Defence Research and Development Canada
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C3MAAD: Multi-Source Object Recognition Algorithm

Version 1.0 : Support to the CORALS 3.0 Planner for the 2012 Rim of the Pacific Exercise.

F. Rhéaume
DRDC Valcartier

Defence Research and Development Canada
Technical Memorandum
DRDC Valcartier TM 2013-426
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Abstract

In order to carry out integrated air & missile defence and provide anti-ship missile defence, the Royal Canadian Navy is meant to conduct naval Command and Control. In this report, the problem of object recognition is studied and an object recognition algorithm is developed to support the threat evaluation, the engageability assessment and the combat power management processes. The new algorithm, called Multi-Source Object Recognition, is specifically suited for a Halifax-class frigate. While it concentrates mostly on the recognition of anti-ship missiles, it is also designed for the recognition of broad classes of aircraft such as jet fighters, surveillance aircraft and helicopters, for instance. With the main objective of providing object recognition, it is integrated to the COmbat Resource ALlocation Support (CORALS) software in both a simulation and a live ship-based setup. The setup was adapted in preparation for the integration on a Halifax-class frigate and for the participation to the 2012 international Rim of the Pacific Exercise (RIMPAC).

Résumé

Dans le cadre des activités de défense maritime aérienne, la Marine royale canadienne mène des opérations de Commandement et de Contrôle navales. Dans ce rapport, le problème de la reconnaissance d’objets est étudié et une capacité de reconnaissance d’objets est développée pour supporter les processus d’évaluation de la menace, d’évaluation de l’engageabilité et de gestion de la puissance de combat. La nouvelle fonctionnalité, appelée classification multi-source d’objets, est spécifiquement adaptée pour une frégate de classe Halifax. Bien qu’elle se concentre principalement sur la reconnaissance des missiles antinavire, elle est également conçue pour reconnaître les grandes catégories d’avion, tels que les chasseurs, les avions de surveillance et les hélicoptères, par exemple. Avec comme objectif principal de fournir la reconnaissance d’objet au logiciel “COmbat Resource ALlocation Support” (CORALS) pour la planification de défense anti-missile, elle est intégrée à la fois dans un environnement de simulation et dans un environnement de test réel sur un navire. La configuration de la fonction de reconnaissance et de l’environnement de test et de simulation a été adaptée en vue de l’intégration sur une frégate de classe Halifax et en vue de la participation à l’exercice international “Rim of the Pacific” (RIMPAC) 2012.

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Executive summary

C3MAAD: Multi-Source Object Recognition Algorithm

F. Rhéaume; DRDC Valcartier TM 2013-426; Defence Research and Development Canada; February 2013.

Background: In order to carry out Integrated Air & Missile Defence (IAMD), the Royal Canadian Navy is meant to conduct naval Command and Control (C2). Naval C2 can be decomposed into four processes: picture compilation, threat evaluation, engageability assessment and combat power management. The picture compilation process includes object detection, object localization, object recognition and object identification. These subprocesses are aimed at supporting threat evaluation, engageability assessment and combat power management.

A problem of particular interest in IAMD is the Anti-Ship Missile Defence (ASMD). Anti-Ship Missiles (ASMs) are guided missiles which can inflict significant damage to a ship. Surface ships, because of their large radar, radio, and thermal signatures, are very vulnerable to ASMs. To counter ASM attacks, warships can decoy and/or destroy the incoming missiles. The COmbat Resource ALlocation Support (CORALS) is an automation and decision support capability for ASMD operations. It has been developed by Defence Research and Development Canada (DRDC) to support the ship command team in planning optimized responses to multiple threats. Before being processed by CORALS, the threats have first to be identified and recognized. In this report, the problem of object recognition is studied and an object recognition algorithm is developed.

Principal results: Based on the review of the uncertainty related to both the measurement of attributes and the modeling of objects and their characteristics, a new Multi-Source Object Recognition (MSOR) algorithm is developed to provide automated object recognition for IAMD. The new algorithm, which is specifically suited for a Halifax-class frigate, concentrates mostly on the recognition of ASMs. It is also designed for recognizing broad classes of aircraft, such as jet fighters, surveillance aircraft and helicopters, for instance. It is integrated with CORALS into both a simulation and a live ship-based setup. Whenever an ASM is recognized by MSOR, it is sent to CORALS for planning. The setup was adapted in preparation for the integration on a Halifax-class frigate and for the participation to the 2012 Rim of the Pacific Exercise (RIMPAC). RIMPAC is the world's largest international maritime exercise and it takes place off the coast of Hawaii. The scenario involves four ASM attacks against the participating ships, where the ASMs are emulated by drones.

Significance of results: The study of the problem of object recognition for IAMD highlights the influence of the many sources of uncertainty on the process. In view of the scarcity of attributes that are available to the recognition function, the work presented in this report permits a determination of the limits of object recognition based on the physical and kinematical attributes provided by the sensor suite of the Halifax-class frigate.

Future work: Future work should concentrate on the refinement of the object recognition algorithm. Among other issues, the likelihoods used for ASM presence estimation should be extended to classes of aircraft. The decision criteria should also be revised and MSOR should be upgraded to run continuously over many time steps. Most importantly, operator-machine functionalities should be added to provide better situation understanding and better decision making. Finally, the analysis of the results obtained for the trials conducted during RIMPAC'12 will allow us to further identify pitfalls and areas for improvement.

Sommaire

C3MAAD: Multi-Source Object Recognition Algorithm

F. Rhéaume ; DRDC Valcartier TM 2013-426 ; Recherche et développement pour la défense Canada; février 2013.

Contexte : Dans le cadre des activités de défense maritime aérienne, la Marine royale canadienne mène des opérations de Commandement et de Contrôle (C2) navales. Le C2 naval peut être décomposé en quatre processus : la compilation de l'image tactique, l'évaluation de la menace, l'évaluation de l'engageabilité et la gestion de la puissance de combat. Le processus de compilation de l'image tactique comprend la détection, la localisation, la reconnaissance et l'identification d'objets. Ces sous-processus servent principalement à soutenir l'évaluation de la menace, l'évaluation de l'engageabilité et la gestion de la puissance de combat.

Un problème d'intérêt particulier en défense maritime aérienne est celui de la défense contre missiles antinavire. Les missiles antinavire sont des missiles guidés qui peuvent infliger des dommages importants à un navire. Les navires de surface, en raison de leurs grandes signatures radar, radio et thermiques, sont très vulnérables aux missiles antinavire. Pour contrer les attaques de missiles, les navires de guerre peuvent leurrer et/ou détruire les missiles. CORALS ('COmbat Resource ALlocation Support') est une capacité de support à la décision et l'automatisation pour les opérations de défense contre missiles antinavires. Il a été développé par Recherche et développement pour le Canada (RDDC) afin de soutenir l'équipe de commandement du navire dans la planification optimale de réponses à de multiples menaces. Avant d'être traitées par CORALS, les menaces doivent d'abord être identifiées et reconnues. Dans ce rapport, le problème de la reconnaissance d'objets est étudié et une capacité de reconnaissance d'objets est développée.

Résultats principaux : Suite à l'étude sur l'incertitude reliée à la fois à la mesure des attributs et la modélisation des objets et de leurs caractéristiques, une nouvelle fonction de Classification Multi-Source d'Objets (CMSO) est développée dans le but de produire une capacité de reconnaissance d'objets automatisée pour la défense maritime aérienne. La nouvelle fonctionnalité, qui est spécifiquement adaptée pour une frégate de classe Halifax, se concentre principalement sur la reconnaissance des missiles antinavire. Elle est également conçue pour reconnaître les grandes catégories d'avion, tels que les chasseurs, les avions de surveillance et les hélicoptères, par exemple. La capacité produite est intégrée avec CORALS à la fois dans un environnement de simulation et dans un environnement de test réel sur un navire. Chaque fois qu'un missile antinavire est reconnu par CMSO, il est ensuite envoyé à CORALS pour la planification de combat. La configuration du CMSO et de l'environnement de test et de simulation a été adaptée en vue de l'intégration sur une frégate de classe Halifax et en vue de la participation à l'exercice maritime RIMPAC 2012.

RIMPAC a lieu au large des côtes d'Hawaï et est le plus grand exercice maritime international du monde. Le scénario de RIMPAC est composé de quatre attaques de missiles antinavire, où les missiles sont émulés par des drones.

Portée des résultats : L'étude du problème de la reconnaissance des objets pour la zone maritime de défense aérienne met en évidence l'influence des nombreuses sources d'incertitude sur le processus. Ajouté à la rareté des attributs qui sont disponibles pour la fonction de reconnaissance, le travail présenté dans ce rapport permet de déterminer les limites de la reconnaissance d'objets basée sur les attributs physiques et cinématiques fournis par la série de capteurs de la frégate de classe Halifax.

Recherches futures : Les travaux futurs devraient se concentrer sur l'amélioration de la fonction de reconnaissance d'objets. En premier lieu, des fonctionnalités opérateur-machine devraient être ajoutées afin de fournir une meilleure compréhension de la situation et une meilleure prise de décision. De plus, les fonctions de vraisemblances utilisées pour l'estimation de présence de missile antinavire devraient être étendues aux classes d'avions. Les critères de décision devraient également être révisés et la fonction de classification multi-source d'objets devrait être améliorée afin de fonctionner de manière continue sur plusieurs instants. Enfin, l'analyse des résultats obtenus pendant les essais menés à l'exercice RIMPAC'12 nous permettra de mieux identifier les problèmes et les points à améliorer.

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1 Introduction

Integrated Air & Missile Defence (IAMD) is defined as the process in which a surface ship employs its sensors and weapons to protect and deny a region of airspace to enemies. In order to achieve IAMD, the Royal Canadian Navy is meant to conduct naval Command and Control (C2). As illustrated in Figure 1, naval C2 can be decomposed into four functions [16]:

1. Picture compilation;
2. Threat evaluation;
3. Engageability assessment; and
4. Combat power management.

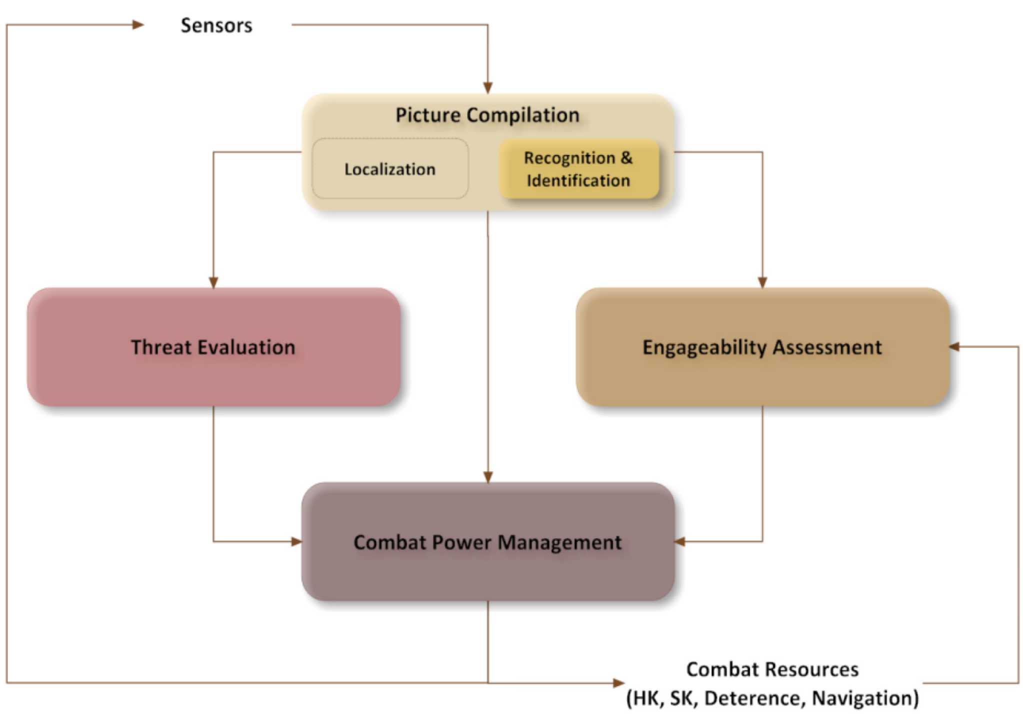

Figure 1: Naval C2 processes.

Picture compilation supports threat evaluation, engageability assessment and combat power management. It includes object detection, object localization, object recognition and object identification. In this report, the main topic concerns object recognition. Object recognition can be defined as the determination of the nature of a detected object in terms of its domain (e.g., air, surface, etc.), category (e.g., anti-ship missile, fighter, etc.), sub-categories (e.g., C802, Mig-29, etc.), nationality/allegiance and activity (e.g., reconnaissance, targeting, engagement, etc.). It differs from object identification, whose goal is to assign a standard identity to an object. The NATO standard identities are: Hostile, Suspect, Neutral, Friend, Assumed friend, and Unknown [8].

A problem of particular interest for IAMD is the Anti-Ship Missile Defence (ASMD). Anti-Ship Missiles (ASMs) are guided missiles which can inflict significant damage to a ship. Surface ships, because of their large radar, radio, and thermal signatures, are very vulnerable to ASMs. To counter ASM attacks, warships can decoy and/or destroy the incoming missiles. ASM attacks can also be prevented by avoiding being detected or destroying the missile launch platform before it fires its ASMs. Before conceiving any defence plan, the ASMs must first be detected and recognized. An ASM that is not detected or recognized will expose the ship to severe consequences.

On a different note, Defence Research and Development Canada (DRDC), in collaboration with the Canadian Forces Maritime Warfare Center (CFMWC), participated in the 2012 Rim of the Pacific Exercise (RIMPAC) to demonstrate and experiment automation and decision support capabilities for Anti-Ship Missile Defence (ASMD) operations. The main objective was to test the third version of the COmbat Resource ALlocation Support (CORALS 3.0) planner [10] in live sea trials. CORALS 3.0 is designed to coordinate combat resources (hardkill and softkill) for a Canadian Naval Task Group. Before planning combat resources against any targets, the targets must first be recognized and identified like described in the naval C2 process. In the case of ASMD, the Anti-Ship Missiles (ASMs) must be recognized as such.

