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Acceleration sensor, and embedded system using location-aware

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요 약 본 논문에서는 실제 값과 같은 데이터의 불확실성과 유사성을 측정 할 수 있는 퍼지 엔트로피와 유사성 측정이 소개되고 있다. 퍼지 엔트로피와 유사성 측정의 디자인이 설명하고 입증했다. 획득 수단은 연산 프로세스에 적용되고 논의되었다. 이러한 의사 결정과 퍼지 게임 이론과 같은 데이터 정량화 결과의 연장도 논의되었다.

Abstract In this paper, fuzzy entropy and similarity measure to measure the uncertainty and similarity of data as real value were introduced. Design of fuzzy entropy and similarity measure were illustrated and proved. Obtained measures were applied to the calculating process and discussed. Extension of data quantification results such as decision making and fuzzy game theory were also discussed.

Key Words : information, uncertainty, similarity, data management

1. Introduction

Transform of heuristic data to numeric value is one of interesting research topic, in which heuristic data vagueness is changed to definite number. Studies on quantifying the uncertainty has been debated between fuzzy set theory and probability [1], however coexistence seemed obvious due to two approaches are complementary rather than competitive. With the obtained research result can give the advantage for dealing with system management including reliable data selection, pattern recognition or even fuzzy game theoretic problem. Design of fuzzy entropy for calculation of uncertainty has been studied by numerous researchers [2-4]. Most of results were concentrated in the designing of fuzzy entropies [2,3], and some parts of them also showed the implicit results of fuzzy entropies [2]. Hence, to apply real data explicit fuzzy entropy has to be needed. In our previous results, fuzzy entropies based on the distance measure has been reported [5,6]. With those designed fuzzy entropies reliable data selection problem has been solved [7].

Counter meaning of fuzzy entropy with respect to fixed data has been considered as the similarity measure and in our previous results [5]. Relation between fuzzy entropy and similarity measure has also studied [7]. In result [5], counter meaning of similarity measure was defined by dissimilarity measure, in which dissimilarity measure was derived through similarity and vise versa. Those relations give us the result that two measures can be obtained through counter measure designing. Obtained similarity measures were also designed with the distance measure, especially well-known Hamming distance measure. Hence, these data analysis make possible to manage the system optimization or design the efficient

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system management.

Fuzzy entropy and similarity measure are introduced to describe the uncertainty and certainty of data, hence data analysis or quantification to the decision theory and fuzzy game theory has been followed. In next chapter, fuzzy entropy and similarity results are introduced and discussed. With application example data quantification results from fuzzy entropy and similarity are verified. Applications to decision theory and fuzzy game theory are shown in Chapter 3. Finally, conclusions are followed in Chapter 4.

2. Fuzzy Entropy and Similarity Measure

Liu's definition of fuzzy entropy is illustrated in the Definition 2.1, which illustrates the four properties of fuzzy entropy definition [2].

Definition 2.1 For $\forall A \in F(X)$ and $\forall D \in P(X)$, fuzzy entropy has following four properties

(E1) $e(D) = 0, \ \forall D \in P(X)$

(E2) $e([1/2]_x) = \max_{A \in F(X)} e(A)$

(E3) $e(A^*) \leq e(A)$, for any sharpening A^* of A

(E4) $e(A) = e(A^c), \ \forall A \in F(X)$

where $[1/2]_X$ is the fuzzy set in which the value of the membership function is 1/2. $F(X)$ is fuzzy set and $P(X)$ is ordinary set.

Next, similarity measure between two sets is defined in Definition 2.2 [2]. On the contrary the properties of Definition 2.1 similarity measure shows that the degree of closeness between two sets containing fuzzy sets or ordinary sets.

Definition 2.2 For $\forall$A, B $\in F(X)$ and $\forall$D $\in P(X)$, similarity measure has following four properties

(S1) s(A,B) = s(B, A), $\forall$A, B $\in F(X)$

(S2) s(D, D^c) = 0, $\forall$D $\in P(X)$

(S3) s(C, C) = $\max_{A,B \in F}$s(A,B), $\forall$C $\in F(X)$

(S4) $\forall$A, B, C $\in F(X)$, if A$\subset$B$\subset$C, then s(A,B) $\geq$ s(A,C) and s(B,C) $\geq$ s(A,C),

$F(X)$ and $P(X)$ denote fuzzy set and ordinary set, respectively.

