Shadows of Fuzzy Sets – A Natural Approach Towards Describing 2-D and Multi-D Fuzzy Uncertainty in Linguistic Terms

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***Abstract*—Fuzzy information processing systems start with expert knowledge which is usually formulated in terms of words from natural language. This knowledge is then usually reformulated in computer-friendly terms of membership functions, and the system transform these input membership functions into the membership functions which describe the result of fuzzy data processing. It is then desirable to translate this fuzzy information back from the computer-friendly membership functions language to the human-friendly natural language. In general, this is difficult even in a 1-D case, when we are interested in a single quantity y; however, the fuzzy research community has accumulated some expertise of describing the resulting 1-D membership functions by words from natural language. The problem becomes even more complicated in 2-D and multi-D cases, when we are interested in several quantities $y_1, \ldots, y_m$, because there are fewer words which describe the relation between several quantities than words describing a single quantity. To reduce this more complicated multi-D problem to a simpler (although still difficult) 1-D case, L. Zadeh proposed, in 1966, to use words to describe fuzzy information about different *combinations* $y = f(y_1, \ldots, y_m)$ of the desired variables. This idea is similar to the use of marginal distributions in probability theory. The corresponding terms are called *shadows* of the original fuzzy set. The main question is: do we lose any information in this translation? Zadeh has shown that under certain conditions, the original fuzzy set can be uniquely reconstructed from its shadows. In this paper, we prove that for appropriately chosen shadows, the reconstruction is *always* unique. Thus, if we manage to describe the original membership function by linguistic terms which describe different combinations y, this description is lossless.**

I. Membership Functions As a Computer-Friendly Translation of Natural Language Terms

Humans often describe their knowledge by terms from natural language like "young", "large", etc. If we want a computer to be able to use this knowledge, we must reformulate it in terms which are understandable to a computer. One of the main objectives of fuzzy methodology is to provide such a translation. Fuzzy logic describes each natural language term t defined on a set X by the corresponding *membership function* $\mu_t(x) : X \to [0, 1]$, a function which describes, for each element x of the domain X, to what extent this element x satisfies the property t.

Fuzzy methodology provides us with the tools (t-norms, t-conorms, fuzzy inference rules, etc.) which are able to process these functions. A typical application of these tools is to the following situation:

- We are interested in the values of some quantities $y_1, \ldots, y_m$ about which we have no direct knowledge (e.g., we may be interested to know how the economy will grow in the next few years).
- What we do know is the relation between these quantities y_i and some other quantities $x_1, \ldots, x_n$ about which we have some (fuzzy) knowledge. For example, for an economy, we may know how it was growing in the past, we may know some specific parameters characterizing its common state, etc. The rules connecting x_i and y_j are also typically described not in precise mathematical form, but rather by words from natural language.

Fuzzy methodology enables us to transform a fuzzy knowledge about x_i and the fuzzy rules which connect x_i and y_j into a fuzzy knowledge about y_j, i.e., into the membership function $\mu(\vec{y})$ on the set of all possible values of $\vec{y} = (y_1, \ldots, y_m)$ (see, e.g., [4], [7]). In short, we get the desired information about y_j, but we get it in terms of membership functions.

II. It Is Desirable to Translate The Result of Fuzzy Data Processing Back Into the Natural Language

A membership function is not something which is natural for a human to understand and to use, it was invented as a way of representing human fuzzy knowledge in a language which is understandable for a computer. From this viewpoint, the fact that the result of using traditional fuzzy methodology is a membership function means that this result is not presented in a very user-friendly form; for the user's convenience, we must translate the result of computer's information processing from the computer-native language of membership functions into the human-friendly natural language.

III. Such a Translation Is Much More Complicated in 2-D and Multi-D Cases Than in 1-D Cases

Even in the 1-D case, when we are interested only in the value of a single quantity y_1, the problem of describing a membership function in terms of natural language is difficult. However, the fuzzy research community has accumulated some expertise of describing the resulting 1-D membership functions by words from natural language.

Often, for a 1-D membership function $\mu(y)$ produced by the fuzzy system, we are able to find a natural language term t for which the corresponding membership function $\mu_t(y)$ is close enough to $\mu(y)$. It is then natural to return this term t as the result of fuzzy information processing.

