A NOVEL DATA FUSION APPROACH USING TWO-LAYER CONFLICT SOLVING

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ABSTRACT

A Two-Layer Conflict Solving data fusion approach is proposed in this work, with an aim to provide another approach to data fusion community. Since the evidence of Dempster-Shafer Theory, algorithms for combining pieces of evidence have drawn a considerable attention from data fusion researchers, along with many alternatives invented. However, none of these approaches receive an agreement for being able to perform very successfully in all scenarios and hence this topic is still in hot discussion. Therefore, the suggested approach in this work will contribute as a novel method and present its own merits.

***Index Terms*—** Conflict solving, data fusion, Dempster-Shafer theory, counter-intuitive results.

1. INTRODUCTION

Data fusion has found more and more applications recently, ranging from fault diagnosis [1], [2], to military defence [3] and so on. Data fusion deals with data which is received from sensors, experts or human linguistic words, etc. Furthermore, much of such knowledge is cognitive and imprecise (incomplete) in some degree. To deal with uncertain knowledge, researchers often use Dempster-Shafer theory (DST) [4], [5] and [6], because it is capable of managing uncertainty due to its framework. DST acts as the pioneer in data fusion algorithms, which was proposed by Dempster and extended by Shafer subsequently. However, data which is received from sensor or from cognitive knowledge can lead to counter-intuitive results if one of the sensors returns bad measurements or cognitive knowledge tends to be unreliable. (Sensors can also be mentioned as experts and vice versa.) This inherent defect pointed out by Zadeh [7], [8] brings criticism as well as many other alternatives invented. For instance, Campos' rule [9] and Dezert Smarandache theory (DSmT) [10], [11] are addressed recently with new insights into data fusion approaches. No matter DST or other ad-hoc rules, none of them have been regarded as a superior method to any other. In this research, a Two-Layer Conflict Solving (TLCS) data fusion approach is aimed at contributing a new fusion algorithm. However, it is necessary to address DST and some alternative rules before introducing TLCS.

1.1. Dempster-Shafer Theory

Serving as a seminal fusion approach, DST stirs up many discussions and studies in data fusion. DST is actually a mathematic theory of evidence, which combines independent sources of information [4], [5] and [6]. By the combination of evidence sources obtained from sensors (experts), more reliable and convincing fusion results are expected afterwards.

First a finite frame of discernments that forms a set Ω should be defined, $\Omega = \{\Psi_1, \Psi_2, \Psi_3, ..., \Psi_n\}$. A power set $\Theta = 2^\Omega$ includes all the possible combinations of propositions (Ψ). Propositions are regarded to be mutually exclusive and exhaustive.

A function m: $2^\Omega \rightarrow [0, 1]$, is called a mass function, also known as *Basic Probability Assignment* (*BPA*).

$$m(\emptyset) = 0, \quad \sum_{A \subseteq \Theta} m(A) = 1. \tag{1}$$

If there is no element in the *BPA*, then the mass is zero. On the other hand, Θ is a power set composed of all the subsets, so that the sum of all the masses must be one. Furthermore, the focal element (mass is larger than zero) is defined as:

$$\{(A, m(A)) \mid A \subseteq \Theta,\ m(A) > 0\}. \tag{2}$$

Belief (*Bel*) and plausibility function (*Pl*) are essential concepts in DST, which are used in decision-making.

$$Bel(A) = \sum_{B \subseteq A} m(B). \tag{3}$$

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$$Pl(A) = \sum_{B \cap A \neq \varnothing} m(B). \tag{4}$$

Bel is called lower bound probability, while *Pl* is the upper bound probability, for the reason that *Bel* is the probability "must be" and on the other hand *Pl* is the probability "might be". Therefore, *Pl* includes more mass than *Bel*, which is illustrated in the following figure.

