Tracking based on graph of pairs of plots

Frédéric Livernet, Aline Campillo-Navetti

Délégation Générale de l'Armement Techniques Navales (DGA TN)
Toulon, France
frederic.livernet@dga.defense.gouv.fr
aline.campillo@dga.defense.gouv.fr

Abstract: Within the framework of a joint technical research cooperation project between Brazil and France, this paper proposes a new type of situation awareness algorithm based on the theory of graphs of pairs of plots (cf. Radar conference IEEE Washington 2010: "Tracking based on graph theory applied to pairs of plots") using Brazilian Navy Aircraft Carrier "São Paulo" as a sensor data platform for the experimental TSV (Tenue de Situation Veille : Situation awareness).

The advantage of this new technique is the possibility to test easily a great number of hypotheses of plots association without recursive filter (Kalman). Thanks to the graph which is able to process a considerable history of plots, it can handle the transitional areas of target ambiguity and unobservability recorded during trials on board "São Paulo" due to the diverse and extreme clutter environment found near the coast or littoral (high false alarm and detection holes).

This paper first describes the context and the issue pertaining to situation awareness within the transitional areas of ambiguity and unobservability of the sensors plots. Afterwards, we will introduce the basics of this new technique for situation awareness, then its advantages in comparison with classical solutions MHT ([1][2][3]) and PHD ([6]). Finally, performance results visualizations based on both simulated and real data recorded on board São Paulo confirms the performances of this new situation awareness technique.

1 Introduction

The tracking quality is partly based on the management of the transitions between observable and unobservable or ambiguous areas. The main objective is to guarantee the unicity of track number for each target over time. This unicity of track number is notably essential for threat evaluation and data link.

<u>An unobservable area</u>, for a track, is an area with miss- detections due to detection holes (low elevation effect), relief, small radial speeds or Doppler treatment, etc…

<u>An ambiguous area</u> for a track, is an area in which several possible solutions exist to estimate the position of this track following false alarm, several close tracks, …

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In the example below (real data recorded on São Paulo), in order to be able to make a link between observable area 1 and observable area 2, for track 1 (red trajectory), a considerable number of hypotheses is going to be tested within unobservable and ambiguous areas. Actually, this kind of event can be quite common.

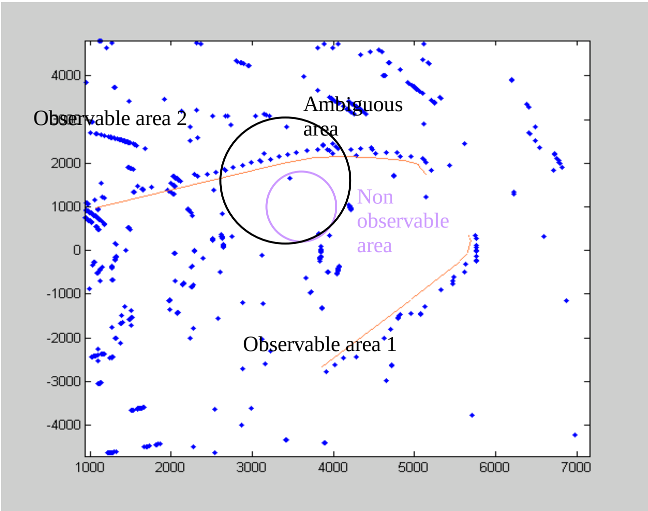

Fig 1: São Paulo data

The unobservable and/or ambiguous areas can have a significant duration (about one minute), leading to many problems for classical techniques based on MHT tracks-Plots ([1],[2],[3]) or PHD Kalman Filter ([6]).

2 List of classical solutions problems (MHT and PHD)

<u>Problem 1</u>: ***significant number of hypotheses to manage***

In case of considerable number of miss-detections or in case of false alarm, we have to manage a significant number of hypotheses. Generally, the classical techniques based on MHT tracks-Plots or PHD Kalman Filter, use thresholding on likelihood to eliminate the less probable hypotheses. But, in cases of detection holes with false alarm (cf. track 1 in the example), it's essential to keep all the hypotheses, even the ones with a very low likelihood, to be able to make a link with the new observable area. A solution for these techniques would be to decrease sharply the detection probability in the hypotheses likelihood calculation, but this would generate a surge of the number of hypotheses to manage. For example, for the track 1 above, after 2 miss-detections, there are already 10 hypotheses, and after 10 miss-detections, there are more than 100 hypotheses.

