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

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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.

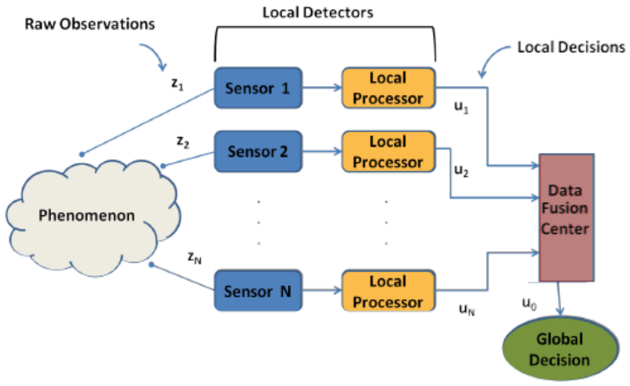

Figure 1: A parallel decision fusion system

In Sequential or Tandem Fusion, the first sensor in the network uses only its own observations to compute its quantized data for use by the next sensor. The last sensor in the network acts as the fusion center and makes the final decision on the set of hypotheses.

In Tree Structure, the sensors at the lowest level of the tree send their processed information to the parent sensors who use their own observations and the information received from child sensors to compute their own summarized data.

1.3 Advantages of Multi Sensor Data Fusion

The multi-sensor fusion system
1) Organize data collection and signal processing from different types of sensor,
2) Produce local and global representations using the multisensory information, and
3) Integrate the information from the different sensors into a continuously updated model of the monitored system.

Advantages of multi sensor data fusion are:
- ***Redundancy*** - Redundant information is provided from a group of sensors or by a single sensor over time when each sensor observes (possibly with different fidelity), the same features of interest.
- ***Complementarily*** - Complementary information from multiple sensors allows for the perception of features that are impossible to be observed using just the information from individual sensors operating separately.
- ***Timeliness*** - More timely information may be provided by multiple sensors due to the actual speed of operation of each sensor, or to the processing parallelism that is possible to be achieved as part of the integration process.
- ***Cost*** - Integrating many sensors into one system can often use many in expensive devices to provide data that is of the same or even superior quality to data from a much more expensive and less robust device.

This paper is organized as follows: Section 2 presents the literature survey on application of Dempster shafer theory. Section 3 discuses on the basic principle of DST and gives some preliminary information. Section 4 introduces the DSE with a brief note on the features and the usage and presents a simple case study. Finally section 5 summarizes this paper with concluding remarks.

2. Related work

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

Demspter 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 $\gamma1, \gamma2, \gamma3 \ldots$ The set of all subsets of θ is given by its power set 2θ. Frame of discernment θ may include a single hypothesis (say, $\gamma1$) or a conjunction of hypotheses (say,$\gamma1 \cap \gamma2$). Any hypothesis γ will refer to a subset of θ for which sources can provide evidence.

For three hypothesis $\gamma1, \gamma2, \gamma3$
$\theta = \{\gamma1, \gamma2, \gamma3\}$
$2\theta = \{\varphi, \{\gamma1\}, \{\gamma2\}, \{\gamma3\}, \{\gamma1, \gamma2\}, \{\gamma1, \gamma3\}, \{\gamma2, \gamma3\}, \theta\}$.

3.2 Probability Mass Assignment

It corresponds to a mapping of each hypothesis $\gamma1, \gamma2, \gamma3 \ldots$ to a value $m(\gamma)$ between 0 and 1, such that:

International Journal of Scientific Engineering and Research (IJSER)
ISSN (Online): 2347-3878
Impact Factor (2018): 5.426

1) The PMA of the null set φ is zero. In other words, belief cannot be assigned to an empty or null hypothesis from an evidence source, i.e., $m(\varphi) = 0$;
2) Belief from the evidence sources comprising of all the possible hypotheses (including combinations of hypotheses) must sum to 1.

i.e., $m(\gamma 1)+m(\gamma 2)+\cdot\cdot\cdot+m(\gamma_n) = 1$ or $\sum_{\gamma \subseteq \theta} m = 1$.

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

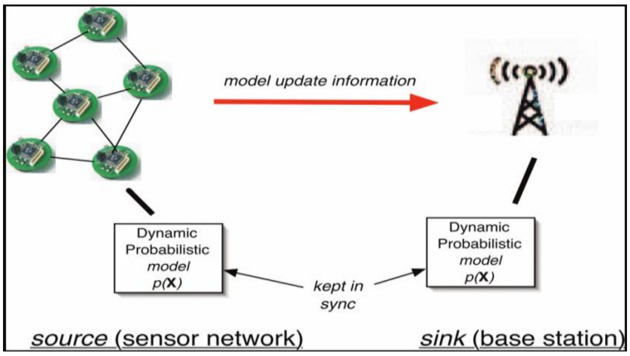

Figure 2: An approach to determine BPA

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:

$$\theta = \{A, B, \{A, B\}\{Someone\ else\}\} \quad (1)$$

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"1.

