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An Application of Similarity Measure of Intuitionistic Fuzzy Soft Set based on Distance in Speech Emotion Recognition

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Abstract – In this study, we first introduced intuitionistic fuzzy soft sets and similarity measures of two intuitionistic fuzzy soft sets. We then construct a decision making method for the speech emotion recognition problem based on the similarity measure of intuitionistic fuzzy soft sets.

Keywords – Soft sets, intuitionistic fuzzy soft sets, hamming distances, speech emotion recognition

I. Introduction

Emotion is a physiological reaction that occurs in situations such as suffering from an event, burning, fearing or rejoicing. Therefore, the change in the emotional state will be reflected in the sound. Speech-based emotion recognition is an old field of study, but it remains current [1]. Acoustical analysis is the most basic method used in Speech Emotion Recognition (SER) studies. Acoustic analysis is used for the digital signal processing of speech signals and the objective evaluation of speech. Basic frequency, formant frequencies, jitter, shimmer can be obtained by acoustic analysis, especially the number of attributes can be expressed with hundreds.

When the emotions of people are examined, it cannot be stated that one person is completely happy or completely sad. So, people can stay under the influence of more than one emotion at the same time. For this reason, uncertainty of people's feelings can be considered as uncertainty problems.

Uncertainty is one of the most common problems in human-machine interaction studies, although it shows itself in every aspect of daily life. Traditional mathematical models fail to find solutions to problems with uncertainty in areas such as engineering, medicine, and social sciences [2]. Soft set theory is used to model problems with uncertainty [3]. The lack of any restriction in the parameters of the soft set makes this theory very practical and easy to use in practice [4]. Intuitionistic fuzzy soft sets are one of the soft sets obtained by expanding soft sets [5,6].

In fuzzy set theory, the measure of uncertainty is an important issue. Similarity and distance measure methods are used to perform this measurement. Hamming and euclidean distance are widely used in the literature. There are many applications in the literature on soft set theory [3, 7-10].

In this study, basic definitions and theorems for soft sets, fuzzy sets, intuitionistic fuzzy sets and intuitionistic fuzzy soft sets were presented. An example is then used to examine the usability of these methods in SER using the distance and similarity measure between the two intuitionistic fuzzy soft (IFS) sets.

II. Preliminaries

In this section, basic definitions related to fuzzy sets, soft sets, fuzzy soft sets and intuitionistic fuzzy soft set theory are given.

Definition 2.1 [11] *Let U be a universe, E be a set of parameters that are describe the elements of U, and $A \subseteq E$. Then, a soft set F_A over U is a set defined by a set valued function f_A representing a mapping*

$$f_A\colon E \to P(U) \text{ such that } f_A(x) = \emptyset \text{ if } x \in E - A \qquad (1)$$

where f_A is called approximate function of the soft set F_A. In other words, the soft set is a parametrized family of subsets of the set U, and therefore it can be written a set of ordered pairs

$$F_A = \{(x, f_A(x)) : x \in E, f_A(x) = \emptyset \text{ if } x \in E - A\}$$

Definition 2.2 [12] *Let U be a universe. Then a fuzzy set X over U is a function defined as follows:*

$$X = \left\{\left(\frac{\mu_X(u)}{u}\right) : u \in U\right\}$$

where $\mu_X : U \to [0.1]$

Here, μ_X called membership function of X, and the value $\mu_X(u)$ is called the grade of membership of $u \in U$. The value represents the degree of u belonging to the fuzzy set X.

Definition 2.3 [13] *Let E be a universe. An intuitionistic fuzzy set A on E can be defined as follows:*

$$A = \{< x, \mu_A(x), \gamma_A(x) >: x \epsilon E\}$$

where, $\mu_A : E \to [0, 1]$ and $\gamma_A : E \to [0, 1]$ such that $0 \le \mu_A(x) + \gamma_A(x) \le 1$ for any $x \in E$.

Here, $\mu_A(x)$ and $\gamma_A(x)$ is the degree of membership and degree of nonmembership of the element x, respectively.

