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On Validating Self-Reported Vessel Location

Application of Statistical Methods to Assessing Automatic Identification System Reports

D. E. Schaub

Defence R&D Canada – Atlantic

Technical Memorandum

DRDC Atlantic TM 2011-320

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Canada

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Abstract

Self-reported information in maritime settings has become increasingly important in issues surrounding navigation, vessel traffic services, and security. While self-reported data may significantly improve the apparent spatial-temporal resolution of vessel positions used to construct the recognized maritime picture, its accuracy is readily compromised by deliberate acts of deception. The present work sought to develop a method of validating automatic identification system positional reports with trusted radar satellite data. The approach presented uses Kalman smoothing to retrospectively interpolate a vessel's path between radar satellite observations, allowing its location to be estimated for an arbitrary moment in time. A given self-report may then be assessed against a contemporaneous radar satellite estimate using a variety of statistical techniques. Evaluations based on probability ratio analysis, classical hypothesis testing, and nested confidence region analysis were considered. Finally, the method's range of applicability was studied by examining the interaction between a vessel's maneuverability and frequency of radar observations. These considerations may be of use in planning future satellite infrastructure.

Résumé

Les informations autosignalées dans le contexte maritime ont vu leur importance s'accroître dans les secteurs de la navigation, des services du trafic maritime et de la sécurité. Bien que les données autosignalées puissent améliorer beaucoup la résolution spatio-temporelle apparente des positions de navires utilisées pour dresser le portrait de la situation maritime générale, leur précision est facile à compromettre par des actes délibérés de déception. Le présent document vise à développer une méthode de validation des signalements de position du Systéme d'identification automatique à l'aide de données satellite radar fiables. L'approche présentée utilise le lissage de Kalman pour interpoler rétrospectivement la trajectoire d'un navire entre des observations par satellite radar, et permettre ainsi l'évaluation de la position de ce navire à un moment arbitraire particulier. Un autosignalement donné peut ensuite être évalué en fonction d'une estimation par satellite radar contemporain au moyen de diverses techniques statistiques. De plus, on a examiné des évaluations axées sur l'analyse du rapport des probabilités, la mise à l'essai d'hypothèses classiques et l'analyse des régions de confiance emboîtées. Enfin, l'éventail d'applicabilité des méthodes a été étudié grâce à l'examen de l'interaction entre la manœuvrabilité d'un navire et la fréquence des observations radar. Ces considérations peuvent être utilisées dans la planification future de l'infrastructure satellite.

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Executive summary

On Validating Self-Reported Vessel Location

D. E. Schaub; DRDC Atlantic TM 2011-320; Defence R&D Canada – Atlantic; January 2012.

Background: Maritime Situational Awareness (MSA) in Canada's North depends critically on surveillance from space-based platforms. Satellites equipped with synthetic aperture radar may be deployed to detect vessels directly, while those carrying special radio apparatus may be used to receive self-reported Automatic Identification System (AIS) messages that fall beyond the range of terrestrial coverage. While the low density of targets in Canada's North facilitates the association of maritime data, the validity of AIS messages (which may be deliberately falsified) remains an issue of concern. In general, uncertainty surrounding the authenticity of self-reported data may be mitigated through evaluation of its consistency with respect to trusted data. The present work considers this problem in the context of Arctic surveillance by evaluating the statistical likelihood that a received AIS message is authentic using a series of trusted radar contacts.

This work supports the DRDC Applied Research Project 11HO *Situational Information for Enabling Development of Northern Awareness (SEDNA)*. The following study was conducted by DRDC Atlantic over a 6 month period.

Results: This work demonstrates that satellite-based radar can be used to authenticate positional data from self-reporting systems such as AIS. A collection of methods based on a common statistical framework were developed that allow both visual and numerical assessment of a given AIS report's plausibility. Using this framework, it was found that the self-reported position of a typical slow-moving bulk carrier could be validated to within approximately 10 nautical miles using radar satellite observations that are repeated every two hours.

Significance: This work provides the surveillance community with a new collection of statistical methods that assess the validity of self-reported vessel position information (e.g., from AIS) using space-based radar data. These techniques may be employed in operational settings to provide operator-based and automated authentication of AIS reports and are of particular value to environments such as the Canadian North where limited terrestrial monitoring increases the reliance on self-reported information in MSA.

Future Plans: Future work will consider more advanced mathematical methods that better represent the uncertainty associated with long periods between radar observations. Issues affecting the planning of future satellites, such as the benefits of collocating AIS receivers on future radar satellites, will also be considered.

Sommaire

On Validating Self-Reported Vessel Location

D. E. Schaub ; DRDC Atlantic TM 2011-320 ; R & D pour la défense Canada – Atlantique ; janvier 2012.

Contexte : La connaissance de la situation maritime (MSA) dans le Nord du Canada dépend de façon critique de la surveillance des plateformes spatiales. Les satellites dotés d'un radar à synthèse d'ouverture peuvent être déployés pour détecter directement des navires, tandis que ceux dotés d'appareils radio spéciaux peuvent être utilisés pour recevoir des messages autosignalés du Système d'identification automatique (SIA) à l'extérieur de la zone de couverture terrestre. Bien que la faible densité de cibles dans le Nord du Canada facilite l'association de données maritimes, la validité des messages SIA (qui peuvent être délibérément falsifiés) demeure préoccupante. En général, on peut réduire l'incertitude relative à l'authenticité des données autosignalées en évaluant leur concordance par rapport à des données fiables. Le présent document examine ce problème dans le contexte de la surveillance de l'Arctique et évalue la probabilité statistique qu'un message SIA reçu soit authentique au moyen d'un groupe de contacts radar fiables.

Le présent travail seconde le projet de recherche appliquée de RDDC 11HO, intitulé Situational Information for Enabling Development of Northern Awareness (SEDNA) [informations sur la situation pour permettre le développement des connaissances dans le Nord]. L'étude suivante a été réalisée par RDDC Atlantique sur une période de six mois.

Résultats principaux : Le présent document montre que le radar par satellite peut être utilisé pour authentifier des données de position provenant de systèmes d'autosignalement, comme le SIA. Un ensemble de méthodes axées sur un cadre statistique commun a été développé et permet l'évaluation à la fois visuelle et numérique de la plausibilité d'un signalement donné du SIA. Grâce à ce cadre, on a découvert que la position autosignalée d'un vraquier lent typique pouvait être validée avec une précision d'environ 10 milles marins à partir d'observations par satellite radar répétées toutes les deux heures.

Portée des résultats : Le présent document fournit au milieu de la surveillance un nouveau jeu de méthodes statistiques qui permet d'évaluer la validité des informations autosignalées sur la position des navires (comme celles du SIA) à partir de données provenant de radars spatiaux. Ces techniques peuvent être utilisées dans un contexte opérationnel pour fournir une authentification automatisée ou manuelle des signalements du SIA, et elles sont particulièrement utiles dans des environnements comme celui du Nord du Canada, où la surveillance terrestre limitée augmente le recours aux informations autosignalées dans la MSA.

