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# Negative information literature review

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## IMPORTANT INFORMATIVE STATEMENTS



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# Abstract

Enabling the sharing and use of vital information to support Royal Canadian Navy (RCN) tactical/operational decision-making and achieving situational awareness is a priority research area for Defence Research and Development Canada (DRDC). In support of this goal, the present research examines negative information. Negative information would originate from what is not present in the information feeds being received. The report gives a clarifying description of negative information followed by a review of multi-disciplinary scientific research that has incorporated negative information into the processing, for varying purposes. The literature reviews follow a consistent format: research area statement, statement on the negative information that was used, a description of the results, and a discussion on the information requirements. A discussion and conclusion follows. Several potential applications to the RCN as well as applications general to the Canadian Armed Forces (CAF) were identified. In addition, challenges in using negative information in an automatic way were suggested. The largest challenge to applying negative information in an RCN setting is likely the modeling of the environment and sensors so that the negative information yields correct assumptions.

# Significance to defence and security

DRDC has begun looking into negative information as a beneficial information source for the Royal Canadian Navy (RCN). It originates from what is not present in the information feeds that they are already receiving. A primary goal of the literature review is to isolate promising research ideas for utilizing negative information to enhance decision-making and situational awareness.

# Résumé

Le partage et l'utilisation de l'information essentielle au soutien de la prise de décisions tactiques/opérationnelles par la Marine royale canadienne (MRC), de même que l'acquisition d'une connaissance de la situation sont des domaines de recherche prioritaires de Recherche et développement pour la défense Canada (RDDC). À l'appui de cet objectif, la présente recherche porte sur l'information négative. Celle-ci proviendrait de ce qui est absent des fils d'information. Le rapport comporte une description claire de l'information négative, suivie d'un examen de la recherche scientifique multidisciplinaire qui tient compte, à des fins diverses, de l'information négative dans le traitement. Les analyses documentaires sont effectuées de façon uniforme : énoncé du domaine de recherche, énoncé sur l'information négative utilisée, description des résultats, examen des besoins en information. Suivent une étude, puis la conclusion. Plusieurs applications éventuelles dans la MRC et, de manière générale, dans les Forces armées canadiennes (FAC) ont été définies. De plus, des difficultés relatives à l'utilisation automatique de l'information négative ont été relevées. La plus grande difficulté que pose l'utilisation de l'information négative au sein de la MRC est probablement la modélisation de l'environnement et des capteurs de sorte que l'information négative produise des hypothèses correctes.

# Importance pour la défense et la sécurité

RDDC commence à s'intéresser à l'information négative comme source d'information utile pour la Marine royale canadienne (MRC). Cette information provient de ce qui est absent des fils d'information actuels. L'un des objectifs principaux des analyses documentaires est d'isoler les idées de recherche prometteuses sur l'utilisation de l'information négative afin d'améliorer la prise de décisions et la connaissance de la situation.

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# 1 Introduction to negative information

## 1.1 Context

Defence Research and Development Canada (DRDC) has expressed priority research topics of relevance to Canada, one of which is to “enable the acquisition, sharing and use of critical information in support of situational awareness and decision making” [1]. To support this objective, DRDC continues its ongoing research into existing and new information sources. Past DRDC research has focused on maximising the exploitation of maritime information for defence, maritime security, and safety [2–5]. The present research examines an underutilized information source to help better support situational awareness and the decision makers.

The idea of taking information that is already collected and teasing out new information, that is not immediately evident, is an enticing thought for decision makers or those using the information to gain awareness of a situation. The extracting out of non-evident information is the premise behind the field of data analytics. In this area of research, DRDC has begun looking into negative information as a beneficial information source for the Royal Canadian Navy (RCN). Negative information would originate from what is not present in the information feeds that they are already receiving. (Negative information is explained fully in the next subsection.) Therefore, while it would be a new information source, it is already accessible.

Negative information is already being used within RCN domains of interest. For example, the absence of information on a vessel could end the tracking of the vessel or initiate other surveillance measures. A change from a vessel being detected to not being detected as it leaves a harbor can indicate a change in the operational status of the vessel. In search and rescue the absence of what is being searched for in one region leads to searching another region.

DRDC is interested in researching the implications and potential new uses of negative information in an RCN context. The goals of this report are as follows:

- To clearly explain negative information;
- To review how negative information is being exploited in scientific research;
- To identify the information requirements so as to be able to use negative information in an automated way;
- To identify promising avenues by which negative information could be exploited to enhance RCN maritime situational awareness and decision making; and
- To identify the challenges of using negative information in an automatic way.

The remainder of this section includes some key information and postulates made by the author, concerning negative information. This is followed by a literature review. The document completes with a discussion, which includes a section on ways to apply reviewed papers to tasks that are either general to the Canadian Armed Forces (CAF) or specific to the RCN. The discussion is followed by some concluding remarks.

## 1.2 What is negative information?

Negative information is something people use without giving it much thought. Starting with an example can clarify the concept before definitions are given. (The following is extrapolated from the Sherlock Holmes case “Silver Blaze” that Hoffman et al. [6, 7] used to illustrate the concept of negative information.)

**Example 1:** *Consider that a house has been robbed while the owners slept. Sherlock Holmes is hired to find the thief and recover the stolen goods. When he arrives to interview the victims, their barking guard dog greets him. The owners apologize saying that he always barks at strangers. As Sherlock proceeds with the investigation, he interviews the people in the house and some neighbours. He asks if they saw or heard anything. They all say no. After the initial interviews, he comes back to the owners and says that he can tell them for sure that the owners are acquainted with the robber. He can conclude this because no one heard the dog bark. The absence of the expected barking, which is negative information, gives him enough information to narrow down the suspect pool to only people the dog knows.*

**Negative information** (or **negative evidence**) is the absence of expected information [7, 8], e.g., the absence of the dog barking. Conversely, **positive information** would be explicit information, e.g., in the sensor realm it would be a measurement from the sensor [6, 9–12]. Examples of positive information in the previous example could have been people hearing the dog bark. **Exploiting negative information** means making an inference from expected but missing information to gain insight [8]. In this example, it was inferred that the owners knew the robber because the dog did not bark.

Another example shows how ubiquitous the use of negative information is in daily life:

**Example 2:** *Consider that you are working in an office setting and need a pencil. You know your colleague has a pencil so you glance into their office. You visually scan the room. Positive information would be locating a pencil on the desk. If you do not see a pencil, however, and you are sure that there is a pencil, then that is negative information. You can use the negative information to conclude that the pencil location is occluded from your field of view. This narrows down the possible locations of the pencil to under or behind any clutter or to being in one of the desk drawers.*

Anytime a person searches for something, they are utilizing negative information when they do not immediately find the object. However, technology is also tasked with searching for objects. For example, if an above water sensor does not detect a surfaced submarine, when it is known that there is a submarine in the area, then it can be inferred that it is submerged and therefore occluded by the water.

Negative information is not simply used for searching, though. It is also used to keep track of objects that cannot be seen. For example, consider that while driving, there is a car in front of you. Earlier you saw that there are actually two cars in front of you but now you cannot see the second car. You did not see the second car turn down a side street so you can assume it is being occluded by the car immediately in front of you. Or, for example, consider a sensor is being jammed over a known area. An aircraft is being tracked, but then the sensor no longer detects the aircraft. It can be assumed that the aircraft has flown into the area being jammed.

Negative information can also be used to self-localize. For example, consider that you are in Toronto, Ontario and emerge from a subway exit onto the street, unaware of what stop you got off at because you were talking with your companions who made the decision to get off the subway. You look up but you cannot see the CN tower. On a mental map, you could rule out any subway exit where you have noticed that the CN Tower is visible as well as any subway exits that exit only into buildings. In robotics, this is akin to the kidnapped robot example (e.g., [6]) where the robot, which previously knew its own location, must figure out where it is located based on the presence and absence of known landmarks after being displaced.

Self-localizing, localizing an external object, and tracking an external object are just a few examples of how humans use negative information. Technology can benefit from negative information when performing similar tasks, as this review will show.

## 1.3 Domain of interest

There is a subtlety to negative information that should now be pointed out. **Negative information is always in the context of a defined domain of interest**. The domain of interest is a subset of the real world (physical, cyber, etc.) that is of interest. In terms of sensors, sometimes the domain of interest will be a sensor controlled area such as Tischler and Vogt [13] claim, though sometimes it could be bigger than the area controlled by the sensor(s).[1] In Example 1, the domain of interest is the physical area that is within earshot of the dog's bark. In Example 2, it is the colleague's office. However, the domain of interest does not always have to be a physical area. In an internet search, the domain of interest could be all people with Facebook accounts and the last name Lapinski. The filtering of all Facebook accounts for people with that last name, to generate a list of people, precedes some sort of analysis that will utilize negative information within the context of that subset of people.

**Postulate 1:** To utilize negative information in an automatic way, it is postulated here that understanding the domain of interest is important for focussing on only pertinent positive and negative information.

Understanding the domain of interest would include defining the domain of interest, noting any features (e.g., mountains, large buildings, how characteristics are represented digitally), and being able to model the domain to the level required to generate useful negative information.

## 1.4 Association with positive information

**Postulate 2:** Based on analysis of the literature utilizing negative information, it is also postulated here that another subtlety of negative information is that it is only useful when combined with existing positive information.

For example, in Example 1, we know the owners were robbed the night before and that their dog barks at strangers but not at people it knows. If neither of those positive pieces of information existed, the fact the dog did not bark the night before means very little. In Example 2, if the

[1] For example, if an airplane flies in an identified area but the sensors do not cover that entire area, then when the airplane is not being sensed by the sensor, the airplane is inferred to be in an area not covered by a sensor.

person did not know there was a pencil in the office, not seeing a pencil upon visual inspection of the office would not narrow down the location of the pencil. This could potentially be an important subtlety when deciding what negative information to record in a database.

## 1.5 What causes negative information?

Hoffmann et al. [6] states that "there are two main reasons for the absence of an expected sensor reading: the target may not be there or the sensor may simply be unable to detect the target (due to occlusions, sensor imperfections, imperfect image processing, etc.)" No other description of the cause of negative information was found to be as complete as this in the literature, despite the sensor bias. Removing the sensor constraint of Hoffmann et al. [6], "the target may not be there" can be transformed to the nonexistence of information (i.e., the information does not exist to be found because, e.g., the dog did not bark, the target was not there, etc.). In addition, "the sensor may simply be unable to detect the target" can be transformed to information gathering limitations.