For 2-D and multi-D problems, when we are interested in the values of several quantities $y_1,\ldots,y_m$, $m\ge 2$, the situation is even more complicated:

- most words from natural language characterize a *single* quantity ("young", "small", etc.), and
- there are much fewer terms from natural language which describe the relation between several quantities: e.g., we can say that y_1 is much larger than y_2, etc.

It is therefore extremely difficult to describe a multi-D membership function $\mu(\vec{y})=\mu(y_1,\ldots,y_m)$ in natural-language terms.

IV. The Idea of Shadows of a Fuzzy Set

To reduce this more complicated multi-D problem to a simpler (although still difficult) 1-D case, L. Zadeh proposed, in [9], instead of trying to find a word or words which describe the original multi-D membership function, to first describe the corresponding multi-D fuzzy set in terms of several 1-D membership functions. If such a reduction is done, then:

- instead of a single extremely complicated problem of describing a multi-D membership function in natural-language terms,
- we get several simpler (although still complicated) problems of describing the corresponding 1-D membership functions in natural-language terms.

Specifically, L. Zadeh suggested to characterize a general (fuzzy) information about a multi-D vector $(y_1,\ldots,y_m)$ (i.e., a general multi-D fuzzy set) by describing different *combinations* $y=f(y_1,\ldots,y_m)$ of the desired variables. For each such combination, we can use the extension principle to describe the resulting information about y by a 1-D fuzzy set, with a membership function $\mu_f(y)$. This 1-D fuzzy set is called a *shadow* of the original multi-D fuzzy set. (This idea is similar to the use of marginal distributions in probability theory.) For example:

- we can use *linear* combinations
$$f(y_1,\ldots,y_m)=a_0+a_1\cdot y_1+\ldots+a_m\cdot y_m; \quad (1)$$
- or, we can use more general *quadratic* combinations
$$f(y_1,\ldots,y_m)=a_0+\sum_{i=1}^m a_i\cdot y_i+\sum_{i=1}^m\sum_{j=1}^m a_{ij}\cdot y_i\cdot y_j. \quad (2)$$

Shadows corresponding to linear combination functions $f(\vec{y})$ will be called *linear* shadows, and shadows corresponding to quadratic combination functions $f(\vec{y})$ will be called *quadratic* shadows.

As a result, instead of trying to solve an extremely complicated problem of directly describing the original multi-D membership function $\mu(y_1,\ldots,y_m)$ by a word from natural language, we try to find this description in several (still complicated but) simpler steps. Namely:

- first, we find relevant combinations $f(y_1,\ldots,y_m)$;
- then, for each such combination, we compute the corresponding membership function $\mu_f(y)$ (i.e., the corresponding shadow of the original fuzzy set); and
- finally, we try to find, for each of the used combinations (shadows), a term from natural language which is the best in describing the corresponding 1-D membership function $\mu_f(y)$.

If we succeed, then we get a natural-language description of the original fuzzy information, e.g., about (y_1,y_2), as a collection of statements of the type: y_1 is large; y_2 is small; y_1+y_2 is medium; etc.

V. The Main Problem of Shadow Theory and What We Are Planning To Do

In short, Zadeh's idea is to replace the original multi-D membership function by several 1-D membership functions corresponding to different combinations of the quantities $y_1,\ldots,y_m$. The important question is: do we lose any information in this replacement?

A similar question appears in *tomography*, where we reconstruct the image from sections.

Zadeh has shown that under certain conditions, the original fuzzy set can be uniquely reconstructed from its shadows. In this paper, we prove that for appropriately chosen shadows, the reconstruction is *always* unique.

Thus, the transition from the original description of a multi-D membership function into a collection of 1-D membership functions (corresponding to different shadows) is *lossless* – in the sense that we can always go back from the description of the shadows to the original multi-D membership function.

Hence, if we manage to find, for each of the resulting 1-D membership functions, a term from natural language which describes this function, then we get a complete ("lossless") description of the original fuzzy set in natural-language terms.