2.1 Illustrations of Fuzzy Entropy and Similarity measure

There are many fuzzy entropy results satisfying Definition 2.1, following entropies can be found in our previous results [5, 6]. Entropy of fuzzy data set with respect to the ordinary set can be designed using distance measure. Our previous results are followed as follows:

$$e(A, A_{near}) = d(A \cap A_{near}, [1]_x) + d(A \cup A_{near}, [0]_X) - 1$$

$$e(A, A_{near}) = d(A \cap A_{near}^C, [0]_X) + d(A \cup A_{near}^C, [1]_x)$$

$$e(A, A_{near}) = 1 - d(A \cap A_{near}, [0]_X) - d(A \cup A_{near}, [1]_x)$$

$A \cap B$ and $A \cup B$ are expressed the minimum and maximum value, expressions are commonly used in fuzzy set theory. Hence, $(A \cap B)$(x) = min(A(x), B(x)) and $(A \cup B)$(x) = max(A(x),B(x)), respectively.

The distance is defined by d($A \cap B$) = $\frac{1}{n}\sum_{i=1}^{n}|\mu_A(x_i) - \mu_B(x_i)|$. A_{near} represents the crisp set "near" to the fuzzy set A. A_{near} can be utilized by various variable as 0 ≤near≤1. For example, the value of crisp set $A_{0.5}$ has one when $\mu_A(x) \geq 0.5$, and is zero otherwise. Above fuzzy entropies are represent the degree of uncertainty between fuzzy set and corresponding deterministic ordinary set A_{near}. Next, similarity measures between two data sets are also followed.

$$s(A, B) = d(A \cap B, [0]_X) + d(A \cup B, [1]_X)$$

$$s(A, B) = 1 - d(A \cap B^C, [0]_X) - d(A \cup B^C, [1]_X)$$

$$s(A, B) = 2 - d(A \cap B), [1]_X) - d(A \cup B, [0]_x)$$

Equations of fuzzy entropy and similarity can be also explained by graphical point of view. Fuzzy entropy means the degree of uncertainty or the dissimilarity between two data sets, fuzzy set and corresponding ordinary set generally. Hence, it can be designed through many ways satisfying Definition 2.1. Similarity measure represents the degree of similarity between all kinds of data sets. Fuzzy entropy and similarity can be explained by graphical illustration in Fig. 1. From Fig. 1 shaded area represent the common information of two fuzzy sets with membership functions. Hence, regions C and D satisfy the definition of similarity measure. Except region of C and D satisfy the dissimilarity between two data sets. Therefore, it is denoted by fuzzy entropy or dissimilarity measure. By Fig. 1 the relation between similarity and dissimilarity has been emphasized in our previous result [5].

Total information between fuzzy sets C and D satisfies following relation naturally. Liu insisted that the entropy can be generated by similarity measure and distance measure, those are denoted by e<s> and e<d>[2]. With the property of $s = 1-d$, we constructed the similarity measure with distance measure d previously. In Liu's result $s+d=1$, d means the dissimilarity measure, and it is natural to obtain following result.

$$D(A, B) = d(A, A \cap B) + d(B, A \cap B) = 1-s(A, B)$$

Therefore similarity measure

$$s<d> = 1- d(A, A \cap B) - d(B, A \cap B)$$

is satisfied by $s = 1-d$.

The relation between similarity measure and dissimilarity measure can be derived as follows

$$D(A,B) + s(A,B) = 1. \quad (1)$$

By the comparison with (1) and Fig. 1 it is clear that is represented by graphical summation of C and D.

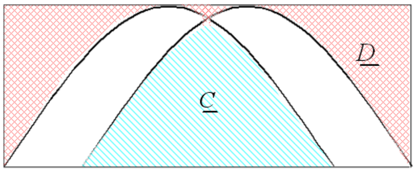


Fig 1. Gaussian type two membership functions

In which the total information of two fuzzy set membership functions are represented by the summation of results similarity and dissimilarity measure. Non-convex fuzzy sets are uncommon for the fuzzy set theory. However, non-convex fuzzy membership functions same results were also obtained [8].