**Postulate 3:** Therefore it is postulated here that the list in Hoffmann et al. [6] translates to **two general causes for negative information:** *the nonexistence of information and information gathering limitations*.

An example of the former is the non-barking dog of Example 1. An example of the latter is the pencil in Example 2 that is not initially visible in the office: not being able to see through opaque solid matter that is occluding the pencil's location is a limitation of our visual spectrum sensing eyes.

## 1.6 Bayesian Inference and terminology

This review document focuses on negative information used in Bayesian Inference theory, a theory which will be discussed shortly. However, Bayesian inference theory is not the only theory where negative information is utilized.

For example, deductive (logical) inference (or reasoning) does incorporate negative information into its formulation. In deductive inference you may have an initial condition and consequence, B and K respectively that are correlated as follows: if B is true then there is an implication on the state of the consequence K; for example it may be that K is also true. Contraposition, which is a form of inference, can then be used to infer a new relationship between B and K using the negative of the consequence and the negative of the initial condition

Using the dog barking example (Example 1), we can reiterate:

If the dog barks, then the dog does not know the person.

Mathematically this may be expressed as:

$$B \rightarrow \neg K$$

where B indicates 'barks' and K indicates 'knows the person' (with ¬K indicating does not know the person).

The contraposition is:

If the person is known, then the dog does not bark

Mathematically this is:

$$K \rightarrow \neg B$$

where ¬B indicates does not bark. Using contraposition, the person is known to the dog because the dog did not bark. Deductive inference can therefore make use of negative information to make conclusions based on evidence.

Another example of a theory that takes into consideration negative information in its formulation is Dempster–Shafer theory. It is a mathematical method of inference (or reasoning) that allows for uncertainty and is based on evidence.

Using Example 1 again, the ears of the people within listening distance of the dog can be considered sensors. These sensors may detect a bark, may not detect a bark, or may be unsure if what they heard was a bark or not. NOTE: the fact the dog barks at a stranger remains certain, as expressed by a probability of 1.0 as does the dog not barking at a person it knows. So we are certain of how the dog reacts. Our ability to detect the dog's reaction is what is being considered.

Table 1 shows this scenario laid out in a Dempster-Shafer formulation [14, 15], with mass numbers included for illustrative purposes. Dempster-Shafer takes into consideration all the possibilities: the dog barked, it did not bark, it neither barked nor did not bark, and it either barked or did not bark but the evidence does not say which (indeterminate). The mass values are numerical representations of the evidence for each possibility, on a scale of 0 to 1, where 0 is no supporting evidence and 1 is all evidence points towards that option. The mass column sums to 1. Evidence for the final row (Any) would be evidence that supports an uncertainty as to whether or not the dog was heard. In contrast, the typical Bayesian formulation would focus on the two possible outcomes: either the dog was heard barking or it was not (false positives and false negatives can also be considered). Taking into consideration evidence that does not indicate one outcome over the other is one aspect of Dempster-Shafer that sets it apart from a Bayesian formulation.

***Table 1:*** *Dempster-Shafer table of possibilities and masses using Example 1.*

| Hypothesis | Mass |
|---|---|
| Null; i.e., neither (bark nor no bark) | 0 |
| Bark | 0.1 |
| No Bark | 0.6 |
| Any; i.e., evidence cannot discern if there was a bark or no bark | 0.3 |

The purpose of this example is to illustrate that negative information, the “No Bark” row of Table 1, naturally gets incorporated into a theory that takes into consideration all possibilities. As well, the example helps illustrate the difference between negative information (i.e., expressed as “no bark”) and indeterminate information (i.e., expressed as the “Any” row).

There are other theories that incorporate negative information (e.g., fuzzy logic), but during the literature review contained here, which focuses on research that reports the results of utilizing negative information to help complete a task, the research almost always used a Bayesian methodology. It should be noted that the initial search for literature was limited to modern literature (since 1990).

The use of negative information presented in this report draws heavily upon Bayesian Inference theory. This report tries to keep discussion of probability theory to a minimum but cannot totally ignore it due to its widespread use in the literature. To understand the definitions of some of the repeating terminology, here is a superficial description of Bayesian inference, followed by some terminology.

### 1.6.1 Bayesian Inference [16]

Bayesian inference theory considers an unknown parameter (or parameters) whose estimate is required. The parameter could be almost anything, such as an object’s position or speed, or the speed of sound in an area of the ocean, or the identity of someone who robbed a house. However, what is observed (e.g., measured) does not give that estimate directly. By knowing something about the probability of the possible true values of the unknown parameter (aka the **prior distribution**) and the probability of how the observations (e.g., measured data) behave given the possible values of the unknown parameter (aka the **observation model**, also known as the likelihood), we can then infer the probability distribution of the possible values of the unknown parameter given the observations (aka the **posterior distribution**). There are then techniques to make a point estimate (i.e., narrow it down to one educated guess of the parameter’s true value) using the posterior distribution, if that is the goal.

Extending this a bit further, the unknown parameter does not have to be only one unknown parameter. It can be a vector of parameters (i.e., multiple parameters). The observation does not have to be only one observation. It could be a time series vector of observations, or a vector of multiple observations (e.g., from different sensors) made at the same time.

### 1.6.2 Terminology

Regarding the terminology of this report:

**State:** the unknown parameter(s) we wish to estimate. In tracking, it could be an object’s position and/or speed and/or orientation, for example.

**Likelihood function:** as mentioned, this is a common name for the observation model.

**Filtering:** in this document it is a recursive estimation of posterior distribution of states [17], done after each set of new observations (typically sensor measurements), given past observations.

**Filter:** an algorithm that does the above. Kalman and particle are two types of filters encountered in the research for this report.

**Tracking:** "is [a] form of filtering where the hidden signal consists of states of moving or stationary targets (position, velocity, etc.) The purpose of tracking is to estimate the position [or state] of these targets as accurately as possible using only indirect and noisy measurements such as azimuths, distances and elevations." [17]

**Extended object tracking:** is when a target cannot be properly modelled as a point due to its non-negligible size compared to the sensor resolution. Measurements can originate from different points on the target. Of note, the targets can cast shadows upon each other. This can cause one target to obscure another target from the sensor. Also, the object extent can be estimated from sensor measurements, which gives the shape and orientation of the object, as well as its location.

# 2 Literature review

The criterion for a paper to be reviewed in this report is that part, if not all, the research reported in the paper pertains to investigating the utilization of negative information (or a variant of the term) to help complete a task. However, several papers have also been included in the report in which negative information is used to complete a task but is not the focus of the research being published. In these cases, the paper occurs at the end of the topic, and is identified as an outlier, with an explanation as to why it is included.

The literature review is broken down into the general topics most commonly found in the literature review: tracking, localization (both self-localization and of an object), autonomous mobile vehicles, and miscellaneous. Classification and Detection support is also included. The summaries to follow are completed in a systematic way. Each summary review follows the same formula throughout:

1. Statement of the area of research and problem(s) discussed in the paper. Statement of whether they looked at real or simulated data.

2. Statement of the negative information that was used, along with any pertinent additional information. A statement of what is inferred by the absence of the expected information.

3. Description of the results of incorporating the negative information.

4. Discussion of the information requirements to utilize the negative information. What information (e.g., positive information, processed information, information about the environment, information about the sensor) needs to be available to utilize negative information?

Similar papers by the same first author are referenced but only one will be reviewed. The goal of the summaries is to present the highlights of the paper with focus on the negative information research, culminating in suggestions on how the ideas presented could lead to appropriate information requirements and exploitation of negative information by the RCN. These last two points will be important to the follow-on research. The references are presented from oldest to newest. Note that the literature search focused on papers from 1990 until the present.

## 2.1 Tracking

Target tracking is commonly recognized as applicable to the CAF. In the tracking literature, there were certain similarities in the papers that can be summarized succinctly: For example, every paper used Bayesian inference to help track targets. They each used a form of filtering to do the tracking. The filters included Kalman [17, 18], particle [17, 19, 20], modified Extended Kalman filters [12], Gaussian Sum Filter [12], Progressive Gaussian Filter [11], Probability Hypothesis Density (PHD) filter [10], and a combination of a particle filter (for the assignment problem when tracking multiple objects) and Extended Kalman filter for tracking [21]. The negative information was incorporated into a likelihood function for the Bayesian inference equation. How, in each paper, the negative information was incorporated into the likelihood functions and ultimately into the tracking algorithms, is beyond the scope of this report. The authors who had multiple papers on the topic of incorporating negative information into tracking algorithms, suggesting expertise in the area, were Wolfgang Koch [8, 10, 12, 22, 23], and Kevin Wyffels [9, 21, 24, 25].

### 2.1.1 Särkkä, S., Tamminen, T., Vehtari, A., and Lampinen, J. (2004), Probabilistic methods in multiple target tracking—Review and Bibliography [17]

1. **Area of Research.** This is a generic overview paper on tracking, not specific to one specialized application of tracking. The bias of the paper is towards ground and air tracking, though, given the examples, rather than, e.g., tracking of other vehicles by self-driving vehicles. The introduction (Chapter 1) and the chapter on incorporating negative information (Chapter 8) are reviewed. Examples appear to be generated using simulated data.

2. **Negative Information Use.** The review paper specifically discusses multisource-generated negative information: they use the lack of sensing by one sensor, but sensing by one or more other sensors, to infer, for example, that the target is outside the surveillance area of the non-detecting sensor or oriented in such a way that the sensor cannot detect it. The expected information is that each sensor detects the target. Therefore, the negative information is that a specific sensor did not detect the target. There is considerable discussion on how at least one sensor needs to detect the target in order to know that the other sensors are not detecting it. The paper does not consider in the discussion that negative information can be generated with just one sensor, if there is reason to believe from previous measurements that the target is expected to be sensed. (However, their 1D example seems to do just that.) The paper also discusses the type of sensor measurements that are conducive to generating negative information: sensor measurements that are not triggered by a target's behaviour. However, if there is reason to believe the target is in an area being sensed, such behaviour-triggered sensors (e.g., listening stations looking for sonar or radio pulses, sensors that only detects a vehicle if it is moving) can generate negative information as well: it is known how the target is not behaving based on no sensor measurement being generated. This is indeed the case in the next paper [19].