This report introduces the problem of object recognition for IAMD and initiates an algorithm to support ASMD. A study case is presented for the Halifax-class frigates and with a focus on ASMD. Section 2 discusses the problem of object recognition and its challenges related to the noncooperative environment. More particularly, it presents how uncertainty acts in the process. Section 3 describes the sensor systems of the Halifax-class ships and the object attributes that each system can measure. The precision, the accuracy and the availability of each attribute is discussed. Section 4 portrays the objects that are susceptible to be found in a designated airspace. Class sets are suggested and defined. Broadly, the Air objects are divided in two classes: the aircraft and the ASMs. Sub-categories are also defined for both the aircraft class and ASM class. An object recognition algorithm designed for the Halifax-class frigates sensor suite is presented in Section 5. The algorithm, called Multi-Source Object Recognition (MSOR), supports the surveillance of Air objects while focusing on the recognition of ASMs. Section 6 presents the integration of the MSOR recognition algorithm in both a simulated environment and onboard a Halifax-class ship. The goal is to support the CORALS 3.0 combat planner by providing it with the recognition of ASMs. In addition to the simulation setup, the sea-going setup prepared for the 2012 Rim of the Pacific Exercise is discussed.

Note that all information contained in this document comes from publicly available UN-CLASSIFIED sources.

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2 Object recognition in noncooperative environments

This chapter introduces the problem of object recognition in noncooperative environments, with a particular emphasis on the notion of uncertainty, discussed in Section 2.1, and in the context of Integrated Air & Missile Defence (IAMD), discussed in Section 2.2.

Naval Command and Control Systems (CCS) deal with two types of objects: cooperative or noncooperative. Generally, cooperative objects are either allied or friendly while noncooperative objects can be neutral or hostile. IAMD is concerned with noncooperative objects. Accordingly, naval surveillance systems are expected to report noncooperative objects. While aircraft can be neutral or hostile, missiles are hostile by their own nature. Cooperative objects can be identified through communications or other means such as Identification Friend or Foe (IFF) [7]. This is impossible with noncooperative objects. To perform noncooperative recognition and identification, the objects need to be observed. Observations are made using either passive or active sensing. The class and identities can then be determined by achieving a comparison between the obtained observations and some reference data.

Some radar tracking systems exploit techniques that rely on radar signatures to classify Air objects in pre-determined categories. These can be known as Noncooperative Target Identification/Recognition (NCTI/R) [19, 13]. These techniques need access to the returned radar signals. In this report, object recognition is performed by considering only the track information output by the tracking systems of the Canadian frigates. The underlying radar signals from which objects are detected and tracked are not considered since they are not accessible on the CCS of the Canadian frigates. The signals are enclosed in the tracking systems.

Objects such as aircraft, missiles or platforms are physical entities that can be discriminated by positional and kinematical attributes[1]. The recognition of objects from a number of classes relies on two principles: object modeling and object measurement. To discriminate objects, object models need to be defined for each class of object. Models are generally defined through different attributes and according to *a priori* knowledge, i.e., knowledge acquired before the missions. Speed, for instance, is an attribute of an object. Given models for the different classes of objects, the recognition of an object as a member of one or many classes can only be possible if there can be a comparison between the models and real measures. One challenge is that the attributes that define the models be measurable. Suppose a model is defined on speed and altitude while the measured attributes are speed and range. In this case, the object class can only be inferred according to speed since it is the only measurable attribute of the model.

[1] In this report, the term platform refers to any type of ship, military of commercial

2.1 Uncertainty

In practice, object recognition that supports IAMD is performed in an uncertain environment. Uncertainty, which may take different forms, makes the recognition problem more complex. As mentioned earlier, object models and object measurements are the main types of information that must be considered for the recognition of noncooperative objects. Uncertainty exists in both the models and the measurements. As shown in Figure 2, the sources of uncertainty can be divided in three different types: incompleteness, resolution and accuracy. The problem of uncertainty can then be divided according to the following combinations:

1. measurement incompleteness,
2. measurement resolution,
3. measurement accuracy,
4. model incompleteness,

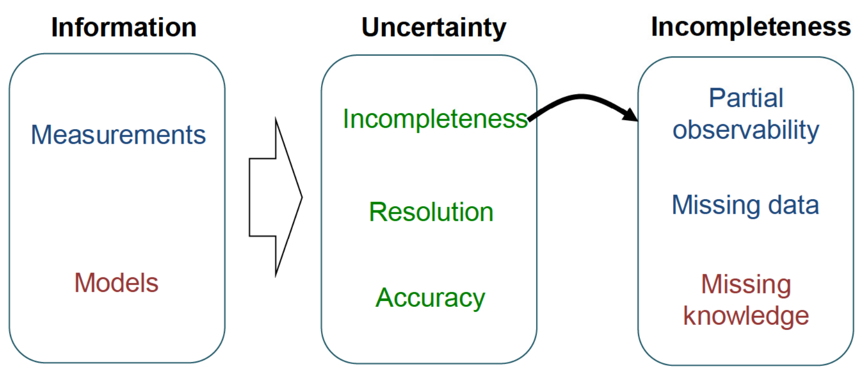


Figure 2: Sources of uncertainty that are found in the process of object modeling and object measurement.

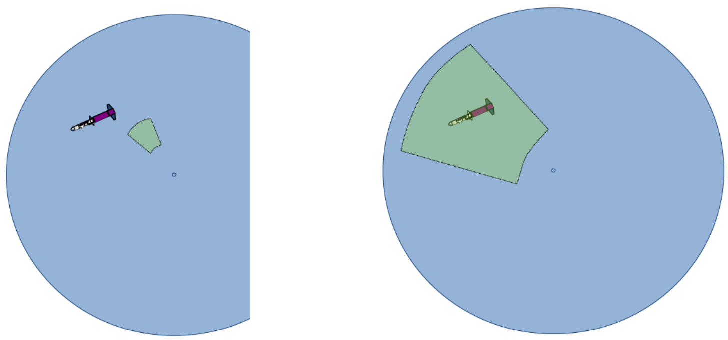
Regarding measurements, incompleteness can have two forms: partial observaibility and missing data. When the attributes that determine the type of an object are not all observable, the object is said to be partially observable. For instance, suppose that weight has been determined as one of the attributes for discriminating classes of Air objects. Because weight is an attribute that cannot be measured by the sensor suite onboard the ship, the observations of Air objects will not provide the weight information. Therefore, the objects for which the corresponding models use weight as a discriminating factor can be said to have some kind of partial observability. For the task of recognizing a particular class of object, the partial observability reduces the amount of information that explains the phenomenon under analysis, thus raising the uncertainty about the object's class.

Measurements can also be called incomplete when missing data occurs. In this case, the attributes under consideration are observable but may not always be measurable. Suppose an object is tracked by a surveillance system and suppose that its range, bearing and speed are updated at regular intervals according to new measurements. For different reasons and for a given period of time, the sensors may not be able to obtain and report new measurements. The track may then be lost for a while or indefinitely. Without new measurement updates, uncertainty of the observed attributes increases. At its worst, the absence of measurement translates into ignorance. A sea-skimming missile that avoids radar detection can represent a good example of ignorance caused by missing measurements.

Like measurements, models may also be incomplete. Models are incomplete when the underlying knowledge or information that is necessary to complete the models is missing. For instance, suppose that the models employed to recognize different types of missiles use their maximum detection range. If there are types of missiles for which there is no information about the detection range, the resulting missile models are incomplete.

Resolution is also a concern for Air object recognition, particularly when the resolution of the measurement is lower than the resolution of the model. Resolution can be defined as the ability to 'resolve' differences. It has to do with the degree at which a measure or a model is able to draw a distinction for some attribute. For instance, if an object's altitude is measured and reported to be "under 30000 ft", it has less resolution than if the reported altitude is "24500 ft". The state in which an attribute can have a wide range of values, or a low resolution, increases the uncertainty. The same applies for object models. If a model is low in its resolution, then either the wrong attributes were chosen or the model simply lacks some supporting knowledge or information. Low resolution suggests that there is doubt about the exact value of a variable or attribute. Therefore, low resolution is a source of uncertainty.

Accuracy of a measurement system is defined as the degree of closeness of measurements of a quantity to that quantity's actual value [18]. Figure 3 illustrates the difference between resolution and accuracy. The example shows a missile which is detected by a surveillance system and whose position is measured. In Figure 3 (a), the position is measured with high resolution in bearing and range and the measured missile position is enclosed in a small area. However, the measure is not accurate since the estimated position falls short of the true position. In Figure 3 (b), the estimated position has a low resolution since it defines a large area. On the other hand, the area defined by the measure contains the true position of the missile. Therefore, although the measure is low in resolution, it is accurate. The accuracy of a measurement system may be specific or it may be unknown or uncertain.



(a) High resolution but racy

(b) High accuracy but low resolution

Figure 3: Missile detection example showing the difference between resolution and accuracy. The green area represents the measured missile position.

Object models that represent the reference world are also associated with different levels of accuracy. This accuracy is mainly related to the degree of uncertainty and unexpectedness about the real object's attributes. For instance, if a jet fighter is modeled with a specific missile loading configuration and if the jet fighter encountered during real operations has a different loading configuration, then the jet fighter model is inaccurate.

2.2 Context

By its own nature, IAMD is a context in which one has to expect not only noncooperative behaviors from its opponents, including hostile actions, but a collection of war strategies and tactics that complicate the task of object recognition. Disinformation, deception, luring, hiding, faking, surprise and diversion are a few examples of tactics that make the problem of object recognition even more difficult. Beyond the individual tactics, not to be recognized by the opponent is one of the most fundamentals principles of war.

In today's world, the Royal Canadian Navy and its allies are now more and more involved in operations taking place in littoral environments [16]. This exposes the platforms to a multitude of threats not normally encountered in the open ocean environment. The littoral is also well-disposed to asymmetric threats, which use methods that differ significantly from the opponent's usual mode of operations. Such a context makes it challenging to perform object recognition, as the types of threats and the conditions in which they are used are not as clearly defined as they were in the past. This impacts object modeling in different ways, such as reduced or missing knowledge, reduced accuracy and resolution as well as reduced ability to estimate the accuracy and resolution themselves, to name just a few.

2.3 Summary

This chapter demonstrated how uncertainty exists in both the object models and the measurements. Three sources of uncertainty were also defined: incompleteness, resolution and accuracy. The chapter also examined how the particular context of IAMD impacts on the overall ability to perform object modeling.

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3 Sensor systems of the Halifax-class ships

The Halifax-class ships are equipped with sensor systems to perform air surveillance and support naval air defence like Anti-Ship Missile Defence (ASMD). The object recognition algorithm presented in this report relies on the following sensor systems: the AN/SPS-49, the SG-150, the Canadian Electronic Warfare System (CANEWS) (AN/SQL-501), the Separate Tracking and Illuminating fire control Radar (STIR) (SPG-503) and the Reprogrammable Advanced Multimode Shipboard Electronic Countermeasures System (RAMSES) (AN/SQL-503). The sensors' attributes are given in Table 1. The AN/SPS-49 and the SG-150 are radar systems capable of detecting and tracking multiple objects. The AN/SPS-49 is a long range search radar while the SG-150 is a medium range search radar capable of detecting low flying aircraft and missiles. They both provide bearing and range information. The STIR is a fire control radar that carries out target acquisition and tracking of air and surface objects. In addition to bearing and range, it provides elevation. The Halifax-class frigates are equipped with two STIRs. The CANEWS is an electronic support measures (ESM) system which can detect, analyze and classify radar emissions. Object types can be inferred from the received and classified radar emissions. The RAMSES (AN/SQL-503) is an electronic countermeasure (ECM) system that also provides emission classification. It relies on its own emission classification database from which object types can be inferred. Halifax-class ships have recently been upgraded with a long-range Infrared Search and Track (IRST) system called SIRIUS. However, because of its small range of less than 10nm, the SIRIUS will not be considered in this report. Note that the numbers displayed in Table 1 are in Imperial units. See Annex A for the conversion to SI units.

Table 1: Input sources available for object recognition.

Sensor system	Type	Range [nm]	Altitude [ft]
AN/SPS-49	Active 2D	3 to 256	100 to 150000
SG-150	Active 2D	0 to 63	0 to 35000
STIR (SPG-503)	Active 3D	0 to 30	0 to 10000
CANEWS (AN/SQL-501)	Passive ESM	Variable	Variable
RAMSES (AN/SQL-503)	Passive ESM	Variable	Variable

Considering the five sensor systems described in Table 1, each detected object may be characterized by a number of attributes that can be exploited in the naval C2 process. The attributes that may be relevant to the recognition of the target class are described in Table 2. Note that radar signals classification can by itself provide the target type directly. For instance, suppose that radar signals from an unknown aircraft are received and classified by either the CANEWS or RAMSES systems. From the radar signal classification and given a database where different types of radar emitters are linked with classes of aircraft or missiles, the class of object can be inferred (e.g., F-14). The availability of radar signals classification depends on many factors such as distance, weather, tactical and operational constraints, for instance. That is why the classification expected from CANEWS or RAMSES may not be available for performing target recognition. In fact CANEWS and RAMSES have a range of no more than 10 nm in the best conditions, approximately. This is a serious limitation for the recognition of objects, since objects detected near to the ships leave not much time to react. The same applies for altitude, which is only available when the STIR is operated for tracking a target. Moreover, the STIR can only track one target at a time.

Table 2: List of target attributes that are produced by the sensor systems onboard the Halifax-class ships. Availability refers to the issue of incompleteness discussed in Section 2.

Feature	Sensor system(s)	Resolution	Accuracy	Availability
Longitude-Latitude	AN/SPS-49, SG-150, STIR	Good	Variable	Variable
Range	AN/SPS-49, SG-150, STIR	Good	Variable	Variable
Bearing	AN/SPS-49, SG-150, STIR	Good	Variable	Variable
Altitude	STIR (SPG-503)	Good	Variable	Bad
Speed	AN/SPS-49, SG-150, STIR	Good	Variable	Variable
Heading	AN/SPS-49, SG-150, STIR	Good	Variable	Variable
IFF	AN/SPS-49	n/a	n/a	n/a
Radar signals classification	CANEWS, RAMSES	Excellent	Excellent	Bad

Estimations of the position, the speed, the heading, the bearing and the range of an object are both provided by the AN/SPS-49 and SG-150 surveillance radar systems. For an object that is detected and tracked by at least one of these systems, those five features should then be available. Their resolution is good, but the accuracy is variable, depending on the update rate of the track. Particularly, speed is more vulnerable to accuracy issues since it is a derivative of position with respect to time.

Another sensing system considered for the recognition of object classes is the Identification Friend or Foe (IFF). IFF is an active system that is used to interrogate a target. In this work, the IFF mode 4 will be considered, which is a military mode from which a target can be declared as friend, possible friend, unknown or no friend. Note that IFF can be a misleading source of information [29, 23]. For instance, it is vulnerable to spoof or misassociation. Under such circumstances, a target reported as friendly may happen to be hostile in reality. On the other hand, ASMs do not react to IFF. Hence, if the target responds to IFF interrogation (positive), then it is probably not an ASM Otherwise, in absence of a response to IFF, nothing can be inferred about the target class.

