Information Fusion using Covariance Intersection in the Frame of the Evidence Theory

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INFORMATION FUSION USING COVARIANCE INTERSECTION IN THE FRAME OF THE EVIDENCE THEORY

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ABSTRACT

This paper presents a multisensor and multitarget tracking architecture with objects eclipses. The architecture is composed of two sub-systems : a multitarget tracking for each sensor and a multitarget and multisensor fusion center. The multitarget tracking uses the Dempster-Shafer theory with proposed distributions of masses, that are functions of the distance between perceived objects and known objects, the sensor reliability and the perception uncertainty. The multisensor fusion is based on the Covariance Intersection algorithm.

1. INTRODUCTION

Information used here can result of sensors conceived to detect during measures, human origin informations reporting the presence and characteristics of objects, and finally data processed by human operators (for example, image data). The objects of interest can disappear or reappear or not be perceived by other sensors. Thus, we use the Dempster-Shafer theory to formalize objects eclipses and the association between the prediction and the perception. The architecture is a parallel sensor topology and is composed of two sub-systems : the multitarget tracking for each of the sensors and a multisensor multitarget fusion center (figure 1). We have a network of geographically distributed sensors, each sensor $S_j(j = 1, ..., J)$ tracks perceived targets using a perception uncertainty and its own sensor reliability. Then, the tracked targets are fused in a fusion center which concludes on the objects presence, a position in the scene and on the associated probability. Because of this fusion center, the sensors are also called sources of informations.

2. MULTI-OBJECTS ASSOCIATION

2.1. Generalities

A lot of technics are developped to associate and to track targets (Maximum Likelihood, Nearest Neightbor method, Joint Probabilistic Data Association Filter [1, 2], Multiple Hypothesis Filter [3, 4, 5], Credibilistic Multisensor Association [6], ...).
The Joint Probabilistic Data Association Filter (JPDAF) and the Probabilistic Multiple Hypothesis Tracking algorithm (PMHT) are the most used filters. The JPDAF can not initialize new tracks and the PMHT algorithm requires to know, as an priori, the number of tracked targets and have an important combinatorial complexity.
In our case, the system must have the ability to re-associate the tracks for an object which has temporally disappeared and initialize new tracks. Morever, the results of information fusion must depend on the sensor reliabilities and perception incertainties.

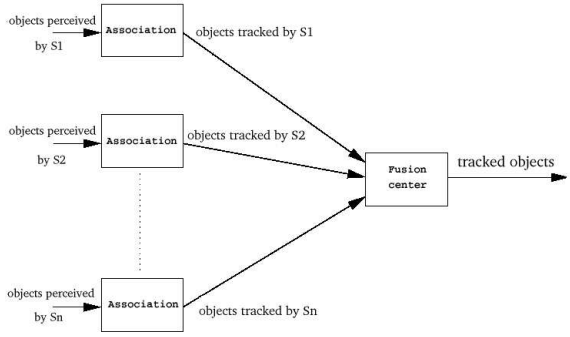

Figure 1: *Multisensor multitarget tracking system*

On account of contraints, we have chose the evidence theory approach and semantic to model target associations [7].
The principle of the system is to associate perceived objects with know objects predicted with a Kalman filter.

2.2. The Kalman-Bucy filter

The Kalman-Bucy filter is a near-optimal method developped in [8] to produce an accurate estimate of the state of a system. In the general case, the representation of the system in the state space consists in the two follow-

ing equations (state equation and measurement equation):

$$\begin{cases} \underline{X}(t+1) &= A(t)\underline{X}(t) + B\underline{U}(t) + G\underline{W}(t) \\ \underline{Y}(t) &= H(t)\underline{X}(t) + \underline{V}(t) \end{cases} \quad (1)$$

with at the instant t :
$\underline{X}(t)$: state vector describing the system,
$\underline{U}(t)$: determinist input of state model,
$\underline{Y}(t)$: observation vector,
$\underline{V}(t)$: observation noise with $\begin{cases} E\{\underline{V}(t)\} = 0 \\ E\{\underline{V}(t)\underline{V}^T(t)\} = R(t) \end{cases}$
$\underline{W}(t)$: plant noise with $\begin{cases} E\{\underline{W}(t)\} = 0 \\ E\{\underline{W}(t)\underline{W}^T(t)\} = Q(t) \end{cases}$
$A(t)$: state transition matrix,
$B(t)$: command matrix,
$H(t)$: observation matrix.
In these conditions, $\underline{\hat{X}}(t|t)$ being the estimate of $X(t)$, the Kalman filter predicts the future state of the system using the process model :

