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Maritime Situational Awareness Use Cases Enabled by Space-Borne Sensors

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ABSTRACT

This paper discusses a technique for predicting a vessel's position over a long time horizon with much lower uncertainty than current methods. Lowering the uncertainty of long-range prediction is a key challenge in maritime situational awareness, and in particular for space-based systems can enable data fusion from sensors with different refresh rates, and help optimize the deployment and scheduling of the assets. These tasks are common to several practical scenarios: search and rescue and long-range vessel tracking in sparse data are two main ones. The proposed modelling is compared to one which is widely used in target tracking applications, using terrestrial and satellite Automatic Identification System (AIS) data, and the implications of the improved uncertainty for scenarios relevant to NATO are discussed.

1.0 BACKGROUND ON SPACE-BORNE SENSING

The CMRE hosted the SCI-275 Workshop on "Maritime Situational Awareness Enabled by Space-based Systems" in February 2015. Among the themes that emerged during that workshop was the realization that space-based sensors are now able to routinely provide data for Maritime Situational Awareness (MSA).

Space-based data include Satellite Automatic Identification System (S-AIS), radio-frequency (RF) transmissions, imagery from Synthetic Aperture Radars (SAR) and Electro-Optical (EO) sensors. Each of these data sources brings its own opportunities and challenges. Space-based SAR is effective for ship detection, especially for the detection of "dark targets" (i.e., non-collaborative vessels). However revisit rates do not provide persistency for vessel tracking. SAR is being operationally utilized by nations, but research challenges remain, including detection of smaller vessels, ship feature extraction (size, direction, classification), and false alarm reduction.

Space-based EO is an emerging capability for ship detection. While a vast virtual constellation currently exists in principle, it is not being exploited operationally for ship detection. Optimal operation in the presence of cloud cover and data management represent significant challenges.

Space-based AIS is providing capability for non-coastal regions with a detection performance and persistence that depend on satellite revisit rates, ship traffic density, and other interference sources (Figure 1). S-AIS is both commercially and nationally available and the number of S-AIS satellites is now significant and is expected to continue to grow.

A particularly interesting development in S-AIS is the emergence of micro- and nano-satellites as cost-effective alternatives to larger satellites. Nano-satellites are light-weight and box-sized, with typical dimensions of the order of 10x10x30 cm. They are low-orbiting devices that can carry a variety of sensors, including AIS transponders, optical cameras and environmental sensors. These sensors can be co-located on the same satellite, which greatly facilitates cross-correlating the measurements from each sensor.

Because of their lower cost, constellations of nano-satellites are more affordable than traditional configurations, and open up a new model for acquiring S-AIS data with low latency. In this model, larger constellations of less expensive satellites (~100s of satellites) are coupled with a network of ground-based receiving stations (~50 stations). The result is that revisit times and data downlink latency can be decreased to minutes instead of hours, which ameliorates one of the major drawbacks of space-based data for MSA: the sparsity of the data.

MSA stands to benefit the most from low-latency S-AIS constellations when they are combined with complementary satellite-based sensing modalities, such as SAR or EO imagery, or with terrestrial sensors such as high-frequency (HF) radar. For example, a common use case in MSA is detecting a vessel with AIS, and then following up on the detection with SAR or EO imagery, which can further pin-point and profile a vessel of interest. This use case arises in monitoring and surveillance operations, or during search and rescue missions, which critically depend on the data refresh rate of the sensors.

However, in practice, several factors negatively impact the achievable data refresh rates of such systems. Thus, it is more useful to consider the *effective data rate,* which is the observed data rate that accounts for these factors. One factor is that vessels may turn off their AIS transmitter, causing intermittence in their broadcasts, which diminishes the usefulness of frequent satellite revisits and of low-latency downlinks.

Another difficulty arises from S-AIS receivers being prone to lower AIS message detection rates than their T-AIS siblings. The AIS protocol, based on time division multiple access (TDMA), was designed for local radio broadcasts between vessels and between terrestrial stations. In the local scenario, a limited number of vessels transmit concurrently, so the likelihood of message collisions is low, and conversely the AIS message detection rate is high. In contrast, at any one time, an S-AIS receiver illuminates a vast regional swath of the globe that may include many vessels. Therefore, for S-AIS, the message collision rate may be higher, and the detection rate lower. This degrades the effective data rate.