Problem 2*: process noises for Kalman filters*

Most of these solutions are constructed on recursive filtering based on Kalman. To manage kinematic transitions among models (for example straight line and turn for IMM), these filters have to increase their uncertainty on their kinematic model in order not to diverge.

Visualization of transitions problems between the two kinematic models, straight line and turn, for this example

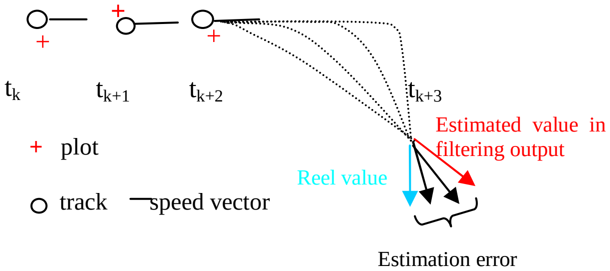

Fig 2: Transition problem

In this case, between t_{k+2} and t_{k+3}, several turn solutions are possible. Therefore, the error of the solution chosen by the recursive filter can be very significant. That explains the necessity to increase the process noise (σ_{k-1}).

This increase has a significant impact in the hypotheses likelihood calculation:

$$Likelihood(I_k) = \frac{1}{\sqrt{2\pi}} \frac{1}{|S_k|^{\frac{1}{2}}} . e^{-\frac{1}{2} I_k^t S_k^{-1} I_k}$$

$$S_k = H_k (F_{k-1} P_{k-1} F_{k-1}^t + Q_{k-1}) H_k^t + R_k$$

$$I_k = (Y_k - H_k F_{k-1} X_{k-1})$$

with :

- Ik innovation = measure - prediction
- Sk covariance matrix associated to innovation Ik
- Fk-1 matrix associated to kinematic model
- Qk-1 covariance matrix associated to process noise
- Rk covariance matrix associated to measurement noise
- Hk transition matrix between measure Y and state X

For a classical Kalman filter with constant speed model, Q_{k-1} is generally like:

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$$Q_{k-1} = \sigma_{q-1}^2 \begin{bmatrix} \frac{\Delta T^4}{4} & \frac{\Delta T^3}{2} & 0 & 0 \\ \frac{\Delta T^3}{2} & \Delta T^2 & 0 & 0 \\ 0 & 0 & \frac{\Delta T^4}{4} & \frac{\Delta T^3}{2} \\ 0 & 0 & \frac{\Delta T^3}{2} & \Delta T^2 \end{bmatrix}$$

with σ_{q-1} process noise corresponding to the maximum acceleration tolerated by the kinematic uncertainty of the tracks.

When Δt becomes significant (detection holes), S_k becomes also very significant and the likelihood (I_k) tends to:

$$\frac{1}{\sqrt{2\pi}} \frac{1}{|S_k|^{\frac{1}{2}}}$$

That engenders that all the hypotheses tend to the same value and become equally probable. Consequently, it’s very difficult to favour one hypothesis over another.

<u>Problem 2 bis:</u> *recursive filtering*

Furthermore, in these transition cases (see previous figure), the kinematic estimation is often erroneous, and that can lead to favour hypotheses kinematically not so good.

Example of impact of this estimation error on hypotheses likelihood calculation for a track, in the particular case of fixed false plots: real case often observed when an air track passes near a stationary surface track (buoy, wave, etc) or false alarm on land (cliff, etc). The air target can pass unseen during a while because of the radar discrimination (2 close echoes):

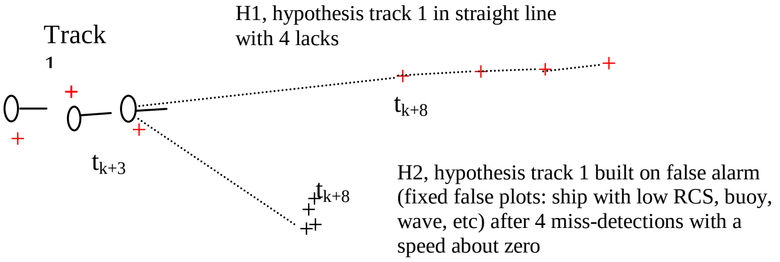

Fig 3: Impact of estimation error

The likelihood between the two hypotheses (H1 and H2) is going to be identical:

- <u>Problem 2 :</u> Indeed, after 4 miss-detections, the two hypotheses will be nearly equally probable because of the significant dimension of the innovation covariance matrix (S_k) in the likelihood calculation.
- <u>Problem 2 bis :</u> The kinematic estimation of hypothesis H2 for the first false plot will generate a speed near zero. The following filtering for fixed plots will have a very good likelihood (as good as the one of hypothesis H1).

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In this case, for track 1, it's very difficult to choose the right hypothesis H1 (track number continuity for PHD): only a fifty-fifty chance.

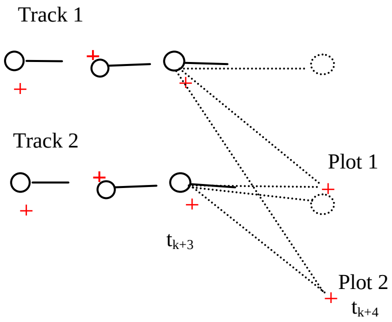
This phenomenon is going to generate, for each track with miss-detections, uncertainty areas on fixed plots. In these areas, the probability to create plausible false hypotheses associated to the track is high. The more Δt increases, the more this area is going to grow and the more probability to privilege hypotheses with null speed built with false alarm for track 1, tends to be significant.

Problem 3: ***Assigning plots to tracks at current scan***

In PHD filter case, merging among hypotheses kinematically close, tends to make track number management difficult. One plot can belong to several hypotheses and also to several tracks. Therefore, there is no global optimal tracks-plots assignment allowing tracks numbering management.

To compensate for this problem, we are generally obliged, for the track number management, to come back to MHT-tracks classical techniques (where a plot can't be shared with several tracks).

Not knowing how to manage ambiguous areas is the main problem for these recursive classical techniques based on MHT-tracks. Indeed, tracks-plots assignment is processed recursively at current scan: plot i is allocated to track j according to criterion of global likelihood like Munkres. But, sometimes, it's necessary to keep plots history before we can choose the best assignment. A plot can be allocated for a while (from 1 to x scans) to several plausible hypotheses, associated to several different tracks. Visualization of track number problem with two hypotheses:



6 possible associations:

- Track 1 – Plot 1
- Track 1 – Plot 2
- Track 1 – Lack
- Track 2 – Plot 1
- Track 2 – Plot 2
- Track 2 – Lack

Fig 4: Possible associations for 2 scans

In this case, we can assume that Munkres is going to give the following global optimal assignments:

Track 1 – Lack: main hypothesis Track 1 – Plot 2: secondary hypothesis
Track 2 – Plot 1: main hypothesis Track 2 – Lack: secondary hypothesis

If at next scan $T_{k+5,}$ there are the following plots (both tracks are turning)

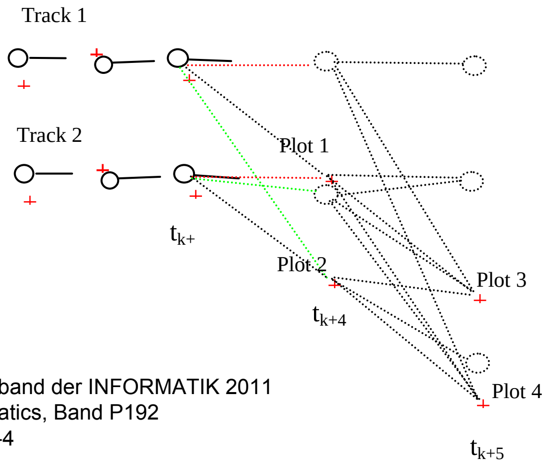


Fig 5: Possible associations for 3 scans

The right associations (« Track 1 – Plot 1 – Plot 3 » and « Track 2 –Plot 2- Plot 4 ») are not tested: indeed, at the previous scan (t_{k+4}), the right association « Track 1 – Plot 1 » has been eliminated during global optimal assignment, because plot 1 has been allocated to track 2.

