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Object tracking and credal classification with kinematic data in a multi-target context

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ABSTRACT

This article proposes a method to classify multiple maneuvering targets at the same time. This task is a much harder problem than classifying a single target, as sensors do not know how to assign captured observations to known targets. This article extends previous results scattered in the literature and unifies them in a single global framework with belief functions. Through two examples, it is shown that the full algorithm using belief functions improves results obtained with standard Bayesian classifiers and that it can be applied to a large variety of applications.

1. Introduction

The problem of joint multi-target tracking and classification, which is as old as the invention of radars, is a much more complex task than the problem of tracking one target. Indeed it includes a step, called the assignment problem, where sensors have to associate known objects to new captured observations. A full multi-target tracking solution includes several interlaced components such as the tracking component, the assignment component, the hypothesis rejection (new or disappeared targets, etc.) and finally the classification step. Probability-based solutions already exist in the literature [1–7].

For about 40 years, other uncertainty models based on non-additive measures have been developed, in particular the Transferable Belief Model [8] based on belief functions [9,10] which is sometimes referred to as the credal model. Applications of this model can be found for example in classification tasks and decision support systems [11]. Direct comparisons with Bayesian solutions are presented in [12,13] with discrete variables or in [14] with continuous variables.

Applications of this theory to multi-target tracking and classification problems are scattered through several articles presenting different approaches. In [15,13] and in [16] various distances between belief functions are used to tackle the assignment problem. Ref. [15] has been recently improved in [17], but these two references only tackles the assignment problem with uncertain observations and do not cope with the tracking problem. In [14] a solution to track and classify a single dynamical target is proposed, but no extension to multi-target tracking is proposed.

The aim of this article is to gather these scattered results, to unify them in a single and consonant framework based on belief functions, and to propose a solution for multi-target tracking and classification using belief functions when no one exists in the recent literature. The proposed solution also includes a step of hypothesis rejection, which means that it manages new and disappeared targets.

The result is a complete solution to multi-target tracking and classification in a cluttered environment. It mimics the standard and well accepted Bayesian solutions, but it extends them, when possible, with belief functions. A short preliminary version of this article was presented in [18].

The well known Interacting Multiple Model (IMM) algorithm is used to track multiple targets. The assignment of the observations to known targets is performed by the means of a generalized Global Nearest Neighbor algorithm. Target management is ensured by a score functions representing the quality of targets tracks. Finally, the classification step is realized with the Transferable Belief Model instead of a classical Bayesian solution.

This article is organized as follows. An introduction to belief function theory is presented in Section 2. Section 3 deals with tracking problems. Assignment and hypothesis rejection problems

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are tackled in Section 4. Bayesian and proposed algorithms are summarized in Section 5. Finally, two application examples are detailed in Section 6. The first one involves an academic example on aircraft classification with constant classes, it allows a comparison with a Bayesian solution. The second example concerns a pedestrian activity recognition, it highlights a first extension of the proposed algorithm to time varying classes.

2. Belief functions

2.1. Main functions

This section introduces basic notions on belief functions theory, which was firstly introduced by Dempster in [9] and extended by Shafer [10] and Smets [8]. Knowledge is expressed on a discrete set $C = \{c_1, c_2, \ldots, c_{nc}\}$ of nc mutually exclusive and exhaustive hypotheses. Frame C is called the *frame of discernment*. A mass $m(A)$ with $A \subseteq C$ is the part of belief supporting A that, due to a lack of information, cannot be given to any strict subset of A [8]. A mass function m (or basic belief assignment) has to satisfy:

$$\sum_{A \subseteq C} m(A) = 1. \quad (1)$$

Throughout this article, 2^C represents all the subsets of C. A set A such that $m(A) > 0$ is called a *focal element* of m.

In addition to the mass function, two other functions are defined in the following manner. The plausibility function Pl represents the total amount of belief that may be given to a subset A of C with further pieces of evidence:

$$Pl(A) = \sum_{A \cap B \neq \emptyset} m(B). \quad (2)$$

Unlike the plausibility function, the belief function Bel represents the amount of belief that is certain and cannot be reduced:

$$Bel(A) = \sum_{A \supseteq B} m(B). \quad (3)$$

These functions are in one-to-one correspondence [10], so they are used indifferently with the same term ***belief function*** when the context is clear.

