# Improved Dempster-Shafer Sensor Fusion using Distance Function and Evidence Weighted Penalty: Application in Object Detection

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Abstract: Dempster-Shafer (DS) combination method can deal with the uncertainty and inconsistency of multi-sensor data fusion and widely used in data fusion, fault detection, pattern recognition, and supplier selection. The original DS theory has limitations such as its inability to handle conflicting data properly which can result into inaccuracy in the output of a multi-sensor data fusion process. To eliminate such limitations of the original DS theory, a novel method is proposed in this paper that uses distance function to measure the credibility of each sensor and uses weighted penalty of faulty sensor evidence to create maximum evidence for the correct detection. A detailed example for object detection with conflicting sensor input is presented which showcases all the steps of the proposed method. A numerical simulation is used to show that the proposed method effectively eliminates the limitations of original DS combination rule and offers an improvement over the current state-of-the-art models.

## 1 INTRODUCTION

In 1960's Arthur P. Dempster introduced a new concept – 'upper and lower probabilities' (Dempster, 2008) which included uncertainty in probability. Later in 1970's Shafer renamed upper and lower probabilities to degree of belief and renamed the theory "Mathematical theory of evidence" (Shafer, 1976). Which is currently known as Dempster-Shafer (DS) theory of evidence. Fundamental to DS theory is the representation of uncertain knowledge in the form of Basic Probability Assignment (BPA). The direct consequence is that, while the actual probability of an individual state may be unknown, it's minimum and maximum values are specified. The belief in the 'unknown' state reflects the weakness of the knowledge. It is considered as generalizations of Bayes theory as probabilities/mass are assigned to multiple possible events as opposed to mutually exclusive singletons in Bayes. Within the framework of DS theory information obtained from multiple sources are represented by degree of belief/mass function. Then they are fused using Dempster's rule of combination. Hence, DS theory is a multi-source data fusion technique to capture more reliable single output combining several input source (Hafeez, 2011). DS information fusion theory has been applied in pattern recognition (Denoeux, 1995; Ma et al., 2016; Denoeux, 2000), decision making and classification (Hafeez, 2011; Deng and Jiang, 2018; Luo, 1993; Bastière, 1998; Beynon et al., 2000), optimization (Chen and Rao, 1998; Kang et al., 2018), risk and fault detection (Jiang et al., 2016a; Xiao, 2017), quality measurement/supplier selection (Sadiq and Rodriguez, 2005; Liu et al., 2018).

A multi-sensor system has two distinct advantages over a single sensor system when used with proper fusion algorithm:

1. A single sensor may provide faulty, erroneous results and there is no way to modify that other than changing the sensor. A multi-sensor system provides results with diverse accuracy. With the help of proper fusion algorithm faulty sensor can be easily detected.
2. Multi-sensor system receives information with wide variety and characteristics. Thus, it helps to create a more robust system with less interference.

But to use DS sensor fusion algorithm for robust application, we have to overcome the fuse paradox presented by Zadeh (Zadeh, 1986). Existing modified methods are divided mainly into three categories:

1. Method 1: Modification of combination equations in DS theory.



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2. Method 2: Revision of original evidence before combination.
3. Method 3: Hybrid technique combining both modification of DS rule and original evidence.

Method 1: Smet's rule (Smets, 2000) is essentially the Dempster rule applied in Smets' Transferable Belief Model. Smet believed that conflict is caused by incompleteness of frame of discernment. So Smet moved mass of conflict directly to empty set as an unknown proposition. In Yager's rule (Yager, 1987), the mass associated with conflict is directly given to universal set, which enlarges the degree of ignorance. Yager's rule provide the same results when conflict is zero. Although these two methods solve the conflict situation theoretically, the uncertainty of the system still exists. Bicheng et al. (Li et al., 2001) modified Yager's rule and conflicting probability of the evidences are distributed to every proposition based on average support. Inagaki (Inagaki, 1991) defined a continuous parametrized class of combination operations which subsumes both Dempster's rule and Yager's rule. Zhang (Zhang, 1994) pointed out that DS rule fails to take into account the focal element intersection. He presented the 'two-frame' representation of DS theory where he measures focal element intersections based on cardinality. But all these methods sometimes violate the theoretical properties of DS combination rule like commutativity and associativity.