Definition 2.4 [14] *An intuitionistic fuzzy soft set (or namely IFS-set) is defined by the set of ordered pairs*

$$\Gamma_A = \{(x, \gamma_A(x)): x \in E, \gamma_A(x) \in \hat{F}(U)\}$$

where $\gamma_A : E \to F(U)$ such that $\gamma_A(x) = \hat{\emptyset}$ if $x \notin A$ and $\hat{\emptyset}$ is intuitionistic fuzzy empty set. Moreover $\gamma_A(x)$ is an intuitionistic fuzzy set. So it is denoted by

$$\gamma_A(x) = \{(u, \mu_A(u), \vartheta_A(u)): u \in U\}$$

for all $x \in E$. Moreover, $\mu_A : U \to [0, 1]$ and $\vartheta_A : U \to [0, 1]$ with the condition $0 \le \mu_A(u) + \vartheta_A(u) \le 1$, for all $u \in U$. The numbers $\mu_A(u)$ and $v_A(u)$ denote the membership degree end non-membership degree of $u \in U$ to the intuitionistic fuzzy set $\gamma_A(x)$, respectively.

Example 2.5 *Suppose that there are three computer in the universe $U = \{u_1, u_2, u_3\}$ under consideration "x_1 =CPU", "x_2 =RAM", "x_3= screen" and "x_4 =HDD". Therefore parameter set is $E = \{x_1, x_2, x_3, x_4\}$. Let $A = \{x_1, x_2, x_3\}$. Then IFS-set Γ_A is represented the following tabular form;*

$$\begin{aligned}\Gamma_A = \{ &(x_1, \{(u_1, 0.2, 0.6), (u_2, 0.5, 0.8), (u_3, 0.2, 0.3)\}),\\ &(x_2, \{(u_1, 0.6, 0.3), (u_2, 0.5, 0.3), (u_3, 0.1, 0.9)\}),\\ &(x_3, \{(u_1, 0.1, 0.4), (u_2, 0.2, 0.5), (u_3, 0.6, 0.3)\})\}\end{aligned}$$

III. Distance and Similarity Measure of Intuitionistic Fuzzy Soft Set

In this section, the basic definitions of distances between two intuitionistic fuzzy soft sets [5] are given. Then, some distances and similarity measures of IFS-sets have been defined.

Definition 3.1 [15] *Let $U = \{x_1, x_2, x_3, ..., x_n\}$ be a universe and A, B be two intuitionistic fuzzy sets over U with their membership function μ_A, μ_B and nonmembership function ϑ_A, ϑ_B, respectively. Then the distances of A and B are defined as,*

1. Hamming distance;

$$d(A, B) = \frac{1}{2}\sum_{i=1}^{n}[|\mu_A(x_i) - \mu_B(x_i)| + |\vartheta_A(x_i) - \vartheta_B(x_i)|]$$

2. Normalized Hamming distance;

$$l(A, B) = \frac{1}{2n}\sum_{i=1}^{n}[|\mu_A(x_i) - \mu_B(x_i)| + |\vartheta_A(x_i) - \vartheta_B(x_i)|]$$

3. Euclidean distance;

$$e(A, B) = \sqrt{\frac{1}{2}\sum_{i=1}^{n}\left[(\mu_A(x_i) - \mu_B(x_i))^2 + ((\vartheta_A(x_i) - \vartheta_B(x_i))^2\right]}$$

4. Normalized Euclidean distance;

$$q(A, B) = \sqrt{\frac{1}{2n}\sum_{i=1}^{n}\left[(\mu_A(x_i) - \mu_B(x_i))^2 + ((\vartheta_A(x_i) - \vartheta_B(x_i))^2\right]}$$

Definition 3.2 [3, 16] *Let $U = \{u_1, u_2, u_3, ...\}$ be a universe, $E = \{x_1, x_2, x_3, ...\}$ be a set of parameters, $A, B \subseteq E$, and F_A and G_B be two soft sets on U with their approximate functions f_A and g_B, respectively.*