2.2 Fuzzy Entropy and Similarity Measure Application

Calculation of uncertainty and certainty for data can be applied to the various fields such as data classification, pattern recognition. Next examples show the reliable data selection problem and calculation of similarity measure between crisp data. Consider 65 students markings of one subject. Its marking is distributed by Gaussian distribution [7]. 5 students are chosen randomly two times. 5 students' markings are 50, 52, 55, 57, and 59 points for first trial, whereas, 12, 46, 53, 55, and 91 points are second trial. Among two trials it seems clear that which one represents middle level or average level students by heuristic approach. However two data sets seemed unclear by calculation of fuzzy entropy even more numerical calculation of each average. This discrepancy can be overcome through application of similarity measure calculation [7]. Mean of 65 students is 52.7. Table 1 represent that the second sample mean is close to the total mean value, however the first one is nearer to the membership degree in the view of membership average. Hence, it is hard to determine which one is reliable data for average level student.

A fuzzy entropy can be design as follows:

$$e(A, A_{near}) = 2d(A, A \cap A_{near}) + 2d(A_{near}, A \cap A_{near}) \quad (2)$$

The average level student's points are between 37 and 71, i.e. $\mu_{A_{05}}(x)=1$ when $37 \le x \le 71$, $\mu_{A_{05}}(x)=0$ otherwise. In the view of fuzzy entropy computation, both cases are calculated for the problem of how much they are in the average level.

Table 1. Sample, Membership value, and Fuzzy entropy for selected 5 data

	Data Information		
	Sample	Membership value	Fuzzy entropy
Trial 1	50	0.983	0.0656
	52	0.999	
	55	0.987	
	57	0.957	
	59	0.910	
Average	54.6	0.980	0.0656
Trial 2	12	0.019	0.0656
	46	0.899	
	53	1.000	
	55	0.987	
	91	0.031	
Average	51.4	0.590	0.0656

Computation results say that

$$e(A,\ A_{0.5}) = 2d(A, A\cap A_{0.5}) + 2d(A_{0.5},\ A\cap A_{0.5})$$
$$= \frac{2}{5}(|1-0.987| + |1-0.999| + [1-0.987| + |1-0.957| + |1-0.91|]$$
$$= 0.0656.$$

In the above, $d(A\cap A_{0.5})$ has to be deleted because of distance between same points. Similarly, trial 2 shows that

$$e(A,\ A_{0.5}) = 2d(A, A\cap A_{0.5}) + 2d(A_{0.5},\ A\cap A_{0.5})$$
$$= \frac{2}{5}(|-.019-0| + |0.031-0|)$$
$$+\frac{2}{5}(|1-0.899| + |1-1| + |1-0.987|)$$
$$= 0.0656.$$

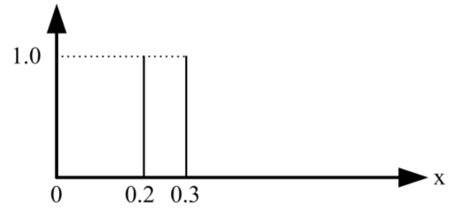
Hence, the fuzzy entropy results indicate that two trials have same degree of uncertainty. Furthermore, they show good certainty because of small entropy value. However, their data points are not proper to represent middle level. The reason for the same fuzzy entropy values of two trials is originated from the property of complementary, that is $e(A) = e(A^c)$, $\forall A \in F(X)$. This drawback was overcome through similarity measure [7].

Table 2. Sample, Similarity measure

	Data Information	
	Sample	Similarity measure
Fig.2(a)	50, 52, 55, 57, 59	0.9832
Fig.2(b)	12, 46, 53, 55, 91	0.5872

With the results, similarities are calculated with designed similarity measure by 0.9832 and 0.5872, respectively. The first trial has the higher similarity value than the second, hence it can be determined that the result is the nearest average level 5 students with only similarity measure. From this decision, with only similarity measure provides which trial is the most reliable data selection for this problem. To obtain same result fuzzy entropy calculation is needed more statistical information. Whereas compared to those results of fuzzy entropy, similarity measure has explicit advantage for reliable data selecting. Similarity computation of single data with respect to the data set is also carried out by the similarity measure design [9].

Similarity measure design between single data and data set were proposed by Chen et al. [10]. They had designed the similarity measure with fuzzy number and related knowledge in fuzzy set theory. However, similarity measure could be designed only for triangular or trapezoidal fuzzy membership function, if fuzzy number method is used [10].