$$\underline{\hat{X}}(t+1|t) = A(t)\underline{\hat{X}}(t|t) \quad (2)$$
$$P(t+1|t) = A(t)P(t|t)A^T(t) + Q(t) \quad (3)$$

The Kalman gain matrix $K(t+1)$ which minimizes the mean square estimation error is given by :

$$K(t+1) = P(t+1|t)C(t+1)^T(R(t+1) + C(t+1)P(t+1|t)C^T(t+1))^{-1} \quad (4)$$

The estimate $\underline{\hat{X}}(t+1|t+1)$ of $X(t+1)$ comes from the update of the prediction using the last measure :

$$\underline{\hat{X}}(t+1|t) \triangleq E\left\{\underline{X}(t+1)|\underline{\hat{Y}}(t), U(t+1), \underline{\hat{Y}}(t+1|t)\right\}$$
$$\underline{\hat{X}}(t+1|t) = A(t)\underline{\hat{X}}(t|t) + B(t)\underline{U}(t+1)$$
$$\underline{\hat{y}}(t+1|t) = C(t+1)\underline{\hat{X}}(t+1|t)$$
$$\underline{\hat{X}}(t+1|t+1) = \underline{\hat{X}}(t+1|t) + K(t+1)(\underline{Y}(t+1) - \underline{\hat{Y}}(t+1))$$
$$P(t+1|t+1) = (I - K(t+1)C(t+1))P(t+1|t)$$

As we want to estimate the position of an object, for this, we define the state vector $\underline{X}(t) = [\ddot{x}(t)\ \dot{x}(t)\ x(t)]^T$ representing the acceleration, the velocity and the position of the object at instant t.

2.3. Theory of Evidence

2.3.1. Generalities

The Evidence theory has been introduced by Dempster [9] [10] and resumed by Shafer under a more accomplished mathematical formalism [11]. The principle of the Evidence theory is to manipulate some beliefs on the hypothesis space Θ, named frame of discernement, composed of N exhausitive and exclusive hypotheses H_i :

$$\Theta = \{H_1, H_2, ..., H_N\} \quad (5)$$

with :

$$\forall i \neq j,\ H_i \cap H_j = \oslash \quad (6)$$

The definition referential 2^Θ is the power set formed by the $2^N - 1$ subsets of Θ, each of them being called a proposition :

$$2^\Theta = \{A/A \subseteq \Theta\} = \{\oslash, H_1, ..., H_N, H_1 \cup H_2, ..., \Theta\} \quad (7)$$

The function $m(.)$ called the Basic Belief Assignment (BBA), represents the repartition of a mass among elements of 2^Θ. Then, the BBA is a function verifying :

$$m\ :\ 2^\Theta \rightarrow [0,1] \quad (8)$$
$$m(\oslash) = 0 \quad (9)$$
$$\sum_{A \subseteq \Theta} m(A) = 1 \quad (10)$$

The modelisation of the belief assigned to each proposition is also called distribution of masses.

2.3.2. Belief measures

Three other belief measures are usually used to represent informations :

- The credibility function collects masses of all the propositions B that imply A. It is defined in the following way :

$$\begin{array}{l} Bel_\Theta : 2^\Theta \rightarrow [0,1] \\ Bel_\Theta(A) = \sum_{B/B \subseteq A \neq \oslash} m_\Theta(B) \end{array} \quad (11)$$

- The plausibility function represents the amount of belief that could potentially be placed in A. It is defined in the following way :

$$\begin{array}{l} Pl_\Theta : 2^\Theta \rightarrow [0,1] \\ Pl_\Theta(A) = \sum_{B/B \cap A \neq \oslash} m_\Theta(B) \end{array} \quad (12)$$

- The pignistic probability is a measure of probability which approximates the credibility and the plausibility. The pignistic probability of a proposition A is the sum of the supposed equiprobabilities of all non-single propositions including A [12] :

$$\begin{array}{l} BetP_\Theta : 2^\Theta \rightarrow [0,1] \\ BetP_\Theta(A) = \sum_{B \in 2^\Theta / A \subset B} \frac{m_\Theta(B)}{|B|} \end{array} \quad (13)$$

  where $|B|$ denotes the cardinality of B.

