Some Measures of Picture Fuzzy Sets and Their Application

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Abstract—To measure the difference of two fuzzy sets (FSs) / intuitionistic sets (IFSs), we can use the distance measure and dissimilarity measure between fuzzy sets/intuitionistic fuzzy set. Characterization of distance/dissimilarity measure between fuzzy sets/intuitionistic fuzzy set is important as it has application in different areas: pattern recognition, image segmentation, and decision making. Picture fuzzy set (PFS) is a generalization of fuzzy set and intuitionistic set, so that it has many application. In this paper, we introduce concepts: difference between PFS-sets, distance measure and dissimilarity measure between picture fuzzy sets, and also provide the formulas for determining these values. We also present an application of dissimilarity measures in the sample recognition problems, can also be considered a decision-making problem.

Index Terms—Picture fuzzy set (PFS), difference between PFS-sets, distance measure and dissimilarity measure between picture fuzzy sets, decision making.

1. Introduction

In many practical problems, we need to compare two objects. Therefore, the question of the process and the way to compare those objects is important. There are some models to measure difference between objects, as a general axiomatic framework for the comparison of fuzzy set. (Bouchon et al. [1]). Fuzzy set and intuitionistic fuzzy set have been used a lot in practical math problems [6,8,9,11]. Distance measure between fuzzy sets and intuitionistic fuzzy sets is also important for many practical applications (Ejegwa et al. [4], Hatzichristiadis et al. [6], Lindblad et al. [8], Muthukumar et al. [12]). Besides, dissimilarity measure between fuzzy sets/intuitionistic fuzzy set is also studied and applied in various matters (Li [7], Faghihi [5], Nguyen [13], Mahmood [10]).

The intuitionistic fuzzy set (IFS) was introduced by Atanassov [21] as a generalization of Zadeh’s fuzzy set [22]. Since its appearance, the IFS theory has received more and more attention and has been used in a wide range of applications [23,24] such as logic programming [25], medical diagnosis, [26-28] pattern recognition [29] decision making, etc. Atanassov and Georgiev [25] presented a logic programming system which uses the IFS theory to model various forms of uncertainty. De et al. [26] studied the Sanchez’s approach for medical diagnosis and extended this concept with the notion of IFS theory. Szmidt and Kacprzyk [27,28] proposed some similarity measures for IFSs and applied them to medical diagnostic reasoning. Li et al. [29] also investigated the similarity measures of IFSs and showed their usefulness in pattern recognitions. Szmith and Kacprzyk [27,28] investigated the group decision making problems based on intuitionistic fuzzy preference relations. They presented a method based on fuzzy linguistic majority to derive the decision results either directly from the individual intuitionistic fuzzy preference relations or by constructing rst a social intuitionistic fuzzy preference relation. Szmidt and Kacprzyk [27,28] proposed a similarity measure to analyze the extent of agreement in a group of experts. The proposed measure takes into account not only a pure distance between intuitionistic fuzzy preferences but also examines if the compared preferences are more similar or more dissimilar to each other. Gabriella et al. [30] constructed a generalized net model of multi-person multi-criteria decision making process based on intuitionistic fuzzy graphs. The model can be used for simulation, investigation and control of the processes of decision making.

In 2014, Cuong introduced the concept of the picture fuzzy set (PFS-sets) [2], in which a given set is represented by three memberships: a degree of positive membership \( \mu_A (u) \), a degree of negative membership \( \gamma_A (u) \), and a degree of neutral membership \( \eta_A (u) \). The refusal degree of an element is calculated as

\[
\xi_A (u) = 1 - (\mu_A (u) + \eta_A (u) + \gamma_A (u)), \forall u \in U
\]

In cases \( \xi_A (u) = 0 \), PFS returns to the traditional IFS set. Obviously, it is recognized that PFS is an extension of IFS where the refusal degree is appended to the definition. Therefore, PFS-sets will have more important implications in practical applications.

After that, Son gave the applications of the picture fuzzy set in clustering problems in [15,16,17]. Nguyen et al. [14] use picture fuzzy sets to applied for Geographic
Data Clustering. N. Van Dinh et al. [19] introduce the picture fuzzy set database. Cuong and Hai [3] studied some fuzzy logic operators for picture fuzzy sets. Nguyen et al [15] investigate the equivalence of two picture fuzzy set and apply them in clustering. But, difference between PFS-sets and dissimilarity between picture fuzzy sets (the concepts are important in application of picture fuzzy sets) are not yet been research.

