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Similarity-Distance Decision-Making Technique and its Applications via Intuitionistic Fuzzy Pairs

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Abstract: The idea of intuitionistic fuzzy sets (IFSs) is a reasonable soft computing construct for resolving ambiguity and vagueness encountered in decision-making situations. Cases such as pattern recognition, diagnostic analysis, etc., have been explored based on intuitionistic fuzzy pairs via similarity-distance measures. Many similarity and distance techniques have been proposed and used to solve decision-making situations. Though the existing similarity measures and their distance counterparts are somewhat significant, they possess some weakness in terms of accuracy and their alignments with the concept of IFSs, which needed to be strengthened to enhance reliable outputs. As a consequent, this paper introduces a novel similarity-distance technique with better performance rating. A comparative analysis is presented to showcase the advantages of the novel similarity-distance over similar existing approaches. Some attributes of the similarity-distance technique are presented. Furthermore, the applications of the novel similarity-distance technique in sundry decision-making situations are explored.

Keywords: similarity measure, decision-making, intuitionistic fuzzy sets, distance measure, intuitionistic fuzzy pairs

1. Introduction

Decision-making is an art of making choice from several alternatives. Often times, the process is characterized with vagueness and uncertainty. The introduction of fuzzy set (Zadeh, 1965) proffered solution to the problem of vagueness and uncertainty in many decision-making situations such as image segmentation, medical diagnosis, pattern recognition, etc. Nonetheless, fuzzy set has a setback because it incorporates only the membership degree υ (MD) of the elements in the nonempty set. The setback of fuzzy set prompted Atanassov (1986) to suggest an idea called intuitionistic fuzzy set (IFS), which captures membership degree υ, nonmembership degree ν, and hesitation margin ϖ with the characteristic that their addition is one.

The idea of IFSs is very resourceful and as such has been applied in many areas. De et al. (2001) applied IFSs to medical decision via composite relation, and Liu and Chen (2017) posited that a group decision-making can be carried out by Heronian aggregation operators under IFSs. Many information measures have been explored to improve the application of IFSs in everyday problems. Some correlation coefficients of IFSs have been proposed and applied to numerous decision-making challenges (Ejegwa & Onyeke, 2021; Thao, 2018). Medical diagnostic problems were solved based on intuitionistic fuzzy correlation coefficients in Thao et al. (2019). A new correlation coefficient of IFSs was studied and applied in Garg and Kumar (2018). TOPSIS approach via correlation coefficient between intuitionistic fuzzy soft sets was discussed and applied (Garg & Arora, 2020). Ejegwa (2021) proposed an enhanced correlation coefficient of IFSs, which was used to solve decision-making challenges that are multicriteria in nature.

The approaches of estimating similarity and distance between IFSs have been discussed as reasonable information measures. Boran and Akay (2014) introduced a biparametric similarity measure and applied the technique to pattern recognition. Approach of estimating similarity of IFSs based on transformation technique has been studied and applied to pattern recognition (Chen & Chang, 2015). In Chen and Randyanto (2013) and Szmidt and Kacprzyk (2004), some similarity techniques of IFSs were introduced and applied to medical diagnostic reasoning. Burillo and Bustince (1996) initiated the concept of distances for IFSs and interval-valued fuzzy sets. Szmidt and Kacprzyk (2000) modified the distances in Burillo and Bustince (1996) and showed that all the three parameters constituting IFSs should be incorporated while computing distances between IFSs. Hatzimichailidis et al. (2012) discussed a novel distance technique between IFSs applied it to cases of pattern recognition. Wang and Xin (2005) introduced a novel weighted distance technique between IFSs with application to the solution of pattern recognition problem, Davvaz and Sadrabadi (2016) revised some existing distance techniques and applied them to diagnostic process. Iqbal and Rizwan (2019) discussed the relevant of IFSs in medicine and pattern recognition using a new similarity technique. Some relevant similarity techniques of IFSs have been considered and applied in diagnostic analysis, pattern recognition, etc. (Hong and Kim, 1999; Li et al., 2007; Shi and Ye, 2013; Ye, 2011).

