AIRBORNE FUSION OF IMAGING AND NON-IMAGING SENSOR INFORMATION FOR MARITIME SURVEILLANCE

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***Abstract* - This paper presents results from an Adaptable Data Fusion Testbed (ADFT) which has been constructed to analyze simulated or real data with the help of modular algorithms for each of the main fusion functions and image interpretation algorithms. The results obtained from data fusion of information coming from an imaging Synthetic Aperture Radar (SAR) and non-imaging sensors (ESM, IFF, 2-D radar) on-board an airborne maritime surveillance platform are presented for a typical scenario of Maritime Air Area Operations. The SAR imagery is analyzed by a four-step hierarchical classifier to obtain ship length, category, type and class.**

1. INTRODUCTION

This paper describes an on-going effort to build an Adaptable Data Fusion Testbed (ADFT) based on a Knowledge-Based System (KBS) BlackBoard (BB) architecture to perform data fusion of imaging and non-imaging sensors present on-board the CP-140 Canadian maritime patrol aircraft. The ADFT architecture must process the data coming from radar, Electronic Support Measures (ESM), Identification Friend of Foe (IFF) and datalink information both for the *planned* Aurora Modernization Program (AMP) and the Maritime Helicopter Project (MHP) which will replace the ageing Sea Kings. The new sensors that are exclusively present on the airborne platforms are of the imaging type, namely the Forward Looking Infra-Red (FLIR) and Synthetic Aperture Radar (SAR) which can operate in Strip Map, RDP and Spotlight modes (Adaptive or Non-Adaptive). The attribute data that these sensors can provide is important in determining the identification of target platforms, particularly the long range features that the Spotlight SAR can furnish.

2. ADFT ARCHITECTURE

The real-time KBS BB shell developed by Lockheed Martin (LM) Canada and Defence Research Establishment Valcartier is the basis of the ADFT infrastructure. This system is totally generic, and could be used to implement any system comprised of components which can be numeric or AI based. It has been implemented in *C++* rather than in a higher-level language (such as LISP, Smalltalk, ...) to satisfy the real-time requirement.

The testbed is designed to accommodate modular interchangeable algorithm implementation and performance evaluation of:

1. Fusion of positional data from imaging and non-imaging sensors;
2. Fusion of attribute information obtained from imaging and non-imaging sensors and other sources such as communication systems, satellites, etc., and
3. Object Recognition (OR) in imaging data.

The algorithms incorporate state-of-the-art tracking in clutter and evidential reasoning for target identification. The end result offers the user a flexible and modular environment providing capability for:

1. addition of user defined sensor simulation models and fusion algorithms;
2. integration with existing models and algorithms, and

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3. evaluation of performance to derive requirement specifications and help in the design phase towards fielding a real Data Fusion (DF) system.

3. FUSION FUNCTION IMPLEMENTATION

Any generic DF application must contain the following set of sequential functions to act on real or simulated data:

1. *registration* to first perform spatial and temporal alignment of the simulated sensor data,

2. an *association* mechanism to then correlate the new incoming data with possible existing tracks found in the BB database and to send associated positional data to positional fusion and associated attribute data (e.g. image features of a given target) to information fusion,

3. *positional estimation* to then update the tracks in the time domain with the associated new data and write this positional information to the BB database, possibly extracting attribute data such as speed, acceleration and sending to information fusion, and

4. *identification estimation* (or information fusion) to then fuse all attribute data through evidential reasoning, whether they originate from imaging (through image understanding and feature extraction) or non-imaging sensors and consequently update the dynamic BB track database.

The control flow for the fusion of information is data driven directly from the simulators. The algorithms used within the DF function include: Jonker-Vogenant-Castanon (JVC) algorithm which is an optimal single-scan associator for the *association* function, Kalman filters for the *positional estimation* function, and LM Canada developed truncated Dempster-Shafer (DS) algorithm for the *identification (ID) estimation* function. The positional estimation function uses radar, IFF, ESM and Link-11 data and ID estimation uses IFF, ESM, Link-11 and imaging features.

