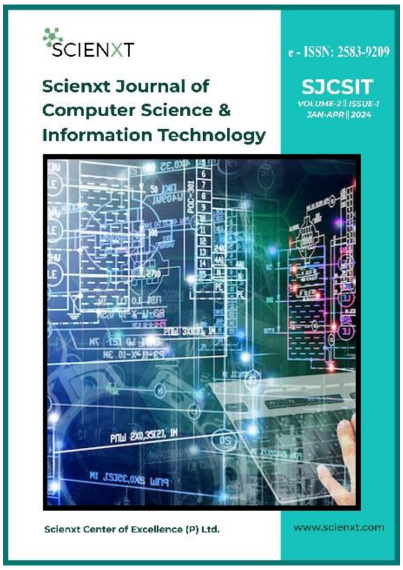

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Analogous likeminded m-distance metric associated with kl-distance metric in if-settings

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Abstract:

Right here, a way for developing new metrics for intuitionistic fuzzy M-distance (divergence) is suggested. A opportunity distribution's distance from $P = p1,\ldots,n$ to some other chance distribution $Q = q1,\ldots,qn$ is measured the use of the M-distance (divergence) metric when the chances in each distributions are monotonically growing or monotonically lowering. Within the discipline of picture segmentation, the intuitionistic fuzzy M - distance (divergence) metric has an expansion of makes use of. The suggested answer additionally separates and minimizes the imperfect and best threshold pix.

Keywords:

Intuitionistic fuzzy set, M-distance (divergence), Image segmentation, Convex function, Monotonic function etc.

1. Introduction:

Information theory (IT) become evolved by means of Shannon [15] in 1948 as a new vicinity of mathematics and a powerful tool for comprehending the complexities of conversation. Renyi [13] took the initiative and generalized the Shannon degree because of the Shannon degree's restrictions in a few circumstances. Following Renyi, severa generalized metrics for various circumstances have been developed. The degree of discrimination between opportunity distributions—one ideal and the other determined—became developed with the aid of Kullback and Leibler [10]. Within the final decades of the twentieth century, there has been a considerable expansion of the frame of literature on divergence measures.

Generalized statistics and divergence measurements have been evolved, according to Besseville [4], Esteban, and Morales [9]. Studies and development in the discipline were revolutionized by Zadeh's [20] introduction of the idea of fuzziness. The degree of fuzzy entropy that corresponds to Shannon's [1] measure of entropy was hooked up through De-Luca and Termini [8].

1.1. Divergences for fuzzy sets:

To quantify the difference between fuzzy units, several measures were advanced [4], [6], and [20] other than that, in 2023 Verma [18, 19] additionally evolved some new concepts concerning this.even as a specific situation turned into substantially investigated in [20], wherein an axiomatic formula of a divergence [14] measure for fuzzy units changed into brought, a complete take a look at at the comparison of fuzzy sets was provided in [6]. It changed into primarily based on the following characteristics of nature.

(i) it's far a symmetric, nonnegative characteristic of the two fuzzy units (i). (ii) A fuzzy set has zero divergence with itself.

(iii) The divergence among fuzzy sets decreases the "more similar" they're. the subsequent formal description applies to these characteristics.

Definition 1.2 (found in [20]):

Consider the universe X. If each pair of fuzzy sets A and B meets the requirements, then the map $D: F(X) \times FS(X) \rightarrow R$ is a divergence measure.

Div.1: $(A, B) = D(B, A)$.

Div.2: $(A, A) = 0$.

Div.3: $(A \cap C, B \cap C) \leq D(A, B)$, for every $C \in FS(X)$.

Div.4: $(A \cup C, B \cup C) \leq D(A, B)$, for every $C \in FS(X)$.

The preceding axiomsdo notdemand that the divergence benon-terrible. The axioms Div.2andDiv.3 (or Div.2 and Div.4) can be used to without difficulty deduce it. Measurements of fuzzy entropy equivalent to Renyi [13] entropy and measurements of fuzzy directed divergence equal to Kullback Leibler [10] divergence degree have been defined with the aid of De-Luca and Termini [8]. The frame of expertise approximately the introduction of divergence metrics has grown substantially in current years. Fuzzy data and divergence measurements have been surveyed with the aid of De-Luca and Termini [8]. Here, we use threshold, a nicely-preferred image segmentation method, to extract the items from a photo. The edge values for segmentation can be selected on the multimodal histogram's valley points if the items can be without difficulty distinguished from the historical past. To maximize the class separatability, which become based on within-magnificence version, between-elegance variance, and total variance of grey stages, Otsu [12] selected the threshold. The literature reports numerous tremendous investigations on various thresholding strategies. Statistics-theoretic metrics have been used by Verma [17] and Kapur et al. [11], breaking point and Pendcock [5] to threshold a photograph.