Method 2: Chen et al. (Chen et al., 2013) used triangular functions to set a fuzzy model for each sensor. Assuming each sensor output is gaussian, BPA was determined from the sensor outputs using the fuzzy model. Then the raw BPA was weighted using the credibility of each BPA before fusing. Sun (Sun et al., 2013) also used fuzzy membership function to convert sensor value to fuzzy value. Support degree was calculated using an error distance function. If sensor output is not gaussian, then fuzzy set methods can't be applied. Instead of distance function, an entropy function (Deng entropy (Deng, 2015)) was used to calculate the credibility of evidence in (Jiang et al., 2016a). This was inspired by Murphy's method (Murphy, 1998), which used an average of BPAs. Murphy's method had first convergence rate but failed to consider the relation between focal elements. Jiang (Jiang et al., 2016b) used an entropy function to measure the weight of the evidence to modify them before applying to DS rule. Later Xiao (Xiao, 2018) applied belief divergence to measure the credibility of evidence, which increased the fusion results slightly. Murphy's method is the simplest to implement and most of the methods within this type is inspired by his method. Most of the other methods are over complicated compared to Murphy's and may not always be useful for real time application. But they do not modify the original DS combination rule and the commutative and associative properties remain intact.

Method 3: Through the comparison between two kinds of conflict resolutions, it is easy to see the underlying logic of two methods. Method 1 cancel the normalization step in DS theory and redistribute the conflict with different measure. Method 2 consider the essential differences propositions of each sensor in multi-sensor systems and solve the conflict by modifying the original evidence. If method 1 and 2 is combined, then the inherent paradoxes of DS rule are solved. Building on this idea, Lin (Lin et al., 2016) and Ye Fang (Ye et al., 2017; Ye et al., 2018) published several new improvements of original DS combination rule. They improve the fusion results but often too complicated and over-engineered to apply for real-time use. These methods also loose commutative and associative properties of DS rule. Also, the amount of improvement of fused results may not be necessary for some specific application.

In this paper, we propose a novel combination method to solve the fusion of multi-sensor conflicting information by using credibility transformation which measures credibility from sensor data and also considers operator 'experience'. We firstly revised the original evidence of each sensor by multiplying it with sensor accuracy. Sensor accuracy can be implemented using operator's extensive knowledge of the system or to optimize the correct fused result. Then we revise the original evidence separately by the introduction of Euclidean distance function. This distance function creates credibility for each sensor which redistributes the conflicting mass. After the redistribution of conflicting information, the multi-sensor system obtains an accurate and effective fusion result.

## 2 THEORETICAL BACKGROUND

### 2.1 Frame of Discernment

The frame of discernment contains M mutually exclusive and exhaustive hypotheses:

$$\Theta = \{\theta_1, \theta_2, ....., \theta_M\} \tag{1}$$

The representation of uncertainties in the DS theory is similar to that in conventional probability theory and involves assigning probabilities to the space $\Theta$. However, the DS theory has one significant new feature: it allows the probability to be assigned to subsets of $\Theta$

as well as the individual element $\theta_i$. Accordingly, we can derive the power set $2^{\theta}$ of DS theory:

$$2^{\theta} = \{\phi, \{\theta_1\}, \{\theta_2\}, ....., \{\theta_1, \theta_M\}, \Theta\} \quad (2)$$

Where $\phi$ is empty set. It is clearly seen in (2) that the power set $2^{\theta}$ has $2^M$ propositions. Any subset except singleton of possible values means their union, for example, $\{\theta_1, \theta_2, \theta_3\} = \theta_1 \cup \theta_2 \cup \theta 3$. Complete probability assignment to power set is called basic probability assignment (BPA).