Yet another difficulty arises from the need to coordinate different satellite-based sensors that operate at different revisit rates. In the use case of vessel monitoring through a low-revisit S-AIS system, a request to augment the available data with SAR images from a separate satellite must take into account that satellite's revisit times and its queue of previously-scheduled acquisitions. Co-locating AIS and SAR (or other complementary sensors) ameliorates this problem, but does not solve it. A related issue that impacts the effective data rate is the need to schedule the acquisition of satellite imagery. While continuous sensing of S-AIS is commonplace, SAR and EO sensors typically capture data on demand: image capture is expensive in terms of energy consumption and storage.

2.0 ENABLING LONG-TERM VESSEL LOCATION PREDICTION WITH LOW UNCERTAINTY

From the above discussion it is clear that while satellite technology is enabling meaningful use cases in MSA, the deployment of space-based assets cannot achieve MSA by itself. What is needed is a combined effort between asset deployment and techniques that leverage these newly available assets. Consider an important use case of MSA as an illustrative, but relevant scenario: *long-range prediction of vessel positions* with low uncertainty around the predicted coordinates. This use case is common to various NATO operations, for example in search-and-rescue and counter piracy. In search-and-rescue, localizing the survivors of a shipwreck with low uncertainty improves the chances of survival. It can also decrease the cost of operations, by providing a more geographically limited, but more highly probable area over which to focus expensive resources. In areas at high risk of piracy, legitimate vessels sometimes turn off their AIS transmitter for several hours to avoid being detected by pirates.

Consider also the common task of correlating Synthetic Aperture Radar (SAR) vessel detections with AIS contacts. The ability to predict accurately vessel positions at longer ranges combined with the availability of SAR increases the prediction performance, especially in the open sea, where terrestrial AIS coverage might be poor. From the point of view of resource optimization and cost containment, a smaller uncertainty region around long-term prediction affords the ability to narrowly target the acquisition of SAR images, which must be planned several hours in advance of the satellite passing over the possible target location. This can potentially reduce the costs incurred when multiple acquisitions become necessary due to a missed target. Finally, for space borne sensors, the ability to predict long-term vessel positions could also relax the requirements in terms of revisit times without a direct impact on the downlink latency: less data would be required to reconstruct and predict vessel trajectories, allowing better resource optimization. From these examples it becomes clear that the interplay between the algorithmic approaches, data sparsity, and asset deployment is crucial.

To address the problem of predicting vessel locations at long range, CMRE has proposed to adoperate a target motion model for which the uncertainty around the predicted position scales linearly with time, a great improvement over other current approaches, which scale cubically. This results in a prediction uncertainty that is orders of magnitude lower than existing techniques. This improved performance can have profound operational effects. For example, vessel positions 10 hours in the future can be predicted within 10 km^2. The approach is general, so it can be applied to any location data, from different sources, and with varying degree of sparsity. This is an advantage operationally, because only one approach is needed to handle predictions at both short and long time scales.

The proposed approach is based on the Ornstein-Uhlenbeck (OU) stochastic process. The OU model is popular in diverse fields, spanning from physics [1]–[4] to finance [5], [6], to biology [7], [8], but has found little application in the tracking community [9], [10]. In contrast, the Nearly Constant Velocity (NCV) [11], [12] motion model has been used as a standard for target tracking in radar [13], [14] and sonar [15], [16], but always in cases where the prediction step is always performed in the short-time, if compared to the sensor time- scan. In the remainder of this paper we compare the performance of the OU and NCV models for long range vessel state prediction.