3. **Results.** They discuss incorporating negative information into a particle filter and Kalman filter. Their examples are based on a (bootstrap) particle filter integration. In a 1D example, using a simple uniform likelihood of non-detection for an occluded area, they do show that incorporating negative information does improve results compared to when lost measurements are modeled as missing. That is, the results are better when lost measurements are modeled as being in a defined area compared to when the lost measurements have no constraint on them. The predicted location of a target stays confined to the occluded area when there is no detection, making the results more realistic. They also show a depiction of a 2D negative information likelihood field where the probability of a sensor missing a target is 0.1 near the sensor, not 0. This is meant to be a more realistic example with imperfect sensors. It also allows for an increased probability of sensing the target when there are overlapping sensor ranges, like what happens in reality. It is less likely that the target will be missed where the sensor ranges overlap, just as would be expected.

4. **Information Requirements.** The information requirements to exploit the negative information include, but are not limited to, a comprehensive model of the environment and sensor, and information on when a sensor is expected to sense a target but does not. For the latter aspect, if there is more than one sensor, then all the sensors that did not detect a target when the others did detect a target need to be stored. If there is only one sensor, then the track of the target needs to be stored so that the lack of detection can be noted.

### 2.1.2 Agate, C.S., Wilkerson, R.M., and Sullivan, K.J. (2004), Utilizing negative information to track ground vehicles through move-stop-move cycles [19]

1. **Area of Research.** The area of research in this paper is tracking ground vehicles. This paper looks at ground-moving indicator radar that requires a vehicle to be moving at a minimum velocity to be detected. If a vehicle is slower than that minimum velocity, the vehicle cannot be distinguished from the background noise. Therefore, to avoid detection from this type of sensor a vehicle can engage in a move-stop-move motion cycle. If the vehicle is stopped long enough any track associated with it ends. When the vehicle starts to move again, a new, unassociated track begins. By exploiting this aspect of the sensor, a target can avoid surveillance. This work uses negative information to continue tracking a target when it ceases to be detected and until it is detected again. Being able to do this not only helps keep track of targets but allows for the opportunity to schedule other sensor measurements of the target given that the stopped location can be inferred. The paper utilizes simulated data.

2. **Negative Information Use.** The authors "refer to the illumination of a region of the ground as a sensor dwell and the illuminated region as the sensor footprint." [19] When the previous sensor dwell had a track estimate, the expected information is that within the sensor footprint there should be a detection of the target. When a detection is missing, it is inferred that the target has stopped moving.

3. **Results.** The bulk of the paper is concerned with explaining the particle filtering that incorporates negative information. It is a good introduction to particle filters and to what situations they best apply. The experimental results are brief and illustrate how a simulation was used to test the filtering algorithm. Note that the goal of the algorithm is for a track not to end when a target has stopped moving, so that the algorithm can continue the same track once the target starts moving again. They show that they are able to do this with the inclusion of negative information. They show graphically, for example, a comparison of when the vehicle is actually stopped compared to the calculated probability of the vehicle being stopped. Temporally, the two essentially align.

4. **Information Requirements.** The information requirements to exploit the negative information include, but are not limited to, the sensor and environment model, the location, duration and footprint of the sensor dwell, the absence of target detection, evidence from processing the returned radar energy in a dwell, the sequence of evidence collected on a target, the target state with respect to time, measurements with respect to time, and sensor position with respect to time.

### 2.1.3 Koch, W. (2007), On exploiting “negative” sensor evidence for target tracking and sensor data fusion [8]

(Other related papers authored or coauthored by Wolfgang Koch include, [8, 10, 12, 22, 23]. Note that this paper appears to be a revision of his 2004 paper [22].)

1. **Area of Research.** The area of research in this paper is tracking for defence and security purposes. Incorporating the use of negative information (evidence) into various defence and security tracking activities is examined. The areas examined are group tracking (when separate objects are sometimes resolvable by the sensor and sometimes not, and sometimes both detected and sometimes neither detected); Electronically Scanned Array (ESA) radar tracking (e.g., surveillance of air traffic); ground moving target indicator tracking (tracking a ground target from the air) and missile tracking where there is sensor jamming. The goal is to improve position or velocity estimates of targets by drawing conclusions from negative information. The paper uses simulated and real data.

2. **Negative Information Use.** The author uses the term negative evidence, rather than negative information, throughout the paper. Negative evidence is expected but missing sensor measurements. The paper uses negative evidence to infer “information on the current target position or a more abstract function of the kinematical target state.” [8]

3. **Results.** The author found that negative evidence could provide positional or (more abstract) kinematic information on a target. The paper illustrates “benefits of processing ‘negative’ sensor information for improving:

   a. tracking of possibly unresolved group targets;

   b. local search for [Interacting Multiple Model]-tracking (ESA radar);

   c. early detection of stopping ground targets; and

   d. tracking in case of radar with adaptive nulling.” [8]

   If the absence of a sensor reading is dependent on its “underlying sensor-to-target geometry,” it was found that triangulation can be done with the negative evidence. That is, given the kinematics of the target and the attributes of a sensor, negative evidence from each different sensor platforms can be fused together to better locate the target. (This does not violate Postulate 2, given that positive information about the target being in the area would be required before it can be assumed that the target is not being detected by the sensors due to sensor-to-target geometry reasons.)

   It is emphasized in the paper that the “prerequisite for processing ‘negative’ evidence is a refined sensor model, which provides additional background information for explaining its data.” [8] This would include information on sensor characteristics including performance. The refined sensor model manifests itself in a problem specific likelihood function.

4. **Information Requirements.** The information requirements to exploit the negative information include, but are not limited to, the sensor model, artificial measurements

representing the negative information, and all the information required to make the Bayesian inferences using the artificial measurements.

#### 2.1.4 Blanding, W.R., Koch, W., and Nickel, U. (2009), Adaptive phased-array tracking in ECM using negative information [12]

1. **Area of Research.** The area of research in this paper is "airborne radar tracking a target in the presence of Electronic Countermeasures (ECM) or jamming." [12] They are researching how to better track a target while it is in a jammer notch (a sensor dead zone). They introduce both corrected angle measurement covariance and negative information as part of their research. The corrected angle measurement covariance provides a "sensor measurement model that more accurately reflects measurement error covariance." [12] They test five track filters: Fixed Extended Kalman Filter (F-EKF) (baseline), Variable EKF (V-EKF) (includes corrected angle measurement covariance but not negative information), Fixed Pseudobearing EKF (F-PB) (includes negative information but not the corrected angle measurement covariance), and Variable Pseudobearing EKF (V-PB EKF) and Gaussian Sum Filter (GS) (which both include negative information and the corrected angle measurement covariance). There are five scenarios that each set of filters is run through. The paper utilizes simulated data.

2. **Negative Information Use.** The expected information is that a target will be detected from a scan or dwell of the sensor. The absence of that information infers that it is either out of sensor range or within the jamming notch.

3. **Results.** Track filter performance is tested using 250 Monte Carlo simulations, per scenario, per filter. The performance is evaluated by assessing track continuity and track errors. The goal of the filter is to maintain a track for an object entering and then exiting a jammer notch. The V-PB EKF and GS filters outperformed the other three filters. Only when both negative information and the corrected angle measurement covariance were incorporated (i.e., V-PB EKF and GS) were the filters able to generally track the object to the end of the scenario. "The performance of the V-PB EKF and GS filter were comparable, although the two filters did perform relatively poorly in one scenario (different scenario for each filter)." [12] The V-PB EKF has a lower computational complexity when compared to the GS filter, which gives it a significant advantage.

   If the corrected angle measurement covariance is seen as a way to better represent the sensor, then this paper shows how important an accurate model of the sensor is when adding in negative information. Without the corrected angle measurement covariance, adding negative information does not help maintain a track while the target is in the jamming notch. However, after reality is better represented, the negative information does improve the results.

4. **Information Requirements.** The information requirements to exploit the negative information include, but are not limited to, accurate models of the sensor, jammer notch, and environment; the tracks in the environment; the absence of detection of a target; as well as the other information needed to use the tracking algorithm.

### 2.1.5 Zea, A., Faion, F., and Hanebeck, U.D. (2015), Exploiting clutter: Negative information for enhanced extended object tracking [11]

1. **Area of Research.** The area of research in this paper is extended object tracking, without a specification of the environment for the tracking. In this research, the object extent is estimated, which gives the shape and orientation of the object, as well as its location. The authors chose two extended object models used in such tracking. A Spatial Distribution Model (SDM) and Kernel Greedy Association Model (Kernel GAM) are employed, which normally only utilize positive information. They then introduced negative information to help limit the extent of targets, using information about where the target is not. There were essentially two questions to answer: 1) Can adding in negative information make a simpler technique (Kernel GAM) comparable to a more complex technique (SDM)? 2) Does adding in negative information allow for improved tracking when occlusions are present? The paper utilizes simulated data.

2. **Negative Information Use.** Unlike many of the negative information papers, negative information is not the absence of sensor measurements in this research. Rather the negative information originates from measurements that are not associated with the target. Negative observations are positive sensor information, but not about the target of interest. Therefore, the expected information is that a measurement is associated with the target of interest. The absence of the expected information infers where the target of interest is not located. The paper differentiates between negative observations (information about where the target is not) and occluded regions, where no observations are available (positive or negative).

3. **Results.** Four experiments using simulated data were undertaken: stationary object no occlusion, stationary object with occlusion, moving object with no occlusion, and moving object with two occlusions. The authors test three algorithms, their regular SDM, an SDM that incorporated negative information: S-SDM, and a Kernal GAM that incorporated negative information: S-GAM. The S-GAM is a simple and easy to implement algorithm while the SDMs are more complex and accurate. In the static, no occlusion experiment, all algorithms did well, though the S-GAM underestimated the extent. In the static with occlusion experiment, the S-GAM was slightly off in its angle and again underestimated the extent. The S-SDM accurately determined the angle and extent of the object, while the SDM did not do well. For a moving target with no occlusions, all methods performed nearly equally well. For a moving target with occlusions, the S-GAM and S-SDM show they can track the target, both its centre and angle, even with little positive information. In conclusion, negative information was key for improving SDM extended object tracking in the presence of occlusions and the easier and faster S-GAM algorithm gave comparable results to the more complex and accurate S-SDM, though the extent was consistently underestimated.

4. **Information Requirements.** The information requirements to exploit the negative information include, but are not limited to, all measurements including indications as to whether they are associated with the target or not, comprehensive model of the sensor, and what is required to create and incorporate what they call Silhouette Models (see paper).

