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Multi-Sensor Management System for Navy Applications

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IMPORTANT INFORMATIVE STATEMENTS

Abstract

This report provides an introduction to Multi-Sensor Resource Manager (MSRM) for application within a Navy Combat Management System (NCMS). The overall objective of the MSRM is to provide commanders with greater perception of their operating environment. The report outlines the emerging and enabling technologies that combine to make MSRM practical.

Perception of the environment is based on a combination of direct sensory measurements and prior knowledge. Gibson's theory states that the sensed environment can supply sufficient details about the stimulus so perception of the stimulus does not depend on prior knowledge or past experience. This theory is data driven and perceives current events. A contending theory is Gregory's that states perception is a constructive process that uses past experience and prior knowledge related to a stimulus to make inferences. The Gregory's theory allows a system to perceive future events based on theory and models. Situation Awareness (SA) requires a combination of both theories.

Naval forces operate in a highly complex environment that contains many system components that change dynamically. Each of the navy platforms, or weapon systems, has the potential to be more effective in achieving mission objectives if they are interconnected with complementary systems. This approach has the potential to enable the Royal Canadian Navy (RCN) to deploy its resources and achieve mission success at significant lower cost thereby freeing up resources to support other missions.

In general, single sensor systems provide partial information on the state of the environment while multi-sensor systems rely on data fusion techniques to combine related data from multiple similar and/or dissimilar sensors. The objective of a multi-sensor system is to produce an output greater than merely the sum of their individual inputs. This results in a significant improvement in both the quality and availability of information relevant to situational awareness than can be acquired from a single sensor type.

The MSRM determines how best to manage, coordinate and organise the use of sensing resources to achieve the mission objectives. It employs feedback from the Information Fusion Processor (IFP) to the sensors to optimally allocate sensors and resources to the mission and compensating, where possible, for gaps caused by failures of one or more sensors. The MSRM performs the functions of cuing, handover and dynamic allocation of resources to achieve mission objectives. The MSRM controls multiple sensors via their individual Sensor Resource Manager (SRM) to support detection, tracking and classification. The MSRM is responsible for ensuring that resources are appropriately allocated in order to garnish the required information at the lowest cost.

The report reviews a number of previously proposed architectures for implementing MSRM and evaluates their suitability for operation within NCMS. The report investigates how the brain has evolved to optimally process multi-sensory information using both a top-down and bottom-up approach to perception. It is shown that this approach closely matches the requirement for MSRM within the context of a NCMS. The data fusion functions of the brain can be modeled as

a Hierarchical-Mesh Data Fusion Processor (HMDFP) which is subsequently proposed as the framework for MSRM.

The concepts and techniques behind MSRM and its relationship to process refinement within the information fusion processor are explored. A Network Resource Manager (NRM) that dynamically allocates network resources to the various SRM is introduced and architecture for MSRM based on the Joint Directory of Laboratories Data Fusion Model (JDL-DFM) is proposed as a solution for use within NCMS.

The report concludes with a summary of the expected benefits of implementing a MSRM within the NCMS and lists the major challenges to implementing such a system. A recommended course of further actions is included.

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1. Introduction

The report provides a non-technical introduction to the benefits and challenges faced in the implementation of a MSRM to support navy missions. The MSRM was introduced by Ponsford [1] as being a critical sub-system of the Holistic Cognitive Enabled –Naval Combat Management System (NCMS). The NCMS illustrated in Figure 1, is a cognitive aid that naval forces use to manage their resources to support mission execution. The NCMS is capable of simultaneously supporting multiple missions and generates a Fire Control Picture (FCP), Common Tactical Picture (CTP) and Common Operational Picture (COP). The NCMS connects the sensor suite to the weapon systems via the C2 system. The C2 system ingests and processes sensor data to generate situational awareness and support operator cognitive tasks including planning, re-planning, sense-making and situational assessment. The core functions of the NCMS are to observe, analyse and take action. The C2 supports objective reasoning to facilitate a commander to take subjective actions.

MSRM is the enabling technology behind future C2 systems that addresses the critical issue of optimising sensors and sensor utilisation for maintaining domain awareness in dynamically changing environments. It achieves this by providing feedback from the C2 system to the sensors such that gaps in the information base can be filled.

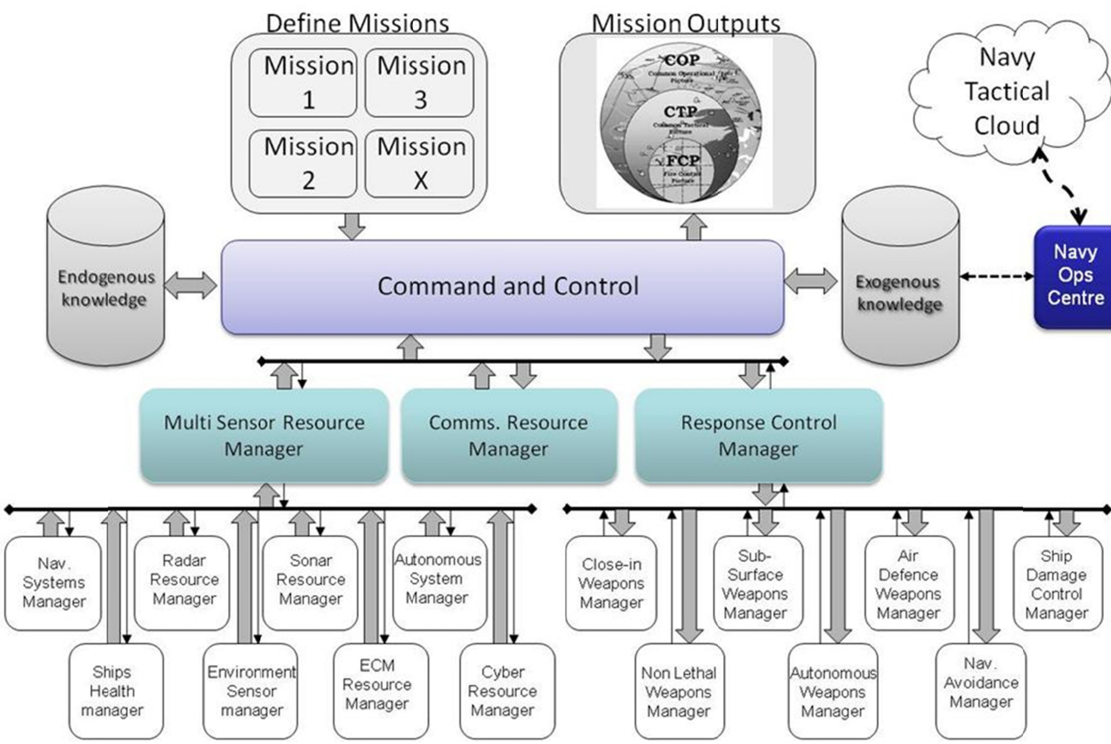


Figure 1 Holistic, Cognitive Enabled NCMS [1]

The objective of the MSRM is to optimally allocate sensing resources to maximise the value of the extractable information to support the current defined mission. The MSRM is a hierarchal system that relays requirements down to sensor specific resource managers. The role of the Sensor Resource Manager (SRM) is to optimally adapt sensor behaviour to dynamic environments and to achieve this in a timely manner such that the information gain remains relevant. As noted in [2], a prompt decision on sensor functions has to be made before the development of the tactical situation has made such a decision obsolete.

The MSRM manages the collection of sensor data to avoid overload of processing and data storage requirements. It achieves this by limiting data collection and processing to that which is relevant to the mission and when appropriate to dynamically assign additional processing and data storage requirements to the sensor or sensors.

In a navy context the primary mission is to provide superior wide-area air defence capability, anti-submarine warfare capability and anti-shipping capability. This requires All Domain Situational Awareness (ADSA). The MSRM achieves this by treating sensors as collective rather than individual entities, with the objective that these resources and sensors are used collectively to maximise the probability of mission success.

The MSRM is designed to improve the effectiveness and efficiency of sensors in generating domain awareness. It achieves this by dynamically selecting a sensor or combination of sensors, from among a set of available sensors, to use during a measurement period in order to optimise overall system performance. The MSRM determines the selection of the next sensor(s) to employ based on prior system measurements to achieve operational objective at minimum cost. In achieving this objective the MSRM may prioritise and share network bandwidth, processing power and data storage among the various sensors via a Network Resource Manager (NRM)

Implementation of a MSRM is feasible as most modern sensors are adaptive and dynamically programmable. Control of a sensor, or sensor group, is undertaken using a sensor specific resource manager – for example a Radar Resource Manager (RRM). The MSRM assigns mission priorities and resources across these individual resource managers.

1.1. Report Structure

This report reviews the current state of the art in MSRM and introduces the potential for software to undertake cognitive tasks to improve overall performance. The report outlines architecture of a future MSRM, applicable to the Royal Canadian Navy (RCN) based on a systems-of-systems approach. The proposed approach physically decouples the complex interactions between the multitude of sensors and SRMs by introducing a hierarchal MSRM that includes a sensor resource analyser and tasker that dynamically flows down mission objectives and system resources to the various SRMs.

The report is composed of 9 sections.

- **Section 1** introduction the topic of MSRM and its role within a NCMS. The objectives and structure of the report are outlined.

- **Section 2** provides overview of the role of MSRM in a NCMS. Definitions of MSRM from the literature are given and a definition guiding this report is proposed. The section provides an historical framework and reviews the role of the Naval Electronic Sensor Operator in the RCN. The section concludes by undertaking a cursory look at how the human brain addresses multi-sensor management and techniques used to avoid sensory overload that could be of value in a MSRM system
- **Section 3** categorises the sensor as used by the RCN and their role in target engagement. Sensor data products and their utility to Situational Awareness (SA) are presented. Cognitive sensing is introduced and the role of the Sensor Resource Manager (SRM) discussed. Examples of SRMs for Radar, Electro-Optical/Infra-Red (EO/IR) and Sonar systems are presented.
- **Section 4;** outlines a number of the key principles and enabling technologies that form the basis of a state-of-the-art MSRM. The section also highlights the importance of the Network Resource Manager (NRM) in ensuring that bandwidth and computational resources are optimally deployed. The section reports on the expected operational benefits from MSRM and looks at some of the challenges that have yet to be addressed.
- **Section 5;** reviews the interactions between the Command and Control (C2) system and the MSRM. Attention is focused on the tasks of risk assessment and risk management. The section introduces the Data Fusion Information Group (DFIG) model and the role of process refinement in improving overall SA. Architectures for multi-sensor fusion are introduced based on models for Human Activity Recognition Chain (HARC) for single and multiple sensors. The benefits of centralise and distributed data fusion are discussed. The section concludes with the presentation of an architecture for MSRM system based on DFIG data fusion model.
- **Section 6;** introduces the role of the human-in-the loop, cognition and artificial intelligence (AI). The role of the MSRM in automating the SRM operator's interaction is discussed. AI and its role in decision making are introduced and the requirement for the commander to understand the rationale behind AI decisions highlighted. Third -generation, Explainable AI is introduced as a potential route for enabling commanders to take ownership of AI decisions and recommendations.
- **Section 7;** This section reviews the use of external knowledge in improving the detection, tracking and classification algorithms to enhance SA. The role of the NRM in dynamically allocating processing and memory resources to individual SRM resources is presented. Key to this section was the requirement for the MSRM to support timely Automatic Target Identification (ATI).
- **Section 8;** presents an historical overview of various architectures used for MSRM. The section concludes with a conceptual architecture for a MSRM and associated Network Resource Manager (NRM) for use in a future Holistic-NCMS as proposed by the author.
- **Section 9;** the report concludes with a summary and recommendation for further work.

2. Multi Sensor Resouce Management for Naval Combat Management Systems

2.1. Definitions

Historically MSRM has meant different things to different people.

- McIntyre [3] defined MSRM as the effective use of available sensing and database capabilities to meet mission goals.
- Manyika and Durrant-Whyte [4] defined MSRM as the process which seeks to manage or coordinate the use of sensing resources in a manner that improves the process of data fusion and ultimately that of perception, synergistically.
- Popoli [5] defined MSRM as the study of ways to improve or optimise the measurement process in a tracking system.
- Buede & Waltz[6] states that MSRM involves the control of one or more sensors on one or more platforms in an intelligent manner over time to achieve the needs of the mission being performed by the platform or platforms in question
- McIntyre [7] also stated that MSRM could be described as a system or process that provides automatic or semi-automatic control of a suite of sensors or measurement devices.

In this report the following definition is proposed:

> *The MSRM provides feedback from the C2 system to sensors to provide superior tactical awareness. It is responsible for the oversight and allocation of sensors and systems, computing resources and databases, to meet multiple, evolving, mission objectives at the most economic cost by ensuring that only necessary data is acquired and processed at the correct moment in time.*

2.2. Historical Overview

Since the beginning of maritime warfare commanders have endeavoured to outsmart their adversary by gaining a competitive advantage by using various resources at their disposal to be the first to perceive, comprehend and engage. Commanders and their crews were subject matter experts in their fields. The collective expertise of the combined battle group was often the deciding factor in naval success rather than just the physical superiority of the fleet.

Until recently, sensors were fewer in number and less capable than they are today. An operator could readily decide which sensor to use, when to use it, point and control it, and even how to interpret the data. Even the environment in which these systems were used was simpler with fewer and less diverse threats. However, technological advances in sensors have resulted in the performance characteristics of modern sensor systems having improved dramatically resulting in more capable and diverse systems [8].

Technological advances and the use of multi-sensor systems have also led to a tremendous increase in the amount of data requiring processing. The number, types, and agility of sensors along with the increased quality and timeliness of data far outstrip the ability of humans to control them. This has resulted in developing management strategies and algorithms for controlling the acquisition of data by multiple, heterogeneous, co-located or spatially distributed sensors. The objective of the management system is to:

- minimise redundant data
- obtain the required measurement accuracy
- minimise compromising radiation
- meeting a set of mission goals

That is, sensor management systems are being developed to optimise the transfer of information from the real world into a locally held, mathematical representation of that world while simultaneously satisfying tactical and strategic goals [3].

Multi-sensor management has historically been used to manage sensors to maximise kinematic information gain on an isolated track. Interest in moving forward is maximising situational awareness in a dynamically changing environment and includes identification of all objects of interest within that environment.

In the words of McIntyre [3], sensor management is nothing more than the study of methods used to improve the measurement process given a fixed set of sensor and computational resources. It is through the use of sensor management that a systematic approach to trade-offs among search, track, and identify can be achieved. This is undertaken to optimise the amount of information gained from sensor tasking which is constrained by performance and equipment limitations and capabilities.

2.3. Naval Electronic Sensor Operators in the Canadian Navy

Naval Electronic Sensor Operators (NESO) in the RCN operates radar and radio detection devices, radar jamming systems and decoys, and gun/missile-firing equipment carried on major naval warships. At sea, NESO work mostly within the ship's 'Operations Room' where they operate some of the most modern and sophisticated warfare equipment at sea today[9].

As members of the ship's combat team, NESO detect, locate and identify friendly and enemy submarines, ships and aircraft. They also support the defence of their ship from all threats. The primary responsibilities of the NESO are to:

- locate and identify unknown radars
- listen to communications from other submarines, ships, aircraft and shore bases
- operate gun and missile-firing equipment used to defend the ship
- conduct intelligence and evidence gathering

The role of the MSRM is to automate this process to manage operator workload to enable the operator to concentrate on key decision making. In this scenario the operator defines the end goal rather than deriving it.

2.4. Biological Inspiration

Biologically-inspired computational intelligence approaches are promising for MSRM modeling and implementation. One of the biological inspirations is coming from the similarity between the ultimate goals of MSRM and the foraging/hunting models in mathematical ecology that have a natural analogy with 'hunting' targets.

Hunters have already had thousands of years of evolution which is a much longer time than humans have had in developing MSRM algorithms [10]. MSRM can be likened to the process of optimising the five primary senses; seeing, hearing, touching, smelling and tasting. In addition, humans also have the secondary senses of balance, pressure, temperature, pain, and motion. The senses work together to let the brain know what is going on around us and helps keep us safe by warning of danger.

The senses work together to provide data for perception of the environment around us. If one sense is not working or only partially working, then the brain optimally allocates resources to the remaining sensors to help compensate for the missing data. The senses collect information about our environment that is interpreted by the brain based on previous experience (and subsequent learning) and by the combination of the information from each of the senses. The brain responds almost automatically to most sensory information which is critical capability for survival. [11].

An example illustrating the utilisation of all our primary senses to correctly identify an object is the simple lemon test. If it looks like a lemon, sound like a lemon, feels like a lemon, smells like a lemon and tastes like a lemon; then we can be confident that it is a lemon. To arrive at this conclusion multiple levels of sensory data needed to be analysed and as each sensor confirms or rejects the classification of the previous sensor the closer we get to positively identifying the object. The brain, segments, processes clusters and cues the next sensor to be prepared to provide the next level of classification.

Hunters and foragers have essentially the same sense organs but over time these have evolved to meet the requirements of predator and prey. For example predators' eyes are placed towards the front of their head, giving them three-dimensional, binocular vision making it easier to judge distance and see small details from further away. This comes at the cost of a limited field of view. Prey animals need all-around vision to see advancing predators. Therefore, their eyes are located on the sides of their head, which gives them a wide field of view (FOV). They are able to look in either direction and are sensitive to the slightest movements. Once observed a predator moves to a tracking mode whereas a prey moves to an avoidance mode.

2.4.1. Perception

Sense organs are used to receive information from the environment. Each sense organ is part of a sensory system which receives sensory inputs and transmits sensory information to the brain.

A major theoretical issue on which psychologists are divided is the extent to which perception relies directly on the information present in the stimulus. Some argue that perceptual processes are not direct, but depend on the perceiver's expectations and previous knowledge as well as the information available in the stimulus itself. This controversy is discussed with respect to Gibson (1966) who has proposed a direct theory of perception which is a 'bottom-up' theory, and Gregory (1970) who has proposed a constructivist (indirect) theory of perception which is a 'top-down' theory [12].

The bottom-up approach uses sensor data to influence perception. Gibson's theory states that perception is defined by the ‘what you see is what you get’ phenomenon. The theory states that the environment can supply sufficient details related to the stimulus so perception of the stimulus may not depend on prior knowledge or past experience. The theory is data driven and perceives current events.

Top-down processing is defined as the development of pattern recognition through the use of contextual information. Gregory's theory, illustrated in Figure 2, states that perception is a constructive process that uses a combination of past experience and prior knowledge to make inferences. His hypothesis is that perception of reality is based on the environment and prior knowledge. This approach helps predict future events and is model driven [12].

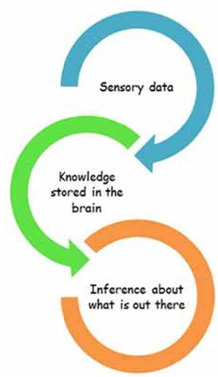


Figure 2 Top-down Processing Model [12]

2.4.2. The Brain – A Distributed Hierarchal Processor

There is not one single area within the brain where all sensory data is combined rather there are multiple function-specific areas that combine information from multiple senses or combine information from other multi-sense regions [13].

The cerebral cortex is the outermost layer that surrounds the brain. The cortex is divided into four different lobes, the frontal, parietal, temporal, and occipital, which are each responsible for processing different types of sensory information.

The cerebral cortex is involved in several functions of the body including [14]:

- determining intelligence
- determining personality

- motor function
- planning and organisation
- touch sensation
- processing sensory information
- language processing

The cerebral cortex contains sensory areas and motor areas. Sensory areas receive input from the thalamus and process information related to the senses. They include the visual cortex of the occipital lobe, auditory cortex of the temporal lobe, gustatory cortex and somatosensory (sensation) cortex of the parietal lobe. Within the sensory areas are association areas which give meaning to sensations and associate sensations with specific stimuli [14].

Multisensory integration is the study of how information from the different sensory modalities, such as sight, sound, touch, smell, self-motion and taste, may be integrated by the nervous system [15]. The modality allows for data to be filtered but not modified [16]. A coherent representation of objects combining modalities enables meaningful perceptual experiences. Multisensory integration also deals with how different sensory modalities interact with one another and alter each other's processing. As an example, the superior colliculus combines sound and vision for the purpose of object localisation.

2.4.2.1. Selective Filtering or Sensory Gating

Although there are several regions of the brain involved in each sensation, the part of the brain involved in selective filtering is where all of these senses intersect. The area of the brain responsible for filtering incoming sensory data prior to it being processed is known as the thalamus.

Classically, the thalamus was thought to function as a relay where sensory neurons meet and were sent to their destination in the cerebral cortex. However it is now understood that in addition to connections from the thalamus to the cerebral cortex, there are also connections from the cortex to the thalamus and that these connections function in manner similar to feedback. When the cortex receives information that it deems a priority for the current task it sends a signal back to the thalamus instructing it to inhibit transmission of other ‘irrelevant’ signals being forwarded from the thalamus to the cortex [17].

This sensory filtering or gating prevents an overload of irrelevant information in the higher cortical centers of the brain. Failure of the thalamus to restrict irrelevant data results in sensory overload that can result in mental illnesses such as Autism disorders and Schizophrenia [18].

2.4.2.2. Synchronisation:

One theory, reported in the literature, is that synchronisation of neural activity permit signals from different sensory areas, related to a common object, to arrive at convergence neurons within the same time window [12]. This allows information from different objects to be ‘time sliced’ so that information from the same object converge and are processed simultaneously.

2.4.2.3. Memory

Memory plays an important role in how the brain organises the world. Short-term memory allows the tracking of an object that is momentarily hidden from view so that it is recognised when it reappears. Memory enables the understanding of the underlying structure of the world so that when parts are sensed they can be related to each other using prior knowledge.

Some theories, such as that proposed by O'Regan [19], suggest that the world itself is used to bring reality together. The brain, via sensory perception merely builds various indices onto the known world. When there is a requirement to know more it can be found in the knowledge of the known world without the requirement for additional sensed data. What keeps things integrated in our mind is because the world out there is integrated, and the brain is just adapting to it. This theory helps explain how individuals with limited or blurred vision can perceive objects in focus.

2.5. Summary

This section has provided an overview of the role of MSRM in a NCMS. Definitions of MSRM from the literature were given and a definition guiding this report proposed. This was followed by a historical overview of sensor management in a naval combat system and reviews the role of the Naval Electronic Sensor Operator (NESO) undertaken. The section concluded by undertaking a cursory look at how the human brain addresses multi-sensor management and techniques used to avoid sensory overload that could be of value in a MSRM system.

3. Sensors and Sensor Resource Managment

3.1. Sensors

Sensors make physical measurements from which information is extracted and can be broadly classified into two categories:

- Passive sensors measure and report on observed changes in their environment. They rely on objects-of-interest being detected by observing disturbances in the background environment. These sensors have the advantage of obtaining information without emitting signals that can be exploited by an adversary. Passive sensors can be effective in cueing active sensors.
- Active sensors transmit known signals that propagate out and are scattered back to a receiver from objects within the path. Signal processing is then used to extract information on the object such as location, speed, size, classification, etc. Operating in an active mode reveals the location of the emitting source that can be exploited by an aderserary.