3.0 A VESSEL DYNAMIC MODEL WITH REDUCED UNCERTAINTY

We consider two models for the vessel dynamics, which give two different measures of uncertainty around the predicted vessel position and velocity. The nearly-constant velocity model (NCV) gives uncertainty around the predicted vessel state that increase cubically with time, while the Ornstein-Uhlenbeck model (OU) gives a reduced uncertainty that increases only linearly with time. Let us indicate the vessel state at time $t \in \mathrm{R}^{+}$ with:

$$\boldsymbol{s}(t) \stackrel{\text{def}}{=} [\boldsymbol{u}(t), \dot{\boldsymbol{u}}(t)]^T,$$

where $\boldsymbol{u}(t) = [x(t), y(t)]^T$ represents the two-coordinate vector, and similarly $\dot{\boldsymbol{u}}(t) = [\dot{x}(t), \dot{y}(t)]^T$ the corresponding velocities in a two-dimensional Cartesian (x, y) reference system. The linear stochastic differential equation (SDE) that characterizes the NCV model is:

$$\mathrm{d}\boldsymbol{s}(t) = \boldsymbol{A}\boldsymbol{s}(t)\mathrm{d}t + \boldsymbol{B}\mathrm{d}\boldsymbol{w}(t),$$

with

$$\boldsymbol{A} = \begin{bmatrix} \boldsymbol{0} & \boldsymbol{I} \\ \boldsymbol{0} & \boldsymbol{0} \end{bmatrix}, \quad \boldsymbol{B} = \begin{bmatrix} \boldsymbol{0} \\ \boldsymbol{C} \end{bmatrix},$$

where $\boldsymbol{I}$ is the identity matrix, $\boldsymbol{0}$ the null matrix, $\boldsymbol{C}$ a generic positive-semidefinite matrix, and $\boldsymbol{w}(t)$ the standard bi-dimensional Wiener process. Thus the NCV model relies on the fact that, for non-manoeuvring vessels $\ddot{\boldsymbol{x}}(t) \approx \boldsymbol{0}$, i.e. there is a "small" effect on $\dot{\boldsymbol{x}}(t)$ that accounts for unpredictable modelling errors [11].

This dynamic model can be used to predict a vessel's future location. In particular, given a vessel's state vector $\mathbf{s}(\mathrm{t}_0)$ at some initial time t_0, we are interested in estimating the vessel's state $\boldsymbol{s}(t|t_0)$ at a future time t. The solution to this problem is known in literature, but for our purposes we are keen to assess the uncertainty around the solution, that is we are interested in assessing the uncertainty around the predicted position and velocity. A typical measure of uncertainty is the expected squared error, which for the position and velocity components, according to the NCV model, can be written in terms of the process variance σ_x^2:

$$E\left[\left(\left(x(t|\mathrm{t}_0) - x(t)\right)^2 \middle| \mathbf{s}(\mathrm{t}_0)\right)\right] = \frac{\sigma_x^2 (t-\mathrm{t}_0)^3}{3}$$

for the position, and:

$$E\left[\left(\left(\dot{x}(t|\mathrm{t}_0) - \dot{x}(t)\right)^2 \middle| \mathbf{s}(\mathrm{t}_0)\right)\right] = \sigma_x^2 (t-\mathrm{t}_0)$$

for the velocity, and with analogous expressions for the y components.

Note how the uncertainty in the position increases cubically as a function of the time difference between the initial observation and the time of the estimate. This poses a problem for long-term prediction of vessel location, which makes the NCV model unusable for prediction horizons longer than an hour. Note that a slightly different formulation of the NCV model [12], also popular in the literature, gives a position error estimate that increases as $(t - t_0)^4$. Either way, as the prediction time horizon increases, the prediction error increases exponentially.

In contrast, the uncertainty associated with the OU model for vessel dynamics is linear in time. The OU SDE is:

$$\mathrm{d}\boldsymbol{s}(t) = \boldsymbol{A}(\boldsymbol{s}(t) - \boldsymbol{v})\mathrm{d}t + \boldsymbol{B}\mathrm{d}\boldsymbol{w}(t).$$

Compared to the NCV model, the OU includes the term $\boldsymbol{v} = [0,0,\boldsymbol{v}^T]^T$, with $v = [v_x, v_y]^T$, which captures the tendency of the velocity to revert to its long-term mean value $\boldsymbol{v}$. Another difference is that for the OU model:

$$\boldsymbol{A} = \begin{bmatrix} \mathbf{0} & \boldsymbol{I} \\ \mathbf{0} & -\boldsymbol{\Gamma} \end{bmatrix},$$

where:

$$\boldsymbol{\Gamma} = \begin{bmatrix} \gamma_x & 0 \\ 0 & \gamma_y \end{bmatrix}$$

captures the strength of the mean-reverting tendency along the components of the velocity.

