Distance based similarity measures for interval-valued intuitionistic fuzzy soft sets and its application.

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Abstract: In this article we have introduced the concept of similarity measure for interval-valued intuitionistic fuzzy soft sets based on distance between two interval-valued intuitionistic fuzzy soft sets, some examples and basic properties are also studied. An algorithm is developed in intuitionistic fuzzy soft set setting for a decision making method. Lastly a fictitious numerical example is given to illustrate possible application in a medical diagnosis problem.

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1. Introduction

The concept of fuzzy set theory was introduced by Prof. L. A. Zadeh [33] in 1965. Several researchers have extended the concept of fuzzy set in multi directions. The traditional fuzzy set is characterized by the membership value or the grade of membership value. In some real life problems in expert system, belief system, information fusion and so on, we must consider the truth-membership as well as the falsity-membership for proper description of an object in uncertain, ambiguous environment. Intuitionistic fuzzy set [1] is appropriate for such a situation. The intuitionistic fuzzy sets can only handle the incomplete information considering both the truth-membership (or simply membership) and falsity-membership (or non-membership) values. But it does not handle the indeterminate and inconsistent information which exists in belief system. F. Smarandache [25, 26] in 1995 introduced the concept of neutrosophic set, which is a generalization of intutionistic fuzzy set became a mathematical tool for handling problems involving imprecise, indeterminacy and inconsistent data. Soft set theory [11,16] has enriched its potentiality since its introduction by Molodtsov in 1999.

Similarity measure is an important topic in the fuzzy set[33] theory. Similarity measure indicates degree of similarity between two fuzzy sets. Wang [29] first introduced the concept of similarity measure of fuzzy sets and gave a computational formula. Science then, similarity measure of fuzzy sets has attracted several researchers' interest and has been investigated more. Similarity measure of fuzzy sets is now being extensively applied in many research fields such as fuzzy clustering, image processing, fuzzy reasoning, fuzzy neural

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network, pattern recognition, medical diagnosis , game theory, coding theory and several problems that contain uncertainties.

Similarity measure between two fuzzy sets(interval-valued fuzzy sets, interval-valued fuzzy soft sets, intuitionistic fuzzy sets, intuitionistic fuzzy soft sets, interval-valued intuitionistic fuzzy sets, interval-valued intuitionistic fuzzy soft sets) have been defined by many authors[5,9,12,20,23,24,27,28,30,31].There are different techniques for measuring similarity measure between two fuzzy sets or between two fuzzy soft sets. Some of them are based on distances and some others are based on matching function. There are techniques based on set-theoretic approach also. Some properties are common to these measures and some are not, which influence the choice of the measure to be used in several applications. One of the significant differences between similarity measure based on matching function *S* and similarity measure S' based on distance is that if $A \cap B = \varphi$, then $S(A,B) = 0$ but S' (A,B) may not be equal to zero, where *A* and *B* are two fuzzy sets. Therefore, distance-based measures are also popular.

Distances between two intuitionistic fuzzy sets A and B is defined by *Szmidt & Kacprzyk* [27]. In some real life problems it is often needed to compare two sets. The sets may be fuzzy, may be vague etc. For example in a problem of image recognition we need to know whether two patters or images are identical or approximately identical or at least to what degree they are identical. Several researchers like Chen [5,6,7], Hu and Li[8] etc. have studied the problem of similarity measure between fuzzy sets and vague sets. P. Majumdar and S. K. Samanta [13,14,15] have studied the similarity measure of soft sets , fuzzy soft sets and intuitionistic fuzzy soft sets. Cagman and Deli [4] studied similarity measure of intuitionistic fuzzy soft sets. A. Mukherjee and S. Sarkar [23] introduced several similarity measures for interval valued intutionistic fuzzy soft sets. Similarity measure for neutrosophic sets [3], neutrosophic soft sets [21], interval valued neutrosophic soft sets [22] also studied.

In this paper several distances between two interval-valued intuitionistic fuzzy soft sets are defined and based on this distances similarity measure between two interval-valued intuitionistic fuzzy soft sets are proposed. An application of similarity measure between two interval-valued intuitionistic fuzzy soft sets in a medical diagnosis problem is also illustrated.

2. Preliminaries

In this section we briefly review some basic definitions related to interval-valued intuitionistic fuzzy soft sets which will be used in the rest of the paper.