### 2.1.6 Jovanoska, S., Govaers, F., Thomä, R., and Koch, W. (2015), Dynamic-occlusion likelihood incorporation in a PHD filter based range-only tracking system [10]

1. **Area of Research.** The area of research in this paper is extended multi-object tracking, in particular of uncooperative targets such as people who are not carrying anything that can aid in their detection or tracking. The authors refer to these people as tag-free people. The authors consider localization and tracking of multiple tag-free persons. To detect and track the uncooperative targets, they utilize Ultra-Wideband Radar (UWB) technology, which can be used to detect and localize "moving objects in poor visibility, through-wall or in multipath conditions" [26]. As people move, one person can occlude another person from the sensor, which makes it difficult to localize and track all the people. This paper develops an occlusion likelihood function (or non-detection likelihood) to incorporate into a PHD filter, as a way to improve localization and tracking. This allows for negative information to be used. A PHD filter is a type of multi-object tracking filter which recursively estimates both the number and state of multiple targets. They do both a numerical trial and a trial on real data using their modified algorithm.

2. **Negative Information Use.** The expected information is that a target is detected in the field of view of the sensor. The absence of that information infers that the target is being occluded by another target.

3. **Results.** The authors compare a conventional PHD filter against their modified PHD filter that uses negative information. They use the Optimal Subpattern Assignment (OSPA) metric to evaluate the performance of the filters. The simulated data experiment has three people moving in a room. The modified PHD filter shows improvement over the unmodified filter, using the OSPA metric, for this experiment. The filter is able to track targets while they are occluded. The real data experiment has two people walking in a room in a predefined path. Similarly, promising results, based on the OSPA metric are found for the modified filter. In both experiments, the authors reported the improvements using the modified filter as significant. Graphical proofs of the improvements are provided.

4. **Information Requirements.** The information requirements to exploit the negative information include, but are not limited to, the sensor model, the people model, the feature extraction from the sensor measurements, and the information required for the occlusion likelihood and the tracking algorithm.

### 2.1.7 Wyffels, K., and Campbell, M. (2015), Negative information for occlusion reasoning in dynamic extended multiobject tracking [21]

Other related papers by Kevin Wyffels include, [9, 24, 25].

1. **Area of Research.** This is an expansion and improvement on an earlier paper [24]. The area of research in this paper is extended multi-object tracking as it pertains to autonomous (urban driving) vehicles. In the paper an autonomous vehicle driving on a road is tasked with being aware (tracking) of the vehicles in front of it, even when the vehicles are occluded by moving occlusions. The authors are interested in improving scene awareness for autonomous vehicles

by introducing negative information into its tracking algorithm. The authors report experimental results using both simulated and real data.

2. **Negative Information Use.** The expected information is a target measurement. Missing information infers the target is occluded or does not exist.

3. **Results.** The authors compared a baseline filter to a modified baseline filter that has been adapted to take into consideration negative information. In the simulation they look at precision and accuracy, providing the equations they use to do so. In the experimental portions they do three studies: a belief sensibility study (i.e., looking at how sensible the belief of the occluded object state is), track maintenance study and model accuracy study. "Simulation and experimental results demonstrate that the use of negative information improves the precision and accuracy of the tracking filter, as well as the sensibility of occluded object state estimates." [21]

4. **Information Requirements.** The information requirements to exploit the negative information include, but are not limited to, the model of the sensor, model of the occlusions including their shadows, the information required to model the negative information and form an occlusion likelihood, positive measurements and negative measurements from the sensor, as well as what is required for the fusion to take place.

### 2.1.8 Shan, M., Worrall, S., Masson, F., and Nebot, E. (2014), Using delayed observations for long-term vehicle tracking in large environments [20]

([27, 28] are not reviewed here due to similarity of work, but are included for completeness.)

The focus of this paper is not about incorporating negative information; however, they have incorporated it into the algorithm they are using. Even though it does not meet that criterion of the literature review, it seems a worthwhile review to include given the unique concept of the paper, more so than how they use negative information. It only marginally fits into this literature review.

1. **Area of Research.** The area of research in this paper is tracking of cooperative vehicles in a disadvantaged environment. The research in this paper is not directed towards a hypothesis concerning negative information. It, however, uses negative information as one of its sources of information to help localize cooperative objects over large areas with limited position observations. The environment is a set of vehicles travelling on roads over a large area that has a limited number of data collection spots set up to track the vehicles. The paper introduces observation harvesting and seeks to test the algorithm. Observation harvesting is a process that contains the following steps: When two or more vehicles come within range of each other, they pass on information about their current position and the position of the vehicles they have encountered. When one of the vehicles comes within range of a data collection point, they not only pass on their own positional information but also the information from vehicles they have passed, to help update the positional estimates of all vehicles. Passing vehicle information back to a central base station in this way is called observation harvesting. The algorithm uses timing profiles and motion models, along with

data collection point observations and observation harvesting, to estimate where a vehicle is located. Real data is used to test the algorithm.

2. **Negative Information Use.** The expected information is a sensor report at a data collection point. The absence of that information infers that a vehicle has not passed a data collection point. After a certain amount of time, this implies it is not near the collection point, which helps better localize the vehicle. (The vehicles themselves only collect positive information about other vehicle positions.)

3. **Results.** There are no negative information results to report. The concept tested is observation harvesting. The tracking algorithm uses old (delayed) information to update position estimates on the vehicles. The paper shows that they are able to "obtain consistent position estimates for multiple vehicles over long periods of time." [20]

4. **Information Requirements.** The information requirements to exploit the negative information include, but are not limited to, a map of the area of interest including sensor locations, timing profiles, motion models, data collection point observations, vehicle observations, tracking information on vehicles, and a temporal count to keep track of how much time has passed since a vehicle has passed a data collection point.

## 2.2 Localization

Tracking, in the previous section, is the systematic localization of an external object's position with the purpose of keeping track of the object. This section looks at the general concept of localization and the research in which negative information is incorporated to improve localization. Here, localization refers to both self-localization and localization of an external object. With respect to the RCN, localization in the absence of tracking would occur most often during the initial search for an object or an event, such as during search and rescue or a disaster. One of the goals of this report is to extrapolate ideas from all areas of research that could be applied to the RCN, therefore papers from the field of robotics appear frequently in this section. The authors who had multiple papers on the topic of incorporating negative information into localization algorithms, suggesting expertise in the area, were Hoffmann et al. [6, 7].

### 2.2.1 Montemerlo, M., and Thrun, S. (2003), Simultaneous localization and mapping with unknown data association using FastSLAM [29]

1. **Area of Research.** The area of research in this paper is Simultaneous Localization and Mapping (SLAM) for autonomous robots. "SLAM addresses the problem of building a map of an unknown environment from a sequence of noisy landmark measurements obtained from a moving robot." [29] While building the map, the robot is also determining its place in the map. The paper introduces an algorithm, FastSLAM that utilizes a particle filter and negative information. It is compared to a previously used Extended Kalman filter approach. Real data is used to test their algorithm.

2. **Negative Information Use.** It is expected that a landmark that has been observed will be observed again. When a landmark is not observed, the negative information is used to lower the odds of the landmark existing. The negative information is used to infer that landmarks do

not exist once the odds are lowered below a threshold value, and thereby removes spurious landmarks from the map being generated. Spurious landmarks might be caused by false positives generated by the feature detection algorithm or by moving objects.

3. **Results.** There was no ground truth landmark data associated with the data set. This made it difficult to measure the accuracy of the map that was generated. “However, incorporating negative information did result in 44 percent fewer landmarks on average, and many fewer landmarks in dynamic areas (e.g., the street).” [29] They did not run FastSLAM without using negative information. This would have given a sense of how the negative information affected the results. However, the algorithm they used steadily outperformed the extended Kalman filter for different levels of odometric noise added to the real data set.

4. **Information Requirements.** The information requirements to utilize negative information include, but are not limited to processed information on the absence of landmarks; processed information on landmarks that are sensed; field of view of the sensor to know if a landmark should be in view; the map that is being built, including current locations of landmarks; the robot’s belief of where it is; and the current judgement score for each landmark’s existence.

### 2.2.2 Hoffmann, J., Spranger, M., Göhring, D., and Jüngel, M. (2005), Making use of what you don’t see: negative information in Markov localization [6]

There is a follow-on paper to this work: [7]

1. **Area of Research.** The area of research in this paper is concerned with self-localization based on landmarks in the field of robotics. The RoboCup Sony 4-Legged league is used as the testbed. This work modifies a Monte Carlo localization technique to include the use of negative information. The technique uses particles which are essentially proposed states of the robot. The intent of the algorithm is for the particles to converge on the correct state of the robot. Both simulated and real data are used to test the algorithm.

2. **Negative Information Use.** The expected information is that there will be a sensor reading of a landmark. “Negative information describes the absence of a sensor reading in a situation where a sensor reading is expected given the current position estimate.” [6] A position estimate is inferred to be less likely if the robot does not detect the expected landmark. The expectation of detecting the landmark is refined by modeling the sensor’s field of view and obstacles (occlusions) in its view. This paper emphasizes that to avoid false negatives, the model needs to take into account these two factors.

3. **Results.** The simulation shows that using negative information makes some particles less likely. Using real data, four experiments are reported on: a localization using one landmark, an analysis of the expected entropy of the belief in the localization with respect to time, using landmarks and field lines to localize, and a kidnapped robot (Section 1.2) experiment. The latter is an experiment where a localized robot is displaced and the recovery time is measured. Adding negative information improves all results when compared to the version of the algorithm that does not include negative information. For the localization experiment, the algorithm is unable to localize without the use of negative information.

4. **Information Requirements.** The information requirements to exploit the negative information include, but are not limited to, what was already being saved by the unmodified original algorithm; a comprehensive model of the sensors including likelihood of detection within the field of view; a map of the region including occlusions, landmarks and field lines (i.e., the lines on the game field); and attributes of the occlusions, landmarks, and field lines.

### 2.2.3 Michaelides, M.P., and Panayiotou, C.G. (2007), Subtract on Negative Add on Positive (SNAP) estimation algorithm for sensor networks [30]

1. **Area of Research.** The area of research in this paper is concerned with the use of wireless sensor networks, densely deployed, which are used for localizing events that create a measureable signal that propagates through the environment. The network consists of "low-cost, low power, multi-functional sensor nodes that are small in size and communicate untethered in short distances" [30], and provide binary measurements (i.e., there is a signal or there is not a signal). The simple algorithm they present, subtract on the negative add on the positive (SNAP), provides a way to estimate the likelihood matrix for an event. The paper compares their algorithm with three other algorithms, one of which did not include negative information. The paper used simulated data to test the algorithm.

