

Control of multi sensor system based on anomaly mapping and expert system

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Abstract: Multi sensor systems have performances that depend on the type of multi sensor data fusion. Multi sensor data fusion of raw detections (plots) has high performances but is seldom used in operational applications. A less efficient data fusion is preferred in the majority of operational multi sensor systems: data fusion of sensor tracks.

Data fusion of sensor tracks is simpler and requires limited resources of communication and central computing but performances are limited because data fusion is unable to create system tracks without sensor tracks.

Multi sensor plot data fusion has not this limitation but the huge number of plots imposes larger bandwidth sensor networks, more powerful central computers and more sophisticated data fusion algorithms. The risk and the cost of this data fusion are considered too important compared with the gain of performances.

The purpose of paper is to present a modular architecture that makes possible to control the complexity of multi sensor plot data fusion. The architecture is a multi algorithm data fusion controlled by anomaly mapping and expert system. Expert system coherently manages sensors and data fusion to fulfil the missions whatever the environment and its evolution.

This approach has been applied with success to the surveillance system of a French navy ship. This system has to detect, track and identify Air and Surface objects with on board active and passive sensors. Some gains are presented in comparison with the legacy system.

1 Introduction

Multi sensor data fusion of raw detections (plots) is seldom used in operational applications. A less efficient data fusion is preferred in the majority of multi sensor systems: the data fusion of sensor tracks.

Sensor Track Data Fusion is simpler and requires limited resources of communication and central computing. This Data Fusion based on decentralized tracking in each sensor is modular and provides a first level of robustness to sensor failures.

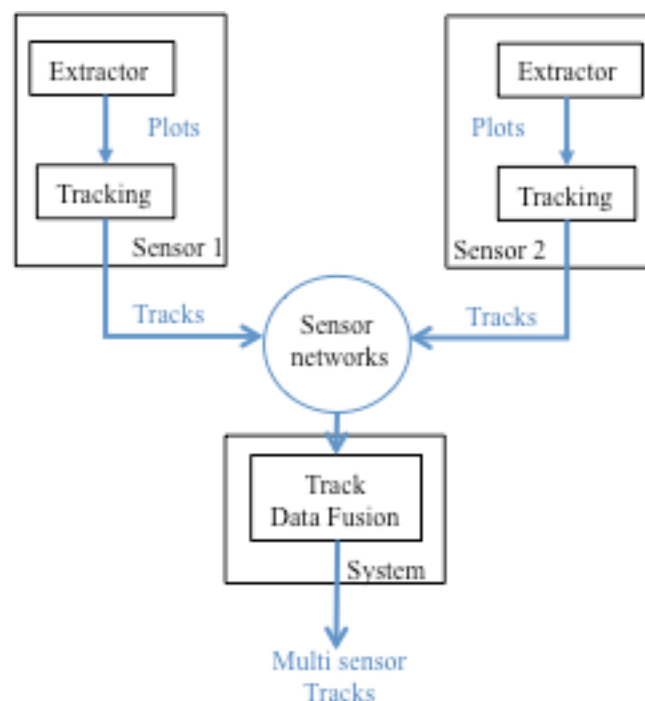


Fig. 1: Sensor Track data fusion

The normalization of the sensor track interfaces makes the extension of data fusion to new sensors possible. But the performances are limited: if the sensors do not individually create sensor track on an object, the data fusion at sensor track level will not allow the creation of a multi sensor track on this object.

Multi sensor plot data fusion has not this limitation and can create tracks if the detections of the sensors are complementary but the huge number of plots imposes larger bandwidth sensor networks, more powerful central computers and more sophisticated data fusion algorithms.

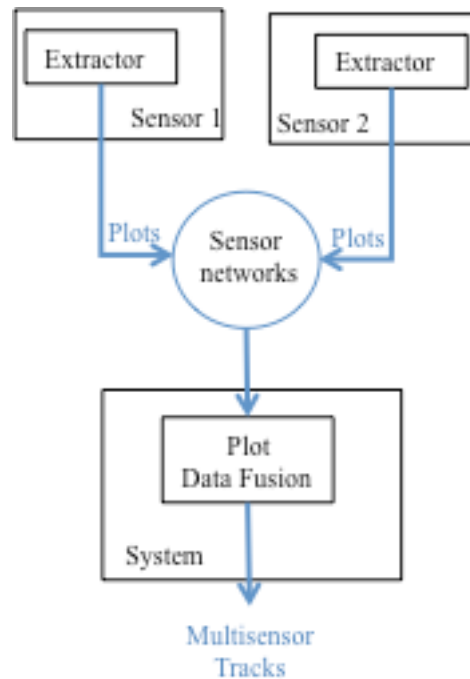


Fig. 2: Multi sensor plot data fusion

The complexity of development and the difficulty of tuning explain the limited use of plot data fusion in operational systems.

After identification of the main issues of multi sensor plot data fusion, the paper presents a modular architecture that limits the risk of development and tuning phases.

