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An improvement for combination rule in evidence theory

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HIGHLIGHTS

- Analyzing and illustrating the phenomenon and the reason of similarity collision in evidence theory.
- Introducing the Basic Probability Assignment sequence computing in the combination process to reduce the effect that similarity collision impacts on evidence weights.
- Proposing a new evidence combination rule which is attested to have the best F-score under the same dataset when compared with other methods.

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ABSTRACT

Evidence theory is an effective tool to make decision from ambiguity, which has been widely used in target recognition, decision making, optimization problem. To reduce its impact on combination results, the conflicting evidence should be assigned to a smaller weight than others when being combined. However, due to the phenomenon of similarity collision, the weight for conflicting evidence probably cannot be reduced effectively in present combination rules for similarity is the main criterion. In this paper, based on the analysis and illustration of similarity collision, a new combination rule is proposed, in which, the impact of similarity collision on evidence weights are reduced obviously by introducing the Basic Probability Assignment sorting before the final combination. In the experiment part, two sets of experiments are designed to show the superiority of the proposed method by comparing the size of each Basic Probability Assignment belonging to the correct decision and the F-Score of classification under the dataset Iris.

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1. Introduction

The theory of evidence proposed by Dempster and Shafer [1] is an effective tool to make decision from uncertain information [2]. It is widely applied in many fields [3] such as decision making [4–6], reliable analyzing [7–9], relationship strength calculation [10], communication science [11,12] and optimal computing [13–15]. Traditionally, unreasonable evidence which is sent back by flawed devices is named as conflicting evidence and combination rule of evidence [16] may be invalid [17,18] when conflicting evidence exists.

To diminish the effect of conflicting evidence, Dubois [19] proposed a combination rule based on transforming the intersection parts of evidence into union parts. However, the method performs poorly when the degree of conflict is high [20]. Murphy [21] proposed a evidence combination method based on calculating the average of all evidence, but Murphy treats all evidence with same weights. To realize a better weight determination of each evidence, similarity of evidence is introduced to compute the conflict degree of each evidence [4–8].

Besides, AM (Ambiguity Measure) [22] of evidence is optional process to modify the weights of evidence. Weights of evidence with big ambiguity part should be smaller for the information it contains is less. Many scholars proposed their methods to realize the calculation of AM [23–29]. Han [30] proposed an evidence combination rule based on Ambiguity Measure method proposed by Deng [31]. Wang [32] proposed another evidence combination rule based on information entropy. Jiang [33] proposed a novel combination rule based on similarity of evidence and penalty function. Zhao [34] proposed a new combination rule based on similarity and support function k_{new}. Xiao [35,36] proposed two combination methods for evidence theory, the former one is based on evidence distance and fuzzy preference while the latter one is based on evidence similarity and Belief Function Entropy. However, both two schemes above still suffer from collision of similarity.

Even though combination rule of evidence has been improved by many scholars, the case that two different pieces of evidence share a same similarity value towards a same evidence is easy to be found, and this phenomenon is collision of similarity. It may lead to

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unreasonable evidence weights and the wrong combination result following which means an wrong decision. In this paper, we found the similarity collision reason and got the method to decrease its effect on evidence combination result. Meanwhile, we presented a complete combination rule based on it, which is proved to have better performance than other compared schemes.

There are 6 parts in this paper. In the Section 1, we introduced what evidence theory and similarity collision, which triggered our research are. In the following part, related works about evidence theory are illustrated to overview the latest research about evidence theory. In the Section 3, we described some formulas and equations used in this paper. And in the "Method presentation" part, which is the Section 4, our study is unfolded in five subparts. In the Section 5, we implemented three methods which were proposed recently, the performance of the methods above and ours were compared in two sets of experiments. In the last part, we summarized our study where both a conclusion and a research direction were made.

2. Related works

In evidence theory each evidence contains several potential decisions which are named as focal-elements, and the probability that the focal-element is the correct decision is denoted as BPA (Basic Probability Assignment). Although Dempster and Shafer proposed the basic combination rule, it will be invalid when highly conflicting evidence is combined [21]. To overcome the shortage above, smaller weights are assigned to conflicting evidence based on evidence similarity. It can be realized by directly calculation between evidence and indirectly computing based on evidence distance [37]. To realize calculation of evidence distance, Cuzzolin [38] explained the distance of evidence in the view of geometric. Jousselme [39] proposed an evidence distance computing method based on different matrix, and similarity of evidence can be obtained by using 1 minus evidence distance. Wen [40] proposed another method based on the cosine value between evidence. Based on similarity of evidence, Deng [31] transferred similarity values into weight of evidence. Wang [32] improved Murphy's [21] combination rule by modifying weights of evidence. Wang [41] proposed a novel method for determined similarity collision but no combination rule is proposed.