Definition 2.1[33] Let X be a non empty collection of objects denoted by x. Then a *fuzzy set* (*FS for short*) α in X is a set of ordered pairs having the form $\alpha = \{(x, \mu_\alpha(x)) : x \in X\}$, where the function $\mu_\alpha : X \to [0,1]$ is called the membership function or grade of membership (also degree of compatibility or degree of truth) of x in α .The interval M = $[0,1]$ is called membership space.

Definition 2.2[34] Let D[0, 1] be the set of closed subintervals of the interval [0, 1]. An *interval-valued fuzzy set* in X, $X \neq \phi$ and Card(X) = n, is an expression A given by $A = \{(x, M_A(x)) : x \in X\}$,where $M_A : X \to D[0,1]$

Definition 2.3 [1] Let X be a non empty set. Then an *intuitionistic fuzzy set (IFS for short)* A is a set having the form $A=\{(x, \mu_A(x), \gamma_A(x)): x\in X\}$ where the functions $\mu_A: X\rightarrow[0,1]$ and $\gamma_A: X\rightarrow[0,1]$ represents the degree of membership and the degree of non-membership respectively of each element $x\in X$ and $0\le\mu_A(x)+\gamma_A(x)\le1$ for each $x\in X$.

Definition 2.4[2] An *interval valued intuitionistic fuzzy set* A over a universe set U is defined as the object of the form $A=\{<x, \mu_A(x), \gamma_A(x)>: x\in U)\}$, where $\mu_A(x): U\rightarrow D[0,1]$ and $\gamma_A(x): U\rightarrow D[0,1]$ are functions such that the condition: $\forall x\in U$, $\sup\mu_A(x)+\sup\gamma_A(x)\le1$ is satisfied(where D[0,1] is the set of all closed subintervals of [0,1]).

Definition 2.5[11,16] Let U be an initial universe and E be a set of parameters. Let $P(U)$ denotes the power set of U and $A\subseteq E$. Then the pair (F,A) is called a *soft set* over U, where F is a mapping given by $F: A\rightarrow P(U)$.

Definition 2.6[17] Let U be an initial universe and E be a set of parameters. Let I^U be the set of all fuzzy subsets of U and A⊆ B . Then the pair (F,A) is called a *fuzzy soft set* over U, where F is a mapping given by $F: A\rightarrow I^U$.

Definition 2.8[32**]** Let U be an initial universe and E be a set of parameters, a pair(*F*,*E*) is called an *interval valued- fuzzy soft set* over *F*(U), where F is a mapping given by F:E→ *F*(U), where F(U) is the set of all interval-valued fuzzy sets of U .

An interval-valued fuzzy soft set is a parameterized family of interval-valued fuzzy subsets of U, thus, its universe is the set of all interval-valued fuzzy sets of U, i.e. *F*(U). An interval-valued fuzzy soft set is also a special case of a soft set because it is still a mapping from parameters to *F*(U),∀ e ∈ *E* , *F*(U) is referred as the interval fuzzy value set of parameters e , it is actually an interval-valued fuzzy set of U where $x\in U$ and $e\in E$, it can be written as: $F(e)=\{(x,\mu_{F(e)}(x)): x\in U\}$ where *F*(U) is the interval-valued fuzzy membership degree that object *x* holds on parameter.

Definition 2.7[10] Let U be an initial universe and E be a set of parameters. Let $IVIFS^U$ be the set of all interval valued intuitionistic fuzzy sets on U and $A\subseteq E$. Then the pair (F,A) is called an *interval valued intuitionistic fuzzy soft set (IVIFSS for short)* over U, where F is a mapping given by $F: A\rightarrow IVIFS^U$.

3. Similarity measures of interval-valued intuitionistic fuzzy soft sets

In this section we define some distances between two interval-valued intuitionistic fuzzy soft sets (IVIFSSs) and similarity measures of IVIFSSs . Some properties and examples are also studied.