Recherches futures : Les recherches futures porteront sur des méthodes mathématiques évoluées qui représentent mieux l'incertitude associée aux longues périodes entre les observations radar. Elles examineront en outre les éléments qui influent sur la planification de nouveaux satellites, comme les avantages du groupement de récepteurs SIA sur de futurs satellites radar.

Acknowledgements

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1 Introduction

1.1 Overview

Maritime Domain Awareness (MDA) depends on access to timely and complete information on factors affecting maritime security, safety, economy, and environment [1]. Information concerning vessel activities, such as spatial-temporal location and identifying characteristics (e.g., vessel name, International Maritime Organization number, etc.) are particularly important and serve as the foundation of the recognized maritime picture (RMP). Traditionally, the RMP has been composed with geo-temporal data from sensors that directly detect the presence of vessels. While self-reported information was also included, this was usually limited to infrequent (e.g., every 6 hours) voluntary weather reports [2].

The role of self-reported data in surveillance has changed significantly with the recent introduction of the Automatic Identification System (AIS), a shipborne technology that allows vessels to automatically share realtime information on identity, location, bearing, etc., for the purpose of collision avoidance, vessel tracking, and facilitating safe navigation. Ships determine their location with the Global Positioning System (GPS) and exchange information through coordinated broadcasts over two channels in the Very High Frequency (VHF) band using Time-Division Multiple Access (TDMA) [3]. Initially developed in Sweden for aviation identification and tracking, AIS has emerged from several competing electronic identification systems to become the de facto automatic identification system for seafaring vessels [4]. Evidence of its widespread adoption may be found with the revision of the Safety of Life at Sea (SOLAS) convention in 2000 that mandates operation of AIS transponders on all cargo vessels of 500 or more gross tonnage, vessels of 300 or more gross tonnage traveling internationally, and all passenger vessels [5]. As broadcasts are both detailed in information and frequently repeated (on the order of seconds or minutes), AIS may present significant value to maritime surveillance.

The use of detection (sensor)-based data alongside its reception-based (self-reported) counterpart introduces trust complexities into products such as the RMP. Whereas data derived from sensor detections depend on the actual presence of a vessel (and therefore accurately reflect the ground truth), reception-based data depend on both what the vessel operator wishes to share and the correct operation of the installed equipment. In the case of AIS, false transmissions are easily broadcast as a result of malfunctioning equipment and/or deliberate acts of deception. The latter is significant on security grounds, for it may be precisely when knowing a vessel's location is most crucial that deception carries the greatest incentive.

In the future, this concern is likely to grow as AIS assumes an ever greater role in forming the RMP. Significant improvement in the apparent spatial-temporal resolution of the RMP will be met with questions surrounding its trustworthiness, a consideration that bears on the deployment of future space-based AIS (S-AIS) reception platforms. For example, equipping a radar satellite with an AIS receiver allows contacts made by radar to validate concurrent AIS messages. On the other hand, deploying S-AIS on a separate platform allows radar and AIS contacts to be interleaved in time, thereby “filling in the gaps” of coverage between infrequent radar observations. These two scenarios are inherently dichotomous, and finding a solution consistent with a given set of objectives requires a mathematical understanding of this problem.

The present work endeavors to improve the understanding of this issue by answering the basic question, “How and to what extent can an AIS report from a given ship be judged truthful as compared to a series of radar contacts attributed to the same vessel?” This question, which assumes prior association of track to identity (Figure 1), is quantitatively addressed using a collection of statistical techniques based on Bayesian interpolation. The techniques described herein may find relevance in assessing the MDA-capabilities of prospective satellite infrastructure such as the RADARSAT Constellation project [6, 7].

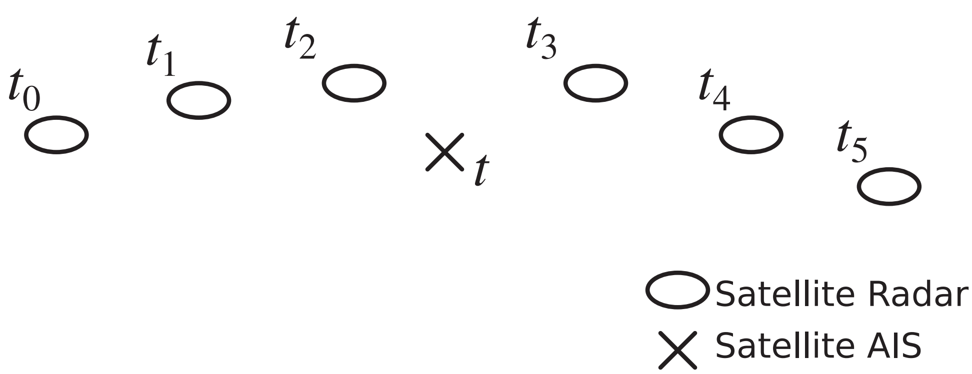

Figure 1: *An illustration of radar satellite observations and a single AIS report. Assessing the consistency of these observations requires finding a radar satellite data interpolation (between the observations at t_2 and t_3) that is contemporaneous with the AIS report.*

1.2 Mathematical Methods

The following analysis frames the ship/radar satellite system as a hidden Markov model, where the ship’s position and velocity form the system state, and the statistics of the vessel’s motion govern the transition from one state to another. Radar satellite contacts are treated as observations of the system and are described by a formal statistical model. As these observations originate from a trusted sensor (the radar satellite), they are assumed to faithfully reflect the ground truth and are only limited by the statistical uncertainty of the measurement process.

A direct comparison between a set of radar satellite observations and a given AIS report is generally precluded by the difference in time between these contacts. In the present work this issue is addressed by finding a retrospective interpolation of radar satellite observations that is contemporaneous with a received AIS message. This interpolation is computed by fusing the estimates of a conventional forward Kalman filter and that of its time-reversed counterpart in a process known as (Bayesian) smoothing. Against this smoothed estimate, an AIS report may be assessed through a variety of statistical techniques. In this report, evaluations based on probability ratio analysis, statistical hypothesis testing, and confidence region analysis are considered. Note that the foregoing approach is easily reformulated for realtime systems by using only the forward Kalman filter estimate.

2 Smoothing Radar Satellite Contacts

2.1 Forward and Reverse Bayesian Filtering

Forward Bayesian filtering is a recursive numerical method that estimates a system's state at a given time through a statistically optimal assimilation of previous observations of the system. In applications where the system is a target being monitored, the state is represented as a random vector whose components comprise position and, typically, some of its time derivatives. In the present discussion, which closely follows the work of [8] for the remainder of §2.1, this vector will be of the form

$$\mathbf{X}_k = \begin{bmatrix} \mathbf{X}_{k,\mathrm{pos}} \\ \mathbf{X}_{k,\mathrm{vel}} \end{bmatrix} \tag{1}$$

where $\mathbf{X}_{k,\mathrm{pos}}$ and $\mathbf{X}_{k,\mathrm{vel}}$ are the random vectors of position and velocity at the instant k.