If A = B, then similarity between F_A and G_B is defined by

$$S(F_A, G_B) = \frac{\sum_{i=1}\overrightarrow{f_A(x_i)} \cdot \overrightarrow{g_B(x_i)}}{\sum_{i=1}\max[\overrightarrow{f_A(x_i)}^2, \overrightarrow{g_B(x_i)}^2]}$$

where

$$\overrightarrow{f_A(x_i)} = (X_{fA(x_i)}(u_1), X_{fA(x_i)}(u_2), X_{fA(x_i)}(u_3), ...)$$
$$\overrightarrow{g_B(x_i)} = (X_{gB(x_i)}(u_1), X_{gB(x_i)}(u_2), X_{gB(x_i)}(u_3), ...)$$

and

$$X_{fA(x_i)}(u_j) = \begin{cases}1, & u_j \in f_A(x_i)\\ 0, & u_j \notin f_A(x_i)\end{cases}$$

$$X_{gB(x_i)}(u_j) = \begin{cases}1, & u_j \in g_B(x_i)\\ 0, & u_j \notin g_B(x_i)\end{cases}$$

Note 3.3 *If $A \ne B$ and $C = A \cap B \ne \emptyset$, then $\overrightarrow{f_A(x_i)} = 0$ for $x_i \in B/C$ and $\overrightarrow{g_B(x_i)} = 0$ for $x_i \in A/C$.*

If $A \cap B = \emptyset$, then $S(F_A, G_B) = 0$ and $S(F_A, F_A^c) = 0$ as $\overrightarrow{f_A(x_i)} \cdot \overrightarrow{f_A^c(x_i)} = 0$ for all i.

Definition 3.4 [3, 16] *Let F_A and G_B be two soft sets over U. Then, F_A and G_B are said to be α-similar, denoted as $F_A \approx^\alpha G_B$, if and only if $S(F_A, G_B) \ge \alpha$ for $\alpha \in (0, 1)$.*

Definition 3.5 [3, 16] *Let $U = \{u_1, u_2, u_3, ...\}$ be a universe, $E = \{x_1, x_2, x_3, ...\}$ be a set of parameters, $A, B \subseteq E$ and F_A, G_B be two soft sets on U with their approximate functions f_A and g_B, respectively. Then, the distances of F_A and G_B are defined as,*

1. Hamming distance;

$$d^S(F_A, G_B) = \frac{1}{m}\left\{\sum_{i=1}^{m}\sum_{j=1}^{n}\left|f_A(x_i)(u_j) - g_B(x_i)(u_j)\right|\right\}$$

2. Normalized Hamming distance;

$$l^S(F_A, F_B) = \frac{1}{mn}\left\{\sum_{i=1}^{m}\sum_{j=1}^{n}\left|f_A(x_i)(u_j) - g_B(x_i)(u_j)\right|\right\}$$

3. Euclidean distance;

$$e^S(F_A, F_B) = \sqrt{\frac{1}{m}\left\{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(f_A(x_i)(u_j) - g_B(x_i)(u_j)\right)^2\right\}}$$

4. Normalized Euclidean distance;

$$q^S(F_A, F_B) = \sqrt{\frac{1}{mn}\left\{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(f_A(x_i)(u_j) - g_B(x_i)(u_j)\right)^2\right\}}$$

Definition 3.6 [3, 16] *Let F_A and G_B be two soft sets over U. Then, by using the Eucledian distance, similarity measure of F_A and G_B is defined as,*

$$s'(F_A, G_B) = \frac{1}{1 + e^S(F_A, G_B)}$$

Another similarity measure of F_A and G_B can be defined as,

$$s''(F_A, G_B) = e^{-\alpha e^S(F_A, G_B)}$$

where α is a positive real number called the steepness measure.

