A New Concept for Deriving the Expected Value of Fuzzy Random Variables

Liang-Hsuan Chen, Chia-Jung Chang

Abstract—Fuzzy random variables have been introduced as an imprecise concept of numeric values for characterizing the imprecise knowledge. The descriptive parameters can be used to describe the primary features of a set of fuzzy random observations. In fuzzy environments, the expected values are usually represented as fuzzy-valued, interval-valued or numeric-valued descriptive parameters using various metrics. Instead of the concept of area metric that is usually adopted in the relevant studies, the numeric expected value is proposed by the concept of distance metric in this study based on two characters (fuzziness and randomness) of FRVs. Comparing with the existing measures, although the results show that the proposed numeric expected value is same with those using the different metric, if only triangular membership functions are used. However, the proposed approach has the advantages of intuitiveness and computational efficiency, when the membership functions are not triangular types. An example with three datasets is provided for verifying the proposed approach.

Keywords—Fuzzy random variables, Distance measure, Expected value.

I. INTRODUCTION

IN practical problems, we often faced a situation in which outcomes of random experiment are not suitable to be described as numeric values, but allowed to be represented as fuzzy values for characterizing the imprecise knowledge. Fuzzy random variables (FRVs) have been introduced as an imprecise concept of numeric values. The concept of FRVs, defined as the extension of classical random variable (CRV), was introduced by Kwakernaak [1], [2]. The various definitions about FRVs have been proposed in the literature. Puri & Ralescu [3] and Diamond & Kloeden [4] viewed an FRV as the extension of a random set. That is, FRVs are collected from a probability space, but are expressed in linguistic terms. Kwakernaak [1] and Kruse & Meyer [5] adopted FRVs to model the imprecise perception of a CRV. Almost all studies followed such definitions to construct various descriptive parameters. Furthermore, Couso & Dubois [6] proposed another view of FRVs, defining the most likely value (the largest membership grade) as the state of a standard randomness and the spread of a fuzzy set as the state of a fuzziness. Thus, FRVs are used to deal with two uncertainties, randomness and fuzziness.

In general, the descriptive parameters are useful to summary the main features of a set of collected data. In classical descriptive statistics, the expected value is well-defined as a measure of center. In fuzzy environments, the expected values are usually developed by the various metrics. To develop the expected value of FRVs, the area metric to measure the difference between two fuzzy numbers is adopted by almost all the existing studies. Three kinds of approaches were used: (1) Hausdorff metric [3] and [7], (2) L_2-metric on the space of Lebesgue integrable [8] and [9], and (3) possibility theory [6] and [10]-[12]. Those approaches addressed the data types of expected value as: (1) fuzzy set [10]-[12], (2) numeric value [3], [5], [8], (3) interval value [9]-[13]. Although various approaches were proposed, they suffer from the cumbersome computations. Instead of the concept of area metric that is usually adopted in the relevant studies, the numeric expected value is proposed by the concept of distance metric in this study based on the two characters (fuzziness and randomness) of FRVs. The proposed approach is based on the concept of distance in the study of Chen & Hsueh [6], [7] to develop the numeric expected value, in which the fuzzy distance is calculated by several α-cuts between a pair of fuzzy numbers. The proposed approach has the advantages of intuitiveness and computational efficiency.

In the following section, we introduce the expected value of FRVs. In Section III, an example with three datasets is used to verify the proposed approach. Finally, some conclusions are provided in Section IV.

II. EXPECTED VALUE

To develop the numeric expected value of FRVs, firstly consider a metric D defined over the class of fuzzy subsets of R, $F(\mathrm{R})$ (i.e., the set of compact fuzzy subsets of the real line). The expected value of an FRV, $\tilde{X}: \Omega \to F(\mathrm{R})$, with respect to the probability space $(\Omega, \mathcal{A}, \mathcal{P})$ is formulated as $E(\tilde{X}) = \int_{\Omega} D(\tilde{X}, \{0\}) \, d\mathcal{P}$, where $\{0\}$ is a singleton (i.e., $\mu_{\{0\}}(x) = 1$, if $x=0$; otherwise, 0).