4. DATABASE ATTRIBUTES FOR IDENTIFICATION

For ID estimation to be properly achieved, all possible attributes that can be measured by all of the sensors must be listed in the Platform DataBase (PDB). The attributes which we have catalogued in the PDB split into 3 groups:

1. Kinematic attributes which can be estimated by tracking by positional estimation, IFF and Link-11: the maximum acceleration ACC, the maximum platform speed V_MAXI and the minimum platform speed V_MINI all serve as bounds to discriminate between possible air target identifications. ALT_MAXIM is the maximum altitude that a platform may reach, which serves as a bound for altitude reported by the IFF.

2. Geometrical attributes which can be estimated by algorithms within the FLIR and the SAR classifiers: in addition to the three geometrical dimensions of height, width and length, one also needs the variables RCS_FOR, RCS_SID, RCS_TOP corresponding respectively to radar cross-section (RCS) of the platform seen from the front, the side and the top. The RCS values are empirically much larger than the geometrical cross-section obtained by the product of the two relevant dimensions (HEI, WID, LEN) since metallic objects offer strong radar backscatter when compared to the geometrical cross-section.

3. Identification attributes proper which can be directly given by the ESM, or as outputs of the FLIR and SAR ISM. ACRO is the acronym of the country name indicated in the GPL and used also to refer to the country that owns the platform in the PDB. In the PDB, ACRO is used by the attribute fusion function to link the PDB platform with the country allegiance indicated in the GPL. The variable EMITTER_LIST is an exhaustive list (labelled by number) of all the emitters that are carried by the platform. The variable PLATYPE forms the first level of platform classification used in this PDB. This variable is closely related to the category descriptor given by the ISM and reflects its platform military utilization. SUBTYPE provides a sub-classification of the platform type.

Some sensors measure attributes quite directly. For example the ESM will provide an emitter list with some confidence level about the accuracy of the list that reflects the confidence in its electromagnetic spectral fit. The IFF can however lead to some complications. An IFF response does lead to an identification of a friendly or commercial target but the lack of a response does not necessarily imply that the interrogated platform is hostile. One has to distribute the lack of a response between at least two declarations: the most probable foe declaration and a less probable friendly or neutral declaration that allows for an IFF equipment that is not working or absent.

Similar complications arise when dealing with kinematic parameters reported occasionally by the tracker in *positional estimation*. Firstly, each physical quantity has a different dimension (speed, acceleration) and an accurate determination is not necessarily needed for fusion. Indeed it is convenient to bin the attribute “speed” into fuzzy classes like “very fast”, “fast”, “average”, “slow” and “very slow” (separately for air and surface targets). Similar binning for acceleration could range from “very large g” to “very small g”. Membership in each class is a measure of how well the measured value fits into the descriptor as described below.

Further, speed or acceleration reports must be fused only if they involve a significant change from past historical behaviour in that track. The reason is two-fold: firstly no single sensor must attempt to repeatedly fuse identical ID declarations otherwise the hypothesis that sensor reports are statistically independent is violated, and secondly the benefits of the fusion of multiple sensors is lost when one sensor dominates the reports. This is clearly the case if positional fusion reports the same value of speed for hours at intervals of a few seconds! Furthermore, a measured value of speed (or acceleration) only indicates that the target is capable of that speed, not that it corresponds to either the maximum or minimum speeds listed in the PDB. It is a reasonable working hypothesis to fuzzify the value reported by the tracker into adjacent “bins” to account for the target being at, say only 80% of its optimal speed (a “very fast” target can occasionally travel “fast”), or travelling with a strong tailwind (a “fast” target can occasionally appear as “very fast”). Finally the concept of binning can be generalized to continuous membership functions of a fuzzy set.