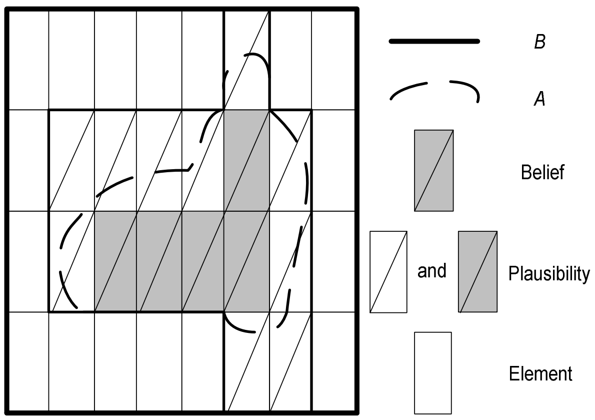

FIGURE 1: Belief and Plausibility. (*B*, *A* in Eq. (3) and Eq. (4))

From Figure 1, one can see that the shaded area (Belief) is smaller than the line noted rectangular area (Plausibility), which also reveals the fact of Eq. (5).

$$Bel(A) \leq Pl(A). \tag{5}$$

After obtaining the above-mentioned concepts, we are able to use DST to fuse independent data sources. And it takes the form:

$$\oplus_{i=1}^{n} m_i(A) = K \sum_{A_1 \cap \ldots \cap A_n = A} \prod_{i=1}^{n} m_i(A_i), \tag{6}$$

$\sum_{A_1 \cap \ldots \cap A_n = A} \prod_{i=1}^{n} m_i(A_i)$ aggregates the consonant opinions (non-conflicting parts) from sensors and then multiplying with K,

$$\text{where, } K = \frac{1}{1-k_c}, \tag{7}$$

$$\text{and } k_c = \sum_{A_1 \cap \ldots \cap A_n = \varnothing} \prod_{i=1}^{n} m_i(A_i). \tag{8}$$

($m_i(A_i)$: means the mass of propositions from sensor i.)

According to the definition of k_c, it calculates the empty intersection of the propositions of all sensors, hence it is also called conflicting coefficient.

1.2. Alternative Rules

After the invention of DST, especially the inherent defect resides in it [7], [8] many other researchers have proposed their own data fusion approaches which serve as ad-hoc alternatives. For example, Murphy's rule [14] is a trade-off rule, which takes the arithmetic average value of two masses. Yager's rule [15] regards that the universal set Θ should include the mass from the conflicting parts, so that the universal set (set with all propositions) is always introduced in Yager's rule. DSmT is a rather comprehensive theory thus referred to [10], [11].

- Murphy's rule

$$m_M(A) = \frac{m_1(A) + m_2(A)}{2}. \tag{9}$$

- Yager's rule

$$m_Y(C) = \sum_{A,B \in 2^{\Theta}, A \cap B = C} m_1(A) m_2(B),$$

$$m_Y(\Theta) = m_1(\Theta) m_2(\Theta) + \sum_{A,B \in 2^{\Theta}, A \cap B = \varnothing} m_1(A) m_2(B). \tag{10}$$

- Campos's rule

$$m_C(A_i) = \frac{DST}{1 + \log\left(\dfrac{1}{1 - \sum_{A_1 \cap \ldots \cap A_n = \varnothing} \prod_{i=1}^{n} m_i(A_i)}\right)}, \tag{11}$$

(log: logarithm to the base 10)

$$m_C(\Theta) = \sum m_i(\Theta) + 1 - \sum_{A \subset \Theta, A \neq \varnothing} m_C(A_i).$$

Campos' rule is recently addressed and explained in [9], in which DST is divided by another coefficient. In addition, the conflicting mass is transferred to $m(\Theta)$.