1.3. Intuitionistic fuzzy sets:

IFSs model situations wherein each point in the universe is given a degree of membership and a stage of non-participation. For that reason, Atanassov provided the subsequent description of an IFS (see [1]):

$A = \{(x, \mu_A(x), \nu_A(x)) | x \in X\}$

Where μ_A and ν_A signify the degree of membership and non-membership of the element to the set, respectively, and $0 \leq \mu(x) + \nu_A(x) \leq 1$ is a function of $\mu_A, \nu_A: X \to [0, 1]$. The function $\pi(x) = 1 - \mu_A(x) - \nu_A(x)$, also known as the intuitionistic fuzzy index or the hesitant index, denotes ignorance regarding membership in A. We may occasionally refer to $A = (\mu_A, \nu_A)$ as just A when there is no possibility of a mistake.

The comparable representation of IF-sets [2, 3] is an interval-valued set, where each element's $x \in X$ corresponding interval is $[\mu(x), 1 - \nu_A(x)]$. It implies that the interval includes the element's real degree of set membership as a result. The breadth of the interval matches the hesitancy index.

We can think of a fuzzy set A on X as an IFS with non-membership degree $1 - A$ and $\pi_A = 0$. Therefore, if $F(X)$= set of all fuzzy sets on X and $IFSs(X)$ = set of all IFSs on X, then $FS(X) \subset IFSs(X)$.

For A, $B \in IFS(X)$, the union, intersection, complement, inclusion, and inclusion relations are defined.

(i) Union of A and B:

$A \cup B = \{(x, \mu A \cup B(x), \nu A \cup B(x))| \ x \in X\}$ where $\mu A \cup B(x) = \max\{\mu_A(x), \nu_A(x)\}$ and $\mu A \cup B(x) = \min\{\nu_A(x), \nu_B(x)\}$.

(ii) Intersection of A and B:

$A \cap B = \{(x, \mu A \cap B(x), \nu A \cap B(x))| \ x \in X\}$where $\mu A \cap B(x) = \min\{\mu_A(x), \nu_A(x)\}$ and $\mu A \cap B(x) = \max\{\nu_A(x), \nu_B(x)\}$.

(iii) Complement of A: $A^C = \{(x, \nu(x), \mu_A(x))| \ x \in X\}$.

(iv) A is a subset of B (denoted by $A \subseteq B$) if and only if for every $x \in X$ it holds that $\mu(x) \leq \mu_B(x)$ and $\nu_A(x) \geq \nu_B(x)$.

1.4. Divergence measures for intuitionistic fuzzy sets:

We define a measure of comparison between two IFSs axiomatically. We first present the axioms and observe how distances, IF-divergences, and IF-dissimilarities relate to each other. Then, we givevariousIF-divergencesand IF- dissimilarities times,aswell assomefundamentalproperties and construction techniques for IF-divergences. To degree the variations between IFSs, severa features have been published inside the literature [6, 7] aside from that, in 2023 Verma [16] also advanced a few new standards regarding this. The maximum common ones are variations. Remember the fact that an IFSs dissimilarity degree, or IF-dissimilarity for short, is a feature$D$ from $IFS(X) \times IFSs(X)$ to R that satisfies the following standards for each A,B,$C \in IFSs(X)$:

IF-Diss.1: $(A, B) = D(B, A)$.

IF-Diss.2: $(A, A) = 0$.

IF-Diss.3: $A \subseteq B \subseteq C$, then $(A, C) \geq \max(D(A, B), D(B, C))$.

The literature has a few instances of dissimilarity metrics. In reality, [6, 7] provides an outline. Some of these comparisons have limitations because there are cases in which such differences lead to paradoxical metrics for IFSs. Consider, for instance, Chen's definition of the dissimilarity [6, 7] and the universe = $\{x_1, \ldots, x_n\}$:

$$D(A,B) = \frac{1}{2n}\sum_{i=1}^{n}|S_A(x_i) - S_B(x_i)|$$

$S(x_i) = |\mu_A(x_i) - \nu_A(x_i)|$ and $S_B(x_i) = |\mu_B(x_i) - \nu_B(x_i)|$ respectively. $D_C(A, B) = 0$ for this dissimilarity measure whenever $S_A(x_i) = S_B(x_i)$ for all $i = 1, \ldots, n$. In reality, the dissimilarity between them is zero if $\mu(x_i) = \nu_A(x_i) = 0$ and $\mu_B(x_i) = \nu_B(x_i) = 0.5$ for all $i = 1, \ldots, n$. The two sets, however, are distinctly different.