3.1.1. Primary Sensors for Target Location

Radar, optics and sonar sensors are examples of primry sensors that can be fielded in both passive and active versions. These primary sensors yield information about distant objects for situation awareness (SA) as well as engagement support (ES) [20]. As noted in [21] one of the current goals of the United States Navy (USN) is the standardisation of sensors for dual use applications such as SA and engagement support.

3.1.2. Position-Sensing Devices

Position-sensing devices and inertial sensors produce real-time local measurements that can be used to control a variety of platforms, including whole ships, steerable radar and communication antennas, gun mounts, unmanned vehicles, as well as missiles in flight.

3.1.3. Ancillary Sensors

Other sensors produce measurements for which the long-term variations in the measured parameters provide information that can be exploited. For example, temperature or atmospheric pressure sensors provide data related to both short and long-term weather prediction that can be utilised to optimise the signal generation and processing algorithms of primary sensors such as radar.

Ancillary sensors are also incorporated into the primary sensors to provide information on the physical condition of that sensor. This data can be used to provide operators with alerts of system failure or system degradation and the cueing of back-up sensors when available.

3.2. Information Available from Primary Sensors

Primary sensors provide information that can be exploited to provide [22]:

- **kinematic state information**, a target's intent can often be inferred from target temporal and spatial behaviour
- **search information** represents the uncertainty of where targets are as a function of spatial position
- **target identification** differentiates one target from among a set of possible target types

These primary sensors form part of a collaborative network. For example, low-resolution long range sensors are used for wide-area searching to locate the presence of a target. This information is then used to cue or hand-over to more capable higher resolution sensors or sensor operating modes to track, classify and engage the target. Combinations of sensors are usually required to provide an effective all-weather capability and special processing modes can determine the presence of a target even though it may take another mode or sensor to localise it. Information regarding the current and past location of a target reduces uncertainty about the intent of an adversary which may include association of non-traditional information types [23].

3.3. Review of Sensor-Dependent Operational Tasks and Missions

Within the navy mission, sensors are core to providing data to support a wide variety of operational tasks and missions including:

- situation awareness
- general foe/friend information
- surveillance
- threat detection, recognition and localisation
- weapons targeting both offensive or defensive
- logistics and maintenance

3.4. The Role of Sensors in Target Engagement

As illustrated in Figure 3, sensors are used to acquire a target of interest, track the target and undertake a threat analysis and engage if appropriate.

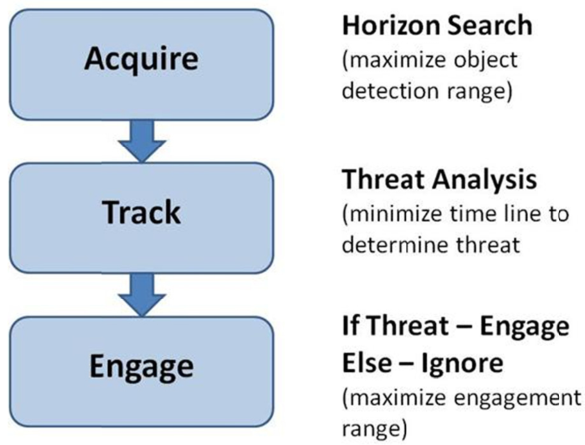


Figure 3 Stages of Target Engagement

An example of a target engagement timeline for an incoming missile is presented in Figure 4. In this example the range at which the missile is first detected is determined by the onboard radar. The radar subsequently tracks the incoming target until it can be identified and an accurate position determined. This may require additional information obtained from other onboard sources to be associated with the track data. At the point where the threat has been established, effective counter measures can be launched and weapon systems engaged. From the time-line presented it can be observed that this range is currently considerable less that the effective kill-range of the onboard weapon system.

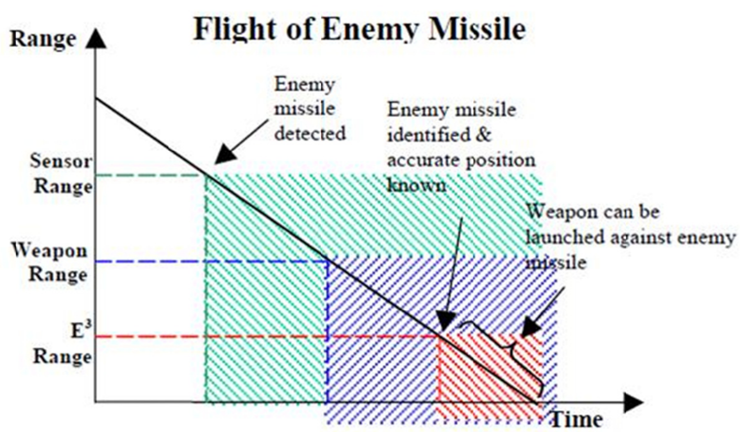


Figure 4 Target Engagement Timeline [24]

The objective of the MSRM is to approximately match the E3 range to that of the onboard weapon range. This requires minimising the time difference from when the missile was first detected to when the threat can be identified. This can be achieved by effectively managing the onboard sensors and systems and when appropriate utilising data obtained from deployed forward looking autonomous and semi-autonomous vehicles, as well as sensors available from other members of the battle force (BF).

3.5. Cognitive Sensing

Cognitive sensing is the process by which a sensor adapts itself based on knowledge of its local environment. This enables the sensor to maximise the information gained on an object-of-interest. Achieving this may require the exchange of information between sensors. The principal components required for cognitive sensing are presented in [25] as:

- informed decision making
- passive environmental sensors and active sensors
- learning algorithms to improve performance and adapt to unknown environmental scenarios
- the knowledge database that contains environmental, clutter, target, and other *a priori* information
- the waveform solution space for known targets of interest
- receiver-to-transmitter feedback to mitigate clutter/interference and maximise target information

The technologies needed to support these six principal components include:

- signal-processing
- algorithms to process target, clutter and environmental information
- digital hardware, including memory
- reconfigurable analog hardware for the sensor receiver and transmitter

A generalised cognitive radar framework is presented in Figure 5. Awareness of the environment is enabled through the use of radar transmitters, radar receivers and environmental sensors. The multi-function radar (MFR) target information processor incorporates multiple radar functions to achieve a better understanding of the target and the environment. The decision process uses past and present target information from multiple radar functions. The schedule and control function provides the necessary feedback to the other cognitive radar processes. An optimal waveform is then synthesised and transmitted into the environment, and the entire process repeated. The repeat cycle of operations adapts the cognitive radar to the environment over time to achieve learning [25].

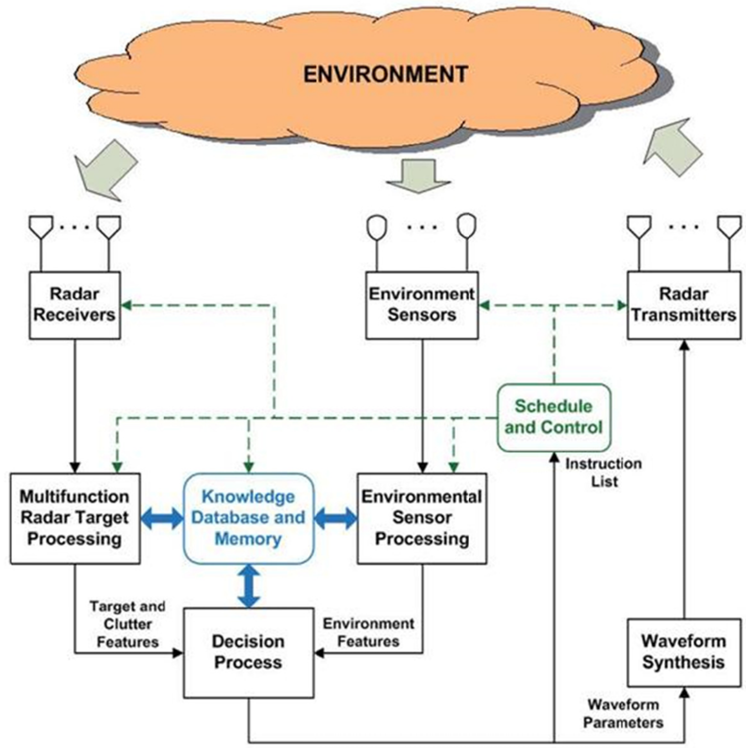


Figure 5 A generalised cognitive radar framework [25].

3.6. Sensor Resource Manager (SRM)

The SRM is the first step in maximising range at which a target can be detected and accurately tracked.

As discussed in the companion report [1], sensor hardware has reached a level of maturity where there is little expectation, in the short term, of significant improvement in their core design. Advances in performance to meet emerging threats will be gained primarily through the optimisation of the signal processing of existing sensor systems to match the operational environment. This process is known as sensor resource management and is achieved using a SRM.

The role of the SRM is to optimally adapt sensor behaviour to dynamic environments and to achieve this in a timely manner so that the information gain remains relevant. SRM makes use of the fact that modern sensors have a large number of controllable parameters that can adapt and self-optimise their performance in a dynamic environment. The SRM performs the function of optimally configuring a sensor to meet defined sensing objectives during an evolving mission.

3.6.1. SRM Responsibility

The SRM is responsible for the management of a single sensor. It is concerned with implementation of ways to improve and optimise the on-going sensing process, and consequently the data fusion process.

This management concerns the control and configuration of the sensor to optimally achieve the sensing objectives. Sensor task scheduling and sensor parameterisation are sensor specific activities undertaken by the SRM.

A SRM controls the degrees of freedom in an agile sensor system to satisfy operational constraints and achieve operational objectives. Modern sensor systems typically operate under resource constraints that prevent the simultaneous use of all resources all of the time. The SRM has the capability of actively manage sensor resources by:

- changing the sensors operating configuration in reaction to previous measurements
- evolving mission requirements
- or otherwise gained knowledge

SRM becomes critical when it is not feasible to collect and process all the data all the time.

3.6.2. Expectations of the SRM

At its simplest level, a SRM is a control process that must deal with [26]:

- highly dynamic environment
- insufficient sensor resources
- varied sensor capabilities
- varied sensor performances
- randomly occurring sensor failures
- counter measures

A SRM is expected to:

- reduce the operator workload by automating sensor allocation
- minimise unnecessary emissions
- prioritise measurement requests to meet evolving mission objectives
- facilitate data fusion by coordinating information requests with sensor observations
- support sensor reconfiguration and degradation due to partial or total failure of a sensor

3.6.3. Levels of Management

SRM concerns the management of a single, multi-mode or multi-function sensor. The following represents the different levels of management that the SRM can perform [27].

- control
- configuration

- allocation

The controller ensures that the system level goals are achieved. Configuration optimises the systems parameters to achieve the sensing objective. The allocator assigns resources based on decision-making about what information needs to be gathered from the environment and what actions need to be taken to gather it. For example, sensors with track-while-scan capabilities can observe and track an object while continuing to scan for additional objects of interest.

As noted [27] this dynamic allocation of resources eliminates the scenario of prioritising attention to the first detected object and not applying sufficient resources to simultaneously seek additional objects of interest.

3.6.4. Other Functions of the SRM

Benaskeur [27] notes that in addition to the tasks discussed in section 3.6.3, the SRM must also undertake several other management tasks implicated by the constraints imposed by the environment, the doctrines and/or the technology. For example:

- **Time management** to ensure synchronisation and real-time operations. Sensor management system is often called upon to respond to high data rates and time-critical requirements under severe limitations.
- **Uncertainty management** ensures that performance degrades gracefully in the presence of increasing uncertainties. Since the SRM often operates on the basis of incomplete, inaccurate, missing and/or misleading information, the sensor management must make the best use of the accurate pieces of information it possesses. An internal model of uncertainty (probability, possibility/fuzzy sets and/or belief) must therefore be included.
- **Emission control management** to minimise emissions that could provide an adversary with information regarding the location of the sensor that subsequently increases the vulnerability of the whole combat system. The use of such sensors must therefore be limited to when and where there is a requirement and may include operation on a Low Probability of Intercept (LPI) mode. An optimisation criterion for the SRM is to minimise the detectability and/or the identification of its own sensor suite. This can be achieved by controlling the emitted power, its duration and the spatial coverage of the active sensors as well as the type of emitted waveform.
- **Countermeasure management** reduces the effects of the enemy countermeasures to the performance of the sensor suite. This concerns the Electronic Protection (EP) that aims at taking actions to protect sensors from any effects of friendly or enemy use of electronic warfare that degrades, neutralises or destroys combat capability.
- **Operator interface management** controls, via the C2 system, the interactions between the operator and the SRM. Within the NCMS the ultimate authority and responsibility belongs to Commander and his staff, therefore the ‘operator interface management’ system must take into account their commands and preferences by providing an interaction interface with the operators.

3.7. Radar Resource Manager

The primary radar and sensor on a modern surface combatant vessel is the MFR. This is typically an Active Phased Array Radar (APAR). These radars are capable of multiplexing their time between many different functions: the primary functions usually being volume surveillance and multiple target tracking.

The APAR radar supports multi-mission capabilities such as swarm defence, anti-piracy, Unmanned Autonomous Vehicles (UAV) control and weapon system support for active missiles. These different types of targets put different requirements on the radar: air defence requires long range, high diving missiles require elevation coverage, sea skimming missiles require fast reaction time, hovering helicopters require spectral information and UAVs require excellent clutter suppression.

MFR have to provide a large number of fire-control channels, simultaneous tracking of both hostile and defending missiles and mid-course guidance commands. As a multi-function and high-performance radar system, APARs have the advantages of flexible beam pointing direction, versatile waveforms, controllable system parameters, as well as the effective resource allocation strategy and powerful data processing capacity. The enabling technology for effective deployment of an APAR system is the radar resource manager that prioritises and schedules tasks as well as parameter control for optimal radar performance under a dynamically changing environment.

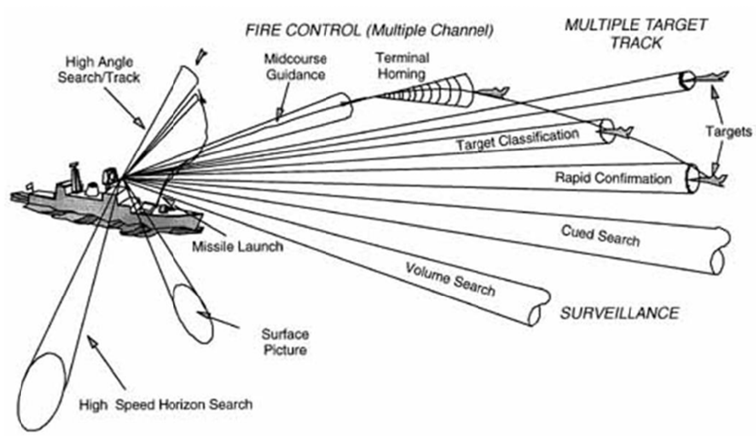


Figure 6 Typical Tasks of a Naval Active Phased Array Radar [28]

A detailed review of the Radar Resource Manager (RRM) for a naval APAR is given by Ding [29].

3.8. Electro-Optical/Infra-Red (EO/IR) Resource Manager

As reported in [21], significant research is being undertaken to adapt and integrate different EO/IR sensors to work together such that they can become greater than the sum of their parts, and therefore provide increased situational awareness. EO/IR sensors serve as the eyes of deployed military forces. EO/IR are critical sensors across RCN missions including navigation, force protection, surface warfare and anti-air defence. EO/IR sensors provide both day and night, long-range visuals on targets that: support target classification and identification, perform threat assessment, assess intent in accordance with the rules of engagement, and support weapons engagement through automatic tracking and fire control solutions. The sensors also support assessment of engagement effectiveness.

As noted by Wilson [21], one way EO/IR sensors are evolving is dual-purposing them for both situational awareness and weapon engagement. Maintaining the technological edge depends not only on improving individual sensor technologies, but also on:

- combining two or more sensors into a single device
- fusing raw data
- on-platform processing of data into useable information
- real-time sharing of that information across all assets, from theater commanders to individual war fighters

Wilson also notes that the stated USN objective for wide field-of-view (FOV) sensors is to add an auto-detection and multi-target tracking capability to achieve:

- wider situational awareness
- greater weapons systems engagement support

The focus is on seamlessly integrating wide FOV and narrow FOV sensors, with the latter supporting identification, threat assessment and determining of false alarms, etc. Shortwave IR sensors provide improved performance over visible band sensors when the visual environment is degraded. The intent is that the imagery provided will relieve some of the workload and improve situational awareness in cluttered environments. The challenge is managing of all this additional imagery and displaying only relevant information that supports the current mission objectives.

Wilson [21], also states that future EO/IR system (or similar hyper-spectral imaging sensor) will significantly increase operator situational awareness by providing the ability to discern land, sea and waterway features, and objects, such as small boats and patrol craft and other objects of interest that have very low radar signatures in near-shore environments where surface radar performance is limited.

3.9. Integrated Sonar Suite

As noted in [30], Integrated Sonar Suite (ISS) systems work primarily on data association and fusion thereby giving an integrated Anti-Submarine Warfare (ASW) picture. ISS is perceived to be fully automatic in operation for detection, classification and localisation of different types of underwater targets. Fire Control Solutions (FCS) work on passive and active sonar data to accurately determine the target range, course, speed and classification. Data fusion and track correlation helps in track assignment in the case of crossing targets. ISS is aided by an integrated sonar prediction model which helps in prediction of expected sonar range from real time bathymetric data.

The development of an integrated sonar suite for surface ships was necessitated by the focus of ASW in littoral waters. As noted in [31] surface ship underwater missions are mainly twofold:

- to sanitise the littoral waters by undertaking Mine Counter Measures (MCM)

➢ to undertake cooperative engagement against any torpedo or other underwater weapon threat

The ISS objectives are:

➢ active detection, tracking, classification and Target Motion Analysis (TMA) of submerged targets
➢ passive detection, tracking, classification and TMA of submerged targets
➢ torpedo detection, classification
➢ deployment of decoys

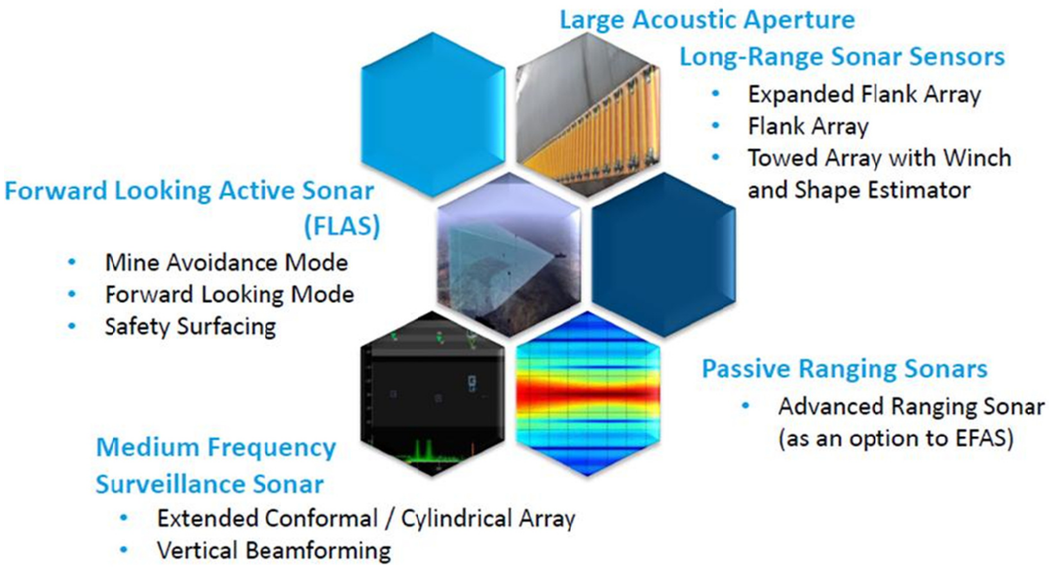


Figure 7 Integrated Sonar Suite [32]

For successful ASW, naval fleets usually combine all their surface, air and subsurface assets and use them tactically. The scouting of a submarine and ASW engagements happens in three distinct phases. They are:

➢ detection
➢ localisation and
➢ targeting

3.10. Summary

This chapter has provided an introduction to the role of sensors that operate in a collaborative network to provide data acquisition, perception and comprehension to improve the effectiveness in countering a threat to the host vessel by increasing the E3 envelope. The chapter discussed the role of the SRM in optimising sensor performance to achieve this objective and concluded with examples of SRMs for radar, EO/IR and sonar systems.

4. Multi Sensor Resource Manager (MSRM)

4.1. Introduction

The previous section introduced the SRM and its use in the optimisation of a single sensor, or group of like sensors. The role of the MSRM is to treat the available sensors and data sources as a collective and using a system-of-systems methodology to dynamically assign sensors and resources to meet evolving sensing objectives at the lowest cost.

4.2. Multi Sensor Resource Manager

The MSRM is the interface that provides feedback from the C2 system to the sensors and regulates the sensors to ensure that only necessary data is collected to support the current and future mission objectives. Whenever there are insufficient resources to perform all the desired tasks the MSRM allocates alternative sensors and resources to lower priority tasks to maximise the effectiveness of the sensing process. The MSRM facilitates obtaining the required level of situation awareness to support overall mission objectives while reducing operator workload and minimising commitment of resources.

The MSRM supports both bottom-up and top-down approaches to perception:

- bottom-up perception is supported by ensuring that the environment is sufficiently sensed to allow the information fusion processor (IFP) to extract the required knowledge of current activity to meet mission objective
- top-down perception is supported by the use of predictive models within the C2 system that use background knowledge to perceive future events that need to be sensed

The MSRM ensures that validation data is collected to support inferences made by model predictions to build trust in these expert systems as well as ensuring that sufficient sensor resources are made available to support future predicted events. The MSRM is also responsible for coordinating the sharing of knowledge between systems to generate additional capability.

4.2.1. Role of the Multi Sensor Resource Manager

The role of the MSRM is to improve the effectiveness of countering an attack by ensuring that sensors provide appropriate, accurate and timely information such that the NCMS can take appropriate action. The overall objective of the MSRM is to maximise the survivability of navy assets [27]. This is achieved by increasing the E3 to allow weapon systems to be engaged earlier [24]. In general, the required track accuracy and update rate increases with diminishing track range. The accuracy and time updates required for threat detection are less than that required for threat response. This difference enables long range, low resolution sensors to be used for threat detection and short-range, high resolution systems to be used for threat response.

Johnson [24] divides sensor management in a multi-sensor environment into two sub-classes

- macro functions that determine of what tasks sensors should perform

- micro functions that determine how a particular sensor will perform its assigned tasking

The MSRM performs the macro functions related to high level strategic decisions about how to best utilise the available sensing resources to achieve the mission objectives. The MSRM addresses the sensor through the individual SRMs. The SRM performs the micro functions of scheduling and optimising the tasked sensor to best carry out sensing requests from the MSRM.