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Although the existing similarity measures and their distance counterparts are somewhat significant, they possess some limitations, which needed to be strengthened to enhance reliable outputs. While some of the similarity-distance measures have low performance indexes (Iqbal and Rizwan, 2019; Shi and Ye, 2013; Szmidt and Kacprzyk, 2000), the ones in Hong and Kim (1999), Li et al. (2007) and Ye (2011) do not take account of the three parameters of IFSs, which adversely influence the performance rating of the similarity-distance measures. The motivation for this work is to propose a robust similarity-distance measure under intuitionistic fuzzy environment, with better performance rating compared with the techniques in Hong and Kim (1999), Iqbal and Rizwan (2019), Li et al. (2007), Shi and Ye (2013), Szmidt and Kacprzyk (2000) and Ye (2011). Specifically, this paper

i. revisits certain existing similarity-distance techniques between IFSs,
ii. proposes an improved similarity-distance technique between IFSs,
iii. presents comparison analyses of the new similarity-distance technique in intuitionistic fuzzy domain, and
iv. applies the new similarity-distance technique to determine some decision-making situations.

For the purpose of organization, the paper is delineated thus; Section II presents the concept of IFSs and reiterates the techniques in Hong and Kim (1999), Iqbal and Rizwan (2019), Li et al. (2007), Shi and Ye (2013), Szmidt and Kacprzyk (2000) and Ye (2011), Section II discusses the novel similarity-distance technique for IFSs and discusses its attributes, Section IV speaks on the applications of the new similarity-distance measure in decision-making via intuitionistic fuzzy information, and Section V gives conclusion of the work with certain recommendations.

2. Preliminaries

Here, the concept of IFSs is presented, and the techniques in Hong and Kim (1999), Iqbal and Rizwan (2019), Li et al. (2007), Shi and Ye (2013), Szmidt and Kacprzyk (2000) and Ye (2011) are reiterated.

2.1. Intuitionistic fuzzy sets

Numerous works on IFSs have been carried out (Atanassov, 1986, 1994). Here, some basic concepts of IFSs are presented. Throughout this work, we assume X is a set that is nonempty.

Definition 2.1. (Atanassov, 1986). An IFS signified by M in X is

$$M = \{< x, \upsilon_M(x), \nu_M(x) >: x \in X\},$$

where υ_M, ν_M: $X \to [0,1]$ are the membership and nonmembership degrees for all $x \in X$, and $0 \leq \upsilon_M(x)+\nu_M(x) \leq 1$.

In addition, $\varpi_M(x) \in [0,1] = 1 - \upsilon_M(x) - \nu_M(x)$ is called the hesitation margin of M.

Definition 2.2. (Atanassov, 1994). If M and N are IFSs in X, then for every $x \in X$,

i. Equality

$$M = N \text{ implies } \upsilon_M(x) = \upsilon_N(x) \text{ and } \nu_M(x) = \nu_N(x).$$

ii. Inclusion

$$M \subseteq M \text{ implies } \upsilon_M(x) \leq \upsilon_N(x) \text{ and } \nu_M(x) \geq \nu_N(x).$$

iii. Complement

$$\overline{M} = \{< x, \nu_m(x), \nu_m(x) >: x \in X\}.$$

iv. Union

$$M \cup N = \{< x, \max(\upsilon_M(x), \upsilon_N(x)), \min(\nu_M(x), \nu_N(x)) >: x \in X\}.$$

v. Intersection

$$M \cap N = \{< x, \min(\upsilon_M(x), \upsilon_N(x)), \max(\nu_M(x), \nu_N(x)) >: x \in X\}.$$

Definition 2.3. (Atanassov, 1994). Intuitionistic fuzzy pair (IFP) is described by $<m,n>$ with the attribute $m + n \leq 1$ for $m,n \in [0,1]$. IFP appraises the IFS for which the constituents (m and n) are taken to mean MD and NMD.

In a nutshell, an IFS $M = \{<x, \upsilon_M(x),\nu_M(x)>: x \in X\}$ can be represented by

$$M = (\upsilon_M(x), \nu_M(x)),$$

called intuitionistic fuzzy number.

2.2. Similarity-distance measure between intuitionistic fuzzy sets

Similarity measure, which is a twin idea of distance measure, is a vehicle used to demonstrate the uses of IFSs in everyday life. Thus, for every similarity measure, there is a distance measure. In what follows, we recall the definitions of similarity and distance measures adapted from literature.

Definition 2.4. For M and N as IFSs in X, the similarity measure of M and N signified by $\tilde{S}(M,N)$ is a mapping $\tilde{S}: IFS \times IFS \to [0,1]$ satisfying

i. $0 \leq \tilde{S}(M,N) \leq 1$
ii. $\tilde{S}(M,N) = 1$ iff $M = N$
iii. $\tilde{S}(M,N) = \tilde{S}(N,M)$
iv. $\tilde{S}(M,O) \leq \tilde{S}(M,N) + \tilde{S}(N,O)$, where O is an IFS in X.