Definition 3.1 Let $U=\{x_1,x_2,x_3,.......,x_n\}$ be the universe, $E=\{e_1,e_2,e_3,.......,x_m\}$ be the set of parameters, A, B ⊆ E and (F,A) , (G,B) be two IVIFSSs on U with their intuitionistic fuzzy approximation functions $F_A(e_i)=\{(x,\mu_A(x),\upsilon_A(x)):x\in U\}$ and $G_B(e_i)=\{(x,\mu_B(x),\upsilon_B(x)):x\in U\}$ respectively, where $\mu_A(x)$: U→D[0,1] and $\nu_A(x)$: U→D[0,1] are functions such that the condition: ∀x∈U, sup$\mu_A(x)$+sup$\nu_A(x)$≤1 and D[0,1] is the set of all closed subintervals of [0,1]. If A = B then we define the following distances between (F,A) and (G,B) :

1.Hamming distance;

$$d_H(F,G)=\frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n}\left\{\left|\bar{\mu}_F(e_i)(x_j)-\bar{\mu}_G(e_i)(x_j)\right|+\left|\bar{\upsilon}_F(e_i)(x_j)-\bar{\upsilon}_G(e_i)(x_j)\right|\right\}$$

2.Normalized Hamming distance;

$$d_{NH}(F,G)=\frac{1}{2n}\sum_{i=1}^{m}\sum_{j=1}^{n}\left\{\left|\bar{\mu}_F(e_i)(x_j)-\bar{\mu}_G(e_i)(x_j)\right|+\left|\bar{\upsilon}_F(e_i)(x_j)-\bar{\upsilon}_G(e_i)(x_j)\right|\right\}$$

3.Euclidean distance;

$$d_E(F,G)=\left[\frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n}\left\{\left(\bar{\mu}_F(e_i)(x_j)-\bar{\mu}_G(e_i)(x_j)\right)^2+\left(\bar{\upsilon}_F(e_i)(x_j)-\bar{\upsilon}_G(e_i)(x_j)\right)^2\right\}\right]^{\frac{1}{2}}$$

4.Normalized Euclidean distance :

$$d_{NE}(F,G)=\left[\frac{1}{2n}\sum_{i=1}^{m}\sum_{j=1}^{n}\left\{\left(\bar{\mu}_F(e_i)(x_j)-\bar{\mu}_G(e_i)(x_j)\right)^2+\left(\bar{\upsilon}_F(e_i)(x_j)-\bar{\upsilon}_G(e_i)(x_j)\right)^2\right\}\right]^{\frac{1}{2}}$$

Where $\bar{\mu}_F(e_i)(x_j)=\frac{1}{2}\{\sup\mu_F(e_i)(x_j)+\inf\ \mu_F(e_i)(x_j)\}$

$$\bar{\mu}_G(e_i)(x_j)=\frac{1}{2}\{\sup\mu_G(e_i)(x_j)+\inf\ \mu_G(e_i)(x_j)\}$$

$$\bar{\nu}_F(e_i)(x_j)=\frac{1}{2}\{\sup\nu_F(e_i)(x_j)+\inf\ \nu_F(e_i)(x_j)\}$$

$$\bar{\nu}_G(e_i)(x_j)=\frac{1}{2}\{\sup\nu_G(e_i)(x_j)+\inf\ \nu_G(e_i)(x_j)\}$$

Definition 3.2 Let U be universe and E be the set of parameters and (F,A) , (G,B) be two IVIFSSs on U , where A = B ⊆ E. Then based on the distances defined in definition 3.1 similarity measure of (F,A) and (G,B) is defined as

$$\text{SM(F,G)} = \frac{1}{1+d(F,G)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.1)}$$

Another similarity measure of (F,A) and (G,B) can also be defined as

$$\text{SM(F,G)} = e^{-\alpha \text{D(F,G)}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.2)}$$

Where $d(F,G)$ is the distance between the IVIFSSs (F,A) and (G,B) and α is a positive real number , called steepness measure.

Definition 3.3 Let (F,A) and (G,B) be two IVIFSSs defined on the universe U . Then the distance between (F,A) and (G,B) is defined as follows

$$d(F,G)=\left[\frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n}\left\{\left|\bar{\mu}_F(e_i)(x_j)-\bar{\mu}_G(e_i)(x_j)\right|^k+\left|\bar{\upsilon}_F(e_i)(x_j)-\bar{\upsilon}_G(e_i)(x_j)\right|^k\right\}\right]^{\frac{1}{k}} \quad \ldots\ldots\ldots\ldots (3.3)$$

and

$$d(F,G)=\left[\frac{1}{2n}\sum_{i=1}^{m}\sum_{j=1}^{n}\left\{\left|\bar{\mu}_F(e_i)(x_j)-\bar{\mu}_G(e_i)(x_j)\right|^k+\left|\bar{\upsilon}_F(e_i)(x_j)-\bar{\upsilon}_G(e_i)(x_j)\right|^k\right\}\right]^{\frac{1}{k}} \quad \ldots\ldots\ldots\ldots (3.4)$$

Where k > 0. If k = 1 then equation (3.3) and (3.4) are respectively reduced to Hamming distance and Normalized Hamming distance. Again if k = 2 then equation (3.3) and (3.4) are respectively reduced to Euclidean distance and Normalized Euclidean distance.

