

An Application of Interval Rough Pythagorean Fuzzy Set in a Multi Attribute Decision Making Problem

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Abstract

This paper aims to define the cosine, sine and cotangent similarity measures of interval rough pythagorean sets and investigate some properties. Furthermore, based on these proposed measures, a multi attribute decision making problem is solved. Finally, through an example to demonstrate the applicability of the proposed measures.

Keywords: Sine hamming similarity measure; cosine hamming similarity measure; cotangent hamming similarity measure; interval rough pythagorean set.

1. Introduction

The basic concept of fuzzy sets was introduced by Zadeh [9]. Here some membership grade is assigned to an element of a fuzzy set. In many situations of real world, apart from the grade of membership, the grade of non-membership is also required. To handle such conditions, the concept of pythagorean fuzzy set was introduced by Yagar [8], as a generalization of intuitionistic fuzzy set. Rough set theory was introduced by Z. Pawlak [6] in 1980. Dubois and Prade [4] combine the rough sets and fuzzy sets. In this paper we introduce the multi-attribute decision making based on hamming similarity measure under interval rough pythagorean environment.

2. Preliminaries

For basic definitions let us see [1–7] and [8]. Throughout this paper let us denote R as complete congruence relation on the universe U . The following abbreviations are used in this work:

- Cosine Hamming Similarity - **CHS**
- Sine Hamming Similarity - **SHS**
- Cotangent Hamming Similarity - **CTHS**

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- Interval Rough Pythagorean Fuzzy - \mathcal{I}_{RPF}

3. CHS Measure of \mathcal{I}_{RPF} Set

This section deals with **CHS** measure of \mathcal{I}_{RPF} set.

Definition 3.1. Let $P^i = \{\langle \alpha_1, \mu_{P^i}(\alpha_1), \nu_{P^i}(\alpha_1) \rangle / \alpha_1 \in U\}$ be an \mathcal{I}_{PF} set of U . The lower and upper-approximations of \mathcal{I}_{PF} is defined as follows:

$$\begin{aligned}\underline{R}(P^i) &= \{\langle \alpha_1, \underline{R}(\mu_{P^i}), \underline{R}(\nu_{P^i}) \rangle, \alpha_1 \in U\} \\ \overline{R}(P^i) &= \{\langle \alpha_1, \overline{R}(\mu_{P^i}), \overline{R}(\nu_{P^i}) \rangle, \alpha_1 \in U\},\end{aligned}$$

where

$$\begin{aligned}\underline{R}(\mu_{P^i})(\alpha_1) &= \bigwedge_{\alpha_2 \in [\alpha_1]_R} \mu_{P^i}(\alpha_2), \quad \underline{R}(\nu_{P^i})(\alpha_1) = \bigvee_{\alpha_2 \in [\alpha_1]_R} \nu_{P^i}(\alpha_2) \\ \overline{R}(\mu_{P^i})(\alpha_1) &= \bigvee_{\alpha_2 \in [\alpha_1]_R} \mu_{P^i}(\alpha_2), \quad \overline{R}(\nu_{P^i})(\alpha_1) = \bigwedge_{\alpha_2 \in [\alpha_1]_R} \nu_{P^i}(\alpha_2)\end{aligned}$$

with the condition that

$$\begin{aligned}0 &\leq \sup \{\underline{R}(\mu_{P^i}(\alpha_1))\}^2 + \sup \{\underline{R}(\nu_{P^i}(\alpha_1))\}^2 \leq 1 \\ 0 &\leq \sup \{\overline{R}(\mu_{P^i}(\alpha_1))\}^2 + \sup \{\overline{R}(\nu_{P^i}(\alpha_1))\}^2 \leq 1.\end{aligned}$$

The pair $R(P^i) = (\underline{R}(P^i), \overline{R}(P^i))$ is called the \mathcal{I}_{RPF} set of U .