VI. The Idea of a Shadow Reformulated in Terms of Sets

In order to formulate and prove our result, we will first recall and use some basic definitions. The membership function $\mu_f(y)$ corresponding to the shadow can be described by the extension principle:

$$\mu_f(y) = \max_{\vec{y}:\ f(\vec{y})=y} \mu(\vec{y}). \tag{3}$$

We would like to somewhat simplify this formula. Namely, one can easily see that for any value y, the resulting value $\mu_f(y)$ does not use all the information about the combination *function* $f(y_1,\ldots,y_m)$; it only uses the level *set* $\{\vec{y}:\ f(\vec{y})=y\}$ corresponding to this combination function. Thus, if any other function $g(\vec{y})$ has the same level set for this y, we will get $\mu_f(y)=\mu_g(y)$. To describe this fact, we can reformulate the formula (3) as a two-step procedure:

- first, for each combination function $f(\vec{y})$ and value y, we form a set
$$S = \{\vec{y}\,|\,f(\vec{y})=y\}; \tag{4}$$
- second, for every such set S, we compute the value
$$\mu(S) = \max_{\vec{y}\in S} \mu(\vec{y}). \tag{5}$$

The formula (5) has a natural interpretation in terms of fuzziness and possibility theory: namely, if we interpret $\mu(\vec{y})$ as the degree of possibility that the "actual" (unknown) value $\vec{y}_{\rm act}$ coincides with the given $\vec{y}$, then $\mu(S)$ describes the degree of possibility that the actual value $\vec{y}_{\rm act}$ is in S. Indeed, $\vec{y}_{\rm act}$ is in S if and only if it coincides with one of the vectors $\vec{y}\in S$. Thus, the degree to which it is possible that $\vec{y}_{\rm act}$ is in S can be computed as a degree of possibility of the following statement:

$$\exists \vec{y}_{\vec{y}\in S}(\vec{y}=\vec{y}_{\rm act}).$$

We assumed that the degree of possibility of each statement $\vec{y}=\vec{y}_{\rm act}$ is equal to $\mu(\vec{y})$; the existential quantifier is, in essence, an infinite "or" operation, so we can use the simple fuzzy "or" operation max to describe it. Therefore, we get the formula (5).

What did we gain by this reformulation?

- In the original Zadeh's formulation, we fix a class of functions $f(\vec{y})$, and translate the original membership function $\mu(\vec{y})$ into several membership functions $\mu_f(y)$ corresponding to different functions from this class. In these terms, the main question is as follows: if we know all these functions $\mu_f(y)$, can we reconstruct the original function $\mu(\vec{y})$ uniquely?
- In the new formulation, instead of fixing a class of functions, we fix a class $\mathcal{S}$ of *sets*. For each set $S\in\mathcal{S}$, we have the degree of possibility $\mu(S)$ of this set which is determined by the formula (5). In these terms, the above question takes the following form: if we know $\mu(S)$ for all $S\in\mathcal{S}$, can we uniquely reconstruct the original fuzzy set (membership function) $\mu(\vec{y})$?

VII. Reconstructing a Fuzzy Set From Its Shadows: Heuristic Idea

In the previous text, we gave an intuitive explanation for the formula (5) which describe the degree $\mu(S)$ in terms of the values $\mu(\vec{y})$. Similar arguments can describe $\mu(\vec{y})$ in terms of $\mu(S)$. Indeed, suppose that we know, for each set $S\in\mathcal{S}$, the degree to which it is possible that the actual vector $\vec{y}_{\rm act}$ is in this set S. A vector $\vec{y}$ is possible if all sets which contain $\vec{y}$ are possible. Thus, the degree to which it is possible that $\vec{y}_{\rm act}$ is equal to $\vec{y}_{\rm act}$ can be computed as a degree of possibility of the following statement:

$$\forall S_{\vec{y}\in S}(\vec{y}_{\rm act}\in S).$$

We assumed that the degree of possibility of each statement $\vec{y}_{\rm act}\in S$ is equal to $\mu(S)$; the universal quantifier is, in essence, an infinite "and" operation, so we can use the simple fuzzy "and" operation min to describe it. Therefore, we get the following heuristic formula:

$$\mu(\vec{y}) = \min_{S:\vec{y}\in S} \mu(S). \tag{6}$$

The question is: when is this heuristic formula correct? We will describe our results in the following two sections.