For different reasons that mostly have to do with the radar domain, the presence of an object in the environment does not guarantee that it will be detected and measured. This detection and tracking issue will not be discussed further in this report. However, it is one of the main issues in ASMD since it is a direct impediment to the whole defence process. Because it cannot be taken care of, an object that is not detected is the worst threat to a ship.

3.1 Relational measures

The measures presented previously, that consist mainly in positional and kinematical information, refer to a unique time (except for speed and heading). When the measures are analyzed over a longer period of time or in relation to other objects, new information can be uncovered that can be relevant to the recognition of Air objects. Here, these measures are qualified as 'relational' because they require an analysis over many time steps or according to other objects. Among these measures, there are:

1. The difference from heading to inverse bearing, denoted HB. HB gives the direction of the object according to the ship. A low HB value means that the object is coming toward the ship.

2. Acceleration.

3. Weave, defined by the maximum divergence in the heading history of the track. The weave gives the extent at which an object changes directions during its flight.

4. Flight maneuvers, such as defensive, offensive or neutral fighter maneuvers, for example [3].

5. Trajectory conformance, which is a check of whether the object follows a designated air corridor or not (e.g., imposed by military or diplomatic requirements).

6. Relations among multiple objects (e.g., close to, behind, etc ...).

As these relational measures relate to a number of basic measures spaced in time or compared one to another, the uncertainty is increased. Before bringing to bear relational measures such as the ones listed above, a study of their associated uncertainty and reliability is required. This task is not discussed further in this report, as the work concentrates on the basic measures presented in Table 2. As an exception, the measure *HB* is considered; *HB* represents the difference from heading to inverse bearing. The uncertainty related to *HB* is related to the uncertainty on the measured heading and bearing of the object.

3.2 Summary

This chapter presented the different sensor systems of the Halifax-class ships. Each of their related attributes are described in terms of resolution, accuracy and availability. Relational measures that are built from the sensor attributes are also discussed as suggestions for further work.

4 Object modeling

This chapter discusses the modeling of Air objects in order to be able to distinguish them into different classes. Among the requirements for object modeling, there are the determination of class sets, the choice of object attributes, their representation in a framework (e.g., Bayesian, discriminant, distance, fuzzy, rules, etc ...) and their valuation. Object modeling is the stage after which a recognition algorithm (k-nearest neighbors, linear discriminant, etc.) can be applied. Section 4.1 presents the classes of objects that are used in this report to perform recognition. Their distinctive attributes are also discussed. Section 4.2 reviews the best attributes for the recognition of Air objects. Finally, a theoretical framework for object modeling is presented in Section 4.3.

4.1 Classes of objects

Objects that are found in a maritime environment fall into three domains: Subsurface, Surface and Air. In this report, Surface and Air objects are considered. Independently of their frequency of occurrence Surface and Air objects are mainly comprised of platforms, aircraft and missiles. The problem of discriminating platforms from Air objects is simple in that the speed and altitude of platforms is very different from Air objects. For the purpose of IAMD and with the focus on ASMD, the study concentrates on Air objects. Platforms are only associated with a single class set and are determined according to the domain, which in this case is the Surface domain. Air objects, on their part, are classified into different categories. Obviously, ASMD systems depend on the recognition of ASMs. As a result, ASMs represent a particular class of Air objects that the object recognition function needs to consider. Besides ASMs, the Air domain comprises aircraft. Aircraft represent a much wider class than ASMs. First, aircraft may differ by their methods of lift, such as fixed-wing or rotorcraft for example. Moreover, aircraft differ in size and flight performance. Figure 4 presents a non-exhaustive hierarchy of classes of objects in the context of IAMD. First, objects are classified into the Surface or Air domain. The Surface domain is not described further and has no sub-categories. Objects in the Air domain are classified into either the ASM or Aircraft classes. The ASMs are sub-divided into classes that represent specific models manufactured around the world. The list of ASMs shown in Figure 4 was provided by the Canadian Force Maritime Warfare Center. Table 3 adds more models and specifies by which countries they are operated. Aircraft are divided into five sub-classes: Unknown, Commercial, Fighter, Helicopter and Surveillance. Classes of aircraft that are not specified in this list include aerostats, personal jets [26], light aircraft such as the Cessna or Piper models and gliders, for instance. These are considered as member of the Unknown class.

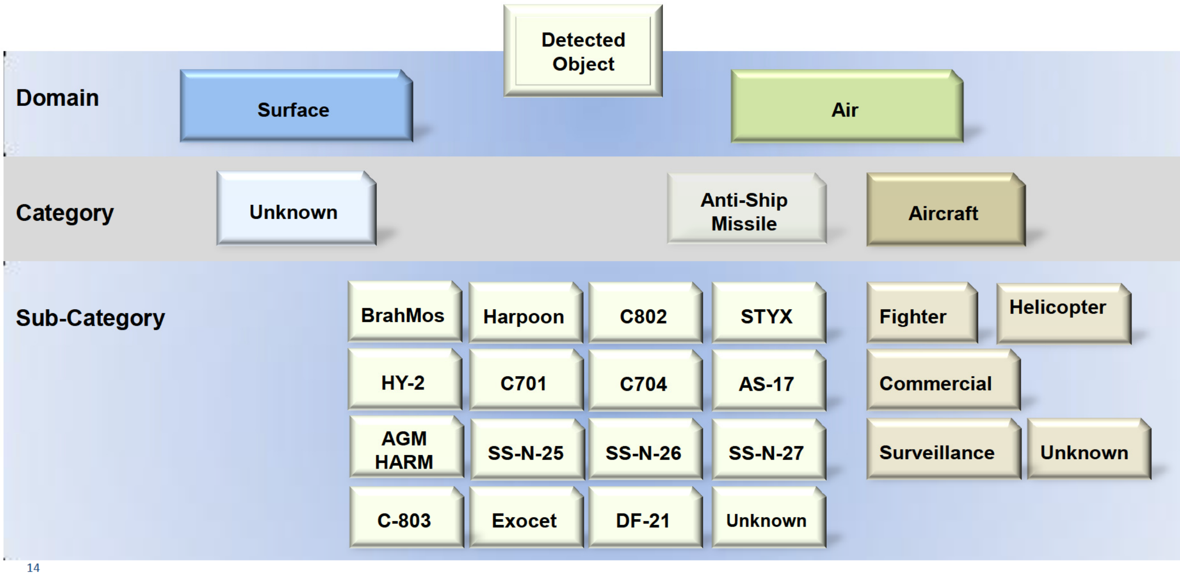


Figure 4: Example of a hierarchy of classes of objects in the context of the Integrated Air & Missile Defence.

4.1.1 ASMs

Of all the classes of objects that the CCS should pay attention to, ASMs are definitely the most critical. There are two types of ASMs: cruise missiles and ballistic missiles. Cruise missiles are conducted using propulsion forces and they rely on the dynamic reaction of air for lift. They fly at approximately constant velocity and maintain an essentially horizontal cruise flight profile for most of the duration of their flight [22]. Ballistic missiles are launched by a powerful initial impulsion to attain very high altitude. They then execute a long range unpowered ballistic trajectory. Their trajectory is called sub-orbital since the ballistic flight reaches space altitude, which allows the missile to maintain hypersonic speed (Mach 5 and above). Although ballistic missile such as the Chinese DF-21D are currently considered to be hardly containable, their efficiency is still not yet demonstrated and remains under debate [20]. Moreover, cruise missiles have many advantages that suggest they are more likely to remain popular. As mentioned in [30], they are relatively inexpensive, compact, accurate, and easier to develop or access than ballistic technology. Most importantly, the technological prerequisites to sustain a ballistic missile force ensures that these capabilities remain confined to a select group of nations. This is not the case for cruise missiles where, according to [30], they are seen as ‘a poor man’s air force’ and where 130 types of cruise missiles are distributed among 75 nations of which 56 countries are pure importers. For all of these reasons, this report focuses on anti-ship cruise missiles. Therefore, the term ASM will strictly refer to anti-ship cruise missile for the remainder of this report, unless stated otherwise.

Table 3: Non-exhaustive list of ASMs by selected countries [6]. Note that ASMs that are listed in many countries may represent different versions. For instance, Iran uses an upgraded version of the Chinese C802, called Noor [5].

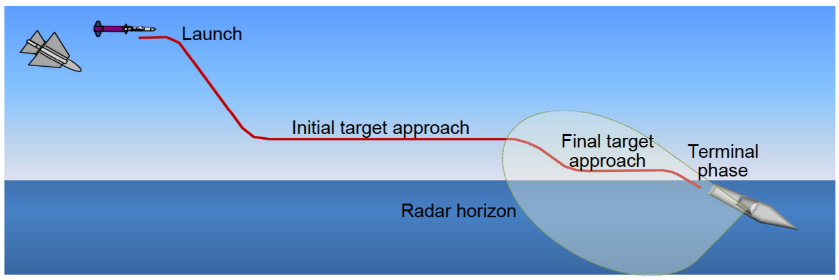
China	Iran	Russia	Syria	Libya	India	Pakistan
C801	C801	SS-NX-27	CSS-NX-5	CSS-NX-6	SS-N-25	UGM-84G
C802	C802	SS-N-25	SS-N-25	SS-NX-26	PJ-10	
YJ-82	C701/FL-10	SS-NX-26	YJ-91	YJ-92	AS-X-20	
YJ-91	YJ-82	AS-17a/b	AS-17a/b	AS-17a/b	AS-17a/b	
SS-N-22	YJ-91		C802	C802	C802	
C701/FL-10	CSS-NX-5					
SS-NX-26	3M54E1					
CSS-NX-5						
AS-17a/b						
3M54E						

ASMs have different kinds of flight profiles. Basically, there are two kinds of profiles: the sea-skimming and the high-diving profiles. Sea-skimming missiles fly very low above the sea, often under 20 ft of altitude. By flying low, they can stay below the enemy's radar horizon for a longer time and the radar clutter from the sea reduces their detectability. Given their low detectability and their high success probability, sea-skimming missiles are considered to be the main threat to ships [25]. Sea-skimming attacks can have different variants. They can be launched from air, surface or subsurface. Note that subsurface and surface launchs have similar flight profiles.

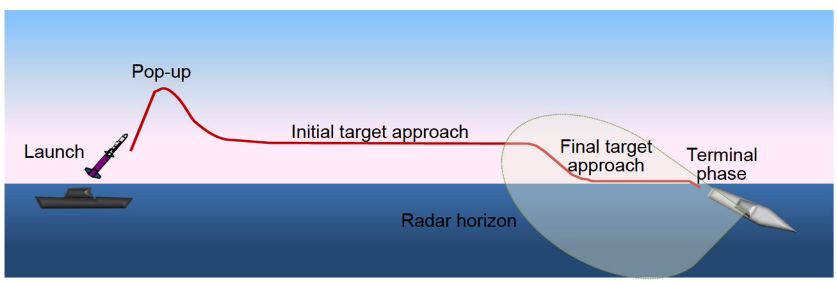
Figure 5 shows the typical profiles of air-launched and surface-launched sea-skimmers. There are generally two phases, the initial target approach and the final target approach, with an additional short terminal phase where the missile dives to hit the waterline of the ship. The terminal phase takes place at less than 1 nm from the targeted ship. During the initial target approach, the missile is sea-skimming but generally has a slightly higher elevation than for the final phase. In the final phase, the missile can descend down to about 15 ft. In general, a ship should only detect sea-skimmers when they reach the radar horizon, which is about 15 to 25 nm [21]. This provides between about 25 and 60 seconds of reaction time, depending on the speed of the ASM. Subsonic sea-skimming ASMs fly at speeds between Mach 0.8 and Mach 0.9, approximately. These include the C-802/YJ-82, the HY-2 Silkworm and the C-704 (manufactured in China), the Exocet (France), the Harpoon RGM-84 (United States), the SS-N-25 Switchblade and the SS-N-2 (Russia), also known as the P-15 Termit, the Sea Eagle (United Kingdom) and the RBS-15 (Sweden). The latest ASM models can fly at supersonic speeds, making them very difficult to defend against and more lethal. Supersonic sea-skimming ASMs include the PJ-10 BrahMos (India/Russia), with a cruising speed between Mach 2.8 and 3.0, the SS-N-26, also known under the names P- 800 Oniks and Yakhont, which has a maximum speed of Mach 2.5, as well as the SS-N-27 (Russia), also called 3M-54 Klub and which flies at up to Mach 2.9 for the last 15 km.

While some sea-skimming ASMs rely on speed to hit their target with success, others use manoeuvers to thwart their target's defence system. For example, the Harpoon can have a pre-programmed trajectory.

Although (non-ballistic) high-diving ASMs are rarer, they are used in some countries. The typical flight profile of a high-diver is illustrated in Figure 6. The Kh-31, also known as AS-17 Krypton, has a similar profile. It is a supersonic air-to-surface missile operated by the Russian Air Force that can fly at high altitude before diving down to the target. Note that there are types of ASMs that can be used in either sea-skimming or high-diving modes, such as the Harpoon.



(a) Air-launched



(b) Surface-launched

Figure 5: Sea-skimmimg flight profiles.

4.1.1.1 ASM characteristics

One way or another, ASMs are always directed at a target, that is the ship under attack. This is a primary characteristic of an ASM: its direction. Note that some ASMs can execute manoeuvers mostly for avoiding detection and averting engagements. However, the manoeuvers are normally performed only during the final target approach, that starts around 5nm from the ship[2]. ASMs are also characterized by their maximum launch angle, which varies according to the ASM model or class.

[2]The range at which begins the final target approach will vary depending on the type of ASM, the ASM operating mode and the weather, among other factors.

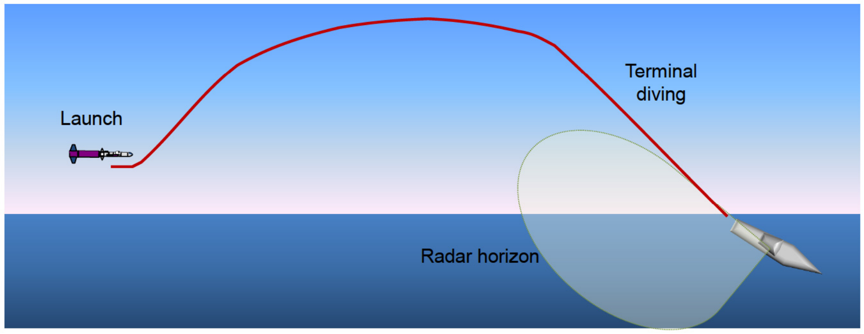


Figure 6: High dive flight profile.