## 2.2 Basic Probability Assignment (BPA) / Mass Function

Evidences in DS theory are acquired by multi-sensor information. Mass function (mass) is a function, $m = 2^{\Theta} \rightarrow [0,1]$ that satisfies (3) and (4):

$$m(\phi) = 0 \quad (3)$$

$$\sum[m(\theta) \forall \theta \in 2^{\Theta}] = 1 \quad (4)$$

Elements of power set having $m(\theta) > 0$ is called focal elements. This can be explained with the help of simple example: Let the three objects to be detected be, $\Theta = \{a, b, c\}$. Powerset $2^{\Theta} = 2^3 = \{\phi, a, b, c, \{a, b\}, \{a, c\}, \{b, c\}, \{a, b, c\}\}$.

Example, from a sensor or by an expert following mass values are assigned, m(a) = 0.2, m(b) = 0.3, m(a,b) = 0.4, m(a,b,c) = 0.1. The above four subsets are called focal elements.

## 2.3 Dempster-Shafer Rule of Combination

The purpose of data fusion is to summarize and simplify information rationally obtained from independent and multiple sources. It emphasizes on the agreement between multiple sources and ignores all the conflicting evidence through normalization. the DS combination rule of two evidences $m_1$ and $m_2$ is defined:

$$m_{1-2}(A) = \frac{\sum_{B \bigcap C = A}\{m_1(B).m_1(C)\}}{1-K} \quad (5)$$

$$K = \sum_{B \bigcap C = \phi}\{m_1(B).m_1(C)\} \quad (6)$$

when A $\neq \phi$ and $m(\phi) = 0$ and K is the degree of conflict in two sources of evidences.

The denominator (1-K) is a normalization factor, which helps aggregation by completely ignoring the conflicting evidence and is calculated by adding up the products of BPA's of all sets where intersection is null. DS combination rule in (5) conforms to both commutative law and associate law.

# 3 PROPOSED IMPROVEMENT TO DS COMBINATION RULE VIA EVIDENCE-BASED SENSOR FUSION IN OBJECT DETECTION

We present the proposed improvement of the DS combination rule using a specific example. Here we want to detect three different kinds of weed (Ragweed, Pigweed and Cocklebur), which are very common in corn fields. But the improved theory can be applied to other detection level sensor fusions as well. The sensors used in detecting the weeds are:

**3D Lidar:** It provides very accurate 3D point cloud of surrounding. Weeds can be scanned as a 3D point cloud data. Scanned point cloud data could be used to train a neural-network to detect the weeds using real-time scans. But this process is computationally very expensive as the hardware must process a huge amount of 3D point cloud data in in real-time.

**2D Lidar, Radar, Ultrasonic:** A 2D lidar provides a scan of a plane which can be used to detect width/height of a specific object. Radar provides distance of an object as a state vector. Ultrasonic sensors provide distance of an object but with a shorter range than Radar. All of the above-mentioned sensors provide useful information if the objects we want to detect have different shape/size and speed. Cars and trucks have different shape. Cars and pedestrian/bicycle have different speeds. These sensors will provide useful information for autonomous vehicle application. Weeds on the other hand are mostly of same size and shape (other than very intricate differences in leaf shape) and stationary. Thus these sensors less likely to provide useful information for weed detection.

**RGB Camera:** Weed images can be used to train a deep neural-network to detect weeds with a reasonable accuracy. Different positioning of cameras can discern certain distinct shapes of weed leaves. These cameras are inexpensive and their accuracy is measurable.

**RGB-D Camera:** Depth information can provide additional features to increase detection accuracy. They are reasonably cheap and accuracy is measurable. How well they work on outside environment depends on hardware quality. We therefore will focus on the RGB or RGB-D cameras as the sensor of choice for this application.

