Pattern Recognition Using the Picture Fuzzy Set Similarity Measure

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Abstract - Fuzzy sets with intuitionistic properties are a more advanced record of the traditional fuzzy set, which is frequently used in a variety of applications to deal with uncertainty and fuzzy situations. In general, similarity/distance measures are an important tool for distinguishing between two sets, and they can also be used to solve pattern recognition difficulties. Despite the fact that different similarity measures have already been proposed, there is still a lot of room for improvement because some of them fail to satisfy the characteristics of similarity measures and produce inconsistent findings. We proposed new similarity measures in this research that may contrast picture Fuzzy Sets. In this study, we attempt to perform pattern recognition on PFSs using the provided similarity measures.

Keywords - Fuzzy sets, Intuitionistic fuzzy sets, Picture Fuzzy Sets, Pattern-recognition, Similarity Measures

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INTRODUCTION

Zadeh [1] was the first to establish the idea of a fuzzy set. The fuzzy set can express the state between "belong to" and "not belong to" by assigning a membership degree between 0 and 1 to items with respect to a set. As a result, fuzzy sets can be used to explain a large number of uncertainties that aren't adequately represented by classical sets. Since its inception, fuzzy set theory has been employed in a large number of applications, counting automatic control, pattern recognition, and decision-making. The hypothesis of fuzzy sets has been found to be unsatisfactory in many actual circumstances. As a result, numerous higher theories have arisen over time, such as intuitionistic fuzzy sets (IFS), Pythagorean fuzzy sets, q-rung fuzzy sets [2], and so on. Intuitionistic fuzzy sets [3] are a higher hypothesis that is a notion of fuzzy sets that ask specialists to provide non-membership opinions on set elements. As a result, IFSs are frequently employed in pattern recognition applications [4].The tools that are frequently employed in those application challenges are similarity and distance measures. These two ideas are complimentary in the sense that by subtracting one from a unit, one can be derived from the other. Because of their global choice of relevancy, these measures came to be intensively explored since their initiation .Picture fuzzy set's similarity measure can be used to solve problems in a diversity of fields, including decision making, machine learning, and pattern detection[7, 8]. Despite the fact that IFSs are more effective than FSs at communicating ambiguous and hazy material, they shortfall a crucial notion, namely degree of neutrality, which is relevant in a variety of circumstances such includes human voting, medical diagnosis, and personal selection, to name a few examples. When it comes to general election, a person has four choices: poll in favour, poll against, abstain from polling, or refuse to poll. Cuong and Kreinvoch [9] created PFS, a novel generalization of FSs and IFSs, to cope with such circumstances. The degree of membership, non-membership, and neutrality for per capita sole element in a PFS is defined, as well as the requirement that a total of these grades that is less than or equal to one. We'll also show some examples of how our measure compares to Wei's similarity measures [6,8].

This paper's key contribution is:

1. New similarity measures have been proposed that can be used to compare PFSs.
2. We've also shown its properties in order to confirm that the recommended measures are present.
3. To show pattern recognition, some numerical examples are provided.

PRELIMINARIES

Definition 1:

Let $M = (c_y \colon y = 1,2,\dots,n)$ be the Universal set.

For $c_y \in M$, Zadeh [1] introduced fuzzy set as:

$$L = \left\{\left(c_y, \delta_L(c_y)\right) : c_y \in M, y = 1,2,\dots,n\right\}$$

Where $\delta_L(c_y)$ stands for membership degree of $c_y \in M$ in the set L such that $0 \le \delta_L(c_y) \le 1$

Definition 2:

For $c_y \in M$, Atanassov [3] introduced intuitionistic fuzzy set as:

$$L = \left\{\left(c_y, \delta_L(c_y), \vartheta_L(c_y)\right) : c_y \in M, y = 1,2,\dots,n\right\}$$