2 Main Issues of plot data fusion

The first issue is the control of plot data fusion complexity. As the sensors are asynchronous, multi sensor tracking are sequenced per sector or per time frame to:

- Correlate system tracks with received plots,
- Create new system tracks with uncorrelated plots,
- Filter system tracks with selected plots.

The system treatments are complex with many interactions between the treatments of correlation, initiation and filtering. Multi sensor data fusion has to fuse sensors of different dimensions: active sensors are 2D (azimuth, distance) or 3D (azimuth, distance, elevation), passive sensors are 1D (azimuth) or 2D (azimuth, elevation). And triangulation algorithm of passive sensor bearings must coexist with association algorithm of bearings to punctual system tracks. Modularity of system treatments is necessary to manage the complexity, to treat all the cases of data fusion and to benefit in each case of the state of the art of algorithms. Modularity is also necessary for adding new sensors and taking into account the evolution of sensors: sensors with beam agility progressively replace the classical sensors with constant antenna rotation.

The second main issue of plot data fusion is the robustness to disturbances. In existing systems based on plot data fusion, the performances of multi sensor data fusion are sometimes locally lower than the performances of the best sensor. Multi sensor system is dependent of many actors: sensors, navigation systems when sensors are mobile, sensor networks. Local disturbances of one of the actors can locally pollute the results of data fusion. The figure 2 presents the different types of disturbances that can affect all the multi sensor system: origins and effects.

	Sensors	Navigation systems	Sensor networks	Plot Data fusion
Origins	Failure Relief, Sea, ducts, Rain, Clouds, Sun, Jamming, Chaff, laser	Failure, GPS jamming	Failure Relief, Sea, ducts, Rain, Jamming	Computer failure
Effects	Huge number of bad detections, poor detection probability	Derive of sensor locations, alignment errors	Increase of latency, loss of messages, loss of connectivity	Drop, false tracks, dual designation, saturation, loss of coverage
Actions	Beams, frequencies, waveform, signal processing, sensor mask	Navigation resetting	Routing on other media	Computer, redundancy, sensor weighting, algorithm choice and tuning, system masks, alignment

Fig. 3: Robustness to disturbances

Figure 2 lists the possible actions to limit the effects of disturbances on the results of plot data fusion: actions at actor level or actions at data fusion level. The challenge is to detect disturbances as soon as possible and to decide where to react to protect plot data fusion: is a local reaction at data fusion level sufficient or is it necessary to react at actor level with consequences on a wider area?

3 Modular architecture

The proposed architecture answers the issues of plot data fusion: complexity control, modularity and robustness to disturbances. This architecture is based on a multi algorithm data fusion and on a control that coherently manages multi algorithms data fusion and sensors.

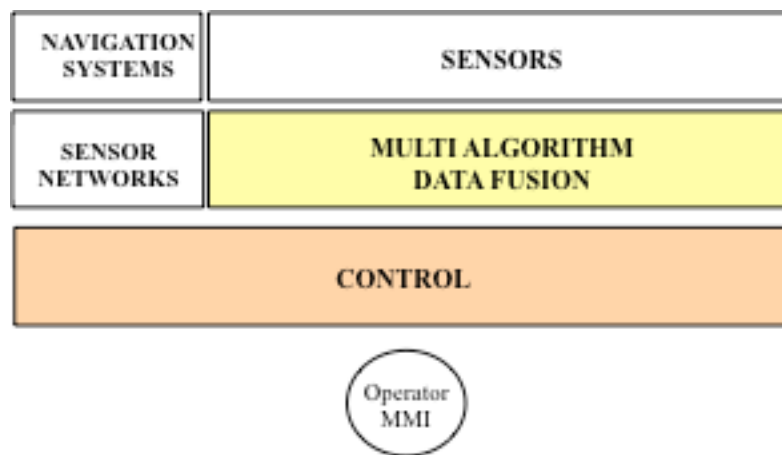


Fig. 4: Global view of modular architecture

3.1 Multi Algorithm Data Fusion

A partial answer to modularity need is multi algorithms data fusion where choice of algorithms and algorithms tunings can be controlled. The functional chain of plot data fusion is organised around three main issues: correlation of plots to existing system tracks, system tracks filtering with correlated plots and new tracks creation with uncorrelated plots. The algorithms of the figure 4 correspond to the state of the art when the evaluation of proposed architecture began 15 years ago.

For correlation of plots to existing system tracks, multi hypothesis algorithm was selected [Bs86] and the main choice of algorithm is the maximum number of hypothesis per track (Nmax). This algorithm choice per range domain depends on the mission priority. The control parameter called hardness of correlation can be tuned per sensor and per cell. The objective of this control is an optimal use of the Nmax hypothesis per track: to avoid spending hypothesis of the track on disturbed sensors and to keep a maximum of hypothesis for the non-disturbed sensors of the cell. (The rules to manage hardness of correlation are given in §3.5 as an example of data fusion control).

