MULTIPLE SENSOR TRACKING IN A SENSE & AVOID CONTEXT

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Abstract

The process of multiple sensor fusion is aimed to take advantage of complementarities and redundancies of different sensors in order to timely provide the best picture of the objects of interest in the surrounding environment.

In a Sense & Avoid (S&A) context, the fusion of co-operative (transponder, ADS-B, ...) and non co-operative (radar, EO/IR) sensors is a key condition to reach the safety requirement for the insertion of UAV in civil traffic.

In this paper, we describe a fusion architecture for the Sense sub-function and illustrate its benefits through the multiple sensor tracking processing. The algorithm is based on a multiple model approach and simulation results show how the use of multiple sensors improve the accuracy of collision prediction and avoidance.

1 General Introduction

2.1 Context of Sense&Avoid

The safe introduction of military UAS (Unmanned Aerial Systems) and possibly civil UAS into the European airspace requires a specific approach taking into consideration the regulatory framework, the correct application of Air Operation procedures, the evolution of the European Sky in the future, and the capability of available or closely available technology.

Many actions have already been undertaken on regulatory aspects by NATO, EUROCONTROL, EASA, RTCA and EUROCAE.

One key issue remains in the requirements, definition and development of a **Sense & Avoid** system, necessary to replace the human presence on board the vehicle, in order to detect the presence of any other traffic or obstacle and to avoid any potential collision, both in controlled or uncontrolled airspaces.

The following issues have to be studied :

- Survey harmonized consideration of studies already started in Europe
- Link with future Single European Sky (SESAR)
- Define how to link and Communicate with Air Traffic Management
- Select potential Sense & Avoid candidate technologies :
    - Co-operative : TCAS, ADS-B (Automatic Dependent Surveillance Broadcast), Transponders, data-link...
    - Non co-operative : radar, EO/IR (Electro-Optical / Infra-Red), acoustic,…
- Take adequate consideration on :
    - Data Link
    - Interface with Flight and Mission Management System
    - Level of Autonomy
    - Human Factors
    - Certification aspects – Safety case
    - Air Operations – Rules of Air

The system is to be considered in 2 separate functions: sense function whose objective is to deliver the intruder trajectory prediction, and avoid function whose objectives is first to provide information for separation (for the ground control station to negotiate with Air Traffic Controller the future trajectory of the UAS) and second to provide the Automatic

Flight Management System with the maneuver to be followed.

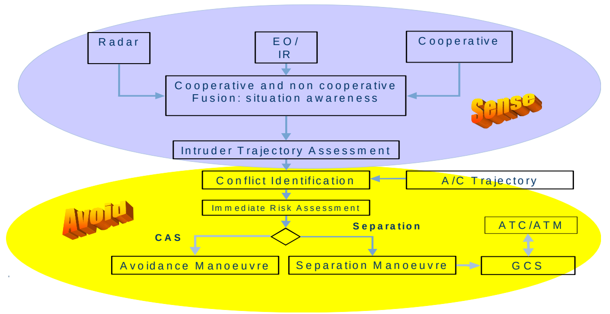

Fig. 1 : Typical functional architecture for S&A system

Both functions will interact with the S&A HMI to provide relevant information to the UAS pilot. The separation assistance function will help the UAS pilot to maintain separation relative with other traffic when separation is not provided by ATC (Air Traffic Control). CA will provide an automatic last instant collision avoidance maneuver with the objective of avoiding an imminent collision. Both functions will be aided by a host aircraft performance model in order to account for actual maneuver performance.

For achieving these functions, when available, some co-operative functions will help as ACAS function (with TCAS compatibility), ADS-B, IFF interrogator but the main innovative parts should be in the non co-operative sensor: such as EO/IR and radar system which could provide an all weather situation awareness.

1.2 Sense Sub-Function

In the present paper, we are most interested in the Sense part only of the S&A since we are willing to highlight the core reasons why fusion is helpful for the situation assessment. So specific points of Avoid sub-function such as optimal trajectory computation or TCAS coordination will not be considered. The Sense sub-function includes available sensors aboard the platform and the fusion process in the embedded central computer. Sensor functions and system functions (fusion) should be tightly coupled, so that the right information is elaborated and provided to the system by the sensors, while the benefit of the system function might be fed back to the sensors as well. This strong integration will allow the whole system to extract the most important part of the sensor capabilities (sensors are experts in their own domain), to combine them in the best suited way taking into account their specificities, and the feedback towards sensors will allow to operate them in an efficient manner so as to improve the knowledge of the surrounding situation, which is the output of the fusion. The two major results of the Sense sub-function would be object trajectory estimate and object classification. This paper will focus on the former aspect of the fusion output.