In this paper, we introduce the concept of difference between PFS-sets, distance measure operators and dissimilarity measure operators between picture fuzzy sets. The rest of paper, in section 2, we recall the concept of picture fuzzy set and we introduce the new concept difference between PFS-sets. The function of distance measure between PFS-sets is defined in section 3. After, we introduce the function of dissimilarity measure between PFS-sets in section 4. We also illustrate with numerical examples the above measures in the sample recognition problems, can also be considered a decision-making problem in section 5.

2. Basic Notions

Definition 1. A picture fuzzy set (PFS) is defined by:

\[ A = \{(u, \mu_A(u), \eta_A(u), \gamma_A(u)) | u \in U\} \]

where: \( \mu_A \) is a positive membership function, \( \eta_A \) is a neural membership function, \( \gamma_A \) is negative membership function of \( A \), in there: \( \mu_A(u), \eta_A(u), \gamma_A(u) \in [0, 1] \) and

\[ 0 \leq \mu_A(u) + \eta_A(u) + \gamma_A(u) \leq 1 \]

for all \( u \in U \).

We denote \( \text{PFS}(U) \) is a collection of picture fuzzy set on \( U \). In which:

\[ U = \{(u, 1, 0, 0) | u \in U\} \]

and:

\[ \emptyset = \{(u, 0, 0, 1) | u \in U\} \]

For \( A, B \in \text{PFS}(U) \), then:

- Union of \( A \) and \( B \) is defined by:
  \[ A \cup B = \{(u, \mu_{A\cup B}(u), \eta_{A\cup B}(u), \gamma_{A\cup B}(u)) | u \in U\} \]
  where:
  \[ \mu_{A\cup B}(u) = \max \{\mu_A(u), \mu_B(u)\}, \eta_{A\cup B}(u) = \min \{\eta_A(u), \eta_B(u)\}, \gamma_{A\cup B}(u) = \min \{\gamma_A(u), \gamma_B(u)\} \]

- Intersection of \( A \) and \( B \) is defined by:
  \[ A \cap B = \{(u, \mu_{A\cap B}(u), \eta_{A\cap B}(u), \gamma_{A\cap B}(u)) | u \in U\} \]
  Where:
  \[ \mu_{A\cap B}(u) = \min \{\mu_A(u), \mu_B(u)\}, \eta_{A\cap B}(u) = \min \{\eta_A(u), \eta_B(u)\}, \gamma_{A\cap B}(u) = \max \{\gamma_A(u), \gamma_B(u)\} \]

- Subset: \( A \subset B \) iff \( A \subset B \)

Now, we define an operator called difference between picture fuzzy sets.

**Definition 2.**

An operator \( - : \text{PFS}(U) \times \text{PFS}(U) \to \text{PFS}(U) \) is a difference between PFS-sets if it satisfies properties:

1. \( A \subset B \iff A = B = \emptyset \)
2. If \( B \subset C \) then \( B - A \subset C - A \)
3. \( (A \cap C) - (B \cap C) \subset A - B \),
4. \( (A \cup C) - (B \cup C) \subset A - B \), For all \( A, B, C \in \text{PFS}(U) \).

**Theorem 1.**
The function \( - : \text{PFS}(U) \times \text{PFS}(U) \to \text{PFS}(U) \) given by:

\[ A - B = \{(u, \mu_{A-B}(u), \eta_{A-B}(u), \gamma_{A-B}(u)) | u \in U\} \]

where:

\[ \mu_{A-B}(u) = \max\{0, \mu_A(u) - \mu_B(u)\}, \]
\[ \eta_{A-B}(u) = \max\{0, \eta_A(u) - \eta_B(u)\}, \]
\[ \gamma_{A-B}(u) = \begin{cases} 1 - \mu_{A-B}(u) - \eta_{A-B}(u) & \text{if } \gamma_A(u) > \gamma_B(u) \\ 1 + \gamma_A(u) - \gamma_B(u) & \text{if } \gamma_A(u) \leq \gamma_B(u) \end{cases} \]

is a difference between PFS-sets.

**Proof.** It is easy to see that

\[ 0 \leq \mu_{A-B}(u) + \eta_{A-B}(u) + \gamma_{A-B}(u) \leq 1 \]

for all \( u \in U \).