## 3.1 Improved Dempster-Shafer Rule of Combination

Problem statement: Let's assume, we have set up 3 sensors to detect weed from real time video feed. Sensor 1 and 2 are RGB camera and Sensor 3 is RGB-D camera. We consider the following detection for a specific frame from continuous video feed:

Table 1: Sensor output of detected weed.

| sensors | Ragweed | Pigweed | Cocklebur |
|---|---|---|---|
| sensor 1: $m_1$ | 0.7 | 0.2 | 0.1 |
| sensor 2: $m_2$ | 0.05 | 0.9 | 0.05 |
| sensor 3: $m_3$ | 0.8 | 0.1 | 0.1 |

If evidences agreed with one another, then we could have used the original DS rule to combine these evidences. But here sensor 2 is clearly at fault as it is disagreeing with sensor 1 and 3 for Ragweed.

Solution: This could have been solved using the methods in section 1. But method 1 (modification of combination equations in DS theory) and method 3 (hybrid technique combining both modification of DS rule and original evidence) both loses the associative and commutative property of DS combination rule. We argue that keeping these two properties are more important than getting a slight improvement in accuracy in fused results. These two properties will help to keep the overall hardware system modular (plug and play). We would be able to plug in new sensors or remove faulty sensors without changing anything major in software. We propose the following method to improve the original DS rule for conflicting information.

**Step 1:** Build a multi sensor information matrix.

$$M = \begin{pmatrix} m_1(H_1) & m_1(H_2) & \cdots & m_1(H_M) \\ m_2(H_1) & m_2(H_2) & \cdots & m_2(H_M) \\ \vdots & \vdots & \ddots & \vdots \\ m_N(H_1) & m_N(H_2) & \cdots & m_N(H_M) \end{pmatrix}$$

$$= \begin{bmatrix} 0.7 & 0.2 & 0.1 \\ 0.05 & 0.9 & 0.05 \\ 0.8 & 0.1 & 0.1 \end{bmatrix}$$

**Step 2:** Penalize weighted evidence. One of the advantages of DS rule is to express domain knowledge as credibility factor. We can penalize the weight of evidence of the faulty sensor to maximize correct fused result. Evidence should be adjusted according to their credibility following this formula:

$m(A)_{adjusted} = m(A) * \alpha$

$\alpha$ = evidence weight of each sensor

For the following calculations we assume $\alpha$ = 1 for all three sensors.

**Step 3:** Measure the relative distance between evidences. Several distance function can be used to measure the relative distance. They all have their own advantages and disadvantages regarding runtime and accuracy (Chen et al., 2017). We have used Euclidean distance function:

$$D(m_i, m_j) = \sqrt{\sum_{t=1}^{M} \left| m_i(H_t) - m_j(H_t) \right|^2}$$

$$= \begin{bmatrix} d(m_1,m_1) & d(m_1,m_2) & d(m_1,m_3) \\ d(m_2,m_1) & d(m_2,m_2) & d(m_2,m_3) \\ d(m_3,m_1) & d(m_3,m_2) & d(m_3,m_3) \end{bmatrix}$$

$$= \begin{bmatrix} 0 & 0.9565 & 0.1414 \\ 0.9565 & 0 & 0.7511 \\ 0.1414 & 0.7511 & 0 \end{bmatrix}$$

$d(m_1, m_2) = \sqrt{(}|0.7–0.05|^2 + |0.2–0.9|^2 + |0.1–0.05|^2) = 0.9565$

Because sensor 2 disagrees with sensor 1 and 3, $d(m_1, m_2)$ and $d(m_2, m_3)$ is larger than $d(m_1, m_3)$.