The approach is illustrated in Figure 8, where the macro requirements are flowed down from the C2 System and parsed to the individual SRM by the MSRM. Implementation of the micro functions to support the macro requirements are undertaken by the sensor specific resource manager.

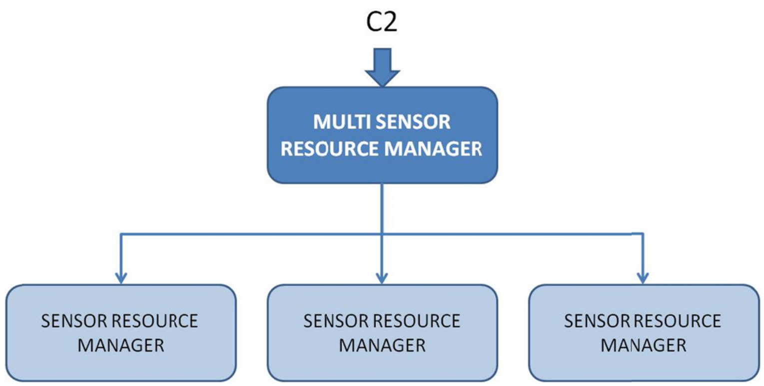


Figure 8 Multi-Sensor Resource Management System

The MSRM uses feedback from the sensors to the C2 system to allow faster adaptation to a changing environment and addresses the problems of insufficient sensor resources, highly dynamic environment, varied sensor performance and capabilities, sensor failure and enemy interference [26].

4.2.2. Requirements for MSRM

The operational requirement of the MSRM is to improve the quality and timeliness of the information that can be extracted from sensor data regarding multiple objects of interest. Different sensors have different attributes that when combined provide greater knowledge of the location, classification and threat level of an object. This leads to the task of optimising sensor resources, in real time, under the operational constraints of each sensor type. Among the common MSRM goals are [33]:

- maximising available sensor resources for search
- optimising sensor resources for tracking
- defending high priority assets in a raid environment

The MSRM allocates individual sensors to complete specific tasks, as defined by the C2 system, in accordance with the needs and priorities of those tasks. The management of the sensors may require that different sensors cooperate to acquire measurements on a common target. For example, dynamically tasking some sensors to fill the coverage gaps of other sensors and therefore provide relevant observations in the areas of tactical interest. The two primary cooperative functions undertaken by the MSRM are cueing and handoff. [27].

The requirements for the MSRM solution presented by Kovalerchuk and Perlovsky [10] are:

- minimise the number of sensors for a given coverage
- maximise the effectiveness of each sensor
- provide dynamic tasking of sensors where multiple sensors cooperate in search, detection, tracking, and identification
- maximise the probability of successfully covering all threat objects
- Implementation of a MSRM provides the opportunity:
- to maximise the available sensor resources for search
- to optimise sensor resources for tracking
- to better defend high priority assets by maximising the target engagement timeline

Kovalerchuk and Perlovsky [10] note that the MSRM goals can be contradictory. For example, typical goals may include the requirement to decrease the overall sensor resource utilisation while increasing the probability that all threat objects are detected and tracked whilst simultaneously minimising the potential of sensor overload of individual units. The chances that all these goals will not contradict each other and will be achieved by a particular solution (assignment of sensors) are low. This consideration leads to the necessity of utilising a multi-objective optimisation approach.

4.2.3. MSRM for Information Gain

Kovalerchuk and Perlovsky [10] proposed the use of MSRM to address the issue of multi-object optimisation. In the scenario presented, two assets are within a common area of interest. They present the argument that if the resources of asset A are fully allocated then there is no room for handling additional tasks. However, if some objects of interest can be handed over to asset B then asset A would be in the position of addressing extra load in the area of higher priority threats.

They also present a situation where the use of individual sensors cannot provide the required level of certainty related to a target so that action can be taken. The situation is illustrated in Figure 9 (a)-(b) which presents the error eclipse for two radars with approximately orthogonal views on a common object-of-interest. In the case presented the uncertainty is characterised by an eclipse where the error in range is considerably less that the error in azimuth. Reaching the required level of certainty is possible by combining the data from the two radars. This is illustrated in Figure 9(c) that shows that the area of uncertainty due to overlap of uncertainty areas for R_1 and R_2 is much smaller with the result of considerable information gain enabling action to be taken at an earlier moment in time.

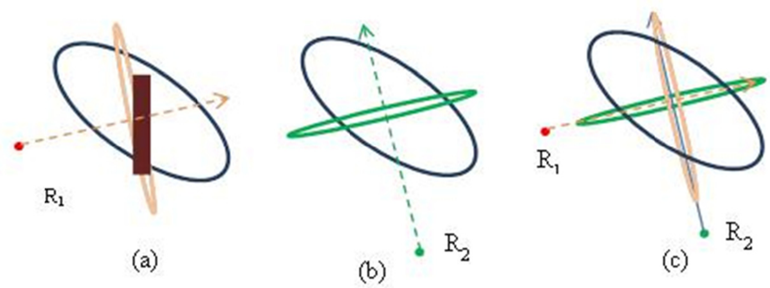


Figure 9 Information gain with allocation of single radar vs. allocation of two radars to the object [10]

4.3. Functions of MSRM

The defining function of the MSRM is the dynamic selection of a sensor, or combination of sensors, from among a set of available sensors, to use during a measurement period in order to optimise overall system performance to a specified goal. The MSRM determines the selection of the next sensor(s) to employ based on prior system measurements to achieve operational objective at minimum cost. This is referred to as 'sensor scheduling'.

4.3.1. MSRM Missions

The three primary MSRM missions are:

- dynamic flow down of mission objectives from the C2 system to the various SRMs including tasking, assignment, parsing and prioritisation
- dynamic allocation of processing resources to the various SRMs
- distribution of external derived sensor parameters to be used within the various SRMs

The MSRM controls the individual SRM so sensors can be cross cued for confirmation and classification. The MSRM system is responsible for:

- sharing computational capabilities across the network
- the control of autonomous entities
- autonomous spatial repositioning of individual sensors

Effective implementation of the MSRM system can lead to graceful degradation in overall system performance of the NCMS in the event of the loss of one or more sensors.

4.4. MSRM as part of a Controlled-loop System

MSRM problem is addressed in [27] on the presumption that it is part of a closed-loop system where the required performance can be specified quantitatively to allow for the definition of the management objective. That is:

- goal specification

- performance evaluation
- action selection

4.4.1. Goal Specification

Goal specification can be divided into two primary categories:

- performance specifications
- robustness specifications

Both specifications must be explicitly stated if the management goals are to be achieved. Performance specifications describe the desired response of the nominal system in absence of uncertainty. The robustness specifications limit the degradation of the performances in presence of uncertainty that may come under various forms. Goal specification must be undertaken under the constraint that the management effort (time and resources consumption) is minimal.

Benaskeur [27] suggests that goal specification may be addressed using control theory, optimisation theory and/or decision theory.

4.4.1.1. Control Theory

In control theory the user specifies the desired level of performance defining the management goal that the closed-loop system is required to achieve [34]. The difference between this and the measured level of performance provides a measure of the system actual behaviour with respect to the desired behaviour. The objective is to minimise this measurement.

4.4.1.2. Optimisation Theory

In optimisation theory the user defines a cost function that, once optimised, leads to the most desirable outcome. This optimisation provides the best trade-off between the sensing action payoff and the associated costs. Khosla [26] presents examples of the application of optimisation theory to MSRM noting that Nash [35] used linear programming to determine sensor-to-target assignment by using the trace of the Kalman filter error covariance matrices as the objective function. Malhotra [36] used Dynamic Programming to solve a Markov process to determine the minimum cost based on a final state and then worked backwards. Washburn [37] used dynamic programming to predict the impact of future sensor management decisions.

4.4.1.3. Decision Theory

In decision theory there is no specified level of performance. The objective is to choose the action that maximises the expected utility function. The best solution is the one that offers the highest utility, i.e., the best achievable performance. Techniques used include; Decision Trees, Probability Theory, knowledge based reasoning, fussy logic etc. Examples are given in [26] and include the use of Bayesian probability theory and influence diagrams [38]. Lopez [39] presented a sensor management scheme based on knowledge-based reasoning and fuzzy decision theory.

4.4.2. Performance Evaluation

This process determines the optimal combination of sensors and systems required to meet the stated surveillance/tracking objective. The criteria for evaluating alternatives are defined quantitatively in the form of measures-of-merit (MOM) that can be determined for each candidate. Information gain is one of most actively used approaches in performance evaluation in SRM and MSRM.

Information collected from widely distributed sensors can be used to determine areas where sensor coverage is degraded and how to allocate alternate resources to compensate. While individual sensors (EO/IR, Radar) can generally determine when a particular portion of the scene is degraded the challenge is to effectively use this information for efficient sensor tasking [10].

4.4.3. Action Selection

When the goal specifications, the environment and the performance measures are known; the core of the sensor management and control problem amounts to selecting the appropriate course of actions (COA). To meet the specifications, the management system reasons and makes commitments on the environment changes (i.e., reactive planning) and commitments on revised goals (i.e., deliberative planning). Dependent on the underlying problem and the model adopted, different techniques exist for action selection. Action selection can be based on Control Theory, Optimisation-based algorithms or Decision Theory.

4.5. Multi-Sensor Management Tasks

As illustrated in Figure 10, Bensaskeur [27] details the tasks to be undertaken in a MSRM as a hierarchy that subdivides the problem into smaller sub-problems that can be considered separately.

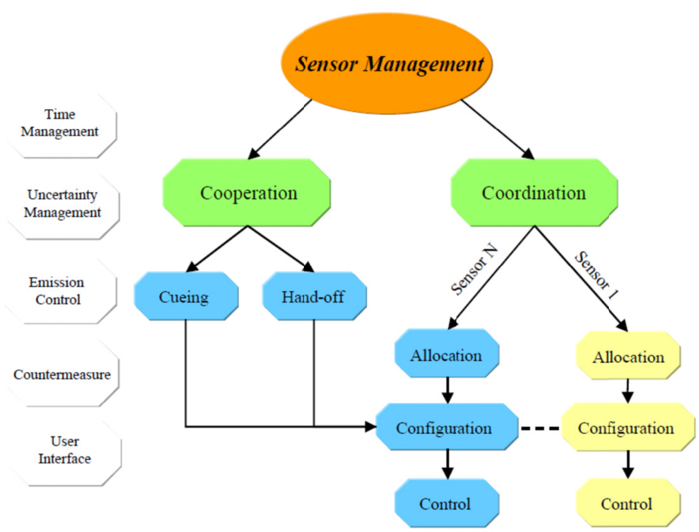


Figure 10 Multi Sensor Management Tasks [27]

The hierarchical approach leaves the single sensor problem untouched and allows the MSRM to focus on the coordination and cooperation of sensors.

- coordination assigns the appropriate sensor or sensors to the tasking
- cooperation dynamically tasks some sensors to fill the coverage gaps of other sensors

The two primary cooperative functions are cueing and hand-off. For example, radar track data may be used to cue an EO/IR system to identify a target of interest. Track data from a surveillance/tracking radar may be used to hand-off to a higher resolution fire-control radar. In both these cases the MSRM would provide input to configure the appropriate SRM to the new task.

The MSRM must also complete various implicit management tasks such as:

- time management to ensures synchronisation and real-time operation such that time critical requirements are met even under sever constraints
- uncertainty management to appropriately weight the data based on accuracy and utility so that the system degrades gracefully in the presence of increasing uncertainties caused by incomplete, inaccurate, missing and/or misleading information

Addressing the uncertainty management problem requires the use of an internal model of uncertainty.

4.6. Emission Control:

MSRM can also be effective in minimising the probability of an adversary jamming a sensor by only having that sensor active at the appropriate time during the evolution of the mission. This operation-on-request relies on the MSRM cueing the primary mission sensor based on knowledge obtained from other systems. Operation-on-request limits an adversary's ability to gain knowledge of the electromagnetic (EM) spectrum of the sensor that would allow them to develop effective Electronic Attack (EA) capabilities.

4.7. Network Resource Manager

The network resource manager optimally allocates a fixed quantity of resources over a network of nodes. Network architectures and topologies were discussed in the companion report [1]. The report highlighted the advantages of implementing a distributed network. A distributed network is a general term for a collection of autonomous computers that appears to an end user of the system as a single computer. A distributed network approach to the NCMS allows easy integration of existing and future systems using a variety of commercial computers and operator displays.

Computers within the network are autonomous and therefore work independently. Resources, such as processing power and memory, can be readily shared within the network even though the computers are at different locations. Key advantages of a distributed network are:

- processors and data storage can be shared across applications
- data used locally can be stored locally and network traffic kept to a minimum

- if data is lost on central site, it can be re-duplicated from the local site
- new locations can be readily added to the network
- no single point of failure

Network Resource Management (NRM) is the process of manipulating resources of a network (e.g., bandwidth, storage, processing power, etc.), in order to improve the performance of the network. Resources are assigned depending on the network needs and the traffic being processed. By managing and allocating resources according to the actual need, the system's efficiency can be increased.

The following network resources are used to increase the system's efficiency in processing data packets [40]:

- bandwidth - limiting the bandwidth of the data-link according to the actual need of the networking processes supported by the data-link
- priority - latency is reduced for the packets with higher priority by processing them ahead of the other packets
- Network Interface Controller (NIC) connects a computer to the network.
- CPUs - on a system with multiple CPUs, a given number of CPUs can be dedicated to support specific network processing

The NRM is used to:

- optimise for throughput, latency, or resource utilisation
- accommodate fault tolerance
- manage multiple application instantiations

In the future it is anticipated that NRM will be able to:

- Automatically generate candidate mappings
- Automatically conduct performance estimates

4.8. Network Centric Sensor Resource Management

The MSRM manages sensors and systems on the host platform and is also responsible for the management of deployable autonomous and semi-autonomous assets to provide a configurable networked sensing system [41]. The network enables the systems to collaborate and self-adapt to both the environment and threat. The MSRM is the enabling technology for implementing a Cooperative Engagement Capability (CEC) that brings Network Centric Operations (NCO), Network Centric Warfare (NCW), Navy Tactical Cloud and Distributed Lethality to the battle space [1]. A prerequisite to implementing a CEC is that the communication time for the transfer of information from one node to another is such that the information remains valid and relevant.

4.9. Distributed Lethality

Distributed lethality is a plan by the USN to assure sea control in coming years by dispersing rather than concentrating naval forces, relying on new weapons, sensors, training and tactics to defeat potential aggressors. The new strategy relies on resilient networks to coordinate the action of warships spread over vast areas of ocean. Every warship is a potential sensor or shooter in the shared effort [42].

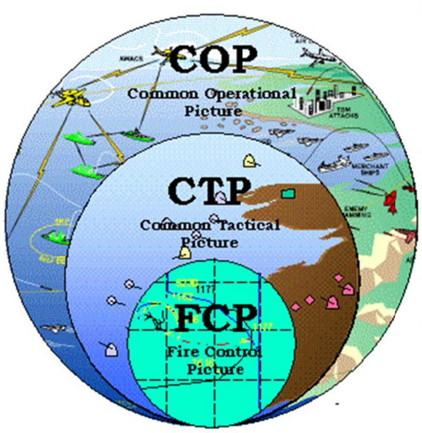
This distributed lethality tactical doctrine implies each ship's crew is trained to find, target, and kill without off-ship support, under a full range of emission control conditions. As ships are added to a surface action group, and other platforms added to the adaptive force package, the group must also be capable of fighting as a team, in any emission control condition [43].

4.10. Requirement for Consistent Battle Space Awareness

Network Centric- Sensor Resource Management is the expansion of MSRM across collaborating platforms. Information superiority is achieved when the Naval Battle Force (NBF) establishes and maintains a shared and consistent battle space awareness across the NBF. As illustrated in Figure 11, information in the Battle Force (BF) is divided into three categories;

- Common Operational Picture (COP)
- Common Tactical Picture (CTP)
- Fire Control Picture (FCP)

Information from all three categories is relevant to the effective and efficient management of BF resources as well as addressing BF threats and operations. Successful implementation of NCO requires consistency between the COP, the CTP and the FCP [24].



COP ~ Non-Real Time (minutes)
- Supports Planning and Force Management
- Deployment
- Movement
- Consists of tactical info, courses of action, enemy order of battle info

CTP ~ Near Real Time (seconds)
- Supports Cueing/Force Management
- Manoeuvre
- Asset Control
- Weapon Sensor Cueing
- Target Weapon Pairing
- Consists of tactical information

FCP ~ Real Time (sub seconds)
- Supports Fire Control
- Launch and In-Flight Fire Support
- Engage on Remote
- Consists of: fire control quality measurements with single threat focus

Figure 11 Three Realms of BF Information [24]

The COP provides top-down information flow of the broader situational awareness to the commanders whilst the CTP and FCP provide tactical bottom-up information flow. To avoid confusion it is crucial that there is consistency in terms of track identification between the tactical and situational displays.

The COP consists of non-real-time tactical information used for mission planning and force management, such as blue and red Courses of Action (COA), a priori knowledge of the enemy, and cultural, political, and geographical features [24]. The CTP consists of near-real-time tactical data and information used for cueing and managing BF resources (sensors, communications and weapons). The FCP is the collection of real-time fire control quality data/measurements used to support weapons during launch and in-flight.

As stated in [24], the challenge involved in attaining 'tactical information superiority' lies in taking full advantage of the capabilities of the distributed sensors and communication resources to best fulfill the dynamically changing needs of the large set of distributed information users. Without implementing the MSRM concept, sensors and other BF resources (links, weapons, etc.) will continue to be managed from a platform-centric perspective which limits their utility to the BF at large. Additionally, both the sensors and communication links have inherent physics-based bounds that limit their area of coverage and accuracy. The MSRM must optimally assign sensors and systems that operate within these limits.

At the highest top-down level is situation awareness. Warfighters must understand everything that they can about the nature of the opposing forces. For example:

- current locations
- movements
- composition
- infrastructure
- capabilities
- communications
- weapons
- threats
- plans

In general the more relevant information that is available the better. For maximum cooperative effectiveness, commanders require the same complete picture of the whereabouts and current capabilities of their own forces, distinguishing accurately between friendly and adversarial forces to minimise or eliminate friendly-fire incidents and maximise the effectiveness of NCO.

Commanders also require an accurate, real-time picture of the environment that they are operating in, for example details of the terrain, the current and anticipated weather, currents and sea-state conditions. In addition knowledge of any areas restricted by the presence of mines or other threats is also desirable.

Generally, in real conflicts, only a few of these factors are actually known to the degree desired. Knowledge of some may be stale and out of date and other factors may only be guessed at and some completely unknown. The better the navy achieves valid situation awareness, the larger the potential competitive advantage they can enjoy [20].

On a shorter time scale, from the bottom-up point of view, effective utilisation of weapons requires detailed and timely information about both the targets and the weapons themselves. Targets must be recognised as such, their positions localised instantaneously, their motion measured to high precision, their most vulnerable aim points identified [20]. Similarly detailed continuous information about the weapons is needed to aim or guide them to a successful interception of target, e.g., weapon position, inertial parameters (such as orientation, velocity, and acceleration) and environmental parameters (wind and tidal currents).

On a much longer time scale, outside actual combat situations, information is needed in several forms to provide for such necessities as equipment maintenance, support and overall logistics. For example; it is necessary to know what has failed or is about to fail, or what the weather will be tomorrow [20].

The goal of an effective CEC is to provide consistent situational awareness distributed across the battle network.

4.11. Expected Operational Benefits from MSRM

Johnson and Green, [24] noted that the realisation of the full benefits of BF sensor resources can only be attained through collaborative inter-platform war fighting schemes or achieving the network-centric paradigm. While these observations are primarily aimed at large battle groups, they also apply to single vessel operations that include autonomous or semi-autonomous vehicles.

The authors state that the BF must be viewed as a single integrated combat system of systems, rather than a collection of loosely connected surface, subsurface and air platforms. When BF system thinking is adopted, the focus shifts from legacy stovepipe systems and platforms with little or no collaboration incentive to optimised use of resources that transcend platform boundaries and span multi-threat dimensions.

As noted in [24], the expected payoffs of achieving network-centric sensor resource management include:

- increased battle space picture accuracy, the MSRM is expected to increase target track accuracy and improve interoperability problem that inhibit inter-platform picture synchronisation
- decreased degraded coverage zones, the MSRM is expected to decrease degraded or no-coverage surveillance zones
- improved surveillance coverage, the MSRM is expected to increase the detection range of the BF
- decreased BF reaction time, the MSRM is expected to decrease the average BF reaction time (aggregate time taken by BF surveillance, command, control and communications systems in responding to an attack)

- optimised economy of resources, the MSRM is expected to better utilise sensor resources an avoid redundancy and non-use by allocating tasks to sensors optimally
- enabled innovative inter-platform sensor usage, the MSRM is expected to enable new sensor-weapon pairings (i.e., remote engagements), avoid legacy stove-piped sensor-weapon pairings and inter-platform sensor operations that would otherwise not be possible or imaginable within narrow decision-making time-lines

The achievement of MSRM across multiple entities supports BF interoperability and information superiority. It ultimately results in the ability to make earlier decisions based on more accurate data and faster, more accurate responses to the increasing threat space. The MSRM enables and encourages the collaboration that leads to a single integrated BF system-of-systems, all of which result in battle space gains.

The expected operational benefits from a MSRM system (presented by Johnson [24]) are:

- effective use of limited sensor resources
- tailoring different sensor capabilities to different mission needs
- cuing sensors based on input from other sensors
- redirecting agile aperture sensors to search in particular sectors or revisit tracks
- managing modes of multi-mode sensors for different tactical applications
- controlling scan rate according to information needs
- effective use of limited operator resources
- limiting operator workload by limiting amount of non-tactical information displayed
- automating lower level control functions
- suppressing sensor-specific details from operator displays and decision-loops
- easing burden of operator interfaces without limiting flexibility of human control
- track picture advances
- enabling automated track quality management through sensor optimisation
- recognising and correcting for track degradation in real-time in an automated fashion
- scheduling track updates only as required for maintaining track quality within bounds
- assigning and updating track quality goals based on each track's tactical significance
- tailoring sensor functions to correct for tracks in dense or obtuse environments
- handling target manoeuvres by using higher-order processing algorithms and techniques
- improving tracking by adaptively modifying processes in real-time, such as modifying the tracking filter or shortening the target revisit time to minimise model mismatch
- sensor fusion and synergism

- controlling different sensors based on their strengths to cooperatively support overall goal
- intra-platform and inter-platform cueing of particular sensors based on tracks maintained by other sensors (one sensor detects, while another tracks)
- minimising or eliminating active sensing (active radar radiation) by using passive sensors for search roles (while maintaining sufficient tracking accuracy)
- improving discrimination techniques by optimising sensor use
- situation assessment improvements
- improving the process of situation assessment by automatically shifting from kinematic tracking to generating target inferences (i.e., target intent, etc.) – enabling feedback link between automated situation assessment function and sensors to improve data collection
- efficiently using sensors for tactical needs by managing sensors based on tactically important data collection schema
- filling in missing information by using sensors to collect data to confirm tactical inferences
- fire control support
- enabling local and remote sensor data collection tasking based on fire control systems (FCS) requirements
- enabling inter-platform engagement coordination strategies

4.12. Challenges to the Implementation of a MSRM

As stated by Johnson [24], the challenge involved in attaining tactical information superiority lies in taking full advantage of the capabilities of the distributed sensors and communication resources to best fulfill the dynamically changing needs of the large set of distributed information users. Without implementing the MSRM concept, sensors and other BF resources (links, weapons, etc.) will continue to be managed from a platform-centric perspective which limits their utility to the BF at large. Additionally, both the sensors and communication links have inherent physics-based bounds that limit their area of coverage and accuracy.

