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Decision Support

Analytic hierarchy process for multi-sensor data fusion based on belief function theory

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ABSTRACT

Multi-sensor data fusion is an evolving technology whereby data from multiple sensor inputs are processed and combined. The data derived from multiple sensors can, however, be uncertain, imperfect, and conflicting. The present study is undertaken to help contribute to the continuous search for viable approaches to overcome the problems associated with data conflict and imperfection. Sensor readings, represented by belief functions, have to be fused according to their corresponding weights. Previous studies have often estimated the weights of sensor readings based on a single criterion. Mono-criteria approaches for the assessment of sensor reading weights are, however, often unreliable and inadequate for the reflection of reality. Accordingly, this work opts for the use of a multi-criteria decision aid. A modified Analytical Hierarchy Process (AHP) that incorporates several criteria is proposed to determine the weights of a sensor reading set. The approach relies on the automation of pairwise comparisons to eliminate subjectivity and reduce inconsistency. It assesses the weight of each sensor reading, and fuses the weighed readings obtained using a modified average combination rule. The efficiency of this approach is evaluated in a target recognition context. Several tests, sensitivity analysis, and comparisons with other approaches available in the literature are described.

1. Introduction

Due to its wide range of applications, multi-sensor data fusion technology has received significant attention in recent research and industry. This technology combines data from multiple sensors to achieve a complete and accurate description of an environment or process of interest. Multi-sensor fusion systems have been widely applied in various areas of robotics, including environment mapping and target recognition, detection and localization. Khaleghi, Khamis, Karray, and Razavi (2013) provided a comprehensive review for multi-sensor data fusion state of the art, exploring its conceptualizations, benefits, challenging aspects, and existing methodologies. The application of multi-sensor data fusion has attracted the attention of several researchers, including Dong and He (2007), Mercier, Cron, Denœux, and Masson (2009) to cite only a few.

A single sensor may not be enough to derive a desired level of target estimation or hypothesis identification, and data fusion from multiple sensors is, therefore, often required. It allows to extract a greater volume of information and to attain a more precise level of recognition. Nevertheless, the data derived from multiple sources (signals or humans) is usually imperfect (imprecise, uncertain, and even conflicting). The imperfection and unreliability of sensor data are often attributed to technical and noise (environmental noise, presence of unknown targets, meteorological conditions, etc.) factors. Guo, Shi, and Deng (2006) classified the causes of sensor unreliability at three levels, namely the levels of the sensor, the data, and the symbol.

Since multiple sensors are uncertain and conflicting, information fusion becomes a fundamental issue. In fact, most fusion systems are optimistic in that they assume that all sensors are reliable and pay more attention to uncertainty modeling and fusion methods. The performance of the fusion system is, however, highly dependent on sensor performance and adaptability to the working environment and ability to estimate the reliability of each sensor readings (pieces of evidence). Sensor reading reliability needs to be incorporated into the fusion process so as to avoid decreasing system performance (Elouedi, Mellouli, & Smets, 2004; Liu,

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Dezert, Pan, & Mercier, 2011; Liang, Feng, & Liu, 2010). In fact, the reliability of pieces of evidence is an index for quantifying sensor performance and weighing readings. Accordingly, weights express reliability and credibility and demonstrate the relative importance of the collected pieces of evidence.

Belief function theory (Shafer, 1976) represents one of the most important tools for modeling and fusing multi-sensor pieces of evidence. It is a powerful mathematical mechanism to deal with imperfection and conflict and a flexible framework for representing and reasoning with various forms of imperfect information and knowledge. Within this theory, information fusion relies on the use of a combination rule allowing the pieces of evidence to be combined. In this context, Dempster's combination rule (Shafer, 1976) plays a central role, since it verifies a number of interesting mathematical properties, such as commutativity and associativity. Counterintuitive behaviors for high conflicts between pieces of evidence might, however, emerge (Zadeh, 1979).

Several methods have been developed to cope with the problems of conflict management (Dubois & Prade, 1988; Smets, 1990; Yager, 1987). Some of those proposals suggested other combination rules to deal with the inconvenient assignment of a total mass to a minority opinion. More recent studies (Deng, Shi, Zhu, & Liu, 2004; Florea & Bossé, 2009; Jiang, Zhang, & Yang, 2008; Martin, Jousselme, & Osswald, 2008) proposed the use of a discounting operation before combining to handle conflicting evidence combination and consider sensor reliability. Murphy (2000) presented a proposal based on the arithmetic average of belief functions to deal with the inconvenience associated with the loss of majority opinion. Later, she proposed a modified average approach where equal weights were assigned to each piece of evidence and the average operation was incorporated into the Dempster's rule.