$\tilde{A} = (0.2, 0.2, 0.2, 0.2; 1.0)$ $\tilde{B} = (0.3, 0.3, 0.3, 0.3; 1)$

Fig. 2. Set 7 of Fig. 10 in [10]

Above example shows the similarity measure computation difference between based on fuzzy number and distance measure. Fig. 2 is expressed clearly as the different singleton pair, so it is questionable whether the degree of similarity between two single data satisfies 0.9 except when matching the fuzzy membership functions pair of Sets 2 and 6. It is commonly required that the similarity between two different crisp sets must be zero. Next, with similarity measure based on distance measure comparisons are carried out for the aforementioned paper example [10].

$$s(A,\ B) = 2 - d((A \cap B,\ [1]_X) - d((A \cup B,\ [0]_X) \quad (3)$$

Our computation results with (3) are illustrated in Table 3.

Table 3. Comparison with the results of Chen and Chen

	Similarity Computation	
	Lee[9]	Chen and Chen
Set1	0.839	0.8357
Set2	1	1
Set3	0.426	0.42
Set4	0.344	0.49
Set5	0.871	0.8
Set6	1	1
Set7	0	0.9
Set8	0.476	0.54
Set9	0.516	0.81
Set10	0.672	0.9
Set11	0.512	0.72
Set12	0.618	0.78

From Table 3, we notice that the 10 sets all have different degrees of similarity except for Set 2 and Set 6. So, (3) has a proper evaluation for the similarity. For the degree of similarity in Set 7, two membership functions are expressed clearly as a different singleton. Therefore, the similarity calculation value between the two membership functions has to satisfy zero. Now we can compute the Set 7 pair similarity as follows.

$$\begin{aligned} s(A,B) &= 2 - d((A \cap B,\ [1]_X) - d((A \cup B),[0]_X) \\ &= 2 - d(([0]_X,\ [1]_X) - d(([1]_X,\ [0]_X \\ &= 2 - 1 - 1 = 0 \end{aligned}$$

Hence, proposed similarity measure based on the distance measure represents useful.

3. Application to Related Topics

Fuzzy entropy and similarity measure can be used as the tool of calculating the degree of dissimilarity and similarity with respect to the considering data. Hence, they have accessibility to the decision theory, system modeling or system management.

3.1 Decision Theory

For decision making, building partial consequence and objective compatibility have been designed through fuzzy set theory [11]. In order to design necessity and possibility of decision it is necessary to formulate objective and consequence as fuzzy membership function.

Compatibility level is composed with necessity and possibility as following formulation:

$$k_{i,j} = (1-\alpha)\prod(\mu_j,\ \pi_{i,j}) + \alpha N(\mu_j,\ \pi_{i,j}), \quad (4)$$

where $\prod(\mu_j,\ \pi_{i,j})$ and $N(\mu_j,\ \pi_{i,j})$ are denoted as possibility and necessity of decision. Furthermore, μ_j and $\pi_{i,j}$ are objective and consequence for considering fact, respectively.

Considering fuzzy membership functions μ_j and $\pi_{i,j}$ are needed to be small entropy, because low entropy value guarantee more certain to the fact. Furthermore possibility is greater than the necessity if the similarity between objective and consequence membership functions become greater. In example of [11], the fuzzy objective $\mu_j(x)$ corresponds to

$$\mu_j(x) = \frac{450-x}{75},\ \text{if } 375 \le x \le 450,$$

$$\mu_j(x) = 1,\ \text{if } 0 \le x \le 375,$$

$$\mu_j(x) = 0,\ \text{if } x \ge 450.$$

Consequence functions satisfies

$\pi_{i,j}(x) = \dfrac{x-375}{25}$, if $375 \le x \le 400$,

$\pi_{i,j}(x) = \dfrac{425-x}{25}$, if $400 \le x \le 425$,

$\pi_{i,j}(x) = 0$, if $x \le 375$ and $x \ge 425$.

Similarity measure between μ_j and π_{ij} has the following structure.

$$s(\mu_j, \pi_{ij}) = d(\mu_j \cap \pi_{ij}, [0]_x) + d(\mu_j \cup \pi_{ij}, [1]_x) \quad (5)$$

It is clear that similarity measure value is proportional to the $\prod(\mu_j, \pi_{ij})$ and $N(\mu_j, \pi_{ij})$ by the graphical presentation of pairs μ_j and π_{ij}. Therefore similarity modification is also applicable to the decision theory.