When $\tilde{S}(M,N)$ approaches 1, it implies M and N are more close (*i.e.*, high similarity rate), and if $\tilde{S}(M,N)$ approaches 0, then M and N are not close, *i.e.*, the similarity/resemblance rate is low.

Definition 2.5. For M and N as IFSs in X, the distance measure of M and N signified by $\tilde{D}(M,N)$ is a mapping $\tilde{S}$: $IFS \times IFS \to [0,1]$ satisfying

i. $0 \leq \tilde{D}(M,N) \leq 1$
ii. $\tilde{D}(M,N) = 0$ iff $M = N$
iii. $\tilde{D}(M,N) = \tilde{D}(N,M)$
iv. $\tilde{D}(M,O) \leq \tilde{D}(M,N) + \tilde{D}(N,O)$, where O is an IFS in X.

When $\widetilde{D}(M,N)$ approaches 0, it implies M and N are more close, and if $\widetilde{D}(M,N)$ approaches 1, then M and N are not close.

From the ongoing, we see that

$$\widetilde{S}(M,N) = 1 - \widetilde{D}(M,N) \text{ and } \widetilde{D}(M,N) = 1 - \widetilde{S}(M,N).$$

Let $X = \{x_1, \ldots, x_n\}$, $n < \infty$, then for the IFSs M and N in X, we present the following similarity-distance measures:

Iqbal and Rizwan (2019)

$$\widetilde{S}_1(M,N) = \frac{1}{2n}\sum_{i=1}^{n}[\sqrt{\upsilon_M(x_i)\upsilon_N(x_i)}+2\sqrt{\nu_M(x_i)\nu_N(x_i)} + \sqrt{\varpi_M(x_i)\varpi_N(x_i)} + \sqrt{(1-\nu_M(x_i))(1-\nu_N(x_i))}],$$

$$\widetilde{D}_1(M,N) = 1 - \frac{1}{2n}\sum_{i=1}^{n}[\sqrt{\upsilon_M(x_i)\upsilon_N(x_i)}+2\sqrt{\nu_M(x_i)\nu_N(x_i)} + \sqrt{\varpi_M(x_i)\varpi_N(x_i)} + \sqrt{(1-\nu_M(x_i))(1-\nu_N(x_i))}].$$

This similarity-distance measure incorporates the three parameters of IFS and as such avoids information leakage and loss.

Hong and Kim (1999)

$$\widetilde{S}_2(M,N) = 1 - \frac{1}{2n}\sum_{i=1}^{n}[|\upsilon_M(x_i) - \upsilon_N(x_i)|+|\nu_M(x_i) - \nu_N(x_i)|],$$

$$\widetilde{D}_2(M,N) = \frac{1}{2n}\sum_{i=1}^{n}[|\upsilon_M(x_i) - \upsilon_N(x_i)|+|\nu_M(x_i) - \nu_N(x_i)|].$$

The similarity-distance measure is not reliable because the hesitation parameter is not captured in the technique.

Li et al. (2007)

$$\widetilde{S}_3(M,N) = 1 - \left(\frac{1}{2n}\sum_{i=1}^{n}[(\upsilon_M(x_i) - \upsilon_N(x_i))^2 + (\nu_M(x_i) - \nu_N(x_i))^2]\right)^{\frac{1}{2}},$$

$$\widetilde{D}_3(M,N) = \left(\frac{1}{2n}\sum_{i=1}^{n}[(\upsilon_M(x_i) - \upsilon_N(x_i))^2 + (\nu_M(x_i) - \nu_N(x_i))^2]\right)^{\frac{1}{2}}.$$

Similarly, this similarity-distance measure is not reliable because the hesitation parameter is not captured in the technique.

Ye (2011)

$$\widetilde{S}_4(M,N) = \frac{1}{n}\sum_{i=1}^{n}\frac{\upsilon_M(x_i)\upsilon_N(x_i) + \nu_M(x_i)\nu_N(x_i)}{\sqrt{\upsilon_M^2(x_i) + \nu_M^2(x_i)}\sqrt{\upsilon_N^2(x_i) + \nu_N^2(x_i)}},$$

$$\widetilde{D}_4(M,N) = 1 - \frac{1}{n}\sum_{i=1}^{n}\frac{\upsilon_M(x_i)\upsilon_N(x_i) + \nu_M(x_i)\nu_N(x_i)}{\sqrt{\upsilon_M^2(x_i) + \nu_M^2(x_i)}\sqrt{\upsilon_N^2(x_i) + \nu_N^2(x_i)}}.$$

Also, this similarity-distance measure is not reliable because the hesitation parameter is not captured in the technique.