2. **Negative Information Use.** The sensors in this research make binary observations. The expected information is that the signal is above a certain threshold. The likelihood matrix that is constructed is used to locate the most likely position of the event. The likelihood matrix is constructed by adding +1 for every contribution where the event was detected and adding -1 for every contribution where the event was not detected. The latter is the negative information contribution. The absence of the expected information infers that it is less likely that the event occurred near the sensor.

3. **Results.** The paper compares their SNAP algorithm with three other algorithms: Centroid Estimator (CE), Maximum Likelihood Estimator (ML), and Add Positive (AP). Only AP does not include negative information, and is equivalent to SNAP, except it only adds on the positive. When no faulty sensors are incorporated into the simulation, SNAP and ML have similarly superior performance compared to the other two algorithms. However, SNAP is less computationally intensive than ML. When faulty sensors are incorporated into the simulation, SNAP (and AP) display a superior fault tolerance to ML. SNAP was found to be less sensitive to false positives and false negative measurements than ML. SNAP is also more fault tolerant than AP. SNAP lost little accuracy when ¼ of the 200 sensors were faulty.

4. **Information Requirements.** The information requirements to exploit the negative information include, but are not limited to, sensor positions, a grid of the area of interest, the region of coverage around a sensor, the alarmed and non-alarmed sensors with respect to the grid, and the +/-1 assigned to the grid for the alarmed and non-alarmed sensors based on the region of sensor coverage.

### 2.2.4 Hester, T., and Stone, P. (2008), Negative information and line observations for Monte Carlo localization [31]

1. **Area of Research.** The area of research in this paper is self-localization in robotics applied to vision-based legged robots. The authors extend a method for using negative information that was previously published [6, 32] to make the scheme more robust to errors when landmarks go unobserved. Like in [6], a particle filter is utilized. The method used to make the scheme more robust only updates the particle with negative information when the landmark has not been detected for t consecutive frames. For example, in [6], the scheme used in that paper is equivalent to t=1. The authors also incorporate "line observations into the probability updates of the algorithm" that is different from the method used in papers they cite [31]. A line observation could include, for example, carpet edges or the edge of a sidewalk, or in the case of the experiment, the lines on a playing field. Both real and simulated data are used to test the algorithm. Real data is used for localization accuracy experiments. Simulated data is used for robot kidnapping experiments, which test self-localization capabilities.

2. **Negative Information Use.** The expected information in the algorithm is a landmark. The algorithm allows for the negative information to only be considered upon repeated missed observations, given that a single observation of a landmark can be easily missed. After the repeated absence of a landmark, the negative information helps the robot infer its location.

3. **Results.** The setup used for the experiments was that used for the RoboCup four legged league, which includes distinct and ambiguous point landmarks as well as ambiguous line landmarks. The algorithm was run with the following four scenarios: using no negative information and no line landmarks (baseline), using negative information and no line landmarks, using line landmarks and no negative information, and using both negative information and line landmarks. The baseline algorithm uses point landmarks for localization purposes. The authors used thresholds to determine when localization and recovery had been achieved in each set of experiments. Regarding both localization accuracy and kidnap recovery time, the robot does best when both negative information and line landmarks are used in the algorithm. With respect to kidnap recovery time, the recovery time when only negative information is used is not significantly different than for the baseline algorithm, while the recovery time when only line landmarks are used is significantly better than for the baseline. In the kidnapped robot experiment, t=5 improves upon results for t=1, suggesting improved results compared to the algorithm used in [6, 32].

4. **Information Requirements.** The information requirements for incorporating negative information include, but are not limited to, a map of the environment including all landmarks, processed results from images, optical field of view of the robot, guesses as to where the robot is, and a count of how many times a landmark is expected but not sensed.

### 2.2.5 Peters, D., and Hammond, T. (2011), Interpolation between AIS reports: probabilistic inferences over vessel path space [33]

1. **Area of Research.** The area of research in this paper is maritime situational awareness (also known as maritime domain awareness). In this research, they "present a method for addressing probabilistic queries about the location of a vessel in the time interval between

two position reports, such as from the Automatic Identification System (AIS).” [33] The example problem they investigate is three vessels with known beginning and end locations, and an oil spill happening during the time interval. The goal is to decide which ship is the most likely culprit. The example also introduces a friendly military vessel which was passing through the area during the timeframe, with a known track. It is known that the military ship is not the culprit. Negative information about what the military vessel did not sense is incorporated into the algorithm. They use simulated data to test their algorithm.

2. **Negative Information Use.** The expected information in the example problem is that the military vessel would detect a vessel within range of its sensors. When the military vessel does not detect a vessel during the timeframe of the scenario, this is used to remove all tracks that take a vessel within detection range of the military vessel, thus altering the position probability density for each vessel. The negative information is used to remove vessel paths that intersect the sensor region. The method they present does not require negative information to be collected but it can be incorporated if available, like in their example.

3. **Results.** Incorporating the negative information helps indicate one vessel is more likely the culprit. Without the use of the negative information, another vessel is indicated.

4. **Information Requirements.** The information requirements for utilizing negative information include, but are not limited to, known ship positions in the area of interest, with respect to time; the sensor models for the sensing vessels; and the set of possible ship tracks generated prior to including negative information.

## 2.3 Autonomous platforms

This section looks at platforms, such as robots, aerial vehicles, and cars that are being programed with reasoning capabilities, aka artificial intelligence. The papers discussed have incorporated negative information to improve a reasoning algorithm. The reasoning is not being applied to self-localization, as in some of the papers in the previous section. The authors who had multiple papers on the topic of incorporating negative information into reasoning algorithms, suggesting expertise in the area, were Tischler and Vogt [13, 34].

### 2.3.1 Tischler, K., and Vogt, H.S. (2007), A sensor data fusion approach for the integration of negative information [13]

This paper is a more detailed version of [34].

1. **Area of Research.** The area of research in this paper is information fusion in advanced driver assistance systems. Information fusion for such systems requires an understanding of the environment. Understanding the environment is expected to be helped by environmental knowledge from multiple vehicles that is fused together and shared. The research on this approach had previously only incorporated positive information, not utilizing information about areas that were observed but no positive information generated. It is important to incorporate that absence of information because it helps in trajectory planning for the vehicle. This paper introduces negative information into the algorithm. This also allows a plausibility

check, to test if the sensors are functioning properly by observing if a sensor does not detect an object, while another sensor does. They test their approach using a simulated environment.

2. **Negative Information Use.** The expected information is that an object will be detected. It is also expected that for overlapping sensor views, both sensors will detect the object. Negative information decreases the probability of the existence of an object being in view. The probability of existence can in turn indicate a sensor failure if overlapping sensors do not both detect the object. The authors also indicate that unoccupied sensed areas can be used to infer where the vehicle can navigate, but that was not the focus of this paper's results.

3. **Results.** The probability of existence of an object will rise when detected and decrease when it is not detected, allowing the track to be terminated once the probability of existence is below a certain level. If only one vehicle has the object in view, because the object is not in view of the second vehicle, then the probability of existence is not penalized for only one detection report. However, if both sensing vehicles are in view of the object, then having conflicting reports on the presence of an object decreases the existence probability until it reaches a predetermined value. Having corroborating detection reports from the vehicles in view of the object increases the existence probability.

   The authors use a traffic simulation environment: two sensing vehicles and one object vehicle. In the scenario where the two sensing vehicles work perfectly, the probability of existence rises and falls based on the rules described above. In the scenario where one of the vehicles has a malfunctioning sensor, the probability of existence goes down when both sensors are in view of the object. The paper finds that the collaborative description of the environment increases in consistency due to this approach, which is the intent of the research.

4. **Information Requirements.** The information that needs to be available to utilize the negative information includes, but is not limited to, any sensor detections (or tracks) and the information contained in the grid-based visibility map used by the algorithm. The algorithm in the paper uses a grid-based visibility map as well as a centralized tracking algorithm, to produce an environmental model for the vehicles that have sensors. The grid should encompass the roads and their nearby environments. The visibility map is dynamic if the sensors are moving. The visibility map requires knowledge of sensor position, orientation, and velocity. The detection probability over the field of view of every sensor is also modelled. The parts of the visibility map with cells outside the field of view are modelled to have detection probabilities of zero. Specific to negative information, however, the information requirements entail that the negative information be incorporated into the visibility map. "In the visibility map, observed vacant areas are documented and in case of overlapping fields of view, the plausibility check incorporates negative information, so sensor failures or other inconsistencies become obvious." [13]

### 2.3.2 Sinha, A., Kirubarajan, T., and Bar-Shalom, Y. (2006), Autonomous search, tracking and classification by multiple cooperative UAVs [18]

The focus of this paper is not about incorporating negative information; however, they have incorporated it into the algorithm they are using. Even though it does not meet that criterion of the literature review, it seems a worthwhile review to include given the unique way negative information is used, as will be described below.

1. **Area of Research.** The area of research in this paper is autonomous decision making by Unmanned Aerial Vehicles (UAVs). The UAVs are tasked with searching out, tracking and classifying targets, autonomously, over a large physical area. The authors introduce a cooperative control algorithm for the UAVs. After (cooperatively) sharing current scan information with each other, "each UAV makes its scan decision and path decision separately, based on information-based objective functions, which incorporate target state information as well as target detection probability and survival probability due to possible hostile fire by targets and collision with other UAVs." [18] As mentioned above, negative information is utilized. Simulated data are used to test the algorithm.

2. **Negative Information Use.** The expected information is a detection of a target when a UAV scans a sector. A sector that contains no detection allows for the inference that the anticipated information content of that sector should be decreased. "The [anticipated] information gain from the sectors is used as the criterion for the scan decisions made by each UAV." [18] Knowing there was no target detected makes the sector less desirable for any of the UAVs to revisit. Both revisiting sectors that had detections and visiting sectors that have not been visited have potentially more information gain than revisiting previously visited sectors that had no detections.

   Technically, their tracking algorithm does incorporate negative information as well. The expected information is a measurement associated with an existing track. If a track is not associated with measurements, it uses the probability of the target not being detected, as well as the track's previous track quality index, to update the track quality index that determines whether a track should be deleted or not.

3. **Results.** In their simulated scenario, the four UAVs detect, track, and classify all targets. There are no negative information results to report.