5. IMAGE SUPPORT MODULES (ISM)

The ISM for either the SAR or the FLIR can also generate a nearly infinite set of declarations from a single given image. Care must be taken to preserve as much independence between the declarations and certainly prevent any conflict. Such an independence can be achieved to a reasonable extent if different features are extracted from the image in different steps or if totally different mathematical algorithms are used in each step. The ISM which LM Canada has designed for image interpretation of SAR data (presently XDM, but later this year ADM) is the 2-D equivalent of the ESM’s 1-D signal interpretation. The present ISM design involves the four steps described in Figure 1, of which the first three have been implemented and tested [1]. The design logic shown in Figure 1 involves a hierarchical decision tree for ship features extraction and ship classification.

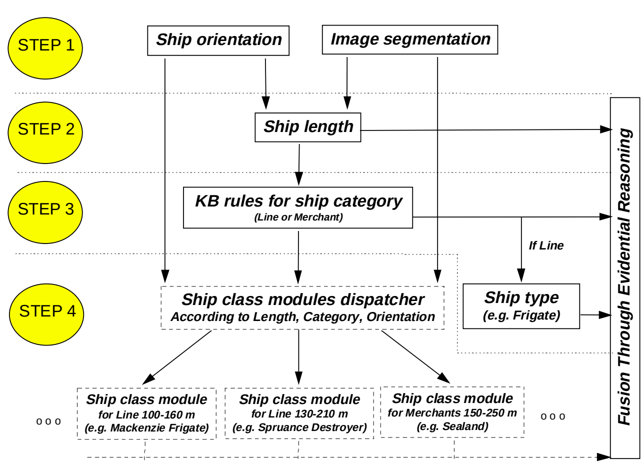

Figure 1 - SAR ISM hierarchical design

The SAR ISM thus preferentially extracts target features at long range feature, namely

1. ship length,
2. ship category: combatant (line), merchant or unrecognized,
3. ship type, e.g. if line, then either frigate, destroyer, cruiser, battleship or aircraft carrier, and
4. ship class, e.g. if frigate, then Halifax class or MacKenzie class.

Given the image acquisition parameters and the navigation data, the first step checks if proper ship orientation is achieved (e.g. the image is sufficiently elongated), and, if so, an image segmentation process detects a target whose image is simply connected. In a second step, a Hough transform then permits an estimation of the ship length, which is immediately sent to MSDF for the ID estimation process. The length reported has an intrinsic uncertainty which is fuzzified into length bins whose width is further discussed below. The reported length is then fused with the length attribute listed for all the ships in the PDB.

In the third step, Artificial Intelligence rules based on the relative position and number of main scatterers (as identified by pixel intensities being above a certain threshold) allow the determination of ship category into “line” or “merchant” categories by locating its superstructure. The presently implemented method is a Neural Net (NN) trained on 37 production rules based on the location of the main radar scatterers in 9 different regions along the length of the ship. The possible outputs of the NN are “line”, “merchant” or “unrecognized”. It should be noted that these categories are only a subset of the NATO STANAG where “line” is only a subset of combatant ships (other combatants include Amphibious Warfare, Mine Warfare, and Patrol ships) and “merchant” is a subset of so-called “non-naval” entities (which include also Fishing, Leisure, and Law Enforcement ships). They are however the main categories relevant for the Aurora missions mentioned earlier. An “unrecognized” declaration from the NN indicates that it could not reach an ID and consequently that declaration is assigned to the ignorance in the DS algorithm for evidential reasoning.