Shi and Ye (2013)

$$\widetilde{S}_5(M,N) = \frac{1}{n}\sum_{i=1}^{n}\frac{\upsilon_M(x_i)\upsilon_N(x_i) + \nu_M(x_i)\nu_N(x_i) + \varpi_M(x_i)\varpi_N(x_i)}{\sqrt{\upsilon_M^2(x_i) + \nu_M^2(x_i) + \varpi_M^2(x_i)}\sqrt{\upsilon_N^2(x_i) + \nu_N^2(x_i) + \varpi_N^2(x_i)}},$$

$$\widetilde{D}_5(M,N) = 1 - \frac{1}{n}\sum_{i=1}^{n}\frac{\upsilon_M(x_i)\upsilon_N(x_i) + \nu_M(x_i)\nu_N(x_i) + \varpi_M(x_i)\varpi_N(x_i)}{\sqrt{\upsilon_M^2(x_i) + \nu_M^2(x_i) + \varpi_M^2(x_i)}\sqrt{\upsilon_N^2(x_i) + \nu_N^2(x_i) + \varpi_N^2(x_i)}}.$$

This similarity-distance measure incorporates the three parameters of IFS and as such avoids information leakage and loss.

Szmidt and Kacprzyk (2000)

$$\widetilde{S}_6(M,N) = 1 - \frac{1}{2}\sum_{i=1}^{n}[|\upsilon_M(x_i) - \upsilon_N(x_i)| + |\nu_M(x_i) - \nu_N(x_i)| + |\varpi_M(x_i) - \varpi_N(x_i)|],$$

$$\widetilde{D}_6(M,N) = \frac{1}{2}\sum_{i=1}^{n}[|\upsilon_M(x_i) - \upsilon_N(x_i)| + |\nu_M(x_i) - \nu_N(x_i)| + |\varpi_M(x_i) - \varpi_N(x_i)|].$$

$$\widetilde{S}_7(M,N) = 1 - \left(\frac{1}{2}\sum_{i=1}^{n}[(\upsilon_M(x_i) - \upsilon_N(x_i))^2 + (\nu_M(x_i) - \nu_N(x_i))^2 + (\varpi_M(x_i) - \varpi_N(x_i))^2]\right)^{\frac{1}{2}},$$

$$\widetilde{D}_7(M,N) = \left(\frac{1}{2}\sum_{i=1}^{n}[(\upsilon_M(x_i) - \upsilon_N(x_i))^2 + (\nu_M(x_i) - \nu_N(x_i))^2 + (\varpi_M(x_i) - \varpi_N(x_i))^2]\right)^{\frac{1}{2}}.$$

$$\widetilde{S}_8(M,N) = 1 - \frac{1}{2n}\sum_{i=1}^{n}[|\upsilon_M(x_i) - \upsilon_N(x_i)| + |\nu_M(x_i) - \nu_N(x_i)| + |\varpi_M(x_i) - \varpi_N(x_i)|],$$

$$\widetilde{D}_8(M,N) = \frac{1}{2n}\sum_{i=1}^{n}[|\upsilon_M(x_i) - \upsilon_N(x_i)| + |\nu_M(x_i) - \nu_N(x_i)| + |\varpi_M(x_i) - \varpi_N(x_i)|].$$

$$\widetilde{S}_9(M,N) = 1 - \left(\frac{1}{2n}\sum_{i=1}^{n}[(\upsilon_M(x_i) - \upsilon_N(x_i))^2 + (\nu_M(x_i) - \nu_N(x_i))^2 + (\varpi_M(x_i) - \varpi_N(x_i))^2]\right)^{\frac{1}{2}},$$

$$\widetilde{D}_9(M,N) = \left(\frac{1}{2n}\sum_{i=1}^{n}[(\upsilon_M(x_i) - \upsilon_N(x_i))^2 + (\nu_M(x_i) - \nu_N(x_i))^2 + (\varpi_M(x_i) - \varpi_N(x_i))^2]\right)^{\frac{1}{2}}.$$

These similarity-distance measures incorporate the three parameters of IFS and as such avoid information leakage and loss.