2.3.3. Distribution of masses

We construct a distribution of masses inspired by Rombaut's studies [13] and by Gruyer's studies [14]. To obtain this distribution, we use a distance function between perceived objects Y_i and objects X_j. Our main hypothesis is that a perceived object can not be at once associated and not associated with a known object.
Then, the frame of discernement is composed of two hypotheses H_1 and H_2 :

- H_1 corresponds to the hypothesis «the perceived object is the known object » : $H_1 = Y_i \mathcal{R} X_j$,
- H_2 corresponds to the hypothesis «the perceived object is not the known object » : $H_2 = Y_i \overline{\mathcal{R}} X_j$,

So, the set Θ is defined by the disjonction of this two hypotheses and corresponds to the proposition « I do not know » : $\Theta = H_1 \cup H_2$.

We define $d_{i,j}$ as the Euclidian distance between a perceived object Y_i and a known object X_j, and $d_{i,j}^{k\sigma}$ as the distance between the known object position and the perceived object position and its uncertainty ellipsoid computed for some $k\sigma$.
The distribution of masses comes from the association between an object X_i perceived by the sensor S_k and a known object Y_j (figure 2). This distribution depends on the Euclidian distance value, so we distinguish three cases :

$$0 \leq d_{i,j} < d_{i,j}^{m\sigma} \quad (14)$$
$$d_{i,j}^{n\sigma} \leq d_{i,j} < d_{i,j}^{m\sigma} \quad (15)$$
$$d_{i,j} \geq d_{i,j}^{m\sigma} \quad (16)$$

Finally, the masses distribution definition is given by :

$$m_{\Theta}^{S_k}\left(X_i \mathcal{R} Y_j\right) = \begin{cases} \frac{\alpha_k}{2}\left(1 + \cos\frac{\pi d_{i,j}}{d_{i,j}^{n\sigma}}\right) & \text{if (14)} \\ 0 & \text{otherwise} \end{cases}$$

$$m_{\Theta}^{S_k}\left(X_i \overline{\mathcal{R}} Y_j\right) = \begin{cases} 0 & \text{if (14)} \\ \frac{\alpha_k}{2}\left(1 + \cos\frac{\pi\left(d_{i,j} - d_{i,j}^{m\sigma}\right)}{2\times\left(d_{i,j}^{m\sigma} - d_{i,j}^{n\sigma}\right)}\right) & \text{if (15)} \\ \alpha_0 & \text{if (16)} \end{cases}$$

$$m_{\Theta}^{S_k}\left(\Theta_{i,j}\right) = \begin{cases} 1 - \frac{\alpha_k}{2}\left(1 + \cos\frac{\pi d_{i,j}}{d_{i,j}^{n\sigma}}\right) & \text{if (14)} \\ 1 - \frac{\alpha_k}{2}\left(1 + \cos\frac{\pi\left(d_{i,j} - d_{i,j}^{m\sigma}\right)}{2\times\left(d_{i,j}^{m\sigma} - d_{i,j}^{n\sigma}\right)}\right) & \text{if (15)} \\ 1 - \alpha_0 & \text{if (16)} \end{cases}$$

with $\alpha_k \in [0,1]$ quantifying the sensor reliability and $n \in \mathbb{R}$, $m \in \mathbb{R}$ with $n < m$.

2.4. Multiobject association

For any sources S_m, the association system have to consider three kinds of objects :

- the $n_Y^{S_m}$ objects $Y_{j_y}^{S_m}(t)$ perceived by the source S_m,
- the $n_X^{S_m}$ known objects $X_{j_x}^{S_m}(t|t-1)$, issued of the tracked object state prediction,
- the $n_Z^{S_m}$ propaged objects $Z_{j_z}^{S_m}(t|t-1)$ issued of the propagation in the time of disappeared objects.

