A Novel TFN-based Complex Basic Belief Assignment Generation Method

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Abstract

In this paper, a novel TFN-based complex basic belief assignment generation method is proposed to improve decision-making accuracy in complex evidence theory.

Keywords: Complex Evidence Theory, Complex Basic Belief Assignment, Triangular Fuzzy Number

1. NTFN Modeling

The selected instances from training data are represented as follows:

$$s_t^p = x_t^p e^{i y_t^p}, \quad p \in \{1, 2, \ldots, K\}; \tag{1}$$

where i is an imaginary unit.

Six elements a_{tm}, b_{tm}, c_{tm}, a_{tp}, b_{tp} and c_{tp} of NTFN of class c with attribute t are defined as:

$$a_{tm} = \min(x_t^p), a_{tp} = \min(y_t^p), \tag{2}$$

$$b_{tm} = \frac{1}{K}\sum_{p=1}^{K} x_t^p, b_{tp} = \frac{1}{K}\sum_{p=1}^{K} y_t^p. \tag{3}$$

$$c_{tm} = \max(x_t^p), c_{tp} = \max(y_t^p). \tag{4}$$

The novel triangular fuzzy function is defined as:

$$\mu_s(x, y) = \mu_s(x) e^{i\mu_s(y)}, \tag{5}$$

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$$\mu_s(x) = \begin{cases} 0, & x < a_{tm}, \\ \dfrac{x - a_{tm}}{b_{tm} - a_{tm}}, & a_{tm} < x < b_{tm}, \\ \dfrac{c_{tm} - x}{c_{tm} - b_{tm}}, & b_{tm} < x < c_{tm}, \\ 0, & x \geq c_{tm}, \end{cases} \tag{6}$$

$$\mu_s(y) = \begin{cases} 0, & y < a_{tp}, \\ \dfrac{y - a_{tp}}{b_{tp} - a_{tp}}, & a_{tp} < y < b_{tp}, \\ \dfrac{c_{tp} - y}{c_{tp} - b_{tp}}, & b_{tp} < y < c_{tp}, \\ 0, & y \geq c_{tp}. \end{cases} \tag{7}$$

With the above steps NTFNs can be created for each attribute of each class of the dataset.

2. CBBA Generation

For a complex attribute $s_t^p = x_t^p e^{iy_t^p}$ of an instance, the membership value M_t are obtained by the NTFN μ_s as:

$$M_t(c_m) = \mu_s(x_t^p, y_t^p) = \mu_s(x_t^p) e^{i\mu_s(y_t^p)}. \tag{8}$$

The membership degree $\mathbb{H}_t$ of the focus elements in FOD $\Theta = \{c_1, \ldots, c_S\}$ is as follows:

$$\mathbb{H}_t(\Theta_i) = \min_{c_m \in \Theta_i} (M_t(c_m)), \tag{9}$$

where $\Theta_i \subseteq \Theta$.

$\mathbb{H}_t$ is processed to obtain CBBA $\mathbb{M}_t$. When $|\sum\limits_{\Theta_i \subseteq \Theta} \mathbb{H}_t(\Theta_i)| \geq 1$, $\mathbb{H}_t$ is processed as follows:

$$\mathbb{M}_t(\Theta_i) = \frac{\mathbb{H}_t(\Theta_i)}{\sum\limits_{\Theta_k \in \Theta} \mathbb{H}_t(\Theta_k)}, \quad \forall \Theta_i \subseteq \Theta, \tag{10}$$

and when $|\sum\limits_{\Theta_i \in \Theta} \mathbb{H}_t(\Theta_i)| < 1$, $\mathbb{H}_t$ is processed as follows:

$$\begin{aligned} \mathbb{M}_t(\Theta) &= \mathbb{H}(\Theta) + 1 - \sum_{\Theta_k \in \Theta} \mathbb{H}(\Theta_k), \\ \mathbb{M}_t(\Theta_i) &= \mathbb{H}(\Theta_i), \quad \Theta_i \subset \Theta. \end{aligned} \tag{11}$$

Then, a CBBA $\mathbb{M}_t$ is obtained by complex feature s_t^p.