Johnson [24] notes that one of the major challenges in transitioning to NCO is that existing sensor management and C2 systems rely heavily on manual participation. For example;

- NESO have to deal with lower level sensor details than is efficient for making timely and accurate decisions
- lack of effective automated decision aids for supporting the management of sensors across BF platforms
- complexity of missions and operational environment produce a multitude of options and an overload of information, leaving commanders with too much information and too little time to make effective decisions
- existing information processor with in the C2 systems are not designed to provide feedback from the tactical picture to re-task sensors to improve the picture in real-time

4.13. Summary

This section has provided an overview of the operational benefits of utilizing a MSRM and has outlined the key principles and enabling technologies. The section has introduced the Network Resource Manager (NRM) and highlighted its importance within the context of the MSRM in ensuring that bandwidth and computational resources are optimally deployed. The section reports on the expected operational benefits from MSRM and looks at some of the challenges that have yet to be addressed. The section reports on the expected operational benefits from MSRM and looks at some of the challenges that have yet to be addressed.

5. The Role of the C2 System in MSRM

5.1. Introduction

The functions of C2 within the context of the NCMS are discussed in detail in the companion report [1]. This section focuses on the elements of the C2 system that specifically relate to the MSRM.

As noted by Costa [44], military situations are inherently uncertain, and the available data is inevitably noisy and incomplete. Therefore the C2 system must address the following questions;

- Is there a threat?
- Is there another explanation?
- What is the level of confidence?
- If there are multiple threats, which ones should be addressed first?
- What are the recommended actions?

In finding answers to these questions, the C2 system may request the MSRM to acquire additional data or seek relevant knowledge from endogenous or exogenous sources. This data is converted to knowledge using information fusion.

5.2. Function of the C2 System in MSRM

The C2 system within the NCMS supports the MSRM system by providing a complete range of continuous planning and execution capabilities to support operations at strategic and tactical levels. This requires being able to model and predict ahead to support actions at the current, near term and long term time horizons.

The MSRM provides the interface between the C2 system and the sensors. It receives information requests from the C2 and directs the sensors to collect the required information. Information requests from the C2 system may be in support of current mission requirements or perceived future requirements.

The primary objective is to identify potential threats at a greater range so that responsive actions can be taken earlier. This requires the C2 system to undertake a number of tasks including;

- risk assessment
- risk management
- planning
- prediction
- decision making

5.2.1. Risk Assessment and Risk Management

The dual tasks of risk assessment and risk management are core to meeting the mission objectives. Risk assessment is the determination of quantitative or qualitative estimates of risk related to a well-defined situation and a recognised threat. Quantitative risk assessment requires calculations of two components of risk: the magnitude of the potential loss and the probability that the loss will occur [45].

Risk management is the identification, evaluation and prioritisation of risks followed by coordinated and economical application of resources to minimise, monitor and control the probability or impact of these risks. Risk management's objective is to assure uncertainty does not deflect the endeavor from its stated goals.

Risk assessment and risk management can be defined by a 5-step, cyclical, continuous process as illustrated in Figure 12 [46].

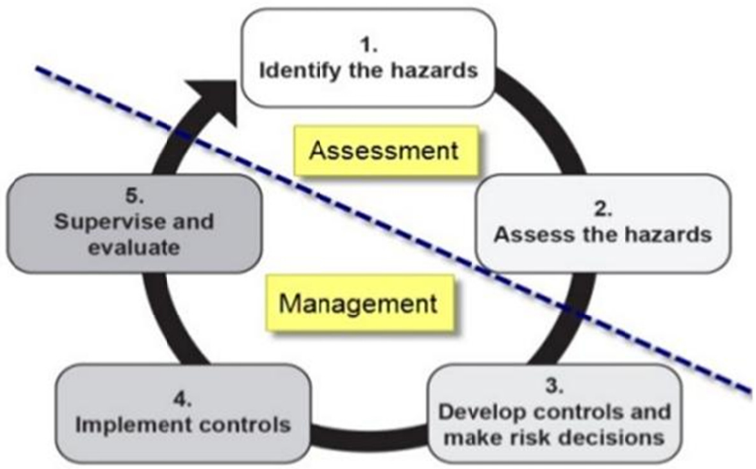


Figure 12 5- Steps to Risk Management [46]

Step 1 and 2 constitute the risk assessment phase. Step 1 identifies the hazard; Step 2 assesses the impact of the hazard. Risk assessment provides for enhanced situational awareness that builds confidence to act in timely, efficient and effective protective manner.

Steps 3 to 5 are the management portions which essentially follow through on actions to effectively manage risks. Commanders must balance risks against costs and take action. Risk assessment is a continuous process and must be assessed and updated during execution as well as planning and preparation. Commanders are required to continually assess the risk to the overall mission and take appropriate remedial action.

5.2.2. Planning, Prediction and Decision Making

Effective MSRM requires that the C2 system includes models for planning, prediction and decision making. Planning is a reasoning process that generates an ordered set of tasks derived from a given goal description. Execution is the enactment of these tasks. The NCMS is required to continually evaluate the situation. It achieves this by;

- monitoring the execution of mission plans
- reacting to conditions affecting the defined goals and plans
- dynamically re-planning so that the end goals may still be achieved

Planning and decision making with the context of the NCMS were discussed in detail in the companion report [1].

5.3. Resource Allocation in a Multi-Sensor Network

When planning resource allocations it is necessary to determine how far into the future the system is required to plan.

Myopic relates to short-term planning. Myopic looks forward one step and picks the action that will provide the best result after the action is executed. Long-term planning explores a multitude of actions and selects an action that is predicted to yield the best result multi-steps ahead. The short term planning provides the best immediate action and is computationally inexpensive. However this myopic solution may not provide the optimal solution at some point in the future.

Long-term planning provides a more optimal solution but is computationally intensive. Khosla [26] proposed a sparse planning method which considers a chain of actions up to a certain time depth when making a decision. The stated advantage over an exhaustive search is that it covers less and less of the action space as the algorithm looks further ahead into the future. This approach results in a significant reduction in processing power [26].

Short-term planning yields better results as a sensor begins to gather information on a target. However long-term planning will yield better results as the target track matures.

5.4. Data Fusion, Sensor Fusion and Information Fusion

Data fusion is the process of integrating multiple data sources to produce more consistent, accurate and useful information than data provided by an individual source. Sensor fusion involves combining sensory data or data derived from disparate sources so that the resulting information has less uncertainty than would be possible when these sources were used individually. Data fusion and sensor fusion are a subset of information fusion. Information fusion is the merging of information from heterogeneous sources with differing conceptual, contextual and typographical representations. Information fusion is used to consolidate data from unstructured or semi-structured resources with the goal of reducing redundancy and uncertainty.

Sensor management and data fusion are two complementary functions. The difference between sensor management and data fusion can be summerised as:

- **Sensor management** addresses how systems can be optimally configured, utilised and coordinated in order to provide the required information, in dynamic environments, at the lowest cost
- **Data fusion** addresses how diverse and sometimes conflicting information is combined in a consistent and coherent manner.

5.4.1. Information Fusion

Information fusion consists of organising a set of data into meaningful reports to answer queries, forge a consistency story and determine situation awareness. Providing situation understanding requires context both in information estimation and data management [47].

Information fusion achieves two objectives;

- estimation (fusion)
- control (sensor management)

Today's rules of engagement have become increasingly fuzzy with the asymmetric threat becoming the normal rather than the exception. To address this threat, commanders have the ability to use an assortment of advanced, networked, sensors to gain a competitive advantage over an adversary. However, there is the danger that in this complex environment the quest for additional information may result in information overload. To address this issue it is critical the C2 system directs the MSRM to regulate the collection and prioritisation of data to the minimal amount necessary to meet the mission objectives.

The goals of today's C2 systems in response to a defined mission are to [48]:

- provide decision makers with a clear, relevant, picture of what is happening
- show how it relates to the current situation
- state what are the response options and their respective consequences

Costa [49] notes that the key to successful tactical decision support systems resides in their ability to deal with increasing amounts of asynchronous data arriving from many diverse sensors, sometimes presenting ambiguous, contradictory or uncertain evidence to support decision-makers. More important, coping in this context requires not only the capacity to collect, store, and access data, but also the ability to make sense of it, and filter to extract data most relevant to solving the decision maker's problem.

Today's operational C2 systems use a rule-based methodology for storing expert knowledge and guiding tactical decision making according to pre-established policies. This technology has been widely used because of its flexibility and relative computational efficiency but, as noted in Costa [49], its simplicity renders the approach incapable of coping with the increasing complexity of modern warfare. The referenced paper notes that alternative schemes to represent complex, intricate situations are usually based on classical logic systems. More specifically, many systems are based on some variation of First-Order Logic (FOL).

FOL is symbolised reasoning in which each sentence, or statement, is broken down into a subject and a predicate. The predicate modifies or defines the properties of the subject. First-order logic can be useful in the creation of computer programs and forms the basis of artificial intelligence (AI). There are more powerful forms of logic, but first-order logic is adequate for most everyday reasoning. For this reason, FOL has become the de facto standard for logical systems from both a theoretical and practical standpoint. However, as noted in [49] systems based on classical FOL lack a theoretically principled, widely accepted, logically coherent methodology for reasoning under uncertainty, thus limiting their suitability for open, uncertain environments where tactical decision support systems operate.

Information fusion is the process that transforms data into information and information into knowledge. Information fusion is divided into two basic levels

- **Low Level Information Fusion** that concerns numerical data such as location, kinematics and target attributes
- **High Level Fusion (HLF)** that concerns abstract symbolic information such as threat intent and goals

Different levels of fusion can take place at all levels within the C2 structure. The Data Fusion Information Group (DFIG) model describes 7 levels of fusion [50] all of which are relevant to the NCMS;

- Level 0: **Data Assessment** (DA) is the estimation and prediction of observable states. Also known as Sub-Object Assessment
- Level 1: **Object Assessment** (OA) is the estimation and prediction of entity states on the basis of data association
- Level 2**: Situation Assessment** (SA) is the estimation and prediction of relations among entities
- Level 3: **Impact Assessment** (IA) is the estimation and prediction of effects on situations of planned or estimated actions
- Level 4**: Process Refinement** (PR) is the adaptive data acquisition and processing to support sensing objectives
- Level 5: **User Refinement** (UR) is the adaptive determination of who queries information and who has access to information
- Level 6: **Mission Management** (MM) is the adaptive determination of spatial-temporal control of assets

Level 0 to level 3 of the fusion model addresses the effective exploitation of data from sensors under the assumption that the sensor configuration has been previously defined [27]. Analysis is undertaken based on current data.

Level 1 answers such questions as [51];

- existence analysis
- identity analysis

- kinematics analysis

Level 2 undertakes a situational assessment at that moment in time, tasks undertaken include:

- behaviour analysis
- activity level analysis
- intent analysis
- relevancy analysis
- capability analysis

Level 3 covers the task of predicting threat behaviour and determines whether a threat or impact exists. This requires reasoning about complex situations in which entities of different types are related to each other in diverse ways. This is particularly true in asymmetric warfare where the threats are elusive, secretive and decentralised. Entities often appear unconnected and their stealthy behaviour is very difficult to predict. Automated methods for reasoning about such complex situations require expressive representation languages that can represent and reason with uncertainty.

High-level information fusion relates to levels above level 1and refers to the ability of a fusion system to use cognition in the form of knowledge, expertise and understanding in order to [52]:

- capture awareness and complex relations
- reason over past and future events
- utilise direct sensing exploitations and tacit reports
- discern the usefulness and intention of results to meet system-level goals

The requirement for reasoning with uncertainty has resulted in the evaluation of many different approaches for addressing HLF of hard and soft information. Two of the most prominent techniques are Bayesian Inference and Dempster-Shafer (D-S) approaches [53]. Bayesian inference unifies learning and inference as a foundational theory of belief dynamics whereas D-S theory addresses ignorance and incompleteness of evidence.

5.4.1.1. Level 4 – Process Refinement

Sensor management differs from sensor control. The Joint Directory of Laboratories Data Fusion Model (JDL-DFM) originally had three levels (object refinement, situation refinement, and threat refinement) but was subsequently amended to add a fourth level called process refinement [3].

Key to MSRM is process refinement. Process refinement is an ongoing monitoring and assessment of the fusion process which refines the process itself and regulates the acquisition of data to achieve optimal results [54]. The MSRM provides the feedback path by which data fusion products are used to control and improve sensor performance.

As illustrated in Figure 13, level 4 (Process Refinement) interacts with each of the other levels.

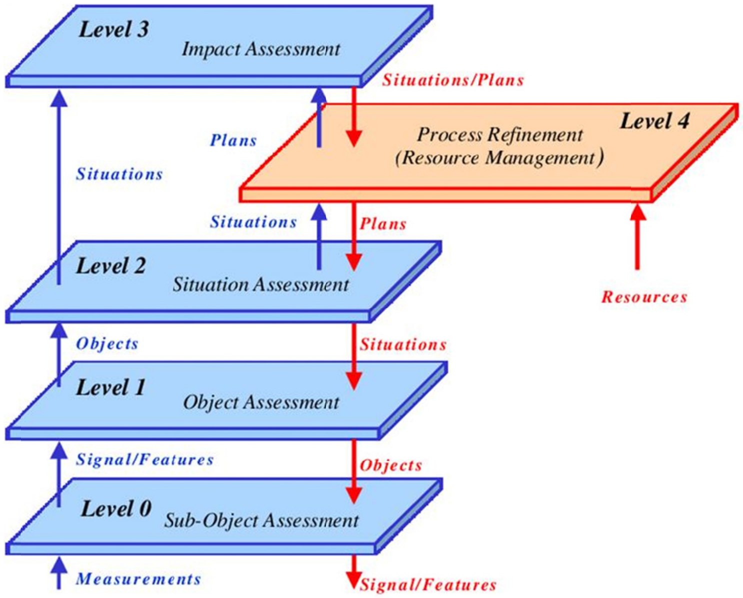


Figure 13 JDL model of data fusion process level 0 - 4[27]

Process refinement addresses both external and internal processes. The external process is concerned with providing sensors with positioning information based on forecasted or anticipated movement. Internal process is concerned with projection, anticipation and forecasting and is accomplished by analysis based on prior or learnt knowledge.

Process refinement supports the development or analysis of [51]:

- adversary intent
- COA that includes a prioritise list identifying the most likely and most dangerous threats
- a set of collection requirements

Level 4 process refinement addresses the optimisation of the whole fusion process [27] and can be subdivided into various functions [3]:

- evaluation of data leading to real-time sensor control to meet predicted requirements
- fault detection and reaction
- performance measurement
- source requirements
- effectiveness measurement
- process control
- knowledge development

- sensor services
- qualified data requirements
- reference data requirements
- fusion control
- position and identity requirements
- situation assessment requirements
- threat assessment requirements
- mission management
- mission requirements
- resource management

McIntyre [3] views a sensor system in terms of the two separable functions of estimation and control. Target state and parameter estimation is the domain of the data fusion process. Mission management, sensor management and sensor scheduling are the domain of control. It is noted that estimation and sensor fusion processes are local, rather than global optimisations. Local here meaning that the estimation process can be partitioned as a subsystem of the sensor system and its control process.

5.5. Role of Process Refinement in MSRM

The MSRM is the interface that provides feedback from the fusion processor to the sensors to improve perception of the environment. The fusion processor initially requests what data needs to be collected to support current mission objectives. The sensors collect the requested data and deliver it to the fusion processor where it is analysed and information is extracted. The fusion processor then delivers feedback in the form of requests to the sensors, via the MSRM, in order to manage the collection of future data to better meet evolving mission objectives.

The MSRM manages the interaction of process refinement (level 4) with object refinement (level 1). In this context, process refinement addresses the external task of providing sensors with positional information based on anticipated movement and also selects the best sensor to provide the required data based on the current mission objectives and environment. Process refinement also addresses the task of acquiring data to support situation assessment (level 2) and impact assessment (level 3).

Exploitation of sensor data from diverse sensors provides the capability of producing significant tactical benefit that contributes to more complete situation awareness. Multi-mode sensor data products support:

- target detection
- location
- classification
- environmental data

The MSRM provides real-time feedback that is used to task and schedule the individual sensors. For example, an object being adequately tracked by a lower value sensor may be removed from the tasking of a higher value sensor so that the higher value sensor is prioritised to focus only on those objects remaining either undetected, require track improvement or target classification.

5.5.1. Level 4 Process Improvement for Enhanced Situational Awareness

Chang and Hill [55]developed a hierarchical valuation function to optimally schedule sensors based on both level 1(OA) and level 2 (SA) feedback received from the process refinement function. Their hierarchical, data fusion, functional model includes estimation and prediction of relations among entities, force structures and cross force relations, communications and perceptual influences, physical context, etc. The referenced paper describes the development of models that estimate relationships among entities which contribute to improving SA that is then used to optimally manage sensors. This is achieved by using the key performance measures of:

- Tracking Quality (TQ) that represents the quality of the track state
- Classification Quality (CQ) that represents the confidence in the classification state

Both TQ and CQ are assigned a numerical weight. The evolution in response to sensor actions can then be represented by a Markov chain which is a stochastic model that describes a sequence of possible events in which the probability of each event depends only on the state attained in the previous event.

For example, the TQ state can be described as:

- undetected
- detected
- new track
- updated track
- coasted track
- dropped track

And the CQ state can be described as:

- unclassified
- low confidence
- medium confidence
- high confidence

The two states (TQ & CQ) are combined within a Morkov model that considers all possible state-combinations to develop appropriate weights that represent priorities. This information is made available to the MSRM and used to focus specific sensors on time critical objects that represent a threat, or cue other sensors to improve both the TQ and CQ of an object of interest to determine if it represents a threat.

5.5.2. MSRM and Interactions with level 2 and Level 3

Resource Management and its interactions with level 2 and level 3 fusions is discussed by Blasch et al., [23] and models for planning, interactions modeling and decision making presented. The authors note that for optimal level 1 processing and maximising knowledge captured at level 2 and level 3, it is necessary to have the ability to control level 1 through 4 processes. In addition, the authors note that if level 2 and 3 processing is used to establish relationships and associations among entities then they require prior knowledge to rapidly assess, interpret and predict what these relationships are. The processes are required to control the fusion process via the resource manager for optimum information-knowledge capture and decision making by:

- planning
- predicting
- anticipating
- adaptively learning

The paper [23] notes that the attributes described above are similar to the characteristics of human perceptual reasoning embodied in an adaptive, anticipatory, closed-loop, feedback information control mechanism known as the Perceptual Reasoning Machine (PRM). The information flow among process resource management elements is illustrated in Figure 14. It can be observed that the PRM consists of a feed-back planning and resource management system whose interacting elements are: assess, anticipate, preplan and act. That is:

- gather and assess current events
- anticipate future events
- preplan and act (predict) on information requirements and likely threats
- plan the allocation of resources and acquisition of data through the control of a separate distributed MSRMS
- interpret and act on acquired data (sensor, spatial and contextual) in light of the overall situation by interpreting conflicting/misleading information

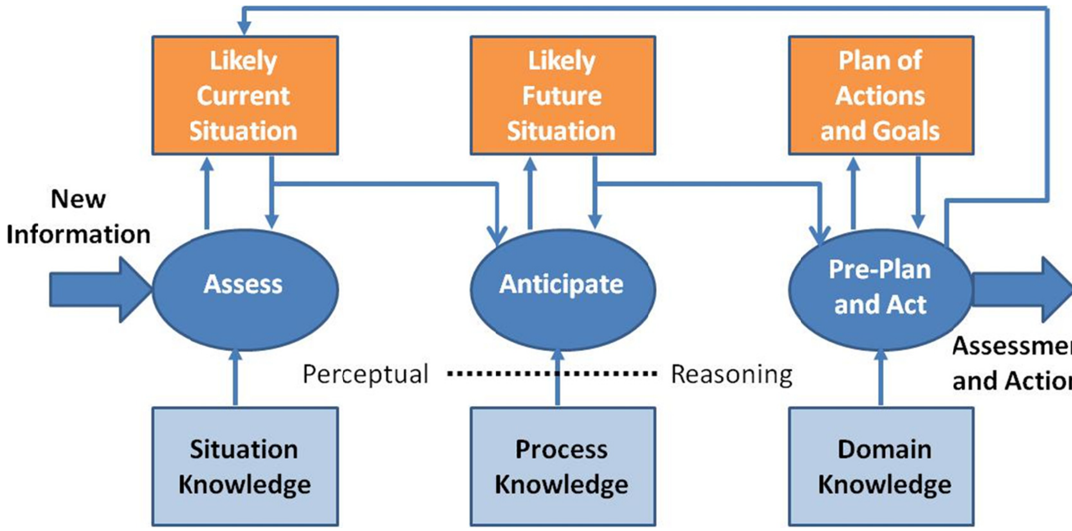


Figure 14 Information Flow among Process Resource Management Elements [23]

5.6. Architectures for Multi-Sensor Fusion

Sensors provide data that is subsequently processed to determine what activity is taking place in the sensed domain. A simple model of a single sensor is the 'Activity Recognition Chain' (ARC) as represented in Figure 15. In this model, data is acquired and preprocessed. The data is then segmented into relevant sub-sets and features extracted using segment specific processing algorithms. The final stage combines the extracted features to track and classify the sensed object.

MSRM must address the problem of handling diverse information received from substantially different sensors that may arrive at different times. In general there will be more than one sensor source and the model can be expanded to include either a centralised data fusion engine as, illustrated in Figure 16, or a distributed hierarchical classifier/fusion engine as illustrated in Figure 17.