We verify all condition in definition 2:
- With condition (D1).
- With condition (D2).

With \( B \subset C \), we have:

\[ \mu_B(u) \leq \mu_C(u), \eta_B(u) \leq \eta_C(u) \text{ and } \gamma_B(u) \geq \gamma_A(u) \]

So that:

\[ \mu_{B-A}(u) = \max\{0, \mu_B(u) - \mu_A(u)\} \leq \max\{0, \mu_C(u) - \mu_A(u)\} = \mu_{C-A}(u), \]
\[ \eta_{B-A}(u) = \max\{0, \eta_B(u) - \eta_A(u)\} \leq \max\{0, \eta_C(u) - \eta_A(u)\} = \eta_{C-A}(u) \]

With negative membership function, we consider some cases:

If \( \gamma_A(u) \leq \gamma_C(u) \leq \gamma_B(u) \) then

\[ \gamma_{B-A}(u) = 1 - \mu_{B-A}(u) - \eta_{B-A}(u) \geq 1 - \mu_{C-A}(u) - \eta_{C-A}(u) = \gamma_{C-A}(u) \]

If \( \gamma_C(u) \leq \gamma_A(u) \leq \gamma_B(u) \) then

\[ \gamma_{B-A}(u) = 1 - \mu_{B-A}(u) - \eta_{B-A}(u) \geq 1 - \mu_{C-A}(u) - \eta_{C-A}(u) \]

So that

\[ \gamma_{B-A}(u) \geq \min\{1 + \gamma_A(u) - \gamma_C(u), 1 - \mu_{C-A}(u) - \eta_{C-A}(u)\} = \gamma_{C-A}(u) \]

If \( \gamma_C(u) \leq \gamma_B(u) \leq \gamma_A(u) \) then
\[ \gamma_{B-A}(u) = 1 - \mu_{B-A}(u) - \eta_{B-A}(u), \]
\[ \geq 1 - \mu_{C-A}(u) - \eta_{C-A}(u) \]

and
\[ \gamma_{B}(u) - \gamma_{A}(u) \geq \gamma_{C}(u) - \gamma_{A}(u). \]
So that
\[ \gamma_{B-A}(u) = \min \left\{ 1 + \gamma_{A}(u) - \gamma_{B}(u), 1 - \mu_{A-B}(u) - \eta_{A-B}(u) \right\}, \]
\[ \geq \min \left\{ 1 + \gamma_{A}(u) - \gamma_{C}(u), 1 - \mu_{C-A}(u) - \eta_{C-A}(u) \right\}. \]
\[ = \gamma_{C-A}(u). \]

• Similarity, it is possible to show that conditions (D3) and (D4) are also satisfied.

**Example 1.** Given \( U = \{u_1, u_2, u_3\} \) and two PFS-sets:
\[ A = \{ (u_1, 0.7, 0.2, 0.1), (u_2, 0.6, 0.1, 0.1), (u_3, 0.6, 0.1, 0.2) \}, \]
\[ B = \{ (u_1, 0.6, 0.3, 0.1), (u_2, 0.7, 0.05, 0.2), (u_3, 0.4, 0.4, 0.1) \}. \]

Then, computing by theorem 1, we have:
\[ A - B = \{ (u_1, 0.1, 0.0, 0.9), (u_2, 0.0, 0.05, 0.9), (u_3, 0.2, 0.0, 0.8) \} \]

### 3. Distance measure of picture fuzzy sets

In this section we define the distance measure between picture fuzzy sets.

**Definition 3.** A function \( D : PFS(U) \times PFS(U) \to [0, +\infty) \) is a distance measure between PFS-sets if it satisfies follow properties

(i) \( \text{PF-dist 1: } D(A, B) = 0 \iff A = B \),

(ii) \( \text{PF-dist 2: } D(A, B) = D(B, A), \) for all \( A, B \in PFS(U) \),

(iii) \( \text{PF-dist 3: } D(A, C) \leq D(A, B) + D(B, C), \) for all \( A, B, C \in PFS(U) \).

There are many formulas that determine the distance between two picture fuzzy sets.

