A Comparative Analysis Of Two Approaches Using The Road Network For Tracking Ground Targets

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Abstract – *This paper examines two multiple ground target tracking methods. Their specificity is that they use the road network as additional prior geographical information to further refine the targets' state estimation. The first method is based on belief functions theory for associating measurements to predictions as well as for determining the road segment relative to an existing target. The second method uses a Variable Structure Interacting Multiple Model method integrated in a Multiple Hypothesis Tracking framework (MHT VS-IMM). Finally both approaches are compared suggesting the possibility of using the advantages of the evidential approach inside the well established MHT framework.*

Keywords: Information fusion, ground target tracking, road network prior knowledge.

1 Introduction

This paper focuses on a typical ground target tracking application for which the EADS company is currently developing several data fusion algorithms. The algorithms contribute to fuse sensor data to produce information to be displayed on a single integrated ground picture. Much work has been conducted in the last three decades on the formalization of Bayesian probabilistic sub-optimal filters to handle multi target, multi-sensor data fusion for air traffic control and ground target surveillance, see [1, 2, 3]. In recent years, some attention and research has focused on the integration of prior knowledge relative to terrain features inside the tracking process. More specifically, the road network information, relevant for tracks that cannot exit into an open field, has often been used in vehicle localization applications where measurement of onboard sensors (telemetry, electro-optical sensors, odometer) are combined with GPS measurements.

The ground targets considered in this paper are mainly vehicles: civil cars, trucks, tanks, that are strictly linked to the road network. However people and buildings can also be usual targets in our surveillance applications. Also all targets aren't usually strictly linked to roads.

These kind of ground scenarios offer the following challenges relative to target behavior and detection, let alone the difficulties regarding the use of multiple sensors which observation volumes can overlap. The ground targets are numerous, often closely spaced, can merge into groups or leave them. Several targets can appear as a single plot if they are far enough. They can be hidden by vegetation or terrain, and their detection can be perturbed in dense false alarm areas. The ground targets can also accelerate, stop, suddenly change their direction, exit roads or stop in an area where they are not visible (forest, tunnel). These specificities can't entirely be handled by an automatic fusion algorithm and a number of operator interactions must be defined.

This work assumes that the algorithm is connected with a GIS that can provide a number of ground features relative to a given location, such as the nearest road segments, the local terrain nature, terrain elevation and slope. The only terrain information used here is the road network information, with is modeled as a set of road segments: a pair of way points. This paper examines an evidential approach and a Bayesian probabilistic tracking method. Both algorithms investigated here use a single GMTI sensor. Also, since the study focuses on measurement modeling, association, filtering and decision, the measurement data are already aligned and are defined here as 2D position coordinates with their covariance matrix.

Section 2 examines a first algorithm that is based on the PhD. research of Gruyer and Royère [4, 5], and Najjar [6]. It models measurements and the target internal state as a fuzzy set. The association between state predictions of existing targets and the new measurements is done using the Dempster Shafer theory using a distance criterion. Once the new state estimation of each target is computed, the road information is used to associate each target with a road segment. The chosen road segment is then used as an observation to refine the state of the target related to it.

Section 3 describes a probabilistic approach based on the Multiple Hypothesis Tracking (MHT) in which a Variable Structure Interacting Multiple Model (VS IMM) is integrated. The hypothesis are organized in a hypothesis tree and symbolize the three different interpretations of a new measurement. It can either be the first measurement of a new track, a false alarm, or the detection of an existing track. Thus each node in the hypothesis tree is an association hypothesis that defines the role of the new measurement. This is why the MHT is considered as a measurement oriented algorithm. The dynamic models that a given target can follow are handled as sub hypothesis, within a given association hypothesis. The specificity of the VS IMM approach is that the set of dynamic models that a target can follow depends on the road segments located near the target's predicted position. We will explicit how to construct a dynamic road model related to the direction and the width of the road. Section 4 analyses both algorithms, than highlights the originality of each approach. Finally concluding remarks in section 5 examine how each technique can bring improvements to the other.

2 The fuzzy set approach

The figure 1 shows the main stages of the algorithm that are described hereunder in the following sub-sections 2.1 to 2.8.