Besides, in the process of evidence combination, the greater the ambiguity degree of the evidence is, the smaller its weight should be. Dubois [23] proposed an ambiguity measure method based on computing the difference of each BPA in BOE (Body of Evidence). Yager [24] proposed an ambiguity measure method based on computing BPAs and *Pl* (*Pl* is introduced in Section 3). Kilr [25] proposed another ambiguity measure method based on replacing *Pl* by the intersection of each BPA. George [26] improved the computing speed by simplifying exponential algorithm in Kilrs method. Kilr [28] proposed another method based on computing the distribution of each BOE but the computation process is difficult.

3. Preliminaries

3.1. Basic evidence combination rule

Let θ be a frame contains N distinct elements $\{H_1, H_2, H_3, \ldots, H_N\}$. Each element H_i is exclusive and exhaustive to the others, A is a subset of $P(\theta)$ which $P(\theta) = 2^{\theta}$. $m(A)$ is a function that maps A to [0,1] and satisfies the following conditions:

$$m(\emptyset) = 0; \qquad \sum_{A\subseteq\theta} m(A) = 1$$

Based on m and frame θ, *Pl* is another function which satisfies the following conditions:

$$Pl(A) = \sum_{B\cap A\neq\emptyset} m(B) = 1 - \bar{A}; \qquad m(A) \leq Pl(A)$$

$\bar{A}$ represents the complement set of A. Based on $m(A)$ and $Pl(A)$, $[m(A), Pl(A)]$ depicts the probability scope that A may be true. Noting that, all the BPAs that constitute BOE should be positive. All the BPAs of focal-elements will constitute the body of evidence (BOE) as below:

$$m : m(A), m(B), m(C), \ldots, m(AB), \ldots, m(\theta) \tag{3.1}$$

In (3.1), $m(A)$ or $m(B)$ are mass functions which represent the BPA of A or B. And a set of evidence can be combined based on the combination rule proposed by Dempster:

$$m(A) = \begin{cases} 0 & A = \emptyset \\ \frac{\sum_{A_i\cap A_j=A} m_1(A_i)m_2(A_j)}{C} & A \neq \emptyset \end{cases} \tag{3.2}$$

$$C = 1 - \sum_{A_i\cap A_j=\emptyset} m_1(A_i)m_2(A_j) \tag{3.3}$$

m is the combination result of m_1 and m_2. When the number of evidence is larger than two, (3.2) and (3.3) will be transformed into (3.4) and (3.5) as bellows:

$$m(A) = \begin{cases} 0 & A = \emptyset \\ \frac{\sum_{A_{i1}\cap A_{j2}\cap,\ldots,\cap A_{in}=A} m_1(A_{i1})m_2(A_{j2})\ldots m_n(A_{in})}{C} & A \neq \emptyset \end{cases} \tag{3.4}$$

$$C = 1 - \sum_{A_{i1}\cap A_{i2}\cap\ldots A_{in}=\emptyset} m_1(A_{i1})m_2(A_{i2})\ldots m_n(A_{in}) \tag{3.5}$$

According to (3.2)–(3.5), combination rule meets the law of commutation and the law of association [4]. Although the evidence combination can be realized by the above formula, an error combination result always follows when a piece of evidence is not supported by the others. To overcome the shortage, smaller weight is assigned to conflicting evidence, and the determination of evidence weight is mainly realized by similarity calculation and Ambiguity Measure.

3.2. Similarity of evidence

Similarity represents the degree of homogeneity among evidence, which is contrary to the distance of evidence. Based on characters of evidence distance [39], similarity of evidence should satisfy the following conditions:

1. Mapping the difference between the evidence into a value between 0 and 1 where 0 stands for a totally different, and the 1 represents a completely agreement.
2. The parameters should be unordered: $sim(m_1, m_2) = sim(m_2, m_1)$.
3. $sim(m_1, m_2) + sim(m_2, m_3)$ should be larger than $sim(m_1, m_3)$ to keep the value range compact.

Based on the conditions above, many scholars proposed their similarity calculation methods. Method proposed by Wang [32] and method proposed by Wen [40] are two methods which are most widely used. Compared with similarity calculation method proposed by Wang. Similarity method proposed by Wen is faster in calculation, but the number of elements in each focal-element is ignored. Similarity of evidence used in this paper is method proposed by Wang which is defined as:

Definition 1 (*Evidence Similarity*)**.** Assuming m_i and m_j are two BOEs under a same discernment frame. The similarity between m_1 and m_2 is:

$$sim(m_i, m_j) = 1 - d_{i,j} = 1 - \sqrt{\frac{1}{2}(\vec{m}_i - \vec{m}_j)^T D(\vec{m}_i - \vec{m}_j)} \tag{3.6}$$

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