Credibilist multi-sensors fusion for the mapping of dynamic environment

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Abstract - In this article, we present how, starting from an credibilist multi-object association algorithm we can carry out an multi-sensor fusion algorithm. The tracking algorithm makes a data association between predicted information and observations. These information are imperfect. The algorithm takes into account the inaccuracy and the uncertainty of the data and the reliability of the sensors. Association is realized with the belief theory. This method can be applied to the fusion of several homogeneous data sources. The problem arises when information are heterogeneous. Here, we answer to this problem by using a decentralized architecture which breaks up into two stages. The first consists in having at first a local processing to each sensor. This local processing makes it possible to obtain a set of homogeneous data. The second stage uses these homogeneous data to carry out a global fusion. This fusion gives a representation and a global view of a dynamic environment around a reference vehicle the most faithful and most reliable by using all available information. Moreover, this very general approach shows the polyvalence of this algorithm which can be in any case used for multi-object matching, local tracking, multi-sensors fusion and global tracking.

Keywords: multi-objet tracking, data association, multi-sensor fusion, belief theory, uncertainty modeling.

1 Introduction

As we already presented in the article [1], it is possible with only one sensor providing a set of data in an very short time interval (i.e. lower than the operating period of observed system) to obtain a multi-objects tracking with satisfactory results. This algorithm uses a fuzzy information representation and the belief theory for the data association in time. More, this multi-object tracking algorithm avoids some problems encountered by other same kind of algorithms like PDAF which is not adjusted to targets crossing, either the JPDAF which take into account a fixed number of targets and doesn’t initialize news tracks, or the MHT which have combinatorial problems [2] [3].

In this article, we will present an extension of this principle to obtain not either a local view of the environment but a global view by using multi-sensors fusion. To carry out this fusion, many architectures are possible: centralized (global processing), decentralized (local then global processing) and hybrid. Usually, the choice of a mode rather than another depends on the precision, the sensitivity to measurements degradation, the calculative complexity and the load of communication. Many works and researchs were already carried out in this field, we can cite as reference [4] who presents a general view of the mathematical techniques used in multi-sensors fusion. In this paper, we will focus on the study of a decentralized architecture which answers much better to our constraints of information conservation and heterogeneous fusion.

When we have several sources, it is imperative to choose a model of knowledge representation the most adapted to each one of these sources. Usually these information are heterogeneous. The aggregation of all these sources at the end of the processing is strongly dependent of these representations. When each source is perfectly represented and modelled, we have then the question to know how to fusion them between them in order to obtain a global vision of our problem the most faithful and the most reliable. In this presentation, we will propose architecture of multi-sensors fusion answering to the criteria sited previously and allowing a better environment representation.

In a more general context, this presentation shows the polyvalence of the multi-object association algorithm already presented in [5] for the local tracking (with one sensor), for the fusion stage, and for a possible global tracking (with many sensors).

2 The belief theory, a tool to uncertain processing

2.1 Generalities

Belief theory, proposed by Shafer [6], allows both to model and to use uncertain and inaccurate data, as well as qualitative and quantitative data. This allow us to keeps a consistency and homogeneity with all concepts and tools developed in the rest of our algorithm shown in [7].
This theory is well known to "take into account what remains unknown and represents perfectly what is already known".

In a general framework, we can say that our problem consists to identify an object designated by a generic variable X among a set of hypotheses Yj. One of these hypotheses is susceptible to be the solution. In our case, we want associate perceived objects X to known objects Yj. Belief theory allows us to value the veracity of P1 propositions representing the matching of our different objects. These propositions can be as well as simple and complex.

Example:
- P1 = "perceived object X is known object Y1"
- P2 = "perceived object X is known objects Yi or Yj"

We must then define a magnitude allowing the characterization of this truth. This magnitude is elementary probabilistic mass m(A) defined on [0,1]. This mass is very closed to the probabilistic mass, with the exception that we don’t share this mass only on single elements but on all elements of the definition referential \( \mathcal{A} = \{ A/A \subseteq \Theta \} \), which regroups all admissible hypotheses, these hypotheses must be exclusive. (Yj \( \cap \) Yk = \( \emptyset \), \( \forall \ i \neq j \)). This distribution is function of the knowledge about the source to model. The whole mass obtain is called «distribution of masses». The sum of these masses is equal to 1 and the mass given to impossible case m(\( \emptyset \)), must be equal to 0.