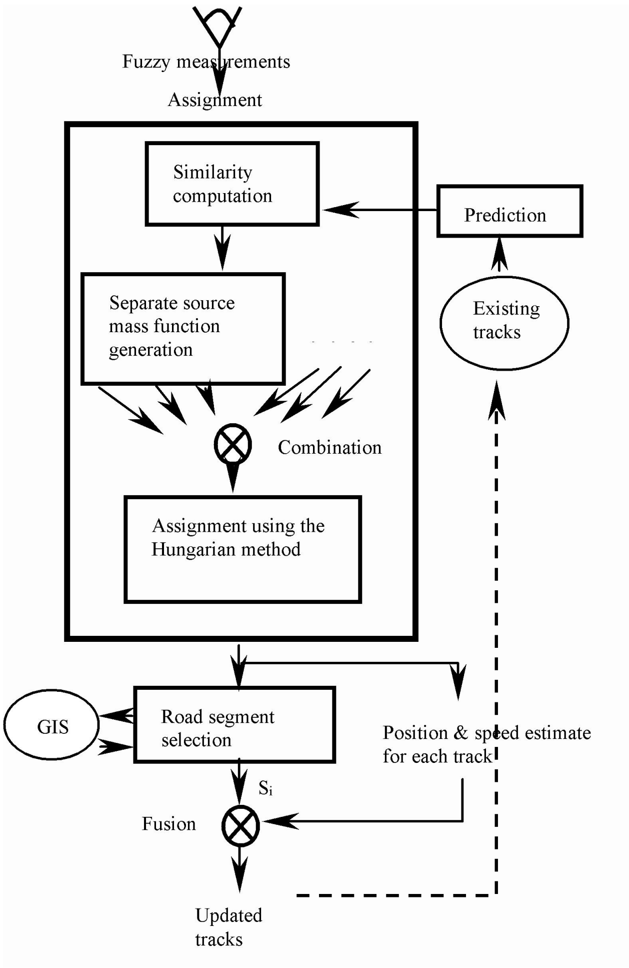

Fig. 1: DST algorithm based on fuzzy measurement model

2.1 Measurement model

It is assumed that the alignment process has converted the measurements in a Cartesian coordinate system in which the measurements as well as the targets' internal state are expressed. The fuzzy measurement is defined by three parameters: the mean position, the support, and its uncertainty. Figure 2 shows a two dimensional example of a fuzzy measurement. The support of the fuzzy measurement indicates the locations where the real measurement can possibly fall, whereas the uncertainty indicates the belief that the measurement is relative to an actual target of interest.

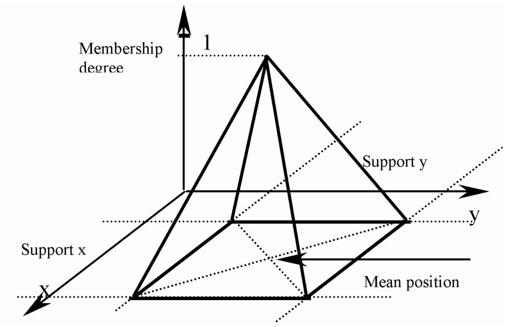

Fig. 2: Fuzzy measurement model

The sensor's reliability will be used later in the association process.

The construction of the fuzzy measurement results from the partition of the measurement space in a set of fuzzy sets. Figure 3 shows an example of a measurement space partition in one dimension (a distance measurement here). Note

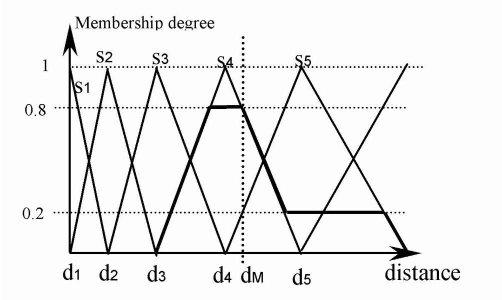

Fig. 3: Example of measurement space partition

that the precision of the sensor decreases as the distances are big. The measurement M indicates a distance d_M that activates the fuzzy sets S_4 and S_5 respectively with a degree of 0.8 and 0.2.

This approach can be generalized to a two dimensional space and used when several sensors examine the same area at the same time. All the measurements are used to activate the fuzzy sets in the measurement space, and these activations are combined with the disjunctive operator max. This combination results in a multimodal fuzzy measurement. The membership degrees are weighted by a measurement density that indicates how many times a given individual fuzzy set was activated. This allows a better distinction between false alarms and actual targets for object extraction from the multimodal fuzzy measurement. The use of a density measurement however only makes sense when several sensors provide redundant data on a given area. We consider that the measurement process produces perceived objects in the form of a support and a uncertainty. They are denoted X_i for $i = 1$ to M in the sequel, and will be associated with the state predictions of existing targets, also modelled as fuzzy sets, and later denoted Y_j for $j = 1$ to N.

2.2 Internal state model and dynamic model

In order to track objects, we need to predict the future state of existing targets at time t_k, at the later time t_{k+1} when the new measurements are received. The internal state's location is modelled as an interval pair $I = [d_1, d_2, d_3, d_4]$, as shown in figure 4. Note that this generalizes the repre-

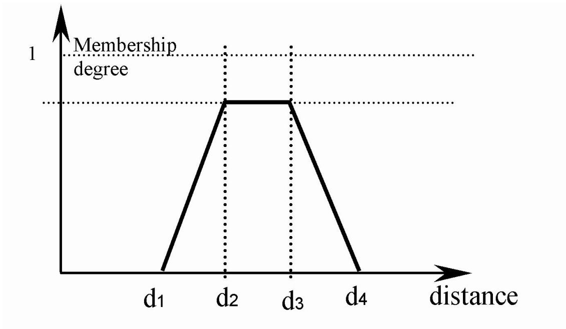

Fig. 4: Representation of a fuzzy internal state

sentation in figure 3 where $d_2 = d_3$. The prediction uses a constant acceleration dynamic model and an extended definition of addition, substraction, multiplication and division adapted to the interval pairs I_x and I_y for a two dimensional state.