1.3 Organization of the Paper

The main focus addressed in the paper are twofold :

- *Multiple sensor architecture* : this addresses the question of what sensor to include in the system, what information to transport between sensors and fusion, and how data processing is distributed among the different components : sensors and fusion,
- *Target trajectory estimation algorithm* : this addresses the question of how a collision or a non collision trajectory can be predicted, keeping in mind the need to obtain the best balance between detection of real collision risk and false alarm.

After a discussion on fusion architecture in Chapter 2, we present the formalism of the multiple sensor tracking problem and the description of the proposed algorithm in Chapter 3. Chapter 4 provides simulation results, and finally we end up with concluding remarks and perspectives.

2 Sensors, Architecture and Processing : Principles

2.1 Sensors of the S&A System

As mentioned earlier, the S&A system includes two families of sensors : co-operative and non co-operative.

By definition, co-operative sensors is based on the “co-operative” nature of the intruder, in which case they usually have the advantage to provide intruder identification. Depending of the level of available information, it can be used to tune the tracking algorithm, improve the classification algorithm, and allow a relevant avoid procedure.

Basically, we may consider two levels of co-operative sensors aboard the intruder (assuming that the UAS platform embedding the S&A system is compatible with both) :

- *IFF Transponder* : there exits multiple types of IFF and modes of operation. In principle, we will consider that it provides intruder identification code and possibly altitude, and that the detector aboard the UAS is able to measure intruder direction (azimuth) and range, with a pretty high precision for range but low for azimuth. The field of view (FOV) is 360°.
- *ADS-B* : if available aboard the intruder, this source of information provides intruder identification and state vector. We will consider only intruder position in the paper. The typical quality is that of GPS system, so high accuracy, unless for some reason GPS is not available, then the quality is given by intruder INS. The FOV is 360°.

Non co-operative sensors are mandatory for an S&A system since intruder might be either non co-operative intentionally, or simply not equipped with co-operative sensors. Sensors that are well suited for S&A application are Radar and EO/IR.

- Radar sensor : to face S&A overall requirements, the radar sensor shall cover at least about ±110° in azimuth and ±15° in elevation, with a revisit time of the class 1 to 2 seconds, and manage its waveform according to the dynamic of the targets it is looking for (see [1][2] for an overall radar solution with colored transmitted waveform and Digital Beam Forming on receive). The major advantage of radar is its capability to get instantaneously the 3D position of the intruder, and potentially the radial (along line of sight (LOS)) component of the velocity vector.
- EO/IR : for the same reason, we consider the need to have a coverage of ±110° in azimuth and ±15° in elevation, with the benefit of very accurate measure of LOS and very high measurement rate.

2.2 Architecture and Processing

As a result of the system constitution, the fusion process has to combine heterogeneous sensor data [3]. Roughly speaking, two steps in the fusion process are successively executed : data correlation, and fusion. Basically, we can remind the following principles :

- Data association (between different sensors) : it is the process that decides which data provided by different sensors correspond to same targets. It is based on statistical distance between common axes of correlation, and the performance is limited by the sensor that provides the worse (less accurate) data. For example, if each of two sensors provide detection (on a common real target) with respectively good and bad quality, it might take some time to decide, with some quality of decision, that both set of data come from the same target. In fact, the delay to decide is mainly limited by the low quality sensor.
- When a positive decision for data association has been obtained, the quality of the fusion of both data set from the different sensors is mostly determined by the high quality sensor.

