the similarity measure between vague values. Let us consider the following table with two vague data set values.

Table-2: Data sets with vague values.

Vague set A	Vague set B
[0.313, 0.628]	[0.411, 0.536]
[0.235, 0.712]	[0.316, 0.481]
[0.183, 0.697]	[0.288, 0.663]
[0.439, 0.511]	[0.387, 0.400]
[0.299, 0.600]	[0.149, 0.811]
[0.199, 0.723]	[0.412, 0.523]
[0.418, 0.532]	[0.319, 0.611]
[0.315, 0.489]	[0.272, 0.593]
[0.163, 0.700]	[0.313, 0.568]
[0.296, 0.483]	[0.400, 0.513]

Transforming Vague Sets into Fuzzy Sets

Liu et al.,(2008) and Lin et al., (2004) proposed different methods for transforming vague sets into fuzzy sets. Some of them are given below:

1. $\mu_{A^M} = t_A(u) + [1- t_A(u) - f_A(u)] / 2$

$=[1 + t_A(u) - f_A(u)] / 2$

This is also called as the Median membership value of the VS.

2. $\mu_{A^i} = 1 - t_A(u) - f_A(u)$, where $0 \le 1- t_A - f_A \le 1$.

This is also called as the Median membership value of the VS.

3. $\mu_{A^D} = t_A(u) + [1- t_A(u) - f_A(u)]\, t_A(u) / [t_A(u) + f_A(u)]$
$=t_A(u) / [t_A(u) + f_A(u)]$.

This is also called the Defuzzification function

The vague data sets of *Table* 2are transformed into fuzzy sets using the above methods, and the data values are presented in the following *Table 3*. The variations in transforming the vague data set into Fuzzy data set are clearly presented in *Figure 5* and *Figure 6*.

Note: The truth and false membership values of the vague set are transformed into the Fuzzy sets using Median membership, Imprecision membership and Defuzzyfication function.

Table-3: Median, Imprecision and Defuzzyfication membership obtained bytransforming vague sets into fuzzy sets.

Vague Set (True and False Membership)	Fuzzy Set (Median Membership)	Fuzzy Set (Imprecision Membership)	Fuzzy Set Defuzzyfication function)
AB	A_1B_1	A_2B_2	A_3B_3
[0.313, 0.628] [0.411,0.536]	0.3425 0.4375	0.059 0.053	0.3326 0.4340
[0.235, 0.712] [0.316,0.481]	0.2615 0.4175	0.053 0.203	0.2482 0.3965
[0.183, 0.697] [0.288,0.663]	0.243 0.3125	0.12 0.049	0.2079 0.3028
[0.439, 0.511] [0.387,0.400]	0.464 0.4935	0.05 0.213	0.4621 0.4917
[0.299, 0.600] [0.149,0.811]	0.3495 0.169	0.101 0.04	0.3326 0.1552
[0.199, 0.723] [0.412,0.523]	0.238 0.4445	0.078 0.065	0.2158 0.4406
[0.418, 0.532] [0.319,0.611]	0.443 0.354	0.05 0.07	0.4400 0.3430
[0.315, 0.489] [0.272,0.593]	0.413 0.3395	0.196 0.135	0.3918 0.3144
[0.163, 0.700] [0.313,0.568]	0.2315 0.3725	0.137 0.119	0.1888 0.3553
[0.296, 0.483] [0.400,0.513]	0.4065 0.4435	0.221 0.087	0.3799 0.4381

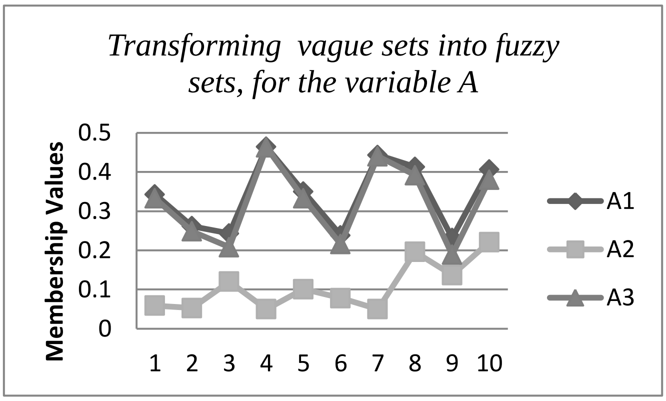

Figure 5: A_1-Median, A_2-Imprecision and A_3-Defuzzyfication membership obtained bytransforming vague sets into fuzzy sets, for the variable A.

Correlation Coefficient of Vague Sets

Bustince&Burillo, (1995), Chiang & Lin, (1999), Kao & Liu, (2002), Park et al., (2009), Robinson & Amirtharaj, (2011a; 2011b; 2012a; 2012b; 2013), Amirtharaj & Robinson, (2013) and Power, (2013) proposed correlation coefficients for different applications of decision making problems. In the following we present a new approach of correlation coefficient for vague sets.