**Theorem 2.**

Given \( U = \{u_1, u_2, \ldots, u_n\} \) is an universe set. For \( A, B \in PFS(U) \). We have some distance measure between picture fuzzy sets

\[ a) D_H(A, B) = \frac{1}{n} \sum_{i=1}^{n} \left[ \frac{|\mu_A(u_i) - \mu_B(u_i)|}{\mu_A(u_i) + \mu_B(u_i)} + \frac{|\eta_A(u_i) - \eta_B(u_i)|}{\eta_A(u_i) + \eta_B(u_i)} + \frac{|\gamma_A(u_i) - \gamma_B(u_i)|}{\gamma_A(u_i) + \gamma_B(u_i)} \right]^{\frac{1}{2}} \]

\[ b) D_E(A, B) = \frac{1}{n} \sum_{i=1}^{n} \left[ \frac{(\mu_A(u_i) - \mu_B(u_i))^2}{\mu_A(u_i) + \mu_B(u_i)} + \frac{(\eta_A(u_i) - \eta_B(u_i))^2}{\eta_A(u_i) + \eta_B(u_i)} + \frac{(\gamma_A(u_i) - \gamma_B(u_i))^2}{\gamma_A(u_i) + \gamma_B(u_i)} \right]^{\frac{1}{2}} \]

\[ c) D_H^n(A, B) = \frac{1}{n} \max_{1 \leq i \leq n} \left[ \frac{|\mu_A(u_i) - \mu_B(u_i)|}{\eta_A(u_i) + \gamma_A(u_i)}, \frac{|\eta_A(u_i) - \eta_B(u_i)|}{\mu_A(u_i) + \gamma_A(u_i)}, \frac{|\gamma_A(u_i) - \gamma_B(u_i)|}{\mu_A(u_i) + \eta_A(u_i)} \right] \]

\[ d) D_E^n(A, B) = \frac{1}{n} \max_{1 \leq i \leq n} \left[ \frac{|\mu_A(u_i) - \mu_B(u_i)|}{\gamma_A(u_i) + \eta_A(u_i)}, \frac{|\eta_A(u_i) - \eta_B(u_i)|}{\gamma_A(u_i) + \mu_A(u_i)}, \frac{|\gamma_A(u_i) - \gamma_B(u_i)|}{\mu_A(u_i) + \eta_A(u_i)} \right]^{\frac{1}{2}} \]

We easy to verify that the functions in theorem 2 are satisfies properties of distance measure between picture fuzzy sets (def. 3). In there, \( D_E(A, B) \) is usually used to measure the distance of objects in geometry, \( D_H(A, B) \) is used in the information theory.

### 4. Dissimilarity of picture fuzzy sets

In this section, we introduce the concept of dissimilarity for picture fuzzy sets.

**Definition 4.** A function \( DM : PFS(U) \times PFS(U) \to R \) is a dissimilarity measure between PFS-sets if it satisfies follow properties:

(i) \( \text{PF-Diss 1: } DM(A, B) = DM(B, A) \)

(ii) \( \text{PF-Diss 2: } DM(A, A) = 0 \).

(iii) \( \text{PF-Diss 3: } \) If \( A \subset B \subset C \) then

\[ DM(A, C) \geq \max \{ DM(A, B), DM(B, C) \}. \]

for all \( A, B, C \in PFS(U) \).

**Theorem 3.** Given \( U = \{u_1, u_2, \ldots, u_n\} \) is an universe set. For any \( A, B \in PFS(U) \), a function \( DM : PFS(U) \times PFS(U) \to R \) is defined by:

\[ DM_C(A, B) = \frac{1}{n} \sum_{i=1}^{n} \left[ |S_A(u_i) - S_B(u_i)| + |\eta_A(u_i) - \eta_B(u_i)| \right] \]

where \( S_A(u_i) = |\mu_A(u_i) - \gamma_A(u_i)| \text{ and } S_B(u_i) = |\mu_B(u_i) - \gamma_B(u_i)| \) is a dissimilarity measure between PFS-sets.

**Proof.**

We check that \( DM_C \) satisfies the conditions of definition 3. Indeed, we have:

PF-Diss 1 and PF-Diss 2 are obviously. With PF-Diss 3, if \( A \subset B \subset C \) we have:

\[ \mu_A(u_i) \leq \mu_B(u_i) \leq \mu_C(u_i) \]
\[ \eta_A(u_i) \leq \eta_B(u_i) \leq \eta_C(u_i) \]
\[ \gamma_A(u_i) \leq \gamma_B(u_i) \leq \gamma_C(u_i) \]

for all \( u_i \in U \).