Filtering is performed by alternately *predicting* a future state ($\mathbf{X}_k$) from earlier data ($\mathbf{X}_{k-1}$) and subsequently *updating* this prediction with newly acquired observations ($\mathbf{Z}_k$) using the statistical models of the sensor measurement processes and the target's kinematics. This process is described by the filtering equations

$$\mathbf{X}_k = F_k \mathbf{X}_{k-1} + \mathbf{V}_k \tag{2}$$

$$\mathbf{Z}_k = H_k \mathbf{X}_k + \mathbf{W}_k \tag{3}$$

where F_k, $\mathbf{V}_k$, H_k, $\mathbf{W}_k$ are the state transition matrix, noise due to the uncertainty in the predicted vessel motion, measurement matrix, and measurement noise, respectively.

Equations 2 and 3 may be reformulated in terms of the associated probability density functions $f_{\mathbf{V}_k}$ and $f_{\mathbf{W}_k}$ (distributed as $\mathbf{V}_k$ and $\mathbf{W}_k$, respectively)

$$f_{X_k|X_{k-1}}\left(\mathbf{x}|\mathbf{x}'\right) = f_{\mathbf{V}_k}\left(\mathbf{x} - F_k\mathbf{x}'\right) \tag{4}$$

$$f_{Z_k|X_k}\left(\mathbf{z}|\mathbf{x}\right) = f_{\mathbf{W}_k}\left(\mathbf{z} - H_k\mathbf{x}\right) \tag{5}$$

where $\mathbf{x}$ and $\mathbf{z}$ are free-running coordinates in the n-dimensional state and m-dimensional observation spaces, respectively. Equation (4), which describes the transition from $\mathbf{X}_{k-1}$ to $\mathbf{X}_k$, is known as the *Markov* transition density since

$$f_{X_k|X_{k-1},Z_{1:k-1}}\left(\mathbf{x}|\mathbf{x}',\mathbf{z},\mathbf{z}',\ldots\right) = f_{X_k|X_{k-1}}\left(\mathbf{x}|\mathbf{x}'\right) \tag{6}$$

that is, the conditional dependence on past observations is entirely subsumed by the dependence on the previous state, a condition that also holds for the sensor likelihood function of (5). Implementation of a Bayesian filter amounts to the successive evaluation of

$$f_{X_k|Z_{1:k-1}}\left(\mathbf{x}|\mathbf{z},\mathbf{z}',\ldots\right) = \int_{\mathbb{R}^n} f_{X_k|X_{k-1}}\left(\mathbf{x}|\mathbf{x}'\right) f_{X_{k-1}|Z_{1:k-1}}\left(\mathbf{x}'|\mathbf{z},\mathbf{z}',\ldots\right) d\mathbf{x}' \tag{7}$$

and

$$f_{X_k|Z_{1:k}}\left(\mathbf{x}|\mathbf{z},\mathbf{z}',...\right) \quad = \quad \frac{f_{Z_k|X_k}\left(\mathbf{z}|\mathbf{x}\right) f_{X_k|Z_{1:k-1}}\left(\mathbf{x}|\mathbf{z},\mathbf{z}',...\right)}{f_{Z_k|Z_{1:k-1}}\left(\mathbf{z}|\mathbf{z}',\mathbf{z}'',...\right)} \tag{8}$$

where $\mathbb{R}^n$ is the n-dimensional state space, and (8) follows from Bayes's rule (after which this filter is named). The denominator of the right-hand side of (8) serves only as a normalizing factor whose explicit evaluation is unnecessary upon the acquisition of k observations.

Although equations (7) and (8) admit arbitrary probability distributions, computational demands are substantially reduced when both the Markov transitions and sensor likelihoods are normally distributed. Known as the Kalman filter[1] , this special case simplifies (7) and (8) to operations on the statistical parameters (mean and covariance) of the normal distribution that can be evaluated in closed form. Without loss of generality, the ensuing analysis will assume such normality conditions.

The random variables and matrices in (2) and (3) encode the physical laws that govern the system, in this case Newtonian mechanics. Under the assumption of time invariance, these matrices are

$$F = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix}, \quad \mathbf{V} = \begin{bmatrix} \frac{1}{2}\Delta t^2 \\ \Delta t \end{bmatrix} \mathbf{a}, \quad H = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \tag{9}$$

where Δt is the time elapsed since the last observation and $\mathbf{a}$ is a zero-mean, normally distributed random vector that models the probabilistic change of acceleration with time. For Δt less than the time difference between observations, (7) defines the state estimate *between* observations

$$f_{X_{k+\Delta t}|Z_{1:k-1}}\left(\mathbf{x}|\mathbf{z},\mathbf{z}',...\right) \tag{10}$$

The choice of H implies that measurements are limited to those reporting position. Observations are not required to span the entire state space when the components of the state vector are statistically correlated. In the system under consideration, updating the position simultaneously updates the state's velocity, as the two become strongly correlated with increasing Δt. This is particularly important when updating estimates with radar satellite observations that report only position.

The filter possesses the characteristics of a hidden Markov Model that may be represented as a Bayesian network (Figure 2). Operation of the filter amounts to a rightward traversal of the network that commences with specifying an initial prior $\mathbf{X}_0$, which is often just the uniform distribution ($p = 1$)[2]. Inspection of Figure 2 also suggests the possibility of

[1] In many cases the Gaussian distribution models the underlying processes well or is otherwise acceptable. In other instances, such an approximation may be questionable.

[2] A uniform prior is not a conventional probability distribution and is therefore an *improper prior*. In this context it is also called uninformative, for it encodes a minimum of prior information. See [9] for a discussion surrounding its use.

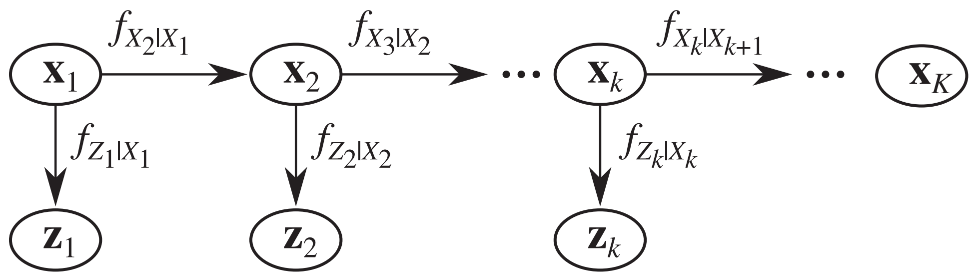

Figure 2: *A Bayesian network showing the hidden Markov model of the filtering problem.*

carrying out a reversed (leftward) traversal by specifying future observations and a final prior $\mathbf{X}_K$. While of limited relevance to conventional real-time and causal systems, such a time-reversed filter is useful in retrospective analysis where it is employed alongside its forward-in-time counterpart to find a smoothed estimate.