VIII. First Result: For a Convex Fuzzy Set, Linear Shadows Reconstruct It Uniquely

In 1-D case, a fuzzy set is called *convex* if the corresponding membership function is continuous, and for every $\alpha>0$, the corresponding α-cut is bounded and convex. We can use a similar definition in multi-D case:

Definition 1. *A fuzzy set $\mu : R^m \to [0,1]$ is called convex if the membership function μ is continuous, and for every $\alpha > 0$, its α-cut $\{\vec{y} \,|\, \mu(\vec{y}) \geq \alpha\}$ is bounded and convex.*

Theorem 1. *A convex fuzzy set can be uniquely reconstructed from its linear shadows.*

Comments.

- For reader's convenience, all the proofs are placed in a special (last) section.
- As we will see from the proof, not only is reconstruction possible, but this reconstruction can be done by using the formula (6).

IX. Second Result: For a General Fuzzy Set, Quadratic Shadows Reconstruct It Uniquely

Theorem 2. *There exists a fuzzy set which cannot be uniquely reconstructed from its linear shadows.*

Since linear functions are not enough, the natural next step is to use quadratic functions. This is already sufficient:

Theorem 3. *A fuzzy set can be uniquely reconstructed from its quadratic shadows.*

Comment. Similarly to Theorem 1, not only is reconstruction possible, but this reconstruction can be done by using the formula (6).

X. Towards the Practical Use of Shadows

A. How Can We Apply The Above Theoretical Results

We have proven that a convex membership function can be uniquely reconstructed from its linear shadows, and that an arbitrary membership functions can be uniquely reconstructed from its quadratic shadows.

Our motivation was to solve a practical problem; to be more specific, we wanted to describe a multi-D membership function by describing several related 1-D membership functions (shadows). How can we apply these theoretical results to our practical problem?

The reconstruction by using formula (6) requires that we use all possible linear or quadratic combinations, and there are infinitely many such possible combinations. In practice, we cannot keep infinitely many combinations, we can only use finitely many such combinations. Thus, we can only get an *approximate* description of the original multi-D membership function.

Let us describe the meaning of this approximation.

B. First Case: Convex Membership Functions, Linear Shadows

Let us first consider the simpler of the two cases, when a membership function $\mu(y_1, \ldots, y_m)$ characterizing m quantities $(y_1, \ldots, y_m)$ is convex. In this case, the actual reconstruction by using formula (6) requires that we use all possible (i.e., infinitely many) linear combinations (1). If we know the values corresponding to all these combinations, then we can use the formula (6) to find $\mu(\vec{y}\,)$ for a given $\vec{y}$. In terms of different linear combinations $f \in L$, the formula (6) can be rewritten as:

$$\mu(\vec{y}\,) = \min_{f : f \in L} \mu_f(f(\vec{y}\,)). \qquad \text{(6a)}$$

In practice, we can only use finitely many possible combinations. So, instead of using the exact formula (6) or (6a), in which the minimum is taken over all possible linear combinations (i.e., over infinitely many of them), we can select finitely many linear combinations

$$y^{(k)} = f^{(k)}(y_1, \ldots, y_m) = a_0^{(k)} + a_1^{(k)} \cdot y_1 + \ldots + a_m^{(k)} \cdot y_m,$$

where $k = 1, \ldots, K$, and use an approximate formula

$$\mu(\vec{y}\,) \approx \min_{k=1,\ldots,K} \mu_{f^{(k)}}(f(\vec{y}\,)). \qquad \text{(6b)}$$

The more linear combinations we consider (i.e., the larger the number K of such combinations), the better our description of the original membership function.

The approximation (6b) has a natural geometric meaning: Namely, one can see that for every linear function $f(y_1, \ldots, y_m)$, and for every α, the α-cut of the membership function μ_f is a segment between two parallel hyperplanes. The α-cut corresponding to a minimum of several membership functions is known to be equal to the intersection of the α-cuts corresponding to different membership functions. Thus, for the membership function (6b), each α-cut is the intersection of several segments of the above type, i.e., a *convex polytope.*

We are assuming that the original membership function is convex, which, by definition, means that its α-cut is closed and convex. In these terms, the above approximation (6b) means that we approximate this convex set by a convex polytope. It is known (see, e.g., [8]), that an arbitrary convex set can be approximated, with an arbitrary accuracy, by a convex polytope: e.g., we can have a inscribed or circumscribed polytope; the more faces we allow in these polytopes, the better the approximation.