Each sensor, sensor S_i for example, will contribute its observation by assigning its beliefs over Θ. This assignment function is called the "probability mass function" of the sensor S_i, denoted by m_i. So, according to sensorS_i's observation, the probability that "the detected person is user.

A" is indicated by a "confidence interval"

$$[Belief_i(A), Plausibility_i(A)] \quad (2)$$

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":

$$Belief_i\ (A) = \sum_{E_k \subseteq A} m_i(E_k) \quad (3)$$

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:

$$Plausibility_{i\,(A)} = 1 - \sum_{E_k \cap A = \emptyset} m_i(E_k) \quad (4)$$

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

$$(m_i \oplus m_j)(A) = \frac{\sum_{E_k \cap E_{k'} = A} (m_i(E_k) m_j(E_{k'}))}{1 - \sum_{E_k \cap E_{k'} = \emptyset} m_i(E_k) m_j(E_{k'})} \quad (5)$$

This combining rule can be generalized by iteration: if we treat m_j not as sensor S_j observation, but rather as the already combined (using Dempster-Shafer combining rule) observation of sensor $S_k$and sensorS_l. 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.

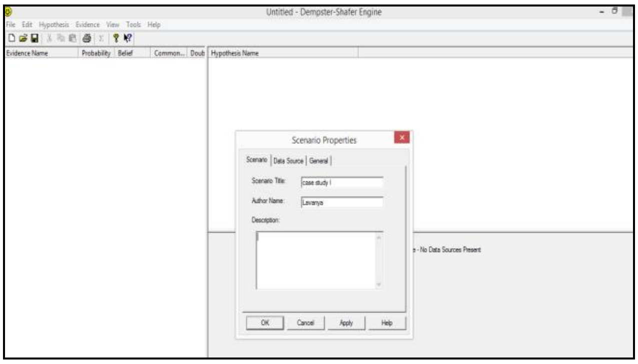

Figure 3: Dempster – Shafer Engine

4.1.1 Scenarios

In DSE, a scenario collects all of the evidence, data sources and hypotheses together. When you create a new document, you are creating a new scenario. General scenario properties can be changed from the Properties item on the File menu. We can record the name of the scenario, who composed the scenario and some more general details. When a scenario is saved to disk using the save commands on the File menu, all the other information (hypotheses, data sources...) is stored with it.

4.1.2 Hypotheses

Hypotheses represent all the possible things that could happen in a scenario. Importantly, hypotheses must not 'overlap'. All the hypotheses must be unique and mutually exclusive. It is also important that all possible hypotheses are recorded. In mathematical terms, hypotheses are elements of the universe of discourse, or frame of discernment.

4.1.3 Data sources

As the name suggests, a data source is a person, organization or some other entity that provides information for the scenario. Care should be taken to ensure that sources are obtained that are as free from bias as possible, and in the case where sources are taken from a large population, that the sources are representative of that population. Increasing the number of data sources will ensure that any results received are of a higher quality however additional data sources require more computation to be performed, as well as more data entry.

4.1.4 Evidence

Pieces of evidence link data sources and hypotheses. Evidence represents how a particular data source feels about the outcome of a particular subset of hypotheses. Typically, each data source will have many pieces of evidence. When we are creating a piece of evidence, we are stating that we have some inclination to believe that the outcome of the scenario lies in the subset of hypotheses selected. As well as stating which hypotheses are involved, we must also quantify our belief. We do this by assigning a probability to the piece of evidence. The probability is a number between zero and one signifying how strongly we believe in the particular piece of evidence.
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: m2(E1)=0.01, m2(E2)=0.89, m2(E3)=0.1;
Sensor 3: m3(E1)=0.58, m3(E2)=0.07, m3(E1UE3)=0.35;
Sensor 4: m4(E1)=0.55, m4(E2)=0.1, m4(E1UE3)=0.35;
Sensor 5: m5(E1)=0.6, m5(E2)=0.1, m5(E1UE3)=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 E1.