Let P_1^i and P_2^i be two \mathcal{I}_{RPF} set in $U = \{u_1, u_2 \dots u_n\}$. A **CHS** measure between P_1^i and P_2^i is defined as follows:

$$\mathbf{CHS}(P_1^i, P_2^i) = \frac{1}{n} \sum_{k=1}^n \cos \left[\frac{\pi}{6} \left(\left| \delta \mu_{P_1^i}(u_k) - \delta \mu_{P_2^i}(u_k) \right| + \left| \delta \nu_{P_1^i}(u_k) - \delta \nu_{P_2^i}(u_k) \right| \right) \right]$$

where

$$\begin{aligned}\delta \mu_{P_1^i}(u_k) &= \frac{(\underline{R}(\mu^-) + \underline{R}(\mu^+) + \overline{R}(\mu^-) + \overline{R}(\mu^+))}{4} \\ \delta \nu_{P_1^i}(u_k) &= \frac{(\underline{R}(\nu^-) + \underline{R}(\nu^+) + \overline{R}(\nu^-) + \overline{R}(\nu^+))}{4} \\ \delta \mu_{P_2^i}(u_k) &= \frac{(\underline{R}(\mu^-) + \underline{R}(\mu^+) + \overline{R}(\mu^-) + \overline{R}(\mu^+))}{4} \\ \delta \nu_{P_2^i}(u_k) &= \frac{(\underline{R}(\nu^-) + \underline{R}(\nu^+) + \overline{R}(\nu^-) + \overline{R}(\nu^+))}{4}\end{aligned}$$

Proposition 3.2. A **CHS** measure between P_1^i and P_2^i satisfies the following properties

1. $0 \leq \mathbf{CHS}(P_1^i, P_2^i) \leq 1$.

$$2. \text{CHS}(P_1^i, P_2^i) = 1 \text{ } P_1^i = P_2^i.$$

$$3. \text{CHS}(P_1^i, P_2^i) = \text{CHS}(P_1^i, P_2^i).$$

Proof.

1. According to the cosine value it is obvious.

2. For any two \mathcal{I}_{RPF} sets P_1^i and P_2^i , if $P_1^i = P_2^i$ then, $\delta\mu_{P_1^i}(u_k) = \delta\mu_{P_2^i}(u_k)$ and $\delta\nu_{P_1^i}(u_k) = \delta\nu_{P_2^i}(u_k)$. Hence $|\delta\mu_{P_1^i}(u_k) - \delta\mu_{P_2^i}(u_k)| = 0$ and $|\delta\nu_{P_1^i}(u_k) - \delta\nu_{P_2^i}(u_k)| = 0$. Thus, $\cos(P_1^i, P_2^i) = 1$. Conversely, if $\cos(P_1^i, P_2^i) = 1$, then $|\delta\mu_{P_1^i}(u_k) - \delta\mu_{P_2^i}(u_k)| = 0$ and $|\delta\nu_{P_1^i}(u_k) - \delta\nu_{P_2^i}(u_k)| = 0$. Since $\cos(0) = 1$. So we can write $\delta\mu_{P_1^i}(u_k) = \delta\mu_{P_2^i}(u_k)$ and $\delta\nu_{P_1^i}(u_k) = \delta\nu_{P_2^i}(u_k)$. Hence $P_1^i = P_2^i$.

3. It is obvious.

□

4. SHS Measure of \mathcal{I}_{RPF} Set

This section deals with **SHS** measure of an \mathcal{I}_{RPF} .

Let P_1^i and P_2^i be two \mathcal{I}_{RPF} in $U = \{u_1, u_2 \dots u_n\}$. A **SHS** between P_1^i and P_2^i is defined as follows:

$$\text{SHS}(P_1^i, P_2^i) = 1 - \left[\frac{1}{n} \sum_{k=1}^n \sin \left[\frac{\pi}{6} \left(|\delta\mu_{P_1^i}(u_k) - \delta\mu_{P_2^i}(u_k)| + |\delta\nu_{P_1^i}(u_k) - \delta\nu_{P_2^i}(u_k)| \right) \right] \right]$$

where

$$\begin{aligned} \delta\mu_{P_1^i}(u_k) &= \frac{(\underline{R}(\mu^-) + \underline{R}(\mu^+) + \overline{R}(\mu^-) + \overline{R}(\mu^+))}{4} \\ \delta\nu_{P_1^i}(u_k) &= \frac{(\underline{R}(\nu^-) + \underline{R}(\nu^+) + \overline{R}(\nu^-) + \overline{R}(\nu^+))}{4} \\ \delta\mu_{P_2^i}(u_k) &= \frac{(\underline{R}(\mu^-) + \underline{R}(\mu^+) + \overline{R}(\mu^-) + \overline{R}(\mu^+))}{4} \\ \delta\nu_{P_2^i}(u_k) &= \frac{(\underline{R}(\nu^-) + \underline{R}(\nu^+) + \overline{R}(\nu^-) + \overline{R}(\nu^+))}{4} \end{aligned}$$