The complete internal state is modelled by a fuzzy set in position, speed and acceleration, and the prediction is computed using the evolution matrix $[A]$ as follows:

$$[x_{k+1|k}] = [A].[x_{k|k}] \tag{1}$$

where $[x_{k|k}] = (x_{t_k}, \dot{x}_{t_k}, \ddot{x}_{t_k})^t$ and

$$[A] = \begin{bmatrix} 1 & \Delta t & (\Delta t)^2/2 \\ 0 & 1 & \Delta t \\ 0 & 0 & 1 \end{bmatrix}. \tag{2}$$

Note that when a target's internal state is initiated by a single fuzzy distance measurement, only the location x_{t_k} is known, and prior values are used to define the fuzzy speed $\dot{x}_{t_k}$ and acceleration $\ddot{x}_{t_k}$, that are modelled as shown in figure 4 with a certainty of 1. The four values of the acceleration interval pair a_1, a_2, a_3, and a_4, represent the prior knowledge on typical acceleration values relative to strong unlikely manoeuvres, and usual soft manoeuvres. When the target's state is updated after association of its prediction with a fuzzy measurement, the speed is updated with the two last position measurements associated to the track. Note that the acceleration profile used in the prediction stays the same and takes into account the variation of the real target motion relative to a constant speed model. Note also that equation (2) does not modify the certainty of the predicted location but only the interval values. The predictions represent the perceived objects denoted Y_j in the sequel; the next section details how to compute the similarity between a new measurement X_i and the prediction of an existing object Y_j leading to the mass function later used in association.

2.3 Computation of the similarity between a prediction Y_j and an observation X_i

The similarity computation between the two fuzzy sets described here is based on a geometrical approach that handles sets with variable certainty and imprecision and returns a real value between 0 and 1 for a total dissimilarity and total similarity respectively. The similarity value (later called s_{ij}) is based on the ratio of a) the volume of the intersection between X_i and Y_j and b) the total volume defined by X_i. Figure 5 shows a partial similarity between X_i and Y_j in the case of a one dimensional measurement space.

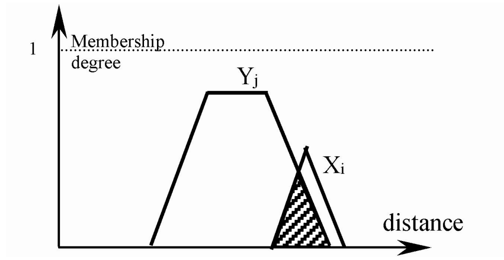

Fig. 5: Similarity between X_i and Y_j

2.4 Generation of a mass function corresponding to the similarity between Y_j and X_i

The similarity s_{ij} computed above is a critical value that must be expressed as a mass function that will later be used in the association process. This section is based on [4] that defines and describes how to build a specialized information source as a mass function. The specialized -or independent - source gives its opinion on the belief that perceived object X_i is similar - and can be associated on a localization basis- to existing object Y_j in the form of a mass function $m^{\Omega}_{i,j}$ defined on $\Omega = \{\omega_j, j = 1, \cdots, N\}$. Each singleton in Ω maps a specific relation between perceived object X_i and existing object Y_j ($\omega_j \overset{\leftrightarrows}{=} X_i \leftrightarrow Y_j$). A specialized source on Ω can be defined and assigned basic belief masses on the events ω_j, $\overline{\omega_j}$, and Ω. The frame of discernment of this particular source, that focuses on perceived object X_i only is thus made of the single hypothesis. These three events define respectively a relationship between X_i and Y_j, an absence of relationship between X_i and Y_j, and total ignorance. The closer the fuzzy measurement is to the prediction, the closer s_{ij} gets to 1, the higher the mass on becomes. Figure 6 illustrates a definition of the masses

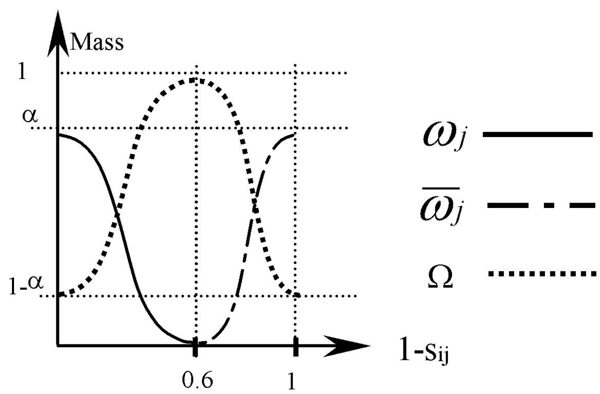

Fig. 6: Mass function generation based on similarity s_{ij} between X_i and Y_j

functions of the dissimilarity value $1 - s_{ij}$. Note that the information source is specialized and never pretends simultaneously that X_i is and is not in relationship with Y_j. When the mass on ω_j is positive, then the mass on $\overline{\omega_j}$ is 0, and conversely. The mass curves can be derived from a sine function.