Conclusion: when there is an ambiguity for a plot allocation with several tracks, it's necessary to wait next scans to resolve this ambiguity and to allocate the plot to the right track. So, we have to store the different tracks-plots association hypotheses on time frame which lasts x scans (x to be defined according to the ambiguity).

3. A new solution using graph theory

Techniques based on graph theory allow solving the different problems described above: building graph of pairs of plots associated to optimal browse graph algorithm (Dantzig's algorithm). [7]

- Graph building allows keeping all the plausible hypotheses (problem 3) without being exponential at combinatory level (problem 1).
- Dantzig's algorithm allows to research in this graph all the plausible optimal hypotheses (problem 3) according to a kinematic likelihood criterion calculated on a time frame lasting several plots without process noise (Problems 2 and 2 bis)
-

Methodology to build a graph of pair of plots

First step: Building a graph from the plots for each sensor:

Each plot delivered by the sensor on a time frame is defined as a vertex or node of the graph. Any arc between two plots is built under the following condition:

Dpair<Vmax ΔT+f(ε) where:

- Dpair distance between the two plots
- ΔT is the time elapsed between the two plots. In any case this time must obey the following condition $\Delta T < n*Ts$ where Ts is the sensor update rate and n a parameter.
- Vmax is the maximum speed for the object of interest
- f(ε) uncertainty on distance which depends on the measurement errors.

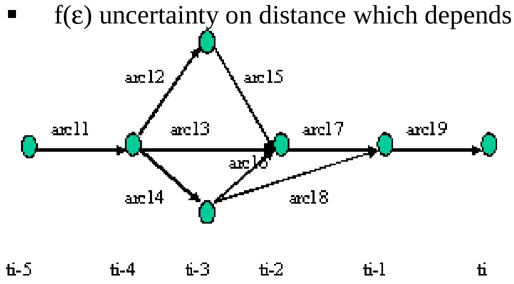


Fig 6: An example of graph

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Second step: Building the graph of pair of plots for each sensor:

The final graph is built upon the graph defined in step one: Nodes of the final graph are the arcs of the previous graph (pairs of plots). Fig. 7 illustrates the graph resulting from Fig. 6

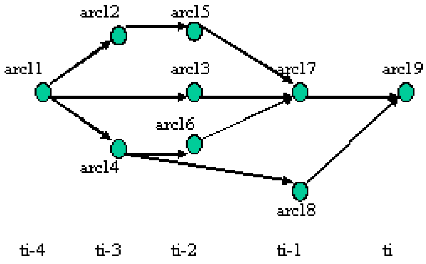

Fig 7: Graph for sensor 1

The same process is applied to a second sensor. Let Fig. 8 the graph be the graph for sensor 2.

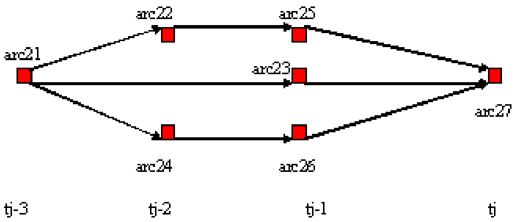

Fig 8: Graph for sensor 2

Methodology to combine several sensors graphs

The two graphs from sensor 1 and sensor 2 described in Fig. 7 and 8 are combined to form a new graph. Any arc between the nodes of the two sensors graph can be created if:

- The time are consistent
- The position and speed are consistent

Starting from graphs in Fig. 7 and 8, the final combined graph is displayed in Fig 9.

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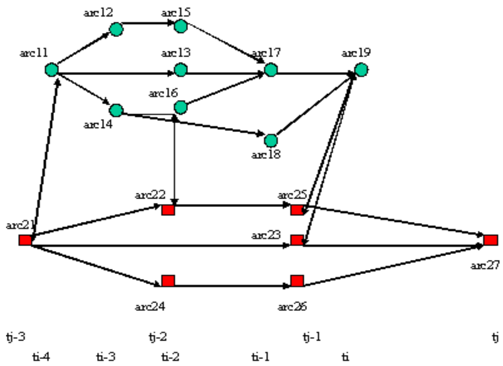

Fig 9: Combination of sensor 1 and sensor 2 graphs

The combination of individual sensors graph is a directed graph, each arc is ordered in the two directions in order to determine the optimal path cover.

