Multi Sensor Data Fusion, Methods and Problems

Rawa Adla¹, Youssef Bazzi², and Nizar Al-Holou¹
¹Department of Electrical and Computer Engineering, University of Detroit Mercy, Detroit, MI, U.S.A
²Department of Electrical and Computer Engineering, Lebanese University, Beirut, Lebanon

Abstract - Sensors, which monitor the surrounding environment in order to enhance our decisions, play a major role in our lives and contribute to our actions. A single sensor, however, is not capable of providing enough information; therefore, multiple sensors have to be integrated in a way to perform the additional task of interpretation, which may be more helpful and informative than what can be observed using a single sensor. Since the nature of sensor’s functional characteristics can lead to output that contains erroneous measurement readings due to noise, measurement errors, and delays, multiple sensors are needed to confirm the certainty of desired actions. For sensors to work properly, a computational system is required in order to fuse sensor data in a process called multi-sensor-data fusion.

This paper presents an overview of multi-sensor-data fusion, using two techniques (Bayes and Dempster-Shafer), with highlights of the techniques’ shortcomings.

Keywords: sensor fusion; Bayes’ theory; Dempster-Shafer; fusion model.

1 Introduction

Sensor-data fusion refers to the integration of data from multiple sensors of identical or different technical characteristics. The merits of the sensor fusion methods are to provide a better estimate of the feature of interest and to provide a result represented by hypothesis that is more accurate than would be obtained when using a single sensor. There are many problems considered when designing a system with a single sensor [1], such as loss of data when a sensor failure occurs, individual sensors providing data only from its own field of view, the frequency of measurements being limited to the time needed for a sensor to process its data, which is limited in accuracy due to the precision of the sensing system of the sensor, and the uncertainty in sensor measurement about objects which have been detected.

In order to enhance the certainty measure of the observed data, a multi-sensor-data fusion system is required. Countless benefits can be derived from using sensor-data fusion methods, depending on the system and the application nature, since each system expects at least one of the following features to exist [2][3]: redundancy, which enables the whole system to be active even when a sensor failure or breakdown channel occurs; improved coverage area, which therefore makes complementary data available; increased confidence in the results and the certainty of information; enhancement of spatial resolution; extended temporal coverage; and improvement in the detection rate of objects.

In the past few decades, sensor-data fusion has been researched and has appended developments for many fields such as science, technology, and engineering. In order to build a multi-sensor-data fusion system, deep understanding of the application characteristics is required. This can help in choosing the suitable data-fusion architecture, and in setting the data transmission facets. Then, determining the optimal fusion technique and acquiring a reliable algorithm for estimation and prediction are required [4].

This paper has been organized as follows: Section II presents types of sensors, and section III defines the levels of data fusion. In section IV the architecture of fusion has been proposed and an overview of multi-sensor fusion models is presented in section V. In Section VI we discuss two methods of combining data which are (Bayes’ and Theory of Evidence). The paper concludes with an evaluation of these two fusion techniques and a declaration of their shortcomings.

2 Types of Sensors

There are two types of sensors: active and passive [5]. In active sensors, the output is generated as a result of stimulation that causes an alteration in the electrical amplitude. This type of sensor requires a power source for excitation and data security because it uses a direct transfer of data. Such examples: sonar, radar, or an ultra-wide band sensor. Alternatively, passive sensors do not require an electrical power source to work; they generate a voltage output using the temperature of the energy they are sensing. Also, passive sensor-data is considered more secure than active sensor-data. As an example of such sensors, a camera senses the amount of light it receives from the environment, and converts it into voltage levels. The variations in these voltages are stored as different pixel values in the computer.

Each of these types of sensors can be further subdivided depending on whether the targets identify themselves
or not; that is, whether they are cooperative or uncooperative sensors [5].

3 Sensor-Data Fusion Levels

In general, the process of sensor-data fusion can be categorized into three levels: low, intermediate, and high-level [4].

- Low-level: Also referred to as raw-data fusion. Raw-data is fused from multi sensors of the same type to generate a new raw data set which is more annotative than the original raw-data, as collected by sensors.

- Intermediate-level: This level of fusion also called feature fusion. It combines different features into a feature map, which is usually used for detection of objects.

- High-level: This level of fusion, known as decision fusion, requires a fusion method to be applied, such as the statistical or fuzzy logic method, to compute a hypothesis value representing the decision.

4 Fusion Architecture

Three different multi-sensor-data fusion architectures exist: centralized, pre-processed, and hybrid [6] [7].