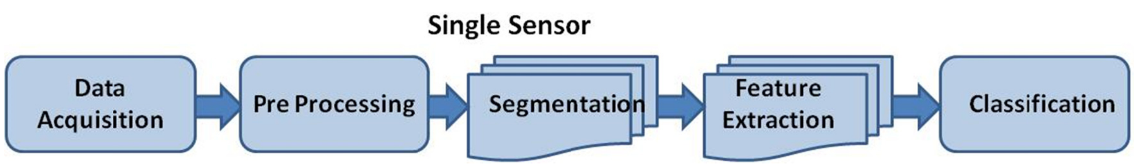


Figure 15 Activity Recognition Chain[56]

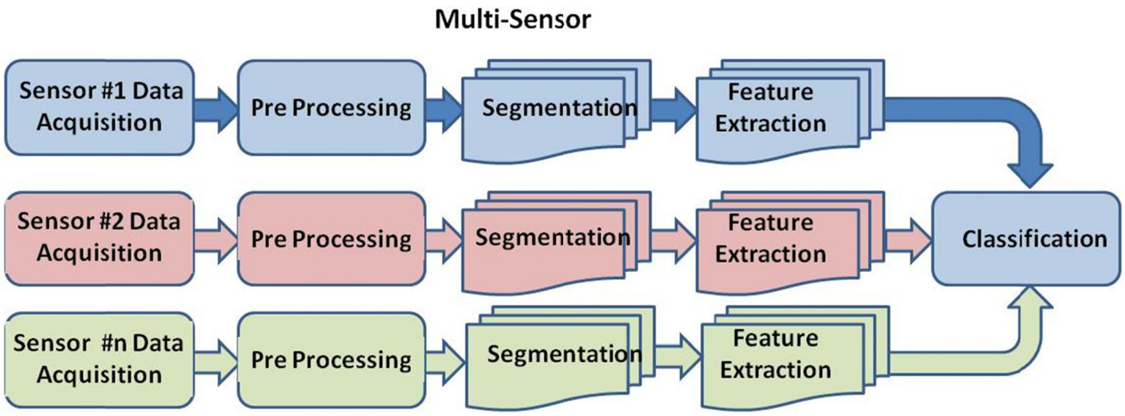


Figure 16 Multi-Sensor Activity Recognition Chain with Centralised Classifier[56]

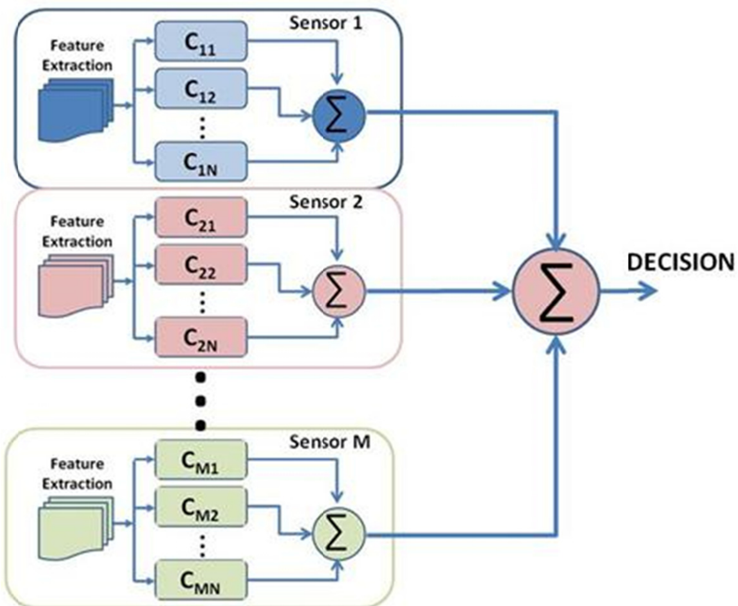


Figure 17 Multi-Sensor Hierarchical Classifier[56]

In the hierarchical decision fusion processor, decisions are passed up a tree of intermediate levels where certain nodes are given higher priorities than other nodes [56]. In the model, the decisions are provided by different level classification entities (hierarchical classification). Each decision is rated according to the classification capabilities of each entity. This weighting procedure supports an optimal exploitation of the classification potential of each individual entity allowing for the definition of a precise collective knowledge structure.

5.7. Centralised or Hierarchical Fusion/Classification

Traditional C2 systems typically incorporate a centralised tracker and fusion processor that accept raw or semi processed data from the sensors. This centralised approach is computational and bandwidth expensive. In the centralised approach, the sensor role is to produce measurements which are transmitted to the centralised tracker and fusion processor. The processor takes the measurements received from each sensor and uses them to refine the current state and determine the future state.

The move today is towards hierarchical or de-centralised operations that cluster similar co-located sensors together and outputs tracked and extracted features to the next level fusion processor. In the de-centralised system, each node's state is only dependent on that node's prior state [26]. This approach has the advantage that trackers can be customised for a particular sensor set. Decentralized configuration avoids issues with time delays and non-synchronous data. Computational loads and communication bandwidth requirements are significantly reduced when compared to centralised system as only relevant information is passed to the next stage.

5.8. Architecture for a MSRM System Based on JDL Data Fusion Model

Figure 18 presents an architecture for a NCMS based on the JDL data fusion model that has been extended to incorporate both a MSRM and NRM. The DSS ingests mission requirements from the C2 system to task the IFP, MSRM and NRM. The DSS support utility refinement and develops the action plan. The MSRM receives data and information requests from the IFP and allocates these requests to individual SRM to complete.

The figure illustrates that MSRM provides information feedback from the data fusion products to the individual sensors.

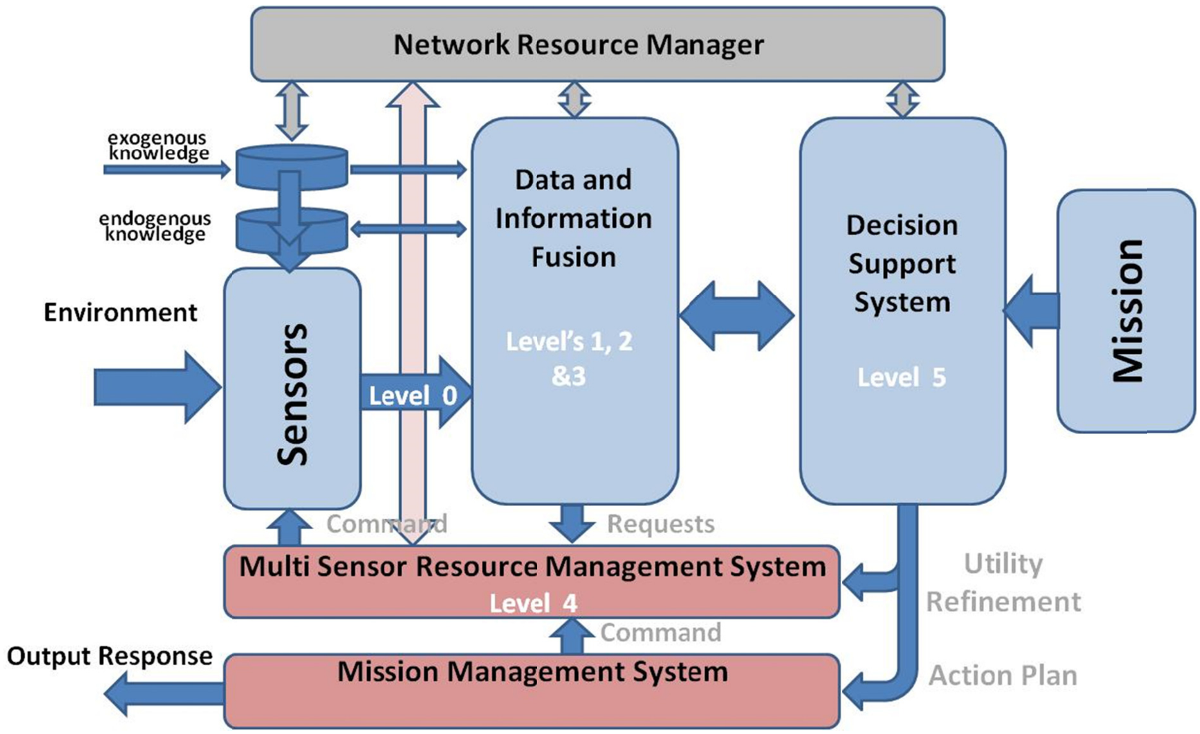


Figure 18 Proposed Architecture for a MSRM System based on JDL data fusion model and incorporating a Network Resource Manager (NRM)

5.9. Summary

This section has reviewed the interactions between the Command and Control (C2) system and the MSRM. Attention focused on the tasks of risk assessment and risk management. The Data Fusion Information Group (DFIG) model was introduced and the role of process refinement in improving overall SA discussed. Architectures for multi-sensor fusion based on models for Human Activity Recognition Chain (HARC) for single and multiple sensors were presented and the benefits of centralise and distributed data fusion was discussed. The section concludes with the presentation of an architecture for MSRM system based on DFIG data fusion model.

6. Human-in-the Loop, Cognition and Artifical Intelligence

The increased sophistication of sensors coupled with the rise in the quantity of data needing processing has pushed the information acquisition problem far beyond what can be handled by human operators [2]. The complexity of modern surface combatants and the diminishing time lines available for action to be taken has placed unrealistic demands on the Naval Electronic Sensor Operators (NESO). Therefore future systems must be designed to incorporate both automatic and semi-automatic operation to facilitate the C2 process.

6.1. Automating the NESO Interaction with Sensors and Systems

As illustrated in Figure 19, the MSRM Human-In-the Loop (HIL) models have evolved from manual operation to semi-autonomous sensor systems. Future MSRM will be fully autonomous with human oversight [24].

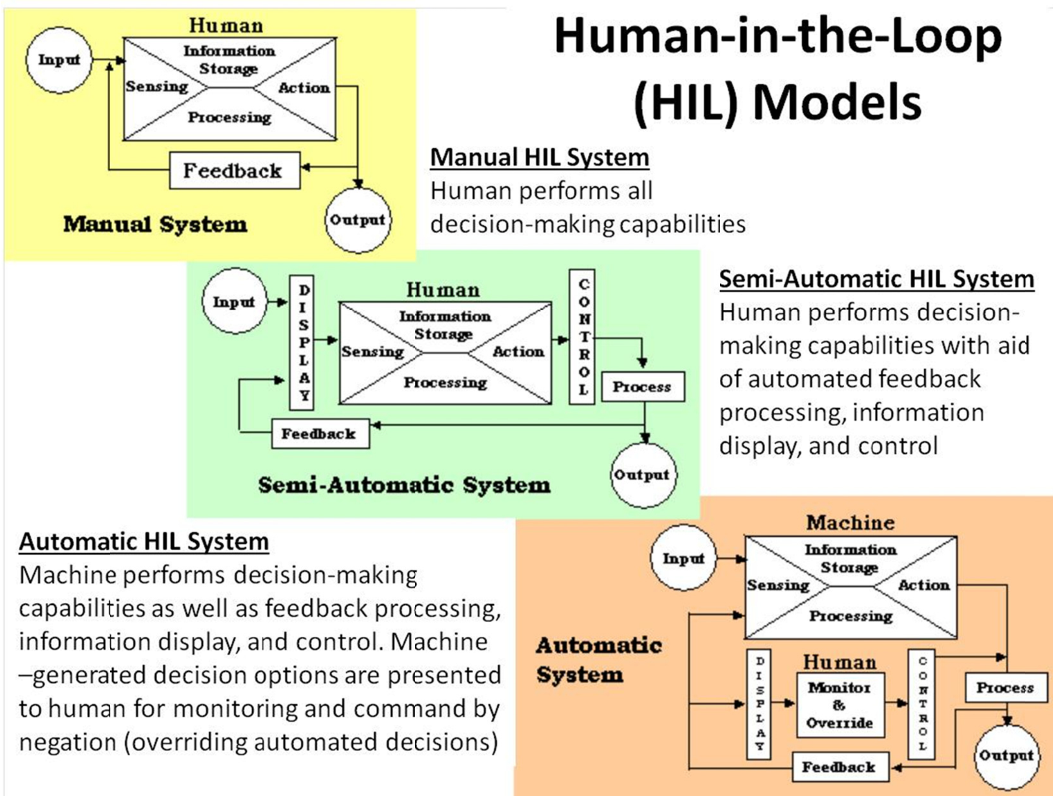


Figure 19 Human-In-the-Loop (HIL) Models [24]

In a fully manual HIL system, the human operator performs all decision-making functions.

In the semi-automatic sensor system automation is used to process and fuse sensor data and to support fire control. In this model, the operator controls the sensor based on feedback from the IFP. This semi-autonomous operation is the environment in which today's NESO works.

In the automatic sensor system the MSRM controls sensors, via their individual SRM, based on inputs received from IFP. In this configuration, the automated sensor manager provides the primary feedback to the sensor under the possible guiding input from the operator. The automated sensor manager is responsible for controlling future sensor behaviour while the operator exercises control by negation. This is the model used during weapon engagements. The sensor is controlled automatically for cueing and establishing track and providing updates to the interceptor.

In an automated sensor management system, the operator concentrates on the overall objective while the system works on the details of the sensor operations. By automating the process operator workload is managed enabling the operator to concentrate on key decision making.

6.2. Artificial Intelligence (AI) for Decision Support

Artificial Intelligence (AI) or Computational Intelligence refers to the Machine Learning (ML) process that mimics the actions undertaken by the human brain. A review of ML and AI was previously presented in the companion report[1].

In June 2017, PricewaterhouseCoopers (PwC), a multinational professional services network headquartered in London, United Kingdom, published a report predicting that between 2017 and 2030 the global economic impact of AI would be approximately $16 trillion USD and in 2030 AI would account for 14% of the global gross domestic product (GDP) [57]. Consumer product enhancements and productivity gains contributing roughly equally to this impact with the U.S.A and China expected to account for the majority of these gains [57]. This figure is driving significant investment into AI research in virtually all sectors of the economy and has significant potential for ensuring military superiority.

AI is an evolving capability that can be broken down into three waves [58]

- **First AI Wave - Handcrafted Knowledge**: Experts devised rule-based algorithms based their own expertise. Most of the AI software being used today is based on AI of this kind.
- **Second AI Wave- Statistical Learning**: Experts developed statistical models and trained these models on various samples to make them more precise and efficient. Statistical learning systems are highly successful at understanding the world around them. They learn and adapt to different situations when appropriately trained. However, unlike first wave systems, they are limited in their logical capacity as they do not rely on precise rules but instead they obtain solutions that are good enough. The most popular framework for implementing second wave AI is the use of neural networks.
- **Third AI Wave: Contextual Adaptation**: In the third wave, the AI systems themselves construct models that explain how the world works. In other words, they self- discover the logical rules which shape their decision-making process. Third wave systems are also designed to ingest information from different sources to help reach a nuanced and well-explained conclusion.

The most rapid progress in AI research in recent years has involved an increasingly data-driven, 'black-box' approach which focuses on providing the user with inputs and outputs without explanation of its internal workings. The popular approach to implementing AI is the development of neural networks. Neural networks are designed to mimic the way a human brain thinks. They involve large numbers of interconnected processors handling vast amounts of data. The goal is to spot patterns among millions of variables using machine learning which crucially, adapts in response to what is learned. The result is deep insights through pattern recognition of trends and behaviours.

Another trend in AI is deep-reinforcement-learning where behavioural goals for the system are specified and the system automatically learns by interacting directly with the environment. This results in a system that can be even more difficult to understand resulting in a knowledge paradox of being given an answer without explanation or knowing how it was derived [59]. The answer just has to be accepted.

In relation to the military command, the commander will be held accountable for decisions made, particularly in the event of failure. If commanders are to trust the recommendations generated by a machine then the machine must, like its human counterpart, provide justification for how that decision was reached and the level of confidence in that decision. This has led to what has been referred to as 3rd Generation AI or Explainable AI.

6.2.1. 3rd Wave - Explainable AI (XAI)

Explainable AI (XAI) is an artificial intelligence whose actions can be easily understood by humans. The technical challenge of explaining AI decisions is also known as the interpretability problem.

How to make AIs fair, accountable and transparent is now one of the most crucial areas of AI research. For example, Defense Advanced Research Projects Agency's (DARPA) XAI program [60] aims to create a suite of machine learning techniques that:

- produce more explainable models, while maintaining a high level of learning performance (prediction accuracy)
- enable human users to understand, appropriately trust and effectively manage the emerging generation of artificially intelligent partners

The object is to ensure that new machine-learning systems will have the ability to explain their rationale, characterise strengths and weaknesses and convey an understanding of how they will behave in the future. The strategy for achieving these goals, as illustrated in Figure 20, is by developing new or modified machine-learning techniques that produce more explainable models that present useful explanation dialogues to the end user. The stated strategy is to pursue a variety of techniques in order to generate a portfolio of methods that will provide future developers with a range of design options covering the performance-versus-explainability trade space.

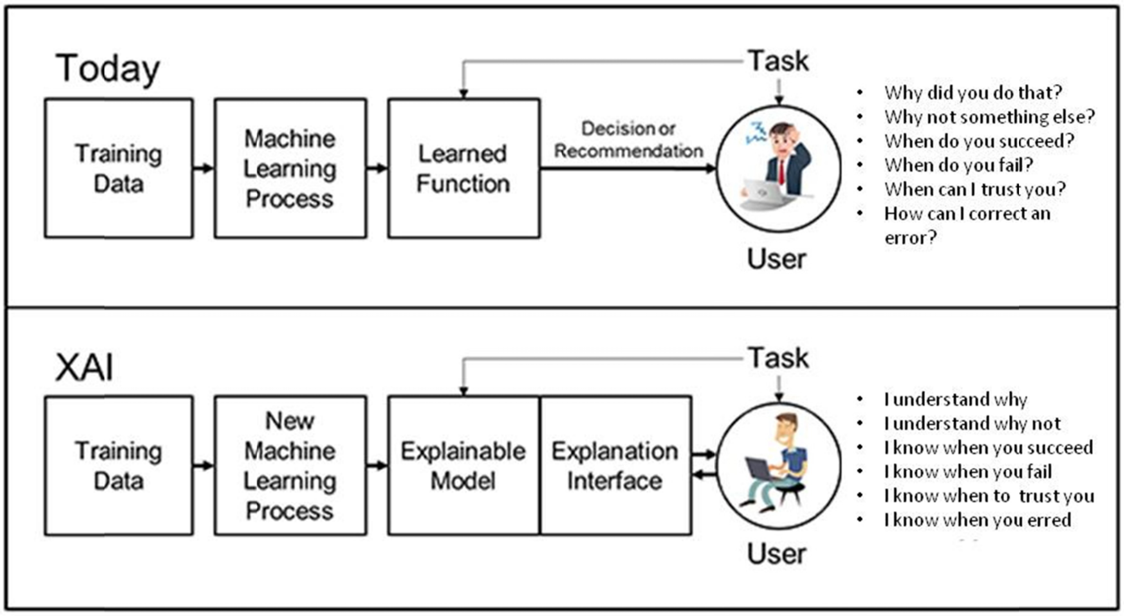


Figure 20 Explainable AI (XAI) [60]

6.3. Summary

This section has introduced the role of the human-in-the loop, cognition and artificial intelligence (AI) in a MSRM. The role of the MSRM in automating the SRM operator's interaction was discussed. AI and its role in decision making is introduced and the requirement for the commander to understand the rationale behind AI decisions highlighted. Third -generation, Explainable AI was introduced as a potential route for enabling commanders to take ownership of AI decisions and recommendations.

7. Knowledge Aided Detection and Tracking

7.1. Introduction

Adaptive signal processing has important application to radar [61], sonar [62] [63]and other sensing systems. The continued exponential growth of digital computing capabilities provide the opportunity to develop and exploit new algorithms to extract information buried deep in the received signal environment.

7.2. Knowledge Aided Signal Processing

Physics-based[1], knowledge-aided (KA) signal processing strategies supported by improvements in real-time embedded computing architectures allow significant flexibility when implementing adaptive sensor systems. In the case of radar, this has been manifested for example in real-time, KA space-time adaptive processing (KA-STAP) system for advanced clutter/interference suppression [64].

Other examples of KA signal processing include detection algorithms. For example a KA detector is presented in [65] where knowledge of the background environment is used to improve the probability of detection of low radar-cross-section targets in both homogeneous and non-homogeneous environments. It achieves this by including a classifier in the detection process to identify the local environment and subsequently adjusting the window dimensions to encase similar environments. The optimal Constant False Alarm Rate (CFAR) is then selected for that environment. Further the detection threshold is adaptively adjusted to minimise the probability of false alarms in high clutter regions. Details regarding other targets that may impact detection threshold are also included such that the bias introduced can be removed.

The DARPA has been pioneering the development of the first ever real-time KA adaptive radar architecture [66]. The impetus for the program is stated as being driven by the ever increasingly complex missions and operational environments encountered by modern radars and the inability of traditional adaptation methods to address rapidly varying interference environments. The DARPA KA sensor signal processing and expert reasoning (KASSPER) program goal is to demonstrate the use of High Performance Embedded Computing (HPEC) architecture capable of integrating high-fidelity environmental knowledge (i.e., priors) into the most computationally demanding subsystem of a modern radar: the adaptive space-time beamformer. This is extremely challenging since it is noted that environmental knowledge is a memory quantity that is inherently difficult to access at the rates required to meet radar front-end throughput requirements.

Feedback from the receiver to the transmitter permits the emitted waveform to be adapted to match the target feature information contained in the backscatter signal. This feedback loop offers the opportunity

[1] Physics-based models are mathematical models in which the equations that constitute the model are those used in physics to describe or define the physical phenomenon being modeled.

for significant improvement in target recognition and detection [67]. Waveforms can be custom configured using knowledge of the environment and target-of-interest. This information is used to adaptively adjust the transmitted signals to the time variant target scene with the goal of maximising information gain. The resulting received data can be segmented and processed in parallel to optimally extract features of interest.

KA signal processing algorithms can utilise both endogenous and exogenous sources of knowledge and enable custom algorithms to be applied to specific coverage regions to address local environments that would allow for example a Navy's APAR radar to see further and with greater accuracy. KA algorithms can be applied in parallel to traditional and other custom algorithms.

The role of the MSRM is to provide the external knowledge and to dynamically instruct the NRM to allocated processing/memory resources. Sharing between sensors ensures that individual SRM have sufficient processing and memory resources to extract the requested information from the sensed environment at the required moment in time.

7.3. Automatic Target Recognition (ATR)

The ultimate goal of the MSRMS is to improve the timeline and accuracy for Automatic Target Recognition (ATR). This is achieved by utilising long range sensors to cue high resolution shorter range sensors. Sensors can be either on the host platform or deployed on forward-looking systems that image, classify and identify threats.

ATR is the ability to classify and/or identify targets or other objects based on data obtained from sensors. As the volume of sensor provided data increases and the operational time of advanced weapon systems decreases, ATR becomes a key discriminating capability to provide knowledge superiority.

The ability to perform ATR with a high probability of success and a low probability of false alarm is limited by the information available. The approach, which promises to significantly improve ATR performance, is to collect multidimensional signatures and combine the information. Correlating data from multiple sensors, co-located or separated, collected across multiple spectral bands has the potential to resolve contradictions [20].