Two parameters τ ($\tau = 0.6$ in figure 6) and α can be used to take into account the tendency to associate easily and the sensor's reliability. The lower τ, the faster the mass on the hypothesis ($\omega_j = X_i \leftrightarrow Y_j$) will decrease. This is a pessimistic approach where measurement and prediction need to be close for association to be considered. This approach works well when the dynamic target models and the sensors are precise. But it can lead to dismiss correct associations that can result in non detection and finally track loss. Inversely a high value for τ favors association which can lead to numerous ambiguities and conflicts when it comes to examining associations between all X_i and Y_j.

The reliability of the sensor is the belief that it is in nominal operation conditions when it delivers its measurement. When the confidence on the sensor's reliability is low, we just discount the basic belief assignment and then transfer a part of the mass from ω_j and $\overline{\omega_j}$ on total ignorance Ω.

2.5 Generation of a mass function relating X_i to each Y_j and assignment

We describe here the combination of all the specialized sources on each object Y_j. These sources each give their opinion on whether the object X_i is related to Y_j. The question is to which existing object Y_j is the observation X_i under consideration related? The opinions produced by the N specialized sources are combined in the frame of discernment $\Omega^* = \{\Omega, *\}$ where the symbol $*$ refers to all possible events that are not covered by the ω_j. This way the frame of discernment defined by the set of hypothesis $\{\omega_1, \cdots, \omega_N, *\}$ is exclusive and exhaustive, it is called the open-extended world in [5]. The event $(X_i \leftrightarrow *)$ means that the observation isn't associated with any known existing object Y_j. Thus X_i can either come from a new target or a false alarm. The N mass functions $m^{\Omega}_{i,j}$ previously defined are then combined on Ω^* which imposes to take their extensions on Ω^*.

The combination process of the N mass functions is based on the Dempster combination and is detailed in [4]. This leads to a resulting mass function called $m^{\Omega^*}_{i,\cdot}$ defined as follows:

$$m^{\Omega^*}_{i,\cdot} = \bigoplus_{j=1}^{N} m^{\Omega}_{i,j} \tag{3}$$

which gives an opinion on the relationship of X_i to all elements in Ω^*. Equation (3) allows us to quantify the relation to the existing predictions from an observation point of view. In the same manner, the basic belief functions $m^{\Omega^*}_{i,j}$ can be aggregated in order to evaluate the relation to the observations from a prediction point of view. This leads to the following equation:

$$m^{\Omega^*}_{\cdot,j} = \bigoplus_{i=1}^{M} m^{\Omega}_{i,j} \tag{4}$$

where M is the total number of perceived objects. This process can lead to ambiguities and conflicts. Ambiguity is defined if a perceived object X_i can be associated to several existing objects while conflict arises when associating a single existing object with several perceived object.

The association algorithm is based on the analysis of the two mass functions $m^{\Omega^*}_{i,\cdot}$ and $m^{\Omega^*}_{\cdot,j}$.

In order to have a number of measurements equal to the number of predictions, fictive objects (measurements or predictions) are added with zero-belief that they can be associated with a counterpart object. Thus the assignment is performed between two sets of the same size. The global belief of associating each Y_j to each X_i is then given by averaging the masses defined by $m^{\Omega^*}_{i,\cdot}$ and $m^{\Omega^*}_{\cdot,j}$.

Next the masses are replaced by 1 minus their value so that they are considered as costs. The assignment problem should *minimize* the *global* cost criterion, and the *Hungarian algorithm* is used. The assignment links each measurement to a single existing track prediction or $*$, producing a decision free from any conflicts and ambiguities. All observations are related to one prediction or to $*$. This last assignment means that the observation is either a false alarm or a new track. Similarly, some predictions can also be related to $*$ which means the existing track disappeared, or was not detected. Gruyer [4] gives an expression of the confidence related to the assignment of N observations and M predictions. Let C_{ij} be the global belief of linking X_i to Y_j and x_{ij} a binary value equal to 1 if the assignment associated X_i and Y_j and 0 otherwise. Then the confidence on the assignment is given by:

$$\Psi = \frac{\sum_{i=1}^{N} \sum_{j=1}^{M} x_{ij} C_{ij}}{\min(N, M)}. \tag{5}$$