Dantzig's algorithm was developed to determine and rank the different paths of the graph according to a predefined criterion. For instance in the famous travelling salesman problem, the criterion is the distance between the different cities.

One key point of the "pair of plots graph based tracking" is the estimation of kinematics consistency criteria between the arcs of the graph. These criteria's are used by « the recursive optimal path cover algorithm such as Dantzig's algorithm [4][5] » to determine the most consistent "hypothesis" /path among the possible one.

<u>Application to classic dynamical and measurement models linear transformations with additive Gaussian noise</u>

The kinematics criteria used by the Dantzig's algorithm is based on the following basic data:

- The speed of each node of the graph:

  $$V_{Xi} = \frac{x_i - x_{i-1}}{t_i - t_{i-1}}$$ where ti, ti-1, xi and xi-1 are the time and position of the plots of the node

- The acceleration between two vertices of each arc:

  $$\Gamma_{X_i} = \frac{V_{Xi} - V_{Xi-1}}{t_i - t_{i-1}}$$ where V_{xi} and V_{xi-1} are the speed of the two vertices.

Using the two kinematics data described above, the criteria used by the Dantzig's algorithm is defined as:

$$C = \prod_{i=1..N} \left(1 - e^{-\frac{(\Delta\Gamma_{X_i})^2}{2G_i^2}}\right)$$ where:

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- N is the number of vertices of any hypothesis or path.
- $\Delta\Gamma_{xi}$ is the variation of acceleration between two consecutive arcs of a path
- G_i a normalization factor.

Dantzig's algorithm determines the "hypothesis"/paths of the graph that minimize C i.e. the one that contain a maximum number of vertices while minimizing mean square acceleration deviation.

Discussion:

Assuming a path $\mathcal{P}$ of the graph corresponds to a track following a constant acceleration kinematic model whose variation can be modeled by a additive noise following a normal law ($\mathcal{N}(0,\sigma_x)$), then for each position X_i of path $\mathcal{P}$:

$X_i = \Gamma t_i^2 + Vx_0\, t_i + X_o + \mathcal{N}(0,\sigma_x)$ (H1)

According to (H1):

- Γ_{xi} is Gaussian whose mean and standard deviation are defined as: $E(\Gamma_{X_i}) = \Gamma$ and $\sigma_\Gamma = \sqrt{\sum_{i=k} f_i(t_k)^2}\,\sigma x$ where f_i is a weighting factor which depends on the time t_i, t_{i-1}, t_{i-2},…
- $\Delta\Gamma_{xi}$ is Gaussian whose mean is 0 and standard deviation is defined as: $\sigma_{\Delta\Gamma xi} = \sqrt{\sum_{i=k} g_i(t_k)^2}\,\sigma x$ where g_i is a weighting factor which depends on the time t_i, t_{i-1}, t_{i-2}, t_{i-3},…

Conclusion:

For each path $\mathcal{P}$; if H1 is true then the probability:

$$P(H_1) = P(C \geq \Delta\Gamma_{Xi}) = e^{-\frac{(\Delta\Gamma_{Xi})^2}{2(\sigma_{\Delta\Gamma Xi})^2}}$$

Else (H1 is not true) the probability for each path that do not fit a constant acceleration kinematic model defined above is

$$P(\overline{H_1}) = 1 - e^{-\frac{(\Delta\Gamma_{Xi})^2}{2(\sigma_{\Delta\Gamma Xi})^2}}$$

Going back to the definition of criteria C:

$$C = \prod_{1..N}\left(1 - e^{-\frac{(\Delta\Gamma_{X_i})^2}{2G_i^2}}\right) = \prod_{1..N} P\overline{\mathrm{H}1}_i$$

This result demonstrates that the "hypotheses" that minimize criteria C are actually the one which contains a maximum number of vertices with a minimum deviation of acceleration.

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4. Advantages of graph of pairs of plots

Advantage 1: Developing a Tracking algorithm Based on Graph of Pairs of Plots (**TGPP**) instead of tracking based on simple graph of plots highly increases the number of "hypothesis"/path managed by the filter.