The third step also performs an attempts at identifying ship class if the NN declaration for “line” is sufficiently large (say >50%). This is due to the correlation between ship length and ship class observed from a survey of about 100 classes of ships in Jane’s Fighting Ships, as shown in Figure 2. Note that this survey is arbitrarily normalized, so that for an actual mission, some knowledge about the relative population of each class could renormalize the data. The smallest width of these distributions can serve as an indication of the binning size needed for the fuzzification of the length attribute in Step 2. The line types which are generated in this fashion can discriminate between frigates, destroyers, cruisers, battleships and carriers (as identified in the PDB). An indication of the fuzziness of the declaration is given by the relative overlap between classes for a given measured length. From the Figure, it can be seen that a length measurement around 250 meters generates propositions for battleships and carriers with roughly the same confidence levels, but a measurement of 180 meters is almost exclusively assigned to cruisers.

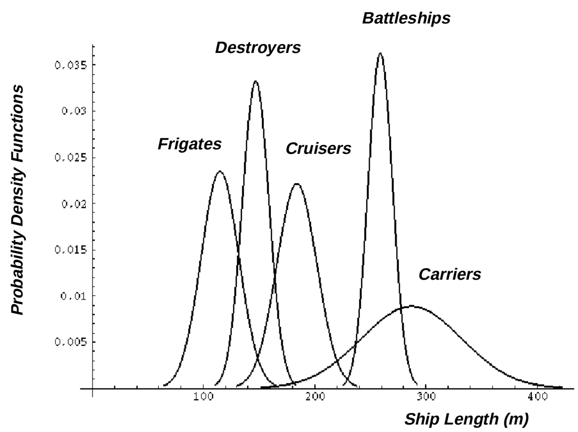

Figure 2 - ISM’s Bayes length classifier step

Finally in the fourth step, yet to be implemented, specialized NNs trained on subsets of the database of ship images (artificially created from a simulator for various aspect and depression angles), that span a given length interval, refine the ID declaration to ship class (e.g. frigate of Halifax class, destroyer of Spruance class). The outputs of the neural net for each possible class are again numbers between 0 and 1 which are interpreted as the level of confidence in obtaining the correct class ID. The neural net also provides an “unrecognized” class which again reflects its inability to reach a conclusion about ship class. This is then attributed to the ignorance in the DS sense, as in step 3.

For the FLIR classifer, a two hidden layer design neural net design is presently being studied and trained on more than two hundred merchant ships. Since merchants, unlike combatants, cannot readily be identified through the radar emitters, the FLIR perfomance will be crucial in determining their type: cargo, RoRo, ferry, oiler/tanker, or passenger. Results will be presented elsewhere, once validation has been quantified on real FLIR imagery.

6. SAR ISM RESULTS

Figure 3 shows the raw SAR imagery in reverse video and histogram equalized (on top), the segmented image with its extracted centerline by the Hough transform and the thresholded major scatterers for the Udaloy destroyer, the Kara cruiser and the Mirka frigate (respectively from left to right). The images are not necessarily to scale. According to the scenario, the SAR acquisition parameters are: an aircraft altitude of 3 km, a range to target of 100km, an aircraft speed of 0.15 km/sec (300 knots), a SAR wavelength of 0.03 m, common ship heading of 45 degrees, slant-range resolution of 0.75 m and cross-range resolution of 2.0 m (intentionally unclassified numbers).

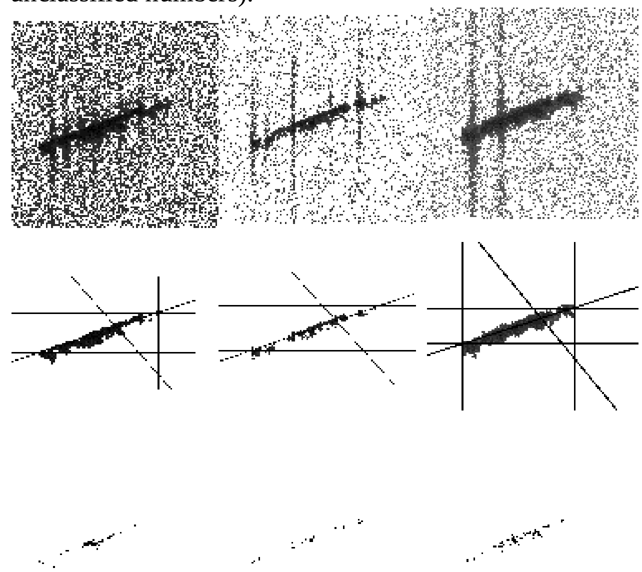

Figure 3 - SAR images of Russian fleet

For each of the 3 imaged ships, the ISM’s hierarchical classifier generates successively 3 attributes, each of which leads to several identity declarations (with associated BPMs in the DS sense) for line ships.