Correlation of data from multiple dispersed sources allow for a fuller understanding of an object or evolving situation. Techniques need to be in place to avoid the potential flood of data that a capable multi-sensor distributed data collection system can create. Key to the successful implementation of a Multi-Sensor system is the ability to automatically provide the operator with recognition, extraction, and viewing of only the minimally required information to meet mission requirements [20].

Multiple simultaneous sources of information can be obtained from spatially dispersed sensors of the same type or from single-sensor systems operating over multiple spectral bands. The higher the dimension of the information that can be collected from a pixel or an object, the better the chance of correctly detecting and classifying it. This approach requires effective data fusion and ATR techniques as well as significant increases in computational memory and throughput [20].

Other techniques that can be used to enable ATR include:

7.3.1. Micro-Doppler Effect

Radar determines the distance an object is away by timing how long it takes the transmitted signal to return from the target that is illuminated by this signal. When this object is not stationary, it causes a shift in frequency known as the Doppler effect. Mechanical vibration or rotation of a target or structures on the target may induce additional frequency modulations on the returned radar signal which generate sidebands about the target's Doppler frequency, called the micro-Doppler effect. Micro-Doppler signatures enable some properties of the target to be determined. This modulation can have a certain pattern, or signature, that can be exploited by ATR algorithms. The micro-Doppler effect will change over time depending on the motion of the target, causing a time and frequency varying signal [68].

7.3.2. Time-frequency analysis

Fourier transform analysis of a signal does not consider its time-varying component from which additional information may be gained. Examples of the early use of time-frequency analysis for classification of Sonar and Radar signals are presented in [69]. An overview of time-frequency analysis can be found in the 2003 Defence R&D Canada report [70]. An example of time-frequency analysis of wind-turbines obtained from an Air Traffic Control radar is presented in Figure 21. As can be observed, the wind turbines create a large target reflection that, by virtue of the spinning blades, has velocity and spatial characteristics that are not unlike those created by aircraft. Detail analysis may provide the capability to correctly classify these returns being from wind turbines rather than from low altitude aircraft [71].

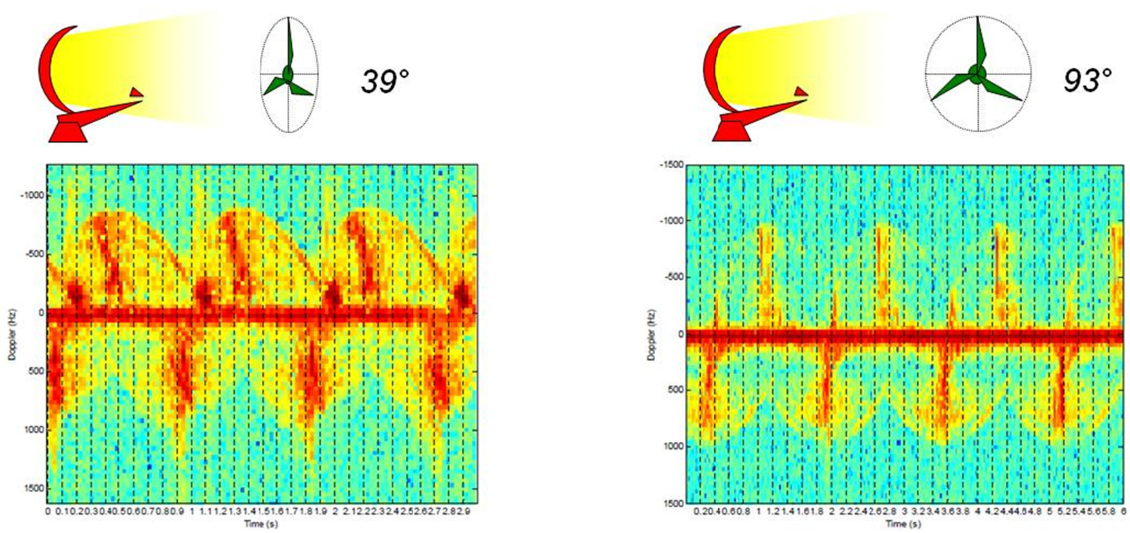


Figure 21 Time Frequency analysis of rotating wind-turbine blades as seen by air-traffic control radar. The plots show micro-Doppler effects at two blade angles of 39 degrees and 93 degrees with-respect to the radar [71].

7.3.3. Resonance Analysis

The isolation and extraction of resonance features from sonar or radar cross-sections is done because resonance features serve to identify remote targets in a similar manner to fingerprints [69]. Once this spectral information is extracted, it can be compared to an existing database containing information about the targets that the system will identify and a decision can be made as to what the illuminated target is. This is done by modeling the received signal then using a statistical estimation method to make a decision about which target in the library best fits the model built using the received signal.

Tracked objects may also be classified based on track characteristic, for example ships can be classified based on the relationship between hull shape, turn angle and drop in forward speed [72][73].

7.4. Tracking

The objective of the tracker is to correlate consecutive detections of targets into tracks. The goal is to provide high confidence location, dynamics and movement history of object-of-interest such that they can be classified and appropriate action taken. Knowledge of the local environment and of the target can be incorporated within the tracker facilitates high confidence tracking. The added knowledge may extend the range at which a target is tracked and to minimise the time taken to accurately fix its location and determine intent [74] [75].

The availability of large memory storage facilities opens up the feasibility of undertaking track retrodiction is an additional processing on top of the traditional track estimation. Typically, a retrodiction window length L is specified. During the retrodiction, all track states are 're-estimated' based the traditional track estimates and some 'future' measurements within a pre-selected time window. Retrodictive tracking enables earlier 'Prediction-of-Intent' based on forensic track analysis. The technique uses reverse time (retrodiction) to extend the track range of a radar. It achieves this by post-processing data that was collected prior to the confirmed detection of a target with the new knowledge that a target now exists within a region of interest [76]. Retrodictive tracking has the potential to aid in determining if an object is a threat and if so where it originated.

7.5. Summary

This section reviews the use of external knowledge in improving the detection, tracking and classification algorithms to enhance SA. The role of the NRM in dynamically allocating processing and memory resources to individual SRM resources is presented. Key to this section was the requirement for the MSRM to support timely Automatic Target Identification (ATI).

8. Architectures for MSRM

As noted in ‘Technology for the United States Navy and Marine Corps, 2000-2035’[20] a system-of-systems architecture facilitates the integration of a number of stand-alone systems to form a larger, more complex system to accomplish a desired objective. Future missions will require coordinated action from integrated sea, air, and land forces that cannot be achieved by a single system or platform. A system-of-systems would include constellations of multiple system types, such as satellites, aircraft, ships, expeditionary units, and control centers. These individual elements, complex in and of themselves, together would constitute a complex system of systems that, when operated as an integrated entity, can achieve warfighting effectiveness greater than the sum of the individual elements.

Efficient information exchange and communication links are essential elements to the system of systems approach. However at the same time individual units must also be capable of operating independently and in isolation[43].

8.1. Bio-Inspired Resource Management for Multiple-Sensor Target Tracking Systems

A bioinspired resource management for multiple-sensor target tracking systems is presented in[77]. The paper notes that the primary objective of multiple-sensor target tracking systems is to achieve certain levels of state estimation accuracy for as many targets as possible. The authors note that when a small number of sensors are directed to collect measurements on alarge number of targets, the decision process that determineswhich sensors are to collect measurements on which targets during the next observation time interval can be daughting. The MSRM problem becoming more difficult as the number of targets relative to the number of sensors increases. The proble being further exacerbated when targets and sensors are not arranged in in a favourable geometric constellation. To address the problem the authors develop a target selection algorithm that is inspired by the principles governing biological swarm theory.

Figure 22 presents a data flow diagram for the distributed sensor management architecture. The architecture consists of decentralised sensor management with a centralised global tracker. The implementation does not allow sensors to directly communicate with each other. However a global track file is continuously broadcast and made available to all sensors. Sensor operate locally and autonomously by tasking their own resources based on the information available in the global track file. Sensor make adjustments to their own tasking decisions bases on an assesment of their anticipated relative contribution to the global track file over the forthcoming data collection time interval. The global track file provides an indirect means for sensors to communicate with each other. Sensors transmit their data only to a central processor where they are correlated and fused to update the grobal track file.

The paper notes that the decentralised approach to sensor management has many benefits . Foremost is robustness that prevents significant degradation in performance with the failure of a few sensors. Decentralisation implementation is scalable allowing for additional sensors to be readily incorporated into the system without adding to the the complexity. Since all tasking decisions are made locally by the sensor the computing and communication bandwidth requirements are less stringent that a purely centralised approach.

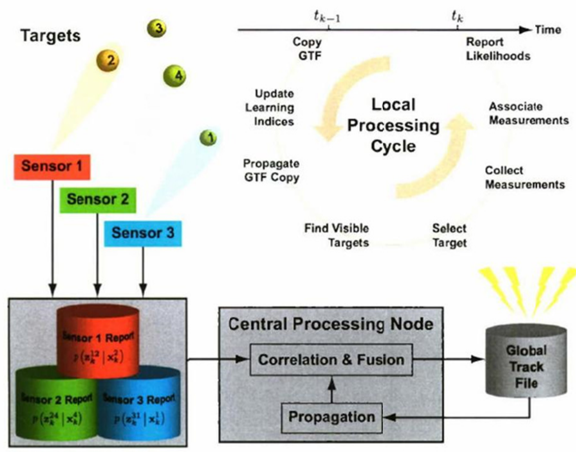


Figure 22 Data Flow diagram for the distributed sensor management architecture for problems with general system dynamics and observation models [77]

8.2. Multi Sensor Resource Management – Example 1

Kovalerchuk and Perlovsky [10] proposed a multi-sensor tasking method for both long-time planning and for real-time MSRM based on Intelligent Multi-objective Modularised Optimisation Model.

The authors note that the number of Radar, EO/IR, Overhead Persistent Infra-Red (OPIR), and other sensors with best capabilities, is limited in the stressing tasking environment relative to sensing needs. Sensor assets differ significantly in number, location, and capability over time. To determine on which object a sensor should collect measurements during the next observation period traditional algorithms favor the object with the expected measurements that would result in the largest gain in relative information. The authors propose a new tasking paradigm OPTIMA for sensors that goes beyond information gain. It includes Sensor Resource Analyser, and the Sensor Tasking Algorithm (Tasker). The Tasker maintains timing constraints, resolution, and geometric differences between sensors, relative to the tasking requirements on track quality and the measurements of object characterisation quality. The Tasker does this using the computational intelligence approach of multi-objective optimisation, which involves evolutionary methods.

In the information gain SRM formulation as proposed in [77] the state estimation and SRM are tightly coupled. In [10]it is noted that this can lead to the complex models and computational challenges that can make it difficult to change one of the components. For instance, it may be challenging to add more optimisation criteria beyond information gain and to incorporate the effect of a new interaction between the sensors. The authors also state that in general the progress in tracking, discrimination, fusion, and SRM technologies is not synchronous. Therefore the tightly coupled formulation makes it difficult to integrate these technologies into a more advanced system. Therefore the state estimation itself is considered as an *external* but connected task to SRM. The proposed new sensor tasking system OPTIMA includes a Sensor Resource Analyser and the Sensor Tasking models and algorithms (Tasker).

8.3. OPTIMA System Architecture with Computational Intelligence Solution

The MSRM system OPTIMA and its context are illustrated in Figure 23, OPTIMA maintains timing constraints, resolution and geometric differences between the sensors relative to the tasking requirements on track quality and the measurements of object characterisation quality. The solution is based on the computational intelligence approach that involves evolutionary methods, dynamic logic, and multi-objective optimisation.

The system design allows a user to select the version of an objective function of the minimal configuration such as minimal number of platforms, minimal cost/value/capabilities of sensor platforms. In the version of the model presented below, it is assumed that all motions of sensor platforms are known, as well as the capabilities (possible degraded) and status of the sensors onboard the platforms.

The OPTIMA Model involves:

- multiple sensors of different types and with varying resolution and capabilities
- sensor locations with respect to the object complex
- timing constraints
- requirements for track quality
- requirements for measurements of object characterisation (discrimination) quality

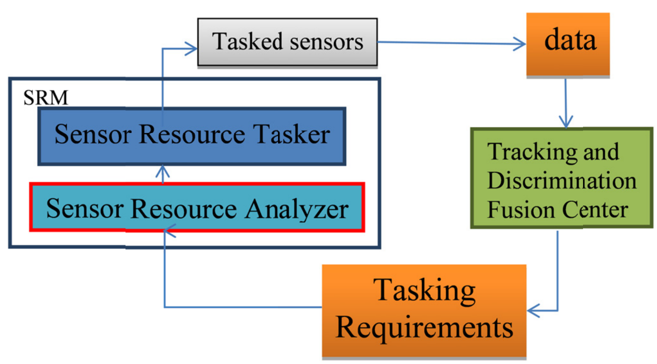


Figure 23 Context of Sensor Resource Management [10]

The authors claim that the main mathematical advantage of their architecture is that it decouples tracking and track estimation algorithms/filters from the optimisation and environment estimation. The other claimed advantages of a new architecture are that it allows:

- a variety of external tracking and discrimination algorithms by computing “flags” representing external algorithms,

- multiple optimisation criteria by selecting/changing modules adapting for a particular scenario,
- multiple tradeoffs between multiplicities of optimisation criteria in multi-objective setting providing mathematically rigorous solutions

The key idea of the proposed approach by [10] is to combine computational intelligence techniques (multi-objective optimisation based on the Pareto border, Integer Liner Programming under uncertainty, and Adaptive Learning methods) with physical considerations (sensor phenomenology and geometry of locations relative to targets). The Computational Intelligence methodologies that are applicable to solve SRM OPTIMA models are evolutionary computing methods including adaptive multi-objective optimisation that exploit genetic algorithms, colony optimisation, particle swarm optimisation, interval, stochastic and fuzzy optimisation, and adaptive dynamic logic of phenomena.

The models and algorithms proposed in this work allow the decreasing of the overall sensor resource usage, while increasing the probability that all threat objects in a raid are tracked, in addition, target characterisation is optimised. Our unique approach is in multi-objective SRM optimisation model and algorithms, as well as in the use of Cramer-Rao Bounds (CRBs), and the algorithms accounting for the association part of the tracking and fusion problem. These CRBs allow to evaluate target characterisation (classification features), and therefore target values. Another uniqueness of our approach is in using flags within the SRM, which encompass all of the information external to the main goals of the program (such as information from tracking algorithms). These flags are readily computed from the available information or information adaptively estimated in real time. These benefits surpass existing state of the art and permit efficient sensor coordination.

8.4. Multi Sensor Management System – Example 2

Hero [41] presents a conceptual block diagram of a multi sensor management system that is reproduced in Figure 24. In this system, once a sensor is selected and a measurement is made, information relevant to the sensing objective is distilled from the raw sensor data. This generally entails fusion of data representing disparate sensing modalities (e.g., optical and acoustic) and other properties, and further combining it with information gleaned from past measurements and possibly also side information from sources extrinsic to the sensor system.

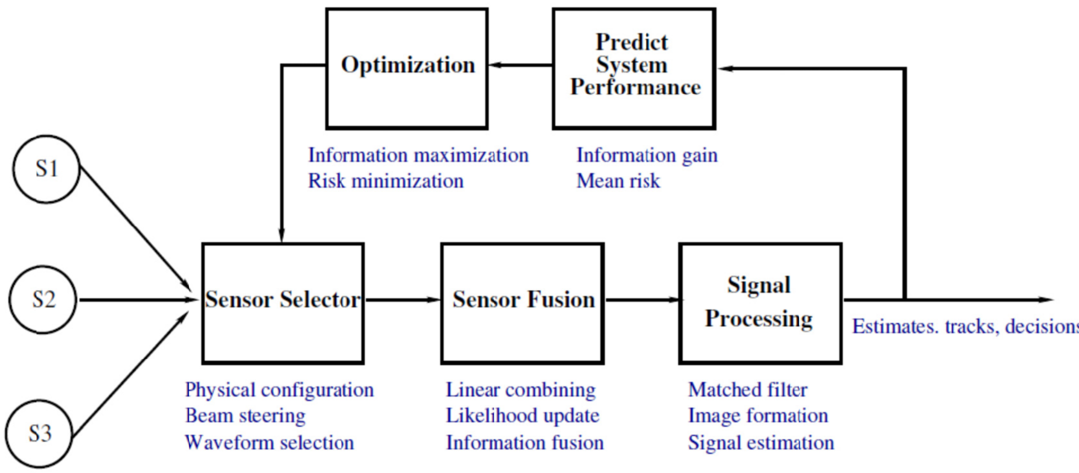


Figure 24 Conceptual block diagram of a sensor management system. The sensor selector selects among sensor actions S1, S2, and S3 based on the output of the optimiser. The optimiser attempts to optimise a system performance metric, such as information gain or mean risk associated with decisions or estimates produced by signal processing algorithms that operate on fused sensor data.[41]

8.5. Multi Sensor Resource Management – Example 3

Johnson [24] presents a top-level functionality MSRM conceptual design reproduced in Figure 25. This diagram shows the interfaces between functions A-J. "CMC" in this diagram refers to the Cooperative Management Capability, the parent system that includes an automated link manager, and automated weapons resource manager, as well as the SRM. Besides external interfaces to the rest of CMC and to Operators and the function of storing data, the key functions of the SRM are determining sensor tasks from the situation/threat input and data input; allocating tasks to sensors based on their capabilities, availability and status; synchronising the decisions among platforms; and tasking the sensors.

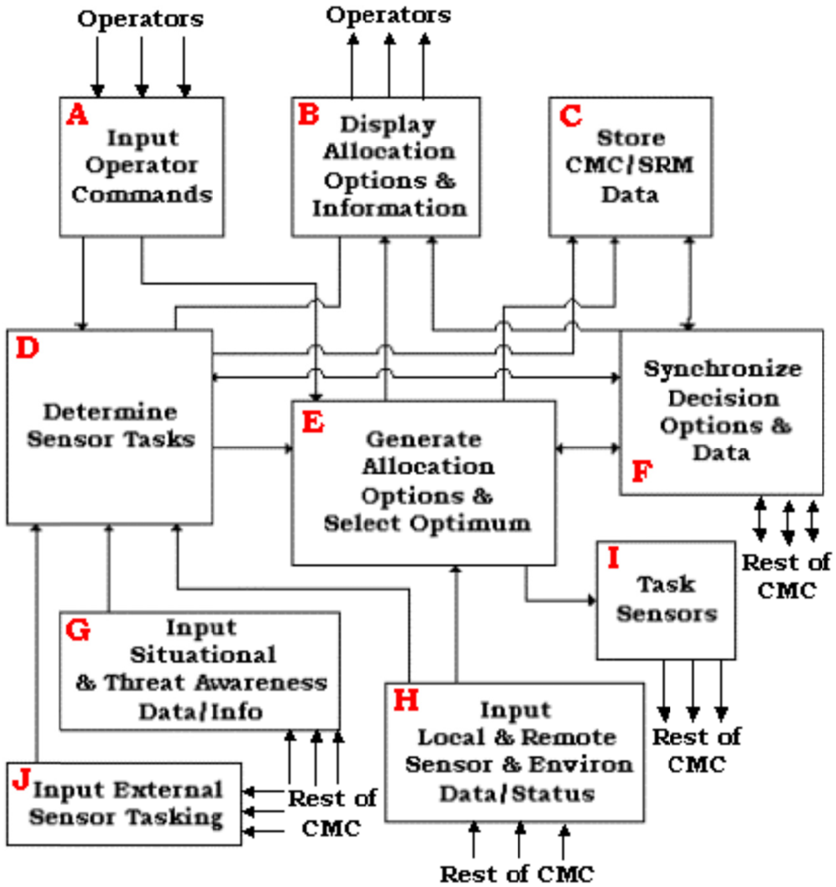


Figure 25 Example of SRM Functionality [24]

8.6. Multi Sensor Resource Management – Example 4

The growth of industry interest in autonomous vessels is driving the development for Multi-sensor resource management [78]. The referenced paper describes a futuristic multi-sensor architecture with an adaptive multi-sensor management system for the control and navigation of autonomous maritime vessels in all weather conditions. A block diagram of the envisaged system taken from the paper is presented Figure 26. The system augments data from onboard imaging sensors (radar, sonar, cameras etc.,), environmental sensors with AIS data and other external information sources. The adaptive multi-sensor management block utilises non-imaging sensor data to derive an assessment of the prevailing weather conditions. It then uses this assessment to adaptively manage the imaging sensors. The system uses computational intelligence to implement cognitive functions to generate various outputs including navigational situation awareness, weather situation awareness and a need-to-learn awareness.

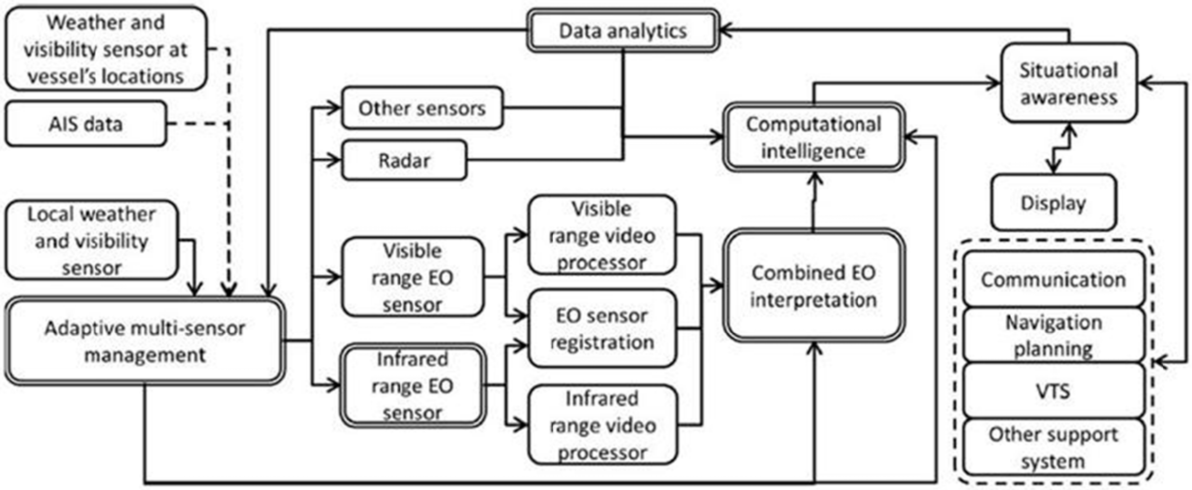


Figure 26 Envision Futuristic Adaptive Multi-sensor Management Architecture for an Autonomous Maritime Vehicle – blocks with double line boundaries are considered critical to the system [78]

Semi-autonomous systems are easier to implement and are less costly. They are generally sufficient for slower moving/evolving scenarios. However complex BF scenarios and high speed targets require autonomous systems which provide the following benefits that can be yielded from implementing an automated sensor manager are necessary for the Naval BF:

- **Reduced workload** – automated manager alleviates the need for the operator to specify each sensor operation or future behaviour. Operator's role can become: override a track's priority, establish degree of allowable active radiation, request special data collection, etc.)
- **Sensor Tasking based on finer detail** – Operator's control ability is based on information shown on display and ability to assimilate information into human decision-making process.