2.6 Track management

A confidence value is updated on each track, that indicates the belief that the track is relative to a real single object of interest. As detailed in [4], the more often new measurements are associated to a given track, the higher the confidence on this track becomes. Inversely, each time a scan of measurements arrives, and that none is associated to the track, its confidence decreases. The initial confidence value of a track that is initiated by a single fuzzy measurement is either fixed at an arbitrary value depending on the application, or depends upon the measurement density. In this last case, the tracker receives redundant information and several measurements can activate the same fuzzy set (the measurement space is partitioned into fuzzy sets). The more redundant measurements the sensors produce on the target, the higher the initial confidence is. Note that the confidence is updated only after association, and that its value is unchanged during the prediction process. Figure 7 shows a geometrical way of updating the track's confidence, represented on the ordinate axis. The abscissa axis represents the normalized update rate. It is computed on a sliding window and equals 1 if each scan inside the sliding window produced a measurement that was associated to the track. Figure 7 shows the steps for increasing the confidence when a

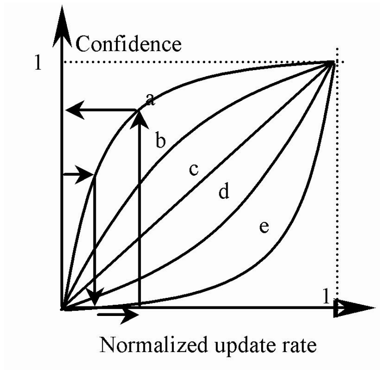

Fig. 7: Updating the track confidence

measurement is received that is associated [1].

2.7 Road network exploitation using belief functions theory

Once association and track update are performed the internal state in position and speed is available for each track. The road network is modeled as a set of segments which locations are known. Considering that the tracks move on roads only, the question is to find the correct road segment for each object in track. First a windowing is performed around the location of each track defining a subset of possible road segments for each track. Royère [5] and Najjar [6] have studied the use of two geometrical criteria to quantify the similarity between the track's state and a given road segment. The road segment selection problem is represented in figure 8. First the position criteria assumes that the track

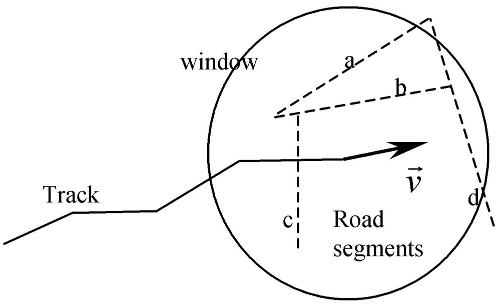

Fig. 8: Road segment selection problem

position is close to the center line of the road it is following. Second the velocity orientation criteria assumes that the track's speed vector is parallel to the road segment's direction. The goal is to decide, for a given track, which of S road segments S_i ($i = 1$ to S) inside the window this track is following. The frame of discernment for a given track is the set of basic hypothesis: $\mathcal{S} = \{S_1, \ldots, S_N\}$. Ref. [5] presents the open extended world where $\mathcal{S}$ is augmented by another hypothesis $*$, which mean that the target under consideration is somewhere else that on the known segments S_i. Thus $\mathcal{S}$ becomes $\mathcal{S}^* = \{S_1, \ldots, S_N, *\}$. The open extended world approach assumes that if the combination of several mass functions, provided by several sensors observing the same object, produces mass on $\emptyset$, this implies that one of the sensors isn't reliable. On the other hand, if mass is produced on $*$, this means the observed objects complies partly with the additional event $*$. In the current road segment selection, $*$ means that the target is on a road segment that is not yet registered in the Geographical Information System, or that it has exited the road into an open field. The modelling of the relationship between the track and a given segment S_i according to a given geometrical criteria (location or velocity orientation) is similar to the approach described in Secs. 2.4 and 2.5. This relationship is modeled by a mass function on the elements S_i, $\overline{S_i}$ and $\mathcal{S}$ where $\overline{S_i}$ includes $*$. Thus for a given target, M criteria and N road segments, we can compute $M \times N$ mass functions.

The $M \times N$ mass functions are combined with the Dempster combination rule; first the two geometrical criteria are combined for each road segment. This results in N mass functions relative to the N segments. Note that some of these functions can contain mass on $\emptyset$ meaning that for that particular segment, the position and orientation criteria are in conflict: they do not produce the same decision: one favors S_i, whereas the other puts more emphasis on $\overline{S_i}$. Next the N mass functions are combined. Finally the pignistic transformation [7] produces a mass on each S_i, $*$, and $\emptyset$, allowing an immediate decision considering the segment that has the maximum pignistic probability. This two-stage combination method is practical, but can lead to a high mass on $\emptyset$ due to a possible conflict between criteria, even if the sensors are all reliable. The conflict appears because each independent source considers a single segment, ignoring the others. This reduces the reliability of the final decision. The mass on $\emptyset$ requires a conflict management method using a conjunctive-disjunctive operator as studied in [5]. Note that an additional criteria such as road continuity (the track stays on the same road between junctions) can be used, see [6].