C. General Case: Arbitrary Membership Functions, Quadratic Shadows

Similarly, when the original multi-D membership function is not convex, instead of using all possible quadratic combinations, we can use finitely many quadratic combinations

$$y^{(k)} = f^{(k)}(y_1, \ldots, y_m) =$$

$$a_0^{(k)} + \sum_{i=1}^{m} a_i^{(k)} \cdot y_i + \sum_{i=1}^{m} \sum_{j=1}^{m} a_{ij}^{(k)} \cdot y_i \cdot y_j.$$

In this case, we also have some geometric meaning for the resulting approximation; namely:

- in the convex case, we are approximating each original α-cut by intersection of "linear" sets, i.e., by polytopes – sets with piece-wise *linear* boundary;

- in the general case, we are approximating each original α-cut by intersection of quadratic sets, i.e., by sets with piece-wise *quadratic* boundary.

Mathematical comment. In view of this geometric interpretation, our choice of quadratic combinations make perfect sense: α-cuts with piece-wise quadratic boundary naturally appear if we consider systems of linear equations with the simplest type of dependent fuzzy uncertainty in the coefficients: namely, systems $\sum_{ij} a_{ij} \cdot x_j = b_i$ in which the only dependence between the coefficient is reflected by the fact that a_{ij} should be a symmetric matrix (i.e., $a_{ij} = a_{ji}$); see, e.g., [1]–[3].

D. Case Study: In Brief

We have just started this research, so we can only give a few preliminary examples of practical applications of this approach. So far, we have mainly analyzed the 2-D case. A typical example where 2-D quantities naturally appear is linear control theory and linear system theory, in which many important characteristics are naturally described by *complex numbers* $z = x + \mathrm{i}y$: e.g., various stability properties of a linear system can be reformulated in terms of the complex eigenvalues of the corresponding linear matrix. A complex number consists of two real-valued quantities: its real part x and its imaginary part y. Therefore, to describe the corresponding 2-D membership function, it is natural to characterize it by using 1-D membership functions describing combinations of x and y. In particular, in [5], [6] (see also references therein), it is shown that we can often get reasonable description in terms of natural language by using:

- linear combinations such as the real part $x = \mathrm{Re}(z)$, the imaginary part $y = \mathrm{Im}(z)$, and, in general, a real part of a linear complex function $\mathrm{Re}(a \cdot z + b)$, and

- quadratic combinations such as $|z|^2 = x^2 + y^2$.

E. A Word of Caution

A reader should be cautioned that shadows are a means to facilitate the natural-language interpretation of a multi-D membership function, but the use of shadows, by itself, does not make necessary lead to a meaningful interpretation even if the mathematical description is there:

- In the above control-systems example, we managed to get the combinations which have an intuitive meaning.

- However, in general, not every combination has such a meaning: e.g., if y_1 is height, and y_2 is weight, then a statement of the type "$y_1^2 + y_2^2$ is small" does not convey intuitive linguistic information (we are thankful to the referee for this convincing example).

So, in searching for the desirable translation, we should always use specific information about this domain.

XI. Proofs

A. Proof of Theorem 1

Let us show that this reconstruction can be done by using the formula (6). If $\vec{y} \in S$, then, due to formula (5), we have $\mu(\vec{y}) \le \mu(S)$. Thus,

$$\mu(\vec{y}) \le \min_{S: \vec{y} \in S} \mu(S). \tag{7}$$

So, to complete our proof, it is sufficient to show that we cannot have

$$\mu(\vec{y}) < \min_{S: \vec{y} \in S} \mu(S). \tag{8}$$

We will prove this impossibility by reduction to a contradiction. Assume that (8) is true for some $\vec{y}^{(0)}$. Let us denote $\mu(\vec{y}^{(0)})$ by α, and