2. TWO-LAYER CONFLICT SOLVING

Because of the counter-intuitive results of DST [7], [8] and other alternatives have limited assistance as remedies, thus a *Two-Layer Conflict Solving* (TLCS) data fusion approach is suggested, which includes two layers to combine pieces of evidence. (Conflict is solved in some degree during combination, so that it is named as conflict solving). The first layer resolves the conflict in some extent, then the second one continues to solve it and hence achieves better results. Psychologically, as clearly stated in [12] 'Decision making has been traditionally studied at three levels: individual, group and organizational.' (Further refer to [13]). This equals to say that decision is made at three layers, in which conflict is unavoidable to be considered and solved: individual is the basic element that holds conflict; group has a larger range which includes conflict while organization is the largest. In such a way, people believe that conflict can be optimally solved, although it is impossible to totally eliminate its negative impacts. Therefore, a TLCS data fusion algorithm is suggested and studied in this work. It could become three layers if several groups of sensors are considered in a larger system. The figure below depicts the scheme of TLCS.

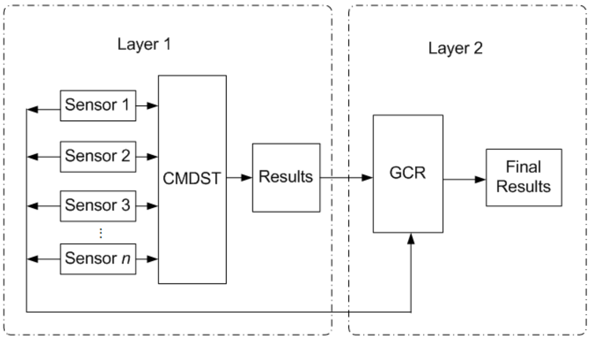

FIGURE 2: Two-layer conflict solving system.

In Figure 2, layer 1 is regarded as working at the individual level because *Conflict Modified Dempster-Shafer theory* (CMDST) is an approach which combines every two sensors' data so that conflict is sort of considered and solved between individuals. After receiving the results from the previous layer, layer 2 collects sensors' original knowledge and fuses them with combined results from CMDST, hence conflict is further resolved at a group level. The following section introduces the first layer, i.e. CMDST.

2.1. CMDST

Based on the idea of DST, CMDST calculates the conflict in a different manner as shown in the formula (cf. Figure 3):

$$k_{\text{cm}} = \sum_{\substack{A_1 \cap A_2 = \varnothing, A_1 \cap A_3 = \varnothing, \cdots, \\ A_1 \cap A_n = \varnothing, \cdots, A_{n-1} \cap A_n = \varnothing}} \prod_{i=1}^{n} m_i(A_i). \tag{12}$$

Within this definition, conflicts are calculated between every two sensors instead of all the sensors together (which is used in DST), this difference can be seen from the condition of summation in Eq. (8) ($A_1 \cap \ldots \cap A_n = \varnothing$) and Eq. (12) ($A_1 \cap A_2 = \varnothing, A_1 \cap A_3 = \varnothing, \cdots, A_1 \cap A_n = \varnothing, \cdots, A_{n-1} \cap A_n = \varnothing$).

Due to the specified way of determining conflicts in Eq. (12), this kind of conflict will very likely be larger than one, whereas in DST the denominator is ($1-k_c$), hence the denominator in DST should be modified as well. First of all, the denominator is modified as:

$$\binom{n}{2} - k_{\text{cm}} = \binom{n}{2} - \sum_{\substack{A_1 \cap A_2 = \varnothing, A_1 \cap A_3 = \varnothing \\ , \cdots, A_1 \cap A_n = \varnothing, \cdots, \\ A_{n-1} \cap A_n = \varnothing}} \prod_{i=1}^{n} m_i(A_i), \tag{13}$$

$$where, \binom{n}{2} = \frac{n!}{2!(n-2)!}. \tag{14}$$

Below is the graphic illustration of DST and CMDST with respect to difference in conflict calculation.