Definition 1. Let $\tilde{X}$ be a triangular FRV, as shown in Fig. 1. A data set consists of n observations denoted as a triple element set $\tilde{X}_i = (a_i, b_i, c_i)$, $i=1,\ldots,n$. Such that, $m = b$, $l = b-a$ and $r = c-b$, represent the most likely value, left spread and right spread, respectively, signifying the most likely values (m) as the state of a standard randomness and the range of spread (l and/or r) as the state of a fuzziness. The α-level sets of $\tilde{X}$, $\tilde{X}_\alpha = \{\omega \in \Omega : \mu_{\tilde{X}}(\omega) \geq \alpha\}$, are closed for all

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$\alpha \in (0,1]$.

Firstly, the expected value proposed by Puri & Ralescu [14], [15] is introduced for the subsequent comparisons. They defined the expected value $E(\tilde{X})^{PR}$ as a fuzzy set for $\tilde{X} \in F(\mathrm{R})$, such that $\left(E(\tilde{X})^{PR}\right)_\alpha = \int_\Omega X_\alpha \, d\mathcal{P}$ for $\alpha \in (0,1]$. Hence, the expected value $E(\tilde{X})^{PR}$ is formulated as

$$E(\tilde{X})^{PR} \equiv \left[\frac{1}{n}\sum_{i=1}^n \tilde{X}_i^{L}, \ \frac{1}{n}\sum_{i=1}^n \tilde{X}_i^{M}, \ \frac{1}{n}\sum_{i=1}^n \tilde{X}_i^{U} \right] \qquad (1)$$

where $\tilde{X}^L$, $\tilde{X}^M$ and $\tilde{X}^U$ are the lower bound, the most likely value and the upper bound of the FRV $\tilde{X}$, respectively. In the followings, we will review some approaches in terms of the concept of area metric, and then introduce the proposed expected value.
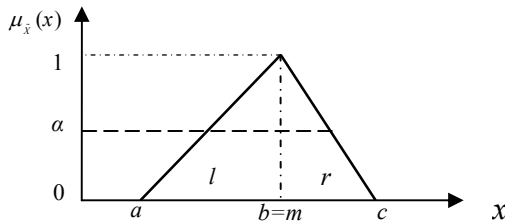

Fig. 1 A generalized triangular FRV

A. The Concept of Area Metric

Gil & Lrpez-Diaz [3] employed the λ-average function (2), suggested by Campos & González [13], to develop the expected value. The λ-average function will produce a numeric value as

$$V_S^\lambda(\tilde{X}) = \int_{(0,1]} \left[\lambda x_{\alpha 2} + (1-\lambda) x_{\alpha 1} \right] dS(\alpha) \qquad (2)$$

where the function V_S^λ is carried out for each $\tilde{X} \in F(\mathrm{R})$ using the α-cuts, $\tilde{X}_\alpha = [x_{\alpha 1}, x_{\alpha 2}]$, for each $\alpha \in (0,1]$. The parameter value of $\lambda \in (0,1]$ is determined as a subjective degree of optimism-pessimism, and S is an additive measure on $(0,1]$ to determine the weight associated with different α-cuts. For the comparison purpose, without loss of generality, we set $\lambda = 1/2$ in Gil &Lrpez-Diaz's approach, and replace $x_{\alpha 1}$ and $x_{\alpha 2}$ by $c_i - \alpha(c_i - b_i)$ and $a_i + \alpha(b_i - a_i)$ in (2), respectively, based on triangular membership functions. Then $V_S^\lambda(\tilde{X}_i) = (1/4)[a_i + c_i + 2b_i]$ can be obtained, and the numeric expected value of FRVs is determined as $E(\tilde{X})^{GL} = E(V_S^\lambda(\tilde{X})) \overset{\lambda=1/2}{=} (1/4)(\bar{a} + \bar{c} + 2\bar{b})$, where $\bar{a}$, $\bar{b}$, and $\bar{c}$ are the corresponding averages.