First the length obtained after centerline detection, which is further fuzzified into bins corresponding to length increments of 40 m (roughly the width of curves in Figure 2). Next the line category with its confidence level (obtained by keeping the top 10% of the strongest pixels). The results of these steps are shown in the following table (identification are in percentages):

TABLE 1: Length and line category results

Ship name	Length interval	Line combatant	Merchant	Unknown
Kara	160-208	81	6	13
Mirka	66-102	86	5	9
Udaloy	133-179	86	5	9

Finally the line type, from a choice of 5 line types: frigate, destroyer, cruiser, battleship or aircraft carrier (identification are again in percentages):

TABLE 2: Results of the SAR ISM classifier

Ship name	Frigate	Destroyer	Cruiser	Battleship	Carrier
Kara	0	10	67	0	4
Mirka	86	0	0	0	0
Udaloy	8	48	29	0	1

Note that all ships are correctly identified by the SAR ISM. The correct ISM declaration for the Udaloy will offset the incorrect ESM reports. In the case of the Mirka, such a small length is flagged to the operator since the algorithm is not certain of correct ID. In this case, the operator should fuse the ISM result (in other scenarios that were run where a similar flag is issued, the operator should decide not to fuse the result).

7. IDENTIFICATION ESTIMATION

The truncated Dempster-Shafer evidential reasoning scheme is used that proves robust under countermeasures and deals efficiently with uncertain, incomplete or poor quality information. An extensive set of realistic databases has been created that contains over 140 platforms, carrying over 170 emitters and representing targets from 24 countries. The evidential reasoning scheme can yield both single ID with an associated confidence level and more generic propositions of interest to the Commanding Officer. Our approach of reasoning over attributes provided by the imagery will allow the ADFT to process in the next phase (currently under way) both FLIR imagery and SAR imagery in different modes (Spot Adaptive and RDP for naval targets, Strip Map and Spotlight Non-Adaptive for land targets).

The DS theory of evidence offers a powerful approach to manage the uncertainties within the problem of target identity. Every sensor declaration about the M possible "values" of an attribute assigns a Basic Probability Mass (BPM) value m_i (i=1...M) to that attribute (present in the database) and generates M propositions which are just the numerical list of platforms in the PDB that can attain the said value for the attribute. For a PDB containing N platforms, the numerical list of platforms which forms a proposition is represented in the current implementation by a string of zeroes and ones in the location of a string of N bits. This is done to speed up calculations by bit manipulations for ensemble operations such as union and intersection, which are needed in DS theory. For physical quantities like speed, length, RCS and image classification attributes like category or class, M is usually greater than 1. This is due either to the fuzzification of the physical quantity or to the inherently complex nature of the algorithmic determination of the attribute (e.g. by NN outputs). DS theory is particularly suited for our application because it requires no a priori information, can resolve conflicts (present in hostile environments due to countermeasures), and can assign a mathematical meaning to ignorance (which is the result of some of the chosen algorithms).