The weighted distance is defined as

$$d^w(F,G)=\left[\frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n}w_j\left\{\left|\bar{\mu}_F(e_i)(x_j)-\bar{\mu}_G(e_i)(x_j)\right|^k+\left|\bar{\upsilon}_F(e_i)(x_j)-\bar{\upsilon}_G(e_i)(x_j)\right|^k\right\}\right]^{\frac{1}{k}} \quad \ldots\ldots\ldots\ldots (3.5)$$

Where $w = (w_1,w_2,w_3,\ldots,w_n)^T$ is the weight vector of x_j (j = 1,2,3, …. ,n) and k > 0. Especially, if k = 1 then (3.5) is reduced to the weighted Hamming distance and If k = 2, then (3.5) is reduced to the weighted Euclidean distance.

Definition 3.4 Based on the weighted distance between two IVIFSSs (F,A) and (G,B) given by equation (3.5) , the similarity measure between (F,A) and (G,B) is defined as

$$\text{SM}(F,G) = \frac{1}{1+d^w(F,G)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.6)$$

Example 3.5 Let U={x_1,x_2,x_3} be the universal set and A={e_1,e_2,e_3} be the set of parameters. Let (F,A) and (G,A) be two interval-valued intuitionistic fuzzy soft sets over U such that their tabular representations are as follows:

(F,A)	e_1	e_2	e_3
x_1	[0.2,0.3],[0.5,0.7]	[0.7,0.8],[0.1,0.2]	[0.4,0.6],[0.0,0.3]
x_2	[0.0,0.2],[0.5,0.6]	[0.3,0.6],[0.1,0.4]	[0.6,0.8],[0.1,0.2]
x_3	[0.3,0.4],[0.5,0.6]	[0.8,0.9],[0.0,0.1]	[0.5,0.6],[0.2,0.3]

(G,A)	e_1	e_2	e_3
x_1	[0.3,0.4],[0.2,0.3]	[0.6,0.8],[0.1,0.2]	[0.6,0.7],[0.2,0.3]
x_2	[0.4,0.5],[0.1,0.2]	[0.2,0.4],[0.4,0.5]	[0.6,0.7],[0.2,0.3]
x_3	[0.5,0.7],[0.2,0.3]	[0.5,0.6],[0.0,0.3]	[0.4,0.6],[0.1,0.2]

Now by definition 3.1 the Hamming distance between (F,A) and (G,A) is given by

$d_H(F,G)=1.55$ and by equation (3.1) similarity measure between (F,A) and (G,A) is given by $S(F,G) \cong 0.39$

Example 3.6 Let U={x_1,x_2,x_3,x_4} be the universal set and A={e_1,e_2,e_3} be the set of parameters. Let (F_1,A) and (G_1,A) be two interval-valued intuitionistic fuzzy soft sets over U such that their tabular representations are as follows:

(F_1,A)	e_1	e_2	e_3
x_1	[0.3,0.4],[0.5,0.6]	[0.1,0.2],[0.6,0.7]	[0.0,0.3],[0.5,0.7]
x_2	[0.6,0.7],[0.1,0.2]	[0.4,0.5],[0.2,0.4]	[0.0,0.3],[0.5,0.7]
x_3	[0.7,0.8],[0.0,0.2]	[0.2,0.4],[0.4,0.5]	[0.5,0.7],[0.2,0.3]
x_4	[0.5,0.8],[0.0,0.2]	[0.3,0.6],[0.1,0.4]	[0.2,0.6],[0.3,0.4]

(G_1,A)	e_1	e_2	e_3
x_1	[0.2,0.35],[0.55,0.65]	[0.05,0.2],[0.5,0.7]	[0.1,0.4],[0.5,0.6]
x_2	[0.6,0.7],[0.1,0.2]	[0.4,0.6],[0.0,0.3]	[0.1,0.2],[0.6,0.7]
x_3	[0.65,0.75],[0.1,0.2]	[0.1,0.3],[0.4,0.5]	[0.5,0.7],[0.1,0.2]
x_4	[0.5,0.7],[0.1,0.2]	[0.4,0.5],[0.1,0.35]	[0.3,0.6],[0.25,0.35]

Now by definition 3.1 the Hamming distance between (F_1,A) and (G_1,A) is given by

$d_H(F_1, G_1) = 0.525$ and by equation (3.1) similarity measure between (F_1,A) and (G_1,A) is given by $S(F_1, G_1) \cong 0.65$.