This limits the amount, types, and degree of detail of information feeding the sensor control decisions. Automating sensor tasking allows more amounts, types, and finer degrees of detailed information to support the decision-making process. (i.e., humans much better at tactical objectives than making decision concerning the fine details of sensor operation)

- **Faster Adaptation** – automated feedback allows much faster adaptation to the changing environment, i.e., earlier detection of tracking performance degradation.

Machine learning (computational intelligence) is the enabling technology for achieving this using a cognitive multi-sensor resource management system known as the Multi-Sensor Resource Manager (MSRM).

8.7. Multi Sensor Resource Management – Example 5

Vasqueza, et al., [79] present a multisensory management system for countering small unmanned air vehicles (sUAV). The paper outlines a multi-sensor architecture that exploits sensor modes including

EO/IR cameras, an acoustic array, and future inclusion of a radar for detection, tracking, and identification (ID) of sUAVs. The paper describes a system that includes multi-sensor multi-target tracking with cueing between sensors and a sensor resource management concept. A radar system is used to cue EO/IR sensors and acoustic sensors are used to validate the target as an SUAV. Fusion of the EO/IR camera data with the radar range data provides a 3D track and ID of the target via human target recognition. The acoustic array is used to increase the level of confidence in the ID of the target as a threat based on classification of the acoustic signatures of potential targets. The ID state of a given track is presented as a Threat / No-Threat / Unknown. It is noted that the system can incorporate other cueing approaches leading to a robust set of options such that reliance on any one sensor is avoided.

8.8. The system concept

The approach taken by the authors is to divide the problem into the areas of detect, track, and ID. In order to provide protection for point defense, the sensor suite needs to conduct wide area detection at long range, build tracks with an acceptable false alarm rate that can be mitigated by narrow area detection and ID components. They therefore divided the available sensors into three categories: Wide Field-Of-View (WFOV), Medium Field-Of-View (MFOV) and Narrow Field-Of-View (NFOV). Raw sensor data are processed to form detections that are then forwarded to a centralised tracking system. Additional external data sources, such as a cooperating air traffic control center, are used to provide information on known air targets in the vicinity.

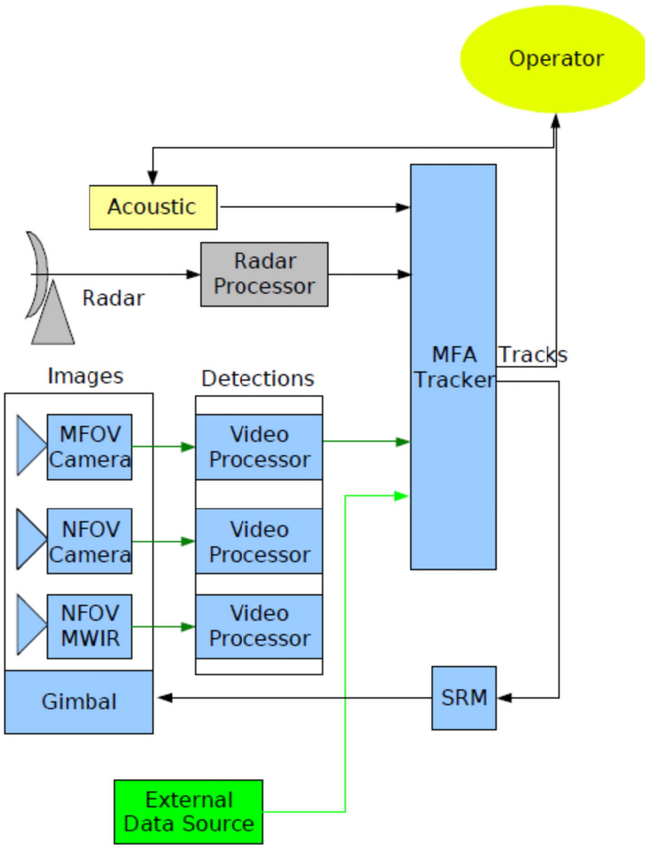


Figure 27 CSUAV system architecture [79].

The authors note two important factors that drove their system design and hence the requirement for multiple sensors. They were the requirement for 3D track and robustness to operating conditions. For instance, the EO/IR sensors, while capable of providing azimuth and elevation estimate they lack the ability to produce accurate range and range rate information that requires the use of a radar. It is noted that a network of EO/IR sensors in the proper geometry could be used to form 3D tracks, but the radar system is preferred as it also provides a night-time capability.

From the paper, the sensor coverage (flattened in 2D) for the system is presented in Figure 28 . The figure illustrated the requirement for a MSRM to provide a control mechanism for the sensors. Notice that the gimballed MFOV-EO, NFOV-EO, and NFOV-IR sensors must be steered to the moving target to be of any use. The MSRM uses track states to maintain the gimbals pointed on target. Once the MFOV-EO camera detects the target, the SRM fine tunes the gimbals so that the NFOV sensors can observe the target.

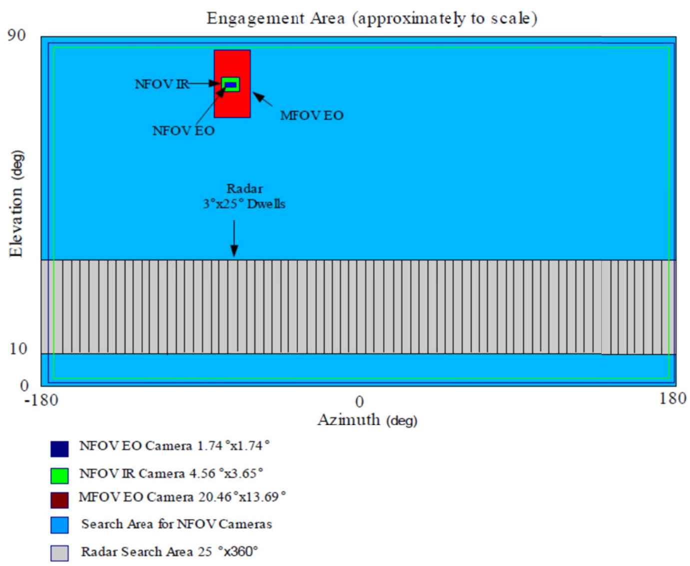


Figure 28 Sensor FOVs.[79]

The state flow for targets under track is presented in Figure 29. A target list is generated by the MFA tracker, and all tracks are initially identified as Unknown. The SRM function will slew the EO/IR sensor suite to unknown targets, providing the user with high-resolution video for use in identifying the target threat state. These IDs are used to update the target list, which affects future decisions by the SRM. Once a threat is declared, the SRM changes to a single target track mode in which all assets are dedicated to providing a 3D track solution on the Threat.

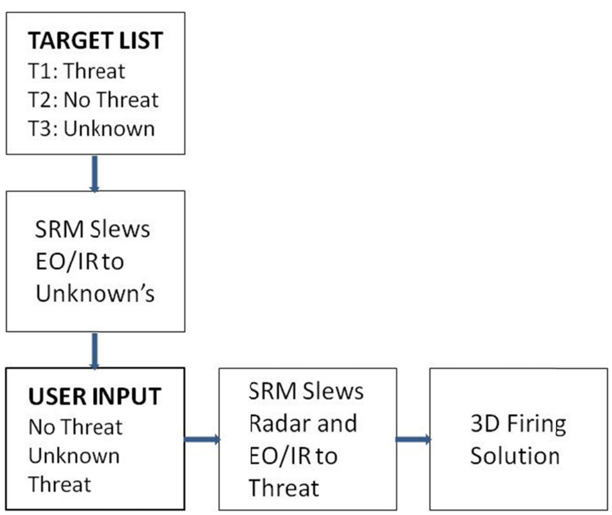


Figure 29 State Flow Diagram [79]

The paper refers to the role of the SRM but in reality the functions being performed match those of a MSRM supporting a SRM. That is the MSRM is used to assign the region of focus for the EO/IR sensor suite based on system level tracks derived from the radar and updated by including information from all sensors. The MSRM function provides the EO/IR sensors with a required pointing location (azimuth and elevation) based on cues from the WFOV sensors. Detections from any WFOV sensor can be used to initiate a target track via the Multiple Frame Association (MFA) tracking system

These target tracks are initially identified as Unknown and added to the MSRM's target list that is then prioritised and used to determine when and where to point the NFOV sensors thus providing the operator with the high resolution information necessary to declare them as either Threat or No Threat. The MSRM maintains a list of tracks that remain in the Unknown and Threat state, and continually cycles through this list.

Once a target is declared a threat the MSRM instructs all sensors to this track. External data sources may also be accessed to provide additional knowledge to aid in the classification and/or identification of the track. The MSRM takes the sensor limitations into account for example the gimbals' slew rates and settling time required to provide accurate data to the operator. Figure 30 presents an example of the EO/IR Detection and Tracking of a SUAV. The top image presents a snapshot of the MWIR video at both long and short range. The image on left demonstrates the ability to generate detections of the sUAV at long range whilst the short range image on the right profiles of the sUAV. The bottom image illustrates the ability of the EO camera to detect the sUAV.

The image on the left depicts the relatively significant challenge associated with detecting the target with the EO camera at long range. The short range image on the right provides a close look at the SUAV, which without additional information would be challenging to distinguish between a small manned aircraft and a sUAV.

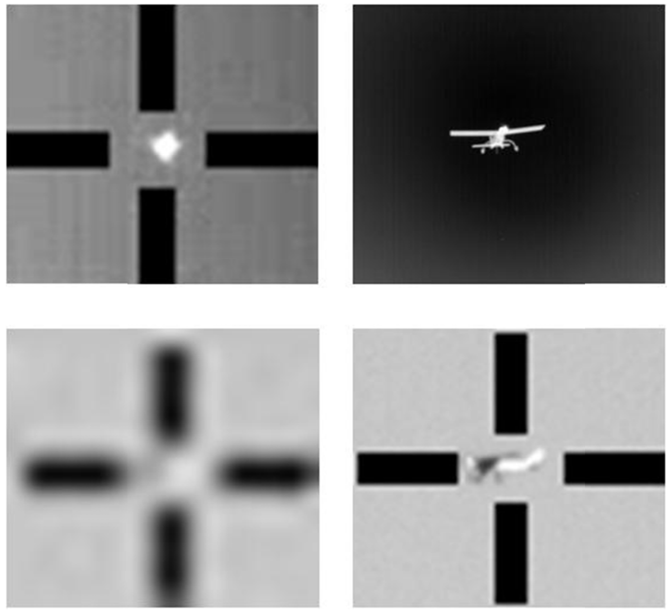


Figure 30 Top: MWIR camera data; (left) target detected at long range with crosshairs to indicate automated detections (right) UAVs IR signature. Bottom: EO camera data (left) target detected at long range with crosshairs to indicate automated detections (right) UAVs EO signature. [79]

8.9. Proposed Architecture for a NCMS Incorporating MSRM based on the JDL data fusion model

The concept behind the proposed solution is based on the architecture used by the human brain. A key feature is the implementation of a Hierarchical- Mesh Fusion Processor (HMFP) (refer section 2.4.2). The HMFP mimics how the human brain has evolved to process complex sensory information with stored memory data in order to take action.

The proposed HMFP architecture is illustrated in Figure 31. It can be observed that there is no single area where all sensory data is combined. This approach ensures that for any defined requirement only data necessary for the execution of that requirement is considered and made available. This has the significant advantage of minimizing delays that may result when non-relevant data is considered. For example, once the 'Operational Picture' processor has determined that there is an imminent threat the tactical, 'Fire Control' processor assumes responsibility without further input (other than abort) until the threat is effectively dealt with as determined by the 'Impact Assessment' processor. The design also ensures that there is no single point of failure.

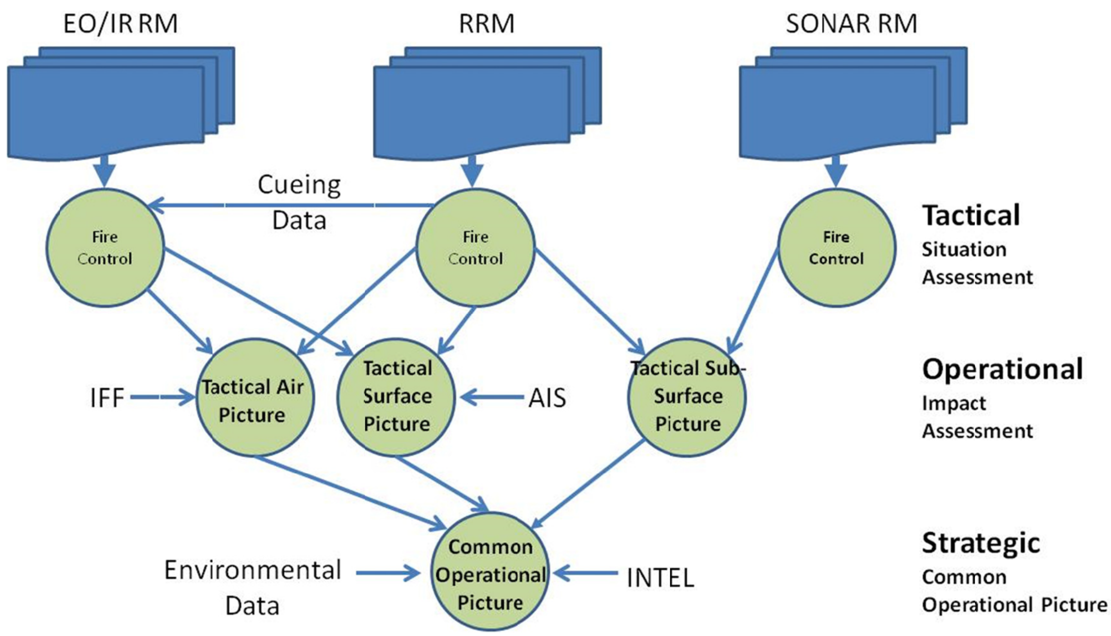


Figure 31 Proposed Hierarchical- Mesh Fusion Processor for NCMS

A functional diagram of the proposed architecture for the MSRM based on interactions between the JDL components (levels 0 to 5) of the fusion processor is presented in Figure 32. The MSRM is represented by Level 4 (Process Refinement) of the Fusion Processor. It can be observed that the Level 4 processor receives instructions from the Decision Support System (Level 5) with Level 5 processor being responsible for:

- Risk Assessment and Risk Management
- Planning, Prediction and Decision Making
- Resource Allocation

In this manner all machine decision making is contained within one function area. The Refinement Process (Level 4) acts in a similar manner to the thalamus of the brain to command, filter and regulate the data (refer section 2.4.2.1) generated by the individual sensors, via their SRMs. The Refinement Processor also receives and sends requests directly with Levels 2 (Situation Assessment) and Level 3 (Impact Assessment). In this manner local, time critical information can be actioned without the delay of flow through to the Decision Support System (Level 5).

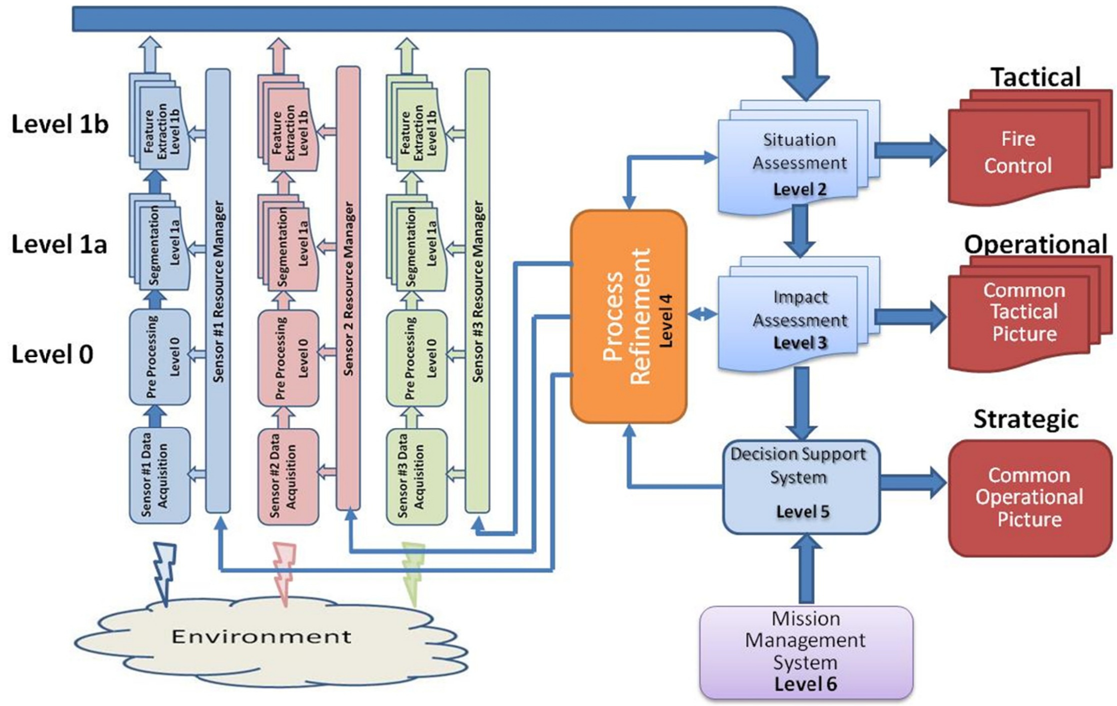


Figure 32 Interactions between the JDL components of the Fusion processor in the proposed MSRM system

Figure 33 presents a proposed architecture for a NCMS based on the HMFP that incorporates a Network Resource Manager (NRM) and both onboard, semi-autonomous, autonomous and Net Centric Operations (NCO). The figure illustrates that sensor management provides information feedback from the data fusion products (level 2, 3 and 5) to the individual sensors via the MSRM. The MSRM is also responsible for tasking the NRM to ensure that adequate processing power and memory is dynamically assigned to the individual sensor activity chains to ensure that they can extract the requested information and forward to the Information Fusion Processor.

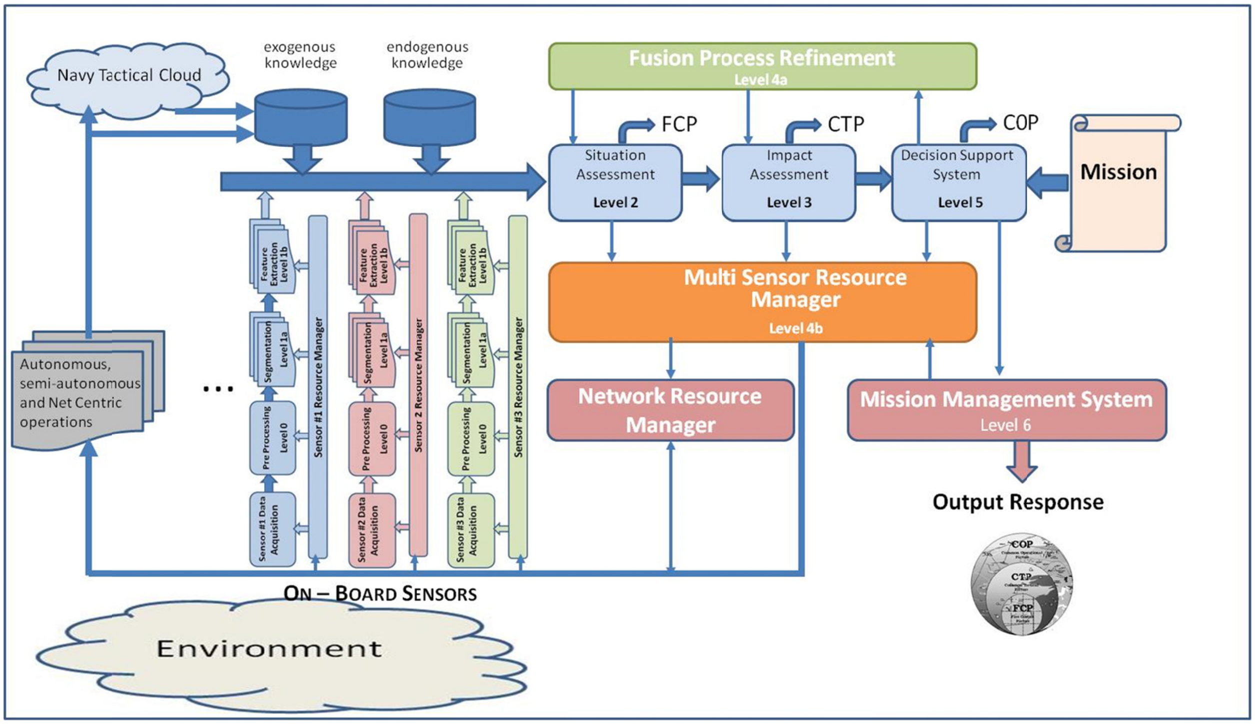


Figure 33 Proposed Architecture for a NCMS Incorporating MSRM based on the JDL data fusion model

The system is initiated with mission requirements flowed down from the C2 system to the Decision Support System (DSS) of the Information Fusion Processor (IFP). The DSS forward sensor requirements to the MSRM that then tasks the individual SRM with their mission objectives. The individual sensor systems are responsible for extracting the requested information and forwarding this information to the Information Fusion Processor.

The data is initially assessed to see if it meets the requirements for supporting Situational Awareness (level 2 fusion) and outputs data to both the FCP and onward to the Impact Assessment processor (Level 3). The level 2 fusion processor may request additional (or less) information, via the MSRM, as required to support mission objectives. This process is repeated for level 3 and for level 5 (DSS) until mission objectives are met.

The proposed architecture ensures commonality between FCP, CTP and COP and that the FCP is maintained in near-real time whereas additional time can be taken to develop both the CTP and COP.

The MSRM is the only feedback loop between the Information Fusion Processor and the Sensors. The MSRM controls request for data to onboard sensors as well as autonomous and semi-autonomous sensors under the control of the own ship. The MSRM is also the interface for requesting data from other independent entities within the context of Net Centric operations.

8.10. Summary

This section has presented a literature overview of various architectures proposed for MSRM. The section concludes with a conceptual architecture for a MSRM based on a HMFP structure that mimics how the the human brain has eveloved to processes and combine complex sensory data to meet diverse mission objectives. The proposed solution is based on the well established JDL data fusion model and is structured so that there is no duplication of functionality. Finally, a Network Resource Manager (NRM) is added to the model to enable the dynamic allocation of computing and network resources based on evolving mission requirements

The proposed system design is a natural evolution of the current NCMS and meets requirements for use in a future Holistic-NCMS previously proposed by the author [1].

Implementation of MSRM as described is expected to lead to the earlier aqusition and identification and engagement of targets of interest.

