A new parameterless credal method to track-to-track assignment problem

Samir Hachour, François Delmotte, and David Mercier

Univ. Lille Nord de France, UArtois, EA 3926 LGI2A, Béthune, France

Abstract. This paper deals with the association step in a multi-sensor multi-target tracking process. A new parameterless credal method for track-to-track assignment is proposed and compared with parameter-dependent methods, namely: the well known Global Nearest Neighbor algorithm (GNN) and a credal method recently proposed by Denœux et al.

1 Introduction

In a multi-sensor context, the target environment can be observed differently depending on sensors positions and observation capabilities. A centralized fusion process can then help to enhance targets detections and recognitions. To realize the merging of targets data, the central system has amongst other things to order targets estimated data in a common way, which is done through the track-to-track assignment step. Numerous probabilistic methods have been proposed to solve this problem such as the Joint Probabilistic Data Association (JPDA) method [1, 2] and the Multi-Hypothesis Tracking (MHT) method [2]. In the latter, probabilities of associations are propagated over time, which makes this method more robust but also more computationally demanding. Other probabilistic methods can also be found in [2–4].

The focus of this paper is on mono-hypothesis data assignments where matchings between sensors estimates are computed at each time step and no other hypotheses are conserved. In two dimensional assignment problems, which means data obtained from two sensors, optimal matchings can be provided using the Munkres algorithm [5]. Performances are therefore dependent on the manner that data are represented and given to the optimal Munkres algorithm. In the standard Global Nearest Neighbor algorithm (GNN) [2], data are simply Mahalanobis distances [6] between sensors positions estimates, and a parameter is needed to manage targets which are partially observed (which do not belong to all sensors fields of view). Recently, an equivalent belief-function-based method was proposed by Denœux et al.[7]. Mahalanobis distances in this method are transformed to mass functions. This method has the ability to perform multiple information based assignments but, as in GNN method, it still depends on a fix parameter in order to build mass functions from distances. Some other equivalent credal solutions can be found in [8, 9]. The method proposed in [8] models information in the same way as in [7] and [9] proposes a comparison study of the recent belief functions assignment methods.

In this paper, a new parameterless credal method based on likelihoods calculations is proposed. Using single sensor simulations this method is shown to perform as good as parameter-dependent methods when their parameters are optimally trained.

The multi-sensor multi-target tracking architecture used in this paper is presented in Section 2. The proposed solution for the assignment problem is exposed in Section 3. Comparison results are then provided in Section 4.

2 Multi-sensor multi-target architecture

A centralized multi-sensor multi-target architecture, simplified to two sensors, is illustrated in Figure 1. It represents the solution implemented by the authors, which has been employed in previous works [10, 11] and which is used in this paper in Section 4.

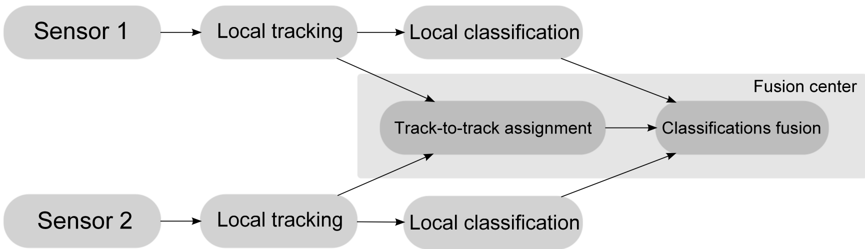

Fig. 1. Track-to-track algorithm based on sensors estimates in a multi-sensor multi-target global scheme.

Each sensor performs a complete tracking and a classification of each target. Details about local tracking and classification algorithms can be found in [11]. Track-to-track assignment can be exclusively performed using distances between sensors estimates, it represents the solution without local classification feedbacks represented in Figure 1.

At each time step k, the set of estimates performed by sensor i is noted $\hat{X}_i(k) = \{\hat{x}_i^1(k), \hat{x}_i^2(k), \ldots, \hat{x}_i^{n_i}(k)\}$, where n_i is the number of targets observed by sensor i at time step k, and $\hat{x}_i^t(k)$, $t \in \{1, \ldots, n_i\}$, is the state estimate of target t.