For filtering, the state of the art was the IMM [BSy01]. The main choice is to use IMM 3D filter or IMM 2D filter with separate filtering in z. This algorithm choice per range domain depends on the presence of 3D sensor or on the possibility to estimate z with distributed 2D sensors. The control parameter per cell is the sensor priority for filtering when the plots are very closed in time. The objective of sensor priority is to use the more accurate and reliable sensors to update the track.

For initialisation of new tracks, the state of the art was a mono sensor auto adaptive algorithm building chains of plots with a score depending on an estimated probability of false alarm of the sensor [Bs86]. The state of the art was also a multi sensor algorithm that accelerates the track creation when two sensor chains of plots correlate. The algorithm choice per range domain is to activate or not multi sensor initialisation. Using multi sensor algorithm presents a risk to generate more false tracks; and this risk is useless for the ranges domains where the coverage of the sensors does not overlap. The parameter is called hardness of initialisation and can be controlled per sensor and per cell. The objective of the control is to adapt the thresholds of confirmation per sensor so that the global consign of track false alarm was satisfied taking into account the number of mono sensor initialisation in the cell.

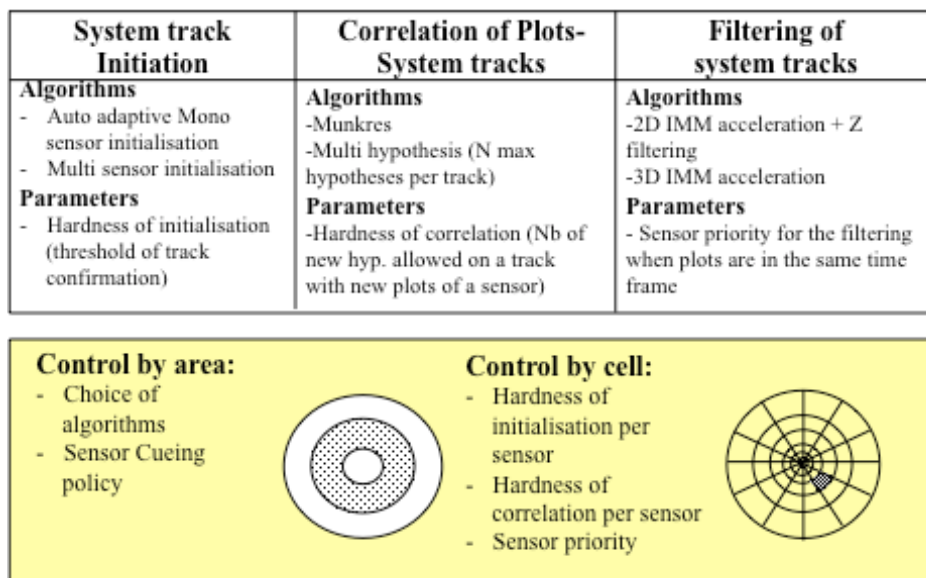


Fig. 5: Multi Algorithm Data Fusion

If the multi sensor system had to be set today, new algorithms should be considered: PHD filter [Vbt08] [Mr00] or graph theory algorithm [LC11]. And a reflexion must be led to determine the parameter of control of these new algorithms. The structure of multi algorithm data fusion is adapted to integrate these new algorithms and their control.

3.2 Architecture of Control

Multi sensor data fusion must always have better performances than the performances of the best sensor. The main challenge to fill this objective is to avoid local degradation of performances when one actor has disturbances.

The proposed control answers this need. After initial conditioning depending on the missions defined by operator, control adapts in real time the tunings of sensors and data fusion. It obeys to the paradigm “analyse, decide and command”. The analyse process is an anomaly mapping to focus on the disturbance areas, the decision process is an expert system which looks dynamically for data fusion and sensor tunings so that anomalies would be corrected, the command process plans the changes of tunings with the objective of insuring track continuity.