Following Fréchet's principle, Körner [16] applied the L_2-metric on the space of Lebesgue integrable as (3) to obtain the definition of the expected value of FRVs as

$$E_F(X) = \left\{ B \in F(\mathrm{R}) : Ed_2^2(X,B) = \inf_{C \in F(\mathrm{R})} Ed_2^2(X,C) \right\}.$$
$$d_2(X,B) = \left\| s_X - s_B \right\|_2$$
$$= \left(n \cdot \int_0^1 \int_{S^{n-1}} \left| s_X(\alpha,u) - s_B(\alpha,u) \right| \mu(du) \, d\alpha \right)^{1/2} \qquad (3)$$

where the support function $s_X(\alpha,u) = \sup\left\{ \langle u,a \rangle : a \in X^\alpha \right\}$, $u \in S^{n-1}$, $\alpha \in [0,1]$, S^{n-1} is the (n-1)-dimensional unit sphere of R, and $\langle \cdot, \cdot \rangle$ is the inner product of the Euclidean space. By using the Steiner point of a fuzzy set, defined as $\sigma_X = n \cdot \int_0^1 \int_{S^{n-1}} u \cdot s_X(u)\mu(du) \, d\alpha$, the approach obtains the numeric expected value of an triangular LR-fuzzy number as

$$E(X_{LR})^{Kr} = Em + \sigma_{X_R} \cdot Er - \sigma_{X_L} \cdot El \qquad (4)$$

where X_L and X_R are the fuzzy set with the membership function $L(x)$ and $R(x)$, respectively (i.e., $L(x)=R(x)=1-x$). And, (4) can be revised as

$$E(X_{LR})^{Kr} = Em + \left(\frac{1}{2}\int_0^1 R^{(-1)}(\alpha)d\alpha \right) \cdot Er - \left(\frac{1}{2}\int_0^1 L^{(-1)}(\alpha)d\alpha \right) \cdot El \qquad (5)$$

where σ_{X_L} and σ_{X_R} are obtained by $\sigma_{X_L} = \frac{1}{2}\int_0^1 L^{(-1)}(\alpha)d\alpha = \frac{1}{4}$ and $\sigma_{X_R} = \frac{1}{2}\int_0^1 R^{(-1)}(\alpha)d\alpha = \frac{1}{4}$, respectively. Therefore, the numeric expected value of FRVs in Körner's approach is $E(X_{LR})^{Kr} = Em + \frac{1}{4} \cdot Er - \frac{1}{4} \cdot El$, which can then be derived as $\frac{1}{4}(\bar{a} + \bar{c} + 2\bar{b})$ based on triangular membership functions.

Based on possibility theory, a numeric expected value is developed by Liu & Liu [9]. For any closed subset $F(\mathrm{R})$ of R, an FRV $\tilde{X}$ connected with a probability space, $X(\omega) = Pos\{X(\omega) \in F(\mathrm{R})\} = \sup_{x \in \mathrm{R}} \mu_{X(\omega)}(x)$ is a measurable function of $\omega \in \Omega$, where $\mu_{X(\omega)}$ is the possibility distribution function of FRV $X(\omega)$. To obtain the well-known uncertain functions, possibility measure (6), necessity measure (7) and the credibility measure (8) of event $\{X \leq r\}$, the numeric expected value of $\tilde{X}$ is defined as (9).

$$Pos\{X \leq r\} = \sup_{t \leq r} \mu_X(t) \qquad (6)$$

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$$Nes\{X \le r\} = 1 - \sup_{t > r} \mu_X(t) \tag{7}$$

$$Cr\{X \le r\} = \frac{1}{2}\big(Pos(X \le r) + Nes(X \le r)\big) \tag{8}$$

$$E(\tilde{X})^{LL} = \int_0^\infty Cr\{X \ge r\}\,dr - \int_{-\infty}^0 Cr\{X \le r\}\,dr \tag{9}$$

where $Cr\{X\} = 1 - Cr\{X^c\}$ is a self-dual set function. Using (9), the expected value of FRVs is $(1/4)\big(a_i + c_i + 2b_i\big)$ based on triangular membership functions, then the numeric expected value of FRVs in Liu & Liu's approach is determined as $E(\tilde{X})^{LL} = (1/4)(\overline{a} + \overline{c} + 2\overline{b})$ [10]-[12].