2.2 The information combination

The information combination coming from different sources has the advantage to increase the information reliability and to reduce the influence of failing information (inaccurate, uncertainty, incomplete and conflicting). But to obtain this result, it’s necessary to have complementary and/or redundant information.

If we have n distinct information sources, each source have it’s own initial masses distribution \( m_n(A) \) (which corresponding to the opinion of the source j about concert situation). The Dempster-Shafer combination rule then consists to obtain a distribution of single mass \( m_n(A) \) by combining the n sets of elementary masses \( m_n(A) \). One thus has a noted orthogonal sum:

\[
m_\Theta = m_{\Theta}^1 \oplus \cdots \oplus m_{\Theta}^n
\]

with \( \oplus \) the operator of Dempster-Shafer combination.

Our new set of masses is constituted of the conjunctions of focal element set on each source:

\[
m_\Theta(A) = \sum_{A_j \cap B_j = A} m_{\Theta}^1(A_j) \cdot m_{\Theta}^2(B_j)
\]

This rule applied on n sources give a iterative combination.

But it is possible to get empty hypotheses conjunction \( (A_j \cap B_j = \emptyset) \) and by definition, we must have the “empty” mass \( m_\Theta(\emptyset) = 0 \) and the sum of the masses on each proposition equal to 1. So it is necessary to re-allocate the mass affected to empty set on all other masses. For that, we need to re-normalise the final set of masses with the re-normalization coefficient \( k_\Theta \):

\[
k_\Theta = \frac{1}{1 - k_\Theta}
\]

This coefficient represents the existing conflict aspect between the two sources.

If \( k_\Theta \) is equal to 0 then the sources are in total concordance. And if \( k_\Theta \) is equal to 1 then the sources are completely in conflicts.

The re-normalization factor is then:

\[
k_\Theta = \frac{1}{1 - k_\Theta}
\]

In framework of a processing in «closed-world», that means with an exhaustive frame of discernment, the combination of a great number of source lead to a combinatorial explosion. This is the principal inconvenient of this combination rule. On the other hand, it offers the advantage of being associative and commutative, which is not the case of the majority of the fusion operators.

2.3 Generalized combination and multi-objects association

In order to succeed in generalizing the Dempster combination rule and thus reducing its combinative complexity, we will limit the reference frame of definition with the constraint that a perceived object can be connected with one and only one known object.

For example, for a detected object to associate among three known objects, we will have the following frame of discernment:

\[
\Theta = \{ Y_1, Y_2, Y_3, \ast \}
\]

with \( Y_1 \) meaning X is in relation with \( Y_1 \)

In order to be sure that the frame of discernment is really exhaustive, a last hypothesis noted "\( \ast \)" is added. This one can be interpreted like the association of an perceived object with any of known objects. In fact \( Y_j \) represent a local view of the world and the "\( \ast \)" represents the rest of the world. In this context, "\( \ast \)" means well: «an object is associated with nothing in local knowledge set». Figure 1 shows this exhaustive distribution of the world with exclusive hypotheses.
We obtain then a distribution of masses made up of the exclusive hypotheses. Their intersections is empty. Furthermore, their combinations do not produce a conflict (the combination of two identical hypotheses of the frame of discernment. The conflict is given by the hypothesis ∅, which is the disjunction of all the hypotheses of the frame.

Total ignorance is represented with the hypothesis Θ, the singleton which corresponds to the empty set (since the hypotheses are exclusive, their intersections is empty).

For instance, from the frame of discernment shown in Figure 1, we find the singleton corresponding to the proposition « X is not in relation with Y_i »

\[ m_{i,j}(Y_j) = K_{i,j} \cdot m_{i,j}(Y_j) \cdot \prod_{k=1\ldots n \atop k \neq j} (1-m_{i,k}(Y_k)) \]

Moreover, if we use an iterative combination, the mass \( m_{i,j}(\Theta) \) is not part of the initial mass set and appears only after the first combination. It replaces the conjunction of the combined masses \( m_{i,j}(\overline{Y}_j) \).