A second characteristic of an ASM is its position or range from the ship. In contrast to ASMs, aircraft such as jet fighters usually respect a minimum distance from an enemy ship, unless they perform a suicidal attack. Therefore, if an object directed at the ship enters in its vicinity, this is a first hint that it is an ASM. More precisely, ASMD can be described by three zones around a ship: surveillance, alert and reactive [24]. While objects in the surveillance and alert zones are not considered as threatening, objects in the reactive zone necessitate immediate response (see Figure 7). Since ASMs are known as the main threat to ships, objects that are situated in the alert and reactive zones should be estimated to have greater chances to be ASMs than those that are out of these zones.

If the current position of an object can give an indication of whether it is an ASM or not, its position at detection also gives a clue. If an object has been detected near a site known for its historical or tactical trend toward ASM launching, then the chances that the object is an ASM are increased. The relative position to other objects is also an indication. For instance, if an object is suddenly detected close to another object that has been already detected and recognized as an enemy aircraft, then it could be an ASM launched by the aircraft.

Moreover, ASMs are characterized by their maximum range. For instance, the maximum range for the Brahmos is about 157 nm, while the maximum range for the C-701 is around 11 nm. Given an objected detected at 25 nm from the ship, it has greater chance to be a Brahmos than a C-701, according to the detection range alone.

Another hint that an ASM is coming is its speed. Although there are many classes of ASMs with different specifications, all ASMs are characterized by their fast speeds, i.e., from high subsonic (around Mach 0.8) to supersonic (Mach 1.2 to 5). Note that aircraft can go supersonic too but they are in general not as fast as ASMs. Most of all, aircraft that can fly supersonic do it for only a short period of time. There cruise speed is subsonic. Speed can also discriminate some models of ASMs, mainly the supersonic from the subsonic models. For instance, a C-802 is about twice slower than a SS-N-26.

One of the best clues as to the presence of an ASM is its altitude. As stated before, most ASMs manufactured around the world are sea-skimming [2]. Sea-skimming missiles, at least in their terminal approach, fly low over the sea level. Their altitude is usually between 15 and 150 ft. Aircraft do not fly that low except at very low speeds and for special purposes (e.g., helicopters in rescue operations). Hence low altitude is a significant discriminant factor between aircraft and ASMs. Also, classes of ASMs can be distinguished by their flight profile in terms of range and altitude. As Figures 5 and 6 show, the altitude of an ASM varies according to its range from the ship. The flight profile usually depends on the model of the ASM (e.g., C-802, Brahmos, etc...) and its mode of operation (each model can have different modes of operation), as well as other considerations such as the weather and sea state.

Most ASMs have a maximum sea state in which they can be used[3]. The maximum sea state of an ASM will vary depending on its class. Broadly speaking, sea-skimming ASMs have a lower maximum sea state than high divers.

Finally, ASMs can also be recognized by their emissivity in terms of infrared signature, their returned radar signal (radar cross section) and their seekers' radar signals. Supersonic ASMs cause a particularly high infrared signal. Hence they differ from other types of object by their infrared intensity. The seekers' radar signals are particular to each specific ASM model. It is a reliable ASM recognition attribute. However, it depends on range and can only be sensed at short ranges, i.e., at less than 10 nm approximately.

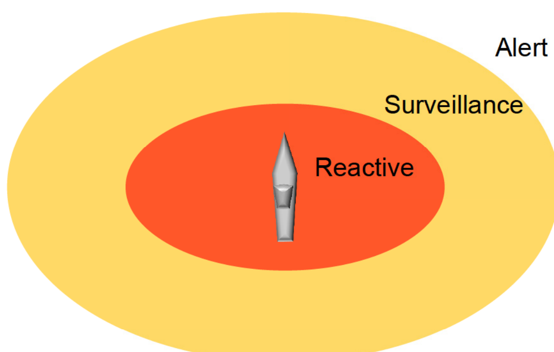


Figure 7: The three defence zones around a ship: surveillance, alert and reactive.

[3]Sea state is described by a code that represents the general condition of the sea in terms of wind waves and swell.

4.1.2 Aircraft

Aircraft, depending on their classes, are mainly characterized by their speed (cruise and maximum), altitude, rate of climb, radar cross section and infrared signatures[4]. Here is a short description of the characteristics of the classes of aircraft considered in this report.

4.1.2.1 Fighter

Fighter aircraft have a subsonic cruise speed that is about the same as commercial airliners, that is around Mach 0.8 and 0.85. In some cases, fighters can burst to supersonic speeds. In contrast to ASMs, most classes of fighters can only sustain supersonic speed for a short period of time. In fact, fighters are generally equipped with afterburners. Afterburner is a technology for increasing thrust that injects additional fuel into the jet engine, hence increasing speed. The drawback of using afterburners is that they burn a lot of fuel. This is why they are used as little as possible. For instance, the F-14 Tomcats used by the Islamic Republic of Iran Air Force can fly up to Mach 2.4 when using afterburners. Note that this number can only be reached at high altitude (about 40000 ft). This applies to other classes of fighters as well. As drag from air friction decreases with altitude, high speeds are performed only in high altitude. For example, the F-14 Tomcats can go no more than Mach 1.2 at low altitude (less than 30000 ft). Some fighters have the ability to fly supersonic without afterburners. This capability is called supercruise and can also be seen in few models such as the F-22 Raptor (United States) or the Eurofighter Typhoon (United Kingdom, Germany). The latter is capable of supercruise at Mach 1.5 [4]. Supercruise also comes at the cost higher fuel consumption, so it is normally restricted to combat operations.

Fighters normally spend most of their time in high altitude (above 35000 ft). First, it allows more speed with less fuel consumption. Second, the higher altitude can be traded off for more speed. Most fighters can go up to around 50000 ft and more, which is not the case for commercial airliners, for instance. The rate of climb is another distinctive characteristic of fighter aircraft. The climb rate of most classes of fighters can be easily above 50000 ft/min, while it is barely more than 2000 ft/min for commercial airliners.

4.1.2.2 Surveillance/Maritime patrol

Surveillance aircraft or maritime patrol aircraft differ from fighters and commercial airliners in that they fly slower. Their patrol speed is generally between 200 and 350 kts, which is about half the cruise speed of fighters and commercial airliners. Their cruising altitude is around 35000ft. For instance, the CP-140 Aurora is a maritime patrol aircraft operated by the Royal Canadian Air Force which has a cruise speed of 350 kts, a maximum speed of 405 kts and a maximum altitude of roughly 35000 ft.

[4] Radar cross section and infrared signatures will not be discussed in this report, as the present work concentrates on kinematical and positional characteristics

4.1.2.3 Helicopter

Helicopters are distinguished from other aircraft by their altitude and speed. The maximum altitude for most helicopters is generally no more than 15000ft and the cruise altitude is normally between 500 ft and 2000 ft. The maximum speed is no more than 200 knots. For instance, the CH-148 Cyclone of the Royal Canadian Air Force has a maximum speed of 165 knots, a cruise speed of 137 knots and its maximum altitude is 15000ft.

4.1.2.4 Commercial airliner/military transport

According to their cruise speed and altitude alone, commercial airliners are similar to military jet fighters. One characteristics that differentiates airliners from fighters is that the latter are usually able to fly supersonic while airliners do not. Also, airliners cannot sustain and perform the same accelerations than fighters. As mentioned previously, their rate of climb is much slower. For instance, the Airbus 320 has a maximum rate of climb of no more than 2500 ft, a cruise speed between Mach 0.71 and Mach 0.79, as well as a cruise altitude of about 36000 ft [31, 1]. Note that some military transport aircraft use variants of commercial airliner models.

4.1.2.5 BQM-74E drone

There exist many models of drones around the world and they are increasingly used in warfare. In this report, only the BQM-74E turbojet-powered aerial target is discussed. BQM-74E drones were used to emulate ASM attacks during the RIMPAC'12 trials. The BQM-74E can fly as low as 7 ft and up to 40000ft. It can therefore perform sea-skimming profiles. However, it is slightly slower than real subsonic ASMs. It has a maximum speed of 515 knots [14]. The drawback for the lower speed is that it is in the speed range of many aircraft.

4.2 Object attributes

On one hand, the sensor systems and the CCS onboard the Halifax-class frigate provide a set of different measured attributes. On the other hand, each class of objects described previously can only be distinguished according to specific attributes. In order to have good class models, a comparison is then required between the measured attributes available on the ship and the attributes from which the classes can be distinguished. Here is a list of the object attributes that could be used based on the issues raised on sensing and relative to the context of IAMD:

1. Altitude is a good class discriminant, but it is rarely available.

2. Speed can discriminate some classes of objects. However, there are many classes of aircraft and missiles that can fly at the same speeds. Whenever a track is associated

with an object, its speed should be available with an accuracy that depends mainly on the update rate of the track by new contacts.

3. Range can give a hint on the class of missile that is attacking the ship. If a track exists for the missile, its range should be available.

4. Position, when compared to pre-determined zones that are specific to a mission, can be an indication of the classes of an object.

5. Taken alone, *HB*, the difference from heading to inverse bearing, tells nothing about the class of an object. However, an object with a large *HB* is not likely to be an ASM attacking the ship. *HB* then gives a clue about the presence of an ASM and its measure should normally be available and accurate enough.

6. The CANEWS and RAMSES radar signals classification functions are very reliable object classifiers when they are available. However, they are only effective at short ranges.

7. The weave of an object, which reflects the heading variation for a period of time, is an indicator of the class of an ASM. However, there are many variants of weave an ASM can take and these depend on many factors. Also, ASMs that can manoeuver usually begin to weave during the terminal phase of the flight. In that case, it might be too late when the weave profile is computed and associated with an ASM class. Furthermore, the estimation of the weave necessitates many measurements in time, thus raising the uncertainty related to the obtained value.

The descriptions given in Section 4.1, indicate that the variables of speed and altitude are not independent. For instance, the speed of aircraft can be higher at high altitude due to the physics of flight. For ASMs, speed and altitude also have dependence with the range. Those three variables define the flight profile of an ASM. However, because there are many flight modes and parameters that can influence the flight profiles, the flight profiles have a high variability. This variability raises their uncertainty. A thorough characterization of each ASM's flight profiles and their variants would be required before envisaging any use for the recognition process.

Furthermore, although there exists uncertainty about the exact attribute values for the different classes of objects, general assumptions can be made about the probable presence of an ASM [24]:

1. The probability that a detected object is an ASM increases continuously as the estimated speed increases.

2. An object with a speed of less than 400 knots (about Mach 0.6) is certainly not an ASM.

3. The probability that a detected object is an ASM increases continuously as the measured altitude decreases.

4. The probability that a detected object is an ASM increases continuously as the measured distance of detection (range) decreases.

5. The probability that a detected object is an ASM increases continuously as the measured heading toward the ship increases (variable HB).

Further to the physical and kinematic attributes described above, the presence of a class of object may also be determined according to some context-related information. Such information may help determine priors for different object hypotheses. The hypotheses may concern the assignation of values to some attributes or they may concern directly the presence of classes of objects.

4.3 Theoretical Framework

Before determining a framework, issues related to object attribute measurement, object attribute modeling and the warfare context of IAMD must be considered. As discussed in the previous sections, although basic attributes such as speed, altitude and range can help discriminate some classes of objects and distinguish aircraft from ASMs, uncertainty related to the attribute values is generally high. Most importantly, the uncertainty level itself is difficult to evaluate. Given the risk associated with ASM attacks, a cautious approach is required. In other words, in the presence of high uncertainty a recognition algorithm should not take decisions unless more certain information comes in.

Based on the description given in Section 4.1, attribute values for the different classes can be interpreted in two ways: overlapping and non-overlapping. Overlapping attributes are those for which two classes or more share same attribute values. For instance, the F-22 Raptor can go from subsonic speeds to about Mach 2.5, which is in the same range as the SS-N-27 ASM. In some cases, classes can be discriminated according to hard limits. When attribute values for different classes are non-overlapping, the classes can be discriminated by a simple limit comparison. For instance, the ASM C-802 has a maximum speed of about Mach 0.9 while the SS-N-26 has a minimum cruise speed of about Mach 2. The C-802 and the SS-N-26 can then be clearly distinguished just by comparing minimum and maximum speed limits. In these non-overlapping cases, the classification of objects can be achieved using a constraint satisfaction problem approach [28], where an object must satisfy a number of constraints or limitations to be declared as a member of a class. The constraint satisfaction problem can also be extended to the case of overlapping classes. In this case, an object may be declared as a member of multiple classes.

Given A a set of attributes, D the domain of values for the attributes in A and C a set of constraints, for each class $i = 1, \ldots, M$ of a M class problem, a set of constraints C_i is defined. Each constraint $c \in C_i$ has the form of a pair $c = \langle t, R \rangle$, where t is an attribute and R is a relation on D. For instance, suppose that the class for the ASM C-802 is defined by a maximum speed of Mach 0.9 and a maximum altitude of 100 ft. The corresponding set of constraints is $C_{(C-802)} = \{c_1, c_2\}$ such that $c_1 = \langle speed, R_1 \rangle \,|\, speed < \text{Mach}\,0.9$ and $c_2 \langle altitude, R_2 \rangle \,|\, altitude < 100\text{ft}$. An object which satisfies both c_1 and c_2 is declared to be in the class C-802.

By considering basic attributes such as speed, altitude and range, the uncertainty related to the inference of class of objects should be lower than if relational attributes are used. The use of only basic attributes comes at a price : classes of objects may be harder to discriminate. In some circumstances, it may not be possible to determine the class of an object. Instead, the object may be associated with many classes rather than a single one. Let us define 'explicitness' as the degree of description of the output of an object recognition function. For instance, the decision 'Aircraft' is less explicit than 'F-22 Raptor' and the decision {C-802, C-704, SS-N-2} is less explicit than {C-802}. Also at the price of lower explicitness, the constraint satisfaction approach, when used with minimum and maximum limits on attributes, can help reduce the uncertainty and thereby the error rate. The compromise between decision uncertainty and decision explicitness is shown in Figure 8.

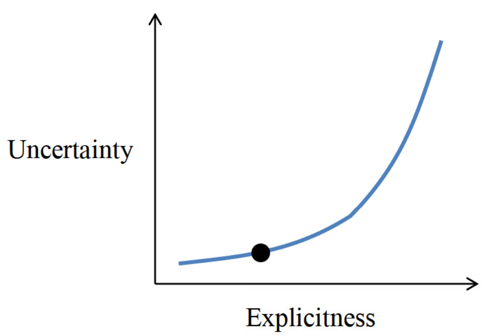


Figure 8: The compromise between decision uncertainty and decision explicitness. The presented approach favors lower uncertainty at the price of lower explicitness.