4. **Information Requirements.** Some information that needs to be available to utilize the negative information includes: values required to compute the expected information gain from each sector; the current track picture; the current position of the UAVs, a record of sectors that have been scanned including if they detected a target or not; sectors that have not been scanned; and the last scan time of each sector. This is an incomplete list but indicates some of the information needed for scan and path decisions that utilize negative information.

### 2.3.3 Hadfield-Menell, D., Groshev, E., Chitnis, R., and Abbeel, P. (2015), Modular task and motion planning in belief space [35]

The focus of this paper is not about incorporating negative information; however, they have incorporated it into the algorithm they are using. The point of this paper was to test the task and motion-planning algorithm that uses negative information. Even though it does not meet that criterion of the literature review, it seems a worthwhile review to include given the multifaceted use of and dependence on negative information by the robot.

1. **Area of Research.** The area of research in this paper is autonomous robots, and more specifically task and motion planning for executing long-horizon tasks when there is uncertainty about the environment. They test their task and motion-planning algorithm against three scenarios: 1) the first task is navigating a hallway. 2) In the second task, the robot must grasp an object from a cluttered table, thus having to reason through and remove obstructions. Three objects on a cluttered table have unobserved positions. 3) In the third task, the robot has to locate a set of keys that are inside one of three desks. They test their approach through simulation.

2. **Negative Information Use.** In each scenario, different negative information is used to accomplish the task. 1) In the first task, the expected information is sensing an obstruction. The robot uses the absence of obstructions to plan its path as it navigates a hallway; i.e., it infers a clear path based on the absence of obstructions. 2) In the second task, the expected information is the sensing of the desired objects. By taking into account occlusions, the robot has to reason where the object is located. Then reason through the obstructions it must remove before it can observe the object and grasp it. 3) In the third task, the expected information is that the keys will be in the desk drawer the robot opens. If the keys are not there, the robot uses the negative information to infer that they must be in another desk.

3. **Results.** There are no negative information results to report. For the results reported, the authors do not claim whether the results are good or bad, only that the main limitation they found was due to the computational complexity of an aspect of their algorithm.

4. **Information Requirements.** The negative information used by the algorithm is the absence of 1) objects blocking the robot's path, 2) objects on a table, 3) keys. The belief state of the robot includes view cones where an object is not observed. The information that needs to be available to utilize negative information is the view cones and a map of the area that is being built by the robot.

### 2.3.4 Koch, A., and Zell, A. (2014), Mapping of passive UHF RFID tags with a mobile robot using outlier detection and negative information [36]

This reference is included for completeness. The paper did not provide enough clear information about the negative information aspect to complete a review on it.

## 2.4 Classification and decision support

Classification (e.g., categorizing, grouping, ranking, sorting) and decision support (e.g., providing analysis to help make a decision) are two applications relevant to the RCN that could benefit from the use of negative information. The previously discussed paper, "Autonomous search, tracking and classification by multiple cooperative UAVs" [18], is an example of classification research as well as decision making research (regarding the UAV). "Mapping of passive UHF RFID tags with a mobile robot using outlier detection and negative information" [36] is also a classification paper. Note, however, neither of these papers met the criteria for this literature review but were included for interest and completeness, respectively. While negative information is used in classification and decision support tasks, it was difficult to locate papers which met the initial requirement for inclusion in the report, that being part, if not all, the research reported in the paper pertains to investigating the utilization of negative information to help complete a task. In addition, sometimes the negative information or negative evidence used in the specific research paper did not align with the definition used in this report. For example, it might be found that negative evidence is defined as phrases contained in radiology reports, such as "no evidence of …" or "no suspicious …", as in "Ad Hoc Classification of Radiology Reports" [37]. In other words, the algorithm is looking for positive information indicating the presence of negative information.

An example of a paper where negative information is the focus and where the definition aligns with this work, is "On word Frequency Information and Negative Evidence in Naïve Bayes Text Classification" [38]. This paper discusses a situation where an algorithm was relying too heavily on negative information for classification which was why another algorithm, that relied less on negative information, improved results. Also, in the decision support paper, "A Bayesian Method for Managing Uncertainties Relating to Distributed Multi-static Sensor Search" [39] there is a section of the paper dedicated to learning from negative searches. However, a description of the results of incorporating the negative information was difficult to tease out since the paper was about an algorithm and methodology the authors were proposing.

Therefore, despite the important applications of classification and decision support, only one paper is presented in this category.

### 2.4.1 Stroppiana, D., Bordogna, G., Boschetti, M., Carrara, P., Boschetti, L., and Brivio, P.A. (2012), Positive and negative information for assessing and revising scores of burn evidence [40]

1. **Area of Research.** The area of research in this paper is mapping burn areas based on multispectral satellite images, using multiple Spectral Indices (SIs). One key issue when using SIs to map burned areas is that none of the spectral indices consistently identifies burned areas in all ecosystems. Secondly, burned areas can be confused with other types of areas. This paper focuses "on the improvement brought by the use of positive and negative information for reducing the commission errors[2] due to misclassification of burns with other surfaces." [40] They test their method using real data. Note that this paper utilizes fuzzy set theory, as opposed to approaching the problem via a Bayesian formulation.

2. **Negative Information Use.** The expected information is evidence of areas that are burned. The negative information indicates evidence of non-burned areas, e.g., shadows and non-forest vegetation. In the paper, SI analysis indicates partial evidence of where there are burned areas (partial positive evidence of burned areas) and indicates partial evidence of where there are not burned areas (partial negative evidence of burned areas). After some data processing, the negative evidence is subtracted from the positive evidence to generate the information required for the region-growing algorithm: highly likely burned areas used for seeds and moderately likely burned areas used for region-growing from those seeds. The region-growing algorithm spatially identifies the burned areas.

[2] Reporting the presence of a feature that is absent.

3. **Results.** The technique they employ in this paper provides a better starting point to apply the region-growing algorithm that is used to map burn areas. The revised technique, using negative evidence, improves the overall accuracy of identifying the burned area from 42.6% to 91.3%. These are preliminary results. More investigation is necessary.

4. **Information Requirements.** The information requirements for exploiting negative information include, but are not limited to, SIs that indicate partial negative evidence and partial positive evidence. To infer partial burn areas from negative information, extra analysis using SIs that indicate partial negative evidence are required.

## 2.5 Miscellaneous

This section looks at a paper that did not fit into the previous categorizations. The paper is on networked systems connected to a sensor, written from a generic perspective.

### 2.5.1 Sijs, J., Noack, B., and Hanebeck, U.D. (2013), Event-based state estimation with negative information [41]

1. **Area of Research.** The area of research in this paper is networked systems connected to a sensor, with a focus on how to reduce the amount of measurements exchanged for resource-limited networks. This paper is not specific to one specialized application. It reduces the number of measurements by proposing an event-based state estimation algorithm that utilizes negative information between events to put a bound on the estimates made between those events. It is compared to an event based state estimator that does not use negative information. Simulated data is used.

2. **Negative Information Use.** The expected information is that the event-sampling criterion has been met. The absence of that information infers that the parameters used to trigger the event-sampling have values constrained within a set of defined values. They are able to use the negative information to better model the estimation error. If no event has been triggered the negative information puts a bound on the estimates used in-between events when no measurement is taken.

3. **Results.** The two algorithms that are being compared achieve similar real estimation errors when using the ground truth. The algorithm that uses negative information produces a modelled estimation error that is better bound on the real estimation error. In other words, the modelled estimation error always contained the true estimation error, which the other algorithm did not. The paper suggests that this “is advantageous in networked control systems where estimation results are being used by a (stabilizing) controller.” [41]

4. **Information Requirements.** This is a mathematically dense paper, and describing in detail what is required to exploit the negative information is beyond the level of this report. At a high level the requirements include, but are not limited to, the time-periodic state estimate portion of the event-based state estimator algorithm that utilizes the negative information. For example, having information about the last event-triggered measurement, the time since the last event, and the subset of parameter values that the event triggering parameters could take, are some of the required information to utilize the negative information.

## 2.6 Non-reviewed reports

For a list of promising reports that were not reviewed under this literature review, please see Annex A.

## 2.7 Review comments

The following looks for commonalities between the papers that were reviewed.

A common theme of the papers included was that they focused on achieving something in the physical plane, (e.g., tracking something in the physical world, localizing something in the physical world, an autonomous platform operating in the physical world) as opposed to, for example, the cyber plane. Looking at why the use of negative information was investigated, the common reasons were to improve scene awareness; to improve state estimate (whether of a target or itself) such as position, velocity, and extent; and to continue tracking a target when it has disappeared. Of note, improving state awareness could be seen as a subcategory of improving scene awareness, and tracking in the absence of information could be seen as a subcategory of improving state awareness. Therefore, improving scene awareness could be seen as the most general reason for introducing the use of negative information into a task in these papers. In some papers, the reason for improving scene awareness was ultimately to improve a decision that needed to be made.

Given that negative information is the absence of expected information, a closer look was taken at the expected information in the papers. It was often expected that an object be detected (e.g., target, landmark, obstruction). The object could be specific (e.g., keys, an airplane already being tracked) or general (e.g., any object within view, any plane flying into view of the sensor). The exceptions in the papers were Section 2.1.5, which expected a sensor measurement to be associated with a target; Sections 2.2.3 and 2.5.1 where a threshold or criterion was expected to be met, which is slightly different than detecting an object; and Section 2.4.1 where the expected information is that evidence of burn areas exists. A common denominator in the exceptions is that there are return signals being received, but another criterion is not being met.

The commonalities of performing tasks in the physical realm, using negative information to improve scene awareness, and the expectation of detecting objects, all seem well suited for the RCN (and CAF) environment they work in.

# 3 Discussion

## 3.1 Applications to the RCN or CAF

In this section, some potential applications of the research reviewed, relevant to either CAF tasks or more specifically RCN tasks, are discussed. A goal of this report was to find promising ways to exploit negative information to enhance RCN maritime situational awareness and decision making; however, some papers had other CAF or general CAF applicability. They are also included here. When appropriate, similar papers are grouped together. The partial paper reference and the section its review is found in are recorded for easy reference. The subsections are divided into discussions on papers that could be directly applied to tasks and papers that could be indirectly applied to tasks. Essentially, the direct application papers already research concepts relevant to the military whereas novel applications take inspiration from existing papers.