Reversing the direction of the network's traversal requires a restatement of the Markov transition density, which may be found from the time-reversed analogue of (2) given by

$$\mathbf{X}_{k-1} = F^{-1}\mathbf{X}_k + \mathbf{V} \tag{11}$$

where the associated *retrodictive* state transition matrix

$$F^{-1} = \begin{bmatrix} 1 & -\Delta t \\ 0 & 1 \end{bmatrix} \tag{12}$$

takes a given state *backwards* in time. Equation (11) follows from multiplying (2) by F^{-1}. Note that the measurement matrix and noise process remain unchanged.

2.2 Bayesian Smoother

Evaluations of (7) and (8) exhibit dependence on the choice of filter direction, a reflection of the fact that neither estimate is optimal. Finding the best estimate requires conditioning on the set of *all* observations in a process known as Bayesian smoothing. The remainder of this section provides a brief description of this process is based on [10].

Using Bayes's rule, the probability density function of the prediction may be expanded as

$$f_{X_{k+\Delta t}|Z_{1:K}}\left(\mathbf{x}|\mathbf{z},\mathbf{z}',\ldots\right) = \frac{f_{X_{k+\Delta t}|Z_{1:k}}\left(\mathbf{x}|\mathbf{z},\mathbf{z}',\ldots\right) f_{Z_{k+1:K}|X_{k+\Delta t},Z_{1:k}}\left(\mathbf{z}'',\mathbf{z}''',\ldots|\mathbf{x},\mathbf{z},\mathbf{z}',\ldots\right)}{f_{Z_{k+1:K}|Z_{1:k}}\left(\mathbf{z}'',\mathbf{z}''',\ldots|\mathbf{z},\mathbf{z}',\ldots\right)} \tag{13}$$

where the denominator of the right-hand side is a normalizing factor and K is the total number of radar satellite observations. Imposing the Markov condition (6) yields

$$f_{X_{k+\Delta t}|Z_{1:K}}\left(\mathbf{x}|\mathbf{z},\mathbf{z}',\ldots\right) \propto f_{X_{k+\Delta t}|Z_{1:k}}\left(\mathbf{x}|\mathbf{z},\mathbf{z}',\ldots\right) f_{Z_{k+1:K}|X_{k+\Delta t}}\left(\mathbf{z}'',\mathbf{z}''',\ldots|\mathbf{x}\right) \tag{14}$$

The first term on the right-hand side is identified as the product of the forward filter, while the second term can be related to the reversed filter through another application of Bayes' rule

$$f_{Z_{k+1:K}|X_{k+\Delta t}}\left(\mathbf{z}'',\mathbf{z}''',...|\mathbf{x}\right) = \frac{f_{X_{k+\Delta t}|Z_{k+1:K}}\left(\mathbf{x}|\mathbf{z}'',\mathbf{z}''',...\right) f_{Z_{k+1:K}}\left(\mathbf{z}'',\mathbf{z}''',...\right)}{f_{X_{k+\Delta t}}\left(\mathbf{x}\right)} \tag{15}$$

where $f_{Z_{k+1}:K}$ is once again a normalizing factor that may be neglected. By specifying a prior $\mathbf{X}_K$, the denominator of the right-hand side may be found recursively from (4). Selection of a non-informative uniform (improper) prior yields a uniform distribution for $\mathbf{X}_{k+\Delta t}$.

To avoid an inconsistent Bayesian network[1], the probability function of (14) must generally be recast as a likelihood function before it is assimilated with the density function produced by the forward filter. This may be accomplished with Bayes's rule provided that the prior is chosen to be sufficiently uninformative. The denominator in (15) may then be neglected by recognizing that a uniform prior for $f_{X_{k+\Delta t}}(\mathbf{x})$ is both maximally uninformative and propagates through time unchanged.

Under these conditions, (13) becomes symmetric with time

$$f_{X_{k+\Delta t}|Z_{1:K}}\left(\mathbf{x}|\mathbf{z},\mathbf{z}',...\right) \propto f_{X_{k+\Delta t}|Z_{1:k}}\left(\mathbf{x}|\mathbf{z},\mathbf{z}',...\right) f_{X_{k+\Delta t}|Z_{k+1:K}}\left(\mathbf{x}|\mathbf{z}'',\mathbf{z}''',...\right) \tag{16}$$

This expression serves as the radar satellite-generated interpolation used in the following analyses. It is optimal for all t (subsequently taken as the time of the AIS observation) and is abbreviated as $f_{X_t|Z^{\mathrm{RAD}}}(\mathbf{x}|\mathbf{z}',\mathbf{z}'',...)$.

[1]A Bayesian network is said to be inconsistent if, for a given set of priors, Bayes's rule does not simultaneously hold at each node.

3 Evaluation of an AIS Report

3.1 Probability Ratio Analysis

A simple assessment of a given AIS report may be carried out by displaying the report's position on a plot that shows (probabilistically) where reports are expected given the set of radar satellite observations. Depicting the location of the AIS report in relation to the regions of high and low probability allows for quick visual assessment of the report's plausibility and the related uncertainty. A distribution bearing this relationship is given by the conditional density function

$$f_{Z^{\text{AIS}}|Z^{\text{RAD}}_{1:K}}\left(\mathbf{z}|\mathbf{z}'=\mathbf{Z}_0,\mathbf{z}''=\mathbf{Z}_1,...\right) \tag{17}$$

whose maximum may be normalized to give

$$f(\mathbf{z}) = \arg\max_{\mathbf{z}'''\in\mathbb{R}^2} \frac{f_{Z^{\text{AIS}}|Z^{\text{RAD}}_{1:K}}\left(\mathbf{z}|\mathbf{z}'=\mathbf{Z}_0,\mathbf{z}''=\mathbf{Z}_1,...\right)}{f_{Z^{\text{AIS}}|Z^{\text{RAD}}_{1:K}}\left(\mathbf{z}'''|\mathbf{z}'=\mathbf{Z}_0,\mathbf{z}''=\mathbf{Z}_1,...\right)} \tag{18}$$

where arg max selects the $\mathbf{z}'''$ that maximizes the denominator of the right-hand side. This expression relates to the radar satellite interpolation (16) and the AIS report probability density through the expansion

$$f_{Z^{\text{AIS}}|Z^{\text{RAD}}_{1:K}}\left(\mathbf{z}|\mathbf{z}'=\mathbf{Z}_0,\mathbf{z}''=\mathbf{Z}_1,...\right) = \int_{\mathbb{R}^2} f_{Z^{\text{AIS}}|X_t}(\mathbf{z}|\mathbf{x})\, f_{X_t|Z^{\text{RAD}}}\left(\mathbf{x}|\mathbf{z}'=\mathbf{Z}_0,\mathbf{z}''=\mathbf{Z}_1,...\right) d\mathbf{x} \tag{19}$$

Imposing the normality conditions of the Kalman filter and similarly assuming that the AIS sensor error is normally distributed, the integral becomes a simple convolution of two Gaussian functions, giving

$$f_{Z^{\text{AIS}}|Z^{\text{RAD}}_{1:K}}(\mathbf{z}) \sim \mathcal{N}\left(\mu_{\text{RAD}}, \Sigma_{\text{AIS}} + \Sigma_{\text{RAD}}\right) \tag{20}$$

where Σ_{AIS} is the associated error covariance (which may be assumed to be the error in the ship's GPS system) and μ_{RAD} is the mean of the radar satellite estimate.