4.3.1 Recognition of ASMs

The approach presented in the previous paragraphs is able to perform discrimination of certain classes of objects but it is limited in terms of explicitness. Under this approach, it might well be possible that a tracked object be recognized as both an aircraft or an ASM, since air-craft and ASMs share common attribute values. Since this work is concerned with ASMD, the evaluation of the presence of an ASM attack from the ship perspective, as part of the recognition function, would be a desirable decision aid. Before suggesting any approach, it is important to understand the nature of this estimation problem.

The problem of ASM presence estimation comes from the fact that the measured attribute data are random with probability distributions. For instance, the measured speeds of ASMs and aircraft can take many values and their respective probability distributions are overlapping. Otherwise, if ASMs and aircraft had separate and non-random speed values, then the problem would be deterministic. It could be solved simply by using logics. But in reality and due to the nature of the ASMD problem, no one can tell in advance what exact value an attribute will take.

Let θ be the parameter that represents the presence of an ASM or not. The estimated parameter $\hat{\theta}$ can then take two values: 'ASM' and 'aircraft' (or 'ASM' and 'not an ASM'). The probability distribution for an attribute A is defined conditionally to the parameter θ and represented by the conditional probabilities $P(A|\theta)$, defined over the domain of A. As mentioned before, ASMD is a problem where ASM attacks on a ship represent rare events with an unpredictable nature. Thus, the determination of conditional probabilities cannot fully rely on a statistical basis. Usually, the determination of the conditional probabilities can rely on historical data on which probability distributions can be built. In ASMD, the historical data is far too scarce to built representative probability distributions. To define the probability distributions, other information or knowledge must be used. Suppose that the attribute A refers to the speed of an observed object. From the specifications of the different aircraft and ASM models, a general portrait of the feasible speeds can be drawn.

For instance, given that aircraft can go as slow as 100 kts (e.g., helicopters) and that they usually remain just under the speed of sound (between Mach 0.7 and Mach 0.9). In the case of ASMs, most models are high subsonic (between Mach 0.8 and Mach 0.9), but some are able to go supersonic; faster than Mach 3. Figure 9 illustrates examples of conditional probabilities $P(Speed|ASM)$ and $P(Speed|Aircraft)$ built from general assumptions and specifications related to the different models of aircraft and ASMs.

The distributions for aircraft are generally associated with smaller speed values than ASMs. However, the distributions are overlapping. Also, the speed range of aircraft is narrower than the speed range of ASMs. Suppose that a speed v is measured from a tracked object, such as illustrated in Figure 9. For example, the measured speed could be $v =$ Mach 0.81. Because in most conditions many aircraft fly around Mach 0.8, the conditional probability $P(Speed = \text{Mach } 0.81|Aircraft)$ was set high. Like aircraft, many ASMs will fly at Mach 0.8. But in contrast to aircraft, a significant number of ASMs can fly supersonic and the resulting speed distribution is spread over a larger interval than aircraft. For this reason, the conditional probability for a speed of Mach 0.81, given that the object is an ASM is lower than for aircraft. That is $P(Speed = \text{Mach } 0.81|ASM) < P(Speed = \text{Mach } 0.81|Aircraft)$. The relevant value for estimating the presence of an ASM (or aircraft) is the posterior prob-ability to be in the presence of an ASM given the speed, $P(ASM|Speed)$.

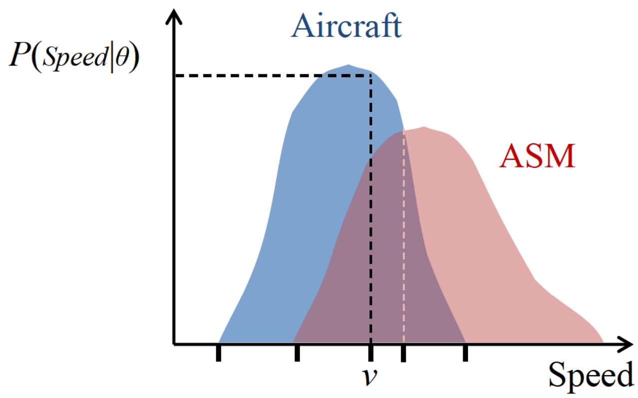


Figure 9: Conditional probabilities $P(Speed|\theta)$ built from general assumptions and specifications related to the different models of aircraft and ASMs. $\theta =$ *{ASM, Aircraft}*.

The posterior probability is the probability of the parameters θ given the evidence provided by the measured speed. To get the posterior probability *P(ASM|Speed)*, Bayesian inference can be used such that

$$P(ASM|Speed = v) = \frac{P(Speed = v|ASM)P(ASM)}{P(Speed = v)}. \quad (1)$$

One of the problems with Equation 1 is that it introduced two more probabilities: *P(Speed =v* and *P(ASM)*. These are called the priors. For example, of out of of the N objects observed in a given area and over a certain period of time (e.g., a number of years), M out of them were missiles, then the prior for the presence of a ASM can be given as $P(ASM) = M/N$. According to this, the prior for the presence of an aircraft would be $P(Aircraft) = (N-M)/M$. Normally, the number of observed missiles during a period of time should be much lower than the number of aircraft. Therefore, the prior $P(ASM)$ would be much lower than $P(Aircraft)$. Unless the conditional probability $P(Speed = v|ASM)$ is much higher than $P(Speed = v|Aircraft)$, the resulting posterior probability $P(ASM|Speed = v)$ would always be lower than $P(Aircraft|Speed = v)$.

Hence, the probability that the observed object is an aircraft given its speed would always be higher than the probability that the observed object is an ASM. In almost any case, such an estimation process would yield that the observed object is an aircraft, not an ASM. There is something wrong with this approach in that it is always biased toward aircraft. The bias is supported by historical data. But as mentioned before, war and ASMD are unpredictable in nature. Therefore historical data is not a reliable indicator of neither the present or the future.

ASMD is not a problem where conclusions can be drawn by analyzing the frequency or proportion of sample data. To account for this and to minimize the amount of subjective information content, the use of flat priors is recommended. In other words, the priors should all be set equal such that $P(ASM) = P(Aircraft)$, thus eliminating any *a priori* assumption that is not related to the measured attributes.

Even if flat priors are used, the Bayesian inference of Equation 1 can still cause problems. In the example shown in Figure 9, the speed v results in $P(Speed = v|ASM) < P(Speed = v|Aircraft)$. For the case where $v =$ Mach 0.81, this means that given an object with a measured speed of Mach 0.81, it is stated that the probability that the object is an ASM is lower than the probability that it is an aircraft. So the prevailing assumption would be that the object is an aircraft. This has huge implications for the ship's command and control process [9]. If an object recognized as an aircraft is indeed an ASM, a ship's probability of survival can be greatly reduced.

Because of the risk associated with a bad decision, the conditional probability distributions must be treated otherwise. Each of the two conditional probability distributions shown in Figure 9, $P(Speed|ASM)$ and $P(Speed|Aircraft)$, was determined independently from the other. The conditional probabilities allow the prediction of some unknown outcomes (speed) based on known variables (presence of a ASM or an aircraft). In this work, the better approach is to consider directly the assignment of a probability distribution to an unobserved variable θ (presence of a ASM or an aircraft) based on known outcomes (e.g., measured speed of the object). This is referred to as the likelihood principle [11]. Under this principle, the likelihood $L(\theta|a)$ gives a measure of how likely any particular value of θ is, given that a measured variable A has the value a. The idea behind the likelihood principle is that inferences from (measured) data to hypotheses (θ) should depend on how likely the actual data are under competing hypotheses, rather than on how likely imaginary data (e.g., speed, altitude) would have been under a single hypothesis. This difference between the likelihood function $L(\theta|a)$ and the posterior probability $P(\theta|a)$ is subtle but makes a lot of sense in the context of IAMD. Instead of using priors and conditional probabilities to obtain posterior probabilities, such as the one given in Equation 1, likelihood functions are defined directly for each of the measured a ttributes. Figure 10 shows the same example as in Figure 9 but where a likelihood function is defined for $\theta = \{ASM, aircraft\}$. This way, the likelihood for ASM and $aircraft$ can be compared against each other. The implication for ASMD is easier to assess, especially for a two class problem. For instance, when the measured speed is $v =$ Mach 0.81, as illustrated in Figure 10, the likelihoods $L(ASM|v =$ Mach $0.81)$ for ASM and $L(ASM|v =$ Mach $0.81)$ for aircraft are equal, meaning that no conclusion can be drawn about the presence of an ASM or not. Knowing that Mach 0.81 is a common speed for both ASMs and aircraft, not to commit on the presence of an ASM is less risky than to conclude that the observed object is an aircraft, which is the case when Equation 1 is used. The likelihoods in Figure 10 also reflects the fact that only ASMs can fly above a certain speed and only aircraft can fly below a certain speed.

The likelihoods are bounded between 0 and 1 inclusively, like probabilities. 1 and 0 represent the degree of belief that the target is (1) or is not (0) an ASM. Because the problem of recognition of ASMs is a two class problem (ASM and aircraft), it is suggested to set ignorance at a degree of 0.5.

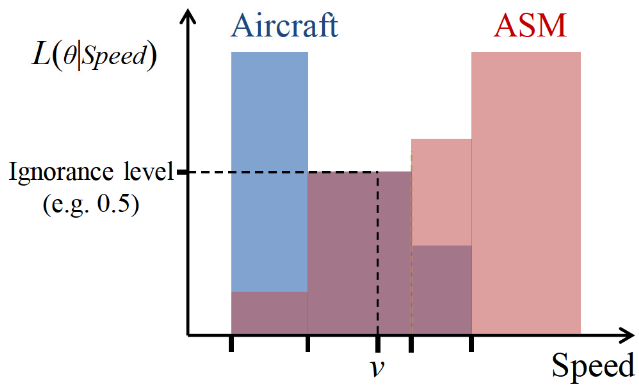


Figure 10: Example of a likelihood function $L(\theta|Speed)$, with $\theta = \{ASM, Aircraft\}$.

4.4 Summary

This chapter presented models for different classes of Air objects. Objects are mainly divided between aircraft and ASMs. The main characteristics for discriminating air objects are mainly altitude, speed as well as position when compared to pre-defined zones. Range can also give a hint about whether the object is an ASM or not. To recognize classes of objects, a constraint satisfaction approach combined with likelihood functions to estimate the presence of ASMs is suggested.

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5 Automated Multi-Source Object Recognition

The recognition algorithm aims at supporting surveillance and providing an estimation of Anti-Ship Missile (ASM) presence. The algorithm is based on the constraint satisfaction approach presented in Section 4.3 as well as the likelihood functions used for the estima-tion of ASM presence. The algorithm is called Multi-Source Object Recognition (MSOR) and is applied to non-collaborating objects. The design concentrates on the discrimination of classes of aircraft and ASMs.

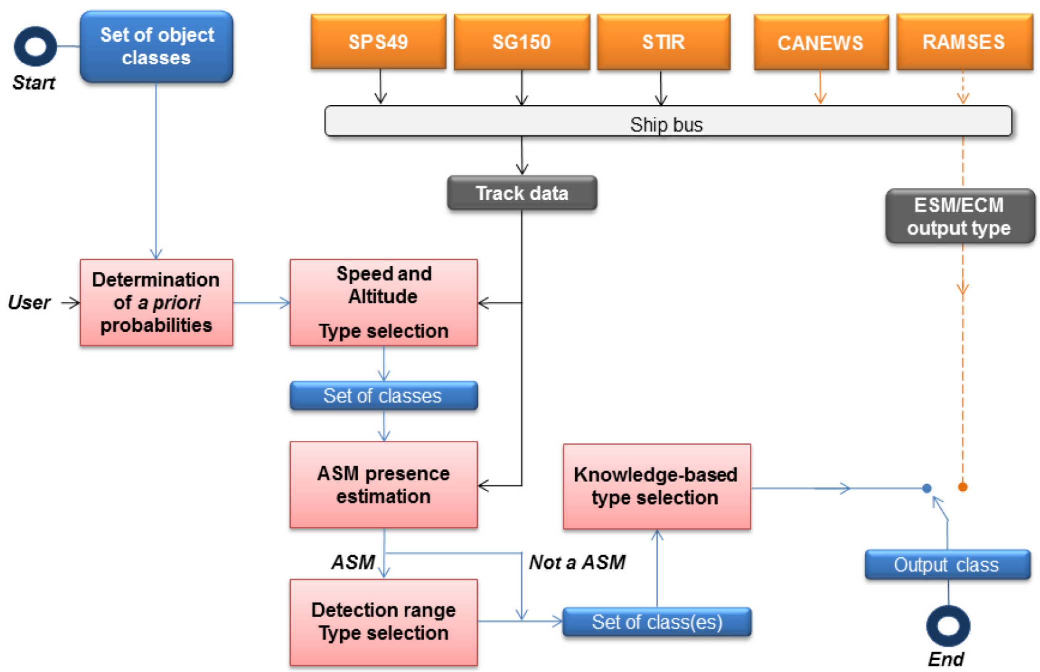

Figure 11: Multi-Source Object Recognition (MSOR) for supporting surveillance and Anti-Ship Missile detection

An Air object may be detected and tracked by one or more surveillance systems onboard the ship. In the current configuration of the Command and Control System (CCS) of the Halifax-class frigates, the different tracks associated with an object and maintained by the AN/SPS-49, the SG-150 or the STIRs are not fused together. Instead, the track used on the CCS is determined based on a priority rule: the SG-150 has precedence over the AN/ SPS- 49 which has precedence over the STIRs. The MSOR algorithm is designed in such way that, whatever the track produced and maintained by any of the tracking systems, its reasoning process adapts to the availability of the information.

Figure 11 presents the diagram of the MSOR algorithm. Given some track data and an initial set of object classes that are likely to be found for the mission at hand, a class selection process is performed based on multiple sources of information. In the event that ESM or ECM reports an object class, the recognition process is shortcut and the class reported by either ESM or ECM prevails. Otherwise, speed and altitude are considered and applied to a constraint satisfaction process.

Each class in the database has a minimum and maximum speed specification, as well as a minimum and maximum altitude specification. For instance, a SSN27 missile has minimum and maximum speeds of 0.8 and 2.9 Mach, and minimum and maximum altitudes of 15 and 50 ft, respectively[5]. Given such information for every class in the dataset, each class for which the reported speed and altitude falls within its minimum and maximum specification is selected.

Figure 12 shows an example of a speed and altitude class selection function. The "**X**" represents the location of the reported speed and altitude on the plan defined by the speed axis and the altitude axis. In this hypothetical case, the output class set associated with the reported speed and altitude contains three classes: the Jet fighter, the AS-17 ASM and the BrahMos ASM.