Definition 3.7 [3] *Let U = {u_1, u_2, ..., u_n} be a universe, E = {x_1, x_2, ..., x_m} be a set of parameters, A, B ⊆ E and Γ_A,Λ_B be two IFS-sets on U with their intuitionistic fuzzy approximate functions $\gamma_A(x_i)$ = {(u, $\mu_A(u)$, $v_A(u)$) : u ∈ U} and $\lambda_B(x_i)$ = {(u, $\mu_B(u)$, $v_B(u)$) : u ∈ U}, respectively.*

If A = B and $\mu_A(x_i)(u_j) - v_A(x_i)(u_j) \neq 0$ or $\mu_B(x_i)(u_j) - v_B(x_i)(u_j) \neq 0$ for at least one i ∈ {1, 2, ..., n} and j ∈ {1, 2, ..., m}, then similarity between Γ_A and Λ_B is defined by

$$S_{IFS}(\Gamma_A, \Lambda_B) = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}\left|\left(\overrightarrow{\mu_A(x_i)(u_j)} - \overrightarrow{\upsilon_A(x_i)(u_j)}\right)\cdot\left(\overrightarrow{\mu_B(x_i)(u_j)} - \overrightarrow{\upsilon_B(x_i)(u_j)}\right)\right|}{\sum_{i=1}^{m}\sum_{j=1}^{n} max\left\{\left\|\overrightarrow{\mu_A(x_i)(u_j)} - \overrightarrow{\upsilon_A(x_i)(u_j)}\right\|^2, \left\|\overrightarrow{\mu_B(x_i)(u_j)} - \overrightarrow{\upsilon_B(x_i)(u_j)}\right\|^2\right\}}$$

where

$$\overrightarrow{\mu_A(x_i)(u_j)} = \left(\mu_A(x_i)(u_1), \mu_A(x_i)(u_2), \dots, \mu_A(x_i)(u_n)\right)$$
$$\overrightarrow{\upsilon_A(x_i)(u_j)} = \left(\upsilon_A(x_i)(u_1), \upsilon_A(x_i)(u_2), \dots, \upsilon_A(x_i)(u_n)\right)$$
$$\overrightarrow{\mu_B(x_i)(u_j)} = \left(\mu_B(x_i)(u_1), \mu_B(x_i)(u_2), \dots, \mu_B(x_i)(u_n)\right)$$
$$\overrightarrow{\upsilon_B(x_i)(u_j)} = \left(\upsilon_B(x_i)(u_1), \upsilon_B(x_i)(u_2), \dots, \upsilon_B(x_i)(u_n)\right)$$

If A = B and $\mu_A(x_i)(u_j) - \upsilon_A(x_i)(u_j) = 0$ and $\mu_B(x_i)(u_j) - \upsilon_B(x_i)(u_j) = 0$ for all i ∈ {1, 2, ..., n} and j ∈ {1, 2, ..., m}, then $S_{IFS}(\Gamma_A,\Lambda_B) = 1$.

Example 3.8 *Assume that U = {u_1, u_2} is a universal set, E = {x_1, x_2, x_3} is a set of parameters, A = {x_1, x_2, x_3}, B = {x_1, x_2, x_3} are subsets of E. If two IFS-sets Γ_A and Λ_B over U are contracted as follows;*

$$\Gamma_A = \{ (x_1, \{(u_1, 0.2, 0.6), (u_2, 0.5, 0.8)\}), (x_2, \{(u_1, 0.6, 0.3), (u_2, 0.5, 0.3)\}), (x_3, \{(u_1, 0.2, 0.8), (u_2, 0.4, 0.7)\})\}$$

$$\Lambda_A = \{(x_1, \{(u_1, 0.4, 0.3), (u_2, 0.4, 0.3)\}), (x_2, \{(u_1, 0.2, 0.6), (u_2, 0.5, 0.1)\}), (x_3, \{(u_1, 0.4, 0.1), (u_2, 0.3, 0.7)\})\}$$