By observing the behaviour of the iterative combination with \( n \) mass sets, we revealed a general behavior which enables us to put in equation the final mass set according to the initial mass sets. This enables us to obtain an independence of our final masses in relation to the recurrence of the combination.

\[ m_{i,j}(\Theta) = K_{i,j} \cdot \prod_{j=1\ldots n} m_{i,j}(\overline{Y}_j) \]

with \( K_{i,j} = \prod_{l=1\ldots n} K_{i,l} \)

This \( K_{i,j} \) is the re-normalization of the \( n \) combinations, it’s mean, the product of the various re-normalization carried out during all the combinations.

\[ m_{i,j}(\overline{Y}_j) = \left[ \prod_{l=1\ldots n-1} K_{i,l} \right] \cdot m_{i,n}(Y_n) \cdot \sum_{k=1\ldots n-1} \left[ m_{i,k}(Y_k) \cdot \left[ \prod_{m=1\ldots n-1} A_m \atop m \neq k \right] \right] \]

with \( A_m = m_{i,m}(\Theta_{i,m}) + m_{i,m}(\overline{Y}_m) \)

\[ K_{i,j} = \frac{1}{1-m_{i,j}(\Theta)} \]

\[ K_{i,j} = \prod_{j=1\ldots n} \left[ 1-m_{i,j}(Y_j) \right] \cdot \left[ 1 + \sum_{j=1\ldots n} \frac{m_{i,j}(Y_j)}{m_{i,j}(Y_j)} \right] \]

The use of an initial mass set generator using the strong hypothesis « that an object can’t be in the same time associated and not associated to an other object » allows to obtain new rules. These rules reducing firstly the influence of the conflict (the combination of two identical mass sets will not produce a conflict) and secondly the complexity of the combination. The rules presented previously become:
From each mass set, we build two matrices

\[ m_{i.}(Y) = \left\{ K_{i.} \cdot m_{i,j}(Y_j) \cdot \prod_{k\neq j} (1 - m_{i,k}(Y_k)) \right\} \quad \text{si } \exists j, m_{i,j}(Y_j) = 0 \]

\[ m_{i.}(Y) = \left\{ K_{i.} \cdot \prod_{j=1}^{n} m_{i,j}(Y_j) \right\} \quad \text{si } \forall j, m_{i,j}(Y_j) = 0 \]

\[ m_{i.}(\Theta) = \left\{ K_{i.} \cdot \prod_{j=1}^{n} m_{i,j}(|\Theta_j|) \cdot \prod_{l \neq j} m_{i,l}(|\Theta_l|) \right\} \quad \text{si } \forall j, m_{i,j}(|\Theta_j|) = 0 \]

From each mass set, we build two matrices \( M^c_i \) and \( M^c_j \) which give the belief that a perceived object is associated with a known object and conversely. The sum of the elements of each column is equal to 1 because of renormalization.

The resulting frames of discernment are:

\[ \Theta_{i.} = \{ Y_{i,1}, Y_{i,2}, \ldots, Y_{i,l}, Y_{i,s} \} \] and

\[ \Theta_{.i} = \{ X_{i,1}, X_{i,2}, \ldots, X_{i,n}, X_{i,r} \} \]

The first index represents the perceived object and the second index the known object. The index “\( \ast \)” is the notion of “empty” or more explicitly the « nothing ». For example \( Y_{i,s} \) is interpreted by the relation « no perceived object \( X \) be in relation with the object known \( Y \) » and \( Y_{i,s} \) by the relation « the perceived object \( X \) is not dependent with any known object » In the first case we can deduce from it that an object has just disappeared and in the second case, that an object has just appeared. These objects, which appeared or disappeared, can be also false alarm.