$$\min_{S: \vec{y}^{(0)} \in S} \mu(S)$$

by $\beta > \alpha$. Let us compute the value $\gamma = (\alpha + \beta)/2$. Then, $\alpha < \gamma < \beta$. Since μ is a membership function of a convex fuzzy set, its γ-cut F_γ is closed and convex. For the point $\vec{y}$, the value of the membership function is $\alpha < \gamma$ and therefore, this point is outside the closed convex γ-cut F_γ. Therefore, by the known properties of convex sets (see, e.g., [8]), there exists a hyperplane S_0 which contains $\vec{y}^{(0)}$ and which is completely outside F_γ. Since S_0 is outside $F_\gamma = \{\vec{y} \,|\, \mu(\vec{y}) \ge \gamma\}$, for all points $\vec{y} \in S$, we have $\mu(\vec{y}) < \gamma$, and therefore,

$$\mu(S_0) = \max_{\vec{y} \in S_0} \mu(\vec{y}) \le \gamma. \tag{9}$$

Since $\vec{y} \in S_0$, we can conclude that

$$\beta = \min_{S: \vec{y}^{(0)} \in S} \mu(S) \le \mu(S_0) \le \gamma,$$

which contradicts to the fact that $\beta > \gamma$. This contradiction shows that the inequality (8) is impossible and therefore, that (6) is indeed true. The theorem is proven.

B. Proof of Theorem 2

For simplicity, let us consider 2-D case, in which $\vec{y} = (y_1, y_2)$. Let μ_1 be a membership function which is a characteristic function of a closed unit disk, i.e., $\mu_1(\vec{y}) = 1$ if $(\vec{y})^2 \le 1$, and $\mu_1(\vec{y}) = 0$ otherwise. Let μ_2 be a membership function which is a characteristic function of a unit circle, i.e., $\mu_1(\vec{y}) = 1$ if $(\vec{y})^2 = 1$, and $\mu_1(\vec{y}) = 0$ otherwise. In a 2-D case, to describe linear shadows, it is sufficient to describe the values $\mu(S)$ for all straight lines. We will show that for each straight line S, $\mu_1(S) = \mu_2(S)$. Indeed, by definition, $\mu_1(S)$ is equal to 1 if S contains points from a disk (i.e., intersects with a disk), and to 0 else. Similarly, $\mu_2(S)$ is equal to 1 if S intersects with a circle, and 0 else.

- If a straight line intersects with a circle, then, of course, it intersects with a disk.
- On the other hand, if a straight line (which is infinite) intersects with a disk, it cannot stay within this bounded disk and it has to go outside somewhere. So, if a straight line intersects with a unit disk, it must also intersect with a unit circle.

In other words, a straight line S intersects with a disk if and only if it intersects with a unit circle. Thus, for every straight line S, $\mu_1(S) = \mu_2(S)$. However, $\mu_1 \ne \mu_2$. The theorem is proven.

C. Proof of Theorem 3

The proof of Theorem 3 is very straightforward. Namely, let us show fix a vector $\vec{y}^{\,(0)}$ and show how we can reconstruct the value $\mu(\vec{y}^{\,(0)})$ from the values $\mu(S)$ known for different quadratic sets S, i.e., for sets

$$S = \{\vec{y} \,|\, f(\vec{y}) = y\}$$

corresponding to quadratic functions $f(\vec{y})$. Indeed, as a particular example of such a quadratic set, we can take a set $S_0 \in \mathcal{S}$ corresponding to the distance function

$$f(y_1, \ldots, y_m) = \left(y_1 - y_1^{(0)}\right)^2 + \ldots + \left(y_m - y_m^{(0)}\right)^2$$

and to $y = 0$. This set S_0 consists of a single point $\vec{y}^{\,(0)}$ and therefore, for this set S_0, the formula (5) leads to $\mu(S_0) = \mu\left(\vec{y}^{\,(0)}\right)$. So, for each $\vec{y}^{\,(0)}$, the value $\mu\left(\vec{y}^{\,(0)}\right)$ can indeed be uniquely reconstructed from the values $\mu(S)$.

Let us now show that this reconstruction can be done by using the formula (6). We have already proven, in the proof of Theorem 1, that the inequality (7) always holds. On the other hand, we have shown that for some S_0 for which $\vec{x} \in S_0$, we have $\mu(\vec{y}) = \mu(S_0)$; thus,

$$\mu(\vec{y}) = \mu(S_0) \ge \min_{S: \vec{y} \in S} \mu(S). \qquad (10)$$

Combining the two inequalities (7) and (10), we get the desired formula (6). The theorem is proven.

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