On a UAS platform which embedded multiple sensors as described in §2.1, common axes of correlation between sensors are only geometric or kinematics parameters, so sensors with low quality geometric parameters will take more time to correlate with other sensors. Also, sensors with incomplete geometric data (ex : EO/IR) would present risks of correlation and again will require more time to secure the association. On the other hand, inside the sensors, there might be other correlation axes that would allow the sensor itself to correlate its successive detections (IFF code, spread and intensity of pixels in EO/IR images, SNR in radar detection …). That is the reason why the proposed design of the fusion of heterogeneous data is a hybrid hierarchical process, where :

- At sensor level :
  - Each sensor is responsible for its tracking : it performs a detection-to-track association, based on geometrical data as well as specific signature (specific correlation axes) of the target in the sensor measurement domain.
  - Each sensor provides the fusion with at least the last detection(s) that has been associated to a sensor track.
  - Each sensor may also provide tracks (output of a kinematics estimator) which could be used by the fusion process.
  - In case of very high data rate sensor, and in particular for sensor data that are not complete (angular only), it turns out to be more efficient to compress data and transmit to the fusion a kinematics summary of the detections, called tracklet. Such process will also lower the computing load in the central computer.
- At fusion level :
  - The data association between sensor and system tracks is mostly based on geometric and/or kinematics data when some velocity estimate is provided. Classification data, that may be available at the system level, could help the data association process to prevent correlation of tracks with inconsistent classification.
  - The result of multiple sensor fusion (kinematics) is obtained through the integration of sensor measurements or sensor tracklets in a kinematics estimator. This will be the most detailed part in the following.
  - Multiple sensor classification : from an Sense & Avoid point of view, classification is aimed to 1) recognize that the track corresponds to an air intruder (some sensors may detect ground objects or false alarm), 2) recognize the class of the intruder to correctly proceed the rules of air. The classification process would use a data base to compare with parameters extracted by the sensors.
  - Sensor management (SM) : it is the process based upon fusion output and “avoid” goals (static objectives or dynamic orders) that generates high level commands to the sensors in order to reach the “avoid” goals. It makes use of sensor characteristics to calculate the expected gain of using or not the sensor resources, and defines the final commands to minimize some overall risk function. In SM, we can also include the feedback of fusion estimate towards sensors in order to improve the processing (e.g. linearization) or their tuning (detection threshold, refresh rate, etc.).

3 Multiple Sensor Tracking Algorithm

3.1 General Principles

We are now concerned with kinematics estimation of aerial vehicles that might be detected in the surrounding environment by the multiple sensors aboard the UAV. The tracking technology is based on Kalman Filter (KF) type algorithm [4].

Target kinematics model

Most of the dynamics behavior that the UAS is supposed to encounter is from civil aviation, but we must also take into account maneuvering targets such as combat systems (aircraft, UCAV).

For the present study, we consider two kinds of behavior for the civil aviation : Constant Velocity (CV) model, and Coordinated Turn (CT) models. These models are the most frequent models in the ATC especially. For CT model, we consider left and right turns, and two amplitudes for the turn : 2°/s that might be typical turn, and 6°/s that represent a maximum value for the aircrafts considered in the study.

For maneuvering target, we add a CT model (left and right turns) at a rate of 9°/s, which corresponds to an acceleration of 4g at 260 m/s.

In case of angular only tracking (ex : EO/IR), range is not observed in the sensor detection. Then, a specific structure of the state vector [7] shall be used to keep separate observable and non observable components of the track.

In other cases, the state vector can be expressed in Cartesian coordinates.

Tracking algorithm

As mentioned above, the civil aircrafts may fly either at a constant velocity (CV), or take a turn with constant speed (CT). Since the objective of the tracking is to detect potential collision between the UAS and any airplane around, the tracking algorithm is expected to estimate the "target" velocity vector as accurately as possible. For that reason, it is preferable to select a multiple model approach with adapted dynamic model, instead of a single model algorithm tuned to cover a large variety of dynamics.

Interacting Multiple Model (IMM)

Among multiple models algorithms, Interacting Multiple Model is widely considered as the most efficient estimator against targets that may have different dynamic behaviors, since it allows to continuously monitor the likelihood of alternative models, and it is also able to anticipate dynamic transition based on prior knowledge.

The description of the IMM algorithm is justified in [5], but we recall its basic steps hereafter.

VS-IMM (Variable Structure IMM)

Although IMM is designed to handle multiple kinematics behaviors, its performance will get worse as long as the number of competing models increase. As a matter of fact, information gathered by the sensors will diffuse across the multiple models, instead of being limited to major models. That is why the "Variable-Structure IMM", proposed in the literature [6], would be well suited to our application. The basic idea is to design a supervision, over the IMM, that would be able to select the most appropriate models and parameters according to the current situation.