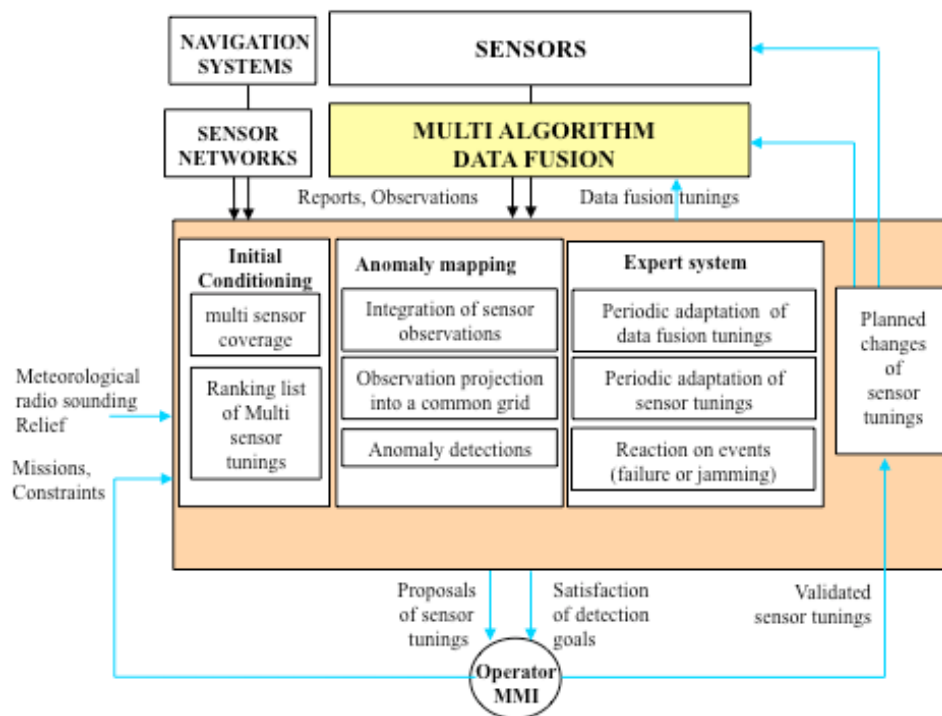


Fig. 6: Architecture of Control

3.3 Initial Conditioning

The operator has to define the missions and the constraints of the system. A mission is a goal of detection (type of object to detect and track, geographical area). Constraints are the unavailable tunings of the sensor due to discretion need (for instance, forbidding of a radar maximum power use). The multi sensor configurations are ranked depending on the coverage of the missions. Multi sensor configuration is the association of sensors in specific tunings. The coverage of each multi sensor configuration is estimated by a prediction tool under the current meteorological conditions and relief.

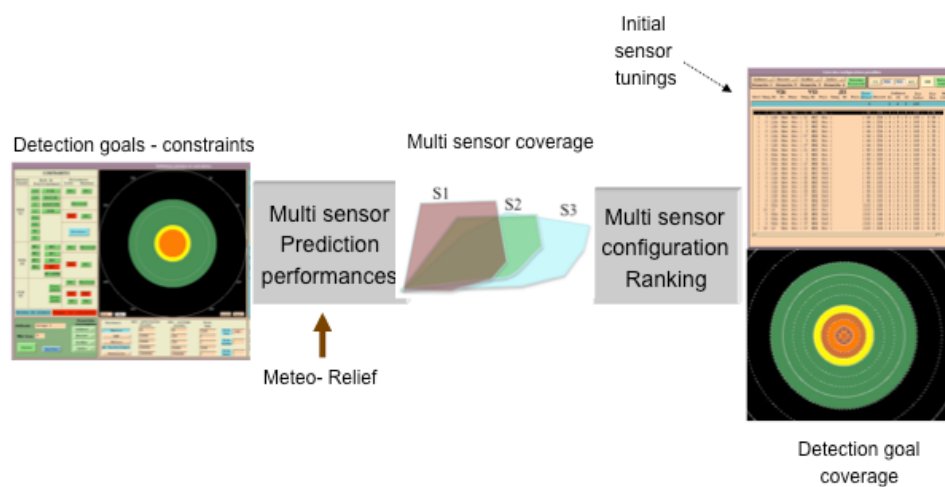


Fig. 7. Initial Conditioning

The right window of figure 7 proposes a ranking list of multi sensor configurations with their missions' coverage (hatched areas on right screen are non covered parts of missions). When the operator selects a multi sensor configuration, the multi algorithm is also configured: the choices per range domain of Nmax hypothesis, 2D/3D filters and mono/multi sensor initialisation are made depending on the overlapping of sensors.

3.4 Anomaly Mapping

The objective of anomaly mapping is to detect in real time the apparition of disturbances on the actors (sensors, navigation system, network, data fusion). All the observations of the actors are taken into account: 1D observations as sensor and network load reports, number of plots per sector, jamming reports or 2D observations as plot density map, track density map. Each observation is integrated during a sliding time window of one or two minutes. The results of integration of each observation are quantified on a limited number of levels.



Fig. 8: 1D integrated observations

The figure 8 shows three 1D integrated observations: number of plots per sector and per sensor, number of initialisation hypothesis per sector and per sensor, number of IRST plots per sector and per band. The quantification is on 4 levels of load (red=high, yellow=important, green= normal, black=light).