Justification

The number of hypothesis for a plot (cf. Fig. 10) is linked to N, the number of possible links in input and M the number of possible links in output:

- For a graph based on plots, only the best N paths are tested, ranked and selected by Dantzig's algorithm
- For a graph based on pair of plots then: M arcs / "hypothesis" are built from the plot leading to MxN possible paths.

Assuming that for a given track, N plots are received per frame, then for M sensor frames, the actual number of possible path is N^M. The number of hypothesis tested by Dantzig's algorithm is:

- $(M-1)x(N)^2$ for a graph based on plot
- $(N)^2+(M-2)\ (N)^3$ for a graph based on pair of plots

The gain in performance for the TGPP Vs a simple graph based on plots algorithm is $(M-2)(N-1)N^2$.

Using the TGPP also improve the probability to select the good plot to "hypothesis"/path association by its capability to take into account incoming information (plots associated to the N links in input) and information in output (plots associated to M links in output).

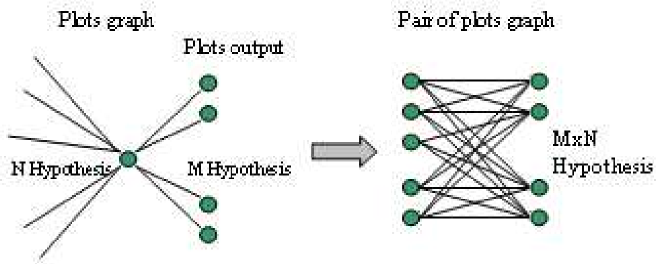

Fig 10: Plots based graph vs. pairs of plots based graph

Advantage 2: the calculation of the kinematic likelihood of the hypotheses, in Dantzig's algorithm, can be done on a 4 plots history (instead of 3 plots in the case of graph of plots). Consequently, it's possible to search for the hypotheses which minimize the acceleration variation.

Example of difficult case linked to problem 2:

Two hypotheses for the same track:

- Hypothesis H1: the track goes on the straight line.

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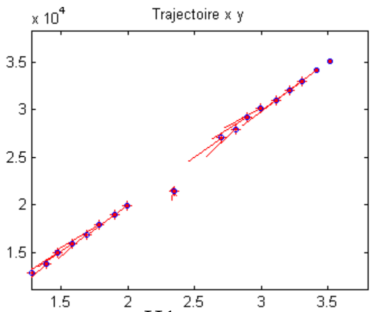
- Hypothesis H2: the track diverges on fixed plots.



H1 H2

Fig 11: Particular case of fixed false plots

Visualization of normalized innovation vs. time for these two hypotheses filtered with Kalman constant speed model with a process noise equal to 10 m/s^2:

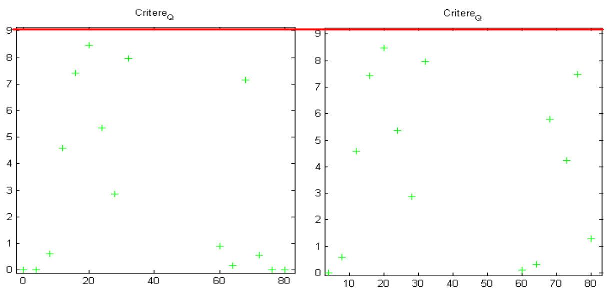
H2  H1

Fig 12: Normalized innovation (Kalman filter)

The normalized innovation for both hypotheses is lower than the threshold of evolution detection (9) of the kinematic model. Consequently, both hypotheses will have close likelihoods and it will be very difficult to favour one over the other.

Visualization of variation of normalized acceleration by measurement noise plots vs. time for both hypotheses in the case of TGPP:

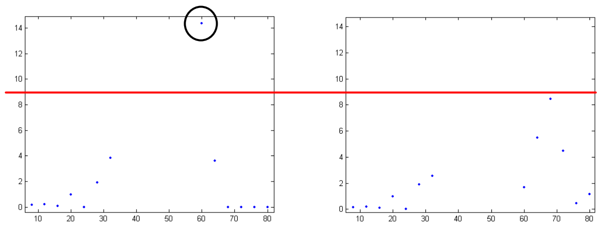
H2  H1

Fig 13: Normalized acceleration variation (TGPP)

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The hypothesis H2 has a value well above the detection threshold (9 = constant acceleration model). In the hypotheses weight calculation, the hypothesis H1 will be strongly favored over the hypothesis H2.