2.8 Track update based on the selected road segment

The track's location and speed internal state is expressed in the form of fuzzy sets. The selected road segment can be used as an additional observation, and update the previous track internal state by Kalman filtering, see Najjar [6]. For this purpose, the internal state can be expressed in a statistical formalism by a mean vector and the corresponding covariance matrix for the target's location and speed. The mean vector must be inside the fuzzy set support, and the standard deviation of each component should by in proportion with the corresponding support value. In [6], the selected road segment provides a map observation that updates the above internal state by linear Kalamn estimation. The map observation is completed by an observation error

[1] Curve a allows the certainty to climb rapidly with a low updating rate; curve c is neutral, and on the other hand, curve e requires a high update rate of the track by measurements for it to survive in the tracker. Curve a is used when the track visibility is low, or that the sensor is in a degraded operation mode since these conditions cause missing or erroneous measurements that limit the association rate. Inversely curve e is used when the target has a high detection probability, the sensors are precise and the target dynamic model is precisely known.

covariance matrix which expresses the precision of the chosen segment. The standard deviation of the location error orthogonal to the road segment corresponds to the road's width; the location error parallel to the road segment is higher and is in proportion of the segment's length. Finally the localization precision of the map features themselves must be added to the map observation covariance matrix. Thus each target that could be related to a road segment is updated and its state is represented with a mean vector and its corresponding covariance matrix. The later can then be converted to fuzzy sets so that a new association with new measurements can take place, as seen in Sec. 2.5.

3 Advantages and drawbacks of a MHT VS IMM approach

This section describes the features and operation constraints of a MHT-IMM tracker. The use of a Variable Structure dynamic model set instead of a fixed model set seems to be a logical and convenient adaptation to the MHT IMM in order to account for the road information. Features supported by the MHT VS IMM are now compared with their counterparts in the evidential approach described in section 2 in terms of estimation precision, robustness, overhead and computational load.

3.1 State and measurement modelling and basic MHT approach

The state and measurements are modelled with the statistical formalism used in the optimal linear Kalman filtering. They are considered as Gaussian random distributions, that can be completely represented by a mean vector and the corresponding covariance matrix. A good way to understand and to describe the MHT approach is to consider it as a generalization of the suboptimal Probabilistic Data Association Filter (PDAF), for a single target, and the Joint Probabilistic Data Association Filter (JPDAF) [2]. However, unlike these algorithms, the MHT is a measurement oriented method in that it considers each measurement received in a new scan as either a) the detection of an existing track, b) a false alarm, or c) the detection of a new track. Also two measurements in the same scan cannot update the same track. Real MTI scans are made of several hundreds of measurements. Therefore it is impossible to keep track of all possible hypothesis; efficient hypothesis tree management methods will be described.

Let us define $\Theta^{k,l}$ an association hypothesis where k indicates the time of the scan under consideration and l is the node (or hypothesis see [2]). A hypothesis can be considered as an "association landscape" that defines how all measurements that were received are associated, and that most of all defines witch measurements are used to form tracks. The goal of the MHT is to single out the most probable hypothesis. Ideally, if all parameters are well modelled, and a sufficient number of hypothesis are kept, then the real association hypothesis must stand out. As a Bayesian algorithm, the MHT computes a posterior probability for each hypothesis, denoted $P\{\Theta^{k,l}|Z^k\}$. This notation indicates that the probability of $\Theta^{k,l}$ is computed posterior to all measurements including those in scan k. This posterior probability is computed using following equation:

$$
\begin{aligned}
P\{\Theta^{k,l}|Z^k\} = \quad & \prod_{i=1}^{m_k}[N_{t_i}[\overset{\mu}{z_i}\ (k)]]^{\tau_i}\beta_{FT}^{\phi}\beta_{NT}^{\nu} \\
& \prod_{t\in\Theta^{k-1,s}} (P_D^{\delta_t}.(1-P_D)^{1-\delta_t}) \\
& (e^{-\frac{(t_k-t_{k-1})}{\tau_0}})^{1-\eta_t}(1-e^{-\frac{(t_k-t_{k-1})}{\tau_0}})^{\eta_t} \\
& P\{\Theta^{k-1,s}|Z^{k-1}\}\frac{1}{c'} \qquad (6)
\end{aligned}
$$