### 3.1.1 Direct applications

Of the papers reviewed, many techniques that were investigated can be directly applied to CAF tasks in an obvious way; for example, multiple target tracking with a bias to ground and air tracking is discussed in [17]; tracking ground vehicles is discussed in [19]; all tracking activities discussed are specifically defense and security related in [8]; airborne radar tracking of a target in the presence of jamming is discussed in [12]; extended object tracking is discussed in [11]; and localization in the realm of maritime situational awareness is discussed in [33]. However, some of the directly applicable papers perhaps are not as obvious:

#### 3.1.1.1 Jovanoska, S., Govaers, F., Thomä, R., and Koch, W. (2015), Dynamic-occlusion likelihood incorporation in a PHD filter based range-only tracking system [10] and Wyffels, K., and Campbell, M. (2015), Negative Information for Occlusion Reasoning in Dynamic Extended Multiobject Tracking [21]

**Section 2.1.6:** The essence of the scenario in the paper [10] is that a moving target temporarily obstructs another moving target. One cannot pre-map the obstruction as the environment is always changing; however, it is important to the algorithm that the obstruction is also sensed by the sensor. They are able to dynamically track missed targets that are behind other targets. They use the distance and width of the occluding object to the sensor to do this.

**Section 2.1.7:** This paper [21] is interested in autonomously tracking vehicles, even when they are occluded by other moving targets, so as to improve scene awareness. There are many CAF situations when immediate scene awareness is important to accomplishing a goal, whether while on the water, in the air or driving on land.

Both these papers are likely directly applicable to the RCN when tracking takes place using sensors that are land-based or shipboard, and are subject to line of sight sensing that is affected by occlusions, such as one moving ship blocking another moving ship or clouds blocking a sensor on a satellite. The algorithms could also be used in real time on aerial surveillance vehicles that have an optic sensor, to keep the optic sensor trained on the target even when it is occluded. The research found in these papers could also be directly applied to creating a tool that helps the operator maintain awareness of occluded objects around them that are dynamically being occluded.

#### 3.1.1.2 Shan, M., Worrall, S., Masson, F., and Nebot, E. (2014), Using delayed observations for long-term vehicle tracking in large environments [20]

**Section 2.1.8:** The area of research in this paper is tracking of cooperative vehicles in a disadvantaged environment. This work is directly applicable in cases where peer-to-peer information exchange is taking place but satellite or GPS tracking is either not feasible, not available or not appropriate. It would be appropriate for land, air, and water. It is noted that if Satellite AIS had not proven feasible, this could have extended the "view" of land based AIS networks.

#### 3.1.1.3 Montemerlo, M., and Thrun, S. (2003), Simultaneous localization and mapping with unknown data association using FastSLAM [29] and Hoffmann, J., Spranger, M., Göhring, D., and Jüngel, M. (2005), Making use of what you don't see: negative information in Markov localization [6] and Hester, T., and Stone, P. (2008), Negative information and line observations for Monte Carlo localization [31]

**Section 2.2.1:** In [29], for an object that has been previously detected, the odds of its existence decreases when the object is expected to be detected but is not. If the odds of existence drop below a threshold value, the object is removed from the map.

**Sections 2.2.2 and 2.2.4:** Both papers, [6] [31], use negative information about expected landmarks to help the robot self-localize.

The SLAM paper [29] could be applied to autonomous UAVs tasked with mapping an unknown area and charting an unobstructed course through an area. It could also be directly applied to both autonomous and semi-autonomous Unmanned Underwater Vehicles (UUVs). Theoretically, for UUVs that do not have access to their own position while submerged, a SLAM algorithm could be used to keep track of its relative location in the unknown ocean environment. An appropriate sensor type would be needed to map the environment. Both [6] and [31] are robot self-localization research papers, with algorithms that could be applied to that aspect of the proposed AUV and UUV application ideas.

#### 3.1.1.4 Michaelides, M.P., and Panayiotou, C.G. (2007), Subtract on negative add on positive (SNAP) estimation algorithm for sensor networks [30]

**Section 2.2.3:** The research in this paper is concerned with using simple sensors for detecting events and then determining the location of the event. Each sensor over an area either detects a signal or does not detect a signal, and the source of the signal is located through their algorithm. This is directly applicable to any CAF scenario where an event propagates, such as an explosion, a release of chemicals, sound propagating through the ocean, etc.

#### 3.1.1.5 Sinha, A., Kirubarajan, T., and Bar-Shalom, Y. (2006), Autonomous search, tracking and classification by multiple cooperative UAVs [18]

**Section 2.3.2:** The RCN is investigating the use of UAVs. The research in this paper could be directly applied to any autonomous UAV program that is set up in the future. However, the premise distills to the generalization of: A search for a target is underway. The search area is segmented. A segment of the search area shows no sign of containing the desired target. It could still contain the desired target at a later time or it is possible the desired target eluded the search technique, but given the negative result when the segment was searched, the importance of researching the segment is demoted. This, as well as the general concept of using information gain as a decision aid tool, are directly applicable to search and rescue decision making, boarding party decision making, as well as general surveillance decision making.

#### 3.1.1.6 Sijs, J., Noack, B., and Hanebeck, U.D. (2013), Event-based state estimation with negative information [41]

**Section 2.5.1:** The RCN is tasked to maintain situational awareness in many types of environments. Some, like the Arctic, have limited infrastructure. This paper describes a method for state estimation based on the detection of significant events that should be useful for bandwidth constrained environments. The research could be directly applied to an event-based surveillance network in an area with limited resources.

### 3.1.2 Novel applications

One of the goals of this literature review is to discuss potential application of the paper's methods to an RCN task. As mentioned earlier, the aim of this section is to take inspiration from existing papers for new research. The following is a collection of ideas that are beyond the obvious direct applications mentioned above. In particular, papers [17], [19], [10], [11] and [12] have been noted previously as having direct applications but are also used here as stimulus for novel applications. Examples will be drawn from AIS for the purposes of illustration. Furthermore, note that the first three share the theme of target tracking applications that are intermittently detected. They use negative information to constrain or refine state estimates.

#### 3.1.2.1 Särkkä, S., Tamminen, T., Vehtari, A., and Lampinen, J. (2004), Probabilistic methods in multiple target tracking – Review and Bibliography [17]

**Section 2.1.1:** The negative information exploitation premise distills to the generalization of: one or more sensors stop sensing a target while at least one sensor continues to sense it. This provides information about the state of the target.

This type of negative information is directly applicable to the RCN tracking task when certain types of sensors are employed for tracking. However, it can also be employed in a more abstract way. For land or space reception networks, if one receiver is receiving a signal while others nearby are not (given a certain height and orientation of the sensor, and the local conditions), someone can infer information about the reception extents of the receivers. So rather than providing information about the state of the target, it exploits negative information to infer the state of the sensor that is no longer receiving the transmissions.

Alternatively, if no sensor is detecting the target but there is knowledge that the target is there, this technique can be used to map sensor "dead zones," where there are sensor limits or obstructions blocking target detection. These obstructions and sensor limits can be modelled into localization and tracking algorithms as discussed in other papers to better localize or track a target.

For example, sailing a boat transmitting AIS up and down the Halifax harbour was once considered as a method to determine the AIS coverage area of a local AIS land-based receiver. This would have provided the coordinates for obstructions and the receiver's extent. This idea exploits negative information to better predict when to expect negative information in the future.

**Possible future work:** Research the application of negative information for mapping dynamic and static sensor dead zones, incorporating that mapping into an existing tracking algorithm and modifying the tracking algorithm to take into account non-detections (negative information).

#### 3.1.2.2 Agate, C.S., Wilkerson, R.M., and Sullivan, K.J. (2004), Utilizing negative information to track ground vehicles through move-stop-move cycles [19]

**Section 2.1.2:** The unique aspect presented in this paper, is related to the kinematics of the tracked object. For this particular sensor, detection requires the target to be moving. The premise distills to the generalization of: A target stops a particular activity and therefore the sensor stops detecting the target. The absence of the detection indicates the absence of the behaviour. Alternatively, the target has masked itself.

For example, if a vessel is broadcasting AIS and is known to be in an area well covered by AIS receivers, then the termination of AIS broadcast represents the change in activity. The behaviour change could indicate that the ship being in distress or trying to be covert. Using the algorithm found in [5], some work led by Lapinski was begun to incorporate such an alert, as indicated in [42]. While the absence of expected information was not called negative information at the time, it is clear now that this terminology is appropriate.

**Possible future research:** Build on the previous work done, using an approach similar to this paper.

### 3.1.2.3 Blanding, W.R., Koch, W., and Nickel, U. (2009), Adaptive phased-array tracking in ECM using negative information [12] and Jovanoska, S., Govaers, F., Thomä, R., and Koch, W. (2015), Dynamic-occlusion likelihood incorporation in a PHD filter based range-only tracking system [10]

**Section 2.1.4:** In [12], the essence of the scenarios is that a moving target may not be detected because it either leaves the extent of the sensor or enters a known area where the sensor should be able to see it but cannot. In the latter situation, using an appropriate model of reality, negative information can be used to help maintain the track of the target through the sensor's blind zone.

**Section 2.1.6:** The essence of the scenario in the paper [10] is that a moving target temporarily obstructs another moving target. See above, in Section 3.1.1.1, for a further general description.

As examples, with regards to blind zones, AIS message collision in space-based AIS reception creates blind zones in high traffic areas. The method in [12] could be used to continue the tracking of a target through a high traffic area. Alternatively, the blind zone could be viewed as a temporary moving obstruction and therefore methods in [10] could be utilized.

**Initial Questions** (from which **future research** might emerge): Is it possible to use these concepts of tracking in the presence of either static or dynamic occlusions to continue tracking AIS broadcasting ships that are broadcasting in areas where the receivers (satellite or land-based) are not receiving all the AIS messages due to persistent or sporadic message collision (satellite) or fluctuating reception limits (land-based)? If so, such prediction methods can be used when AIS messages are not being received. A consideration: there are occlusions (something preventing reception) but there are no occlusions to measure. However, is it worth the effort to develop the prediction methods, given that there is a name associated with AIS ships, which makes associating the contact with the correct historical contact very easy? This would need to be assessed as well.

### 3.1.2.4 Zea, A., Faion, F., and Hanebeck, U.D. (2015), Exploiting clutter: Negative information for enhanced extended object tracking [11] and Stroppiana, D., Bordogna, G., Boschetti, M., Carrara, P., Boschetti, L., and Brivio, P.A. (2012), Positive and negative information for assessing and revising scores of burn evidence [40]

**Sections 2.1.5 and 2.4.1:** The negative information premise in both these papers may be summarized as the use of positive information about non-targets as negative information about the target. In the latter paper, [40], it is more specifically using positive information about non-targets (non-burn areas) to reduce the false positives of the positive information about targets (burn areas).

