Multi Sensor Data Fusion and Smart Decision Making Using Dempster-Shafer Theory: A Case Study

Angeline Frieda K¹, Johnsi Stella I²

¹,² St. Joseph's College of Engineering, Chennai, India

Abstract: Parallel distributed detection system consists of several separate sensor-detector nodes (separated spatially or by their principles of operation), each with some processing capabilities. These local sensor-detectors send some information on an observed phenomenon to a centrally located Data Fusion Center for aggregation and decision making. Several techniques are developed to combine data from sensor – detector nodes. This article focuses on heterogeneous sensor data fusion using Dempster-Shafer evidence theory, which is one of the most effective approaches for sensor data fusion. The Dempster – Shafer theory of evidence has uncertainty management and inference mechanisms analogous to our human reasoning process. This paper describes the use of Dempster-Shafer theory for multi sensor data fusion and demonstrates the easiness of using Dempster-Shafer engine for obtaining inference through a simple case study.

Keywords: Data fusion, Decision making, Dempster-Shafer theory, Dempster-Shafer engine

1. Introduction

Data Fusion is the process of combining information from several different sources pertaining to the same event, environment or phenomenon. The field of data fusion is of significance in any application where a large amount of data must be combined, fused and distilled to obtain information of appropriate quality and integrity on which decisions can be made. Data fusion finds application in many military systems, in civilian surveillance and monitoring tasks, in process control and in information systems. In this section, some preliminaries of sensor data fusion and its basic terminologies are given.

1.1 Fusion Objectives

The basic intuition behind incorporating multiple information sources to collect information is that the aggregated data might be more reliable (less noisy) and therefore can aid in better understanding of the phenomenon under surveillance. Typically, the fusion objectives of a specific application scenario include one or more of the following functions:

- Detecting presence of an object or environmental condition
- Object recognition and classification
- Target tracking
- Health monitoring and flagging changes
- Intelligent decision making and situation assessment

If sensors used to collect observations merely duplicate information acquisition, the fusion process essentially incorporates redundancy for enhancing reliability. This situation might not facilitate better understanding of the phenomenon in question. Therefore, most multi-sensor fusion systems incorporate heterogeneous sensors so that a wide range of information with varying degrees of uncertainty can be collected and fused for end decision making.

1.2 Data Fusion Architectures

Set of sensors are physically distributed around in an environment for sensing the phenomenon of interest. In a centralized data fusion system, the raw sensor observations are communicated to a central fusion center that solves a classical hypothesis testing problem and decides on one of the possible hypotheses. A distinct alternative is a distributed data fusion system, where each sensor has an associated local processor which can extract useful information from the raw sensor observations prior to communication. A summary of the local observations (test statistics) is sent to the fusion center which then makes a decision on the basis of the messages received.

Several different topologies are employed in real-world systems all of which fall under the umbrella of distributed fusion.

In Parallel Decision Fusion shown in Figure 1, the local sensors form a bank of data collection nodes which map their observation vectors to local decisions. These are then sent forward through dedicated communication channels to the decision fusion center which then processes the received local decisions and produces a global decision on the set of hypotheses.
Multi-sensor data fusion techniques are widely used to meld data acquired by sensors deployed in the environment to infer the context information necessary for the comprehension of the environment. A comprehensive survey on the application of Dempster-Shafer theory for multi sensor data fusion is presented in this section.

The authors in [1] adopts Dempster-Shafer evidence theory for fusing sensory information collected from heterogeneous sensors, assigns probability mass assignments (PMAs) to the raw sensor readings, and finally performs mass combination to derive a conclusion about the occupancy status in a room. In [2] the authors demonstrates that Dempster-Shafer evidence theory may be successfully applied to unsupervised classification in multisource remote sensing. An extensive frame work employing Dempster-Shafer theory for fire detection, detection of people activity in the home and road traffic incident is presented in [3], [4], [5]. In the literature [6], based on the obtained results, the authors discuss the potential contribution of theory of evidence as a decision-making tool for water quality management. Dempster-Shafer approach for sensor data fusion for Internet of Things (IoT) is reported in [7],[8]. Plenty of research work has been done on data fusion using other approaches like, Fuzzy theory, Artificial neural network, Support vector machine, Kalman filter and particle filter. The advantage of Dempster Shafer theory in handling uncertainty makes it an important approach for sensor data fusion.

3. Sensor Fusion Using Dempster-Shafer Theory

Dempster first introduced the well-known evidence theory which was later extended by his student, Shafer. This theory, known as DSET is mostly known to represent uncertainties or imprecision in a hypothesis. The hypotheses characterizes all the possible states of the system. These hypotheses are assigned a probability mass assignment (PMA) which when combined leads to a decision. The process of forming mass assignment function and combining the same is thus crucial for accurate prediction, DSET attains the goal of data fusion by means of a combination rule applied to evidence sources.