This is because, over time, non-manoeuvring vessels typically tend to drift toward their (long-term) average velocity, even though at any given time their instantaneous velocity may be different. Such a process is called mean-reverting and the tendency of the velocity to move back towards a central value is greater when the process is further away from the centre.

The solution to the OU SDE is in [4], [5], [18], and the corresponding expected mean-squared error expressions are:

$$\mathrm{E}\left[\left(\left(\mathrm{x}(\mathrm{t}|\mathrm{t}_0) - \mathrm{x}(\mathrm{t})\right)^2 \middle| \mathrm{s}(\mathrm{t}_0)\right)\right] = \frac{\sigma_\mathrm{x}^2}{\gamma_\mathrm{x}^3} \mathrm{f}\left(\gamma_\mathrm{x}(\mathrm{t} - \mathrm{t}_0)\right)$$

for the position, and:

$$E\left[\left(\left(\dot{x}(t|\mathrm{t}_0) - \dot{x}(t)\right)^2 \middle| \mathbf{s}(\mathrm{t}_0)\right)\right] = \frac{\sigma_x^2}{\gamma_x} g\left(\gamma_x(t - t_0)\right)$$

for the velocity, where $f(t)$ and $g(t)$ are the prediction position and velocity normalized variance expressions:

$$\mathrm{f(t)} \stackrel{\text{def}}{=} \frac{1}{2}(2\mathrm{t} - 4\mathrm{e}^{-\mathrm{t}} - \mathrm{e}^{-2\mathrm{t}} - 3),$$

$$\mathrm{g(t)} \stackrel{\text{def}}{=} \frac{1}{2}(1 - 2^{-2\mathrm{t}}).$$

Thus the expected prediction error increases only linearly with time for both the position and velocity components of the vessel state vector. This characteristic makes the OU dynamic model suited for long-term vessel state prediction.

4.0 EVALUATION ON REAL-WORLD DATA

We evaluated the vessel state prediction performance of the OU and NCV models on real-world satellite and terrestrial AIS data. The dataset consists of the entirety of AIS messages broadcast by vessels navigating in the Mediterranean Sea in two months (August and September) of 2014 and collected by the CMRE as part of its standing research activities in computational MSA.

The parameters for the OU and NCV models are estimated from a processed subset of the given dataset. The processed subset is obtained as follows: first, the AIS dataset is divided in three parts, according to the AIS vessel types of cargo, tanker, and passenger; data from other types of vessels are discarded. This is necessary because these three types of vessels generally differ in size and tonnage, and consequently their motion patterns are different. Therefore, the OU and NVC model parameters must be estimated separately for each vessel category. We used the Traffic Route Extraction and Anomaly Detection (TREAD) methodology [19] to categorize the vessels and form ensemble trajectories for each category. Note that using TREAD is a convenience, not a requirement, and any pre-processing technique can be used. Second, since we assume that vessels are non- manoeuvring, we break every observed trajectory into piecewise linear segments. The predictions are computed on these segments. The trajectories from the pre-processed data set are illustrated in Figure 1.