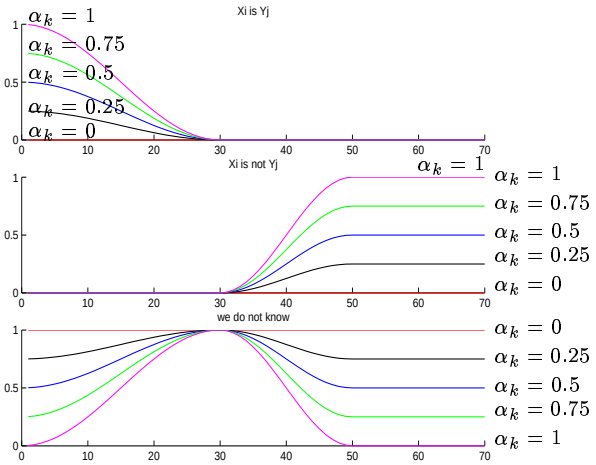

Figure 2: distribution of masses

The association consists in the discrimination of beliefs constructed between the perceived objects and the known objects $m_{XY}^{S_m}(.)$ and between the perceived objects and the propaged objects $m_{XZ}^{S_m}(.)$. The decision rule comes from the maximisation of belief :

$$d(., Y_{j_y}^{S_m}) = \max_{j_x}\left\{m_{\Theta_{XY}}^{S_m}\left(X_{j_x}^{S_m}(t|t-1)\mathcal{R}Y_{j_y}^{S_m}(t)\right)\right\} \quad (17)$$
$$d(., Y_{j_y}^{S_m}) = \max_{j_x}\left\{M_{XY}^{S_m}\right\} \quad (18)$$

With the proposed distribution of masses, this decision criterion also corresponds to the maximum of credibility.
So, the following rules are applied for the decision:

- If $m_{\Theta_{XY}}^{S_m}\left(X_{j_x}{}^{S_m}(t|t-1)\mathcal{R}Y_j^{S_m}(t)\right) > 0$, then $X_{j_x}^{S_m}(t|t-1)$ and $Y_{j_y}^{S_m}$ are associated like a tracked object. We estimate the tracked object state and the covariance of estimation error using the perceived parameters.
- If $m_{\Theta_{XY}}^{S_m}\left(X_{j_x}^{S_m}(t|t-1)\overline{\mathcal{R}}Y_j^{S_m}(t)\right) \neq 1$ and $\neq 0$ then $X_{n_x^{S_m}}(t|t-1)$ and $Y_{n_y^{S_m}}$ are associated like an object propaged in time because of the incertitude on its trajectory. We estimate the propaged object state and the covariance of estimation error using the perceived parameters.
- If $m_{\Theta_{XY}}^{S_m}\left(X_{j_x}^{S_m}(t|t-1)\overline{\mathcal{R}}Y_j^{S_m}(t)\right) = 1$ then $X_{n_x}^{S_m}(t|t-1)$ and $Y_{n_y}^{S_m}$ are not associated. We considerate that the object has disappeared, so we propage its previous estimation parameters in the time.

If no prediction can be associated with a perception, then the perceived object becomes a new tracked object.

3. MULTI-SENSORS FUSION

3.1. Masses aggregation

We fuse the independant sources using the Dempster's combination rule, an orthogonal sum with associative and commutative properties. For two sources S_1 and S_2, the combination is defined by :

$$m_\Theta(A) = m_\Theta^{S_1} \oplus m_\Theta^{S_2} \tag{19}$$

$$m_\Theta(A) = \frac{1}{1-k_\Theta} \sum_{A_i \cap B_j = A} m_\Theta^{S_1}(A_i)\, m_\Theta^{S_2}(B_j) \tag{20}$$

$$k_\Theta = \sum_{A_i \cap B_j = \emptyset} m_\Theta^{S_1}(A_i)\, m_\Theta^{S_2}(B_j) \tag{21}$$

Here, the coefficient k_Θ represents the existing conflict between the sources S_1 and S_2. For $k_\Theta = 1$, the two information sources are totally in conflict and for $k_\Theta = 0$, the two information sources are totally in agreement.