In our application, the dynamic selection of models would be based on :

- target classification that can be accessed through co-operative sensors.
- Current target kinematics estimates such as altitude, or speed.

3.2 Formulation and algorithm

The algorithm presented hereafter is limited to tracking aspect of multiple sensor processing. This is basically one of the major objectives of the sense sub-function to provide an accurate track and prediction capabilities on surrounding objects.

3.2.1 Target dynamic model

Consider the target state vector defined in a Cartesian frame :

$$X_k = [x_k \quad y_k \quad z_k \quad \dot{x}_k \quad \dot{y}_k \quad \dot{z}_k]^T \qquad (1)$$

The target dynamics is modeled as :

$$X_{k+1} = F(t_{k-1}, t_k).X_k + v_k \qquad (2)$$

where F is the propagation matrix from time t_{k-1} to time t_k, and ν_k is called the process noise, with covariance matrix equal to Q, embedding the fluctuations of the target around its nominal behavior modeled by F, and σ_q^2 is the power spectral density of ν_k.

For a CV model, we have :

$$F_{CV}(t_{k-1}, t_k) = F_{CV}(\Delta T) = \begin{pmatrix} I(3) & \Delta T.I(3) \\ Z(3) & I(3) \end{pmatrix} \tag{3}$$

and

$$Q_{CV}(t_{k-1}, t_k) = Q_{CV}(\Delta T) = \sigma_q^2 \begin{pmatrix} \frac{\Delta T^3}{3}.I(3) & \frac{\Delta T^2}{2}.I(3) \\ \frac{\Delta T^2}{2}.I(3) & \Delta T.I(3) \end{pmatrix} \tag{4}$$

with the following notations :

- Z(n) is a square null matrix of dimension n,
- I(n) is a square identity matrix of dimension n,
- and $\Delta T = t_k - t_{k-1}$.

For the CT model with fixed turn rate ω in the horizontal plane (constant ground speed) and CV in the vertical axis, we have :

$$F_{CT}(t_{k-1}, t_k) = \begin{pmatrix} 1 & 0 & 0 & \frac{\sin(\omega(t_k - t_{k-1}))}{\omega} & -\frac{1-\cos(\omega(t_k - t_{k-1}))}{\omega} & 0 \\ 0 & 1 & 0 & \frac{1-\cos(\omega(t_k - t_{k-1}))}{\omega} & \frac{\sin(\omega(t_k - t_{k-1}))}{\omega} & 0 \\ 0 & 0 & 1 & 0 & 0 & t_k - t_{k-1} \\ 0 & 0 & 0 & \cos(\omega(t_k - t_{k-1})) & -\sin(\omega(t_k - t_{k-1})) & 0 \\ 0 & 0 & 0 & \sin(\omega(t_k - t_{k-1})) & \cos(\omega(t_k - t_{k-1})) & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \tag{5}$$

and process noise covariance (Q) matrix will be kept the same as CV.

3.2.2 Sensor measurement models

The following functional relationships and error characteristics are used to extract the target state vector hidden behind the sensor measurements. We have to deal with both relative (spherical) measurements provided by Radar and EO/IR, as well as IFF range and azimuth, and absolute measurements provided by ADS-B and IFF altitude.

<u>Range</u> (*i* is with respect to Radar or IFF) :

$$h_R^i(X_k) = \sqrt{(x_k - x_k^p)^2 + (y_k - y_k^p)^2 + (z_k - z_k^p)^2} + w_k^{r-i} \tag{6}$$

<u>Azimuth</u> (*i* is with respect to Radar, EO/IR or IFF) :

$$h_{Az}^i(X_k) = \arctan\frac{x_k - x_i^p}{y_k - y_i^p} + w_k^{Az\_i} \tag{7}$$

<u>Elevation</u> (*i* is with respect to Radar or EO/IR) :

$$h_S^i(X_k) = \arctan\frac{z_k - z_k^p}{\sqrt{(x_k - x_k^p)^2 + (y_k - y_k^p)^2}} + w_k^{S\_i} \tag{8}$$

<u>Radial relative velocity</u> (*i* is with respect to Radar) :

$$h_{\dot{D}}^i(X_k) = \frac{(x_k - x_k^p).(Vx_k - Vx_k^p) + (y_k - y_k^p).(Vy_k - Vy_k^p) + (z_k - z_k^p).(Vz_k - Vz_k^p)}{\sqrt{(x_k - x_k^p)^2 + (y_k - y_k^p)^2 + (z_k - z_k^p)^2}} + w_k^{\dot{D}\_i} \tag{9}$$

with

$$X_k^p = \left[x_k^p \quad y_k^p \quad z_k^p \quad \dot{x}_k^p \quad \dot{y}_k^p \quad \dot{z}_k^p\right]^T \tag{10}$$

as the own ship state vector.