3. New Similarity-distance Technique of Intuitionistic Fuzzy Sets

A new similarity-distance technique for IFSs that incorporates the three characteristic features of IFS to avoid information loss is introduced. Suppose we have IFSs $\boldsymbol{M}$ and $\boldsymbol{N}$ in $X = \{x_1, \ldots, x_n\},\ n < \infty$, the new similarity-distance measure is

$$\widetilde{S}(M,N) = \frac{1}{n}\sum_{i=1}^{n}\left[\sqrt{\upsilon_M(x_i)\upsilon_N(x_i)} + \sqrt{\nu_M(x_i)\nu_N(x_i)} + \sqrt{\varpi_M(x_i)\varpi_N(x_i)}\right],$$

$$\widetilde{D}(M,N) = 1 - \frac{1}{n}\sum_{i=1}^{n}\left[\sqrt{\upsilon_M(x_i)\upsilon_N(x_i)} + \sqrt{\nu_M(x_i)\nu_N(x_i)} + \sqrt{\varpi_M(x_i)\varpi_N(x_i)}\right].$$

Proposition 3.1. If M and N are IFSs in X, then

i. $\widetilde{S}(M,N) = \widetilde{S}(N,M)$
ii. $\widetilde{D}(M,N) = \widetilde{D}(N,M)$
iii. $\widetilde{S}(M,N) = \widetilde{S}(\breve{M},\breve{N})$
iv. $\widetilde{D}(M,N) = \widetilde{D}(\breve{M},\breve{N})$.

Proof. Clearly,

$$\begin{aligned}\widetilde{S}(M,N) &= \frac{1}{n}\sum_{i=1}^{n}\left[\sqrt{\upsilon_M(x_i)\upsilon_N(x_i)} + \sqrt{\nu_M(x_i)\nu_N(x_i)} + \sqrt{\varpi_M(x_i)\varpi_N(x_i)}\right]\\ &= \frac{1}{n}\sum_{i=1}^{n}\left[\sqrt{\upsilon_N(x_i)\upsilon_M(x_i)} + \sqrt{\nu_N(x_i)\nu_M(x_i)} + \sqrt{\varpi_N(x_i)\varpi_M(x_i)}\right]\\ &= \widetilde{S}(N,M)\end{aligned}$$

Similarly, the proofs of (ii)–(iv) follow.

Proposition 3.2. If M, N, and O are IFSs in X with the inclusion $M \subseteq N \subseteq O$, then

i. $\widetilde{S}(M,N) \geq \widetilde{S}(M,0)$
ii. $\widetilde{S}(N,O) \geq \widetilde{S}(M,0)$
iii. $\widetilde{S}(M,0) \leq \max\left[\widetilde{S}(M,N), \widetilde{S}(N,O)\right]$.

Proof. The results are easy to see, so we omit.

Corollary 3.3. If M, N and O are IFSs in X with the inclusion $M \subseteq N \subseteq O$, then

i. $\widetilde{S}(M,N) \leq \widetilde{S}(M,0)$
ii. $\widetilde{S}(N,O) \leq \widetilde{S}(M,0)$
iii. $\widetilde{S}(M,0) \geq \max\left[\widetilde{S}(M,N), \widetilde{S}(N,O)\right]$.

Theorem 3.4. Suppose $\widetilde{S}(M,N)$ measures the similarity between IFSs M and N in X, then $0 \leq \widetilde{S}(M,N) \leq 1$.

Proof. To prove this, we show that $\widetilde{S}(M,N) \geq 0$ and $\widetilde{S}(M,N) \leq 1$. Certainly, $\widetilde{S}(M,N) \geq 0$ since

$$\sqrt{\upsilon_M(x_i)\upsilon_N(x_i)} \geq 0,\ \sqrt{\nu_M(x_i)\nu_N(x_i)} \geq 0 \text{ and } \sqrt{\varpi_M(x_i)\varpi_N(x_i)} \geq 0.$$

Now, we show that $\widetilde{S}(M,N) \leq 1$. Let us assume that

$$\sum_{i=1}^{n}\sqrt{\upsilon_M(x_i)\upsilon_N(x_i)} = \sigma,\ \sum_{i=1}^{n}\sqrt{\nu_M(x_i)\nu_N(x_i)} = \tau \text{ and } \sum_{i=1}^{n}\sqrt{\varpi_M(x_i)\varpi_N(x_i)} = \varrho.$$