The following stage consists in establishing the best decision on association using these two matrices obtained previously. As we use a referential of definition built with singleton hypotheses, except \( \Theta \) and \( \ast \), the use of credibilist measure would not add any useful information to final decision. This redistribution would simply reinforce the fact that our perceived object is really in relation with a known object. This is why we use as our decision criterion the maximum of belief on each column of the two belief matrices.

\[ d(Y_j) = \max[M^c_{i,j}] \]

This rule answers the question « which is the known object \( Y \) in relation with the perceived object \( X \) ». We have the same rule for the known objects:

\[ d(X_j) = \max[M^c_{i,j}] \]

Unfortunately, a problem appears when the decision obtain from a matrix is ambiguous (this ambiguity quantifies the duality and the uncertainty of a relation) or when the decisions between the two belief matrices are in conflict (this conflict represents antagonism between two relations resulting each one from a different belief matrix). These both problems of conflicts and ambiguities are solved by using an assignment algorithm known under the name of the Hungarian algorithm [9][10]. This algorithm has the advantage of ensuring that the decision taken is not « good » but « the best ». By the " best " we mean that if we have a known object and some sensor defective or frustrate to perceive it, then we are unlikely to know what this object correspond to, and therefore we have a little chance to ensure that the association is good. But among all the available possibility, we must certify that the decision is the " best " of all possible decision.

3. Local/global Multi-sensors fusion (decentralized)

3.1 Introduction

Until now, the algorithm that we used was limited to the processing of the impacts given by only one sensor. We will see now the problem to extend its use to multi-sensors fusion. For that, we will privilege a decentralized fusion method because this one allows firstly a local processing of each sensor then a global processing. This algorithm is generalizable with any type of sensor. Only the fuzzy modelling of the sensors and the multi-modal quantities extraction are likely to receive some change [11]. But in all cases, the output of each local processing associated with a sensor will provide a single type of object. That is very interesting because information obtained then is homogeneous. Moreover this fusion architecture has a better resistance to the breakdowns and deterioration of one of the sensors. Indeed, the destruction of one of the sensors will not have a strong influence on the final global result. Then, the idea is to use this homogeneity of information and the association algorithm previously seen to fusion at each time all the perceived objects generated by each sensor. Each sensor is then seen like a source of independent information. To summarize our idea, instead of to associate objects perceived with known objects, we will now associate perceived objects resulting from different sources.

3.2 Extension of combination rules to multi-sensors fusion

To go from the local reference mark of each sensor to the global reference mark, it is necessary to fusion all the information obtained in each local processing (for each sensor). For that, we use an iterative fusion in two-two times. With the first combination, we do not have any problem, we use the association algorithm previously seen and we obtain our first global association. More we will have objects associated between them via several sensors and more we will be able to increase their certainty. On the other hand, if an object is detected by only one sensor, then either it keeps its certainty, or we
can reduce this certainty, this depends of the employed strategy.

Into the general framework of a data fusion coming from a set of sensors, we will be in a delicate situation when we will have to associate the objects seen by the third sensor with the result of the previous association (the two first sensors). In order to make possible this last association, it is imperative to fuse the objects which were associated during the first association in order to obtain a new set of objects. Indeed, the association is always made between two sets of data.

The adaptive combination operator of Dubois and Prade [12] is often used and seems well adapted to this problem, nevertheless the treated data must be sampled to fusion them and this combination is not associative.

The solution that we chose was to combine all the sensors in two-two time and thus to generate sets of intermediate associations. With all these partial combinations, we build a matrix containing all associations (table 1). Once this matrix filtered, we obtain a final matrix where the lines will represent the detected objects after fusion and the columns will represent the perceived objects before fusion (table 2).

Thus, we are able to see measurements which characterize each final object. This method has the advantages firstly to not sample any used information, secondly to not lose and to not deteriorate any information obtained during the upstream local processing. Thus we keep the full representation of an object (inaccuracy, uncertainty and reliability) and finally, with this local then global processing, we can ensure a local (with only one sensor) and global (set of sensors) multi-objects tracking.

3.3 Example

In this example, we use three simulated telemetric sensors with a range of 50 meters, an open cone of 22 degrees and an inaccuracy of 20% onto the distance. Each sensor gives an impact per degree. Into the environment cover by the sensors, there are four objects (vehicles).