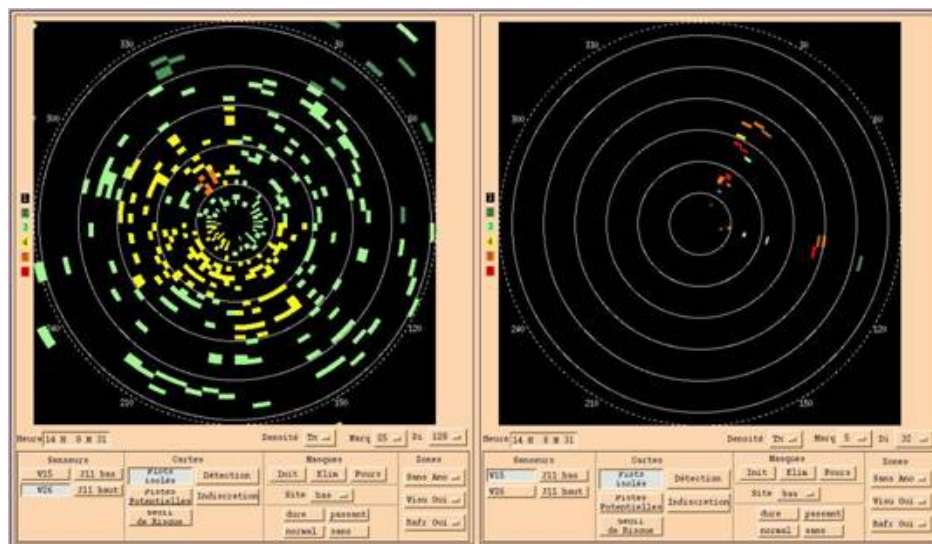


Fig. 9: 2D integrated observations

The figure 9 shows two 2D integrated observations: number of plots per cell for a sensor, number of potential tracks per cell for another sensor. The quantification is on 6 levels of load (from red=high to black=light).

All integrated observations are then projected onto a common multi sensor grid and a treatment of anomaly detection associates level of anomaly (no anomaly, middle anomaly, high anomaly) to each observation per cell. The figure 10 shows the results of anomaly detection on 2D observations of figure 9.

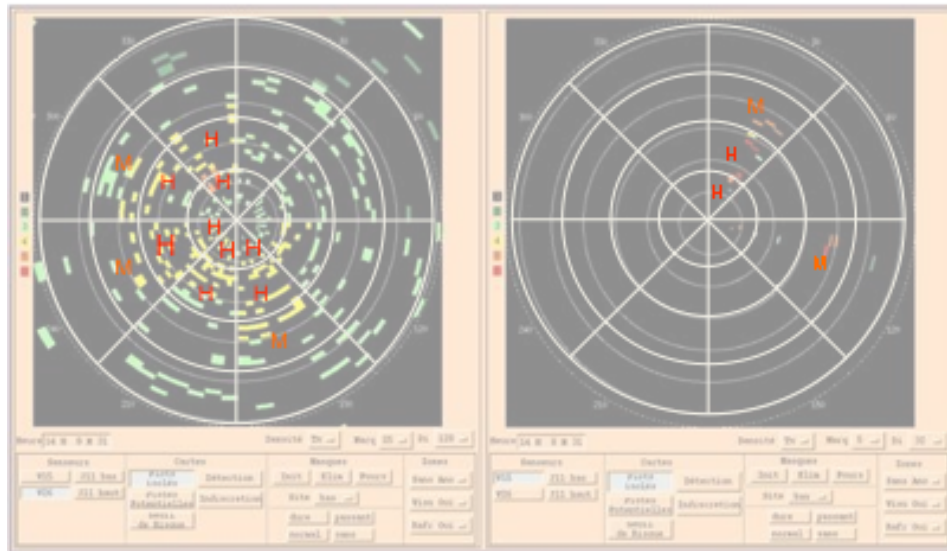


Fig. 10: Detection of anomaly

The anomaly is set on 3 levels (H = High, anomaly M= Middle anomaly, Black= no anomaly).

3.5 Expert system

The detection of anomalies characterizes the reliability of sensors in each common cell.

Expert system tries first to protect the multi sensor data fusion from the disturbed sensors by adaptation of data fusion parameters. This reaction on algorithm parameters can be quick and can correct the local anomalies as soon as they appear. This is the periodic adaptation of data fusion parameter (see “Expert system” box of figure 6).

The inputs of rules used for the parameter adaptation are anomaly maps and sensor overlapping on the missions. There are sets of rules for correlation hardness, initialisation hardness and for filtering sensor priority. Expert system is interesting because it authorises the enrichment of the rule sets on lessons learned. For example, false plot anomalies were not sufficient to adapt initialisation hardness. It was necessary to add anomalies that characterise the spatial and temporal correlation of clutter. Inputs such as jamming anomalies, potential track anomalies, sensor plot filtering anomalies were added depending on the type of sensor.

An example of a rule set is given for correlation hardness. The figure 11 presents the level of correlation hardness that can be adjusted per cell and per sensor.