Nevertheless, since the information sources in multi-sensor data fusion are always unequally important, the concept of weights of pieces of evidence has been introduced. In fact, the literature presents several proposals (Chen, Shi, Deng, & Zhu, 2005; Chen & Que, 2005; Deng et al., 2004) that assess the weights of pieces of evidence using a single criterion (distance of evidence or similarity measures). The use of a single criterion to assess the weight of sensor information is, however, not reliable since the mono-criteria approach is not enough sufficient to reflect reality. Conflict is not the unique criterion for use in weight assessment; sensor reading imperfection should also be taken into account for it reflects the reasonability of a given piece of evidence.

Both conflict and reading imperfection can be quantified using different measures (multiple criteria). Considering that multi-criteria decision aid (MCDA) is an appropriate decision support approach that provides valuable tools for solving complex problems where multiple conflicting decision factors have to be considered, the present study opts for the application of an MCDA-based approach using the Analytical Hierarchy Process (AHP) (Saaty, 1980). Accordingly, multiple assessment criteria are introduced based on the AHP method to estimate the weights of a sensor readings set.

The AHP is one of the most popular methods used in the MCDA approach. It allows users to assess the relative weight of each element of the hierarchy (criteria and decision alternatives) using pairwise comparisons. The major advantage of the AHP is its ability to decompose, in a detailed, structured, and systematic way, the decision problem into more easily comprehended sub-problems that can be analyzed independently. Despite its popularity, AHP has been criticized by several researchers for presenting a number of drawbacks. This method is reported to entail a lot of subjectivity particularly in the pairwise comparison of the different criteria involved. It may be difficult for the decision maker to judgmentally compare two criteria and assign them an objective weight according to their relative importance. AHP is also described to present a high number of judgments that the decision maker has to give on the actions set. The method is also limited by the problem of inconsistency in judgment. Another drawback of AHP relates to the lack of representation of ignorance. In fact, several attempts have been made to overcome the inadequacies of AHP. The combined DS/AHP (Dempster–Shafer/Analytic Hierarchy Process) (Beynon, Curry, & Morgan, 2000; Beynon, 2002) is a ranking approach that incorporates belief function theory with the philosophy of the AHP method.

The present study is interested in the use of multi-sensor data fusion to solve conflicting and imperfect data problems and in the automation of pairwise comparisons to eliminate subjectivity and reduce inconsistency. It aims to determine the relative importance (weight) associated to each sensor piece of evidence based on a modified AHP method and to fuse the weighed readings, represented by belief functions, using a modified average combination rule. The conflict between the sensors (conflict, distance and dissimilarity measures) and the imperfection of the information provided by each sensor (contradiction, imprecision and ambiguity measures) are both taken into account during weight calculation.

Section 2 provides an inventory of the basic concepts in the belief function theory. The third section presents an overview on the combination rules and approaches used for conflict management in this theory. The AHP method is introduced in Section 4. The fifth section is devoted to the presentation of assessment criteria. Section 6 presents a modified average combination rule based on AHP method and describes the process of weighing and fusing sensor readings. Section 7 provides a description for a modified version of the fusion strategy. Section 8 includes the experimental results and discussion on a target recognition application. In this application, sensor readings, represented by belief functions, are weighed and fused to reduce conflict and imperfection. Several tests, sensitivity analyses, and comparisons with other approaches available in the literature are also described. The final section contains a brief conclusion and avenues for further research.

2. Basics of belief function theory

The belief function theory was initially introduced by Dempster (1967), later formalized by Shafer (1976), and axiomatically justified by Smets and Kennes (1994) in a transferable belief model. It is a general framework for modeling uncertainty and imprecision where the available information is imperfect. Furthermore, the belief function theory is considered as an interesting alternative for information fusion and decision making using combination and decision rules, respectively.

A belief function model is defined by a finite and exhaustive set Θ called *frame of discernment* of the problem under consideration. The set containing all subsets of Θ is named the *power set* and denoted by 2^{Θ}.

A *Basic Probability Assignment function* (BPA) is a mapping m: $2^{\Theta} \rightarrow [0, 1]$. It assigns to every subset $A \subseteq \Theta$ a number $m(A)$, called the mass of A which represents the degree of belief attributed exactly to A, and to no one of its subsets. This function must satisfy the following conditions: $m(\emptyset) = 0$, and $\Sigma\{m(A)/A \subseteq \Theta\} = 1$.

When $m(A) > 0$, A is named *focal element* of m. The set of focal elements of m is noted $\Im$ and the pair $(\Im, m)$ is called *body of evidence* (BOE).

A BPA can equivalently be represented by its associated belief and plausibility functions. A *belief function* is a mapping *Bel*: $2^{\Theta} \rightarrow [0, 1]$, defined as:

$$Bel(A) = \sum_{B \subseteq A} m(B) \forall A \subseteq \Theta \quad (1)$$