Then we can obtain

$$\overrightarrow{\mu_A(x_1)(u_j)} = (0.2, 0.5), \quad \overrightarrow{\upsilon_A(x_1)(u_j)} = (0.6, 0.8)$$
$$\overrightarrow{\mu_A(x_2)(u_j)} = (0.6, 0.5), \quad \overrightarrow{\upsilon_A(x_2)(u_j)} = (0.3, 0.3)$$
$$\overrightarrow{\mu_A(x_3)(u_j)} = (0.2, 0.4), \quad \overrightarrow{\upsilon_A(x_3)(u_j)} = (0.8, 0.7)$$
$$\overrightarrow{\mu_B(x_1)(u_j)} = (0.4, 0.4), \quad \overrightarrow{\upsilon_B(x_1)(u_j)} = (0.3, 0.3)$$
$$\overrightarrow{\mu_B(x_2)(u_j)} = (0.2, 0.5), \quad \overrightarrow{\upsilon_B(x_2)(u_j)} = (0.6, 0.1)$$
$$\overrightarrow{\mu_B(x_3)(u_j)} = (0.4, 0.3), \quad \overrightarrow{\upsilon_B(x_3)(u_j)} = (0.1, 0.7)$$

and

$$\overrightarrow{\mu_A(x_1)(u_j)} - \overrightarrow{\upsilon_A(x_1)(u_j)} = (-0.4, -0.3)$$
$$\overrightarrow{\mu_A(x_2)(u_j)} - \overrightarrow{\upsilon_A(x_2)(u_j)} = (0.3, 0.2)$$
$$\overrightarrow{\mu_A(x_3)(u_j)} - \overrightarrow{\upsilon_A(x_3)(u_j)} = (-0.6, -0.3)$$
$$\overrightarrow{\mu_B(x_1)(u_j)} - \overrightarrow{\upsilon_B(x_1)(u_j)} = (0.1, 0.1)$$
$$\overrightarrow{\mu_B(x_2)(u_j)} - \overrightarrow{\upsilon_B(x_2)(u_j)} = (-0.4, 0.4)$$
$$\overrightarrow{\mu_B(x_3)(u_j)} - \overrightarrow{\upsilon_B(x_3)(u_j)} = (0.3, -0.4)$$

Now the similarity between Γ_A and Λ_B is calculated as $S_{IFS}(\Gamma_A,\Lambda_B)$ = 0.53

Theorem 3.9 [3] *Let E be a parameter set, A, B ⊆ E and Γ_A and Λ_B be two IFS-sets over U. Then the followings hold;*

i. $S_{IFS}(\Gamma_A, \Lambda_B) = S_{IFS}(\Lambda_B, \Gamma_A)$
ii. $0 \leq S_{IFS}(\Gamma_A, \Lambda_B) \leq 1$
iii. $S_{IFS}(\Gamma_A, \Gamma_A) = 1$

Proof: *Proof easly can be made by using Definition 3.7.*

Definition 3.10 [3] *Let U = {u_1, u_2, ..., u_n} be a universe, E = {x_1, x_2, ..., x_m} be a set of parameters, A, B ⊆ E and Γ_A, Λ_B be two IFS-sets on U with their intuitionistic fuzzy approximate functions $\gamma_A(x_i)$ = {(u, $\mu_A(u)$, $v_A(u)$) : u ∈ U} and $\lambda_B(x_i)$ = {(u, $\mu_B(u)$, $v_B(u)$) : u ∈ U}, respectively. Then the distances of Γ_A and Λ_B are defined as,*

1. Hamming distance;

$$d_{IFS}^S(\Gamma_A, \Lambda_B) = \frac{1}{2m}\left\{\sum_{i=1}^{m}\sum_{j=1}^{n}\left|\mu_A(x_i)(u_j) - \mu_B(x_i)(u_j)\right| + \left|v_A(x_i)(u_j) - v_B(x_i)(u_j)\right|\right\}$$

2. Normalized Hamming distance;

$$l_{IFS}^S(\Gamma_A, \Lambda_B) = \frac{1}{2mn}\left\{\sum_{i=1}^{m}\sum_{j=1}^{n}\left|\mu_A(x_i)(u_j) - \mu_B(x_i)(u_j)\right| + \left|v_A(x_i)(u_j) - v_B(x_i)(u_j)\right|\right\}$$

3. Euclidean distance;

$$e_{IFS}^S(\Gamma_A, \Lambda_B) = \sqrt{\frac{1}{2m}\sum_{i=1}^{m}\sum_{j=1}^{n}\left[\left(\mu_A(x_i)(u_j) - \mu_B(x_i)(u_j)\right)^2 + \left(v_A(x_i)(u_j) - v_B(x_i)(u_j)\right)^2\right]}$$