This can be easily explained because the normalization factor for the normalized innovation of the Kalman filter is proportional to Δt2. On the contrary, the normalization factor over acceleration variation for the TGPP in inversely proportional to Δt2. Indeed, when ΔT is constant the weighting factor associated to $\sigma\Delta\Gamma_{xi}^2$ (cf. discussion criteria C at §III) for TGPP is: $\frac{20}{\Delta T^4}\sigma x^2$.

The higher Δt is, the more the TGPP will penalize the hypotheses with an acceleration fluctuation.

Advantage 3: Thanks to advantage 2, the graph of pairs of plots can easily manage large detection holes: indeed, the building of arcs between pairs of plots with a significant detection hole (large Δt) can use the criterion of kinematic consistency over 4 plots to strongly limit the number of arcs of the graph in comparison with the one of the graph of plots. The only case which is not solved by this technique is the one where there is a lot of isolated plots for a same track (one plot -> x misses -> one plot -> y lacks … . with x and y > 10). In this case, it's difficult to build pairs of plots. But actually (see figure below), the tracks are detected by more or less short periods, and theses periods are generally very rarely less than 2 radars scans.

Visualization of arcs of pairs of plots on real trial on São Paulo:

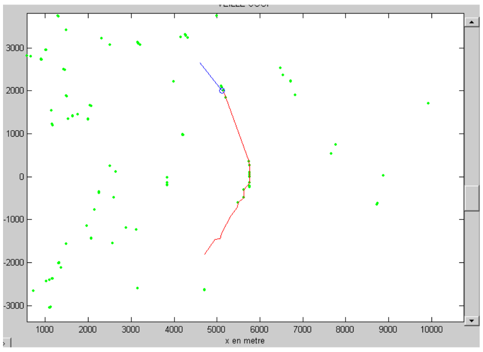

Fig 14: Arcs of pairs of plots (real data)

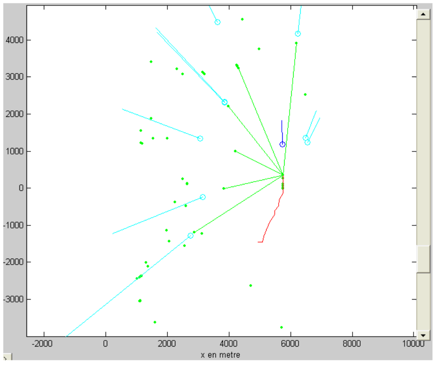

Fig 15: Arcs of plots (real data)

Fig 14 : At this moment, there is only one arc (kinematically coherent) linking the two observable areas.

In case of the graph of plots, we need to build much more arcs of plots, because at least 3 plots are needed to verify the kinematic coherence (consequently, a lot of plausible acceleration solutions). Recall paragraph 1: after 10 misses, there are more than 100 kinematically plausible hypotheses, while with a time frame of 4 plots (graph of pairs of plots) we have not more than one…

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Advantage 4: In the case of a multiplatform environment, the use of TGPP has the following benefits

- Independence from the errors (bias) between the reference frames of each sensor.
- Ease the integration of sensors delivering only tracks (a track update contains the same information used to define a pair of plots (position and speed).
- Ability to reduce significantly the number of association between arcs using plots (thanks to kinematics consistency test) compared to a graph based on plots only.

5. Description of the overall TGPP algorithm

The proposed algorithm has been designed to allow simple and quick testing of a large number of possible plots to plots and/or tracks associations while taking into account:

- Maneuvering target in false alarm area
- Miss-detection in false alarm area
- Close and non discriminated targets
- Sensor with low performance tracking system
- Bias, alignment errors between sensors on board and/or distributed on several platforms.

Application of the TGPP algorithm to multisensory, multitarget multiplatform case is a three steps process:

Step 1: Iterative building of the multisensor graph on a set of detection frames

Step 2: For each track:

- Use of Dantzig's algorithm to determine the weight associated to each node of the optimal paths (hypothesis) associated to the track.
- Normalization of the weight (each weight is turned into likelihood) and ranking of all the paths (hypothesis).