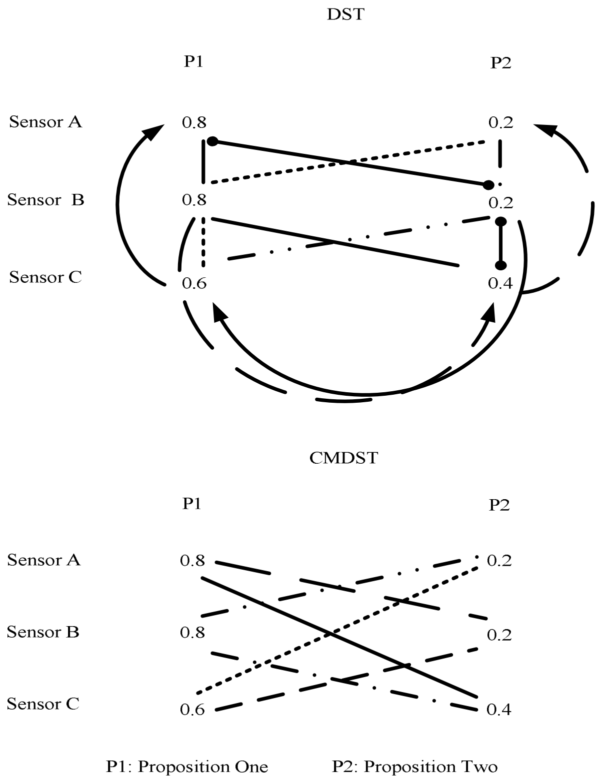

FIGURE 3: Conflict calculation in DST and CMDST.

In Figure 3, conflict in DST associates three sensors together. The same line always connects three sensors in DST, while it connects only two sensors in CMDST. For example, in DST, one pair of conflict is:

$$A(P1)\cdot B(P2)\cdot C(P2) = 0.8\cdot 0.2\cdot 0.4 = 0.064.$$

As for CMDST, this pair of conflict is decomposed into two parts as:

$$A(P1)\cdot B(P2) + A(P1)\cdot C(P2) = 0.8\cdot 0.2 + 0.8\cdot 0.4 = 0.48.$$

Other pairs of conflict can be determined likewise. It can be readily seen that the total conflict in CMDST is likely to be larger than one, so that Eq. (13) is chosen.

In Eq. (13), the reason for choosing $\binom{n}{2}$ (binomial coefficient) is that there are $\binom{n}{2}$ possible combinations for calculating conflicts (n is the number of sensors). Thus, K_{cm} (K in DST) is:

$$K_{cm} = \frac{1}{\binom{n}{2} - \sum\limits_{\substack{A_1\cap A_2=\varnothing, A_1\cap A_3=\varnothing,\cdots,\\ A_1\cap A_n=\varnothing,\cdots, A_{n-1}\cap A_n=\varnothing}} \prod_{i=1}^{n} m_i(A_i)}. \quad (15)$$

Finally, CMDST is formed as:

$$\oplus_{i=1}^{n} m_i(A) = K_{cm} \sum_{\substack{A_1\cap A_2=A, A_1\cap A_3=A\\ ,\cdots, A_1\cap A_n=A,\cdots,\\ A_{n-1}\cap A_n=A}} \prod_{i=1}^{n} m_i(A_i). \quad (16)$$

2.2. Group Conflict Redistribution

As stated in [12] and [13], decision making is also studied in a group level. Hence, Group Conflict Redistribution (GCR, layer 2 in Figure 1) acts as group conflict solving strategy, solving conflict in a larger extent compared to individual level (CMDST). Distinguishing from layer 1 (CMDST), GCR combines sensors' propositions in a group manner which means all sensors shall participate in this procedure.

$$m(A) = \frac{\sum\limits_{A_1\cap\ldots\cap A_n=A} m_i(A_i) + (\binom{n}{2} + \left|\log(\binom{n}{2} - k_{cm})\right|)\cdot CMDST(A)}{n + \binom{n}{2} + \left|\log(\binom{n}{2} - k_{cm})\right|}. \quad (17)$$

(n: number of sensors; log: logarithm to the base 10; $|\ \ |$: absolute value sign.) In Eq. (17), the denominator includes the number of sensors n and how many possible combinations ($\binom{n}{2}$) among sensors as well as conflict evaluation term $\left|\log(\binom{n}{2} - k_{cm})\right|$. In the numerator part, sensors' original propositions $\sum\limits_{A_1\cap\ldots\cap A_n=A} m_i(A_i)$ are calculated with corresponding CMDST results which are obtained from layer 1. Finally, the sum of final fused results remains '1'.