**Step 4:** Create similarity matrix.

$sim(m_i, m_j) = I - D(m_i, m_j)$

$$= \begin{bmatrix} 1 & 0.0435 & 0.8586 \\ 0.0435 & 1 & 0.2489 \\ 0.8586 & 0.2489 & 1 \end{bmatrix}$$

**Step 5:** Create Supplementary matrix or vector.

$$sup(m_i, m_j) = \sum_{j=1 and j \neq i}^{N} sim(m_i, m_j) = \begin{bmatrix} 0.9021 \\ 0.2924 \\ 1.1075 \end{bmatrix}$$

**Step 6:** Create credibility matrix or vector.

$$crd(m_i) = \frac{sup(m_i)}{\sum_{i=1}^{N} sup(m_i)} = \begin{bmatrix} 0.3919 \\ 0.127 \\ 0.4811 \end{bmatrix}$$

Here, sensor 2 has the lowest credibility. Between sensor 1 and 3, sensor 3 showed higher evidence for

Ragweed (which is true detection). As a result, sensor 3 has higher credibility than sensor 1.

**Step 7:** Modify the original evidence.

$m(A) = \sum_{i=1}^{N} m_i(A).crd(m_i)$

m{Ragweed} = 0.7 * 0.3919 + 0.05 * 0.127 + 0.8 * 0.4811 = 0.6655

m{Pigweed} = 0.2 * 0.3919 + 0.9 * 0.127 + 0.1 * 0.4811 = 0.2419

m{Cocklebur} = 0.1 * 0.3919 + 0.05 * 0.127 + 0.1 * 0.4811 = 0.0943

After normalizing,

m{Ragweed} = 0.6644

m{Pigweed} = 0.2415

m{Cocklebur} = 0.0941

Table 2: Modified evidence.

| sensors | Ragweed | Pigweed | Cocklebur |
|---|---|---|---|
| sensor 1: $m_1$ | 0.6644 | 0.2415 | 0.0941 |
| sensor 2: $m_2$ | 0.6644 | 0.2415 | 0.0941 |
| sensor 3: $m_3$ | 0.6644 | 0.2415 | 0.0941 |

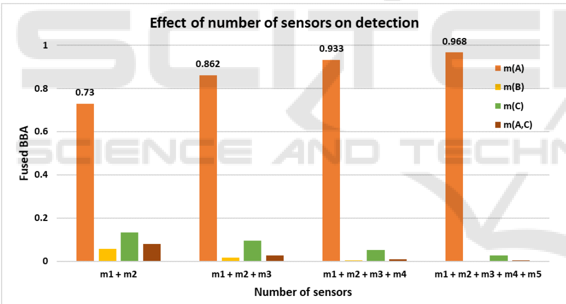


Figure 1: Increasing the number of sensors increases fused detection accuracy (m(A)).

Fusing the evidences of 3 sensors (from table 4):

$m_{123}(Ragweed) = 0.5796/0.6064 = 0.9506$

$m_{123}(Pigweed) = 0.0276/0.6064 = 0.0455$

$m_{123}(Cocklebur) = 0.0016/0.6064 = 0.0026$

Clearly the proposed method overcomes the inherent paradoxes of original DS rule and detected Ragweed with 95.06 % accuracy after fusing the results. On the other hand, if we have used the original evidences, the results would have been:

$m_{123}(Ragweed)_{original} = 0.59$

$m_{123}(Pigweed)_{original} = 0.38$

$m_{123}(Cocklebur)_{original} = 0.03$

Which provides higher confidence on pigweed.

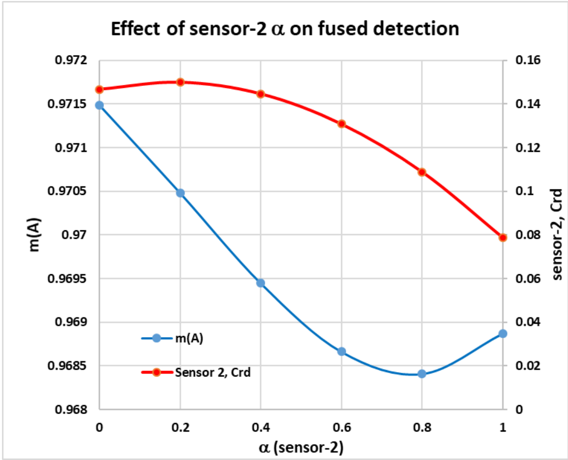


Figure 2: Effect of sensor 2 evidence weight (α) value on fused detection accuracy (m(A)) and credibility (step 6: crd($m_i$)).