3.1 Frame of Discernment

It is given by the finite universal set θ which represents the collection of mutually exclusive and exhaustive possibilities or hypotheses γ1, γ2, γ3 . . . The set of all subsets of θ is given by its power set 2θ. Frame of discernment θ may include a single hypothesis (say, γ1) or a conjunction of hypotheses (say,γ1∧γ2). Any hypothesis γ will refer to a subset of θ for which sources can provide evidence.

For three hypothesis γ1, γ2, γ3
θ = {γ1, γ2, γ3}
2θ = {∅, {γ1}, {γ2}, {γ3}, {γ1, γ2}, {γ1, γ3}, {γ2, γ3}, {γ1, γ2, γ3}, θ}.

3.2 Probability Mass Assignment

It corresponds to a mapping of each hypothesis γ1, γ2, γ3 . . . to a value m(γ) between 0 and 1, such that:

\[ m(\emptyset) = 0, \quad m(\gamma) = 1, \quad 0 \leq m(\gamma) \leq 1, \quad m(\gamma_1 \cup \gamma_2) = m(\gamma_1) + m(\gamma_2) - m(\gamma_1 \cap \gamma_2), \quad \forall \gamma_1, \gamma_2. \]
1) The PMA of the null set $\varnothing$ is zero. In other words, belief cannot be assigned to an empty or null hypothesis from an evidence source, i.e., $m(\varnothing) = 0$;

2) Belief from the evidence sources comprising of all the possible hypotheses (including combinations of hypotheses) must sum to 1.

$$i.e., m(\gamma_1) + m(\gamma_2) + \ldots + m(\gamma_n) = 1$$

$$\sum_{\gamma \in \Theta} m = 1.$$ 

The measure $m(\gamma)$ is the degree of evidence supporting the claim that a specific element of $\Theta$ belongs to the set $\gamma$, but not to any special subset of $\gamma$.

![Diagram](image)

**Figure 2: An approach to determine BPA**

In real data fusion application systems based on DS theory, the basic probability assignment (BPA) function should be given so that the combined BPA can be obtained through Dempster’s rule of combination. Determination of basic probability assignment, which is the main and the first step in evidence theory, is an important task. There are different approaches to determine BPA. One such approach is given below:

Step 1: Use the existing sample data to build the normal distribution, which describe the model attributes of instances.

Step 2: Calculate the distance measure between the collected attribute of the sample data and the model attribute.

Step 3: Calculate the probability which the sample data belongs to the model category.

Step 4: Normalized the probability measure to obtain the BPA function.

### 3.3 Dempster-Shafer sensor fusion algorithm

The Bayesian theory is the canonical method for statistical inference problems. The Dempster-Shafer decision theory is considered a generalized Bayesian theory. It allows distributing support for proposition (e.g., this is user A) not only to a proposition itself but also to the union of propositions that include it (e.g., “this is likely either user A or user B”). In a Dempster-Shafer reasoning system, all possible mutually exclusive context facts (or events) of the same kind are enumerated in “the frame of discernment”.

For example, if we know that there is person in an instrumented room, and we want to recognize whether s/he is the already-registered user A, user B, or somebody else, then our “frame of discernment” about this person is:

$$\theta = \{A, B, \{A, B\}, \{\text{Someone else}\}\}$$

Meaning s/he is “user-A”, “user-B”, “either user-A or user-B”, or “neither user-A nor user-B, must be somebody else”.

Each sensor, sensor $S_i$ for example, will contribute its observation by assigning its beliefs over $\Theta$. This assignment function is called the “probability mass function” of the sensor $S_i$, denoted by $m_i$. So, according to sensor $S_i$’s observation, the probability that “the detected person is user A” is indicated by a “confidence interval”

$$[\text{Belief}_i(A), \text{Plausibility}_i(A)]$$

The lower bound of the confidence interval is the belief confidence, which accounts for all evidence $E_k$ that supports the given proposition “user A”.

$$\text{Belief}_i(A) = \sum_{E_k \subseteq \Theta} m_i(E_k)$$

The upper bound of the confidence interval is the plausibility confidence, which accounts for all the observations that do not rule out the given proposition:

$$\text{Plausibility}_i(A) = 1 - \sum_{E_k \subseteq \Theta} m_i(E_k)$$

For each possible proposition (e.g., user-A), Dempster-Shafer theory gives a rule of combining sensor $S_i$’s observation $m_i$ and sensor $S_j$’s observation $m_j$.

$$m_1 \oplus m_2 \leq m_k$$

This combining rule can be generalized by iteration: if we treat $m_k$ not as sensor $S_j$ observation, but rather as the already combined (using Dempster-Shafer combining rule) observation of sensor $S_j$ and sensor $S_i$. Compared with Bayesian theory, the Dempster-Shafer theory of evidence feels closer to our human perception and reasoning processes. Its capability to assign uncertainty or ignorance to propositions is a powerful tool for dealing with a large range of problems that otherwise would seem intractable.