Theorem 3.7 If S(F,G) be the similarity measure between two IVIFSSs (F,E) and (G,E) then

(i) S(F,G) = S(G,F)
(ii) $0 \leq S(F,G) \leq 1$
(iii) S(F,G) = 1 if and only if (F,E) = (G,E).

Proof: Obvious from the definition 3.2.

Definition 3.8 Let (F,A) and (G,B) be two IVIFSSs over U. Then (F,A) and (G,B) are said be α -similar , denoted by $(F,A)\overset{\alpha}{\simeq}(G,B)$ if and only if S((F,A),(G,B)) > α for α ∈ (0,1). We call the two IVIFSSs significantly similar if S((F,A),(G,B)) > $\frac{1}{2}$.

Example 3.9 In example **3.4** $S(F,G) = 0.39 < \frac{1}{2}$ and in example **3.5** $S(F_1, G_1) = 0.65 > \frac{1}{2}$. Therefore the IVIFSSs (F,E) and (G,E) are not significantly similar but (F_1,E) and (G_1,E) are significantly similar.

4. Application In Medical Diagnosis Problem

In this section we construct a decision making method for a medical diagnosis problem based on similarity measure of two interval-valued intuitionistic fuzzy soft sets (IVIFSSs). The algorithm of this method is as follows:

Step 1: construct a IVIFSS (F,A) over the universe U based on an expert.
Step 2: construct a IVIFSS (G,A) over the universe U based on a responsible person for the problem.
Step 3: calculate the distances of (F,A) and (G,A).

Step 4: calculate similarity measure of (F,A) and (G,A).
Step 5: estimate result by using the similarity.

Here we are giving an example of a decision making method. The similarity measure of two IVIFSSs based on Hamming distance can be applied to detect whether a ill person is suffering from a certain disease or not. In this problem we will try to estimate the possibility that an ill person having certain symptoms is suffering from brain cancer. For this we first construct a model IVIFSS for illness and another IVIFSS for ill person . Then we find the similarity measure of these two IVIFSSs. If they are significantly similar then we conclude that the person is possibly suffering from cancer.

Example 4.1 Let U be the universal set , which contains only two elements x_1 (brain cancer) and x_2 (not brain cancer) i.e. U={x_1,x_2}. Here the set of parameters E is a set of certain visible symptoms. Let E = {e_1,e_2,e_3,e_4,e_5,e_6}, where e_1 = headache, e_2 = seizures, e_3 = nausea and vomiting , e_4 = vision or hearing problems , e_5 = weakness and e_6 = behavioural and cognitive problems.

Step 1: Construct a IVIFSS (F,A) over U for brain cancer as given below, which can be prepared with the help of an expert (a doctor or a medical person).

(F,A)	e_1	e_2	e_3	e_4
x_1	[0.4,0.5],[0.3,0.4]	[0.3,0.4],[0.4,0.6]	[0.2,0.3],[0.4,0.7]	[0.4,0.6],[0.2,0.4]
x_2	[0.2,0.3],[0.6,0.7]	[0.5,0.6],[0.2,0.4]	[0.5,0.6],[0.3,0.4]	[0.7,0.8],[0.0,0.2]

e_5	e_6
[0.4,0.5],[0.4,0.5]	[0.6,0.7],[0.2,0.3]
[0.4,0.6],[0.2,0.4]	[0.1,0.4],[0.5,0.6]

Step 2: Construct a IVIFSS (G,B) over U based on data of a ill person as given below

(G,B)	e_1	e_2	e_3	e_4
x_1	[0.35,0.5],[0.25,0.45]	[0.2,0.4],[0.5,0.6]	[0.15,0.35],[0.4,0.65]	[0.4,0.6],[0.2,0.4]
x_2	[0.1,0.25],[0.5,0.75]	[0.4,0.6],[0.3,0.4]	[0.4,0.55],[0.3,0.45]	[0.6,0.75],[0.1,0.2]

e_5	e_6
[0.3,0.5],[0.4,0.5]	[0.5,0.7],[0.1,0.3]
[0.3,0.5],[0.1,0.4]	[0.0,0.3],[0.55,0.7]

Where A=B=E={e_1,e_2,e_3,e_4,e_5,e_6}.