Then, we have

$$\begin{aligned}\widetilde{S}(M,N) &= \frac{1}{n}\sum_{i=1}^{n}\left[\sqrt{\upsilon_M(x_i)\upsilon_N(x_i)} + \sqrt{\nu_M(x_i)\nu_N(x_i)} + \sqrt{\varpi_M(x_i)\varpi_N(x_i)}\right]\\ &\leq \frac{\sum_{i=1}^{n}\sqrt{\upsilon_M(x_i)\upsilon_N(x_i)} + \sum_{i=1}^{n}\sqrt{\nu_M(x_i)\nu_N(x_i)} + \sum_{i=1}^{n}\sqrt{\varpi_M(x_i)\varpi_N(x_i)}}{n}\\ &= \frac{\sigma+\tau+\varrho}{n}.\end{aligned}$$

Certainly, $\widetilde{S}(M,N) \leq \frac{\sigma+\tau+\varrho}{n}$ implies $\widetilde{S}(M,N) - 1 \leq \frac{\sigma+\tau+\varrho}{n} - 1$. But

$$\begin{aligned}\widetilde{S}(M,N) - 1 &\leq \frac{\sigma+\tau+\varrho}{n} - 1 = \frac{\sigma+\tau+\varrho-n}{n}\\ &= \frac{-(n-\sigma-\tau-\varrho)}{n} \leq 0.\end{aligned}$$

So, $\widetilde{S}(M,N) - 1 \leq 0$ implies $\widetilde{S}(M,N) \leq 1$. Thus $0 \leq \widetilde{S}(M,N) \leq 1$.

Corollary 3.5. Suppose $\widetilde{D}(M,N)$ measures the distance between IFSs M and N in X, then $0 \leq \widetilde{D}(M,N) \leq 1$.

3.1. Numerical illustrations and comparison

Here, we present some numerical illustrations of the similarity-distance measures and carry out a comparative analysis to ascertain the preeminence of the new similarity-distance technique.

Example I. Suppose M and N are IFSs in $X = \{x, y, z\}$ defined by

$$M = \{(x,\ 0.6, 0.2),\ (y,\ 0.2, 0.5),\ (z,\ 0.3, 0.2)\},$$

$$N = \{(x,\ 0.5, 0.4),\ (y,\ 0.1, 0.4),\ (z,\ 0.1, 0.5)\}.$$

Example II. Suppose $\breve{M}$ and $\breve{N}$ are IFSs in $X = \{w, x, y, z\}$ defined by

$$\breve{M} = \{(w,\ 0.8, 0.05),\ (x,\ 0, 1),\ (y,\ 0.5, 0.4),\ (z,\ 0.3, 0.4)\},$$

$$\breve{N} = \{(w,\ 1, 0),\ (x,\ 0.3, 0.5),\ (y,\ 0.55, 0.4),\ (z,\ 0.6, 0.3)\}.$$

After computing the hesitation parameters, we use the techniques in Szmidt and Kacprzyk (2004), Thao (2018), Thao et al. (2019), Ye (2011), Zadeh (1965), Ye (2011) and the proposed technique to obtain the results in Tables 1 and 2.

The results indicate that the new similarity technique yields the most reliable index for the relationship between the IFSs. The limitation of the similarity measures presented in Hong and Kim (1999), Iqbal and Rizwan (2019), Li et al. (2007) and Ye (2011) is that the hesitation parameter is not incorporated in the computation, and thus, the results cannot be reliable due to information loss. Though the similarity techniques in Shi and Ye (2013) and Szmidt and Kacprzyk (2000) considered the complete parameters of IFS, their outputs could not sufficiently measure the similarity between the IFSs. Thus, the new technique is better than the similarity techniques in Hong and Kim (1999), Iqbal and Rizwan (2019), Li et al. (2007), Shi and Ye (2013), Szmidt and

Table 1
Results of similarity measures

Methods	Example I	Example II
Iqbal and Rizwan (2019)	0.8517	0.8280
Hong and Kim (1999)	0.8334	0.8250
Li et al. (2007)	0.8175	0.7538
Ye (2011)	0.1486	0.2543
Shi and Ye (2013)	0.2982	0.1947
Szmidt and Kacprzyk (2000)	0.3000	−0.2500
	0.6394	0.2964
	0.7667	0.6875
	0.7919	0.6481
New technique	**0.9614**	**0.9121**