The AIS likelihood given in (19) may exhibit additional uncertainty arising from error in the message timestamp. As the present work assumes synchronization between the AIS transponder's interal clock and the Global Positioning System, this error no greater than ± 2 s [11] and may be neglected. In circumstances where this assumption fails to hold, (19) must be adjusted commensurately.

3.2 Critical-Value Tests

Evaluation of a ship's reported location may also take the form of a classical hypothesis test, which seeks to answer the question "Is there sufficient ground to believe that the AIS report is incorrect?" In what follows, the null and alternative hypotheses (H_0 and H_1, respectively) are defined as:

- H_0: The ship's AIS-reported position matches the radar satellite observations to within the uncertainty of the measurement processes.
- H_1: The estimated positions do not match to within the uncertainty of the measurement processes or the assumed probability distributions are incorrect.

Formulation of the test begins by specifying the random variables X_{AIS} and X_{RAD} that describe the uncertainty in the AIS and radar satellite measurements, respectively. These variables share a common mean under the null hypothesis but are assumed to be otherwise uncorrelated. Thus,

$$X_{\text{AIS}} - X_{\text{RAD}} \sim \mathcal{N}(\mathbf{0}, \Sigma_T) \tag{21}$$

where $\Sigma_T = \Sigma_{\text{AIS}} + \Sigma_{\text{RAD}}$. The test may now be stated formally as

$$H_0 : \quad \mathbb{E}[X_{\text{AIS}} - X_{\text{RAD}}] = 0 \tag{22}$$

$$H_1 : \quad \mathbb{E}[X_{\text{AIS}} - X_{\text{RAD}}] \neq 0 \qquad \text{or} \tag{23}$$

$$X_{\text{AIS}} - X_{\text{RAD}} \not\sim \mathcal{N}(\mathbf{0}, \Sigma_T) \tag{24}$$

where $\mathbb{E}[\,\cdot\,]$ is the expected value operator. The resulting test statistic is defined as

$$T = \Delta\mathbf{x}^t \Sigma_T^{-1} \Delta\mathbf{x} \tag{25}$$

where the superscripts $^{-1}$ and ^{t} effect matrix inversion and transpose respectively, $\Delta\mathbf{x}$ is the difference between the two means ($\mu_{\text{smooth}} - \mu_{\text{AIS}}$), and T assumes a chi-squared distribution possessing two degrees of freedom

$$T \sim \chi^2(2) \tag{26}$$

The evaluation of H_0 is performed by first computing Σ_T from the covariances of the radar satellite interpolation given in (16) and AIS measurement, and then evaluating T with (25). The decision process

$$\text{if } T > T_{\text{crit}} \text{ then reject } H_0 \tag{27}$$

is then made for a given critical value T_{crit}, which corresponds to a preselected significance level (α) and may be found in a standard statistical table (cf [12]) or computed using a statistics software package. Note that while a failure to reject the null hypothesis does not equate to its validation, a rejection of H_0 does imply, with the confidence of the α level, that the vessel's AIS report conflicts with radar satellite observations.

The foregoing test for equivalency may be extended by evaluating agreement to *within* a certain distance. The multivariate analysis that results involves inequalities that add considerable complexity to the simple formulation of the equivalency test. Further information may be found in [13].

3.3 Confidence Region Analysis

The basic hypothesis test of §3.2 can be extended with confidence interval analysis. In contrast to computing the *p*-value of the null hypothesis, such an approach presents the difference between the radar satellite and AIS positions in the form of a single or nested set of confidence intervals, allowing statements such as "the difference between the ship's self report and the radar satellite interpolation is 3±1 nautical miles, nineteen times out of twenty." This can be further extended by calculating nested confidence *regions* that convey the directional dependence of discrepancies. These regions satisfy

$$C/100 = \int_{R\subset\mathbb{R}^2} f_{Z_{1:K}^{\mathrm{RAD}}|Z^{\mathrm{AIS}}}(\mathbf{z})\, d\mathbf{z} \tag{28}$$

where C is the level of confidence (e.g., 95%), and R is bounded by an isovalue contour ($f_{Z_{1:K}^{\mathrm{RAD}}|Z^{\mathrm{AIS}}}$ is constant on ∂R).

3.4 Example Problem

The foregoing methods are easily illustrated by way of a simple example based on a ship sailing through the Northwest Passage in the Canadian Arctic. This vessel is observed near the northeastern shore of Victoria Island by a radar satellite (assumed to be a RADARSAT-II [14]) traveling in a circumpolar low earth orbit with a revisit period of 101 minutes. Approximately midway between two radar observations[1] (60 minutes after the first and 41 minutes before the second), another satellite receives an AIS transmission from the same vessel.

The ship's estimated positions *at the time of the first and second radar contacts* (as attributed to the forward and reverse Kalman filters operating on all past and future observations) are given in Table 1 as $\mathbf{X}_1^{\mathrm{RAD}}$ and $\mathbf{X}_2^{\mathrm{RAD}}$, respectively. The ship's estimated positions *at the time of the AIS transmission* attributed to Kalman prediction, retrodiction, and smoothing are given in Table 3.4 as $\mathbf{X}_{1,+60\text{ min}}^{\mathrm{RAD}}$, $\mathbf{X}_{2,-41\text{ min}}^{\mathrm{RAD}}$, and $\mathbf{X}_{\mathrm{smooth}}^{\mathrm{RAD}}$, respectively. These estimates are also shown graphically in Figure 3 ($\mathbf{X}_{1,+60\text{ min}}^{\mathrm{RAD}}$ and $\mathbf{X}_{2,-41\text{ min}}^{\mathrm{RAD}}$) and Figure 4 ($\mathbf{X}_{\mathrm{smooth}}^{\mathrm{RAD}}$).

The example values were selected to be approximately consistent with the actual geospatial error inherent to observations made by RADARSAT II operating in ultrafine mode [15]. The evaluation of the AIS transmission is carried out for two hypothetical sets of coordinates, one plausible and the other implausible ($\mathbf{x}_1^{\mathrm{AIS}}$ and $\mathbf{x}_2^{\mathrm{AIS}}$, respectively in Table 1). The three example analyses that follow are based on these estimates.

[1] In the case of RADARSAT-II, the first and second observations would be taken by left- and right-looking beams, respectively.