To avoid such absurd circumstances, a measure of contrast must be delivered that has stronger houses than dissimilarities. An IF- divergence may be defined as a measure of distinction that should fulfill the subsequent rational houses, which is the identical concept as fuzzy divergences.

(i) the two IF-units are measured by this nonnegative, symmetric quantity.

(ii) An IF-set has 0 IF-divergence with itself.

(iii) The IF-divergence between two IF-units decreases as they come to be "more" just like each other.

(iv) The IF-divergence turns into a divergence for fuzzy units.

Formally, the following axiomatic definition describes the concept of a divergence degree for IFSs.

DEFINITION 1.5:

Assuming X is a finite universe, $IFS(X)$ is the collection of all $IFSs$ on X. If a map D_{IF}: $IFS(X) \times IFSs(X) \rightarrow R$ has the properties listed below for any $A, B \in IFSs(X)$, it is an $IFSs$ divergence measure (also known as an IF-divergence).

IF-Diss.1: $D_I(A, B) = D_{IF}(B, A)$. **I**

F- Diss.2: $D_I(A, A) = 0$.

IF-Div.3: $D_I(A \cap C, B \cap C) \leq D_{IF}(A, B)$, for every $C \in IFSs(X)$.

IF-Div.4: $D_I(A \cup C, B \cup C) \leq D_{IF}(A, B)$, for every $C \in IFSs(X)$.

2. Our results:

2.1. The first measure of m-divergence metric in intuitionistic fuzzy setting:

The first such measure is defined by

subject to $\mu_B(x_1) < \mu_B(x_2) < \cdots < \mu_B(x_n)$ and $\nu_B(x_1) < \nu_B(x_2) < \cdots < \nu_B(x_n)$.

Also, $\mu(x_1) < \mu_A(x_2) < \cdots < \mu_A(x_n)$ and $\nu_A(x_1) < \nu_A(x_2) < \cdots < \nu_A(x_n)$. Now,

$D = \ln \partial \; 1 \quad + \ln (\;) \quad - \ln(\;) \frac{\nu_A \; x_1}{} \quad \frac{\mu_A(x_2) - \mu_A(\;) x_1}{} - \ln \quad \frac{\nu_A(x_2) - \nu_A(\;) x_1}{}$

$\partial\mu \quad x_1) \quad _A(\; _B(x_1) \quad \frac{\mu_A \; x_1}{\nu(x_1)} \quad \mu(x_2) - \mu_B(x_1) \quad \nu(x_2) - \nu_B(x_1)$

and

$$\frac{\partial}{\partial\mu_A(x_1)}\left(\frac{\partial D_1}{\partial\mu_A(x_1)}\right)=\frac{1}{\mu_A(x_1)}+\frac{1}{\mu_A(x_2)-\mu_A(x_1)}+\frac{1}{\nu_A(x_1)}+\frac{1}{\nu_A(x_2)-\nu_A(x_1)}>0$$

similarly

$$\frac{\partial D1}{\partial\mu A(x2)}=\ln\frac{\mu A(x2)-\mu A(x1)}{\mu B(x2)-\mu B(x1)}+\ln\frac{\nu A(x2)-\nu A(x1)}{\nu B(x2)-\nu B(x1)}-\ln\frac{\mu A(x3)-\mu A(x2)}{\mu B(x3)-\mu B(x2)}-\ln\frac{\nu A(x3)-\nu A(x2)}{\nu B(x3)-\nu B(x2)}$$

and

$$\frac{\partial}{\partial\mu_A(x_2)}\left(\frac{\partial D_1}{\partial\mu_A(x_2)}\right)=\frac{1}{\mu_A(x_2)-\mu_A(x_1)}+\frac{1}{\nu_A(x_2)-\nu_A(x_1)}+\frac{1}{\mu_A(x_3)-\mu_A(x_2)}+\frac{1}{\nu_A(x_3)-\nu_A(x_2)}>0$$

$\ldots$

$$\frac{\partial D1}{\partial\mu(xn)}=\ln\frac{\mu(xn)-\mu A(xn-1)}{\mu B(xn)-\mu B(xn-1)}\,\frac{\nu A(xn)-\nu A(xn-1)}{\nu B(xn)-\nu B(xn-1)}\,\frac{1-\mu A(xn)}{1-\mu B(xn)}\,\frac{1-\nu A(xn)}{1-\nu B(xn)}$$