As an example, the negative information exploitation idea could be applied to on-water situations.

Consider the situation where a non-broadcasting (or detected) ship is the target. In the north: information about where icebergs are (non-targets) and ice conditions can tell you where the target is not. The negative space would be the areas to look for a non-broadcasting ship.

**Possible future research:** Creating dynamic map layers of non-targets that can be used to isolate physical areas of interest for surveillance or tracking.

#### 3.1.2.5 Miscellaneous ideas

Possible future research: An algorithm that maps dynamic objects and uses negative information to figure out the open spaces between the dynamic objects, could be applied to UUVs in the arctic, when they are trying to surface in an ever-changing ice floe above them or trying to locate the ship they were launched from. Being able to map and track dynamic objects would be key.

## 3.2 The challenges of using negative information in an automatic way

Based on the literature review, certain challenges in using negative information in an automatic way have been identified:

For example, comprehensive modelling is required. [8, 17] To use negative information, the environment (whether physical, cyber, or other) needs to be understood, including the possible outcomes. The physics of the problem needs to be known. In addition, the sensor needs to be accurately modeled. The need for comprehensive modelling is repeatedly stated in the literature, for example [8] [13] [22] [6] [21], as one of the most important rules for using negative information to get usable results. In terms of sensors, “the measurement process and the field of view have to be modelled as exactly as possible.” [13] Also, any static or dynamic situations, such as occlusions, that disrupt measurements need to be identified and modelled. In general, the reasons for positive information, negative information, false positive information, and false negative information, each of which may be functions of many parameters, need to be understood. For example, if a sensor only detects an object when it is moving above a certain threshold speed, then this has to be incorporated into the model. If a person repeatedly searches the same drawer for an object then it could mean that they subconsciously understand that they do not always recognize the presence of an object that is within their field of view. Such an understanding of false negatives needs to be incorporated into the model.

Another identified challenge is that electronically storing the required negative information involves making practical decisions. Whether analysis is being done in real time, near real time or in after-the-fact time, negative information needs to be stored in order to use it. Electronically storing the required information to make negative information inferences, whether storing long-term or temporarily, requires some forethought. Consider making a list of all things you could see that you do not, things you could hear that you do not, things you could smell that you do not, things you could taste that you do not and things you could feel that you do not, during the next 60 seconds of your life. An overwhelming thought. This thought experiment shows that it is impossible to store all possible negative information that could one day be needed for doing data analysis. Storing the absence of information can potentially make information storage grow considerably. For example, without anticipating the need of negative information, a database or algorithm may only store the location, date, and time of objects detected by a surveillance flight. For a surveillance flight, the area of sensor coverage would be constantly moving with the path of the flight. If the absence of detected objects is required to make negative information based inferences automatically, then this requirement can increase the data stored considerably. If the algorithm or database stores position and time of the non-detection events every second with respect to the plane's position, during a two-hour flight that only located two objects, then at the end of the two hours there would have been 7198 data entries about non-detections. Therefore, even for a known problem that negative information is useful to help solve, some forethought on what to store and the trade-off of high fidelity and low-fidelity data, needs to be analysed so that the system is not tasked unnecessarily with data that is less valuable than the positive data. This was not a popular topic in the literature reviewed, and will likely require further research.

Another challenge to using negative information is that it only narrows down choices or improves estimates [8]. "Negative information is ambiguous and provides less evidence than positive information" [13]. Sherlock was not able to name the robber in Example 1 using negative information. The precise location of the pencil was not determined through negative information in Example 2. The literature implies that negative information can only be used to narrow down choices. Using negative information is an alternative when the required explicit positive information is not available. For example, when you do not have the positive information telling you where a ship is, employing inference is an alternative. By combining the negative information with existing but less useful, positive information, such as prior ship locations, sensor dead zones, knowledge of the coastline, and traffic lanes, can help narrow down where a ship might be. Using negative information is an alternative when the required positive information is not available. Therefore, it can be suggested that the value of negative information is quite low when the positive information that will give the more precise evidence exists but is quite high when negative information combined with less informative positive information is the best information available.

Another challenge is that while negative information might be a concept easily understood by statisticians, people versed in logic and deductive reasoning, etc., for a layperson, the concept of negative information can be challenging to understand [13]. This is an important challenge for designing how negative information is going to be used: will an in-depth understanding be required, a superficial understanding be required, or no understanding be required, by the end user. Note that this report did not start with the definition of negative information (negative information is the absence of expected information), but rather it started with an example. Anecdotally, when explaining it to people, it seems they find it easier to understand the concept of negative information through an example than through its definition. Positive information is a more familiar topic for people, though the word positive is rarely used. The complexity of the concept could be a roadblock to using negative information, but with proper application of S&T, we should be able to meet the challenge. In a similar vein, the techniques used for exploiting negative information, e.g., Bayesian, might be challenging to implement and understand for those without the proper background [8, 17]. This will limit the number of people who can properly implement techniques.

# 4 Concluding remarks

Negative information is a ubiquitous concept that is naturally applied to daily activities. It is not until the desire to design algorithms and machines to mimic human capabilities that the concept needs to be unpacked and analysed. This paper has presented a review of literature that contains research into the application of negative information to improve a variety of methods. It has presented the starting point for further research into the topic of negative information.

As stated earlier, the goals of this report are as follows:

- To clearly explain negative information;
- To review how negative information is being exploited in scientific research;
- To identify the information requirements so as to be able to use negative information in an automatic, ongoing, way;
- To identify promising avenues by which negative information could be exploited to enhance RCN maritime situational awareness and decision making; and
- To identify the challenges of using negative information in an automatic way.

Section 1.2 laid out the concept of negative information. Section 2 reviewed the research and identified the information requirements to exploit negative information, on a per-paper basis. Section 3.1 identified some ways that negative information could be exploited to aid not only the RCN but also the CAF. Section 3.2 outlined some challenges that should be expected when trying to utilize negative information.

Likely, the largest challenges to applying negative information in an RCN setting would be 1) the modeling of the environment and sensors so that utilizing negative information yields correct assumptions, and 2) the practical decisions that need to be made to electronically store the required negative information to be able to utilize it in an automatic way, without tasking the system unnecessarily.

Going forward, Section 3.1 should be reviewed internally to narrow down the most promising ideas of negative information application. The section should also be presented to and commented on by the operational community (e.g., Regional Joint task forces, CJOC, CFMWC). Once a subset of the ideas is chosen, they should be reviewed with subject matter experts to validate the ideas and choose the best idea to start evaluating in practice.

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# Annex A Non-reviewed references

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# List of symbols/abbreviations/acronyms/initialisms

| | |
|---|---|
| AIS | Automatic Identification System |
| AP | Add Positive |
| CAF | Canadian Armed Forces |
| CE | Centroid Estimator |
| CFMWC | Canadian Forces Maritime Warfare Centre |
| CJOC | Canadian Joint Operations Command |
| DND | Department of National Defence |
| DRDC | Defence Research and Development Canada |
| DSTKIM | Director Science and Technology Knowledge and Information Management |
| ECM | Electronic Countermeasures |
| ESA | Electronically Scanned Array |
| FastSLAM | a variation of SLAM |
| F-EKF | Fixed Extended Kalman Filter |
| F-PB | Pseudobearing Extended Kalman Filter |
| GS | Gaussian Sum Filter |
| Kernal GAM | Kernel Greedy Association Model |
| ML | Maximum Likelihood Estimator |
| OSPA metric | Optimal Subpattern Assignment Metric |
| PHD | Probability Hypothesis Density |
| R&D | Research & Development |
| RCN | Roya Canadian Navy |
| SDM | Spatial Distribution Model |
| S-GAM | Kernal Greedy Association Model that incorporated negative information |
| SI | Spectral Indice |
| SLAM | Simultaneous Localization and Mapping |
| SNAP | Subtract on the Negative, Add on the Positive |
| S-SDM | Spatial Distribution Model that Incorporated Negative Information |
| UAV | Unmanned Aerial Vehicle |
| UUV | Unmanned Underwater Vehicles |
| UWB radar | Ultra-Wideband Radar |

| | |
|---|---|
| V-EKF | Variable Extended Kalman Filter |
| V-PB EKF | Variable Pseudobearing Extended Kalman Filter |

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Enabling the sharing and use of vital information to support Royal Canadian Navy (RCN) tactical/operational decision-making and achieving situational awareness is a priority research area for Defence Research and Development Canada (DRDC). In support of this goal, the present research examines negative information. Negative information would originate from what is not present in the information feeds being received. The report gives a clarifying description of negative information followed by a review of multi-disciplinary scientific research that has incorporated negative information into the processing, for varying purposes. The literature reviews follow a consistent format: research area statement, statement on the negative information that was used, a description of the results, and a discussion on the information requirements. A discussion and conclusion follows. Several potential applications to the RCN as well as applications general to the Canadian Armed Forces (CAF) were identified. In addition, challenges in using negative information in an automatic way were suggested. The largest challenge to applying negative information in an RCN setting is likely the modeling of the environment and sensors so that the negative information yields correct assumptions.

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Le partage et l’utilisation de l’information essentielle au soutien de la prise de décisions tactiques/opérationnelles par la Marine royale canadienne (MRC), de même que l’acquisition d’une connaissance de la situation sont des domaines de recherche prioritaires de Recherche et développement pour la défense Canada (RDDC). À l’appui de cet objectif, la présente recherche porte sur l’information négative. Celle-ci proviendrait de ce qui est absent des fils d’information. Le rapport comporte une description claire de l’information négative, suivie d’un examen de la recherche scientifique multidisciplinaire qui tient compte, à des fins diverses, de l’information négative dans le traitement. Les analyses documentaires sont effectuées de façon uniforme : énoncé du domaine de recherche, énoncé sur l’information négative utilisée, description des résultats, examen des besoins en information. Suivent une étude, puis la conclusion. Plusieurs applications éventuelles dans la MRC et, de manière générale, dans les Forces armées canadiennes (FAC) ont été définies. De plus, des difficultés relatives à l’utilisation automatique de l’information négative ont été relevées. La plus grande difficulté que pose l’utilisation de l’information négative au sein de la MRC est probablement la modélisation de l’environnement et des capteurs de sorte que l’information négative produise des hypothèses correctes.

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Negative Information; Negative Evidence; Negative Observations