Our aim is to aggregate objects tracked by sensors S_m in relation with the predicted object present in the scene. These predictions are issued of the Covariance Intersection algorithm between estimates of the same objects tracked by different sensors at the previous instant.

3.2. The Covariance Intersection algorithm

The Covariance Intersection Algorithm [15] is a data fusion algorithm with a convex combination of the mean and covariance estimates.
Let's consider two objects $\mathcal{A}$ and $\mathcal{B}$ with means and associated covariance estimates $\{a, A\}$ and $\{b, B\}$. The estimated means of a and b are $\overline{a}$ and $\overline{b}$ and the error estimates are $\widetilde{a} = a - \overline{a}$ and $\widetilde{b} = b - \overline{b}$. The mean squared error and the cross correlation are :

$$\overline{P}_{aa} = E\left\{\widetilde{a}\widetilde{a}^T\right\} \tag{22}$$

$$\overline{P}_{bb} = E\left\{\widetilde{b}\widetilde{b}^T\right\} \tag{23}$$

$$\overline{P}_{ab} = E\left\{\widetilde{a}\widetilde{b}^T\right\} \tag{24}$$

$\overline{P}_{aa}$ and $\overline{P}_{bb}$ may be not known but consistent estimates are known :

$$P_{aa} \geq \overline{P}_{aa} \quad , \quad P_{bb} \geq \overline{P}_{bb} \tag{25}$$

The cross correlation $\overline{P}_{ab}$ between two estimates is also unknown [16].
The combination of $\mathcal{A}\{a, A\}$ and $\mathcal{B}\{b, B\}$ to yield a new estimate $\mathcal{C}\{c, C\}$ is defined by :

$$C^{-1} = \left(\omega A^{-1} + (1-\omega) B^{-1}\right) \tag{26}$$

$$c = C\left(\omega A^{-1} a + (1-\omega) B^{-1} b\right) \tag{27}$$

This Covariance Intersection (CI) algorithm can be easily extended to n estimates :

$$C = \left(\sum_{i=1}^{n} \omega_i A_i^{-1}\right)^{-1} \tag{28}$$

$$c = C\left(\sum_{i=1}^{n} \omega_i A_i^{-1} a_i\right) \tag{29}$$

where a_i are the statistical means and A_i the covariance of the i^{th} estimate $\mathcal{A}_i$, and $\sum_{i=1}^{n} \omega_i = 1$.

3.3. Decision

For each sensor m, we search among the tracked objects $\mathcal{A}_i^{S_m}(t)$ for the ones which are in relation with the prediction of fused object, noted $\mathcal{C}_{t|t-1}$ using Dempster's rule combination :

$$m_\Theta\left(\mathcal{C}_{t|t-1}\mathcal{R}\mathcal{A}_j\right) = \bigoplus_{m=1}^{M} m_\Theta^{S_m}\left(\mathcal{C}_{t|t-1}\mathcal{R}\mathcal{A}_j^{S_m}\right) \tag{30}$$

Objects tracked by the M sensors associated to its prediction in the scene is obtained by a decision rule :

$$d(\mathcal{C}(t|t-1), .) = \max_j \left\{m_\Theta\left(\mathcal{C}_{t|t-1}\mathcal{R}\mathcal{A}_j\right)\right\} \tag{31}$$

The weights ω_i, associated to a tracked object by sensor i, are calculated using masses of objects tracked by m sensors $(m = 1, .., M)$ issued of the decision rule. These masses come from tracking sub-systems after decision, thus ω_i depends on sensors reliabilities and the credibilities associated to tracked objects :

$$\omega_i = \frac{m_\Theta^{S_i}\left(\mathcal{C}_{t|t-1}\mathcal{R}\mathcal{A}^{S_i}\right)}{\sum_{m=1}^{M} m_\Theta^{S_m}\left(\mathcal{C}_{t|t-1}\mathcal{R}\mathcal{A}^{S_m}\right)} \tag{32}$$

With all the selected objects, we fuse their state vectors and their covariances with the CI algorithm to calculate the covariance of the estimation error $C_{t|t}$ and the state vector $c_{t|t}$ of the fused object.