$\ldots$

$$\frac{\partial}{\partial\mu_A(x_2)}\left(\frac{\partial D_1}{\partial\mu_A(x_2)}\right) = \frac{1}{n}\left[\frac{1}{\mu_A(x_n)-\mu_A(x_{n-1})} + \frac{1}{\nu_A(x_n)-\nu_A(x_{n-1})} + \frac{1}{1-\mu_A(x_n)} + \frac{1}{1-\nu_A(x_n)}\right] > 0$$

and $\frac{\partial^2 D_1}{\partial\mu_A(x_i)\partial\mu_A(x_{i+1})} = -\frac{1}{\mu_A(x_{i+1})-\mu_A(x_i)} - \frac{1}{\nu_A(x_{i+1})-\nu_A(x_i)}$.

Hence, $\frac{\partial}{\partial\mu_A(x_i)}\left(\frac{\partial D_1}{\partial\mu_A(x_i)}\right) \frac{\partial}{\partial\mu_A(x_{i+1})}\left(\frac{\partial D_1}{\partial\mu_A(x_{i+1})}\right) - \left(\frac{\partial^2 D_1}{\partial\mu_A(x_i)\partial\mu_A(x_{i+1})}\right)^2 > 0.$

Obviously, $D_1(A,B)$ is a convex function of $\mu_A(x_1), \mu_A(x_2), \ldots, \mu_A(x_n)$ and $\nu_A(x_1), \nu_A(x_2), \ldots\ldots, \nu_A(x_n)$. Its minimum value subject to $\sum_{i=1}^{n} \mu(x_i) + \nu_A(x_i) = 1$ is given as follows

$$\frac{\mu_A(x_2)+\nu_A(x_2)-\mu_A(x_1)-\nu_A(x_1)}{\mu(x_1)+\nu_A(x_1)} = \frac{\mu_B(x_2)+\nu_B(x_2)-\mu_B(x_1)-\nu_B(x_1)}{\mu_B(x_1)+\nu_B(x_1)},$$

$$\frac{\mu_A(x_3)+\nu_A(x_3)-\mu_A(x_2)-\nu_A(x_2)}{\mu_A(x_2)+\nu_A(x_2)-\mu_A(x_1)-\nu_A(x_1)} = \frac{\mu_B(x_3)+\nu_B(x_3)-\mu_B(x_2)-\nu_B(x_2)}{\mu_B(x_2)+\nu_B(x_2)-\mu_B(x_1)-\nu_B(x_1)}, \cdots\cdots,$$

$$\frac{\mu_A(x_n)+\nu_A(x_n)-\mu_A(x_{n-1})-\nu_A(x_{n-1})}{\mu_A(x_{n-1})+\nu_A(x_{n-1})-\mu_A(x_{n-2})-\nu_A(x_{n-2})} = \frac{\mu_B(x_n)+\nu_B(x_n)-\mu_B(x_{n-1})-\nu_B(x_{n-1})}{\mu_B(x_{n-1})+\nu_B(x_{n-1})-\mu_B(x_{n-2})-\nu_B(x_{n-2})}$$

$$\frac{\mu_A(x_n)+\nu_A(x_n)-\mu_A(x_{n-1})-\nu_A(x_{n-1})}{1-\mu_A(x_n)-\nu_A(x_n)} = \frac{\mu_B(x_n)+\nu_B(x_n)-\mu_B(x_{n-1})-\nu_B(x_{n-1})}{1-\mu_B(x_n)-\nu_B(x_n)}.$$

This condition is met if $\mu_A(x_1) + \nu_A(x_1) = \mu_B(x_1) + \nu_B(x_1), \mu_A(x_2) + \nu_A(x_2) = \mu_B(x_2)$ +

$\nu(x_2)$, … … , $\mu_A(x_n) + \nu_A(x_n) = \mu_B(x_n) + \nu_B(x_n)$ *i. e.* $A = B$. So that when $A = B$ and $D_1(A, B) \geq 0$,

$D_1(A, B)$ has its minimal value. In intuitionistic fuzzy settings where both $\mu(x_i) + \nu_A(x_i)$ and $\mu_B(x_i)$