However, traditional DS has the major inconvenience of being an NP-hard problem. As various evidences are combined over time, DS combination rules will have a tendency to generate more and more propositions which in turn will have to be combined with new input evidences. Since this problem increases exponentially, the number of retained solutions must be limited. Our truncated version of DS theory of evidence performs the conventional combination rules of DS theory but retains the final solution proposition according to the following criteria [2]:

1. All combined propositions which have BPM > BPM_MAX are retained (presently chosen as 0.05).
2. All combined propositions which have BPM < BPM_MIN are eliminated (presently chosen as 0.001).
3. If the number of retained propositions in step 1 is smaller than MAX_NUM, the subroutine will retain, by decreasing BPM, the propositions consisting of one element (singleton) until MAX_NUM is reached. If MAX_NUM is not reached, one retains, by decreasing BPM, the propositions consisting of two elements. The process is repeated until MAX_NUM is reached (presently chosen as 8). This step takes into consideration that the platform's commanding officer favours propositions of the singleton type. An Expected Utility Interval truncation scheme is presently also under study.

8. IDENTIFICATION RESULTS

The DF algorithms have been tested on complex scenarios representative of the main Aurora missions, namely Maritime Air Area Operations, Direct Fleet Support, Counter Drug Operations and Martime Sovereignty Patrols. This paper deals only with the Maritime Air Area Operations scenario (due to paper length restrictions).

The ID evolution for the Mirka frigate is shown in Figure 4 and the proposition list in Table 3 below.

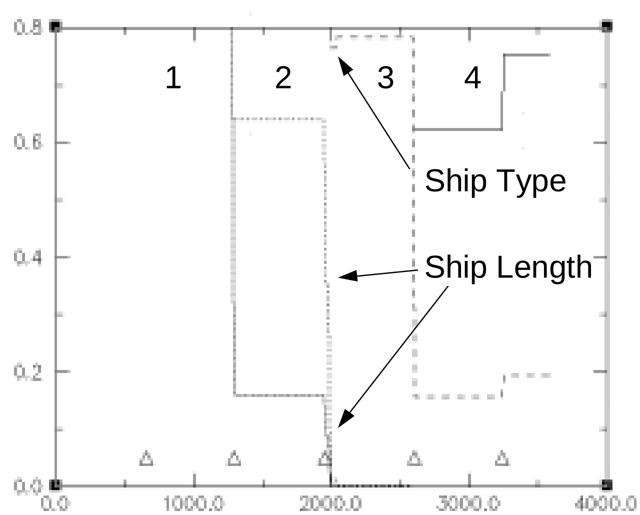

Figure 4 - ID evolution for the Mirka

Five triangles at the bottom of the figure represent the time at which an ESM report has been fused. After the first 10 minutes (t=656s), the Kara-Azov and the Mirka are not properly resolved (within an angle of 1º). The emitter #92 belonging to the Kara-Azov and other platforms is detected, initiating proposition 1 in which the Mirka-II is absent. Then, at t=1293s, the emitter #103 is detected which belong to the Mirka-II and to the Kara-Azov. As a result, proposition 2 emerges. The ground-truth shows that, this time, it is emitted by the Mirka-II. At t=1950 s, the emitter #56 is detected which only belong to the Mirka-II. The BPM associated to proposition 2 decreases. A SAR image is acquired and analyzed at time t=1980 s. The fusion of the Ship-Length attribute confirms the elimination of proposition 2 (the Kara is a cruiser two times longer than the Mirka-II) and proposition 3 becomes preeminent. The fusion of the Ship Type attribute at time t=2040 s increases the BPM of the proposition 3. Then, at time t=2606 s and 3243 s, two emitters (#44, #55) belonging only to the Mirka-II reinforces proposition 4.

TABLE: 3 - Propositions generated for the Mirka frigate

Prop #	Platforms
1	{Kirov-Ushakov/Lazarev/Velikyi, Kara-Azov}
2	{Kara-Azov}
3	{Mirka-I, Mirka-II, Sam-Kotlin}
4	{Mirka-II}

Figure 5 shows, for the Udaloy-II, the same type of information shown in Figure 4 and Table 4 gives the proposition list.