For each time step k, the distance between the state estimate of target t by sensor i and state estimate of target ℓ by sensor j is defined by:

$$d_{t,\ell}(k) = (\hat{x}_i^t(k) - \hat{x}_j(k)^\ell)^T (Cov_{t,\ell}(k))^{-1} (\hat{x}_i^t(k) - \hat{x}_j^\ell(k)), \tag{1}$$

with $t \in \{1, \ldots, n_i\}$, $\ell \in \{1, \ldots, n_j\}$, n_i and n_j respectively the number of targets observed by sensors i and j at time step k, and the global covariance matrix $Cov_{t,\ell}(k)$ taken equal to the mean value of the covariance matrix of target t estimated by sensor i (noted $P_i^t(k)$) and the covariance matrix of target ℓ estimated by sensor j (noted $P_j^\ell(k)$):

$$Cov_{t,\ell}(k) = \frac{1}{2}(P_i^t(k) + P_j^\ell(k)) \; . \tag{2}$$

Local classifications performed by sensors can be used to enhance track-to-track assignment step. This is done using the feedback assignment strategy given in Figure 2.

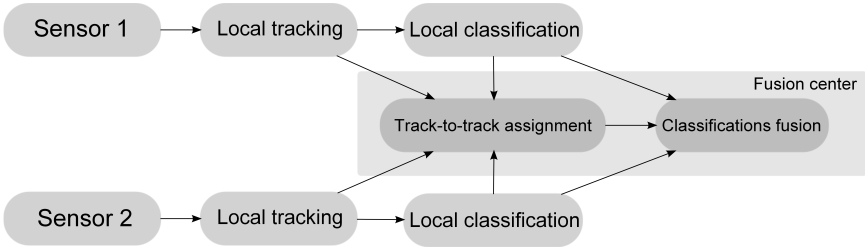

Fig. 2. Track-to-track algorithm based on sensors estimates and local classification results in a multi-sensor multi-target global scheme.

Suppose targets local classifications results are given in the form of mass functions m expressed on a the frame 2^C, where $C = \{c_1, c_2, ...\}$ represents the set of all the possible classes. Such additional information can then be used in the assignment step as explained in details in [7].

The association methods compared in Section 4 to achieve track-to-track matchings are all based on distances expressed by (1).

3 A non-parametric credal solution for the assignment problem

In this section, a parameterless credal method is presented to perform the associations from the distances expressed by (1). In this solution, mass functions modeling does not need any parameter design. It is based on likelihoods seen as plausibility functions as in Smet's works [12] (Similar notions can also be found in [13]).

Time step k has been omitted for the sake of simplicity.

Let $r_{t,\ell} \in \{0,1\}$ be the relation that $\hat{x}_i^t$ is associated or not with $\hat{x}_j^\ell$ ($r_{t,l} = 1$ means that target t estimated by sensor i corresponds to target ℓ estimated by sensor j, $r_{t,\ell} = 0$ otherwise).

For each estimated target $t \in \{1,\ldots,n_i\}$ given by a sensor i, a plausibility function Pl_t is built on the set $\hat{X}_j^{*_t} = \{\hat{x}_j^1, \ldots, \hat{x}_j^{n_j}, *_j\}$ of sensor j known targets, element $*_t$ meaning that a new target is associated with $\hat{x}_i^t$. The set $\hat{X}_j^{*_t}$ can be shortly denoted $\{1,\ldots,n_j,*_t\}$. The plausibility Pl_t is defined by:

$$Pl_t(\{\ell\}) = G_{\ell,t}, \ \ \forall \ell \in \{1,\ldots,n_j\}, \tag{3}$$

where $G_{\ell,t}$ is a likelihood measure calculated as:

$$G_{\ell,t} = \frac{exp[-d_{\ell,t}^2/2]}{\sqrt{(2\pi)^q |Cov_{\ell,t}|}}, \ \ \ell \in \{1,...,n_j\} \ , \tag{4}$$

with q the dimension of the estimated state vector $\hat{x}$ and $Cov_{\ell,t}$ defined as in (2).

Plausibility $Pl_t(\{\ell\})$ indicates the plausibility that target with state $\hat{x}_i^t$ is associated with target with state $\hat{x}_j^\ell$.