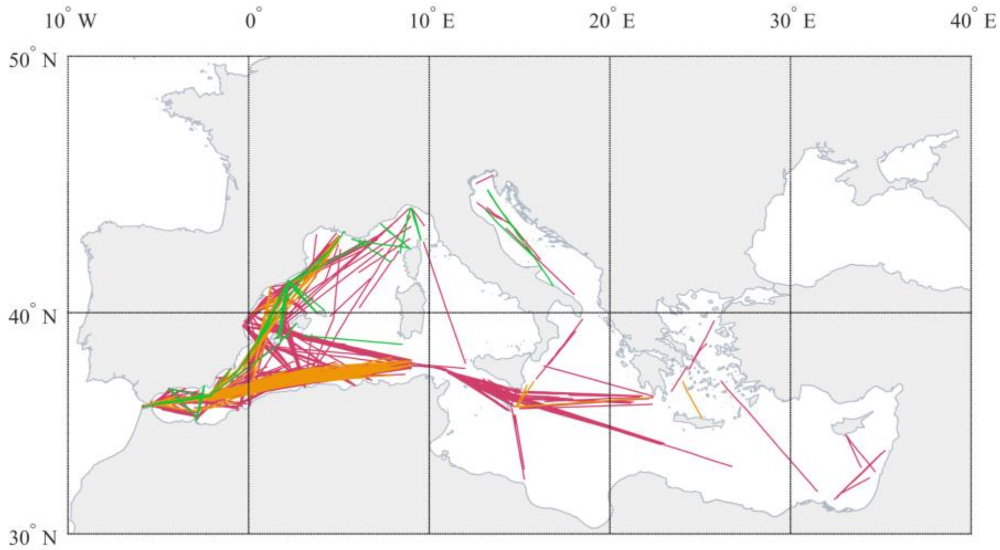

Figure 1: The quasi-rectilinear trajectories under consideration in the validation study; the colour indicates the vessel categories: pink for cargo, orange for tanker, and green for passenger. These trajectories result from a subset of AIS messages collected over the Mediterranean Sea from multiple AIS networks during August and September 2014.

The prediction procedure is repeated for all the trajectories for the different motion models, leading us to a collection of prediction errors relative to the target position and velocity. The OU motion model is characterized by three parameters for each coordinate: the noise level $_{,y}$, the desired speed $v_{x,y}$, and the reversion rate $\gamma_{x,y}$, The NCV motion model has instead just one parameter for each coordinate: the noise level $\sigma_{x,y}$. For both models, the parameters are estimated using maximum likelihood (ML) estimation [17], [18], [20].

We compare the performance of the two models. First, we demonstrate how the OU model outperforms the NCV model on a single-vessel example: the expected prediction mean-squared error from the OU model increases linearly and matches the empirical error more closely than the NCV model. Second, we consider the issue of accuracy of the estimated prediction error: this concept is captured by the variance around the estimated prediction error. We show that the OU model gives lower variance than the NCV and matches the empirical variance more closely.

4.1 Single Tanker

As an example, we consider a single tanker of 270 meters in length and 48 in breadth sailing north-eastwards from the Gibraltar Strait to East Mediterranean, as depicted in Figure 2.

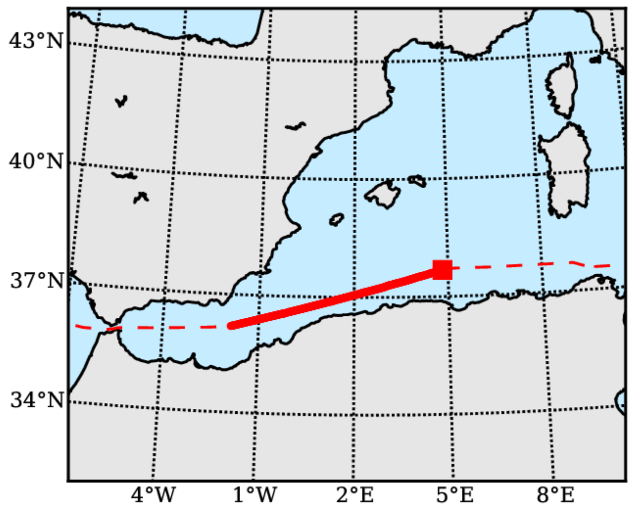

Figure 2: Trajectory of the example vessel under consideration: a tanker vessel of 270 meters in length and 48 in breadth sailing in the northeast direction from the Gibraltar Strait to the East Mediterranean. The solid line denotes the trajectory segment under consideration, and the square the last AIS message from the segment.

A prediction from the initial point of the trajectory, located in the origin, up to 20 hours is performed for both OU and NCV and then compared with the true vessel position. Figure 3 shows the vessel trajectory, the OU and NCV predictions and their corresponding uncertainties (95th percentiles). This case of study shows clearly that even if the NCV prediction is reasonably close to the true vessel position, its uncertainty is disproportionately large. In contrast, the OU prediction is not only closer to the true vessel position compared to the NCV prediction, but it also has a significantly smaller uncertainty (orders of magnitude).