Equation 6 represents the Bayesian approach where the posterior knowledge $P\{\Theta^{k-1,s}|Z^{k-1}\}$ at scan $k-1$ becomes prior knowledge when measurements from scan k arrive. Thus the hypothesis probabilities are computed recursively. Equation (6) shows the kind of prior knowledge that is needed for the MHT operation. First β_{FT} and β_{NT} are the volumic density of false alarms and new track detections. These can possibly be adapted to the specific scanned area. The number of measurements in the scan is called m_k. The average life time of a track is called τ_0. Variables ϕ and ν are respectively the number of measurements considered as false alarms and as new tracks in the scan k, according to the definition of the hypothesis $\Theta^{k,l}$ under consideration. The volumic probability density that existing track t_i produces a measurement at location $\vec{z_i}(k)$ is called $[N_{t_i}[\vec{z_i}(k)]]$. The product on all existing tracks in hypothesis $\Theta^{k-1,s}$ is denoted $\prod_{t\in\Theta^{k-1,s}}$. The event that measurement $\vec{z_i}(k)$ is the detection of an existing track is symbolized by the boolean τ_i. The event that track $t\in\Theta^{k-1,s}$ is detected in scan k is denoted η_t. The detection probability of an existing track is denoted P_D. Note that this probability can be adapted to each existing track prediction. Finally c' is the sum of all the expressions similar to that in brackets in equation (6), relating to all the other possible association scenarios $\Theta^{k,l}$. This guarantees that the sum of $P\{\Theta^{k,l}|Z^k\}$ over all $\Theta^{k,l}$ is 1.

3.2 Insertion of the IMM method inside the MHT framework

The hypothesis tree defines all the possible measurement association hypothesis. The posterior probability of each hypothesis can be computed using the previous posterior probability of the "father" hypothesis in the tree by the Bayesian recursive equation (6).

It is fundamental to note that inside a given association hypothesis $\Theta^{k,l}$, it is possible to define a set of sub-hypothesis that specify which dynamic model each target is following, between time t_{k-1} and current time t_k. If there exists N targets in $\Theta^{k-1,s}$, and M dynamic models, then the number of sub hypothesis inside the MHT node is $N\times M$. The recursive equation 6 can easily be updated to take these dynamic model sub-hypothesis into account.

A Variable Structure IMM can be inserted in the MHT framework as well, when the targets under consideration are assumed to be linked to the road network. In this case the IMM's dynamic model interaction that takes place just after updating at time t_{k-1} must be modified. Instead of considering a fixed model structure, the models (the roads) that a given target can follow from time t_{k-1} to time t_k depend on the road junctions that are traversed during the trajectory prediction from t_{k-1} to t_k.

The use of a variable structure allows to consider only the models that the target can possibly follow. Moreover the models are precise since they are based on known road characteristics. The road dynamic models assume that the targets' velocities are parallel to the road direction, and that their position is on the road centre-line. The model noise that is expressed in the model noise covariance matrix accounts for unknown manoeuvres parallel and orthogonal to the road's direction. In particular the model noise in location orthogonal to the road's direction in function of the road's width. The more precise the dynamic models are, the more accurate the internal state estimation is.

3.3 Management techniques specific to the MHT

Some hypothesis management method must be used to limit the combinatory explosion of the number of hypothesis. First it is possible to partition the surveillance area into independent geographical sectors where independent MHT trackers operate. This is called clustering. Two independent MHT algorithms fuse when their hypothesis generation cannot continue independently. This happens when tracks from both MHTs compete for the same measurement. Second, a validation window can be used around the prediction of each track to limit the number of measurements that are processed. Measurements that fall outside these windows initiate a new MHT algorithm that may fuse with existing tracks after a while. A classical way of reducing hypothesis in a tree is pruning, consisting in deleting hypothesis with the lowest probabilities. Combining is an other possible simplification in the tree, consisting in identifying association scenarios that produce the same track "landscape". These management techniques also require a noticeable computing load, although they are mandatory for an MHT to operate.

3.4 Track management

Each track inside each association hypothesis has a score that is updated after each scan, which allows the confirmation of tentative tracks, as well as track deletion. The score of a given track is the ratio of the scenario's (or hypothesis) posterior probability to the probability of the same scenario where the track's measurements are all considered as false alarms. Hence the track's score measures its contribution to the probability of the scenario that includes it. The more the track detection satisfies the parameters used for the MHT, the higher the score increments. The score decreases when an existing track is not detected, but here again, if the specified detection probability is low, and the track's average life time is low, then the score will experience a limited slump because the algorithm considers a non detection as normal.

4 Feature comparison

This section compares the features of the algorithms examined in Secs. 2 and 3. For more clarity, we will respectively refer to the evidential/fuzzy approach and the MHT approach as method 1 and method 2.

Method 1 is more descriptive and provides a powerful and flexible means of expressing belief by use of the Dempster-Shafer theory. The flexibility comes from the numerous ways to define a frame of discernment, the mass functions, the combination operators, and the conflict management methods. Method 2 is more normative. The hypothesis probabilities as well as the track's scores are defined in a theoretical framework where all results can be demonstrated. Namely, performance predictions can be derived depending on the difference between the prior information used in the algorithm, and the actual values.

Method 1 has little operational requirements whereas the optimal linear estimation in method 2 requires that model and measurement noises be Gaussian and independent. These conditions are rarely met. However the Kalman filter and probabilistic methods that use it are robust to fluctuating measurement conditions, concerning track maintenance.