So that:

\[ S_A(u_i) = |\mu_A(u_i) - \gamma_A(u_i)| \]
\[ \geq S_B(u_i) = |\mu_B(u_i) - \gamma_B(u_i)| \]
\[ \geq S_C(u_i) = |\mu_C(u_i) - \gamma_C(u_i)| \]

and

\[ |\eta_A(u_i) - \eta_B(u_i)| \geq \max \{ |\eta_A(u_i) - \eta_B(u_i)|, |\eta_B(u_i) - \eta_C(u_i)| \}. \]

Hence,

\[ DM_C(A, C) \geq \max \{ DM_C(A, B), DM_C(B, C) \}. \]

It means PF-Diss 3 satisfy.

We have some dissimilarity measure in theorem 3, as follows.

**Theorem 4.** Given \( U = \{u_1, u_2, \ldots, u_n\} \) is an universe set. For any \( A, B \in PFS(U) \). We have:

\[ a) DM_H(A, B) = \frac{1}{n} \sum_{i=1}^{n} \left[ |\mu_A(u_i) - \mu_B(u_i)| + |\eta_A(u_i) - \eta_B(u_i)| + |\gamma_A(u_i) - \gamma_B(u_i)| \right] \]

\[ b) DM_L(A, B) = \frac{1}{n} \sum_{i=1}^{n} \left[ |S_A(u_i) - S_B(u_i)| + |\mu_A(u_i) - \mu_B(u_i)| + |\eta_A(u_i) - \eta_B(u_i)| \right] \]

\[ c) DM_O(A, B) = \frac{1}{n} \sum_{i=1}^{n} \left[ (\mu_A(u_i) - \mu_B(u_i))^2 + (\eta_A(u_i) - \eta_B(u_i))^2 + (\gamma_A(u_i) - \gamma_B(u_i))^2 \right]^{\frac{1}{2}} \]

are the dissimilarity measure between picture fuzzy sets.

The proof of this theorem is similar to the theorem 3.
5. Examples of sample identification

In this section, we will give some examples using distance and dissimilarity measure $DM (A, B)$ in sample identification. Note that when using similar measure, there are two patterns $A_1, A_2$ and an un-identifier sample $B$. If $DM (A_1, B) < DM (A_2, B)$ the we consider that sample $B$ belongs to the pattern $A_1$.

Example 2. Assume that there are two patterns denoted by picture fuzzy sets on $U = \{u_1,u_2,u_3\}$ as follows

$$A_1 = \{(u_1, 0.1, 0.1, 0.1), u_2, 0.1, 0.4, 0.3\},$$
$$A_2 = \{(u_1, 0.7, 0.1, 0.2), u_2, 0.1, 0.1, 0.8), u_3, 0.1, 0.1, 0.7\},$$

Now, there is a sample:
$$B = \{(u_1, 0.4, 0.0, 0.4), u_2, 0.6, 0.1, 0.2), u_3, 0.1, 0.1, 0.8\}$$

**Question:** which pattern does $B$ belong to? (decision-making problem)

- Applying the distant measure $D_H (A, B)$ we have:

$$D_H (A_1, B) = 0.2$$

- Applying the dissimilarity measure $DM_L (A, B)$ we have:

$$DM_L (A_1, B) = \frac{21}{15} < DM_L (A_2, B) = \frac{27}{15}$$

In this example, we see that using the distant measure $D_H (A, B)$ can not be used to classify the sample $B$. But, we can see that $B$ belongs to pattern $A_1$ if we use the dissimilarity measure $DM_L (A, B)$.

Example 3. Assume that there are three patterns denoted by picture fuzzy sets on $U = \{u_1,u_2,u_3\}$ as follows

$$A_1 = \{(u_1, 0.4, 0.5, 0.1), u_2, 0.7, 0.1, 0.1), u_3, 0.3, 0.3, 0.2\},$$
$$A_2 = \{(u_1, 0.5, 0.4, 0.0), u_2, 0.7, 0.2, 0.1), u_3, 0.4, 0.3, 0.2\},$$
$$A_3 = \{(u_1, 0.4, 0.4, 0.1), u_2, 0.6, 0.1, 0.1), u_3, 0.4, 0.1, 0.4\}$$