Absolute horizontal position (for ADS-B only) :

$$\begin{bmatrix} x_k^{ads-b} \\ y_k^{ads-b} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix} .X_k + \begin{bmatrix} w_k^{x\_ads-b} \\ w_k^{y\_ads-b} \end{bmatrix} \tag{11}$$

Note that $w_k^{x\_ads-b}$ and $w_k^{y\_ads-b}$ Cartesian noise components result from the conversion of {latitude; longitude} provided by ADS-B, so they are correlated (the corresponding covariance matrix is not diagonal).

Intruder altitude provided by IFF sensor is directly converted along z axis of the tracking reference frame.

Except for ADS-B horizontal position errors, the reminder of the measurement errors are considered to be uncorrelated with each other.

3.2.3 Kalman filtering

Taking into account the hypotheses of our application, we use a Kalman filter based technology in order to perform a real time multiple sensor tracking. The Extended Kalman Filter version is developed since relationships between target state and most of sensor measurements are nonlinear. We recall the different steps of a standard Extended Kalman Filter (EKF) such as those applied in our simulation.

Initialization	X_0, P_0
Prédiction	$\hat{X}_{k+1/k} = f_k(\hat{X}_{k/k})$ $P_{k+1/k} = F_k.P_{k/k}.F_k^T + Q_k$ $\hat{Y}_{k+1/k} = h_{k+1}(\hat{X}_{k+1/k}, 0)$
Innovation	$I_{k+1} = Y_{k+1} - \hat{Y}_{k+1/k}$ $S_{k+1} = H_{k+1}.P_{k+1/k}.H_{k+1}^T + R_{k+1}$ with $H_{k+1} = \left.\frac{\partial h_{k+1}(X)}{\partial X}\right\|_{X=\hat{X}_{k+1/k}}$
EKF gain	$G_{k+1} = P_{k+1/k}.H_{k+1}^T.S_{k+1}^{-1}$
Filtering	$\hat{X}_{k+1/k+1} = X_{k+1/k} + G_{k+1}.I_{k+1}$ $P_{k+1/k+1} = P_{k+1/k} - G_{k+1}.S_{k+1}.G_{k+1}^T$

Table 1 : Standard EKF structure algorithm

In a practical execution of the multiple sensor tracking, we have to deal with OOSM : Out-Of-Sequence Measurements. As a matter of fact, and due to different sources of delay in the system (sensors publishing data by batch, processing delay, etc.), there is no reason why the sensors will deliver their data respecting the overall chronological order. Algorithmic solutions exist (see [3] for instance) and need to be evaluated.

The definite solution needs also to deal with passive only tracking or maintenance. In that case, Modified Spherical Coordinates [7] may be implemented. This will not be further considered in the following simulations.

3.2.4 IMM algorithm

Interacting Multiple Model is the state of the art of tracking algorithm when multiple dynamic behavior has to be considered. The structure of the algorithm is shown on Fig.2. The most important properties of the IMM are :

- Competing dynamic models and evaluation of their probability through likelihood computation and Bayes theorem.
- Interaction between models (also called mixing), in which prior information promotes or inhibits transition from one model to another, through a Markov chain.