Proposition 4.1. The \mathcal{I}_{RPF} **SHS** measure between P_1^i and P_2^i satisfies the following properties

1. $0 \leq \text{SHS}(P_1^i, P_2^i) \leq 1$.
2. $\text{SHS}(P_1^i, P_2^i) = 1$ if and only if $P_1^i = P_2^i$.
3. $\text{SHS}(P_1^i, P_2^i) = \text{SHS}(P_1^i, P_2^i)$.

Proof. Proof is similar to Proposition 3.2.

□

5. CTHS Measure of \mathcal{I}_{RPF} Set

In this section we introduce the notion of **CTHS** measure of \mathcal{I}_{RPF} set.

Let P_1^i and P_2^i be two \mathcal{I}_{RPF} set in $U = \{u_1, u_2 \dots u_n\}$. A **CTHS** measure between P_1^i and P_2^i is defined as follows:

$$\text{CTHS}(P_1^i, P_2^i) = \frac{1}{n} \sum_{k=1}^n \cot \left[\frac{\pi}{4} + \frac{\pi}{12} \left(\left| \delta \mu_{P_1^i}(u_k) - \delta \mu_{P_2^i}(u_k) \right| + \left| \delta v_{P_1^i}(u_k) - \delta v_{P_2^i}(u_k) \right| \right) \right]$$

where

$$\begin{aligned} \delta \mu_{P_1^i}(u_k) &= \frac{(\underline{R}(\mu^-) + \underline{R}(\mu^+) + \overline{R}(\mu^-) + \overline{R}(\mu^+))}{4} \\ \delta v_{P_1^i}(u_k) &= \frac{(\underline{R}(v^-) + \underline{R}(v^+) + \overline{R}(v^-) + \overline{R}(v^+))}{4} \\ \delta \mu_{P_2^i}(u_k) &= \frac{(\underline{R}(\mu^-) + \underline{R}(\mu^+) + \overline{R}(\mu^-) + \overline{R}(\mu^+))}{4} \\ \delta v_{P_2^i}(u_k) &= \frac{(\underline{R}(v^-) + \underline{R}(v^+) + \overline{R}(v^-) + \overline{R}(v^+))}{4} \end{aligned}$$

Proposition 5.1. The \mathcal{I}_{RPF} **CTHS** measure between P_1^i and P_2^i satisfies the following properties

1. $\text{CTHS}(P_1^i, P_2^i) = 1$ if and only if $P_1^i = P_2^i$.
2. $\text{CTHS}(P_1^i, P_2^i) = \text{CTHS}(P_2^i, P_1^i)$.

Proof. Proof is similar to Proposition 3.2. □

6. MADM Problem Under \mathcal{I}_{RPF} Hamming Similarity Measure

In this section, we apply \mathcal{I}_{RPF} **CHS**, **SHS** and **CTHS** measures between \mathcal{I}_{RPF} sets to the *MADM* problem. Consider $K = \{K_1, K_2 \dots K_m\}$ be the set of attributes and $R = \{\tilde{Q}_1, \tilde{Q}_2 \dots \tilde{Q}_n\}$ be a set of alternatives.

Algorithm:

Step 1: Nomination of decision matrix with n alternatives and m attributes.