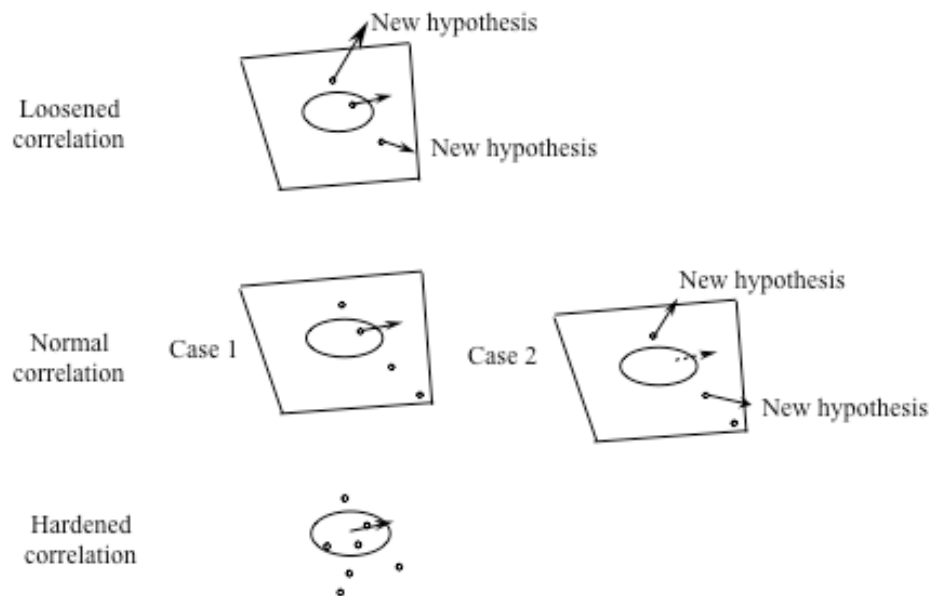


Fig. 11: Hardness of correlation

On figure 11, the arrows represent tracks and their hypothesis and the points represent plots. Correlation windows are also drawn: small window takes into account the covariance errors of track in uniform movement, large window adds potential acceleration of the track from the last update. 3 levels of correlation hardness are set: loosened, normal and hardened. Correlation hardness depends on sensor false alarm probability. If false alarm probability is low, creation of new track hypothesis is authorised even if the plots are in large window: this is the loosened correlation. If the probability of false alarm is middle, creation of new track hypothesis is only authorised if there is no plot in the small window: this is the normal correlation. If the probability of false alarm is important, creation of new track hypothesis is not authorised: this is the hardened correlation.

The set of rules used to manage correlation hardness per cell and per sensor is presented on figure 12.

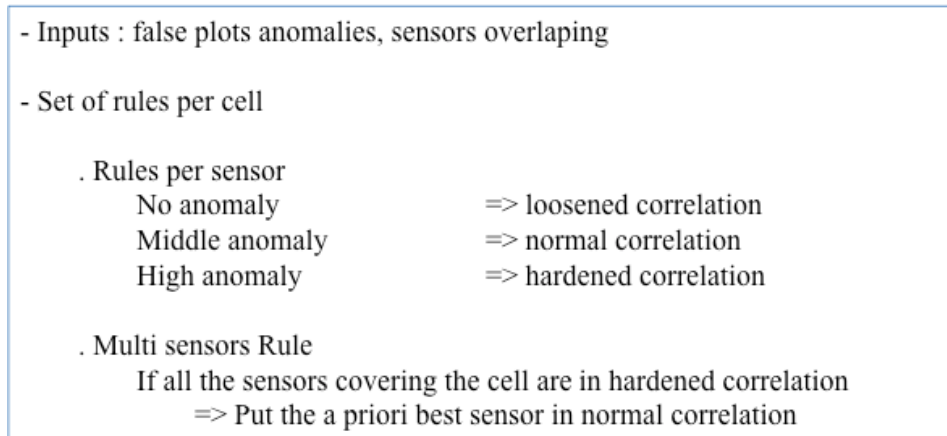


Fig. 12: Set of rules for correlation tuning by cell

The false alarm probability is directly estimated by false plots anomalies. The rules adjust correlation hardness per sensor depending on the false plots anomalies of the sensor. And a multi sensor rule verifies that the mission covering sensor of the cell are not all in hardened correlation inhibiting the tracking of a manoeuvring object. In this case, the rule changes correlation hardness of the a priori best sensor: from hardened to normal.

In parallel of periodic adaptation of data fusion parameter, expert system examines if the sensor tunings are always adapted to the evolution of environment and proposes, if necessary, changes of sensor tunings. This is the periodic adaptation of sensor tunings of the figure 6. The inputs are the anomaly maps and the sensor coverage of the missions. A vote for changing sensor tunings is made for each sensor and for each cell. If there is no sensor anomaly, the vote is to choose more energetic tunings to improve sensor coverage. If sensor anomaly is middle, the vote is to keep the current tuning. If sensor anomaly is high, the vote is to choose sensor tunings that filter sensor disturbance. The figure 13 illustrates the principle of votes per sensor and the multi sensor synthesis per cell.