### 4. Dempster Shafer Engine

#### 4.1 Dempster Shafer Engine (DSE) Overview

DSE [9] is a program that allows you to take a situation, get accounts from different sources, and then combine these accounts in a statistically accurate way. DSE implements Dempster Shafer theory, or The Mathematical Theory of Evidence, as devised by A. P. Dempster and G. Shafer. Important note on the terms: Scenarios, Hypotheses, Data Sources, Evidence and Combining Evidence is given in this section.
To normalize probabilities:

• Choose ‘Normalize Probabilities’ from the Tools Menu. This menu item will only be available if there is at least one data source associated with the scenario.

• If you want to normalize just the current data source, choose ‘Current Data Source’ from the Normalize Probabilities Dialog. Choose ‘All Data Sources’ to normalize all data sources.

• Click Ok to normalize the probabilities for the selected data sources. The probabilities will be scaled so that the sum will be one.

• You cannot normalize probabilities for the results view. Normalizing probabilities is a good idea before combining evidence.

4.1.5 Combining Evidence

The purpose of collecting all the pieces of evidence from the relevant data sources is so that we can combine all the conflicting evidence together to give a more coherent view of the probable outcome of the scenario. This process is known as combining evidence.

Before evidence can be combined, the sum of the probabilities assigned to each piece of evidence must total one for each data source. This is to ensure that the evidence presented by each data source is equal in weight; no data source is more important than any other data source. DSE provides the Normalize Probabilities function to ensure this is the case. To combine evidence:

• Choose ‘Combine Evidence’ from the Tools Menu. This menu item will only be available if there are at least two data sources associated with the scenario.

• The Combine Evidence Dialog will appear, and combination of evidence will begin. If successful, the results will be displayed.

4.1.6 Results

Once the combination of evidence has completed, a new menu item will appear in the View menu - Results. This allows the results of the combination to be viewed at any time. The most probable outcomes can be viewed by looking at the Chart View. You should note that once evidence has been combined, CURRENT will appear in the Status Bar. Should you perform an action such as changing the probability of a piece of evidence, CURRENT will disappear, indicating that the results are no longer up to date. To see the correct results, evidence must be combined again.

The combination of evidence cannot complete in the rare case where two data sources are in total contradiction that is when one data source is sure that one set of hypotheses will prevail, and another data source is sure that another set is the answer. Combination also produces the Weight of Conflict, displayed in the Status Bar. This number shows how ‘close’ the various data sources were - a result close to zero indicates that the data sources were in harmony, larger values indicate disparity.

4.2 DST Application Case study

In a multi sensor based automatic target recognition system, suppose that the targets are E1, E2 and E3. From five different sensors, the system collects the following data:

Sensor 1: m1(E1)=0.41, m1(E2)=0.29, m1(E3)=0.3;
Sensor 2: \(m_2(E_1)=0.01, m_2(E_2)=0.89, m_2(E_3)=0.1\);
Sensor 3: \(m_3(E_1)=0.58, m_3(E_2)=0.07, m_3(E_1UE_3)=0.35\);
Sensor 4: \(m_4(E_1)=0.55, m_4(E_2)=0.1, m_4(E_1UE_3)=0.35\);
Sensor 5: \(m_5(E_1)=0.6, m_5(E_2)=0.1, m_5(E_1UE_3)=0.3\);
Dempster Shafer theory is applied to determine the most probable decision on recognition of the target. The use of DSE for this problem is shown in the following figures and the outcome shows that the most probable target is \(E_1\).

5. Conclusion

In this paper, an approach for multi sensor data fusion adopting Dempster Shafer theory is explained clearly and is illustrated through a case study. The open source software DSE is employed for evaluating the outcome and the easiness of the usage of application software is demonstrated. This article may be useful for researchers working in the field of Internet of Things where there is issue of data uncertainty.

References


Author Profile

Angeline Frieda K received B.E degree in Electronics and Communication Engineering from St. Joseph’s College of Engineering in 2017. Currently she is pursuing M.E degree in Embedded System and Technologies in the same college.

Johnsi Stella I is teaching faculty at St. Joseph’s College of Engineering. Her research area includes application mathematics and wireless sensor networks.