Now, there is a sample:
$$B = \{(u_1, 0.1, 0.1, 0.6), u_2, 0.7, 0.1, 0.2), u_3, 0.8, 0.1, 0.1\}$$

**Question:** which pattern does $B$ belong to? (decision-making problem)

- Applying the dissimilarity measure $DM_M (A, B)$ we have:

$$DM_M (A_1, B) = DM_M (A_3, B) = \frac{21}{9}$$
$$DM_M (A_2, B) = \frac{27}{9},$$

- Applying the distance measure $D_E (A, B)$ we have:

$$D_E (A_1, B) = 0.9; \quad D_E (A_2, B) = 0.916515139;$$
$$D_E (A_3, B) = 0.836600265$$

In this example, we see that using the dissimilarity measure $DM_H (A, B)$ can not be used to classify the sample $B$. But, we can see that $B$ belongs to pattern $A_3$ if we use the distance measure $D_E (A, B)$.

Example 4. Assume that there are three patterns denoted by picture fuzzy sets on $U = \{u_1,u_2,u_3,u_4\}$ as follows:

$$A_1 = \{(u_1, 0.3, 0.4, 0.1), (u_2, 0.3, 0.4, 0.1), (u_3, 0.6, 0.1, 0.2), (u_4, 0.6, 0.1, 0.2)\}$$
$$A_2 = \{(u_1, 0.4, 0.4, 0.1), (u_2, 0.3, 0.2, 0.4), (u_3, 0.6, 0.1, 0.3), (u_4, 0.5, 0.2, 0.2)\}$$
$$A_3 = \{(u_1, 0.4, 0.4, 0.1), (u_2, 0.3, 0.1, 0.3), (u_3, 0.6, 0.1, 0.2), (u_4, 0.5, 0.2, 0.1)\}$$

Now, there is a sample:
$$B = \{(u_1, 0.35, 0.65, 0), (u_2, 0.55, 0.35, 0.1), (u_3, 0.65, 0.1, 0.1), (u_4, 0.6, 0.15, 0.2)\}$$

**Question:** which pattern does $B$ belong to? (decision-making problem)

- Applying the distance measure $D^n_H (A, B)$ we have:

$$D^n_H (A_1, B) = D^n_H (A_3, B) = 0.7;$$
$$D^n_H (A_2, B) = 0.85.$$

- Applying the dissimilarity measure $DM_C (A, B)$ we have:

$$DM_C (A_1, B) = 0.0875;$$
$$DM_C (A_2, B) = DM_C (A_3, B) = 0.1$$

In this example, we see that using the distance measure $D^n_H (A, B)$ can not be used to classify the sample $B$. But, we can see that $B$ belongs to pattern $A_1$ if we use the dissimilarity measure $DM_C (A, B)$.

Example 5. Assume that there are two patterns denoted by picture fuzzy sets on $U = \{u_1,u_2\}$ as follows

$$A_1 = \{(u_1, 0.4, 0.5, 0.1), (u_2, 0.3, 0.4, 0.2)\}$$
$$A_2 = \{(u_1, 0.5, 0.4, 0.1), (u_2, 0.4, 0.3, 0.1)\}.$$

Now, there is a sample:
$$B = \{(u_1, 0.1, 0.1, 0.1), (u_2, 0.5, 0.5, 0.0)\}$$

**Question:** which pattern does $B$ belong to? (decision-making problem)

- Applying the distant measure $D^n_E (A, B)$ we have:

$$D^n_E (A_1, B) = D^n_E (A_2, B) = 0.44721$$

- Applying the dissimilarity measure $DM_O (A, B)$ we have:

$$DM_O (A_1, B) = 0.3265;$$
$$DM_O (A_2, B) = 0.3041241.$$ 

In this example, we see that using the distant measure $D^n_E (A, B)$ can not be used to classify the sample $B$. But, we can see that $B$ belongs to pattern $A_2$ if we use the dissimilarity measure $DM_O (A, B)$.

6. Conclusion

In this paper, we introduce the concepts of the difference between PFS-sets, distance measure and dissimilarity between picture fuzzy sets. We give some distant measure and dissimilarity measure of picture fuzzy sets.

Finally, we applied the similarity measures in the sample recognition problems, can also be considered a decision-making problem. Since, we see that dissimilarity is a useful way to deal with realistic problems and can be extended in other application fields. In the future, we will study the properties of these measure and applications of them in practical problems.
References