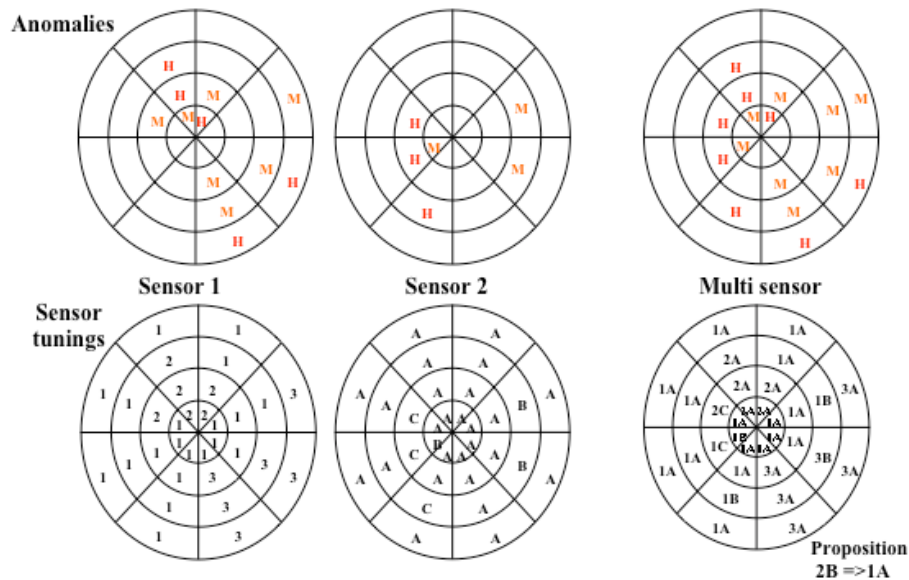


Fig. 13: Principles of majority poll

In this example, the initial multi sensor configuration is 2B. After the votes, multi sensor configuration 1A have the majority. The multi sensor configuration 1A is proposed to the operator. Information on the new configuration coverage of the missions and on time to change from 2B to 1A is presented to the operator who has to validate the new configuration.

4 Navy applications

The proposed architecture was tested on surveillance multi sensor system of a French navy ship. This system has active and passive sensors and Tactical Data Links (TDL). The active sensors are several radars, 3D air radar, 2D air and surface radars (azimuth, elevation, range), 2D navigation radars (azimuth, range). The passive sensors are 2D IRST (azimuth, elevation) and 1D Radar Electronic Support Measurement (azimuth). The legacy system is based on plot data fusion and enriches the tactical picture with tracks received from the others ships by TDL.

An experimental surveillance system based on the proposed architecture was developed. Two types of assessments were then led:

- Comparison of experimental system versus legacy system had the objective to assess the improvement due to the modular architecture and the control,

- Comparison of multi platform plot data fusion versus TDL track data fusion had the objective to demonstrate the interest of the proposed architecture and to assess the improvement due to multi platform plot data fusion.

Tests were led on a ground-based platform and at sea. This paper presents the results obtained on the ground-based platform.

4.1 Methodology of evaluation

For the assessment on the ground-based platform, a hybrid simulation of sensors and TDL was developed with a capability to mix synthetic data delivered by models and real data recorded on ship.

Several scenarios were selected and these scenarios were played for different environments for which real recorded data of sensors were available.

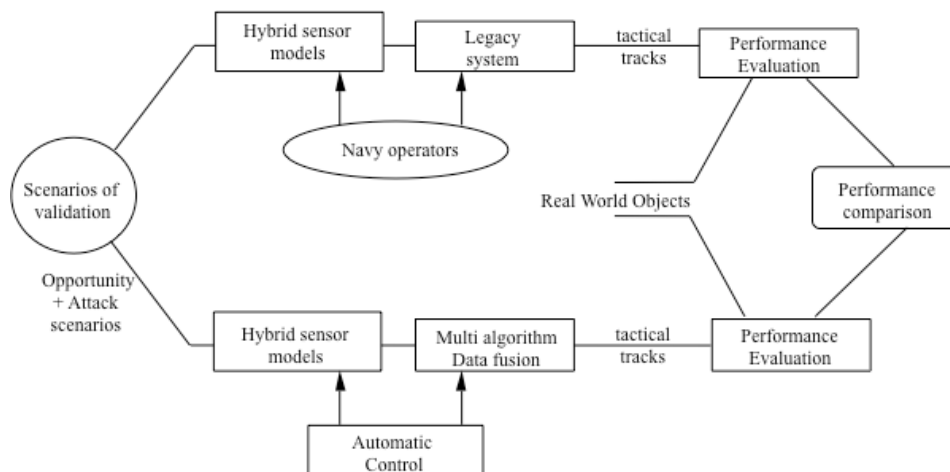


Fig. 14: Methodology of evaluation

The legacy system was first assessed: navy operators tuned the legacy system (masks and sensor tunings) on opportunity traffic for the different environments. Thus, for each environment, attack scenarios were played on tuned system and corresponding tactical pictures were recorded. The situational awareness performances were assessed with records on different criteria: number of false tracks, ranges of track creation on threats, continuity and accuracy of the tracks...

The Multi algorithm data fusion was then assessed: automatic control tuned the system (hardness and sensor tunings) on opportunity traffic for the different environments. Thus, for each environment, once the system tuned, the situational awareness performances were evaluated on the same way than for the legacy system.

4.2 Improvement due to architecture and control

To assess the improvement due to the architecture and the control, the experimental system and the legacy system were compared on selected scenarios considering only on board sensors of the ship.

In first context crisis scenario, threats were fighters, UAV and subsonic missiles. In second war context scenario, threats were supersonic and subsonic missiles.