Table 1: Parameters of the example problem considered in this section.

Estimate	Description	Parameter	Value	Units
$\mathbf{x}_1^{\mathrm{RAD}}$	State Mean	μ_1	$\begin{bmatrix} (73,110) \\ 12 \end{bmatrix}$	$^\circ$N,$^\circ$ W kn NE
	Position Covariance	Σ_{1x}	$\begin{bmatrix} 11 & 0 \\ 0 & 11 \end{bmatrix}$	m^2
	Velocity Covariance	Σ_{1v}	$\begin{bmatrix} 0.003 & 0 \\ 0 & 0.003 \end{bmatrix}$	kn^2
	Position-Velocity Covariances	$\Sigma_{1vx}, \Sigma_{1xv}$	$\begin{bmatrix} 0.18 & 0 \\ 0 & 0.18 \end{bmatrix}$	$\mathrm{kn} \cdot \mathrm{m}$
$\mathbf{x}_2^{\mathrm{RAD}}$	State Mean	μ_2	$\begin{bmatrix} (73.4,109.5) \\ 13 \end{bmatrix}$	$^\circ$N,$^\circ$ W kn N
	Position Covariance	Σ_{2x}	$\begin{bmatrix} 13 & 0 \\ 0 & 13 \end{bmatrix}$	m^2
	Velocity Covariance	Σ_{2v}	$\begin{bmatrix} 0.004 & 0 \\ 0 & 0.004 \end{bmatrix}$	kn^2
	Position-Velocity Covariances	$\Sigma_{2vx}, \Sigma_{2xv}$	$\begin{bmatrix} 0.21 & 0 \\ 0 & 0.21 \end{bmatrix}$	$\mathrm{kn} \cdot \mathrm{m}$
$\mathbf{x}_{1,2}^{\mathrm{RAD}}$	Acceleration Mean	$\mu_{\mathbf{a}}$	$\mathbf{0}$	kn/hr
	Acceleration Covariance	$\Sigma_{\mathbf{a}}$	$\begin{bmatrix} 15 & 0 \\ 0 & 15 \end{bmatrix}$	$\mathrm{kn}^2/\mathrm{hr}^2$
$\mathbf{x}_1^{\mathrm{AIS}}$	Position Mean	μ_{AIS}	$(73.21, 109.47)$	
	Position Covariance	Σ_{AIS}	$\begin{bmatrix} 10 & 0 \\ 0 & 10 \end{bmatrix}$	m^2
$\mathbf{x}_2^{\mathrm{AIS}}$	Position Mean	μ_{AIS}	$(73.23, 109.77)$	
	Position Covariance	Σ_{AIS}	$\begin{bmatrix} 10 & 0 \\ 0 & 10 \end{bmatrix}$	m^2

3.4.1 Probability Ratio Analysis

Figure 5 shows the two AIS reports plotted against a normalized distribution that represents the probability of detecting a genuine self-report for the interpolation of the given radar satellite observations. The greater plausibility of the first report is clearly visible.

Table 2: *Estimated vessel state for the moment the AIS message is received. Three estimates are possible: one based on bringing the first radar observation 60 minutes forward in time with the forward Kalman filter ($\mathbf{x}^{\mathrm{RAD}}_{1,+60\ \mathrm{min}}$), another based on bringing the second radar observation 41 minutes backwards in time with the reverse Kalman filter ($\mathbf{x}^{\mathrm{RAD}}_{2,-41\ \mathrm{min}}$), and a third based on fusing the first two into a smoothed estimate with the Kalman smoother ($\mathbf{x}^{\mathrm{RAD}}_{\mathrm{smooth}}$). The single direction and smoothed estimates are shown graphically in Figure 3 and Figure 4, respectively. Note the reduction in covariance of the smoothed estimate.*

Estimate	Description	Parameter	Value	Units
$\mathbf{x}^{\mathrm{RAD}}_{1,+60\ \mathrm{min}}$	Position Mean	$\mu_{1,+60\ \mathrm{min},x}$	$(73.14, 109.60)$	$^\circ$N,$^\circ$W
	Position Covariance	$\Sigma_{1,+60\ \mathrm{min},x}$	$\begin{bmatrix} 7.51 & 0 \\ 0 & 7.51 \end{bmatrix}$	NM^2
$\mathbf{x}^{\mathrm{RAD}}_{2,-41\ \mathrm{min}}$	Position Mean	$\mu_{2,-41\ \mathrm{min},x}$	$(73.25, 109.5)$	$^\circ$N,$^\circ$W
	Position Covariance	$\Sigma_{2,-41\ \mathrm{min},x}$	$\begin{bmatrix} 3.51 & 0 \\ 0 & 3.51 \end{bmatrix}$	NM^2
$\mathbf{x}^{\mathrm{RAD}}_{\mathrm{smooth}}$	Position Mean	μ_{smooth}	$(73.22, 109.53)$	$^\circ$N,$^\circ$W
	Position Covariance	Σ_{smooth}	$\begin{bmatrix} 2.39 & 0 \\ 0 & 2.39 \end{bmatrix}$	NM^2

3.4.2 Critical-Value Test

Evaluating (25) with the coordinates of Table 1 and 3.4 yields the test statistics $T_1 = 0.61$ and $T_2 = 7.60$ for $\mathbf{x}^{\mathrm{AIS}}_1$ and $\mathbf{x}^{\mathrm{AIS}}_2$, respectively. For a significance level of $\alpha = 0.05$, the critical value is 5.99, and the plausibility of $\mathbf{x}^{\mathrm{AIS}}_2$ is rejected. However, were the significance level to be chosen instead as $\alpha = 0.01$, the critical value becomes 9.21, and neither AIS report would be deemed implausible. A summary of the decision process is provided in Table 3.

3.4.3 Confidence Region Analysis

The two AIS reports are shown in relation to the 80%, 90%, 95%, and 99% confidence regions (whose diameters are 5.5 NM, 6.7 NM, 7.6 NM, 9.4 NM, respectively) in Figure 6. This plot carries a quantitative frequentist interpretation. For example, one may say "Given the radar satellite data, in 95 out of 100 instances the vessel's actual location falls some-