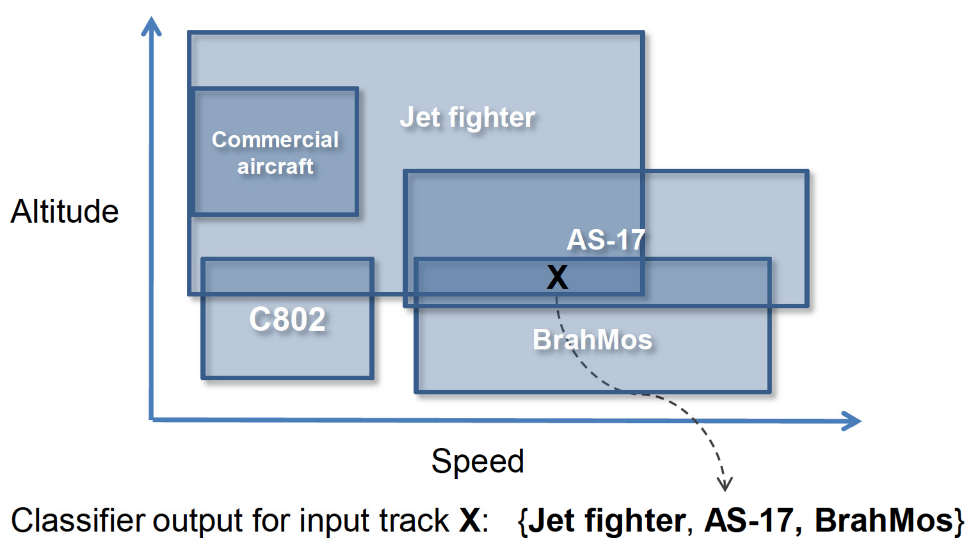

Figure 12: Example of a Speed and Altitude class selection function.

Note that altitude may not be available depending on which tracking system reports to the CCS. The different cases are presented in Table 4. If SG-150 is the responsible tracker, than all that can be concluded is that the object's altitude is between 0 and 35000 ft. If SPS-49

[5]All the specifications given in this report are unclassified data. Most of the data was found on wikipedia.com.

is the responsible tracker, than the altitude is between 100 and 150000 ft. If the STIR is the responsible tracker, than the object's altitude is provided in the reported track. In the case where SPS-49 or SG-150 is the responsible tracker, some discrimination of object classes can be performed with some limitation. For example, if SPS-49 reports the target, it cannot be a missile C-701 since the altitude of a C-701 is typically below 100 ft.

Table 4: Available altitude information according to the responsible tracker used by the CCS.

Responsible tracker	Altitude [ft]
AN/SPS-49	Inferred: Between 0 and 35000
SG-150	Inferred: Between 100 and 15000
STIR (SPG-503)	Given

The estimation process of the presence of an ASM is independent from the class selection process described above. The process is described in Section 5.1. Firstly, it aims to inform the operator of the probability, or the degree of belief, that the observed object is an ASM. Secondly, the estimation process plays a role in the MSOR process, as illustrated in Figure 11. In fact, if the set of classes produced by the Speed and Altitude selection process contains both ASM and non-ASM classes, the computed probability about the presence of an ASM is used to discard classes.

Table 5: Interpretation of the computed probability about the presence of an ASM.

Probability	*Interpretation*
< 0.5	There is enough evidence to conclude that the object is not an ASM
0.5	Ignorance: it lacks clear evidence to conclude about the presence or not of an ASM
> 0.5	There is enough evidence to conclude that the object is an ASM.

Table 5 presents the different cases of estimated probability and their interpretation. The value for ignorance is set to 0.5. If the ASM probability is lower than 0.5, ASM classes are discarded. Otherwise, if the ASM probability is greater than 0.5, non-ASM classes are discarded so that the class set contains only ASM classes. In that case where the ASM probability is greater than 0.5, a detection range filter is applied to eliminate ASM classes whose range specifications are not long enough to reach the ship.

Figure 13 illustrates the application of a detection range filter. The presented example has a class set consisting in four classes of ASMs: HY-2, C-701, SS-N-27 and AS-17. The dotted line represents the range of the tracked target X. The four vertical bars correspond to the maximum range specifications of the four ASMs. As shown in the figure, the classes HY-2 and SS-N-27 have maximum ranges which are greater than the range of the object X, while the classes C-701 and AS-17 have maximum ranges which are lower than the range of X. Therefore only the classes HY-2 and SS-N-27 can reach the ship at the distance of X. Because the object has been recognized by the ASM probability estimator as an ASM aimng at the ship, the classes HY-2 and SS-N-27 are associated with X and the classes C-701 and AS-17 are discarded.

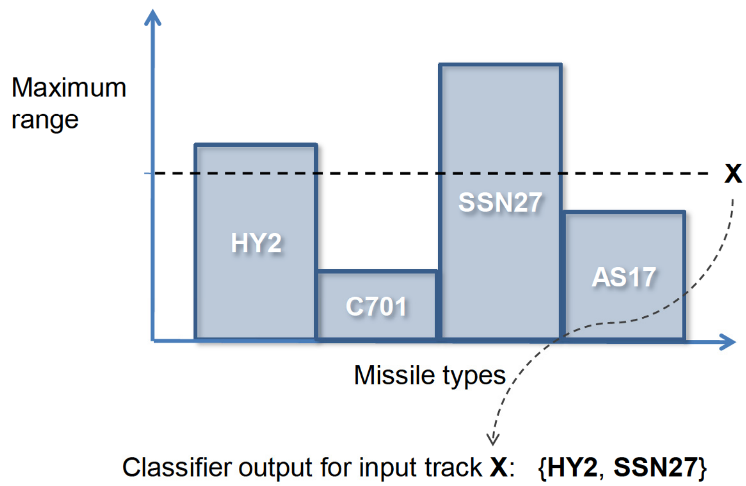

Figure 13: Example of a detection range classifier which filters out classes whose maximum range specifications are lower than the range of the track.

At this stage, the class set should hold a minimal number of ASM or non-ASM classes. If for some reason the set is empty, that is, no class corresponded to the selection process described above, a generic class is returned to the operator (e.g., Aircraft/Unknown or ASM/Unknown). The generic class is determined depending on whether the ASM probability is greater or lower than 0.5 (generic ASM or generic aircraft).

If more than one object class remains, knowledge-based selection process is performed. Given a list of candidate classes to be associated with a track, the knowledge-based class selection process uses intelligence and mission related information to infer the most likely class. For this current version, it is proposed that each class be characterized by a user-defined weight $w \in [0, 1]$ that reflects the *a priori* probability of the presence of the object class for the mission at hand. If there is a tie in the *a priori* probabilities of the remaining classes, it is resolved by returning the fastest type.

5.1 Estimation of ASM Presence

ASM presence estimation depends on a wide variety of criteria and contextual information. Among them are the speed, the distance, the altitude, the heading (calculated from the own ship perspective), the zone in which the target is positioned and the IFF response. The estimation process of the presence of an ASM simply returns a probability, or likelihood, that the object is an ASM. As shown in Figure 14, the estimation uses the sum of independent likelihood functions computed on each attribute and described in Section 4.3.1.

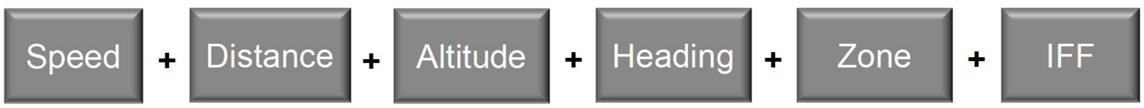

Figure 14: Attributes used for the estimation of ASM presence.

Each likelihood function, defined for each measured object attribute, can be seen as the opinion of an individual ‘expert’. There are then multiple experts that form a pool where each of them declares its probability of ASM presence. Faced with multiple declarations, there are many ways to make a decision. For instance, the decision rule could be based on a majority vote, a maximum probability vote or a minimum probability vote, to name just a few. In this work, the decision rule based on the average probability is used. All likelihoods are then combined into one by averaging them. The method is known as a linear opinion pool [12] and is defined according to

$$L(\theta) = \sum_{i=1}^{n} w_i L(\theta|i), \tag{2}$$

where n is the number of sources, $L(\theta|i)$ is the probability for θ according to attribute i, $L(\theta)$ is the combined probability distribution and w_i is the weight associated to attribute i, where $\sum_i w_i = 1$. The weights expresses the importance of the attributes against each other, as some attributes may be more meaningful than others.

In the case of the ASM probability estimation, the combined likelihood or probability is given by

$$L(ASM) = \sum_{i=1}^{6} w_i L(ASM|i), \tag{3}$$

where i=$\{$speed, altitude, distance, heading, zone, IFF$\}$ and where $w_i = 1/6, \forall i$.

As shown in Table 5 and as mentioned before, when the estimated ASM probability is greater than 0.5, the object under consideration is recognized as an ASM by the MSOR algorithm. Examples of the speed, altitude, heading, detection range, object zone position and IFF likelihood functions are illustrated in Figures 15, 16, 18, 19 and 20, respectively.

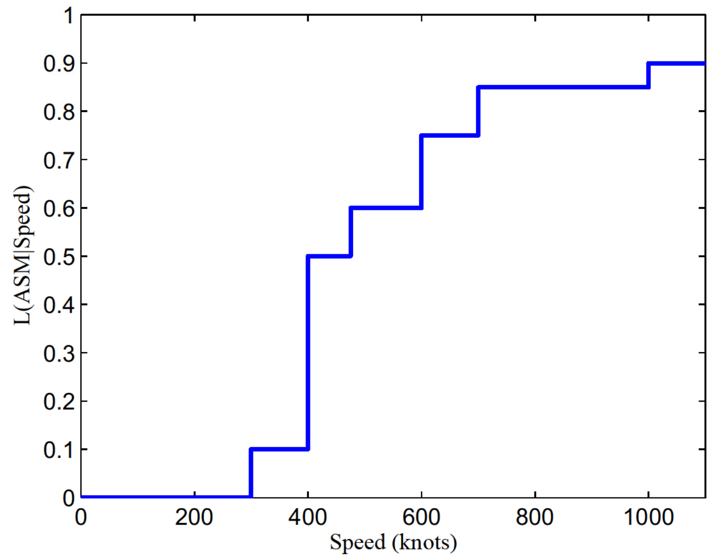

Figure 15: Speed likelihood function. For example, $L(ASM|Speed = 900) = 0.85$.

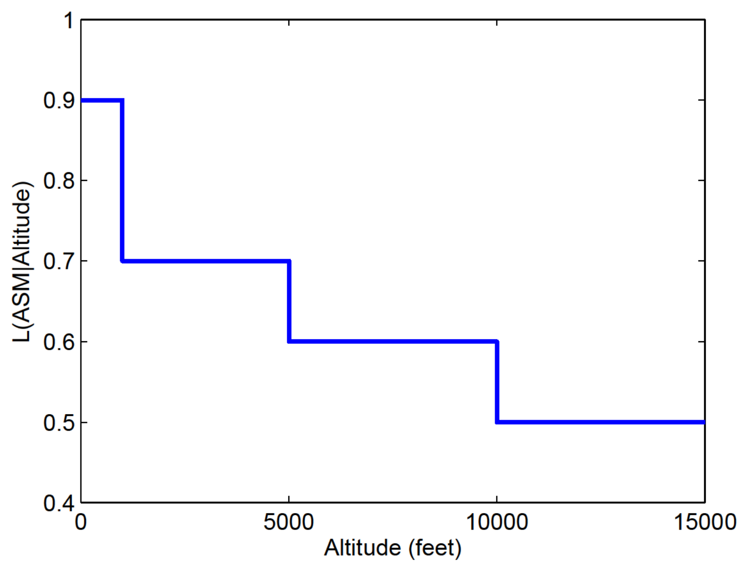

Figure 16: Altitude likelihood function. For example, $L(ASM|Altitude = 8000) = 0.6$.

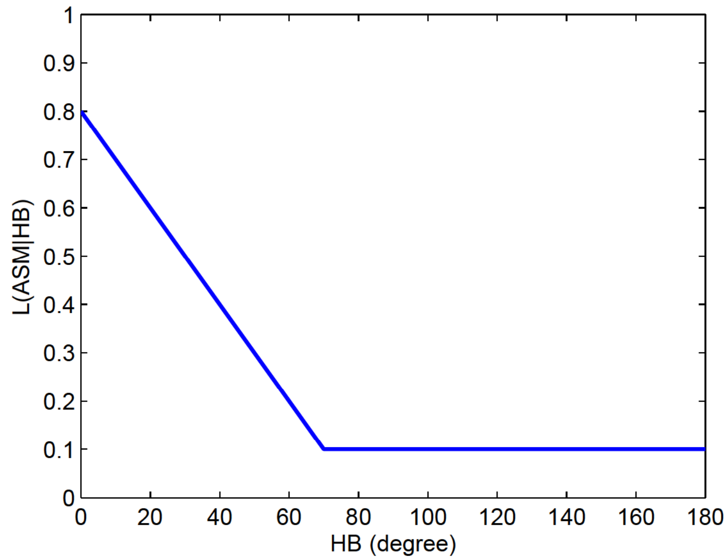

Figure 17: Heading likelihood function (HB: difference from heading to inverse bearing). For example, $L(ASM|HB = 50) = 0.3$.

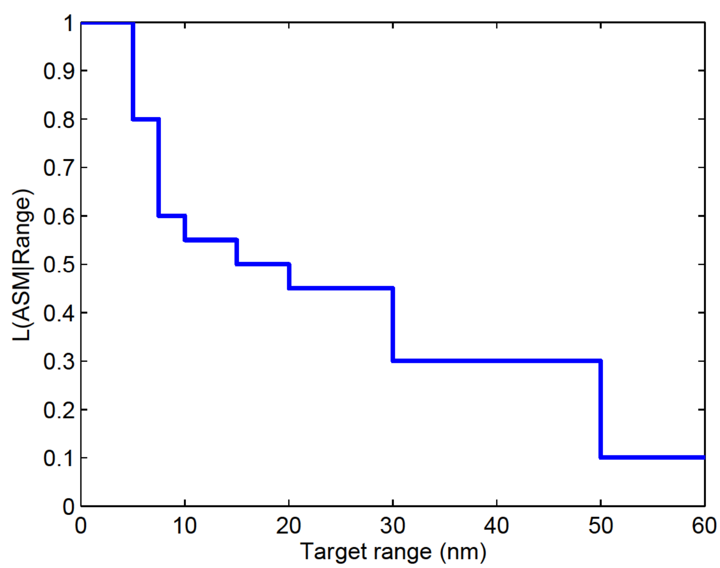

Figure 18: Detection range likelihood function. For example, $L(ASM|Distance = 25) = 0.45$.