4. Normalized Euclidean distance;

$$q_{IFS}^S(\Gamma_A, \Lambda_B) = \sqrt{\frac{1}{2mn}\sum_{i=1}^{m}\sum_{j=1}^{n}\left[\left(\mu_A(x_i)(u_j) - \mu_B(x_i)(u_j)\right)^2 + \left(v_A(x_i)(u_j) - v_B(x_i)(u_j)\right)^2\right]}$$

Example 3.11 [3] *Let us consider the Example 3.8. Then, the distances of Γ_A and Λ_B are calculated as follows;*

$$d_{IFS}^S(\Gamma_A, \Lambda_B) = 0.66$$

$$l_{IFS}^{S}(\Gamma_A, \Lambda_B) = 0{,}33$$
$$e_{IFS}^{S}(\Gamma_A, \Lambda_B) = 0.45$$
$$q_{IFS}^{S}(\Gamma_A, \Lambda_B) = 0{,}32$$

Theorem 3.12 [3] *Let E be a parameter set, A, B ⊆ E and Γ_A and Λ_B be two IFS-sets over U. Then the followings hold;*

i. $d_{IFS}^{S}(\Gamma_A, \Lambda_B) \leq n$
ii. $l_{IFS}^{S}(\Gamma_A, \Lambda_B) \leq 1$
iii. $e_{IFS}^{S}(\Gamma_A, \Lambda_B) \leq \sqrt{n}$
iv. $q_{IFS}^{S}(\Gamma_A, \Lambda_B) \leq 1$

Proof: *Proof easily can be made by using Definition 3.10.*

Definition 3.13 [3] *Let Γ_A and Λ_B be two IFS-sets over U. Then, by using the Hamming distance, similarity measure of Γ_A and Λ_B is defined as,*

$$S'_{IFS}(\Gamma_A, \Lambda_B) = \frac{1}{1 + d_{IFS}^{S}(\Gamma_A, \Lambda_B)}$$

Another similarity measure of F_A and G_B can be defined as,

$$S''_{IFS}(\Gamma_A, \Lambda_B) = e^{-\alpha d_{IFS}^{S}(\Gamma_A, \Lambda_B)}$$

where α is a positive real number called the steepness measure.

Definition 3.14 [3] *Let Γ_A and Λ_B be two IFS-sets over U. Then, Γ_A and Λ_B are said to be α-similar, denoted as $\Gamma_A \approx^{\alpha} \Lambda_B$, if and only if $S'(\Gamma_A, \Lambda_B) \geq \alpha$ for $\alpha \in (0, 1)$.*

We call the two IFS-sets significantly similar if $S'(\Gamma_A, \Lambda_B) > \frac{1}{2}$.

Example 3.15 *Let us consider the Example 3.11. Similarity measure of Γ_A and Λ_B is obtained as,*

$$S'_{IFS}(\Gamma_A, \Lambda_B) = \frac{1}{1 + d_{IFS}^{S}(\Gamma_A, \Lambda_B)} = 0.68$$

Γ_A and Λ_B is significantly similar because $S'_{IFS}(\Gamma_A, \Lambda_B) = 0.68 > \frac{1}{2}$

IV. Application of SER

In this section we construct a method for speech emotion recognition based on similarity measure of intuitionistic fuzzy soft sets (IFSSs). The algorithm of this method is as follows:

Step 1. Constructs a IFS-set Γ_A over *U* based on an expert,
Step 2. Constructs a IFS-set Λ_B over *U* based on a responsible person for the problem,
Step 3. Calculate the distances of Γ_A and Λ_B,
Step 4. Calculate the similarity measure of Γ_A and Λ_B,
Step 5. Estimate result by using the similarity

Here is an example for SER. The data used are F0, F1, F2 and F3 parameters of fear and neutral states in EMO-DB dataset [17]. The parameters were obtained by SPAC [18] package program. The parameters were normalized to 0-1 with the z-score normalization method in order to remove the unit differences in the parameters obtained. The similarity measure of two IFSSs (neutral, fear) based on normalized Hamming distance can be applied. Then we find the similarity measure of these IFSSs.