If a tracked object is fused but is not associated to the predicted object, then $m_\Theta^{S_i}\left(\mathcal{C}_{t|t-1}\overline{\mathcal{R}}\mathcal{A}^{S_i}\right)$ is close to 1 and the associated weight ω_i is close to 0. Thus, this object do not occur in the fusion of estimates.
If no object $\mathcal{C}(t|t-1)$ can be fused with the object issued of the prediction, then we considerate that the object $\mathcal{C}$ has disappeared.
If no objects $\mathcal{A}_j^{S_m}$ can be associated with the objects issued of the prediction $\mathcal{C}_{t|t-1}$, then we considerate it like an appearance. To manage appearances, with CI algorithm, we fuse non-associated objects tracked by sensors.

The distribution of masses of the fused objects $\mathcal{A}_j^{S_m}$ issued of sensors are aggregated with the Dempster's combination rule to produce a credibility on the presence of objects in the scene. A mass $m_\Theta\left(\mathcal{C}(t|t-1)\,\mathcal{R}\,\mathcal{A}(t)\right)$ issued of this combination allows to know the credibility, at instant t, of the association between the prediction and the objects tracked by all sensors.

4. SOME RESULTS

The parameters of the masses distribution are $n = 3$ and $m = 5$ in the equations 14, 15 and 16.

We have made some experiments with a system composed of two sensors. The sensor 0 perceives three objets (figure 3a) with a reliability $\alpha_0 = 0.90$. The object positions uncertainty is 10%. The sensor 1 perceives two objets (figure 3b) with a reliability $\alpha_1 = 0.40$. The objects are perceived by the two sensors but can be hidden.

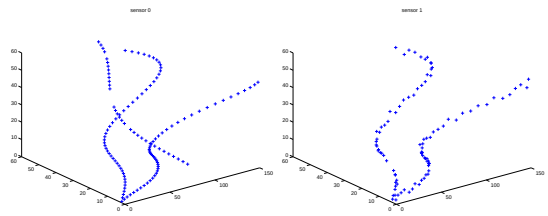

Figure 3: *Positions perceived by two sensors*

Each sensor tracks correctly the perceived objects ($\triangle$ for the first object, $\Diamond$ for the second and $*$ for the third).

On sensor 0, the system reassociates the hidden object (figure 4) after the temporal propagation (o).

On sensor 1, the system tracks perfectly the two objects in spite of the uncertainty on the positions and reassociate the hidden object (figure 6) after the temporal propagation (o).

The credibility associated with object 0, perceived by sensor 0, corresponds to a correct association.

The credibility associated with object 0, perceived by sensor 1, corresponds to an association after two propagations because of the bad perception of the position.

The position prediction of the different objects based on the Covariance Intersection Algorithm allows to track the objets perceived by only one of the sensors (figure 8).

The proposed fusion between a predicted object position and the object tracked by each sensor allows the Covariance Intersection to be a function of the distribution of masses by using the credibility on the tracking.

The credibility resulting of fused objects (9) gives the confidence about the presence of an object in the scene.

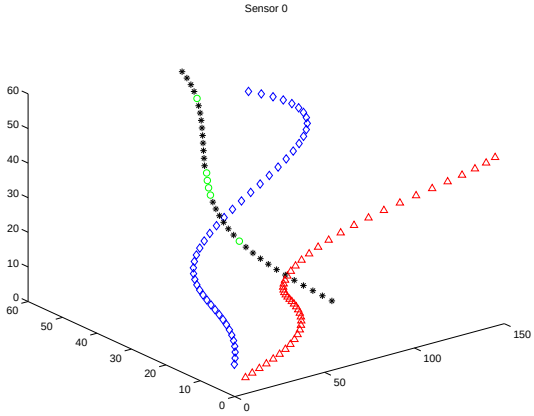

Figure 4: *Results of the tracking algorithm (sensor 0)*

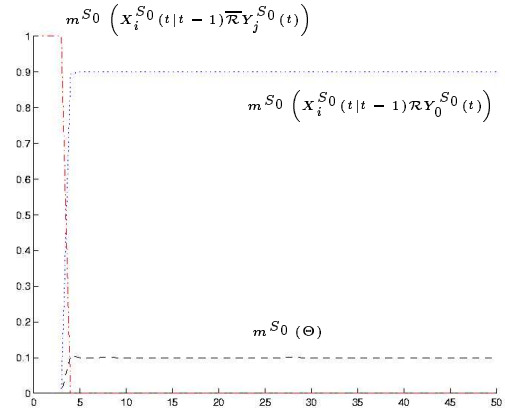

Figure 5: *Distribution of masses issued of the multiobject association for object 0 in sensor 0*