The maximum plausibility that target with state $\hat{x}_i^t$ will be associated to one of the n_j already known targets by sensors j corresponds to $\max_{\ell=1,\ldots,n_j}(Pl_t(\{\ell\})) \leq 1$. This maximum can be lower than one, in particular if the frame of discernment formed by the set of known objects is not exhaustive. Indeed, a target with state $\hat{x}_i^t$ can correspond to a new object ($*_t$). The plausibility of this event is thus defined by:

$$Pl_t(\{*_t\}) = 1 - \max_{\ell=1,\ldots,n_j}(Pl_t(\{\ell\})). \tag{5}$$

Pl_t is then defined on a an exhaustive closed-world $\hat{X}_j \cup \{*_t\}$, the corresponding mass function is denoted by m_t and is obtained by a direct application of the Generalized Bayesian Theorem (GBT)[14, 15], recalled here for convenience:

$$m_t(A) = \prod_{\ell \in A} Pl_t(\{\ell\}) \prod_{\ell \in \bar{A}} (1 - Pl_t(\{\ell\})), \;\; \forall A \subseteq \hat{X}_j^{*_t}. \tag{6}$$

Each mass function m_t, regarding the association of target $\hat{x}_i^t$, can then be combined with any other mass functions based on other additional information (e.g. shape, color, class, etc.) [7].

Once all mass functions m_t have been computed for each estimated target t, they are transformed into pignistic probabilities $BetP_t$ using the pignistic transformation [14].

The best assignment relation is then chosen as the one maximizing the following criterion:

$$\max \sum_{\ell,t} BetP_t(\{\ell\}) r_{\ell,t}, \;\; \ell = \{1,\ldots,n_i+n_j\}, t = \{1,\ldots,n_j\} \;. \tag{7}$$

with the following constraints:

$$\sum_{\ell}^{n_i+n_j} r_{\ell,t} \leq 1 \;, \tag{8}$$

$$\sum_{t}^{n_j} r_{\ell,t} = 1 \;, \tag{9}$$

$$r_{\ell,t} \in \{0,1\} \; . \forall \ell \in \{1,\ldots,n_i+n_j\}, \forall t \in \{1,\ldots,n_j\} \tag{10}$$

As Denœux et al.'s and GNN approaches, this problem can be solved using Hungarian or Munkres algorithms [5].

The constraint expressed by (8) means that sensor i's estimation of a given target state can be assigned to sensor j's estimation of a given target state, if not, it is considered as a new target's state. The constraint expressed by (9) means that a target known by sensor j can be matched with a target of sensor i. If the target is not known by sensor i, it is assigned to the extraneous element ($*$).

The assignment problem is illustrated in Table 1. Note that this description is based on sensor $i's$ point of view (to which elements of sensor i are assigned the elements of sensor j?). The same process may be performed for sensor j point of view (to which elements of sensor j elements of sensor i are associated). As Mercier et al.'s method [8], this process is generally not symmetric.

Table 1. Pignistic probabilities assignment matrix.

	$\hat{x}_i^1$	$\hat{x}_i^2$	$\ldots$	$\hat{x}_i^{n_i}$
$\hat{x}_j^1$	$BetP_{1,1}$	$BetP_{1,2}$	$\ldots$	$BetP_{1,n_i}$
$\hat{x}_j^2$	$BetP_{2,1}$	$BetP_{2,2}$	$\ldots$	$BetP_{2,n_i}$
$\vdots$	$\vdots$	$\vdots$	$\ldots$	$\vdots$
$\hat{x}_j^{n_j}$	$BetP_{n_j,1}$	$BetP_{n_j,2}$	$\ldots$	$BetP_{n_j,n_i}$
$*_1$	$BetP_{*_1,1}$	0	$\ldots$	0
$*_2$	0	$BetP_{*_2,2}$	$\ldots$	0
$\vdots$	$\vdots$	$\vdots$	$\ldots$	$\vdots$
$*_{n_i}$	0	0	$\ldots$	$BetP_{*_{n_i},n_i}$

4 Simulations results

In this section, two scenarios of test are exposed to illustrate comparisons between GNN algorithm, Denoeux et al.'s algorithm and the proposed algorithm.

GNN algorithm depends on a parameter noted λ which allows GNN algorithm to manage objects detection, the real λ being equal to the maximum distance between an observation and a prediction in Munkres algorithm. In Denœux et al.'s algorithm [7], a parameter noted γ is used to transform distances into mass functions: the weight $\exp(-\gamma d_{t,\ell})$, with $d_{t,\ell}$ the distance between objects t and ℓ, supports the belief in favor of the association of t with ℓ, and $1-\exp(-\gamma d_{t,\ell})$ supports the converse (non-association of t with ℓ).