Table 2
Results of distance measures

Methods	Example I	Example II
Iqbal and Rizwan (2019)	0.1483	0.1720
Hong and Kim (1999)	0.1666	0.1750
Li et al. (2007)	0.1825	0.2462
Ye (2011)	0.8514	0.7457
Shi and Ye (2013)	0.7018	0.8053
Szmidt and Kacprzyk (2000)	0.7000	1.2500
	0.3606	0.7036
	0.2333	0.3125
	0.2081	0.3519
New technique	**0.0386**	**0.0879**

Kacprzyk (2000) and Ye (2011). In a nutshell, the new similarity technique has edge over the existing approaches studied in this work because

(i) it considers the complete parameters of IFS to avoid error due to omission distinct from the approaches in Hong and Kim (1999), Iqbal and Rizwan (2019), Li et al. (2007) and Ye (2011).
(ii) it yields the most reasonable and precise output among the considered approaches.

Similarly, the observation is the same for the distance measures, which are the similarity measures counterpart.

4. Decision-making Via the Novel Similarity-distance Technique

This section applies the new similarity-distance technique to determine certain decision-making cases such as classification of building materials, marital choice-making, and collation and announcement of electoral result.

Case I

Suppose that there are three patterns of building materials represented by intuitionistic fuzzy pairs P_1, P_2, and P_3 in the feature space $X = \{c_1,\ c_2,\ c_3\}$ as follows:

$$P_1 = \{(c_1,\ 0.34, 0.34), (c_2, 0.19, 0.48),\ (c_3,\ 0.02, 0.12)\}$$

$$P_2 = \{(c_1,\ 0.35, 0.33), (c_2, 0.2, 0.47),\ (c_3,\ 0.02, 0.5)\}$$

$$P_3 = \{(c_1,\ 0.33, 0.35), (c_2, 0.21, 0.46),\ (c_3,\ 0.01, 0.13)\}$$

Assume that there is a pattern U that is unclassified with patterns P_1, P_2, and P_3 represented by an IFP

$$U = \{(c_1,\ 0.4, 0.31), (c_2, 0.24, 0.44),\ (c_3,\ 0.04, 0.2)\}.$$

We find the similarity-distance of the unidentified pattern with the classified patterns to ascertain which class the unknown pattern belongs using the new technique. The following results are obtained:

$$\widetilde{S}(P_1, U) = 0.6923,\ \widetilde{S}(P_2, U) = 0.9755,\ \widetilde{S}(P_3, U) = 0.9833.$$

$$\widetilde{D}(P_1, U) = 0.3077,\ \widetilde{D}(P_2, U) = 0.0245,\ \widetilde{D}(P_3, U) = 0.0167.$$

The results show that the unclassified pattern U belongs to P_3 since

$$\widetilde{S}(P_3, U)\ > \widetilde{S}(P_2, U) > \widetilde{S}(P_1, U),\ \text{and}\ \widetilde{D}(P_3, U) < \widetilde{D}(P_2, U) < \widetilde{D}(P_1, U).$$

Case II

In this case, a scenario of marital choice is presented using intuitionistic fuzzy decision-making approach via similarity-distance technique. Let us assume that a bachelor B is searching for a bride represented by IFPs. The bachelor is guided by the following features: $C = \{c_1,\ c_2,\ c_3, c_4,\ c_5\}$, where $c_1 =$ cooking ability, $c_2 =$ faithfulness and submissiveness, $c_3 =$ home-keeping, $c_4 =$ physical beauty, $c_5 =$ industriousness. The bachelor transformed these linguistic variables into IFPs

$$B = \{(c_1,\ 0.8, 0.1), (c_2, 0.9, 0.05),\ (c_3,\ 0.8, 0.2),\ (c_4, 0.7, 0.15), (c_5,\ 0.9, 0.1)\}.$$

After a careful consultations and search, the bachelor found three ladies with the suitable qualities represented by IFPs:

$$L_1 = \{(c_1,\ 0.7, 0.2), (c_2, 0.3, 0.5),\ (c_3,\ 0.9, 0),\ (c_4, 0.9, 0.1), (c_5,\ 1, 0)\},$$

$$L_2 = \{(c_1,\ 0.5, 0.5), (c_2, 0.8, 0.1),\ (c_3,\ 0.4, 0.3),\ (c_4, 0.7, 0.2), (c_5,\ 0.3, 0.5)\},$$

$$L_3 = \{(c_1,\ 0.46, 0.5), (c_2, 0.5, 0.2),\ (c_3,\ 0.8, 0.05), (c_4, 0.4, 0.5), (c_5,\ 0.5, 0.3)\}.$$