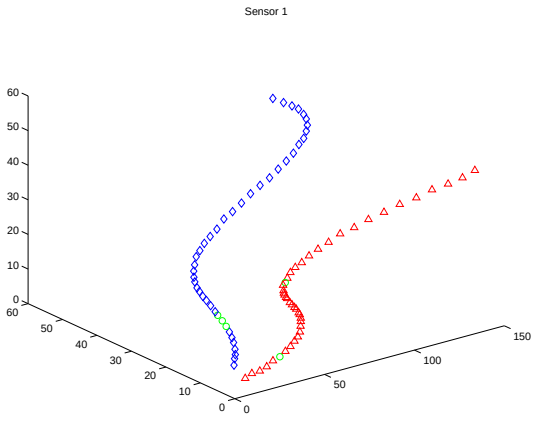

Figure 6: *Results of the tracking algorithm (sensor 1)*

5. CONCLUSION AND PERSPECTIVES

We have presented a multisensor and multitarget fusion architecture using the Covariance Intersection Algorithm

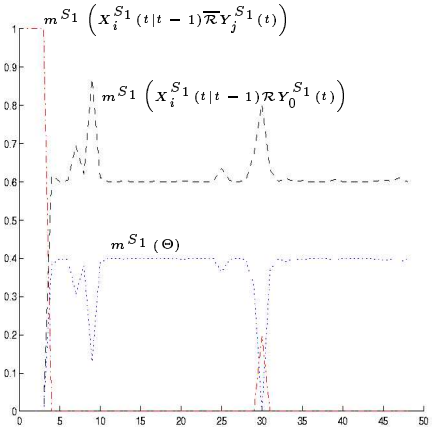

Figure 7: *Distribution of masses issued of the multiobject association for object 0 in sensor 1*

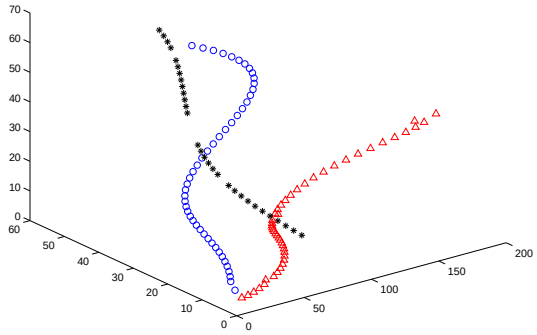

Figure 8: *Results of the multisensor fusion (△ for the first object, ◊ for the second and ∗ for the third)*

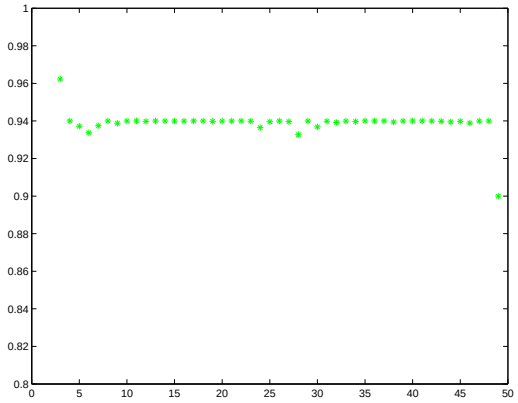

Figure 9: *Credibility about the presence of the object 0 in the scene*

and the Dempster-Shafer theory. The proposed belief structure allows to associate a perceived objetct with a known object using the sensor reliability, the distance between their positions and the perception uncertainty. We detect correctly the objects in the scene and their trajectory even with a large perception uncertainty. Morever the results show that we can reassociate a perceived object to a propaged disappeared object trajectory.
Currently, we are working on the application of this architecture to the tracking of sportsmen articulations in the aim of 3D reconstruction for integration of mecanic models.

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