Step 3: Calculate Hamming distance of (F,A) and (G,B):
Now by definition **3.1** the Hamming distance between (F,A) and (G,B) is given by
$d_H(F,G)$= 0.525
Step 4: Calculate similarity measure between (F,A) and (G,B):

Now by equation (3.1) similarity measure between (F,A) and (G,B) is given by

$S(F,G) \cong 0.65 > \frac{1}{2}$

Step 5: Here the two IVIFSSs i.e. two sets of symptoms (F,A) and (G,B) are significantly similar, therefore we conclude that the person is possibly suffering from brain cancer.

Example 4.2 Now we consider example 4.1 with a different ill person.

Step 1: Construct a IVIFSS (F,A) over U for brain cancer as in example 4.1, which can be prepared with the help of a medical person.

Step 2: Construct a IVIFSS (H,C) over U based on data of a ill person as given below

(H,C)	e_1	e_2	e_3	e_4
x_1	[0.0,0.3],[0.5,0.7]	[0.2,0.3],[0.6,0.7]	[0.0,0.1],[0.7,0.8]	[0.2,0.3],[0.5,0.7]
x_2	[0.6,0.8],[0.1,0.2]	[0.3,0.4],[0.5,0.6]	[0.3,0.4],[0.35,0.55]	[0.3,0.5],[0.4,0.5]

e_5	e_6
[0.1,0.3],[0.6,0.7]	[0.3,0.4],[0.5,0.6]
[0.2,0.3],[0.6,0.7]	[0.0,0.1],[0.7,0.8]

Step 3: Calculate Hamming distance between (F,A) and (H,C):

Now by definition **3.1** the Hamming distance between (F,A) and (H,C) is given by
$d_H(F,H) = 3.1$

Step 4: Calculate similarity measure of (F,A) and (H,C):

Now by equation (3.1) similarity measure between (F,A) and (H,C) is given by

$S(F,H) \cong 0.24 < \frac{1}{2}$

Step 5: Here the two IVIFSSs i.e. two sets of symptoms (F,A) and (H,C) are not significantly similar, therefore we conclude that the person is not possibly suffering from brain cancer.

5 Conclusion

In this paper we have defined distances between two IVFISSs and proposed similarity measures of two IVIFSSs based on distances between two IVIFSSs. Then we construct a decision making method based on similarity measures. Finally we give two simple examples to show the possibilities of diagnosis of a certain diseases. In these examples if we use the other distances, we can obtain similar results. Thus we can use the method to solve the problem that contain uncertainty such as problem in social, economic system, pattern recognition, medical diagnosis, game theory, coding theory and so on.

***References*:**

[1] K. Atanassov, Intuitionistic fuzzy sets, Fuzzy Sets and Systems 20 (1986) 87−96.