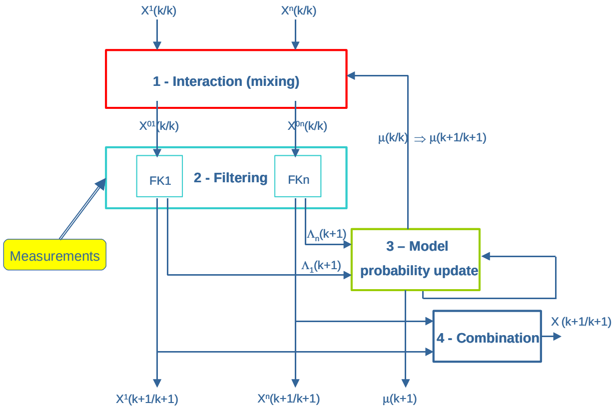

Fig. 2 : IMM structure algorithm

3.2.5 Dynamic selection of models

It is well known that IMM tracking algorithms might turn out to be inaccurate as long as the number of competing models increases. Somehow, information provided by measurements gets lost in timely irrelevant models, and will degrade the tracking accuracy through the combination step. For that reason we propose to use VS-IMM approach to dynamically manage the set of IMM models.

The selection of models can be based on the following information :

- *Target classification* : as a matter of fact, some sensors (typically cooperative and EO/IR) may provide some information about the class of the target. Accordingly, we can select the limited set of dynamic models that are suited to the corresponding class (combat platform, airliner, etc.).
- *Current state vector estimate* : altitude and speed typically could help to evaluate the type and maneuverability of the intruder, and so to tune the candidate models. Also, accurate estimation of the current state vector would help in selecting models in a “neighborhood” of the current active models. Prior knowledge on intruder dynamics capabilities would help in that sense.

4 Numerical simulations

4.1 Scenario for simulations

To illustrate multiple sensor tracking facing intruders which perform maneuvers, we choose the following scenario (Fig.3) :

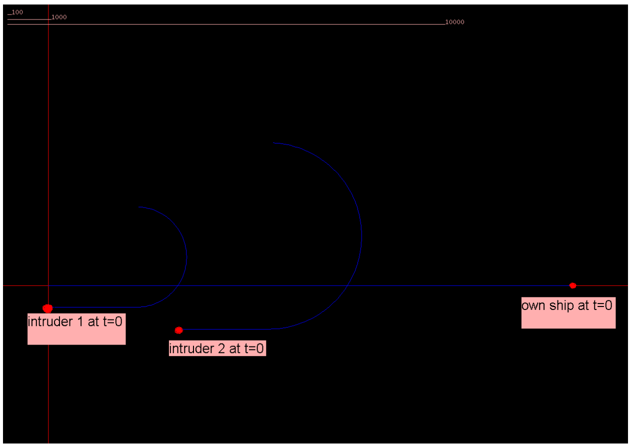

Fig. 3 : Geometry of the scenario.

Intruder 1 : low maneuvering UAV, at 60 m/s, going straight at constant speed, then performing a turn left at 3°/sec.

Intruder 2 : maneuvering UCAV at 260 m/s, going straight at constant speed, then performing a turn left at 7°/sec.

Own ship UAV with multiple sensor tracking algorithm, going straight at 60 m/s, towards intruders.

Algorithm main parameters :

- IMM with 7 models : CV, left and right CT at 2°/sec, 6°/sec, and 9°/sec.
- Configuration 1 :
  - Radar sensor (non co-operative) with following errors statistics (rms) : 50 m in range, 1° in azimuth and elevation, and 2.5 m/s in closing velocity, refresh rate of 2 seconds.
  - Track initialization on the first 4 Radar detections.
- Configuration 2 :
  - IFF sensor (co-operative) with following errors statistics (rms) : 150 m in range, 3° in azimuth and 10% of altitude, refresh rate of 1 second.
  - EO/IR sensor (non co-operative) with following errors statistics (rms): 0.2° in azimuth and elevation, refresh rate of 10 Hz.
  - Track initialization on the first 4 IFF detections.
- Configuration 3 :
  - Radar and EO/IR sensors (non co-operative) with errors statistics as provided in respectively configurations 1 and 2.
  - Track initialization on the first 4 Radar detections.

4.2 Simulation results

Results for the 3 configurations are provided respectively if Figures 4, 5 and 6.