- Centralized fusion: This architecture is employed when sensors of the same type are selected. The fusion process combines raw data from all sensors in a central processor. This process requires a time synchronization of all sensors’ data. The advantage of centralizing fusion is secured data, and there is no data loss in the preprocessing. On the other hand, centralizing fusion requires sending all the collected data to the central processor, which is not acceptable in some applications.

- Pre-processed fusion: known as distributed fusion. Used for sensors of the same or different types. In this architecture, the central processor is relieved from preprocessing the raw data from the individual sensors.

- Hybrid fusion: This fusion architecture involves a mix of centralized and pre-processed fusion schemes. In practice, this is the best set-up of fusion architecture.

5 Fusion Models

There are several fusion models to consider when designing a multi-sensor-data fusion system. They will be reviewed in this section.

5.1 Joint Directors of Laboratories- JDL Model:

The JDL model was proposed by the US. Department of Defense (DoD) in 1986 [8]. The JDL model consists of: five levels of data processing, as follows [8]: Level 0 is Source Preprocessing, which determines the time, type, and identity of the collected data. Level 1 is Object Refinement, a level that combines information received from Level 0, in order to generate a representation of individual objects. Level 2 is a Situation Refinement, which defines the relationship between objects and detected targets and incorporates environmental information and observations. Level 2 is Threat Refinement, in which inferences are constructed about the target to have a solid base for decisions and actions. These inferences are based on priori information and prediction about the next state. Level 4 is a Processing, which consists of three processes: monitoring data fusion efficiency, defining the missing information needed to enhance multi-level data fusion, and allocating sensors in order to accomplish the aim of the fusion process. At the same time, the JDL model has a database management system responsible for controlling data fusion processes, and a bus for interconnection between levels [3] [8].

5.2 Waterfall Model

This model assigns the priority of processing to the lower levels first. The fusion process is based on six levels of processing [9]; these levels can be matched to the JDL model levels: The first two levels, Sensing and Signal Processing, are similar to the first level in the JDL model (Level 0). The next two levels, Levels 3 and 4, are Feature Extraction and Pattern Processing, and these levels relate to Level 1 of the JDL model. Level 5 is a Situation Assessment that can be matched to Level 2 in the JDL model. Level 6 is Decision Making that is equivalent to the Threat Refinement level in the JDL model (Level 3).

The advantage of the Waterfall model is the simplicity in understanding and applying, but it has a major limitation, as there is no feedback loop between levels.

5.3 Intelligence Cycle–Based Model

The Intelligence Cycle–Based model is a cyclic model that captures some inherent processing behaviors among stages. It consists of five stages: planning, collection, collation, evaluation, and the dissemination stage [1] [10].

Stage-1 is the Planning and Direction stage, where determinations of the requirements take place; Stage-2 is the Collection stage, which collects required information; and Stage-3 is a Collation stage, that streamlines the collected information. Stage-4 is Evaluation stage, where the fusion process occurs, and the last, Stage-5 is the Dissemination stage, that distributes the fused inferences.
5.4 Boyd Model

The Boyd model is considered a cyclical model [11]. Its cycle has four stages of processing: observation, orientation, decision, and action. Each stage can be matched to a specific level of the JDL model [3]:

The Observation stage is similar to Source Preprocessing in the JDL model and to the Collection stage of the Intelligence Cycle model. The Orientation stage is comparable to Levels 1, 2, and 3 of the JDL model, and it can be considered similar to the Collection and Collation stages of Intelligence cycle model. The Decision stage is comparable to the processing level in the JDL model and equivalent to the “evaluation and dissemination stages” of the Intelligence cycle model. While the Action stage has no match to any level in the JDL model, it can be considered as the Dissemination stage of the Intelligence cycle model. A better fusion process model can be obtained by a combination of the intelligence cycle and Boyd models, such as the Omnibus Model.

5.5 Omnibus Model

This model is based on a combination of the Intelligence cycle and Boyd models. The cyclic structure of this model can be compared to the Boyd loop, with more enhancements to the structure of the processing levels [12].

The observation step of the Boyd model has been modeled as a sensing and signal processing. While the orientation step of the Boyd model is conducted as feature extraction and pattern processing. The decision step of the Boyd model has been replaced in Omnibus by two phases: context processing and decision making. The action step of the Boyd model is divided into control and resource tasking.

The Omnibus model is considered more efficient and generalized than other fusion models, such as Waterfall, Intelligence cycle, or Boyd models. The Omnibus model employs the strengths of other previous models and at the same time is considered very easy to employ in a sensor fusion system.

5.6 Thomopoulos Model

The architecture of this model is based on three levels of data processing: signal level, evidence level, and dynamic level [13].