Step 3: The different ranked hypotheses are processed to handle the following cases: raid, merging, splitting, false alarm, and miss-detection.

One advantage on using a graph based on pair of plots solution is the ability for each arc (hypothesis) to only calculate and store specifics parameters between nodes of the graph. These parameters permit Dantzig's algorithm to quickly calculate the weight of the optimal paths (defined in step 2), instead of using a high time consuming algorithm such as IMM filter for the classical MHT IMM filter.

6. Graph based tracking performance

Comparison between IMM MHT or PHD Filter (with management of track numbers like MHT) and TGPP:

1. Using real data from São Paulo sensor

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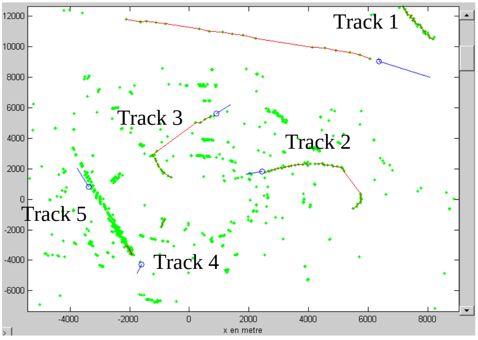

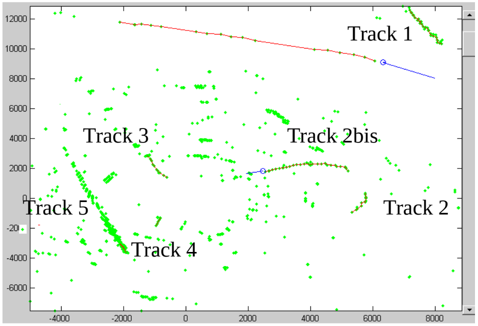

Fig 16: Tracking result with TGPP Fig 17: Tracking result with IMM MHT or PHD filter

- Track 1: same for the both solutions
- Track 2: the track is lost for MHT solution and is recreated after wards as Track 2 bis.
- Track 3: the track is lost for the MHT solution and is never recreated (because of false alarm)
- Tracks 4 and 5: Theses are false tracks on Rio-Niterói Bridge. The tracks are lost for the MHT solution and they are in lack for the TGPP. Remark: the two false tracks for the TGPP have not diverged with false alarm similarly to what happened with MHT solution.

2. On a real multi-target multi-platform scenario the robustness of TGPP algorithm was demonstrated. Indeed the TGPP did not lose the tracks (specifically their track number for PHD) during the scenario while the IMM MHT did. Fig. 18 illustrates, red circles when the IMM MHT lost the tracks (or track number) in a difficult environment with target maneuver and miss detections.

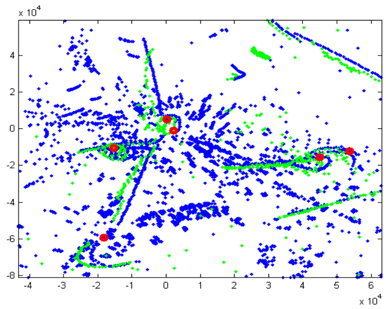

Fig 18: MHT IMM filter performance

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7. Conclusion

The aim of this paper was to present a new distributed multi-sensor multi-target tracking algorithm: the TGPP able to cope with high false alarm/clutter rate and maneuvering targets under real time constraints.

Comparison of performances using real data recorded during sea trials with MHT IMM filter (or PHD filter) has been tested and confirmed the advantage of the TGPP filter.

Thanks to the ability to manage in real time an important number of hypotheses and the use of a robust and efficient criterion to select the right hypothesis, the TGPP filter can cope with the following constraints corresponding to the new navy missions:

- Highly maneuvering targets in cluttered environment
- **Significant detection holes**
- Under sampling, observability issues, non Gaussian measurements,
- Increasing number of sensors and platforms
- …

The TGPP filter can be extended to track fusion or to a hybrid plot and track fusion taking into account for instance multi function radar tracking capabilities and constraints.

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