[2] K. Atanassov, G. Gargov, Interval valued intuitionistic fuzzy sets, Fuzzy Sets and Systems 31 (1989) 343−349.
[3] S, Broumi and F, Smarandache, ” Several similarity measures of neutrosophic sets”, Neutrosophic Sets and Systems, An International Journal in Information Science and Engineering, December (2013).
[4] Naim Cagman, Irfan Deli, Similarity measure of intuitionistic fuzzy soft sets and their decision making, arXiv : 1301.0456vI [math.LO] 3jan 2013.
[5] Shyi-Ming Chen, Ming-Shiow Yeh, Pei-Yung , A comparison of similarity measures of fuzzy values, Fuzzy Sets and Systems 72 (1995) 79-89.
[6] S. M. Chen, Measures of similarity between vague sets, Fuzzy Sets and Systems 74 (1995) 217−223.
[7] S. M. Chen, Similarity measures between vague sets and between elements, *IEEE* Transactions on System, Man and Cybernetics (Part B), 27(1) (1997) 153–168.
[8] Kai Hu and Jinquan Li, The entropy and similarity measure of interval valued intuitionistic fuzzy sets and their relationship, Int. J. Fuzzy Syst. 15(3) September 2013.
[9] Hong-mei Ju and Feng-Ying Wang, A similarity measure for interval-valued fuzzy sets and its application in supporting medical diagnostic reasoning, The Tenth International Symposium on Operations Research and Its Applications (ISORA 2011) 251–257.
[10] Y. Jiang, Y. Tang, Q. Chen, H. Liu and J. Tung, Interval -valued intuitionistic fuzzy soft sets and their properties, Computers and Mathematics with Applications 60(2010) 906-918.
[11] D. Molodtsov, Soft set theory−first results, Computers and Mathematics with Application 37 (1999) 19−31.
[12] Zhizhen Liang and Pengfei Shi, Similarity measures on intuitionistic fuzzy sets, Pattern Recognition Letters 24 (2003) 2687–2693.
[13] Pinaki Majumdar and S. K. Samanta, Similarity measure of soft sets, New Mathematics and Natural Computation 4 (1) (2008) 1–12.
[14] Pinaki Majumdar and S. K. Samanta, On similarity measures of fuzzy soft sets, International Journal of Advance Soft Computing and Applications 3 (2) July 2011.
[15] Pinaki Majumder and S. K. Samanta, On distance based similarity measure between intuitionistic fuzzy soft sets, Anusandhan 12 (22) (2010) 41−50.
[16] P. K. Maji, R. Biswas and A. R. Roy, Soft set theory, Computers and Mathematics with Applications 45 (4-5) (2003) 555−562.
[17] P. K. Maji, R. Biswas and A. R. Roy, Fuzzy Soft Sets, Journal of Fuzzy Mathematics 9 (3) (2001) 589−602.
[18] P. K. Maji, R. Biswas and A. R. Roy, Intuitionistic fuzzy soft sets, Journal of Fuzzy Mathematics 12 (3) (2004) 669−683.
[19] Won Keun Min, Similarity in soft set theory, Applied Mathematics Letters 25 (2012) 310–314.
[20] A. Mukherjee and S. Sarkar, Similarity measures of interval-valued fuzzy soft sets, Annals of Fuzzy Mathematics and Informatics, 8(9) (2014) 447– 460.
[21] A. Mukherjee and S. Sarkar, Several similarity measures of neutrosophic soft sets and its application in real life problems, Annals of Pure and Applied Mathematics, 7(1) (2014) 1−6.
[22] A. Mukherjee and S. Sarkar, Several similarity measures of interval valued neutrosophic soft sets and their applications in pattern recognition problems, Neutrosophic sets and systems, 6 (2014) 55–61.

[23] A. Mukherjee and S. Sarkar, Similarity measures for interval-valued intuitionistic fuzzy soft sets and its application in medical diagnosis problem, New Trends In Mathematical Sciences 2(3) (2014) 159–165.
[24] Jin Han Park, Ki Moon Lim, Jong Seo Park and Young Chel Kwun, Distances between interval-valued intuitionistic fuzzy sets, Journal of Physics, Conference Series 96 (2008) 012089.
[25] F. Smarandache, Neutrosophic Logic and Set, mss., http://fs.gallup.unm.edu/neutrosophy.htm, 1995.
[26] F. Smarandache, Neutrosophy, neutrosophic probability, set and logic, American Res. Press, Rehoboth, USA, 1998, 105p.
[27] E. Szmidt and J.Kacprzyk , Distances between intuitionistic fuzzy sets, Fuzzy Sets and Systems 114 (2000) 505−518.
[28] Cui-Ping Wei, Pei Wangb and Yu-Zhong Zhang, Entropy, similarity measure of interval- valued intuitionistic fuzzy sets and their applications, Information Sciences 181 (2011) 4273–4286.
[29] P. Z. Wang, Fuzzy sets and its applications, Shanghai Science and Technology Press, Shanghai 1983 in Chinese.
[30] Weiqiong Wang, Xiaolong Xin, Distance measure between intuitionistic fuzzy sets, Pattern Recognition Letters 26 (2005) 2063–2069.
[31] Zeshu Xu, Some similarity measures of intuitionistic fuzzy sets and their applications to multiple attribute decision makin, Fuzzy Optim. Decis. Mak. 6 (2007) 109−121.
[32] X.B.Yang, T.Y.Lin, J.Y.Yang, Y.Li and D.Yu , Combination of interval-valued fuzzy set and soft set, Computers and Mathematics with Applications 58(3) (2009) 521−527.
[33] L.A. Zadeh, Fuzzy set, Information and Control 8 (1965) 338−353 .
[34] L.A. Zadeh, The concept of a linguistic variable and its application to approximate reasoning-1, Information Sciences 8 (1975) 199−249.