Formalized in [9], a link between parameters λ and γ can be stated. As λ is the maximum distance from which a non association is established for each observation, the following relation can be considered: $\exp(-\gamma\lambda) = 1-\exp(-\gamma\lambda)$, which means:

$$\gamma = \frac{-\log(0.5)}{\lambda}. \tag{11}$$

A first scenario is illustrated in Figure 3. Four nearby targets have to be tracked. The idea is to match estimations of sensor 1 (circles) to estimations of sensor 2 (stars). This scenario 1 aims to show the impact on the association decision when parameters are not optimally defined. False assignment rates averaged over 10 different measurement noise realizations [11] for each association algorithm for different values of parameters λ and γ are depicted in Figure 4. It can be seen that changes in parameters λ and γ have clearly an effect on the performances of the parameter-dependent algorithms. Indeed, large values of γ correspond to low values of λ which is seen as the detection distance. Low values of the detection distance force the parameter-dependent algorithms to decide that some or all the incoming targets are new ones and some or all known targets are non-detected. This is the reason of the increasing false decision rates of the parameter-dependent algorithms in Figure 3.

Maximizing plausibilities instead of pignistic probabilities in (7) in the proposed approach give similar results in these scenarios.

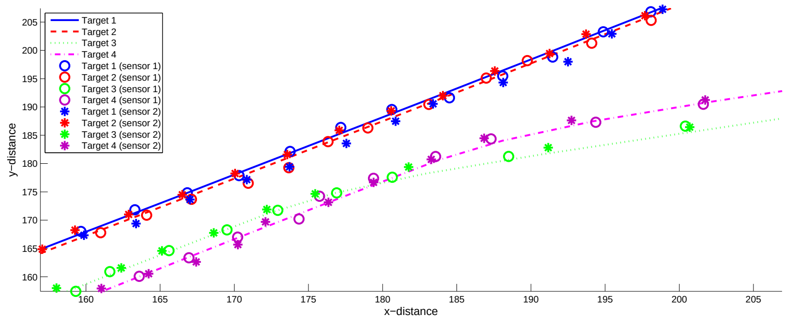

Fig. 3. Scenario 1 description: four conflicting targets. Estimations of sensor 1 are given by circles. Estimations of sensor 2 are given by stars.

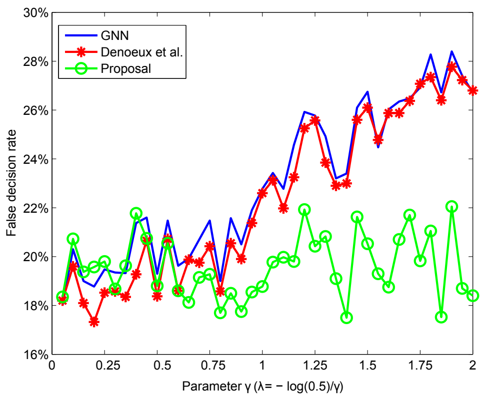

Fig. 4. False decision rates aggregated over 10 noise realizations with different values of parameters γ (and then λ (11)).

A second simulation, depicted in Figure 5, aims to illustrate the benefit of the use of additional information in the assignment step (cf Figure 2). In this case, classification mass functions are combined with mass functions provided by distances for the two credal algorithms. Since, the GNN algorithm is based on distances only as entering data, no method allowing the integration of additional information for GNN algorithm was already proposed. In this simulation, optimal parameters λ and γ are used. In Figure 6, it can be observed that additional information enhances the credal algorithms performances. Additional information (classes, velocity, etc.) can help to resolve the conflicting assignment situation. Thanks to the general formel aspect of belief functions theory, multiple information can be modelled and combined, which leads to a more accurate assignment decisions.

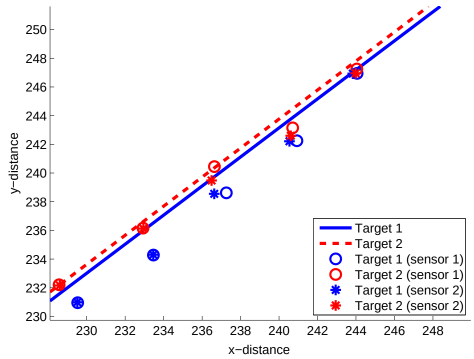

Fig. 5. Scenario 2 description: two nearby targets. Estimations of sensor 1 are given by circles. Estimations of sensor 2 are given by stars.