B. The Proposed Concept of Distance Metric

Different from the use of the concept of area metric, the proposed expected value is developed by employing the concept of α-cut between a pair of fuzzy numbers. For the ith fuzzy observation $\tilde{X}_i$, the distance of a fuzzy random observation $\tilde{X}_i$ from the single point $\{0\}$ at the kth α-level is defined as $(1/2)\Big[\big((\tilde{X}_i)^L_{\alpha_k} - (\{0\})^L_{\alpha_k}\big) + \big((\tilde{X}_i)^U_{\alpha_k} - (\{0\})^U_{\alpha_k}\big)\Big]$, which are illustrated in Fig. 2 as the average distance between two fuzzy numbers at the kth α-level (let $\alpha_k = k/h - 1$, $k = 0$, 1, …, h-1).Hence, the mean distance between the ith fuzzy random observation and $\{0\}$is determined as the average from $h\alpha$-cuts as

$$D(\tilde{X}_i, \{0\}) \equiv \frac{1}{2h}\sum_{k=0}^{h-1}\Big[\big((\tilde{X}_i)^L_{\alpha_k} - (\{0\})^L_{\alpha_k}\big) + \big((\tilde{X}_i)^U_{\alpha_k} - (\{0\})^U_{\alpha_k}\big)\Big] \tag{10}$$
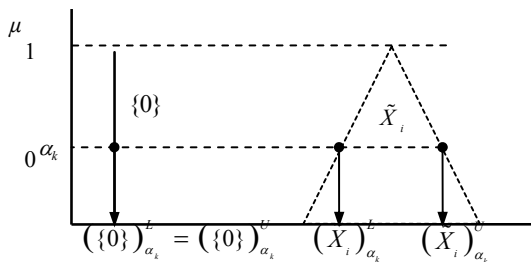

Fig. 2 The distance of a fuzzy random observation $\tilde{X}_i$ from the single point $\{0\}$

The expected value can be formulated as the average of the distance measures $D(\tilde{X}_i, \{0\})$, $i = 1$, …, n, from n fuzzy random observations:

$$E(\tilde{X})^{CC} \equiv \frac{1}{n}\sum_{i=1}^n\left\{\frac{1}{2h}\sum_{k=0}^{h-1}\begin{bmatrix}\big((\tilde{X}_i)^L_{\alpha_k} - (\{0\})^L_{\alpha_k}\big) + \\ \big((\tilde{X}_i)^U_{\alpha_k} - (\{0\})^U_{\alpha_k}\big)\end{bmatrix}\right\} \tag{11}$$

Thus, we can have

$$E(\tilde{X})^{CC} = \frac{1}{n} \cdot \sum_{i=1}^n \frac{1}{2h}\sum_{k=0}^{h-1}\Big[(\tilde{X}_i)^L_{\alpha_k} + (\tilde{X}_i)^U_{\alpha_k}\Big]$$

$$= \frac{1}{4}(\overline{a} + \overline{c} + 2\overline{b}) = \overline{m} - \frac{1}{4}\cdot\overline{l} + \frac{1}{4}\cdot\overline{r}\,,\ \forall\, h \ge 2$$

based on triangular membership functions. It is noted that the proposed expected value contains two parts, i.e., $\overline{m}$ and $-(1/4)\cdot\overline{l} + (1/4)\cdot\overline{r}$, in which $\overline{m}$ is contributed from the randomness, while $-(1/4)\cdot\overline{l} + (1/4)\cdot\overline{r}$ can be attributed from the fuzziness. In addition, obviously the proposed expected value $E(\tilde{X})^{CC}$ is same as those from the other approaches, such as Gil & Lrpez-Diaz [12], [17], Körner [13], and Liu & Liu [9], i.e., $E(\tilde{X})^{GL} = E(X_{LR})^{Kr} = E(\tilde{X})^{LL} = E(\tilde{X})^{CC}$, when triangular membership functions are adopted. However, the proposed approach is intuitive in the formulation, and is efficient in computations, when the membership functions are not triangular type. With the non-triangular membership functions, the existing approaches should carry out the more complicated computations by the area metric, comparing with the proposed approach.