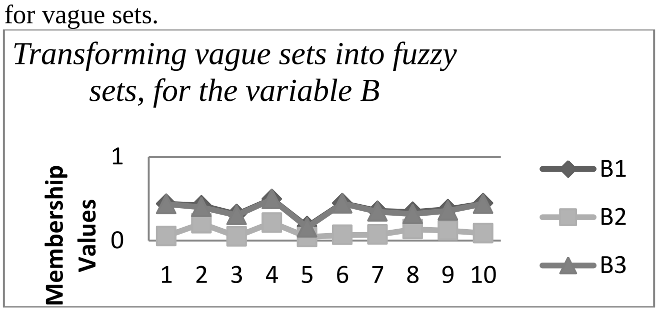

Figure 6: B_1-Median, B_2-Imprecision and B_3-Defuzzyfication membership obtained by transforming vague sets into fuzzy sets, for the variable

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Correlation of Crisp sets

Let (X_1,Y_1), (X_2,Y_2), . . . , (X_n,Y_n) be a random sample of size n from a joint probability density function $f_{X,Y}(x,y)$, let $\overline{X}$ and $\overline{Y}$ be the sample means of variables X and Y, respectively, then the sample correlation coefficient $\rho(X,Y)$ is given as:

$$\rho(A,B)=\frac{\sum_{i=1}^{n}(x_i-\overline{X})(y_i-\overline{Y})}{\left(\sum_{i=1}^{n}(x_i-\overline{X})^2.\sum_{i=1}^{n}(y_i-\overline{Y})^2\right)^{0.5}}$$,Where

$$\overline{X}=\frac{1}{n}\sum_{i=1}^{n}(x_i);\ \ \overline{Y}=\frac{1}{n}\sum_{i=1}^{n}(y_i).$$

Correlation of Fuzzy sets

Suppose we have the random sample $x_1, x_2,\ldots,x_n$ in X with a sequence of paired data $\left(\mu_A(x_1),\mu_B(x_1)\right),\ \left(\mu_A(x_2),\mu_B(x_2)\right),\ \ldots,\ \left(\mu_A(x_n),\mu_B(x_n)\right)$ which correspond to the membership values of fuzzy sets A and B defined on X, then the correlation coefficient is given as:

$$\rho_{FS}(A,B)=\frac{\sum_{i=1}^{n}(\mu_A(x_i)-\overline{\mu_A})(\mu_B(x_i)-\overline{\mu_B})}{\left(\sum_{i=1}^{n}(\mu_A(x_i)-\overline{\mu_A})^2.\sum_{i=1}^{n}(\mu_B(x_i)-\overline{\mu_B})^2\right)^{0.5}},$$

where $\overline{\mu_A}=\frac{1}{n}\sum_{i=1}^{n}\mu_A(x_i);\ \ \overline{\mu_B}=\frac{1}{n}\sum_{i=1}^{n}\mu_B(x_i).$

Correlation between Vague sets

$$A=\left\{\left\langle x,\left[t_A(x),1-f_A(x)\right]\right\rangle\ /\ x\in X\right\},$$
$$B=\left\{\left\langle x,\left[t_B(x),1-f_B(x)\right]\right\rangle\ /\ x\in X\right\}.$$

Robinson & Amirtharaj, (2011a) proposed a correlation coefficient for vague sets which took into account the truth membership degree, false membership degree and the hesitation or vague degree and derived it in the interval [0,1].Let $X = \{x_1, x_2, ...,x_n\}$ be the finite universal set and $A, B\in$ VS(X) be given by

And the length of the vague values are given by $\pi_A(x) = 1-t_A(x)-f_A(x)$, $\pi_B(x) = 1-t_B(x)-f_B(x)$.

Now for each $A\in$ VS(X), the informational vague energy of A is defined as follows:

$$E_{VS}(A)=\frac{1}{n}\sum_{i=1}^{n}\left[t_A^2(x_i)+\left(1-f_A(x_i)\right)^2+\pi_A^2(x_i)\right],$$

The correlation of A and B is given by the formula:

$$C_{VS}(A,B)=\frac{1}{n}\sum_{i=1}^{n}\left[t_A(x_i)t_B(x_i)+\left(1-f_A(x_i)\right)\left(1-f_B(x_i)\right)+\pi_A(x_i)\pi_B(x_i)\right],$$

Furthermore, the correlation coefficient of A and B is defined by the formula:

$$K_{VS}(A,B)=\frac{C_{VS}(A,B)}{\sqrt{E_{VS}(A)\,.\,E_{VS}(B)}},$$ where $0\le K_{VS}(A,B)\le 1$.