By deploying the new similarity-distance technique to ascertain which of the ladies is compatible to the bachelor requirements, the following results are obtained:

$$\widetilde{S}(L_1, B) = 0.8962, \widetilde{S}(L_2, B) = 0.8791,\ \widetilde{S}(L_3, B) = 0.8913.$$

$$\widetilde{D}(L_1, B) = 0.1038,\ \widetilde{D}(L_2, B) = 0.1209,\ \widetilde{D}(L_3, B) = 0.1087.$$

From the results, it is clear that the bachelor B is more suitable to be married to L_1 since

$$\widetilde{S}(L_1, B) > \widetilde{S}(L_3, B) > \widetilde{S}(L_2, B)\ \text{and}$$

$$\widetilde{D}(L_1, B) < \widetilde{D}(L_3, B) < \widetilde{D}(L_2, B).$$

Case III

The case of an election where votes are presented as IFPs is presented in this experimental example. Let us assume that four candidates C_1, C_2, C_3, C_4 are vying for a position P in an election within five districts $D = \{d_1, d_2, d_3, d_4, d_5\}$. Suppose that the vote requirement for the position is an IFP

$$P = \{(d_1, 0.7, 0.1), (d_2, 0.8, 0.1), (d_3, 0.7, 0.1), (d_4, 0.9, 0), (d_5, 0.8, 0.1)\}$$

After votes were cast in the five districts, each of the aspirants gathered the following votes as IFPs:

$$C_1 = \{(d_1, 0.5, 0.4), (d_2, 0.8, 0.2), (d_3, 0.4, 0.3), (d_4, 0.6, 0.2), (d_5, 0.7, 0.2)\},$$

$$C_2 = \{(d_1, 0.8, 0.1), (d_2, 0.6, 0.3), (d_3, 0.6, 0.1), (d_4, 0.3, 0.5), (d_5, 0.8, 0.1)\},$$

$$C_3 = \{(d_1, 0.6, 0.3), (d_2, 0.7, 0.05), (d_3, 0.7, 0.1), (d_4, 0.2, 0.6), (d_5, 0.8, 0.1)\},$$

$$C_4 = \{(d_1, 0.7, 0.1), (d_2, 0.8, 0.1), (d_3, 0.5, 0.4), (d_4, 0.8, 0.1), (d_5, 0.5, 0.3)\}.$$

The winner of the poll is decided by the greatest similarity/smallest distance value between the position and the aspirants. The similarity-distance indexes are collated using the new similarity-distance technique, and the following results are presented:

$$\widetilde{S}(C_1, P) = 0.9375, \widetilde{S}(C_2, P) = 0.8852, \widetilde{S}(C_3, P) = 0.9011, \widetilde{S}(C_4, P) = 0.9757.$$

$$\widetilde{D}(C_1, P) = 0.0625, \widetilde{D}(C_2, P) = 0.1148, \widetilde{D}(C_3, P) = 0.0989, \widetilde{D}(C_4, P) = 0.0243.$$

From the collated results, it is easy to see that the winner of the poll is C_4 since

$$\widetilde{S}(C_4, P) > \widetilde{S}(C_1, P) > \widetilde{S}(C_3, P) > \widetilde{S}(C_2, P), \text{ and}$$

$$\widetilde{D}(C_4, P) < \widetilde{D}(C_1, P) < \widetilde{D}(C_3, P) < \widetilde{D}(C_2, P).$$

5. Conclusion

In a way to fortify the capacity of similarity-distance measure under IFSs as a key player in decision-making technique, we introduced an enhanced similarity-distance technique adjudged to be more effective in estimating relationship between IFSs in comparison to other existing technique in Hong and Kim (1999), Iqbal and Rizwan (2019), Li et al. (2007), Shi and Ye (2013), Szmidt and Kacprzyk (2000) and Ye (2011). Some properties of the new technique were mathematically presented, and the advantages of the new technique have been discussed. Finally, we have demonstrated how decision-making could be processed in pattern recognition of building materials, marital choice-making, and declaration of electioneering results. The veracity of the similarity-distance measure could be tested in q-rung othorpair fuzzy environment for advanced applications. Although the novel similarity-distance technique outperformed the existing approaches, it cannot be used in an environment that considers more than three parameters like in the case of picture fuzzy sets.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

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