9. Summary and Conclusions

9.1. Summary

This report provides a non-technical introduction to the use of MSRM for enhancing the performance of the NCMS. Naval forces operate in a highly complex environment that contains many system components that change dynamically. Each of the navy's platforms or weapon systems has the potential to be more effective in its mission objectives if it is sensory systems are interconnected in an appropriate manner. This approach has the significant potential to enable the Royal Canadian Navy (RCN) to deploy its resources and achieve mission success at lower cost and risk.

Core to the development of a modern NCMS is the ability to combine related data from multiple similar and/or dissimilar sensors to generate overall SA and then to interrogate this data to extract relevant information to support mission objective of extending the Effective Engagement Envelope (E3).

The objective of a multi-sensor system is to produce an effect greater than just the sum of individual sensors. This report has looked at how the human brain has evolved to optimally process multi-sensory information and avoid sensory overload. This evolutionary achievement has been used as the basis for developing a biologically inspired MSRM.

It is shown that individual sensor performance is improved using a SRM that dynamically optimises system parameters to the environment to achieve improved target detection, tracking and classification. However, reliance only on SRM to achieve this may result in sensory data overload. The primary role of the MSRM is to control multiple sensors, via their individual Sensor Resource Manager (SRM) to ensure that resources are appropriately allocated in order to garnish the required information at the minimum cost

It has been shown that the implementation of a MSRM will provide SA at the lowest cost. Sensor assets differ significantly in number, location and capability. The MSRM is used to determine which sensors are assigned to collect measurements on an object of interest during subsequent observation periods for largest gain in relative information. The MSRM can use either endogenous or exogenous knowledge related to the environment, or target, to optimise the performance of a sensor.

The MSRM utilises feed-back from the C2 system to address gaps in SA coverage. The MSR allocates sensors and systems, computing resources and databases, to meet multiple, evolving, mission objectives at the most economic cost by ensuring that only necessary data is acquired and processed at any moment in time.

The role of the MSRM is restricted to that of managing multiple sensors as a hierarchical system by flowing requirements to the individual SRM. The SRM remain responsible for determining how the sensor will be configured and optimised to meet the requirements. The MSRM performs the functions of tasking and assignment of resources. In addition, in overload situations the MSRM parses lower priority targets to secondary sensors and systems.

9.2. Conclusions

The MSRM is the interface that provides feed-back from the IFP and DSS to the SRM's. The MSRM develops options for collecting future information, allocation of resources and directing individual SRM towards the achievement of the mission goals. The MSRM supports both a bottom-up and top-down approach to perception that leads to improved SA. The bottom-up approach supports the acquisition of sensor data to meet current mission requirements whereas the top-down approach uses prior knowledge and modeling to infer future sensing requirements.

The goal of the MSRM is to select the optimal available sensor to perform the right task at the right time on the right object based on external performance measures or criteria. The information fusion processor (IFP) requests data from the MSRM and subsequently assesses the extracted information. The information processor provides feedback related to quality of the data provided.

The MSRM determines how best to manage, coordinate and organise the use of sensing resources to improve SA and uses feedback from one sensor to improve the performance of another using cuing, handover and dynamic allocation of resources. The MSRM also endeavours to provide total domain awareness by optimally allocating sensors and resources to the mission and compensating, where possible, for gaps caused by failures of one or more sensors.

The report concluded with the presentation of proposed architecture for data acquisition and processing component of the NCMS that incorporates a MSRM based on the JDL data fusion model. The implementation of a MSRM is expected to increase the range at which a threat is detected, tracked and classified, thereby reducing the time-line to when an appropriate response action can be taken. The proposed MSRM has the potential to upgrade legacy platforms and systems to meet future operational requirements at the lowest cost.

9.3. Anticipated advantages of implementing MSRM within a NCMS

As noted in [24], the anticipated advantages of implementing a MSRM system within a NCMS that connects across local, semi autonomous, autonomous and platforms are:

- **Increased Battle Space Picture Accuracy**: The MSRM is expected to increase target track accuracy and improve interoperability problem that inhibit inter-platform picture synchronization.
- **Decreased Degraded Coverage Zones**: The MSRM is expected to decrease "degraded" or "no-coverage" surveillance zones.
- **Improved Surveillance Coverage**: The MSRM is expected to increase the detection range of the BF.
- **Decreased BF Reaction Time:** The MSRM is expected to decrease the average BF reaction time (aggregate time taken by BF surveillance, command, control, and communications systems in responding to an attack).
- **Optimized Economy of Resources**: The MSRM is expected to better utilize sensor resources an avoid redundancy and non-use by allocating tasks to sensors optimally.

- **Enabled Innovative Inter-platform Sensor Usage**: The MSRM is expected to enable new sensor-weapon pairings (i.e., remote engagements), avoid legacy stove-piped sensor-weapon pairings, and inter-platform sensor operations that would otherwise not be possible or imaginable within narrow decision-making time-lines

Other operational benefits as discussed in [24] include:

1. **Effective Use of Limited Sensor Resources**
   - Tailoring different sensor capabilities to different mission needs
   - Cueing sensors based on input from other sensors
   - Redirecting agile aperture sensors to search in particular sectors or revisit tracks
   - Managing modes of multi-mode sensors for different tactical applications
   - Controlling scan rate according to information needs
2. **Effective use of Limited Operator Resources**
   - Limiting operator workload by limiting amount of non-tactical information displayed
   - Automating lower level control functions
   - Suppressing sensor-specific details from Operator displays and decision-loops
   - Easing burden of Operator interfaces without limiting flexibility of human control
3. **Track Picture Advances**
   - Enabling automated track quality management through sensor optimization
   - Recognizing and correcting for track degradation in an automated fashion & in real-time
   - Scheduling track updates only as required for maintaining track quality within bounds
   - Assigning (& updating) track quality goals based on each track's tactical significance
   - Tailoring sensor functions to correct for tracks in dense or obtuse environments
   - Handling target maneuvers by using higher-order processing algorithms and techniques
   - Improving tracking by adaptively modifying processes in real-time, such as modifying the tracking filter or shortening the target revisit time to minimize model mismatch
4. **Sensor Fusion and Synergism**

- Controlling different sensors based on their strengths to cooperatively support overall goal

- Intra-platform and inter-platform cueing of particular sensors based on tracks maintained by other sensors (one sensor detects, while another tracks)

- Minimizing or eliminating active sensing (active radar radiation) by using passive sensors for search roles (while maintaining sufficient tracking accuracy)

- Improving discrimination techniques by optimizing sensor use

5. Situation Assessment Improvements

- Improving process of situation assessment by automatically shifting from kinematic tracking to generating target inferences (i.e., target intent, etc.) – enabling feedback link between automated situation assessment function and sensors (to improve data collection)

- Efficiently using sensors for tactical needs – managing sensors based on tactically important data collection schema

- Filling in missing information – using sensors to collect data to confirm tactical inferences (identified detected targets, resolve clustered targets, etc.)

6. Fire Control Support

- Enabling local and remote sensor data collection tasking based on weapon's need

- Enabling inter-platform engagement coordination strategies (possibly engagement on remote and forward pass)

9.4. Challenges to implementing MSRM system within a NCMS

As stated in [24] the primary challenge to attaining tactical information superiority lies in the ability to fully exploit the capabilities of the distributed sensors and communication resources to optimally fulfill the dynamically changing needs of the large set of distributed information users.

Without implementing the MSRM concept, sensors and other BF resources (links, weapons, etc.) will continue to be managed from a platform-centric perspective, which limits their utility to the BF at large.

Implementation of NCMS that incorporates the MSRM will continue to have inherent physics-based bounds that limit their area of coverage, accuracy and capacity. These limits present bounds that the MSRM must work within.

9.5. Recommended Cource of Action:

The following section summerises the role of the MSRM within the NCMS and recommends action that can be taken to further develop the concepts related to MSRM and Domain Awareness.

- The Naval Combat Management System (NCMS) is a computer and software system that integrates the sensors and weapons systems into a single integrated system. It is a cognitive aid that connects the sensors to the weapons systems via a Command and Control (C2) function. The primary goal of the NCMS is to provide knowledge superiority over an adversary, which enables a commander to see first, understand first, act first, and finish first.

- The NCMS supports objective reasoning to facilitate a commander to take subjective actions.

- The NCMS is a complex system that consists of a collection of task-oriented and dedicated systems. The sensor and weapons suites are mature technologies and no significant innovation is expected to occur in the near future. Therefore, advances in the performance of NCMS will be gained primarily by processing data from existing systems and utilising this data in such a way that the resulting product is greater than just the sum-of-the-parts.
  - Access to big-data is typically on a fee-per-use base. Models azre required that identify primary and secondary information sources. Access to big-data also requires the continuous verification of trusted data sources and the quality of the information provided. Utilising commercial cloud computing infrastructure rather than maintaining data centres offer the potential for cost savings and ease of access. For example, utilising processing resources on the 'cloud' can significantly reduce bandwidth requirements when knowledge is transferred rather than data. This can be a significant advantage when considering the bandwidth limitation of ship-shore-ship long-range communication systems used to transmit data via satellite with high-frequency sky-wave propagation as a backup.

- The proposed MSRM system with the NCMS is based on a systems-of-systems design that pools resources and capabilities together to provide more functionality and performance than simply the sum of the constituent systems.

9.5.1. Proposed Next Steps

- Investigation and prototyping of a Multi-Sensor Resource Manager (MSRM) to implement a system-of-systems approach to the sensor suite.
- MSRM technology is a means to collectively manage multiple sensors to support tracking and fusion. The MSRM treats multiple, diverse, sensors as a collective unit and employs a systems-of-systems design to maximize the value of the sensed data.
- Dynamic Allocation of Computing Resources (memory/processor power) between sensors on an as required basis to gain as much information as possible concerning targets of interest.
- Investigation into the application of High Level Information Fusion (Level 4 - Process Refinement) techniques and algorithms to the problem of optimizing and managing sensors.

- Agile System of Systems Design for ISR Navy – maximizing the benefit of available systems.
- Networking and Information Flow Control Issues for ISR - With multiple heterogeneous sensors distributed across a network in a hierarchical manner, it is important to manage the network, retention/storage of information (e.g., measurements, tracks, decisions, uncertainties) and the flow of information across various trackers and fusion nodes.
- Cross-seeding of sensors. Cross-seeding refers to when data from one sensor is used to improve the performance of another. For example it is well know that radar accuracy is primarily determined by the resolution of the radar system but can be degraded by adverse atmospheric conditions. The question for researchers is; if we know, in real-time what the atmospheric conditions are can this information be used to compensate for any degradation in system performance?
- Investigation into how cognition can be used to introduce placidity within the NCMS to re-assign resources and re-configure systems to maintain a basic capability in event of overload or failure of any single part within the chain.
- Investigation of impact of big-data and cloud computing on NCMS.
- Development of multi-purpose, distributed, adaptable, web-enabled, cloud-based, service oriented architectural frameworks that remain 'evergreen' to evolving technologies by being able to integrate advanced analytics and other services in support of decision making.
- Research into the exploitation of open unstructured data in C2 fusion systems: Investigates the ability to augment the situation assessment and understanding with actionable knowledge extracted from unstructured data in real-time is novel and not yet proven in defence and security applications.
- R&D in exploitation of advanced analytics applicable to NCMS: This research includes data mining, machine learning, artificial intelligence, etc., to compile situation understanding, situation forecasting and resource management, automating and providing enhanced advanced analytics enabled decision support capability
- R&D in the use of Artificial Intelligence to reduce mission management costs: Artificial Intelligence (AI) has the promise of significantly reducing the costs associated with mission management through the automated and autonomous submission of collection taskings.
- Development of modelling and simulation related to the exploitation of advanced data analytics to improve situational awareness, forecasting, resource management and decision making.
- Investigation into the use of real-time assets to maintain relevancy and/or calibration of non-real time sensors/models (Domain Awareness/Weather etc)

List of Symbols, Abbreviations, Acronyms and Initialisms

2D	Two Dimensional
3D	Three Dimensional
AI	Artificial Intelligence
ADSA	All Domain Situational Awareness
APAR	Active Phased Array Radar
ARC	Activity Recognition Chain
ASW	Anti-Submarine Weapons
ATI	Automatic Target Identification
ATR	Automatic Target Recognition
BF	Battle Force
C2	Command and Control
CEC	Cooperative Engagement Capability
CE-NCMS	Cognitive Enabled Naval Combat Management System
CFAR	Constant False |Alarm Rate
CQ	Classification Quality
COA	Courses of Action
COE	Common Operating Environment
COP	Common Operating Picture
CRBs	Cramer-Rao Bounds
CTP	Combined Tactical Picture
D-S	Dempster-Shafer
DA	Data Assessment
DARPA	Defense Advanced Research Projects Agency
DCGS	Data Fusion Information Group
DND	Department of National Defence
DRDC	Defence Research and Development Canada
DSS	Decision Support System
E3	Effective Engagement Envelope
EA	Electronic Attack

EM	Electromagnetic
EO	Electro-Optical
EO/IR	Electro-Optical/Infra-Red
EP	Electronic Protection
ESM	Electronic Support Measures
EW	Electronic Warfare
F2T2EA	Find, Fix, Track, Target, Engage, Assess
F5	Find, Fix, Finish, Feedback, Fire
FCP	Fire Control Picture
FCS	Fire Control Solution
FLAS	Forward Looking Active Sonar
FOL	First-Order Logic
FOV	Field-Of-View
GDP	Gross Domastic Product
GMLS	Guided Missile Launching System
GIG	Global Information Grid
GPS	Global Positioning System
HARC	Human Activity Recognition Chain
HIL	Human-In-the Loop
HLF	High Level Fusion
HMFP	Hierarchical- Mesh Fusion Processor
HSI	Human-Systems Integration
HPEC	High Performance Embedded Computing
IA	Impact Assessment
ID	Identification
IaaS	Infrastructure as a service
IFF	Identify Friend or Foe
IFP	Information Fusion Processor
IOD	Information Oriented Design
IOS	Information Oriented Software
IRGCN	Iranian Revolutionary Guard Corps Many

IRIN	Islamic Republic of Iran Navy
ISS	Integrated Sonar Suite
KA	Knowledge-Aided
JDL-DFM	Joint Directory of Laboratories Data Fusion Model
LAN	Local Area Network
LLIF	Low Level Information Fusion
LPI	Low Probability of Intercept
MCM	Mine Counter Measures
MFOV	Medium Field-Of-View
MFA	Multi Frame Association
MFR	Multi Function Radar
MI	Machine Intelligence
MWIR	Mid Wavelength InfraRed
MM	Mission Management
MOM	Measures-of-Merit
MSRM	Multi-Sensor Resource Manager
NBF	Naval Battle Force
NCMS	Naval Combat Management System
NCO	Network Centric Operations
NCW	Network-Centric Warfare
NESO	Naval Electronic Sensor Operators
NFOV	Narrow Field-Of-View
NIB	Non-Interference Basis
NIFC-CA	Navy Integrated Fire Control-Counter Air
NOC	Naval Operations Centres
NPB	Non-Protected Basis
NRM	Network Resource Manager
OA	Object Assessment
OPIR	Overhead Persistent InfraRed
ORTS	Operational Readiness Test System
OSA	Open Systems Architecture

PwC	Pricewaterhouse Coopers
PGM	Precision-Guided Munitions
PR	Process Refinement
PRM	Perceptual Reasoning Machine
R&D	Research and Development
RCN	Royal Canadian Navy
RRM	Radar Resource Manager
SA	Situation Assessment
SRM	Sensor Resource Manager
STAP	Space-Time Adaptive Processing
sUAV	small Unmanned Air Vehicles
TQ	Tracking Quality (TQ)
TMA	Target Motion Analysis
UAV	Unmanned Autonomous Vehicle
UR	User Refinement
U.S.	United States
USMC	United Sates Marine Corps
USN	United Sates Navy
WCS	Weapon Control System
WFOV	Wide Field-Of-View
XAI	Explainable AI

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This report provides an introduction to Multi-Sensor Resource Manager (MSRM) for application within a Navy Combat Management System (NCMS). The overall objective of the MSRM is to provide commanders with greater perception of their operating environment. The report outlines the emerging and enabling technologies that combine to make MSRM practical.

Perception of the environment is based on a combination of direct sensory measurements and prior knowledge. Gibson's theory states that the sensed environment can supply sufficient details about the stimulus so perception of the stimulus does not depend on prior knowledge or past experience. This theory is data driven and perceives current events. A contending theory is Gregory's that states perception is a constructive process that uses past experience and prior knowledge related to a stimulus to make inferences. The Gregory's theory allows a system to perceive future events based on theory and models. Situation Awareness (SA) requires a combination of both theories.

Naval forces operate in a highly complex environment that contains many system components that change dynamically. Each of the navy platforms, or weapon systems, has the potential to be more effective in achieving mission objectives if they are interconnected with complementary systems. This approach has the potential to enable the Royal Canadian Navy (RCN) to deploy its resources and achieve mission success at significant lower cost thereby freeing up resources to support other missions.

In general, single sensor systems provide partial information on the state of the environment while multi-sensor systems rely on data fusion techniques to combine related data from multiple similar and/or dissimilar sensors. The objective of a multi-sensor system is to produce an output greater than merely the sum of their individual inputs. This results in a significant improvement in both the quality and availability of information relevant to situational awareness than can be acquired from a single sensor type.

The MSRM determines how best to manage, coordinate and organise the use of sensing resources to achieve the mission objectives. It employs feedback from the Information Fusion Processor (IFP) to the sensors to optimally allocate sensors and resources to the mission and compensating, where possible, for gaps caused by failures of one or more sensors. The MSRM performs the functions of cuing, handover and dynamic allocation of resources to achieve mission objectives. The MSRM controls multiple sensors via their individual Sensor Resource Manager (SRM) to support detection, tracking and classification. The MSRM is responsible for ensuring that resources are appropriately allocated in order to garnish the required information at the lowest cost.

The report reviews a number of previously proposed architectures for implementing MSRM and evaluates their suitability for operation within NCMS. The report investigates how the brain has evolved to optimally process multi-sensory information using both a top-down and bottom-up approach to perception. It is shown that this approach closely matches the requirement for MSRM within the context of a NCMS. The data fusion functions of the brain can be modeled as a Hierarchical-Mesh Data Fusion Processor (HMDFP) which is subsequently proposed as the framework for MSRM.

The concepts and techniques behind MSRM and its relationship to process refinement within the information fusion processor are explored. A Network Resource Manager (NRM) that dynamically allocates network resources to the various SRM is introduced and architecture for MSRM based on the Joint Directory of Laboratories Data Fusion Model (JDL-DFM) is proposed as a solution for use within NCMS.

The report concludes with a summary of the expected benefits of implementing a MSRM within the NCMS and lists the major challenges to implementing such a system. A recommended course of further actions is included.

Le présent rapport fournit une introduction au gestionnaire de ressources multicapteurs (GRMC) qui servira dans un système de gestion du combat de la Marine (SGCM). L'objectif global du GRMC est de donner aux commandants une meilleure perception de leur environnement opérationnel. Le rapport décrit les technologies émergentes et habilitantes qui se combinent pour rendre le GRMC pratique.

La perception de l'environnement est basée sur une combinaison de mesures sensorielles directes et de connaissances préalables. Selon la théorie de Gibson, l'environnement détecté peut fournir suffisamment de détails sur le stimulus pour que la perception de celui-ci ne dépende pas de connaissances ou d'expériences antérieures. Cette théorie est axée sur les données et perçoit les événements actuels. Elle est toutefois contredite par celle de Grégoire selon laquelle la perception est un processus constructif qui utilise l'expérience passée et les connaissances préalables liées à un stimulus pour faire des inférences. La théorie de Grégoire permet à un système de percevoir les événements futurs à partir d'une théorie et de modèles. Quoi qu'il en soit, la connaissance de la situation (CS) exige une combinaison des deux théories.

Les forces navales opèrent dans un environnement très complexe où se retrouvent de nombreux éléments systémiques qui évoluent dynamiquement. Chacune des plateformes, ou systèmes d'armes, de la Marine est susceptible d'atteindre plus efficacement les objectifs de la mission lorsqu'elle est interreliée à des systèmes complémentaires. Cette approche permettrait à la Marine royale du Canada (MRC) de déployer ses ressources et de remplir ses missions avec succès à un coût nettement inférieur, libérant ainsi des ressources pour appuyer d'autres missions.

En règle générale, les systèmes à capteur unique fournissent des renseignements partiels sur l'état de l'environnement, alors que les systèmes multicapteurs s'appuient sur des techniques de fusion des données pour combiner l'information connexe fournie par plusieurs capteurs, qu'ils soient similaires ou différents. L'utilisation d'un système multicapteurs a pour but de produire une sortie qui soit supérieure à la simple somme de ses entrées individuelles. La qualité et la disponibilité de l'information ayant trait à la connaissance de la situation et provenant obtenue d'un seul type de capteur s'en trouve ainsi considérablement améliorée.

Le GRMC détermine la meilleure façon de gérer, de coordonner et d'organiser l'utilisation des ressources de détection pour atteindre les objectifs de la mission. Il utilise le retour d'information du processeur de fusion des données (IFD) aux capteurs pour allouer de manière optimale ces derniers et les ressources à la mission et compenser, si possible, les écarts causés par la panne d'un ou de plusieurs capteurs. Le GRMC remplit les fonctions de coordination, de transfert et d'allocation dynamique des ressources pour atteindre les objectifs de la mission. Il contrôle plusieurs capteurs par l'intermédiaire de leur propre gestionnaire de ressources de détection (GRD) pour prendre en charge la détection, le pistage et la classification. Il lui incombe d'allouer adéquatement les ressources pour faire en sorte que les renseignements nécessaires soient obtenus au coût le plus bas possible.

Le rapport passe en revue un certain nombre d'architectures déjà proposées pour la mise en œuvre du GRMC et évalue leur aptitude à fonctionner au sein du SGCM. Il examine comment le cerveau a évolué pour traiter de façon optimale l'information multisensorielle en utilisant une approche à la fois descendante et ascendante de la perception. Il est démontré que cette approche correspond de près au besoin d'un GRMC dans le contexte d'un SGCM. Les fonctions de fusion de données du cerveau peuvent être modélisées comme un processeur de fusion de données à maillage hiérarchique (HMDFP) qui est ensuite proposé comme cadre pour le GRMC.

Les concepts et les techniques qui sous-tendent le GRMC et sa relation avec l'amélioration du processus au sein du processeur de fusion de l'information sont examinés. Un gestionnaire de ressources réseau (GRR) qui alloue dynamiquement les ressources réseau aux différents SRM est présenté, et une architecture de GRMC basée sur le modèle de fusion des données du Joint Directors of Laboratories (JDL-DFM) est proposée comme solution à utiliser au sein du SGCM.

Le rapport se termine par un résumé des avantages escomptés de la mise en œuvre d'un GRMC au sein du SGMC et répertorie les principaux défis à relever pour mettre en œuvre un tel système. Un plan d'action recommandé est inclus.