Proposition: (Robinson & Amirtharaj, 2011a)

For $A, B\in$ VS(X), the following are true:

i) $0\le C_{VS}(A,B)\le 1,$

ii) $C_{VS}(A,B)=C_{VS}(B,A),$

iii) $K_{VS}(A,B)=K_{VS}(B,A),$

iv) $0\le K_{VS}(A,B)\le 1.$

Here we propose a new correlation coefficient for two VSs, A and B, so that we could express not onlya relative strength but also a positive or negative relationship between A and B. Next, we takeinto account all three terms describing a vague set (truth membership, false membership values and thehesitation margins) because each of them influences the results.Suppose that we have a random sample $x_1, x_2,\ldots,x_n$ in X with a sequence of paired data

$$\left[\left(t_A(x_1), f_A(x_1),\pi_A(x_1)\right),\left(t_B(x_1), f_B(x_1),\pi_B(x_1)\right)\right],$$
$$\left[\left(t_A(x_2), f_A(x_2),\pi_A(x_2)\right),\left(t_B(x_2), f_B(x_2),\pi_B(x_2)\right)\right],$$
$$\ldots,\left[\left(t_A(x_n), f_A(x_n),\pi_A(x_n)\right),\left(t_B(x_n), f_B(x_n),\pi_B(x_n)\right)\right]$$

which correspond to the truth membership values, false memberships values and hesitationmargins of vague sets$A$ and B defined on X, then the correlation coefficient is givenas:

Definition:

The correlation coefficient between two vague sets A and B is defined as

$$\rho_{VS}(A,B)=\frac{1}{3}\left(\rho_1(A,B)+\rho_2(A,B)+\rho_3(A,B)\right),$$

$$\rho_1(A,B)=\frac{\sum_{i=1}^{n}(t_A(x_i)-\overline{t_A})(t_B(x_i)-\overline{t_B})}{\left(\sum_{i=1}^{n}(t_A(x_i)-\overline{t_A})^2.\sum_{i=1}^{n}(t_B(x_i)-\overline{t_B})^2\right)^{0.5}},$$

$$\rho_2(A,B)=\frac{\sum_{i=1}^{n}(f_A(x_i)-\overline{f_A})(f_B(x_i)-\overline{f_B})}{\left(\sum_{i=1}^{n}(f_A(x_i)-\overline{f_A})^2.\sum_{i=1}^{n}(f_B(x_i)-\overline{f_B})^2\right)^{0.5}},$$

$$\rho_3(A,B)=\frac{\sum_{i=1}^{n}(\pi_A(x_i)-\overline{\pi_A})(\pi_B(x_i)-\overline{\pi_B})}{\left(\sum_{i=1}^{n}(\pi_A(x_i)-\overline{\pi_A})^2.\sum_{i=1}^{n}(\pi_B(x_i)-\overline{\pi_B})^2\right)^{0.5}},$$

Where

$$\overline{t_A} = \frac{1}{n}\sum_{i=1}^{n} t_A(x_i);\ \overline{t_B} = \frac{1}{n}\sum_{i=1}^{n} t_B(x_i);\ \overline{f_A} = \frac{1}{n}\sum_{i=1}^{n} f_A(x_i);\ \overline{f_B} = \frac{1}{n}\sum_{i=1}^{n} f_B(x_i);$$

$$\overline{\pi_A} = \frac{1}{n}\sum_{i=1}^{n} \pi_A(x_i);\ \overline{\pi_B} = \frac{1}{n}\sum_{i=1}^{n} \pi_B(x_i).$$

This correlation coefficient satisfies the following properties:

1. $\rho_{VS}(A,B) = \rho_{VS}(B,A),$
2. If $A=B$, then $\rho_{VS}(A,B) = 1,$
3. $\left|\rho_{VS}(A,B)\right| \le 1.$

III. CONCLUSION

The relationship between vague sets and intuitionistic fuzzy sets is studied in this paper. The general models for transforming vague sets into fuzzy sets are also discussed andthe validity of the transformation models is analysed. The relationship among vague sets, intuitionistic fuzzy sets, fuzzy sets was studied.In this paper an approach to find correlation coefficient in the situations where the attribute values are characterized by vague fuzzy numbers is presented. Differences between VSs and IFSs were presented, and a new Correlation coefficient for VSs is presented. From this study it can be seen that Correlation coefficient for vague sets needs to be exclusively defined using its special properties, even though in the literature it is believed that VSs are indeed IFSs. In future, the relationship between correlation coefficient of vague sets and fuzzy sets can be studied more exclusively. This proposed approach provides us an effective and practical way to deal when the information arevague values and has greater applications in decision making problems.

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