The signal level is a correlation and learning process that integrates sensor data. The evidence level is used to describe the statistical model that processes data from different sensors in some form of local inference. The dynamic level combines different observations in a centralized or decentralized fashion, assuming that a mathematical model that describes the process from which data is collected is known [13].

6 Fusion Techniques

Once the fusion architecture is designed, one or more fusion techniques should be implemented to fuse the data at different levels, keeping in mind that uncertainty exists in all descriptions of the sensing and data fusion process. Then, an explicit measurement of this uncertainty must be provided, in order to fuse the sensory information in an efficient and predictable manner [14]. However, there are many methods used for representing uncertainty; almost all of the theoretical developments are based on the use of probabilistic models [14].

Probabilistic models have an important aspect when developing data fusion methods. It is an essential requirement to obtain a well understanding of probabilistic modeling techniques when a data fusion is required in any coherent manner [14]. This section discusses two approaches used in sensor fusion systems, Bayesian network ‘Posteriori’ as a probabilistic model technique and an alternative method to the probability; theory of evidence by Dempster-Shafer. The Bayes’ approach deals with probability values in which incomplete information which leads to uncertainty is not accounted for, that is: \( P_A + P_A = 1 \). Where Dempsetr-Shafer accounts for incomplete information in the mass function: \( m(A, A, A) = 1 \).

6.1 Multi Sensor Data Fusion Using Bayes’ Technique

The main objective when developing a sensor fusion system is to integrate data from multiple sensors, whether identical or different, active or passive, in order to generate reliable estimation about the object of interest, as depicted in Fig.1. Several methods are modeled when multi-sensor fusion is required, such as: Deciding, Guiding, Averaging, Bayesian statistics, and Integration [15].

![Fig. 1. General model of multi-sensor data fusion](image)
In general, the model of sensor fusion consists of a set of sensors \( S_i = \{s_1, s_2, s_3, \ldots, s_m\} \), where each sensor’s output is represented by an array of likelihood values; that is, the conditional probabilities. This array represents the environment of interest, which could be modeled by a single state \( T \) represented by finite types of targets, \( T_i = \{t_1, t_2, t_3, \ldots, t_n\} \). A single sensor \( S \) observes targets \( t_n \) and returns a single value for each type \( T \). These values form the Likelihood Probability array, \( P(s|t_i) \), which are illustrated in Table I.

When more than one sensor is employed in the system, a sensor fusion method must be applied to integrate the various observations in order to make an assessment of each target type being detected. In the case of another sensor \( S_2 \) introduced to detect or observe the same target types, namely \( t_1, t_2, t_3, t_4, \ldots, t_n \), a second likelihood array is generated as in Table I. For every sensor in the system, a likelihood vector is generated.

**Table I. Likelihood Vectors from Sensor1 (S1) and Sensor2 (S2)**

<table>
<thead>
<tr>
<th>Target type</th>
<th>( t_1 )</th>
<th>( t_2 )</th>
<th>( t_3 )</th>
<th>( \ldots )</th>
<th>( t_n )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensor S1</td>
<td>( P(s_{1</td>
<td>t_1}) )</td>
<td>( P(s_{1</td>
<td>t_2}) )</td>
<td>( P(s_{1</td>
</tr>
<tr>
<td>Sensor S2</td>
<td>( P(s_{2</td>
<td>t_1}) )</td>
<td>( P(s_{2</td>
<td>t_2}) )</td>
<td>( P(s_{2</td>
</tr>
</tbody>
</table>

### 6.1 Bayes’ Theorem

Bayes’ rule is based on the joint and the conditional probability [16].

\[
P(T_i|S) = \frac{P(S|T_i)P(T_i)}{\sum P(S|T_j)P(T_j)} \quad (1)
\]

Where,

- \( P(T) \): The prior beliefs about the values of \( T_i \).

### 6.2 Multi Sensor Date Fusion Using Theory of Evidences

This theory was developed by Dempster and Shafer [17] [18], as a mathematical method that generalizes Bayesian theory, which allows the representation of ignorance. The Bayesian theory assigns for each evidence only one possible event, while Dempster-Shafer associates evidence with multiple possible events. The Dempster-Shafer theory assumes that the states for which we have probabilities are independent with respect to our subjective probability judgments. The implementation of this method to a specific
problem normally involves two steps [18]. The first step is to solve the uncertainties into a priori independent items of evidence. The second is a computation using the Dempster-Shafer method, as illustrated in Table III.