Step 2: Definition of ideal alternative:

For benefit type attribute:

$$Z^* = \left\{ \left(\min \underline{R}(\mu_{\tilde{Q}_i}), \max \underline{R}(v_{\tilde{Q}_i}) \right), \left(\max \overline{R}(\mu_{\tilde{Q}_i}), \min \overline{R}(v_{\tilde{Q}_i}) \right) \right\}.$$

For cost type attribute:

$$Z^* = \left\{ \left(\max \underline{R}(\mu_{\tilde{Q}_i}), \min \underline{R}(v_{\tilde{Q}_i}) \right), \left(\min \overline{R}(\mu_{\tilde{Q}_i}), \max \overline{R}(v_{\tilde{Q}_i}) \right) \right\}.$$

Step 3: We calculate \mathcal{I}_{RP} similarity measure between the ideal alternative Z^* and each alternative $Q_i, i = 1, 2, \dots, n$.

Step 4: The best alternative is opted with the highest similarity value.

7. Numerical Example

Let us consider a decision maker wants to select the bike for random use from $\{\tilde{Q}_1, \tilde{Q}_2, \tilde{Q}_3\}$, by considering mileage K_1 , reasonable price K_2 , features K_3 and the risk factor K_4 . By the above proposed measure, problem is solved by the following steps:

Step 1: The decision maker construct the decision matrix with respect to the three alternatives in terms of \mathcal{I}_{RPF} number.

	K_1	K_2	K_3	K_4
\tilde{Q}_1	$([.3, .4], [.5, .7]), ([.3, .4], [.5, .7])$	$([.5, .6], [.8, .9]), ([.5, .6], [.8, .9])$	$([.1, .2], [.7, .8]), ([.5, .8], [.4, .6])$	$([.1, .2], [.7, .8]), ([.5, .8], [.4, .6])$
\tilde{Q}_2	$([.7, .8], [.6, .7]), ([.7, .8], [.6, .7])$	$([.7, .8], [.6, .7]), ([.8, .9], [.4, .5])$	$([.5, .6], [.4, .5]), ([.5, .6], [.4, .5])$	$([.7, .8], [.6, .7]), ([.8, .9], [.4, .5])$
\tilde{Q}_3	$([.5, .7], [.3, .4]), ([.8, .9], [.1, .2])$	$([.5, .7], [.3, .4]), ([.8, .9], [.1, .2])$	$([.5, .7], [.3, .4]), ([.8, .9], [.1, .2])$	$([.8, .9], [.1, .2]), ([.8, .9], [.1, .2])$

Table 1:

Step 2: The benefit type attributes are K_1, K_2, K_3 and cost type attribute is K_4 . Then the ideal alternative is,

$$Z^* = \begin{cases} \langle ([.3, .4], [.6, .7]), ([.8, .9], [.1, .2]) \rangle \\ \langle ([.5, .6], [.8, .9]), ([.8, .9], [.1, .2]) \rangle \\ \langle ([.1, .2], [.7, .8]), ([.8, .9], [.1, .2]) \rangle \\ \langle ([.1, .2], [.7, .8]), ([.8, .9], [.1, .2]) \rangle \end{cases}$$

Step 3: Calculate the \mathcal{I}_{RPF} hamming similarity measure of the alternatives

$$\text{CHS}(Q_1, Z^*) = .249975$$

$$\text{CHS}(Q_2, Z^*) = .249988$$

$$\text{CHS}(Q_3, Z^*) = .249972$$

$$\text{SHS}(Q_1, Z^*) = .9966$$

$$\text{SHS}(Q_2, Z^*) = .9975$$

$$\text{SHS}(Q_3, Z^*) = .9963$$

$$\text{CTHS}(Q_1, Z^*) = 12.2243$$

$$\text{CTHS}(Q_2, Z^*) = 13.3690$$

$$\text{CTHS}(Q_3, Z^*) = 11.8483$$

Stop 4: Select the highest value.

$$\begin{aligned}\mathbf{CHS}(Q_2, Z^*) &> \mathbf{CHS}(Q_1, Z^*) > \mathbf{CHS}(Q_3, Z^*) \\ \mathbf{SHS}(Q_2, Z^*) &> \mathbf{SHS}(Q_1, Z^*) > \mathbf{SHS}(Q_3, Z^*) \\ \mathbf{CTHS}(Q_2, Z^*) &> \mathbf{CTHS}(Q_1, Z^*) > \mathbf{CTHS}(Q_3, Z^*)\end{aligned}$$

Hence Q_2 is the best alternative for random use.

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