$+ \nu(x_i)$ are monotonically increasing, we can utilize this $D_1(A, B)$ as an M-distance metric. As a result, the minimal M-distance probability distribution is provided when there are no constraints other than the natural constraint $\sum_{i=1}^{n} \mu(x_i) + \nu_A(x_i) = 1$ and the inequality constraints $\mu_A(x_i) + \nu_A(x_i) \geq 0$, $1 \geq \mu_A(x_i)$

$+ \nu_A(x_i) \geq \mu_A(x_{i-1}) + \nu_A(x_{i-1})$, $i = 1, \ldots, n$, the minimum M-distance probability distribution is given by $\mu_A(x_1) + \nu_A(x_1) = \mu_B(x_1) + \nu_B(x_1)$, $\mu_A(x_2) + \nu_A(x_2) =$

$\mu(x_2) + \nu_B(x_2)$, … … …… , $\mu_A(x_n) + \nu_A(x_n) = \mu_B(x_n) + \nu_B(x_n)$ and is same as the apriori distribution.

1.1 THE SECOND MEASURE OF M-DIVERGENCE METRIC IN INTUITIONISTIC FUZZY SETTING

The second such measure is defined by

$$D_2(A, B) = (1 + \mu_A(x_1)) \ln \frac{1+a\mu_A(x_1)}{1+a\mu(x_1)} + (1 + \nu_A(x_1)) \ln \frac{1+a\nu_A(x_1)}{1+a\nu(x_1)}$$

$$+ a\left(\mu_A(x_2) - \mu_A(x_1)\right) \ln \frac{\mu_A(x_2)-\mu_A(x_1)}{\mu(x_2)-\mu_B(x_1)} + a\left(\nu_A(x_2) - \nu_A(x_1)\right) \ln \frac{\nu_A(x_2)-\nu_A(x_1)}{\nu(x_2)-\nu_B(x_1)} + \ldots$$

subject to $\mu_B(x_1) < \mu_B(x_2) < \cdots < \mu_B(x_n)$ and $\nu_B(x_1) < \nu_B(x_2) < \cdots < \nu_B(x_n)$. Also,

$\mu(x_1) < \mu_A(x_2) < \cdots < \mu_A(x_n)$ and $\nu_A(x_1) < \nu_A(x_2) < \cdots < \nu_A(x_n)$.

Now, $\dfrac{\partial D_2}{\partial \mu(x1)}$ $\dfrac{1+a\mu_A(x_1)}{1+a\mu B(x1)}$ $\dfrac{1+a\nu_A(x_1)}{1+a\nu B(x1)}$ $\dfrac{\mu_A(x_2)-\mu_A(x_1)}{\mu B(x2)-\mu B(x1)}$ $\dfrac{\nu_A(x_2)-\nu_A(x_1)}{\nu B(x2)-\nu B(x1)}$,

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so $\dfrac{\partial}{\partial\mu_A(x_1)}\left(\dfrac{\partial D_2}{\partial\mu_1(x)}\right) = \dfrac{a}{1+a(\mu_A(x_1)+\mu_A(x_2))} + \dfrac{a}{\mu_A(x_1)+\nu_A(x)}$

$)-\mu(x)-\nu(x)$ > 0

similarly

$\dfrac{\partial D2}{\partial\mu A(x2)} = a\ln\dfrac{\mu A(x2)-\mu A(x1)}{\mu B(x2)-\mu B(x1)} + a\ln\dfrac{\nu A(x2)-\nu A(x1)}{\nu B(x2)-\nu B(x1)} - a\ln\dfrac{\mu A(x3)-\mu A(x2)}{\mu B(x3)-\mu B(x2)} - a\ln\dfrac{\nu A(x3)-\nu A(x2)}{\nu B(x3)-\nu B(x2)}$

and

$\dfrac{\partial}{\partial\mu A(x2)}\left(\dfrac{\partial D_2}{\partial\mu A(x2)}\right) = \dfrac{a}{\mu A(x2)-\mu A(x1)} + \dfrac{a}{\nu A(x2)-\nu A(x1)} + \dfrac{a}{\mu A(x3)-\mu A(x2)} + \dfrac{a}{\nu A(x3)-\nu A(x2)} > 0$

… [illegible]

$$\frac{\partial}{\partial\mu_A(x_2)}\left(\frac{\partial D_1}{\partial\mu_A(x_n)}\right) = \mu^a_A(x_{n-1}) - \mu_A(x_{n-1}) + \nu^a_A(x_{n+1}) - \nu_A(x_{n+1}) + \mu^a_A(x_n) - \mu_A(x_n) + \nu(x) - \nu(x) > 0$$

and $\frac{\partial^2 D_1}{\partial\mu_A(x_i)\partial\mu_A(x_{i+1})} = -\mu^a_A(x_{i+1}) - \mu_A(x_i) - \nu^a_A(x_i) - \nu(x)$.