Method 1 models measurements and internal states in an economical way using fuzzy sets that support imprecision as well as uncertainty. A lower uncertainty results from redundant measurements that activate the same fuzzy set. Also the sensor's measurement space can adaptively be partitioned in fuzzy sets reflecting the sensor's characteristics in different track-sensor geometrical configurations. In method 2, state and imprecision are accounted for but in a more complex statistical formalism. Sensor precision is accounted for; but there is no provision for target certainty or sensor reliability in the measurement processes modelling. Sensor reliability can be reflected by fixing proper values for the false alarm volumic density and the detection probability, function of space and time.

Association is one of the features where both methods differ the most, in the approach and in the computing load. The economical way of modelling measurements and target state pays off; indeed, the computation of the similarity between predictions and observations is simple, as well as the determination and combination of the mass functions provided by each independent information source [4]. The assignment is performed on a simple criterion and the "*" hypothesis allows to manage the event that an observation can't be associated to any existing track, or that an existing track has not been detected. Method 2 provides a more exhaustive framework since a complete hypothesis generation is performed on the three possible origins of the measurement. This causes a high computing load and necessity for tree management methods [1]; however this method clearly differentiates a false alarm from a new target, which method 1 doesn't.

The track state updating in method 1 is also simple: in some applications, the new state takes the values of the measurement that was associated to the prediction. In other cases, the measurements that were used are weighted relative to their similarity to the prediction they were associated to, and make up the updated state. On the other hand, Kalman filtering results from estimation theory, and uses precise dynamic and measurement models. Depending on the imprecision of the system and measurement process and the correlation between measurement values and target state, the filter balances the confidence on the prediction or on the measurement.

Method 1 accounts for the sensor reliability in that the sources increase mass on ignorance (Θ) instead of making an assertion. Method 2 again uses the false alarm density and the detection probability but there is no separate consideration on measurement uncertainty (is the measurement relative to an object of interest), and sensor reliability (is the sensor operating as it is supposed to).

Both methods quantify the certainty relative to tracks by a score that can lead to track deletion. Method 1 first uses the certainty from the measurement density when the track is created, then a very empiric method for track certainty update, which doesn't account for similarity between prediction and the associated measurement. However this similarity was accounted for to select the global association and to compute the confidence on the association, see Eq. (5).

Method 1 allows to regulate the ease to associate by fixing the profiles in figure 6. An optimistic curve would allows more mass to be put on association events. Method 2 uses no dedicated parameter to influence association, although the same result could be artificially achieved by overestimating the model or measurement error in the filter's covariance matrices.

Finally the road information is accounted for using two criteria in method 1. The road segment selection for a given track uses independent sources and combines them in the same manner than for association, resulting in a low computation load. In the mass function combination process, conflict between the criteria can arise, requiring dedicated techniques for conflict management causing additional complexity.

Method 2 integrates a VS IMM method within the MHT framework combining the benefits of both approaches.

5 Conclusion

An evidential/fuzzy tracking approach has been described for tracking multiple targets. Independent information sources were used to quantify belief in association between the prediction of existing targets and observations by means of mass functions. These were combined to compute the cost of each individual association. The Hungarian algorithm was used to select the best association free from any ambiguity or conflict, based on a global cost criterion. A method for selecting a road segment for each target was described using mass functions for a location and an velocity orientation criterion. The combination of both criteria requires a conflict management method.

We have described a second method based on the integration of the VS IMM algorithm in the MHT general framework.

Comparing both track methods shows that the MHT although it is derived from a well established optimal probabilistic approach, needs a careful evaluation of its operation parameters such as false alarm density, average track life or detection probability for correct tracking. In fact the MHT, as a Bayesian method, uses much prior information.

The classical MHT approach is more reassuring since all parameters have a theoretical meaning, whereas the means to control the evidence-based method are more experimental.

The MHT approach, even when it is optimised will always require a high computing processing load. The integration of the VS IMM for using the road information is not more complex than using an IMM. On the other hand, the evidential approach basically requires little computing, but the management of imprecision, uncertainty, and conflict can become complex when several criteria are combined.

The evidential method offers a number of intuitive ways to directly act upon precise features like measurement uncertainty, inclination for association, sensor reliability. An additional advantage of this framework is that it allows to quantify conflicting beliefs, and to determine the conflict's origin.

A promising idea is to use an evidential approach inside the MHT framework for hypothesis management. This allows to measure the degree of belief on basic association hypothesis or on families of hypothesis such as target decided to take road j. When the belief is sufficiently concentrated on these single hypothesis, a hard decision can be taken, that simplifies the hypothesis tree. Conversely, if to much mass still remains on disjunctions of basic hypothesis, then the branches in the hypothesis tree must be kept and expanded to the next measurement scan. In spite of the caution that is needed to formalize the frame of discernment, the mass functions and the combination operators, we think that integrating means to manage uncertainty as well as imprecision, sensor reliability and conflict in proven tracking approaches can lead to improved tracking in real world ground surveillance applications.

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