A belief function whose focal elements are singletons is called a *Bayesian belief function*, it corresponds to a probability distribution and respects the property of additivity:

$$Pl(A \cup B) = Pl(A) + Pl(B), \quad (4)$$

with $(A, B) \subseteq 2^C$ and $A \cap B \neq \emptyset$. In general, this relation is false and belief functions are non-additive measures.

A belief function such that $m(C) = 1$ respects $Pl(A) = 1$ for all A subsets of C, $A \neq \emptyset$. Denoted by m_0, it is called the *vacuous belief function* and represents the full ignorance.

2.2. Fusion rule and discounting

When more than one mass function is expressed on the same frame of discernment, they can be fused to obtain a single representation. The conjunctive combination used in this work assumes independent and absolutely reliable sources. Let m_1 and m_2 be two mass functions provided by two distinct sources and expressed on the same frame of discernment C, their conjunctive combination is defined as follows:

$$m_{12}(A) = (m_1 \circledcirc m_2)(A) = \sum_{A_1 \cap A_2 = A} m_1(A_1) m_2(A_2). \quad (5)$$

Eq. (5) is the unnormalized rule, the normalized rule is referred to as Dempster's rule of combination, and is defined by:

$$m_{12}(A) = \frac{\sum_{A_1 \cap A_2 = A} m_1(A_1) m_2(A_2)}{1 - \sum_{A_1 \cap A_2 = \emptyset} m_1(A_1) m_2(A_2)}. \quad (6)$$

This rule is used in order to update *a priori* beliefs with online measurements, as in Section 2.4.

The last example in this article involves the discounting of a source of information. Such a discounting assumes that you can estimate the reliability of a source by a factor $\lambda \in [0, 1]$. If $\lambda = 1$, the source is considered as absolutely reliable, while if $\lambda = 0$, the source must be discarded and replaced by a vacuous belief. Thus the discounting m^λ of a given source mass function m is defined by:

$$\begin{cases} m^\lambda(A) = \lambda m(A) & \text{if } A \neq C, \\ m^\lambda(C) = \lambda m(C) + 1 - \lambda & \text{otherwise.} \end{cases} \quad (7)$$

If several sources of information m_i have to be fused, each one with its own reliability λ_i, a classical approach is to first discount all of them, and then to conjunctively fuse them using Eq. (5). Several other fusion rules are defined, and for a review, readers can refer to [19]. For example, contextual data can be included also in the fusion process, see [20], and reliability factors can be adapted online [21], although this is not used in this article.

2.3. Decision rule

Several belief function interpretations exist, among them the Upper/Lower Probabilities (ULP), usually called imprecise probabilities, and the Transferable Belief Model (TBM) of Smets. Basically these models are equal when considering static knowledge, but differ when conditioning steps are involved. Readers interested in this topic can refer to [22]. In a few words, within an ULP model, conditioning requires to condition every probability measure $P(A)$ compatible with the bounds defined by $Bel(A) \leqslant P(A) \leqslant Pl(A)$. Then, the new bounds $Bel(.|.)$ and $Pl(.|.)$ must be recomputed by checking every conditioned probability measures, and taking the new maximum and minimum, while within the TBM it suffices to condition only the original $Bel(A)$ and $Pl(A)$. Thus, the ULP model is more computationally demanding. In a recent article [23], the ULP model has been advocated in a classification problem. But the authors of this article do not find the provided examples conclusive and the advantage of the ULP model over the TBM remains unclear. Since it is more complex to use, the TBM has been chosen in this article, as in [14] for instance.

The TBM represents and manages knowledge with a two level model. The first one, referred to as the credal level, concerns the representation and the manipulation of the data. It is the place where data are encoded, combined and updated with belief functions without assuming probability measures [12]. Decisions are made when necessary at a second level called the pignistic level, where belief functions are transformed into a probability measures using the pignistic transformation justified in [24] through rationality requirements and basic axioms. Pignistic probability $BetP$ is defined by:

$$BetP(\{c_i\}) = \sum_{c_i \in A} \frac{m(A)}{|A|(1 - m(\emptyset))}. \quad (8)$$

Let us remark that other decision rules have been introduced for belief functions, among them the maximum of plausibility [25]. Comparing the drawbacks and advantages of all the decision rules is outside the scope of this article, farther information can be found in [24].

2.4. Generalized Bayes theorem

Bayes theorem enables to compute the *a posteriori* probability from an *a priori* one. With likelihoods $l(c_i|z) = P(z|c_i)$, where z is a