3.2 Characteristics of Relative Information Measure

Definition of relative information has not been formulated by researchers. In [12], they just proposed fuzzy relative information measure $R[A,B]$ as the fuzzy relative information measure of B to A. Hence, definition of fuzzy relative information measure will be presented through analyzing the definition of $R[A,B]$.

Proposition 3.1 Fuzzy relative information measure $R[A,B]$ satisfies following properties:

(i) if $R[A,B] = 0$ and only if there is no intersection between A and B, or A,B are ordinary sets.

(ii) $R[A,B] = R[B,A]$ if and only if $H(A) = H(B)$.

(iii) $R[A,B]$ takes maximum value and $R[A,B] \ge R[B,A]$ if and only if A is contained in B, i.e, $\mu_A(x) \le \mu_B(x)$ for $\forall x \in X$.

(iv) If $A \subset B \subset C$, then $R(B,A) \ge R(C,A)$ and $R(A, B) = R(A, C) = R(B, C)$.

Liu insisted that entropy can be calculated from the similarity measure and dissimilarity measure, which is denoted by $s+d=1$ [2]. With this concept relative information measure can be designed via similarity measure. By the definition of entropy for certain fact, $H(A \cap B)$ and $H(A)$ satisfy $H((A \cap B),(A \cap B)_{near}$ and $H(A, A_{near})$, respectively. Where, $(A \cap B)_{near}$ satisfies the same definition of A_{near}. Roughly, it can be satisfied that

$$R[A, B] = \frac{1-s((A\cap B),(A\cap B)_{near}}{1-s(A, A_{near})}. \quad (6)$$

Where, $s((A\cap B),(A\cap B)_{near}) = 1- H((A\cap B), (A\cap B)_{\neq ar})$ and $s(A, A_{\neq ar}) = 1 - H(A, A_{near})$.

This measure also satisfies Proposition 3.1. Next, another relative information measure satisfying Proposition 3.1 without virtual ordinary sets $(A\cap B)_{near}$ and A_{near} is considered.

3.3 Fuzzy Coaliation in Game Theory

Coalition vectors $\alpha \in [0,1]^N$ are chosen inbetween zero and one, where is a set of players. Each fuzzy coalition is identified with a point in the hypercube $\alpha \in [0,1]^N$, while an ordinary coalition is regarded as a vertex of this hypercube, a point in $\alpha \in [0,1]^N$. Hence, optimal choice of fuzzy coalition vector to minimized payoff function is needed. Whereas opponents also try to make minimized other side payoff function [13].

$$\min_u U(x_i, s_j, u) = \min_u U(x_i, s_j)$$
$$\min_d U(x_i, s_j, d) = \min_d V(x_i, s_j)$$

Where, $i \in N$ and $j \in N$ are number of players and strategies, respectively. Furthermore, $u = f(x, s)$ and $d = g(x, s)$ are inputs to minimize payoff functions. In order to determine input variable player participation degree is determined by adjusting coalition vector. Problem can be transformed to determine is to determine α_i, which constitutes $u = \sum_{i=1,j=1}^{N,M} \alpha_i x_i s_j$, and it minimize $U(x_i, s_j)$. Here, $\alpha_i x_i = x(a_i)$ are considered as the fuzzy set with membership values. Also strategies are considered as the ordinary set elements.

Then, it is possible to calculate the similarity measure between μ_x and fixed values. It was also verified that the calculation of similarity measure between fuzzy set and single datum [9]. Hence, similarity measure is applicable to determine the coalition vector of fuzzy game theory.

4. Conclusions

For information data groups, each datum or data set can be represented by uncertainty or certainty for fixed numerical values. Furthermore, it also has a correlation between the degree of similarity and dissimilarity. These meanings are expressed by fuzzy entropy and similarity measure. First, fuzzy entropy and similarity are introduced, and discussed their meaning and application. Usefulness was verified through discussing the previous application results. Two measures are applied to the reliable data selection problem, and similarity quantification of single datum or data set with respect to the ordinary set or fuzzy set. Fuzzy set analysis can be also applied to decision theory or system management problem, especially in fuzzy game theory. For decision making considered objective and consequence are needed. Decision tools, necessity and possibility, are proportional to the similarity measure between objective and consequence membership function. Hence, the conventional decision procedure, designing compatibility level, can be replaced with similarity measure. Finally, for more reliable combination of strategy similarity measure is also useful.

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