By applying the local processing to each sensor, we obtain three sets of perceived objects. In figure 2, we have the perceived objects provided by the first sensor, in figure 3 we have the result obtained with the second sensor and in figure 4, we have the environment perception of the third sensor.

Figures 5 and 6 present the detected objects by each sensor with their fuzzy representations (positions, inaccuracy and uncertainty). As we can see it, with use of figure 7, the first fusion made with sensors 1 and 2 gives a set of five perceived objects. Figure 8 gives the result of the second partial fusion made with sensors 1 and 3, this fusion generates five perceived objects. And finally we see with figure 9 that the third fusion produces a set of four perceived objects.

The combination of all these partial fusion (figure 10) leads to a global sensor fusion where five objects could be extracted from the environment cover by the three sensors.
Figure 5: Fuzzy quantities for each object

Figure 6: Fuzzy quantities perceived by each sensor

Figure 7: Partial association (fusion of sensors 1 and 2)

Figure 8: Partial association (fusion of sensors 1 and 3)

Figure 9: Partial association (fusion of sensors 2 and 3)
In a first time, the final result is put in a symmetrical square matrix. Its size is the number of perceived objects generated by the set of sensors. In our example, there are 11 initial objects. We have «1» when two observations are associated and «0» if not (see Table 1).

The final stage consists in removing the redundant lines of this fusion matrix in order to obtain a final fusion matrix where the number of lines represents the number of perceived objects in the global map and each column represents a perceived object in the local map. Thus, for each final object (line) we have the observations which represent it (columns). Table 2 gives this final matrix.

**Table 1: global fusion matrix**

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**Table 2: Final global fusion matrix after filtering**

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**Figure 10: Final global association (fusion of sensors 1, 2 et 3)**

### 3.4 Final Fuzzy estimation

We have just seen how to carry out a multi-sensors fusion with the advantages to keep intact all the characteristics about each local perceived object. So, it is always possible to have access to uncertainty and inaccuracy information to each object and each sensor. This fusion method also makes it possible to access at any moment to the reliability on each sensor.

It was presented in [1] how to locally quantify confidence on the association of a set of objects, with this fusion, it is possible in the same way to quantify global confidence. In order to obtain for each object a modelling with a single fuzzy quantity, it is necessary to calculate their final fuzzy estimate in the global map.

A fuzzy modelling or a distribution of possibility represents each object before fusion.

If we apply the property of closing which wants that the result of the operation remains within the same theoretical framework, then the operators adapted to our fusion problem limit themselves to the fuzzy and the possibilists operators.

Among these operators, we can cite the averages operators, OWA operators [13], the adaptive combinations operators [12] with all their extensions such as fusion by priority suggested by L. Roux [14] or the rule of progressive combination suggested by M. Oussalah [15].

### 3.5 Extension to global multi-object tracking

To this step of the fusion stage, we have a set of perceived objects in the global map. In order to be able to carry out multi-objects tracking, we can simply use the same association algorithm for this time to associate global perceived objects with global known objects (predictions). That well shows the efficiency and the general aspect of this multi-objects association algorithm which can be used as well as for the multi-objects tracking, multi-sensors fusion and the global multi-objects tracking.

### 4 Conclusions

We have presented in this article the construction of a multi-sensors fusion algorithm using the sensors and the data imperfections. This algorithm does not have the claim to be the best solution. Nevertheless, this article shows well the facility with which it is possible firstly to extend the use of a credibilist association algorithm to a homogeneous and/or heterogeneous multi-sensors data fusion, and secondly to build a global map storing all the information on the sensors and the data imperfection.

It is significant to notice that the set of stages used to the design of this algorithm ensures a data processing and a data combination as well as associative and commutative.

For this moment, we do not take into account the problem of the asynchronous information fusion.
This temporal aspect of the fusion and the handling of asynchronous data is, at this present time, studied by C Royère [16]. Moreover, this algorithm must be integrated in the perception system of the Heudiasyc laboratory vehicle (STRADA). It will have for principal function to provide the dynamic environment map around a vehicle with embedded sensors to characterize the current road situation.

References