In this application, it has been tried to predict whether a person has fear. For this, the IFS-set for the emotion of neutral and fear was created. Then, the similarity measure was calculated for these two IFS-sets. If the two data sets are significantly similar, it will be concluded that IFS-sets are not suitable for SER.

Example 4.1 *Assume that our universal set contain only two elements fear and neutral, i.e. $U = \{u_1, u_2\}$. Here the set of parameters A = B = E is the set of certain visible acoustic features, let us say, $E = \{x_1, x_2, x_3, x_4, x_5, x_6\}$ where x_1 = fundamental frequency(F0), x_2 = formant frequency(F1), x3 = formant frequency(F2), x4 = formant frequency(F3), x5 =jitter and x6 =shimmer.*

Step 1. *Constructs a IFS-set Γ_A over U for fear is given below.*

$$\begin{aligned}\Gamma_A = \{ & (x_1, \{(u_1, 0.5, 0.2), (u_2, 0.2, 0.3)\}), \\ & (x_2, \{(u_1, 0.4, 0.2), (u_2, 0.4, 0.5)\}), \\ & (x_3, \{(u_1, 0.3, 0.1), (u_2, 0.4, 0.2)\}), \\ & (x_4, \{(u_1, 0.4, 0.3), (u_2, 0.5, 0.3)\}), \\ & (x_5, \{(u_1, 0.3, 0.5), (u_2, 0.4, 0.4)\}), \\ & (x_6, \{(u_1, 0.3, 0.1), (u_2, 0.4, 0.2)\}) \}\end{aligned}$$

Then we can obtain

$$\overrightarrow{\mu_A(x_1)(u_j)} = (0.5, 0.2), \qquad \overrightarrow{\upsilon_A(x_1)(u_j)} = (0.2, 0.3)$$
$$\overrightarrow{\mu_A(x_2)(u_j)} = (0.4, 0.4), \qquad \overrightarrow{\upsilon_A(x_2)(u_j)} = (0.2, 0.5)$$
$$\overrightarrow{\mu_A(x_3)(u_j)} = (0.3, 0.4), \qquad \overrightarrow{\upsilon_A(x_3)(u_j)} = (0.1, 0.2)$$
$$\overrightarrow{\mu_A(x_4)(u_j)} = (0.4, 0.5), \qquad \overrightarrow{\upsilon_A(x_4)(u_j)} = (0.3, 0.3)$$
$$\overrightarrow{\mu_A(x_5)(u_j)} = (0.3, 0.4), \qquad \overrightarrow{\upsilon_A(x_5)(u_j)} = (0.5, 0.4)$$
$$\overrightarrow{\mu_A(x_6)(u_j)} = (0.3, 0.4), \qquad \overrightarrow{\upsilon_A(x_6)(u_j)} = (0.1, 0.2)$$

and

$$\overrightarrow{\mu_A(x_1)(u_j)} - \overrightarrow{\upsilon_A(x_1)(u_j)} = (0.3, -0.1)$$
$$\overrightarrow{\mu_A(x_2)(u_j)} - \overrightarrow{\upsilon_A(x_2)(u_j)} = (0.2, -0.1)$$
$$\overrightarrow{\mu_A(x_3)(u_j)} - \overrightarrow{\upsilon_A(x_3)(u_j)} = (0.2, 0.2)$$
$$\overrightarrow{\mu_A(x_4)(u_j)} - \overrightarrow{\upsilon_A(x_4)(u_j)} = (0.1, 0.2)$$
$$\overrightarrow{\mu_A(x_5)(u_j)} - \overrightarrow{\upsilon_A(x_5)(u_j)} = (-0.2, 0.0)$$
$$\overrightarrow{\mu_A(x_6)(u_j)} - \overrightarrow{\upsilon_A(x_6)(u_j)} = (0.2, 0.2)$$