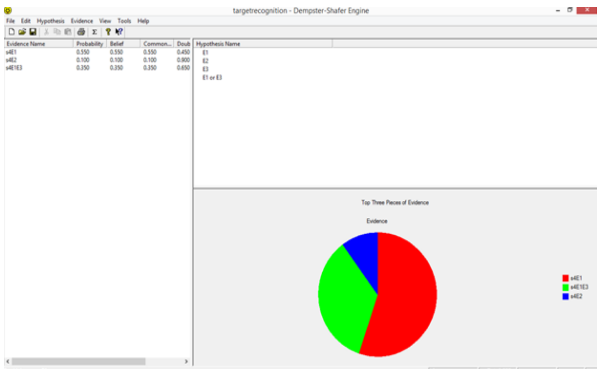

Figure 4: Sensor 4 observation

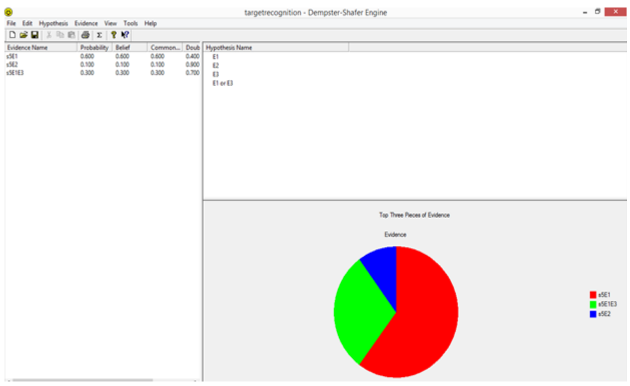

Figure 5: Sensor 5 observation

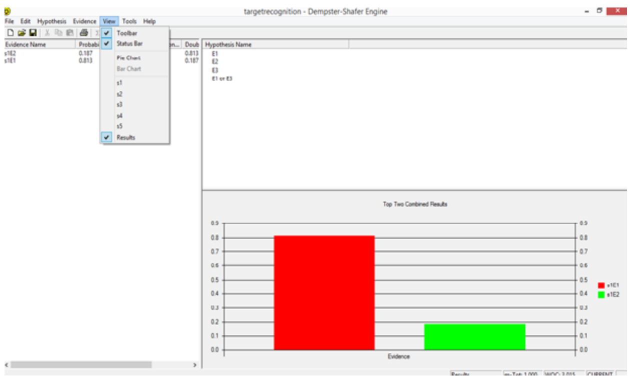

Figure 6: Outcome of sensor data fusion

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

[1] NashreenNesa, IndrajitBanerjee , " IoT-Based Sensor Data Fusion for Occupancy Sensing Using Dempster–Shafer Evidence Theory for Smart Buildings", IEEE Internet Of Things Journal, Vol. 4, No. 5, pp.1563-1570 OCTOBER 2017.
[2] S. Le Hegarat-Mascle, I. Bloch, and D. Vidal-Madjar, "Application of Dempster–Shafer evidence theory to unsupervised classification in multisource remote sensing," IEEE Trans. Geosci. Remote Sens., vol. 35, no. 4, pp. 1018–1031, Jul. 1997.
[3] E. Zervas, A. Mpimpoudis, C. Anagnostopoulos, O. Sekkas, and S. Hadjiefthymiades, "Multisensor data fusion for fire detection," Inf. Fusion, Elsevier Science Publishers B. V. Amsterdam, The Netherlands,vol. 12, no. 3, pp. 150–159, 2011.
[4] S. Mckeever, J. Ye, L. Coyle, C. Bleakley, and S. Dobson, "Activity recognition using temporal evidence theory," J. Ambient Intell. Smart Environ., vol. 2, no. 3, pp. 253–269, 2010.
[5] D. Zeng, J. Xu, and G. Xu, "Data fusion for traffic incident detection using D-S evidence theory with probabilistic SVMs," J. Comput., vol. 3, no. 10, pp. 36–43, 2008.
[6] R. Sadiq and M. J. Rodriguez, "Interpreting drinking water quality in the distribution system using Dempster–Shafer theory of evidence," Chemosphere, vol. 59, no. 2, pp. 177–188, 2005.
[7] Hemanth Kumar , Pratik Pimparkar, Data Fusion for the Internet of Things,International Journal of Scientific and Research Publications, Volume 8, Issue 3, pp278-282 March 2018
[8] Huadong Wu1, Mel Siegel, Rainer Stiefelhagen, JieYang, 'Sensor Fusion Using Dempster-Shafer Theory' IEEE Instrumentation and Measurement Technology Conference USA, 21-23 May 2002
[9] Dempster-Shafer Engine - Aonaware Home www.aonaware.com/dse.htm

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