## 4 SIMULATION RESULTS AND ANALYSIS

The following example is used to further analyze and compare the proposed method. Let us consider a multi-sensor-based target recognition problem associated with the sensor reports that are collected from five different types of sensors. These sensor reports which are modeled as the BBAs are given in Table 5 (Xiao, 2019), where the frame of discernment $\Theta$ that consists of three potential objects is given by $\Theta = \{A, B, C\}$. Last column of Table 5 also contains the credibility values of each sensor from step 6 of proposed method. Sensors are providing conflicting information. A is the correctly detected object, m(A) should have the highest value after fusion. Sensor 2 (evidence $m_2$) is providing conflicting information with respect to other 4 sensors. Mass value $m_2(A)$ is zero for sensor 2.

Figure 1. shows how evidence of A, m(A) increased with increasing number of sensors. It is interesting to see that fused result of m1 $\oplus$ $m_2$ providing high evidence of A. This shows the underlying mechanism of the improved algorithm. Because original evidences are modified before applying fusion algorithm, conflicting sensor doesn't affect the final fused evidence at any stages of fusion. It also shows increasing the number of consistent sensors increases the possibility of correct detection. Figure 2. shows how the evidence weight (step 2: α) of the conflicting sensor (sensor 2) affects the overall fused result. The proposed algorithm calculates the credibility of a sensor (step 6: Crd) from its evidences, which is pre-

Table 3: Fusion of sensor 1 and 2 using Eq. (5) and (6).

| sensors | $m_1$(Rag) = 0.6644 | $m_1$ (Pig) = 0.2415 | $m_1$(Cockle) = 0.0941 |
|---|---|---|---|
| $m_2$(Rag) = 0.6644 | $m_{1-2}$(Rag) = 0.4414 | $m_{1-2}(\phi)$ = 0.1605 | $m_{1-2}(\phi)$ = 0.0625 |
| $m_2$(Pig) = 0.2415 | $m_{1-2}(\phi)$ = 0.1605 | $m_{1-2}$(Pig) = 0.0583 | $m_{1-2}(\phi)$ = 0.0227 |
| $m_2$(Cockle) = 0.0941 | $m_{1-2}(\phi)$ = 0.0625 | $m_{1-2}(\phi)$ = 0.0227 | $m_{1-2}(Cockle)$ = 0.0088 |
| K = $\sum\phi$ = 0.1605 + 0.0625 + 0.1605 + 0.0227 + .0625 + .0227 = 0.4914; 1 – K = 0.5086 | | | |

Table 4: Fusion of sensor 1, 2 and 3.

| sensors | $m_3$(Rag) = 0.6644 | $m_3$ (Pig) = 0.2415 | $m_3$(Cockle) = 0.0941 |
|---|---|---|---|
| $m_1 2$(Rag) = 0.8678 | $m_{1-2-3}$(Rag) = 0.5765 | $m_{1-2-3}(\phi)$ = 0.2095 | $m_{1-2-3}(\phi)$ = 0.0186 |
| $m_1 2$(Pig) = 0.1146 | $m_{1-2-3}(\phi)$ = 0.0761 | $m_{1-2-3}$(Pig) = 0.0276 | $m_{1-2-3}(\phi)$ = 0.0107 |
| $m_1 2$(Cockle) = 0.0173 | $m_{1-2-3}(\phi)$ = 0.0115 | $m_{1-2-3}(\phi)$ = 0.0042 | $m_{1-2-3}(Cockle)$ = 0.0016 |
| K = $\sum\phi$ =0.2095 + 0.0186 + 0.0761 + .0107 + .0115 + .0042 = 0.3936; 1 – K = 0.6064 | | | |