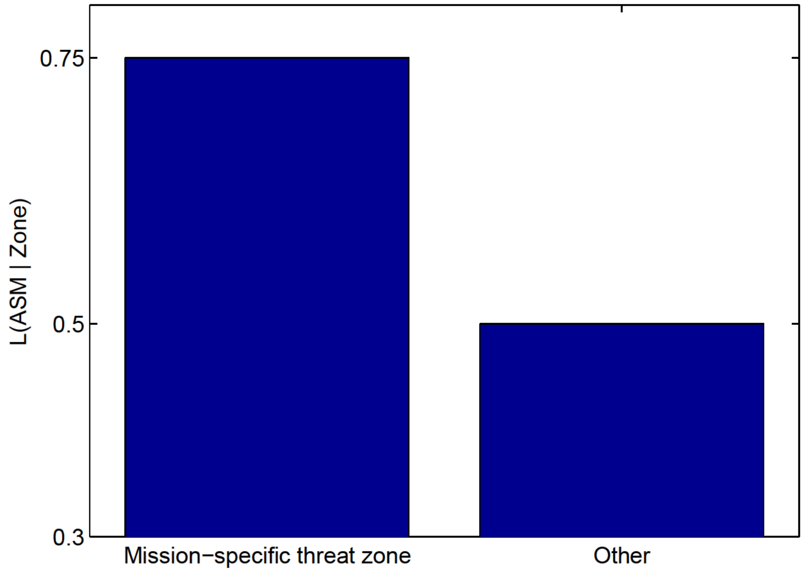

Figure 19: Zone probability likelihood in terms of two object position possibilities: 1) in the mission-specific threat zone, 2) out of the mission-specific threat zone (other). For example, $L(ASM|Zone = \text{'}Other'\text{'}) = 0.5$.

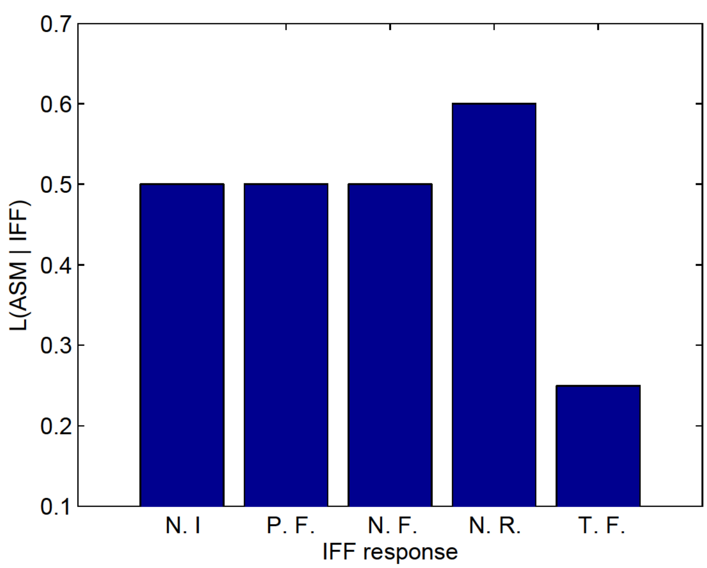

Figure 20: IFF probability likelihood in terms of the following IFF responses: Not Interrogated (N.I.), Possible Friend (P.F.), No Friend (N.F.), No Response (N.R.) and True Friend (T.F.). For example, $L(ASM|IFF = \text{'}PossibleFriend'\text{'}) = 0.5$.

The values used in the illustrated functions are inspired from the object model analysis presented in Section 4.

In this report, the following IFF responses are considered: "Not interrogated", "possible friend", "no friend", "No response" and "True friend". In the case where IFF is positive, the probability about the presence of an ASM is 0, that is $L(ASM|IFF =' yes') = 0$. In the case where it is negative (or 'no'), the probability about the presence of an ASM is 0.5, that is $L(ASM|IFF =' no') = 0.5$.

Figure 21 illustrates an example of ASM presence estimation using the linear opinion pool.

Track :	Speed = **700** knots	→	L(ASM|Speed) = **0.75**
	Altitude = **500** feet	→	L(ASM|Altitude) = **0.9**
	HB = **0.2**	→	L(ASM|HB) = **0.8**
	Range = **19** nm	→	L(ASM|Distance) = **0.5**
	Zone = **'out'**	→	L(ASM|Zone) = **0.5**
	IFF4 = **'not interrogated'**	→	L(ASM|IFF4) = **0.5**

$$\left[\begin{array}{c} L(ASM|Speed) + L(ASM|Altitude) + L(ASM|HB) + L(ASM|Distance) + \\ L(ASM|Zone) + L(ASM|IFF4) \end{array} \right] /6$$

$$= \mathbf{0.66}$$

Figure 21: ASM probability estimation example.

5.2 Summary

This chapter presented the MSOR algorithm for supporting surveillance and ASM detection. The algorithm first uses a speed and altitude selection process. An ASM presence estimation process is then performed based on linear opinion pool which combines the likelihoods for speed, altitude, distance, heading, position (in threat zones) and IFF. In case where a track is recognized as an ASM, a detection range type filter is applied to keep only the classes of ASMs for which the maximum range is greater or equal to the detection range.

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6 Support to the CORALS 3.0 Planner for the 2012 Rim of the Pacific Exercise

The COmbat Resource ALlocation Support (CORALS) planner is a combat power management capability that has been developed to support the ship command team in planning optimized responses to multiple threats [10]. One key feature of CORALS is its ability to provide different and significant decision-support capabilities ranging from optimizing deployment times for combat resources against single targets to the sophisticated coordination of combat resources for engagements involving multiple targets. CORALS is an automation and decision support capability for ASMD operations. It supports the command team in planning optimized responses against multiple and multi-axis targets. The main inputs to CORALS are the threats which must be defended against.

Before being processed by CORALS, the threats have first to be identified and recognized. This is where the MSOR function presented in this report takes place. Figure 22 shows CORALS' software setup [15]. It serves two purposes. Firstly, it is designed to be run over the CCS of a Halifax-class frigate and in preparation for the RIMPAC'12 sea trials. Secondly, it can also be used in simulation mode through the STAGE [27] and SADM modeling and simulation softwares. Note that MSOR does not provide full identification in terms of the NATO standard definition[6] [8]. It concentrates on recognition. However, when it recognizes an ASM, the latter's identity is considered to be hostile as it is passed to CORALS for combat power management planning.

MSOR is embedded in two components which are represented under the name Recognition and Identification (R&I): the live R&I and the simulation R&I. The live and simulation component each process different kinds of information, but they produce the same output: the class or type of each tracked object. In the context of ASMD, the latter amounts to recognizing entities of ASM that CORALS will then engage thanks to its combat power management capability [17]. Both the live and simulation R&I components use the MSOR recognition algorithm presented in this report.

6.1 Simulation R&I

The simulation R&I component reads the object tracks (aircraft and missiles) simulated by the SADM software. The main function of the R&I component is the recognition of the object class, which is performed using the MSOR algorithm. Besides object class recognition, the simulation R&I is also charged with the following tasks:

1. data transmission from SADM to CORALS,

[6]Identification can be defined as the assignment of a standard identity to an object. The possible identities are: Hostile, Suspect, Neutral, Friend, Assumed friend, and Unknown.

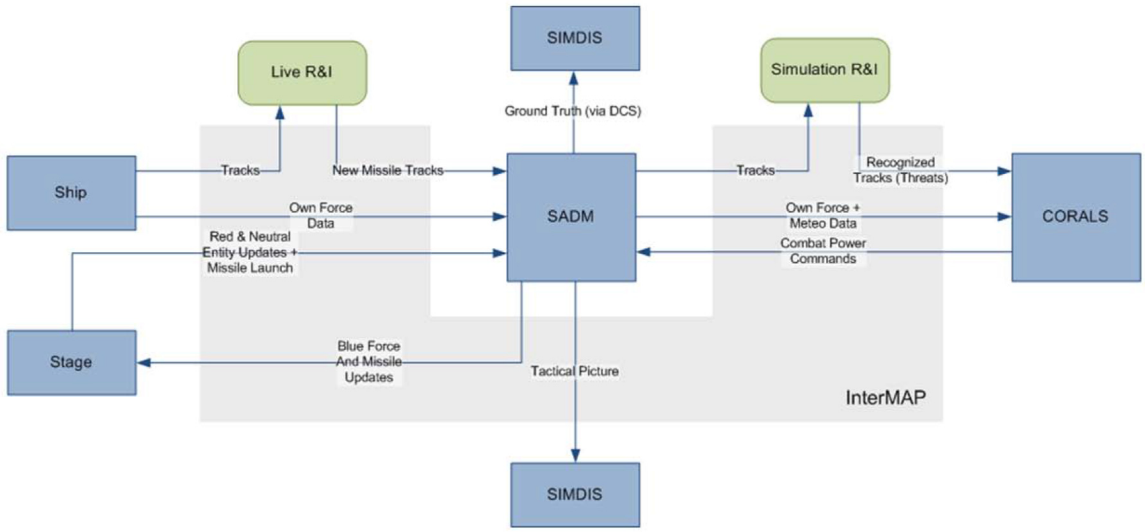

Figure 22: CORALS' software setup.

2. track filtering, which eliminates tracks that are under a certain degree of quality, and
3. track processing, which includes units conversions and the calculation of the closest point of approach.

6.2 Live R&I

The live R&I component is used for dealing with real data obtained onboard a Halifax class frigate. The objects tracks produced on the CCS of the ship are read by the live R&I component. As for the simulation R&I, a track filtering function and a track processing function are executed. The MSOR is then executed on each track to estimate the presence of an ASM and provide an object class (e.g., Jet fighter, Air surveillance, ASM C-802, etc.). See [15] for more details on the live and simulation system setups.

6.3 RIMPAC'12 trials

The Rim of the Pacific Exercise (RIMPAC) is the world's largest international maritime exercise. It is hosted and administered by the United States Navy, with the United States Marine Corps, United States Coast Guard, and Hawaii National Guard forces under the leadership of the Governor of Hawaii. It seeks to enhance interoperability between Pacific Rim armed forces, as a mean of promoting stability in the region to the benefit of all participating nations. The exercises are viewed as key to military readiness.

The 2012 RIMPAC scenario consists in four target attacks against the defending ships. The participating Canadian frigate is HMCS Ottawa. This is the frigate in which the CORALS system was installed. The four targets that emulate ASM attacks are played by BQM-74E drones. More can be found about the trials in [17].

6.3.1 MSOR Implementation

The implementation of the MSOR recognition algorithm for the RIMPAC'12 trials requires particular preparation and adjustments.

First, since the scenarios involved do not have pre-determined threat zones or tactical zones, the zone attribute for the estimation of ASM presence is not implemented.

Also, to comply with SADM's restricted list of ASM models, the MSOR ASM models for RIMPAC'12 are restricted to only the C-802 and the AS-17 ASM. The aircraft classes included in the MSOR database are Jet Fighter, Commercial, Helicopter, Surveillance and Unknown. The Unknown aircraft class is supposed to be output only when no other aircraft class has been recognized by the MSOR. A Surface class also exists for objects detected at the surface of the sea (boats).

One of the most important considerations in the implementation of the MSOR algorithm for RIMPAC is the BQM-74E specifications. The BQM-74E drones that play the role of ASMs during the trials do not have the same specifications as real ASMs. Their speeds were expected to be between 475 and 500 kts. Among the C-802 and the AS-17 ASMs, the C-802 is the one which is the closest to the BQM-74E in terms of flight speed and altitude. Still, the BQM-74E is slower than the C-802, whose cruise speed is almost 600 kts. For this reason, the C-802 entry in the MSOR database was modified such that the minimum speed for the C-802 was decreased to 425 kts. According to this modification and according to speed alone, a BQM-74E should then be recognized as a C-802 ASM.

In this current version, the track quality for objects that are detected and tracked by one of the tracking systems onboard the ship (SPS-49, SG-150 or SPG-503) is checked against a pre-defined acceptance level. If the track quality is above the pre-determined level, the track is selected for classification by the MSOR algorithm. The level of the track quality is related to the number of updates a track has had for a period of time. A user-defined time delay has been added between track quality checking and transmission to MSOR, so that the track quality can be even further improved.

Upon reception of the track, the MSOR algorithm will perform track classification and output a class associated with the track. The class and the track will then be sent for further processing by CORALS. The benefit for this approach is that the reaction time from target detection to engagement planning is maximized.

However, this approach to the recognition of objects relies only on the first time of the track. It does not profit from further track updates which could improve the track accuracy and which could allow the computation of measures that require multiple time steps, like flight maneuvers.

The testing of the CORALS planner at RIMPAC'12 is closely tied to the ability of the MSOR algorithm to recognize adequately the BQM-74E drones like ASMs (C-802). Any error from MSOR can prevent decent testing of CORALS. In the worst case, if no BQM-74E are recognized by MSOR, no ASM will be transmitted to CORALS. To correct for possible error possibilities by MSOR, a function for manually overriding the MSOR class output has been added.

Figure 23 illustrates the phases involved prior to the execution of the CORALS planner during the RIMPAC trials. The phases are:

Phase 1: The BQM-74E drone is launched and flies toward the ship, simulating an ASM attack.

Phase 2: HMCS Ottawa's surveillance and tracking system detects and tracks the BQM-74E. The track data is then sent to MSOR for object recognition.

Phase 3: The MSOR algorithm returns a class estimation for the tracked BQM-74E. Unless any mistake occurs, the class returned should be the C-802 ASM.

Phase 4: SADM simulates the object recognized by the MSOR algorithm. Under the case that a C-802 ASM has been recognized by MSOR, a C-802 ASM is created and simulated in SADM according to the track data. Note that the resulting flight trajectory and dynamics can vary from the one performed by the BQM-74E. For instance, if the track data contains no altitude information about the BQM-74E, the ASM created in SADM is initiated with a default altitude.

Phase 5: The simulated ASM in SADM is input to the MSOR algorithm for classification. The estimated class for the simulated ASM in SADM is transmitted to CORALS. The class is displayed on CORALS' Operator-Machine Interface (OMI) along with other relevant information.

The reasons for creating and simulating an ASM in SADM, after reception of the BQM- 74E track data and before calling CORALS, depend on software programming issues that will not be discussed in this report. However, this setup is more challenging for the recognition of objects. In fact, the MSOR algorithm is called twice on the same object (BQM-74E), but in the second time it is called on a simulation of the real object. This increases the chance of error.

The results of the RIMPAC'12 sea trials are presently under analysis and will be analyzed in a future report.