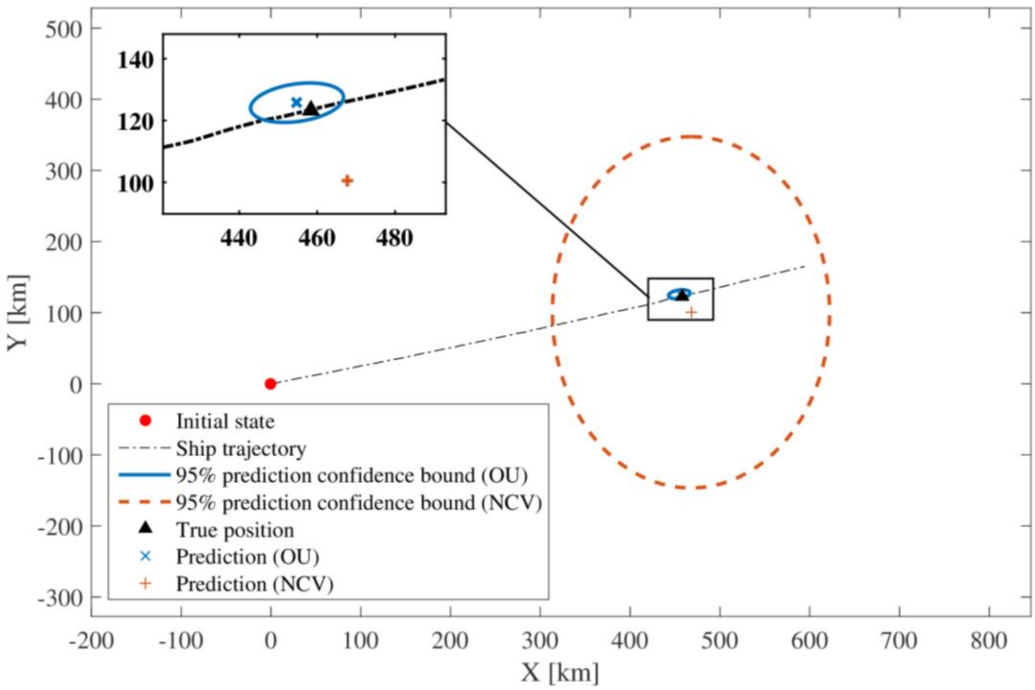

Figure 3: The predicted tanker position 20 hours after the initial state, according to the NCV and OU models. The OU model gives a more accurate position prediction coupled with a much lower uncertainty, measured by the 95% prediction confidence bound.

For the same tanker vessel, the empirical Standard Deviation (SD) of the prediction errors along x and y with respect to the prediction time horizon is reported in Figure 4, and compared with the theoretical curves. It is clear that the OU process better models the empirical variability of the vessel position than the NCV model for medium-longer time horizons ($t > 5$ hours). For shorter time horizons ($t < 1$ hour) the OU and NCV models produce very similar results, as expected. The deviation from the expected OU curve after approximately 15 hours is due to insufficient data, which produces unreliable statistics. For example, the last data point of these curves ($t > 25$ h) consists of a single sample. This result merely points to a practical issue – one needs enough samples to estimate the model fitness – and it does not imply a diminishing theoretical bound in the OU model performance. To produce a statistically significant model assessment, in the next subsection we construct these curves using *all* the trajectories available from the dataset of extracted routes.