The two scenarios were played in three environments for which real data were recorded on ship: calm sea with duct, middle sea with duct and heavy sea. The hybrid simulation mixed the synthetic detections and the real false detections recorded on ship. Figures 15 and 16 present the results of evaluation with a focus on two complementary performances: the track creation ranges on threats and the number of false tracks. These performances are complementary because it is useless to have good track creation ranges if there are too many false tracks.

		calm sea - Duct	Middle sea - Duct	Heavy sea
Crisis Context	UAV, fighters	11%	28%	0%
	missile	39%	64%	6%
War Context	subson missiles.	27%	14%	4%
	superson missiles.	5%	2%	4%

Fig. 15: Improvement of track creation ranges

		calm sea - Duct	Middle sea - Duct	Heavy sea
Crisis Context	0 - 15 NM	88%	19%	57%
	0-100 NM	69%	6%	53%
War Context	0 - 15 NM	85%	84%	44%
	0-100 NM	59%	43%	46%

Fig 16: Reduction of false tracks

The results show that the automatic control gives better track creation ranges on threats and reduces significantly the number of false tracks. In general, the gain is more visible on reduction of false tracks than on track creation ranges. The crisis context scenario in middle sea with duct is an exception with a important gain on UAV and missile creation ranges and a limited reduction of false tracks. The trade-off between the two performances is different because navy operators have put many sensor masks on legacy system to have a very low number of false tracks but some masks drastically impact the track creation ranges on UAV and missiles.

4.3 Improvement due to multi platform data fusion

To assess the improvement due to multi platform plot data fusion, the experimental system and the legacy system were compared on one scenario considering the capability of detection of three ships. The experimental system elaborated tactical picture by plot data fusion of ships. The latencies induced by sensor network were simply modelled. The legacy system elaborated tactical picture by plot data fusion of on board sensors and by enrichment of local tracks with TDL tracks received from the two other ships.

Selected scenario was a 3 missiles scenario: the missiles have typical trajectories, low altitude trajectory or diving trajectories. The scenario was played in four environments for which real detections were recorded: two offshore environments (standard propagation and duct) and two coastal environments (standard propagation and duct). The coastal environments had masks of relief, which affected the detection of low altitude missile. Figures 17 and 18 present the results of engagement possibilities. The engagement is possible when the accuracy of the track is sufficient. Figure 17 shows the possibilities of engagement for the most difficult environment.

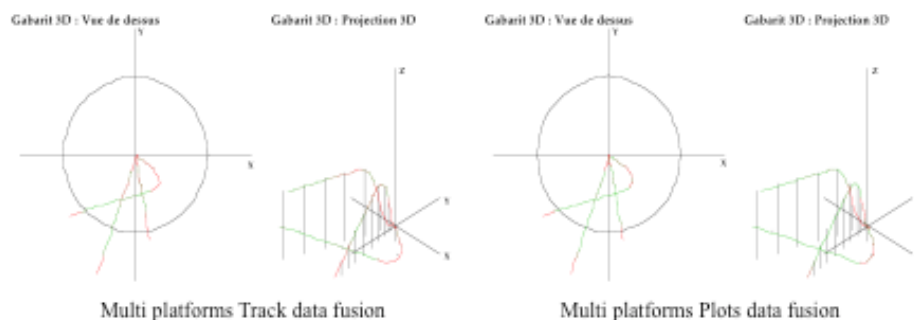


Fig. 17: Comparative results on coastal environment with duct

The parts of trajectories where engagement is possible are in green; improvement of multi platform data fusion can be seen on low altitude missile behind relief and on diving trajectories of the other missiles.

Engagement Possibilities	Offshore standard propagation	Offshore Duct	Near the coast standard propagation	Near the Coast Duct
Track data fusion	52,5 %	52 %	43 %	40,9%
Plots data fusion	63,6 %	63,5%	60,5%	62%
Gain	21%	22%	41%	51%

Fig. 18: Comparative results on 4 environments

Figure 18 presents the engagement possibilities in the four environments. In the two

coastal environments, the improvement of engagement possibilities grows up to 50%. Multi platform data fusion is especially interesting in difficult environments where the complementarity of sensors can compensate the poor individual probability of detection of each sensor.

The applicability of proposed architecture with automatic control to multi platform was also demonstrated during this evaluation: modularity of this solution allowed to extend easily plot data fusion to remote sensors of other ships.

Conclusions

The multi sensor data fusion is much more efficient than track data fusion especially when the environment of detection is difficult. The multi sensor data fusion can create and maintain continuous tracks when individual sensors are unable to create tracks. The expert system of the control has demonstrated its efficiency to optimize sensor and algorithm tunings in relation to the missions and to the environment.

The complexity of plot data fusion can be managed with the modular architecture based on multi algorithm data fusion and on automatic control. This architecture guaranties the modularity of the system for adding new sensors or for integrating new data fusion algorithms. The advantage of expert system of easily enriching rule sets makes possible improvements of multi sensor system for life.

Acknowledgments

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