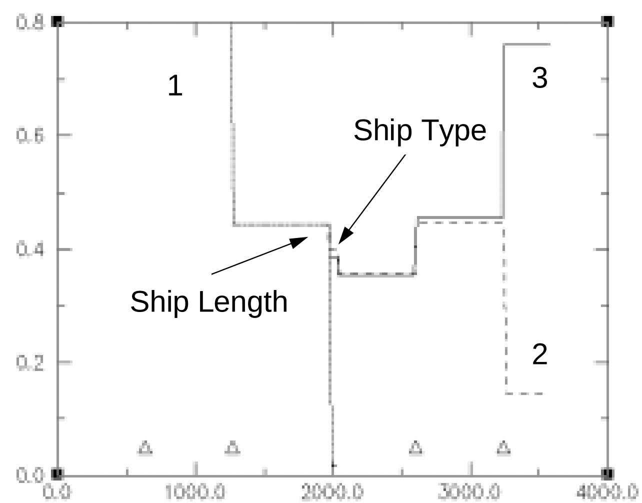

Figure 5- ID evolution for the Udaloy II

At t=637s, the emitter #97 is detected which belong to the ships of class Udaloy and to the modified-Kiev initializing proposition 1. Then, at t=1275s, emitter #129 is fused. It does not normally belong to the Udaloy-II but it has been placed intentionally in her list of emitters to simulate countermeasure. It actually worked since the BPM associated to proposition 1 dropped and proposition 2 carrying a false identity has been initiated. A SAR image is acquired an analysed at t=1980s. The fusion of the Ship-Length attribute on two propositions has the effect of decreasing the BPM associated to proposition 2 while creating proposition 3 by retaining from proposition 1 the ships of class Udaloy. The fusion of the Ship Type helps in decreasing the BPM associated to the false identity (proposition 2). At time t=2606 s, emitter #71 is detected which unfortunately will not help in discarding proposition 2 since this emitter belong to the ships of classes Udaloy and Sovremenny.

TABLE 4 Propositions generated for the Udaloy destroyer

Prop #	Platforms
1	{Modified-Kiev, Udaloy-II/Kulakov/Spiridonov}
2	{Sovremenny-II/Osmotrite/Boyevoy}
3	{Udaloy-II/Kulakov/Spiridonov}

The decision will be made at time t=3243 s, when emitter #93 belonging only to the ships of the class Udaloy is detected and fused.

Similar temporal evolution and proposition lists can be generated for the Kara but are omitted here (due to paper length restrictions).

9. CONCLUSIONS

A KBS BB-based architecture has been chosen for the airborne fusion testbed at LM Canada. The KBS BB environment allows incremental implementation of any MSDF function in a context-dependent way. It has been tested on many scenarios relevant to missions of the CP-140 Aurora and with the Aurora's non-imaging and imaging sensors. Analysis of SAR imagery proceeds through a hierarchical classifier that extracts long range attributes from Spotlight SAR imagery such as ship length, category, type and class. Image interpretation results (coming from a SAR imagery simulator and CAD models of ships) and platform identification results for a Maritime Air Area Operations scenario was presented. Through a proper interpretation of the non-imaging sensor reports and an appropriate understanding of features extracted from images, sensor declarations can be generated which consist of sets of propositions with an associated confidence level. These propositions consist in a list of platforms that realize the attribute "value" and are mathematically treated using a truncated Dempster-Shafer evidential reasoning scheme. A special effort has been made during the generation of the PDB to enumerate all possible attributes that the sensor inputs can provide.

10. REFERENCES

[1] Gagnon L., Klepko R., "Hierarchical Classifier Design for Airborne SAR Images of Ships, in Proc SPIE Aerosense'98, Vol. 3371, April 1998.

[2] Jouan A., Gagnon L., Shahbazian E., Valin P., "Fusion of Imagery Attributes with Non Imaging Sensors Reports by Truncated Dempster-Shafer Evidential Reasoning", in Proc. FUSION'98, July 1998, Vol. II, pp. 549-556, and references herein.