III. ILLUSTRATIVE EXAMPLE

Three datasets are used in this section to exemplify the various approaches mentioned before to determine the expected values of FRVs. The first dataset contains the fuzzy random observations with symmetric triangular membership functions, while the asymmetrical fuzzy random observations are considered in the other two datasets.

Three datasets, as listed in Table I, were analyzed by Sakawa & Yano [10]-[12], Wu [18] and Chen & Hsueh [19], respectively. After performing the approaches in Puri & Ralescu [15], Gil & Lrpez-Diaz [3], Körner [13], Liu & Liu [9] and the proposed $E(\tilde{X})^{CC}$, the obtained expected values are showed in Table II. As described in Section II, all the approaches, excluding Puri & Ralescu [10], [11], results in the same expected value. However, the proposed approach is more efficiently in computational process.

TABLE I
THREE DATASETS OF FUZZY RANDOM OBSERVATIONS

No.	Dataset-1	Dataset-2	Dataset-3
1	(3.5, 4.0, 4.5)	(111, 162, 194)	(19, 30, 39)
2	(5.0, 5.5, 6.0)	(88, 120, 160)	(7, 20, 30)
3	(6.5, 7.5, 8.5)	(161, 222, 288)	(14, 25, 37)
4	(6.0, 6.5, 7.0)	(83, 131, 194)	(33, 45, 55)
5	(8.0, 8.5, 9.0)	(51, 67, 83)	(26, 38, 46)
6	(7.0, 8.0, 9.0)	(124, 169, 213)	(32, 43, 52)
7	(10.0, 10.5, 11.0)	(62, 81, 102)	(23, 40, 51)
8	(9.0, 9.5, 10.0)	(138, 192, 241)	(27, 38, 50)
9		(82, 116, 159)	(25, 37, 49)
10		(41, 55, 71)	(49, 60, 72)
11		(168, 252, 367)	(49, 59, 68)
12		(178, 232, 346)	(43, 54, 62)
13		(111, 144, 198)	(47, 61, 64)
14		(78, 103, 148)	(24, 34, 42)
15		(167, 212, 267)	(29, 38, 47)
16			(48, 64, 73)
17			(43, 56, 63)
18			(52, 63, 72)
19			(50, 66, 71)
20			(37, 49, 58)
21			(45, 55, 67)
22			(56, 67, 81)
23			(43, 53, 62)
24			(45, 54, 64)
25			(57, 70, 77)
26			(59, 68, 78)
27			(55, 65, 74)
28			(70, 75, 89)
29			(74, 84, 91)
30			(68, 80, 86)

TABLE II
EXPECTED VALUES OBTAINED BY DIFFERENT APPROACHES

Approach	Dataset-1	Dataset-2	Dataset-3
$E(\tilde{X})^{PR}$	(6.88,7.50,8.13)	(109.53,150.53,202.07)	(41.63,53.03,62.33)
$E(\tilde{X})^{GL}$	7.50	153.17	52.51
$E(X_{LR})^{Kr}$	7.50	153.17	52.51
$E(\tilde{X})^{LL}$	7.50	153.17	52.51
$E(\tilde{X})^{CC}$	7.50	153.17	52.51

IV. CONCLUSION

Considering the nature of fuzziness and randomness in FRVs, this study proposed the numeric expected value of FRVs based on the distance metric. The two parts of the expected value, $\overline{m}$ and $-(1/4) \cdot \overline{l} + (1/4) \cdot \overline{r}$, can be considered as the measures for randomness and fuzziness, respectively. Through the derivative processes in this study, the expressions of the expected value, presented by Gil & Lrpez-Diaz's approach, Körner's approach, Liu & Liu's approach and our proposed approach, have the same value, although different concepts of metric are adopted, when triangular membership functions are adopted. However, the development of the proposed approach is intuitive, and has the advantage of computational efficiency, if the membership functions are not triangular type.

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