Where $\delta_L(c_y)$ stands for membership degree and $\vartheta_L(c_y)$ stands for non-membership degree of $c_y \in M$

in the set L such that $0 \le \delta_L(c_y) + \vartheta_L(c_y) \le 1$

Definition 3:

For $c_y \in M$, Cuong[10] introduced picture fuzzy set as:

$$L = \{(c_y, \delta_L(c_y), \theta_L(c_y), \vartheta_L(c_y)) : c_y \in M\}, \quad y = 1,2,\dots,n$$

where $\delta_L(c_y)$ stands for membership degree, $\vartheta_L(c_y)$ stands for non-membership degree and $\theta_L(c_y)$ stands for neutral degree of $c_y \in M$ in the set L such that $0 \le \delta_L(c_y) + \vartheta_L(c_y) + \theta_L(c_y) \le 1$

Theorem: [3] If a function *S:PFS*(*M*) × *PFS*(*M*) → *R* satisfies the following properties, thenit is a similarity measure on PFS(M):

(1) $0 \le S(L, D) \le 1$

(2) $S(L, D) = S(D, L)$

(3) $S(L, D) = 1$; if A=B

(4) if $L \subseteq D \subseteq V$, then $S(L, D) \ge S(L, V)$ and $S(D, V) \ge S(L, V)$

EXISTING SIMILARITY MEASURES

Wei [8] Cosine Similarity measure as:-

$$S_1(L,D) = \frac{1}{n}\sum_{y=1}^{n} \frac{\delta_L(c_y)\delta_D(c_y) + \vartheta_L(c_y)\vartheta_D(c_y) + \theta_L(c_y)\theta_D(c_y)}{\left(\delta_L(c_y)^2 + \vartheta_L(c_y)^2 + \theta_L(c_y)^2\right)^{\frac{1}{2}} \times \left(\delta_D(c_y)^2 + \vartheta_D(c_y)^2 + \theta_D(c_y)^2\right)^{\frac{1}{2}}}$$

Wei [8] introduced Set-theoretic similarity measure:-

$$S_2(L,D) = \frac{1}{n}\sum_{y=1}^{n} \frac{\delta_L(c_y)\delta_D(c_y) + \vartheta_L(c_y)\vartheta_D(c_y) + \theta_L(c_y)\theta_D(c_y)}{max\left(\left(\delta_L(c_y)^2 + \vartheta_L(c_y)^2 + \theta_L(c_y)^2\right), \left(\delta_D(c_y)^2 + \vartheta_D(c_y)^2 + \theta_D(c_y)^2\right)\right)}$$

Wei [6] introduced Cosine function-based similarity measures:-

$$S_3(L,D) = \frac{1}{n}\sum_{y=1}^{n} cos\left(\frac{\pi}{2}\, max(|\,\delta_L(c_y) - \delta_D(c_y)\,|, |\,\vartheta_L(c_y) - \vartheta_D(c_y)\,|, |\,\theta_L(c_y) - \theta_D(c_y)\,|)\right)$$

Wei [6] introduced cotangent function-based similarity measure by:-

$$S_4(L,D) = \frac{1}{n}\sum_{y=1}^{n} cot\left(\frac{\pi}{4} + \frac{\pi}{4}\, max(|\,\delta_L(c_y) - \delta_D(c_y)\,|, |\,\vartheta_L(c_y) - \vartheta_D(c_y)\,|, |\,\theta_L(c_y) - \theta_D(c_y)\,|)\right)$$

PROPOSED MEASURE

$$S_Z(L,D) = 1 - \frac{1}{n}\sum_{y=1}^{n}(|\,\delta_L(c_y) - \delta_D(c_y)\,| + |\,\vartheta_L(c_y) - \vartheta_D(c_y)\,| + |\,\theta_L(c_y) - \theta_D(c_y)\,|)$$

PATTERN RECOGNITION

The correlation coefficient, as we all know, counts the direct dependant level of two things. The correlation coefficient rises in proportion to the degree of trust. Digital image processing, clustering analysis, pattern identification, and decision making are just a few of the applications (Meng et al.) [11]. In pattern recognition, an unknown pattern is classified into some known patterns using numerous fuzzy information measures such as the divergence measure, correlation coefficient, distance measure, similarity measure, and others.