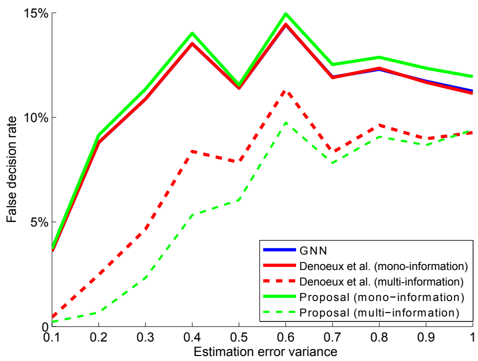

Fig. 6. False decision rates aggregated over 10 noise realizations, mono-information refers to distance and multi-information refers to distance and class.

5 Conclusion

This paper provides a new parameterless credal method to the assignment task in multi-target tracking.

Contrarily to equivalent methods which are parameter-dependent, this one does not need any parameter. Parameters in the concerned methods allows new elements appearances to be managed (detection of new targets in the case of observation-to-track assignment or partially observed targets in track-to-track assignment). A more natural appearance management solution is provided in this paper, it is based on a better understanding of targets environment.

Comparisons on conflicting scenarios show that the proposed method performs equally to parameter-dependent methods, when their parameters are optimally trained.

Moreover, it is shown that credal algorithms performances can be enhanced, when additional information are available.

The ability of the credal methods to preserve the information on imprecise sets would represent an important advantage for a future multi-scan and multi-hypothesis based approaches.

The authors are very grateful to Prof. T. Denœux for having shared the Matlab^{TM}code of Denœux et al.'s assignment algorithm [7].

References

1. T.E. Fortmann, Y. Bar-Shalom, and M. Scheffe. Multi-target tracking using joint probabilistic data association. In *Proceedings of the 19th IEEE Conference on Decision and Control including the Symposium on Adaptive Processes.*, volume 19, pages 807–812. IEEE, 1980.
2. S.S. Blackman and R. Popoli. *Design and analysis of modern tracking systems*. Artech House, Norwood, MA, USA, 1999.
3. J. Vermaak, S.J. Godsill, and P. Perez. Monte carlo filtering for multi target tracking and data association. *IEEE Transactions on Aerospace and Electronic Systems*, 41(1):309–332, January 2005.
4. Y. Bar-Shalom. *Tracking and data association*. Academic Press Professional, San Diego, USA, 1987.
5. F. Bourgeois and J-C. Lassalle. An extension of the Munkres algorithm for the assignment problem to rectangular matrices. *Communications of the ACM*, 14(12):802–804, 1971.
6. G.J. McLachlan. Mahalanobis distance. *Resonance*, 4(6):20–26, 1999.
7. T. Denœux, N. El Zoghby, V. Cherfaoui, and A. Jouglet. Optimal object association in the Dempster-Shafer framework. *IEEE Transactions on Cybernetics*, to appear.
8. D. Mercier, É. Lefèvre, and D. Jolly. Object association with belief functions, an application with vehicles. *Information Sciences*, 181(24):5485–5500, 2011.
9. S. Hachour, F. Delmotte, and D. Mercier. Comparison of credal assignment algorithms in kinematic data tracking context. In *15th International conference on Information Processing and Management of Uncertainty in Knowledge-Based Systems (IPMU)*, 2014, accepted.
10. S. Hachour, F. Delmotte, D. Mercier, and E. Lefèvre. Multi-Sensor Multi-Target tracking with robust kinematic data based credal classification. In *8th Workshop, Sensor Data Fusion: Trends, Solutions, Application , SDF 2013, Bonn, Germany, octobre*, 2013.
11. S. Hachour, F. Delmotte, D. Mercier, and E. Lefèvre. Object tracking and credal classification with kinematic data in a multi-target context. *Information Fusion*. In press.
12. P. Smets. Belief functions on real numbers. *International Journal of Approximate Reasoning*, 40(3):181–223, November 2005. 00105.
13. A. Appriou. Multisensor data fusion in situation assessment processes. In *Qualitative and quantitative practical reasoning*, pages 1–15. Springer, 1997.
14. P. Smets. Belief functions: the disjunctive rule of combination and the Generalized Bayesian Theorem. *International Journal of Approximate Reasoning*, 9(1):1–35, 1993.
15. F. Delmotte and P. Smets. Target identification based on the Transferable Belief Model interpretation of Dempster-Shafer model. *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans*, 34(4):457–471, 2004.