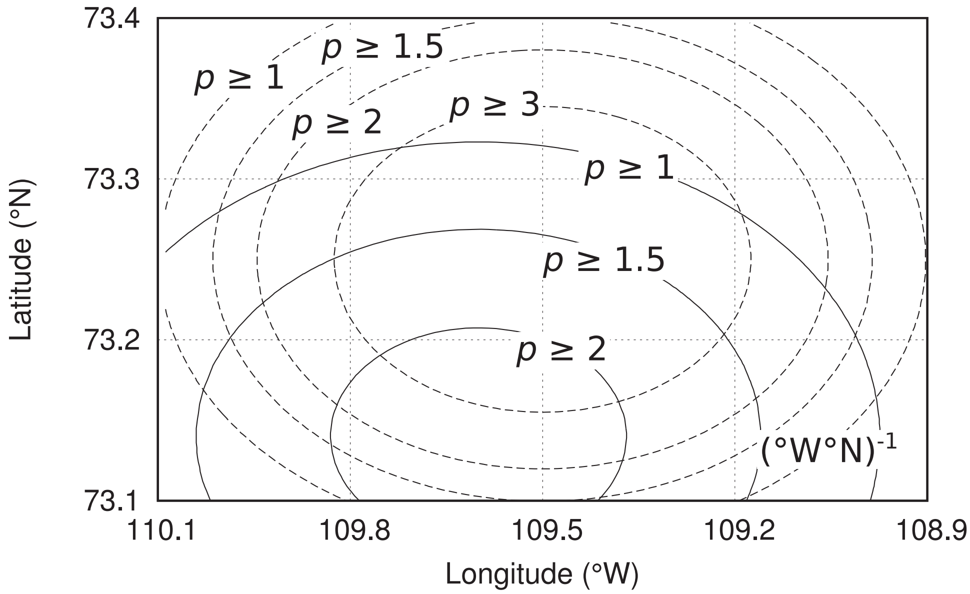

Figure 3: *Predicted probability density (p) of vessel location (shown as isovalue contours) for the moment at which the AIS message is received. The estimates $\mathbf{x}^{\mathrm{RAD}}_{1,+60\ \mathrm{min}}$ (solid line) and $\mathbf{x}^{\mathrm{RAD}}_{2,-41\ \mathrm{min}}$ (broken line) were generated by the forward and reverse Kalman predictors, respectively.*

Table 3: *Critical value-based decision table. Note how the outcome depends on the choice of significance level. Whereas the first report is plausible in each case, the second report is rejected for $\alpha = 0.05$ but deemed possible against the more stringent $\alpha = 0.01$.*

AIS Report	Test Statistic (T)	$\alpha = 0.05$ ($T_{\mathrm{crit}} = 5.99$)	$\alpha = 0.01$ ($T_{\mathrm{crit}} = 9.21$)
$\mathbf{x}^{\mathrm{AIS}}_1$	0.61	Do Not Reject H_0	Do Not Reject H_0
$\mathbf{x}^{\mathrm{AIS}}_2$	7.60	Reject H_0	Do Not Reject H_0

where within the 95% confidence region." Such a presentation also allows a subjective assessment of the hypothesis test's statistical power and the resultant likelihood of a Type II error (failure to reject an invalid null hypothesis).

The kinematic data given in Table 1 correspond approximately to the maneuverability of a bulk carrier. By assuming that an observation takes place every two hours and taking the confidence region to be one standard deviation, the foregoing analysis may be used to show that such a vessel can be located to within a circular region with a diameter on the order of

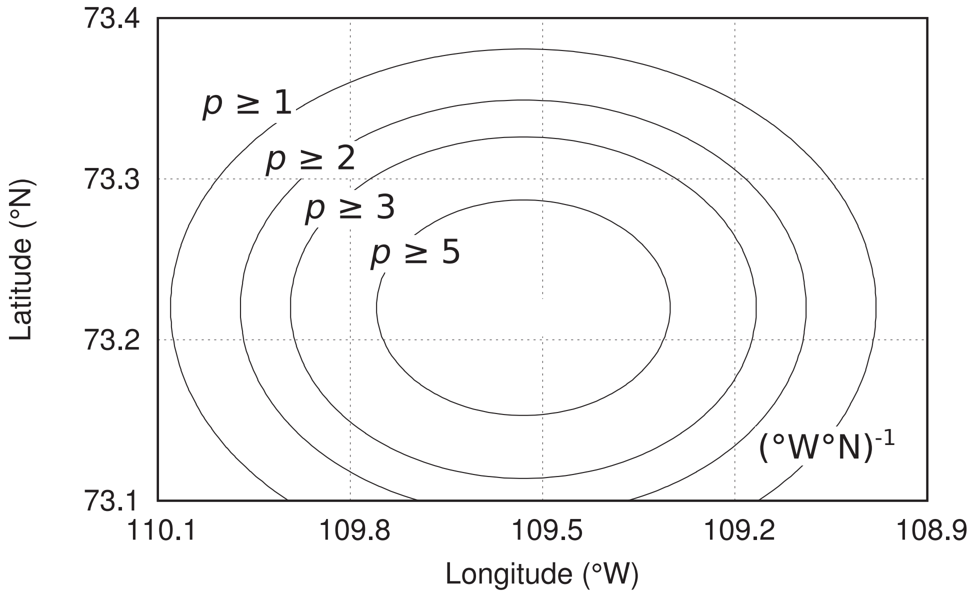

Figure 4: *Smoothed probability density (p) of vessel location (shown as isovalue contours) for the moment at which the AIS message is received. The estimate* $\mathbf{x}^{\text{RAD}}_{\text{smooth}}$ *was generated by the Kalman smoother.*

10 NM.

3.5 Discussion

The approaches described in the previous sections are suited to a variety of uses. Graphical displays of the probability ratio or confidence regions are valuable in human-based analysis, as they convey not only the estimated discrepancies, but their uncertainties as well. Alternatively, the critical value test could be run automatically in operating environments where radar satellite observations are consolidated alongside AIS reports. Any mismatch (as defined by a p-value that is exceeded by a preselected significance threshold) could be flagged and forwarded to an operator for follow-up examination.

The foregoing analysis rests on the validity of the Kalman smoothing. Should the assumption of normality be questionable, consideration may be given to a conservative approach wherein the variance attributed to the transition and/or observation is overstated (at the cost of increasing the estimate uncertainty). Alternatively, where the actual probability distributions are available, they may be used in lieu of Gaussian approximations. While the attendant numerical integration incurs considerably greater computational expense, this approach is feasible on modest computer systems.

For each of the methods described, inferential power wanes with increasing variance in