Table 5: The BBA for a multi-sensor object recognition.

| BBA | {A} | {B} | {C} | {A,C} | Credibility (step 6) |
|---|---|---|---|---|---|
| sensor 1: $m_1$ | 0.41 | 0.29 | 0.30 | 0 | 0.195 |
| sensor 2: $m_2$ | 0 | 0.9 | 0.1 | 0 | 0.078 |
| sensor 3: $m_3$ | 0.58 | 0.07 | 0 | 0.35 | 0.239 |
| sensor 4: $m_4$ | 0.55 | 0.1 | 0 | 0.35 | 0.243 |
| sensor 5: $m_5$ | 0.6 | 0.1 | 0 | 0.3 | 0.242 |

Table 6: Combination results of the evidences in terms of different combination rules.

| Methods | {A} | {B} | {C} | {A,C} |
|---|---|---|---|---|
| Dempster (Shafer, 1976) | 0 | 0.142 | 0.8578 | 0 |
| Murphy (Murphy, 1998) | 0.962 | 0.021 | 0.0138 | 0.0032 |
| Deng (Deng, 2015) | 0.982 | 0.0039 | 0.0107 | 0.0034 |
| Zhang (Zhang and Deng, 2017) | 0.982 | 0.0034 | 0.0115 | 0.0032 |
| Xiao (Xiao, 2019) | 0.9905 | 0.0002 | 0.0061 | 0.0043 |
| Proposed | 0.9715 | 0.0003 | 0.025 | 0.0031 |

sented at the final column of Table 5. If the sensor has conflicting evidence, the algorithm calculates lowest credibility of that sensor. But if we penalize the evidences of the conflicting sensor with a weight lower than 1, credibility of that sensor goes up. Because conflict of evidence goes down. As a result, as $\alpha$ goes down, Crd goes up for sensor 2 to a certain limit. In other words, by penalizing the evidences of the faulty sensor, we are decreasing the faulty evidence and increasing the sensor's credibility. Fused evidence $m_{12345}$(A) has the highest value for $\alpha = 0$. So, the algorithm will calculate highest evidence value of correctly detected object, when we set $\alpha = 0$ for the sensor with lowest credibility.

From Table 5, it can be observed that the evidence $m_2$ conflicts highly with other evidences. The fusion of the results are obtained by different combination approaches and are presented in Table 6. As shown in Table 6, Dempster's combination rule generates counterintuitive result and recognizes the object C as the target, even though the other four evidences support the target A. Whereas the methods proposed by Murphy, Deng, Zhang, Xiao and the proposed method present reasonable results and recognize the target A. The proposed method achieved better results compared to Dempster-Shafer and Murphy's method. Although the proposed method achieved slightly lower accuracy compared to Xiao, Deng and Zhang's method However, the proposed method is computationally less expensive and requires less steps when compared with these methods. The proposed method also successfully eliminates all the limitations of original DS method indicated by Zadeh.

# 5 CONCLUSIONS

Since conflicting information may occur in multi-sensor systems, robust multi-sensor fusion is needed to achieve reliable and accurate information in such a system. In this paper, a novel method for multi-sensor data fusion is proposed by considering both of the credibility degree between the evidences and penalizing the evidence of faulty sensor. The proposed method consists of two main rules. Firstly, an Euclidean distance was proposed to measure the distance between the bodies of the evidences; then, the credibility degree of the evidences is calculated. Secondly, a weighted evidence value is given to all the sensors. By assigning the evidence weight value to a small number to a sensor deemed less reliable (the sensor with lowest credibility), highest detection accuracy is achieved. Modified evidences are fused by applying the Dempster's combination rule. A detailed example for weed detection from an autonomous robot with conflicting sensor input is presented which showcases all the steps of the proposed method. A numerical simulation is used to show that the proposed method is comparably effective while offering a more computationally feasible algorithm than other related methods to handle the conflicting evidence combination problem under multi-sensor environment

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