As a result, in this part, we make use of our proposed similarity measures to identify patterns while also demonstrating the supremacy of our proposed similarity measures using correlation, similarity, and divergence metrics developed by other researchers. In general, in an image fuzzy environment, we can frame a pattern detection task as follows:

Given m patterns, a pattern recognition problem $L_1, L_2, \dots, L_m$ and a sample D in a universal set $M = (c_1, c_2, \dots, c_n)$ as a picture fuzzy set, where $L_y = \left(\left(c_y, \delta_L(c_y), \vartheta_L(c_y), \theta_L(c_y)\right) : c_y \in M\right)$ for y=1,2,..,m and

$D_y = \left(\left(c_y, \delta_D(c_y), \vartheta_D(c_y), \theta_D(c_y) \right) : c_y \in M \right)$ for y=1,2,..,m

Which of the L_y, y=1,2,...,m patterns does D belong to? The following methods are used to answer this question:

We achieve this in two steps with the correlation and similarity measures:

ST1: Calculate the correlation and similarity measure. C(L_y, D) ∀ y=1,2,...,m

ST2: Allow D to be a part of pattern L_i^* ; in which C(L_i^* , D) = max(C(L_y, D) : y = 1, 2, ..., m)

EXAMPLE

Consider three known patterns L_1, L_2, L_3 are picture fuzzy sets on the universal set by $M = \{c_1, c_2\}$

L_1 = ((c_1, 0.1, 0.2, 0.5),(c_2, 0.4, 0.5, 0.1))

L_2 = ((c_1, 0.3, 0.3, 0.1),(c_2, 0.4, 0.2, 0.1))

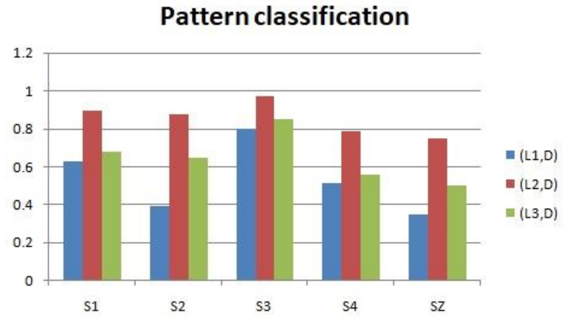
L_3 = ((c_1, 0.1, 0.2, 0.1),(c_2, 0.2, 0.5, 0.2))

Let D be an unknown sample on the universal set, which is also a picture fuzzy set

D= ((c_1, 0.5, 0.2, 0.0),(c_2, 0.3, 0.2, 0.1))

We categorize the unknown sample D to one of the known patterns using several fuzzy compatibility measures, and Table displays the results.

Measures	(L_1, D)	(L_2, D)	(L_3, D)	Comments
$S_1(L, D)$	0.6268	0.8946	0.6823	L_2
$S_2(L, D)$	0.3947	0.8781	0.6448	L_2
$S_3(L, D)$	0.7991	0.9693	0.8500	L_2
$S_4(L, D)$	0.5135	0.7903	0.5611	L_2
$S_Z(L, D)$	0.3500	0.7500	0.5000	L_2



CONCLUSION

From above table we have seen that:

1) In Measure S_1, B belongs to the L_2 pattern class.

2) In Measure S_2, B belongs to the L_2 pattern class.

3) In Measure S_3, B belongs to the L_2 pattern class.

4) In Measure S_4, B belongs to the L_2 pattern class.

5) In Measure S_Z, B belongs to the L_2 pattern class.

Thus, proposed measures are performing consistently with existing measures and it is also an potent method because it is providing precise decision.

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