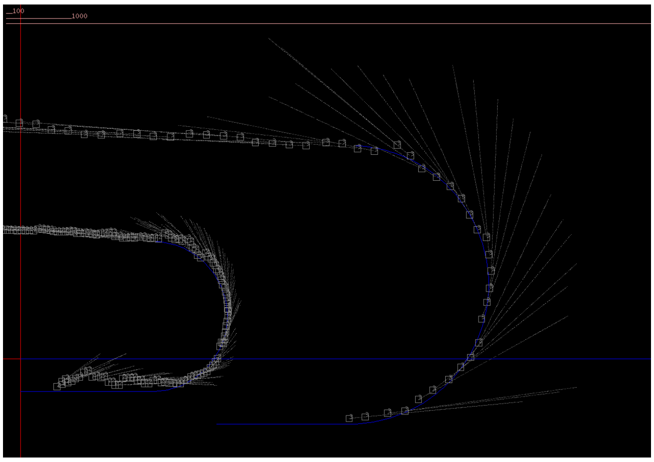

Fig. 4 : Radar only tracking.

We can observe in Figure 4 (Configuration 1) that the IMM tracking is able to detect and follow both intruders maneuvers, even though their turn rate does not match any one of the IMM models. We can observe however that the target heading might still have some fluctuations, during the first part of the trajectory especially.

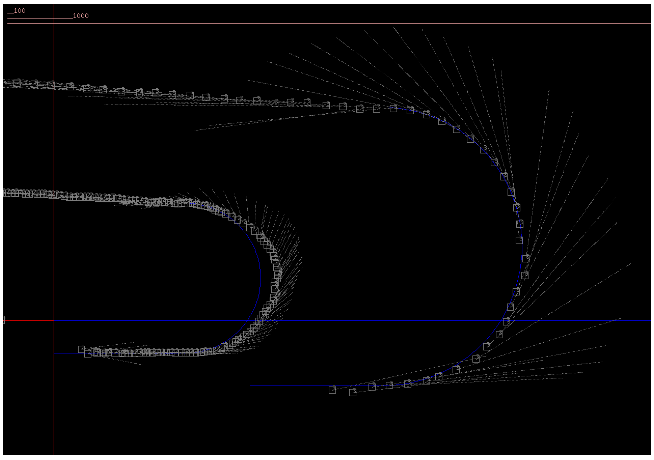

Fig. 5 : IFF with EO/IR tracking.

In Configuration 2 which needs a co-operative intruder to get range measurement, the accuracy of the EO/IR allows the tracking to have a very accurate heading estimate, with the smoothing effect of EO/IR high data rate, and to follow pretty well the intruder maneuver. Note that there is a delay on the track due to lack of observability of passive tracking during the turn and not very accurate range given by IFF.

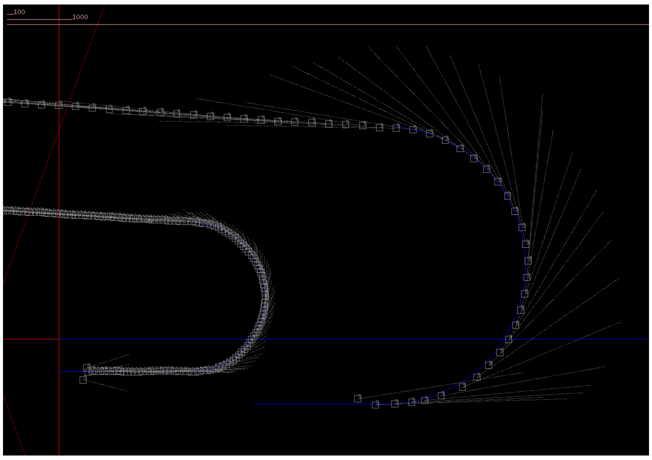

Fig. 6 : Radar and EO/IR tracking.

Looking at Configuration 3 result in Figure 6, we see how accurate is the joint Radar-EO/IR tracking, during non maneuvering and maneuvering phases. This result is obtained thanks to complementarities and accuracy of both sensors (full 3D-observability through Radar measurements (range) combined with very accurate and high frequency LOS of EO/IR), Both position and velocity vectors are extremely accurate, allowing a much more reliable trajectory prediction and then collision avoidance.

5 Conclusion

In this paper, we explained why a multiple sensor system with data fusion algorithm is a key point in the design of a Sense & Avoid solution, in order to fulfill safety requirements that are necessary for the insertion of UAS in controlled and uncontrolled airspaces.

Co-operative and non co-operative sensors are necessary, since they have really specific contributions and complementarities.

This benefits are illustrated through the design and evaluation of multiple sensor tracking, using multiple model approach, in order to have an accurate estimation of intruder current and future trajectory, facing low but also potentially high maneuverable intruders.

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