Three functions in Dempster-Shafer theory must be noted due to their importance [16]:

1) The Basic Probability Assignment function or Mass function (bpa or m): This is the fundamental of Dempster/Shafer theory. It is presented by a mass function \( m \) and defined as follows in (4):

\[
m: P(x) \rightarrow [0,1] \\
m(\emptyset) = 0 \\
\sum_{A \in P(x)} m(A) = 1 
\] (4)

Where,
\( P(x) \) is the power set of \( x \)
\( \emptyset \) is the null set
\( A \) is a set in the power set \( (A \in P(x)) \). [19]

2) The Belief function (Bel): represents the lower boundary of the pba interval. Where the Belief for a set \( A \) is defined in (5):

\[
Bel(A) = \sum_{B \mid B \subseteq A} m(B) 
\] (5)

Where,
\( B \) is a proper subset of set \( A \).

3) The Plausibility function (Pl): is the upper boundary of the pba interval. The plausibility for a set \( A \) is defined in (6):

\[
Pl(A) = \sum_{B \mid B \cap \bar{A} = \emptyset} m(B) 
\] (6)

Based on the basis that all assignments should be added up to one, we can derive these two measures from each other in (7):

\[
Pl(A) = 1 - Bel(\bar{A}) 
\] (7)

Where,
\( \bar{A} \) is the classical complement of \( A \).

6.2.1 Dempster –Shafer Method of Fusion

Since the Dempster-Shafer method of integration of two events is a conjunctive relation (AND), then the integration of two masses \( m_1 \) and \( m_2 \) is performed as in (8) [20]:

\[
m_{12}(A) = \sum_{B \cap C = A} m_1(B).m_2(C) / 1 - K 
\] (8)

Where,
\( A \neq \emptyset \),
\( m_{12}(\emptyset) = 0 \\
K = \sum_{B \cap C = \emptyset} m_1(B).m_2(C) 
\)

K is the conflict degree between evidences, and \((1-K)\) is used as a normalization factor.

### TABLE III. INTEGRATION OF SENSOR1 (S1) AND SENSOR2 (S2) USING DEMPSTER/SHAFER

<table>
<thead>
<tr>
<th>Sensor1 (S1)</th>
<th>Sensor2 (S2)</th>
<th>m1(A1)</th>
<th>m1(A2)</th>
<th>m1(An)</th>
<th>m1(A1.m2(B1))</th>
<th>m1(A2.m2(B1))</th>
<th>m1(An.m2(B1))</th>
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</thead>
<tbody>
<tr>
<td>m2(B1)</td>
<td>m2(B1)</td>
<td>m2(B1)</td>
<td>m2(B1)</td>
<td>m2(B1)</td>
<td>m2(B1)</td>
<td>m2(B1)</td>
<td>m2(B1)</td>
</tr>
<tr>
<td>m2(B2)</td>
<td>m2(B2)</td>
<td>m2(B2)</td>
<td>m2(B2)</td>
<td>m2(B2)</td>
<td>m2(B2)</td>
<td>m2(B2)</td>
<td>m2(B2)</td>
</tr>
<tr>
<td>m2(B3)</td>
<td>m2(B3)</td>
<td>m2(B3)</td>
<td>m2(B3)</td>
<td>m2(B3)</td>
<td>m2(B3)</td>
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<td>m2(B3)</td>
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</tr>
<tr>
<td>m2(Bm)</td>
<td>m2(Bm)</td>
<td>m2(Bm)</td>
<td>m2(Bm)</td>
<td>m2(Bm)</td>
<td>m2(Bm)</td>
<td>m2(Bm)</td>
<td>m2(Bm)</td>
</tr>
</tbody>
</table>

Dempster/Shafer theory is considered as a forward straight method to express pieces of evidence with different levels of abstraction, and it can be used to combine pieces of evidence, which is not always available when using other methods of fusion.

7 Conclusion

This paper presents a review of multi-sensor fusion and the requirement for building a data fusion system. Two fusion techniques were proposed: Bayes and Dempster/Shafer’s theories. While Bayes’ theory does not account for incomplete information, it is the sum of a probability, and its complement in a sample space is one. Dempster/Shafer accounts for ignorance or incomplete information, so the sum
of the probability and its complement with ignorance is equal to one.

Both methods represent the hypothesis with a single value (posterior or support). Dempster/Shaf er introduces an upper boundary called plausibility; therefore, it gives more room for the decision making process. However, both theories require a prior knowledge of the state; Bayes’ theory requires a priori probability, and Dempster/Shaf er requires a mass function. Based on the prior information available, one method has an advantage over the other.

One of the major problems when using both techniques is that both assume independency in their computation process between events, and this assumption leads to uncertainty in the hypothesis, sometimes adding or taking away part of the value associated with the hypothesis. In our ongoing research we were able to show that when we quantified dependency between two sensors’ events (outputs), we accounted for uncertainty, but the assumption of independence does not control the performance of the system.

8 References