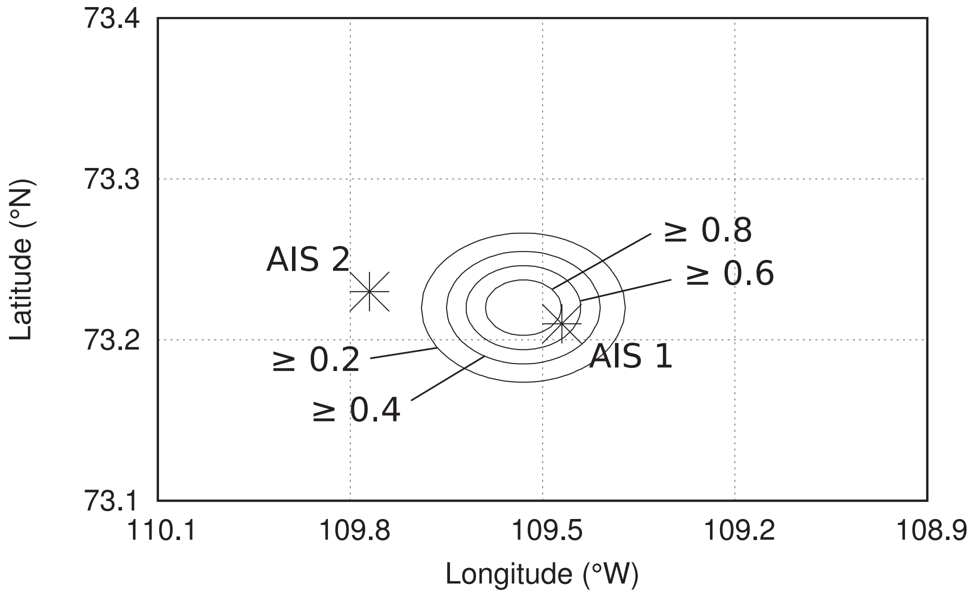

Figure 5: *Normalized probability distribution describing the relative probability of receiving an AIS report given the radar satellite interpolation (shown as isovalue contours). Normalization entailed scaling the function to a maximum value of unity. The two hypothetical AIS positions are shown overlaid.*

the radar satellite-based estimates. In the filter prediction/retrodiction problem, growth of the positional variance with time is linear with uncertainty in velocity and quadratic with acceleration (this relates directly to the dead reckoning problem). Inspection of (16) reveals that while smoothing lessens the variance, improvement amounts only to a constant linear scaling. Conditions of infrequent observations (such as those typical to remote regions of the Arctic) places the utmost importance in using optimally refined kinematic models in determining transition densities. Such refinement may include sea ice constraints that limit the navigable waters and/or speed for a given ice class and ship-specific capabilities such as acceleration, maneuverability, and fuel consumption.

Long durations between observations may also present a challenge in finding the appropriate transition density. Over short intervals of time, a vessel's motion is governed primarily by Newton's first law, where acceleration (change of speed or bearing) affects its course only marginally. However, for periods that approach or exceed the characteristic time required to reach full speed or come to a complete stop, the resultant path depends to a far greater extent on the actions of the ship's crew. Consequently, for the frequency of radar observations considered in this work, Bayesian smoothing may be appropriate for a slow-moving bulk carrier but not for an agile frigate capable of attaining maximum speed in any direction in the span of minutes. The resultant difficulty is epistemic in nature, and retaining a statistical framework requires assigning probabilities to the possible actions

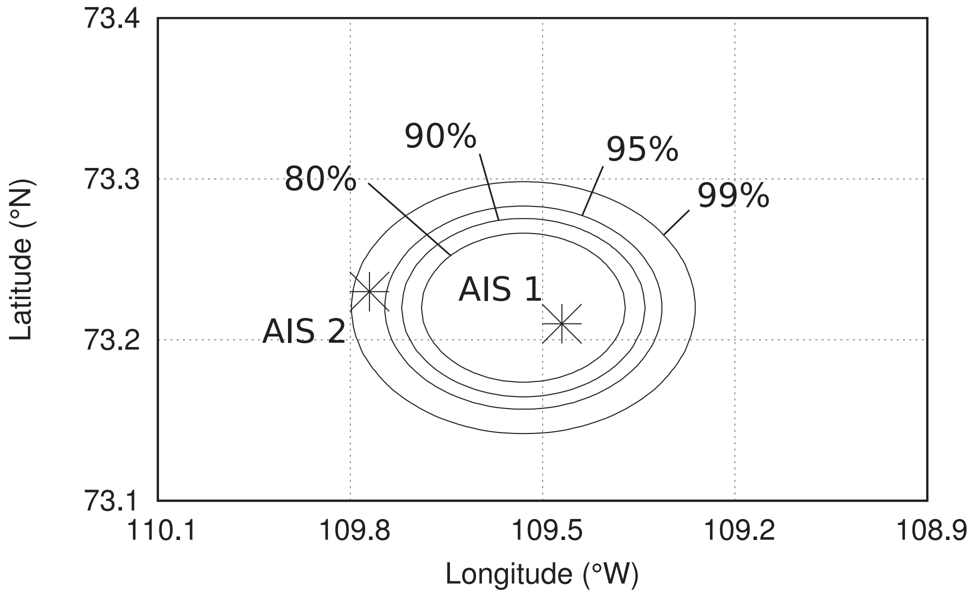

Figure 6: *The 80%, 90%, 95%, and 99% confidence regions for the position of an AIS report given the radar satellite interpolation. The two hypothetical AIS positions are shown overlaid.*

of the ship's crew. As human decision defies the simple characterization afforded by the uncertainty in physical processes, this issue places a fundamental limit on the statistical inference that can be drawn when trusted observations are infrequent with respect to the maneuverability of the vessel under surveillance.

4 Conclusion

This report considered the problem of validating self-reported information with sensor-based data in maritime settings. A specific method of using radar satellite contacts to assess vessel location reported through the automatic identification system was developed. Based on Kalman smoothing, this approach rests on interpolating a vessel's course from radar satellite data in a manner that allows its location to be estimated as a probability distribution at an arbitrary moment in time. By computing an estimate of the ship's position for the instant when an automatic identification system report is received, a statistical comparison between the trusted radar satellite data and the self-report can be carried out through a variety of analyses. Three different statistical evaluations were considered: analysis of probability ratio, classical hypothesis testing, and nested confidence region analysis. The applicability of this method and its limitations as they relate to vessel maneuverability and observation frequency was discussed.

Future work may explore analysis based on non-additive probability measures. While statistics based on conventional (additive) probability theory is well suited to *aleatory* uncertainty (whose mathematical characterization is unambiguous), the uncertainty in the Markov transition density becomes strongly *epistemic* with time. This latter form occurs when no a priori probability distributions can be mathematically justified. Such is the case, for example, when considering the possible actions of an unknown ship's crew. Non-additive measures allow a formal representation of this uncertainty in the form of belief/plausibility functions (Dempster–Shafer Theory), possibility/necessity measures (possibility theory), and, more generally, partially ordered sets and plausibility measures.

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Self-reported information in maritime settings has become increasingly important in issues surrounding navigation, vessel traffic services, and security. While self-reported data may significantly improve the apparent spatial-temporal resolution of vessel positions used to construct the recognized maritime picture, its accuracy is readily compromised by deliberate acts of deception. The present work sought to develop a method of validating automatic identification system positional reports with trusted radar satellite data. The approach presented uses Kalman smoothing to retrospectively interpolate a vessel's path between radar satellite observations, allowing its location to be estimated for an arbitrary moment in time. A given self-report may then be assessed against a contemporaneous radar satellite estimate using a variety of statistical techniques. Evaluations based on probability ratio analysis, classical hypothesis testing, and nested confidence region analysis were considered. Finally, the method's range of applicability was studied by examining the interaction between a vessel's maneuverability and frequency of radar observations. These considerations may be of use in planning future satellite infrastructure.

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