2.3. Numerical Examples

To show the effect of TLCS, a numerical example is given. Suppose there are five sensors predicting tomorrow's weather.

TABLE 1: Five sensors' propositions in weather.

	Sunny	*Rainy*	*Stormy*
Sensor A	0.99	0.01	0
Sensor B	0	0.01	0.99
Sensor C	0.99	0.01	0
Sensor D	0.7	0.2	0.1
Sensor E	0.65	0.25	0.1

In Table 1, one can readily observe that '*Sunny*' is strongly emphasized by these sensors except sensor B. Table 2 presents the combined results using DST, Murphy, Yager, Campos and TLCS accordingly.

2.3.1. Results and Discussions

In Table 2, DST always shows '0' (counter-intuitive results) for '*Sunny*' because sensor B assigns '0' to it. In Campos' and Yager's rule, $m(\Theta)$ (represents ambiguity or ignorance) achieves a large number, since there is a high conflict among sensors. Murphy's rule prefers '*Sunny*' when more sensors are introduced.

As for TLCS, it does not provide counter-intuitive results, even sensor B assigns '0' to '*Sunny*' and presents close to real situation conclusions. It could be ascribed to the use of two layers to solve conflict, in which sensors' disagreement with each other is considerably resolved.

3. CONCLUSIONS

DST presents undesirable results if one of the sensors has ill-proposed data. Other alternative rules either take a trade-off strategy or transfer high conflict to universal set (Θ), which leads the results more uncertain to decision makers.

The suggested TLCS decomposes solving of conflict in two layers, namely in two levels (individual and group). Each of them plays its own role in solving conflict. Cooperation of these two levels avoids counter-intuitive results and presents reliable ones. Therefore, TLCS is proposed as a novel algorithm in data fusion.

TABLE 2: Combined results by different rules. $(m(S):m(Sunny);\, m(R):m(Rainy);\, m(St):m(Stormy);\, m(\Theta):m(R\cup S\cup St))$

	A, B	A, B, C	A, B, C, D	A, B, C, D, E
DST	$m(S)=0$ $m(R)=1$ $m(St)=0$	$m(S)=0$ $m(R)=1$ $m(St)=0$	$m(S)=0$ $m(R)=1$ $m(St)=0$	$m(S)=0$ $m(R)=1$ $m(St)=0$
Murphy	$m(S)=0.495$ $m(R)=0.01$ $m(St)=0.495$	$m(S)=0.66$ $m(R)=0.01$ $m(St)=0.33$	$m(S)=0.67$ $m(R)=0.056$ $m(St)=0.274$	$m(S)=0.666$ $m(R)=0.096$ $m(St)=0.238$
Yager	$m(S)=0$ $m(R)=0.0001$ $m(St)=0$ $m(\Theta)=0.9999$	$m(S)=0$ $m(R)=0.000001$ $m(St)=0$ $m(\Theta)=0.999999$	$m(S)=0$ $m(R)=0$ $m(St)=0$ $m(\Theta)=1$	$m(S)=0$ $m(R)=0$ $m(St)=0$ $m(\Theta)=1$
Campos	$m(S)=0$ $m(R)=0.2$ $m(St)=0$ $m(\Theta)=0.8$	$m(S)=0$ $m(R)=0.14$ $m(St)=0$ $m(\Theta)=0.86$	$m(S)=0$ $m(R)=0.13$ $m(St)=0$ $m(\Theta)=0.87$	$m(S)=0$ $m(R)=0.12$ $m(St)=0$ $m(\Theta)=0.88$
TLCS	$m(S)=0.14$ $m(R)=0.72$ $m(St)=0.14$	$m(S)=0.82$ $m(R)=0.005$ $m(St)=0.165$	$m(S)=0.85$ $m(R)=0.02$ $m(St)=0.13$	$m(S)=0.85$ $m(R)=0.04$ $m(St)=0.11$

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