Step 2. *Constructs a IFS-set Λ_B over U based on data of neutral person:*

$$\begin{aligned}\Lambda_B = \{ & (x_1, \{(u_1, 0.2, 0.1), (u_2, 0.4, 0.5)\}), \\ & (x_2, \{(u_1, 0.3, 0.6), (u_2, 0.4, 0.2)\}), \\ & (x_3, \{(u_1, 0.4, 0.2), (u_2, 0.3, 0.4)\}), \\ & (x_4, \{(u_1, 0.4, 0.5), (u_2, 0.5, 0.2)\}), \\ & (x_5, \{(u_1, 0.3, 0.2), (u_2, 0.2, 0.5)\}), \\ & (x_6, \{(u_1, 0.5, 0.5), (u_2, 0.6, 0.4)\}) \}\end{aligned}$$

Then we can obtain

$$\overrightarrow{\mu_B(x_1)(u_j)} = (0.2, 0.4), \qquad \overrightarrow{\upsilon_B(x_1)(u_j)} = (0.1, 0.5)$$
$$\overrightarrow{\mu_B(x_2)(u_j)} = (0.3, 0.4), \qquad \overrightarrow{\upsilon_B(x_2)(u_j)} = (0.6, 0.2)$$
$$\overrightarrow{\mu_B(x_3)(u_j)} = (0.4, 0.3), \qquad \overrightarrow{\upsilon_B(x_3)(u_j)} = (0.2, 0.4)$$
$$\overrightarrow{\mu_B(x_4)(u_j)} = (0.4, 0.5), \qquad \overrightarrow{\upsilon_B(x_4)(u_j)} = (0.5, 0.2)$$

$$\overrightarrow{\mu_B(x_5)(u_J)} = (0.3, 0.2), \qquad \overrightarrow{\upsilon_B(x_5)(u_J)} = (0.2, 0.5)$$
$$\overrightarrow{\mu_B(x_6)(u_J)} = (0.5, 0.6), \qquad \overrightarrow{\upsilon_B(x_6)(u_J)} = (0.5, 0.4)$$

and

$$\overrightarrow{\mu_B(x_1)(u_J)} - \overrightarrow{\upsilon_B(x_1)(u_J)} = (0.1, -0.1)$$
$$\overrightarrow{\mu_B(x_2)(u_J)} - \overrightarrow{\upsilon_B(x_2)(u_J)} = (-0.3, 0.2)$$
$$\overrightarrow{\mu_B(x_3)(u_J)} - \overrightarrow{\upsilon_B(x_3)(u_J)} = (0.2, -0.1)$$
$$\overrightarrow{\mu_B(x_4)(u_J)} - \overrightarrow{\upsilon_B(x_4)(u_J)} = (-0.1, 0.3)$$
$$\overrightarrow{\mu_B(x_5)(u_J)} - \overrightarrow{\upsilon_B(x_5)(u_J)} = (0.1, -0.3)$$
$$\overrightarrow{\mu_B(x_6)(u_J)} - \overrightarrow{\upsilon_B(x_6)(u_J)} = (0.0, 0.2)$$

Step 3. *Calculate Hamming distances of* Γ_A *and* Λ_B,

$$d^S_{IFS}(\Gamma_A, \Lambda_B) \cong 0{,}28$$

Step 4. *Calculate similarity distances of* Γ_A *and* Λ_B,

$$S'_{IFS}(\Gamma_A, \Lambda_B) = \frac{1}{1 + d^S_{IFS}(\Gamma_A, \Lambda_B)} \cong 0.78 > \frac{1}{2}$$

Step 5. *Hence the two IFS-sets, i.e. two emotions* Γ_A *and* Λ_B *are not significantly similar. Therefore, these two emotions are different from each other.*

V. Conclusion

In this study, four types of distances between two IFS-sets and proposed similarity measures of two IFS-sets have been defined. Then, an emotion recognition application based on the similarity measures have been construct for SER. Then, an emotion recognition application based on the similarity measures have been construct for SER. The results of the application showed that the two emotions were different. This result shows that IFS-sets can be used in SER applications. In future studies, the parameter set can be expanded and multiple emotions can be included in the problem.

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