Hence, $\left(\frac{\partial}{\partial\mu_A(x_i)}\left(\frac{\partial D_1}{\partial\mu_A(x_i)}\right)\right)\cdot\left(\frac{\partial}{\partial\mu_A(x_{i+1})}\left(\frac{\partial D_1}{\partial\mu_A(x_{i+1})}\right)\right) - \left(\frac{\partial^2 D_1}{\partial\mu_A(x_i)\partial\mu_A(x_{i+1})}\right)^2 > 0.$

Obviously, $D_2(A, B)$ is a convex function of $\mu_A(x_1), \mu_A(x_2), \ldots, \mu_A(x_n)$ and $\nu_A(x_1), \nu_A(x_2), \ldots$

$\ldots, \nu_A(x_n)$. Its minimum value subject to $\sum_{i=1}^{n} \mu(x_i) + \nu_A(x_i) = 1$ is given as follows

$\underline{\mu A(x2)+\nu A(x2)-\mu A(x1)-\nu A(x1)}$ =

$\underline{\mu B(x2)+\nu B(x2)-\mu B(x1)-\nu B(x1)}$

$1+a(\mu A(x1)+\nu A(x1))$

$1+a(\mu B(x1)+\nu B(x1))$

$\underline{\mu A(x3)+\nu A(x3)-\mu A(x2)-\nu A(x2)}$ $\underline{\mu B(x3)+\nu B(x3)-\mu B(x2)-\nu B(x2)}$

$\mu A(x2)+\nu A(x2)-\mu A(x1)-\nu A(x1)$ = $\mu B(x2)+\nu B(x2)-\mu B(x1)-\nu B(x1)$, …

…,

$\underline{\mu A(xn+1)+\nu A(xn+1)-\mu A(xn)-\nu A(xn)}$

$\underline{\mu B(xn+1)+\nu B(xn+1)-\mu B(xn)-\nu B(xn)}$

$\mu A(xn)+\nu A(xn)-\mu A(xn-1)-\nu A(xn-1)$ = $\mu B(xn)+\nu B(xn)-\mu B(xn-1)-\nu B(xn-1)$.

This condition is met if $\mu_A(x_1) + \nu_A(x_1) = \mu_B(x_1) + \nu_B(x_1), \mu_A(x_2) + \nu_A(x_2) = \mu_B(x_2) +$

$\nu(x_2), \ldots \ldots, \mu_A(x_n) + \nu_A(x_n) = \mu_B(x_n) + \nu_B(x_n)$ $i.e.$ $A = B$. So that when $A = B$ and $D_2(A,B) \geq 0$,

$D_2(A, B)$ has its minimal value. In intuitionistic fuzzy settings where both $\mu_A(x_i) + \nu_A(x_i)$ and $\mu_B(x_i)$

$+ \nu(x_i)$ are monotonically increasing, we can utilize this $D_2(A, B)$ as an M-distance metric. As a result, the minimal M-distance probability distribution is provided when there are no constraints other than the natural constraint $\sum_{i=1}^{n} \mu(x_i) + \nu_A(x_i) = 1$ and the inequality constraints $\mu_A(x_i) + \nu_A(x_i) \geq 0$, $1 \geq \mu_A(x_i)$

$+ \nu_A(x_i) \geq \mu_A(x_{i-1}) + \nu_A(x_{i-1})$, $i = 1, \ldots, n$, the minimum M-distance probability distribution is given by $\mu_A(x_1) + \nu_A(x_1) = \mu_B(x_1) + \nu_B(x_1)$, $\mu_A(x_2) + \nu_A(x_2) =$

$\mu(x_2) + \nu_B(x_2)$, … … …… , $\mu_A(x_n) + \nu_A(x_n) = \mu_B(x_n) + \nu_B(x_n)$ and is same as the apriori distribution.

CONCLUSION

In this communication an approach to develop measures of intuitionistic fuzzy M-distance metric using aggregation operators is proposed. The proposed measure is a distance measure. To add flexibility in applications the divergence (distance) measures may be generalized by using a parameter. In the literature related to image segmentation is not done, but this is a measure to its own right and can be used for thresholding in some situations because different measures have their suitability in different situations. Finally, we have studied the most usual measures of IF-sets, concluding that they are IF-M-distance metric.

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