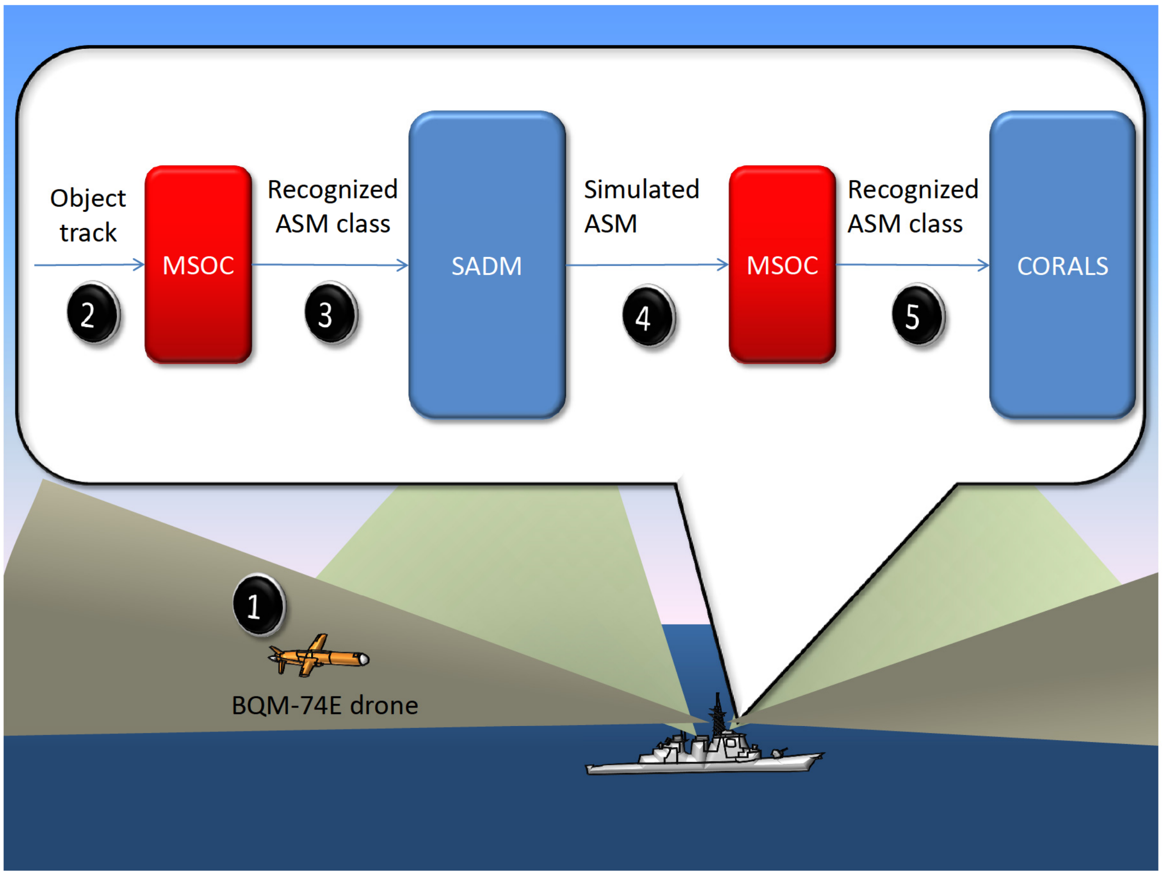

Figure 23: Steps required from BQM-74E detection and tracking to engagement planning by CORALS.

6.4 Summary

This chapter presented how the MSOR algorithm was integrated with CORALS in a setup built for connection to the CCS of a Halifax-class frigate and in preparation for the 2012 RIMPAC sea trials. The roles of both the live and the simulation components are described given the five phases involved prior to the execution of the CORALS planner during the RIMPAC trials.

7 Conclusion

This report is written in an effort to achieve three objectives: 1) initiate a characterization of the problem of object recognition in IAMD and with an emphasis on ASMs; 2) Prepare an object recognition algorithm for a Halifax-class frigate; 3) Integrate the object recognition algorithm with CORALS 3.0 and prepare for the RIMPAC'12 sea trials.

The characterization of the problem of object recognition in IAMD focused on the following issues:

1. The sources of uncertainty related to IAMD and in the context of littoral warfare and asymmetric threats.

2. The current naval sensor systems of the Royal Canadian Navy's Halifax-class frigates.

3. The modeling of objects, which includes the determination and definition of classes of objects, the determination of attributes and the definition of a framework for representing the models.

The proposed MSOR algorithm uses the speed, the altitude, the detection range, the heading, the zone and the IFF response to classify objects. While it concentrates on the recognition of the presence of ASMs, it is designed to recognize specific classes of aircraft and ASMs. The algorithm is based on a framework that mixes a constraint satisfaction approach and likelihood inference.

The integration with CORALS 3.0 and the preparation for the RIMPAC'12 sea trials requires two object recognition modules: one that deals with live tracks produced by the sensing systems onboard the ship and another that deals with simulated objects produced by the SADM modeling and simulation software. Since in RIMPAC'12 a drone is used to emulate a real ASM, some parameters of the MSOR algorithm need adjustments. Therefore, the speed specification for a C-802 ASM had to be lowered to comply with the drone's speed specifications.

7.1 Remarks

The biggest issues with object recognition in a noncooperative environment are the uncertainty regarding both the measurements and the modeling of objects, as well as the risks involved with the assessment of the recognition function's outputs. Most of all, the uncertainty itself is hard to evaluate. Among the sources of uncertainty, is the enemy's proclivity to hide information from its opponents. This issue must play a role in the choice of the theoretical framework and the algorithm. For instance, any approach based on population sampling is not appropriate for this kind of problem. In the same way, the evaluation of the probability distribution for an observable attribute conditional on a class of object and the determination of priors are both difficult to perform. This promotes the use of likelihood functions that rather express the probability for a class of object conditional on an attribute value.

According to the current search and surveillance systems onboard the Halifax-class ships, the available attributes for recognition are scarce. There are mostly the basic positional and kinematical attributes, such as speed and altitude, but they are only partially effective for discriminating aircraft from ASMs, and for discriminating classes of ASMs and aircraft. Speed is good for the recognition of supersonic ASMs. However, the problem with speed is that a significant number of ASMs are subsonic just like aircraft, such as jet fighters or even commercial airliners. Altitude is a better discriminant of aircraft and ASMs, but it is rarely available on the current tracking systems onboard the Halifax-class frigates. The detection range can give some hint about which classes an observed object cannot belong to, based on its maximum range, but it is only a partial information that does not tell much about the class of an Air object. The same applies for the heading, the zone and the IFF attributes, which only provide a glimpse about the nature of the observed objects. To add more information, relational measures that necessitate analyses over many time steps or between many objects can be considered, such as weave maneuvers. However, the whole domain of possibilities must be explored beforehand for each measure and for each class of object. Given the noncooperative and unpredictable nature of IAMD, this is a considerable effort that requires deep investigation guided by subject-matter expertise.

To compose with the low amount of information and the uncertainty related to it, the output of the MSOR recognition algorithm presented in this report has a low explicitness. That is, explicitness is traded for lower uncertainty and error rate.

Although the results from the RIMPAC'12 sea trials have not been analyzed yet, the preparation for the RIMPAC'12 sea trials and the integration with CORALS 3.0 highlighted the fact that the evaluation of ASMD capabilities is limited by many factors. The most prominent factor is the use of a drone instead of a real ASM, which does not emulate perfectly the characteristics of a real ASM. There are also the constraints imposed by the use of the SADM simulator. So it should kept in mind that the tests, whether they are simulated or conducted at sea with live physical simulations of ASMs, do not correspond exactly to the real IAMD in war time. It is therefore important to identify the discrepancies between the trials and real IAMD, as well as the modifications of the developed capabilities to comply with the trials' particularities.

7.2 Recommendations

Here are some recommendations based on the work presented in this report:

1. Consider the flight profiles of ASMs rather than considering the attributes independently. The flight profiles of ASMs are mainly described by their speed, altitude and

range. The study of flight profiles for the discrimination of classes of ASMs requires an extensive examination where all possible flight possibilities are surveyed for each class of ASM. A thorough characterization of each ASM's flight profiles and their variant would be required before envisaging any use for the recognition process.

2. Consider the rate of climb as an additional attribute. The rate of climb can help discriminate types of aircraft.
3. Consider the sea state as an additional attribute to support the recognition of ASMs.
4. Implement a function to associate class probabilities to zones, such as suggested in [17].
5. Add minimum and maximum probability thresholds on the ASM presence estimation function. According to this threshold, ignorance would be returned if the computed probability is between the minimum and maximum threshold. The decision would then be delayed until newer information comes in.
6. Extend the use of likelihood functions to more classes of objects, such as classes of aircraft or classes of ASMs. It is currently used only for the estimation of the presence of an ASM
7. The current MSOR algorithm is discontinuous in time. It is executed only once for each track it receives. It could be modified to run over many time steps in such way that it would be updated each time the track is updated or according to some time interval.
8. Revise the class set and refine the characterization of each class.
9. Align the recognition output with NATO's recognition confidence levels: Certain target, Probable target and Possible target.
10. Add operator interaction functionalities through the operator machine interface of CORALS. Among the functionalities, the operator should be able to overwrite the recognition values output by the automated algorithm. Most importantly, the automated recognition algorithm should only be used as a support to the overall recognition decision process. In addition to the returned class by the recognition function, a list of other possible membership classes and their associated probabilities should be displayed. The operator should also be able to look for the reasons behind each class returned by the automated recognition algorithm and in terms of the attributes considered for the suggested decision.
11. Relational measures should be studied, starting with the simplest ones. For instance, weave maneuvers should be characterized for the different classes of ASMs and aircraft.

12. If ASM recognition and identification is a challenge in ASMD, ASM detection and tracking looks to be even more challenging. The most important factor is the time of detection and consequently the reaction time available for defence. ASMs are specifically designed for being detected as late as possible. Some of the newest ASMs combine supersonic speeds, sea-skimming profiles and maneuverability, which makes them very hard to detect with the current naval search and surveillance systems. An object recognition algorithm can only be as good as the inputs it received. This is why a characterization of the problem of target detection and tracking should be required, where the performance of target detection and tracking can be estimated for different kinds of targets and according to different conditions. The situations in which the ship is vulnerable and which render any further action precarious should be examined. For instance, a sea-skimming missile flying at Mach 3 and detected at 10 km from a ship would leave only about 10 seconds for reaction. In such circumstance, the problem is detection more than anything else.

Finally, the analysis of the results obtained for the trials conducted during RIMPAC'12 will allow us to further identify pitfalls and areas for improvements.

Annex A: Unit conversion tables

Table A.1: Conversions between common units of length.

		kilometers (km)	mile (m)	nautical mile (nm)	feet (ft)
1 km	=	1	0.62137	0.53996	3280.8
1 m	=	1.609344	1	0.86897	5280
1 nm	=	1.852	1.15077	1	6076.12
1 ft	=	3.048e-4	1.89393e-4	1.64578e-4	1

Table A.2: Conversions between common units of speed. Mach 1 corresponds to standard sea level conditions (corresponding to a temperature of 15 degrees Celsius), the speed of sound is 340.3 m/s[5] (1225 km/h, or 761.2 mph, or 661.5 knots, or 1116 ft/s).

		m/s	km/h	mph	knot	ft/s
1 m/s	=	1	3.6	2.236936	1.943844	3.280840
1 km/h	=	0.277778	1	0.621371	0.539957	0.911344
1 mph	=	0.44704	1.609344	1	0.868976	1.466667
1 knot	=	0.514444	1.852	1.150779	1	1.687810
1 ft/s	=	0.3048	1.09728	0.681818	0.592484	1
Mach 1	=	340.3	1225	761.2	661.5	1116

Table A.3: Classification of Mach regimes. Note that in this report, the transonic regime is included with the subsonic one.

Regime	Subsonic	Transonic	Sonic	Supersonic	Hypersonic	High-hypersonic
Mach	$<$1.0	0.8-1.2	1.0	1.2-5.0	5.0-10.0	$>$10.0

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List of Acronyms

Acronym	Definition
ASM	Anti-Ship Missile
ASMD	Anti-Ship Missile Defence
CFMWC	Canadian Forces Maritime Warfare Centre
CANEWS	Canadian Electronic Warfare System
C2	Command and Control
CCS	Command and Control System
CORALS	COmbat Resource ALlocation Support
DRDC	Defence Research and Development Canada
ECM	Electronic Countermeasure
ESM	Electronic Support Measures
HMCS	Her Majesty's Canadian Ship
IAMD	Integrated Air & Missile Defence
IFF	Identification Friend or Foe
IRST	Infrared Search and Track
MSOR	Multi-Source Object Recognition
NATO	North Atlantic Treaty Organization
NCTI/R	Noncooperative Target Identification/Recognition
OMI	Operator-Machine Interface
RAMSES	Reprogrammable Advanced Multimode Shipboard Electronic Countermeasures System
RIMPAC	Rim of the Pacific Exercise
R&I	Recognition and Identification
SADM	Ship Air Defence Model
STIR	Separate Target Illumination Radar

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In order to carry out integrated air & missile defence and provide anti-ship missile defence, the Royal Canadian Navy is meant to conduct naval Command and Control. In this report, the problem of object recognition is studied and an object recognition algorithm is developed to support the threat evaluation, the engageability assessment and the combat power management processes. The new algorithm, called Multi-Source Object Recognition, is specifically suited for a Halifax-class frigate. While it concentrates mostly on the recognition of anti-ship missiles, it is also designed for the recognition of broad classes of aircraft such as jet fighters, surveillance aircraft and helicopters, for instance. With the main objective of providing object recognition, it is integrated to the COmbat Resource ALlocation Support (CORALS) software in both a simulation and a live ship-based setup. The setup was adapted in preparation for the integration on a Halifax-class frigate and for the participation to the 2012 international Rim of the Pacific Exercise (RIMPAC).

Dans le cadre des activités de défense maritime aérienne, la Marine royale canadienne mène des opérations de Commandement et de Contrôle navales. Dans ce rapport, le problème de la reconnaissance d'objets est étudié et une capacité de reconnaissance d'objets est développée pour supporter les processus d'évaluation de la menace, d'évaluation de l'engageabilité et de gestion de la puissance de combat. La nouvelle fonctionnalité, appelée classification multi-source d'objets, est spécifiquement adaptée pour une frégate de classe Halifax. Bien qu'elle se concentre principalement sur la reconnaissance des missiles anti-navire, elle est également conçue pour reconnaître les grandes catégories d'avion, tels que les chasseurs, les avions de surveillance et les hélicoptères, par exemple. Avec comme objectif principal de fournir la reconnaissance d'objet au logiciel "COmbat Resource ALlocation Support" (CORALS) pour la planification de défense anti-missile, elle est intégrée à la fois dans un environnement de simulation et dans un environnement de test réel sur un navire. La configuration de la fonction de reconnaissance et de l'environnement de test et de simulation a été adaptée en vue de l'intégration sur une frégate de classe Halifax et en vue de la participation à l'exercice international "Rim of the Pacific" (RIMPAC) 2012.

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