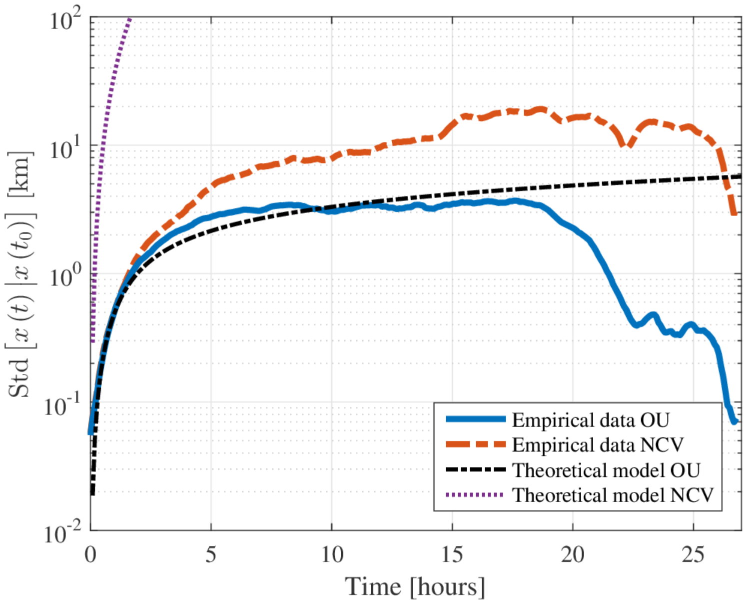

Figure 4: The empirical standard deviation for the tanker vessel x position prediction errors, under the NCV and OU motion models. The OU model better matches the empirical results, while the NCV model diverges quickly for time horizons above 1 hour. Similar curves exist for the y coordinate [REFERENCE JOURNAL PAPER].

4.2 Ensemble Performance Assessment

Figure 5 shows the prediction error variance for vessel velocity over the prediction horizon, for the cargo, tanker and passenger traffic categories. The left chart shows the OU model results; the right chart the NCV model results, under the two different choices for the exponent $p = 3,4$. For the comparison between OU and NCV to be fair, it is necessary to consider scaled quantities of the statistical variance under the two models. Furthermore, the time axis for the OU results must be scaled by the reversion rate. The interested reader can refer to [17], [18][19], [20] for the detailed technical justification for the scaling. For the purposes of this paper, the expressions in the vertical axis labels in the figures capture the scaling, and the OU time axis has been properly adjusted.

It is clear from Figure 5 that the OU model better represents the uncertainty in prediction error of the vessel velocity. The OU model increases initially but then settles to an asymptotic value. The empirical uncertainties for all three vessel types follow closely the theoretical curve. In contrast, the NCV model matches the empirical uncertainty only for very short prediction-time horizons, and diverges quickly even for medium-term predictions.

Figure 6 shows analogous results for the uncertainty in the prediction error of the vessel position. Again, the OU model follows closely the empirical results for all three types of vessels, while the NCV model diverges quickly for moderate and long prediction-time horizons.

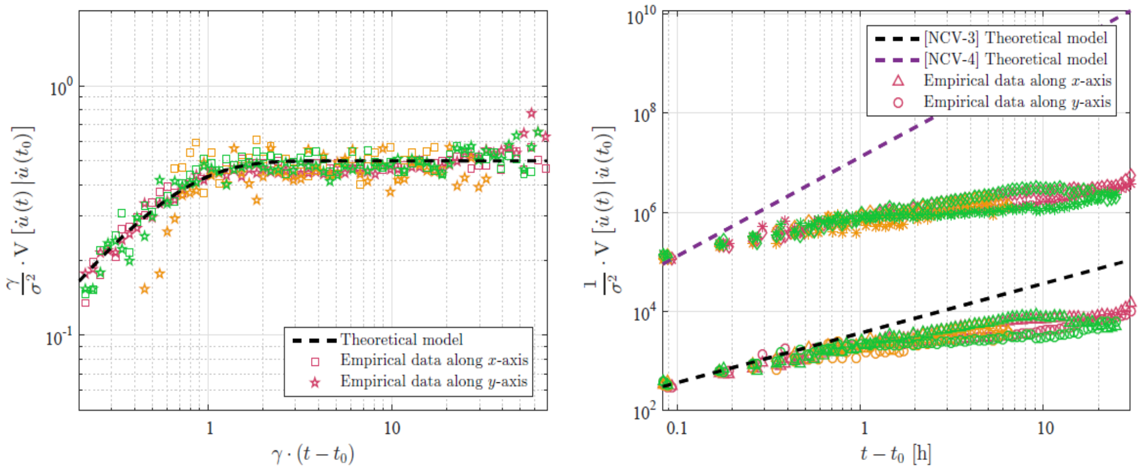

Figure 5: Normalized variance of the prediction error in the target velocity assuming the OU (left) and NCV (right) target motion models, for the three traffic categories: cargo (pink), tanker (green), and passenger (orange). Vessel velocity components along the x-axis and y-axis are identified using triangle and square markers, respectively.

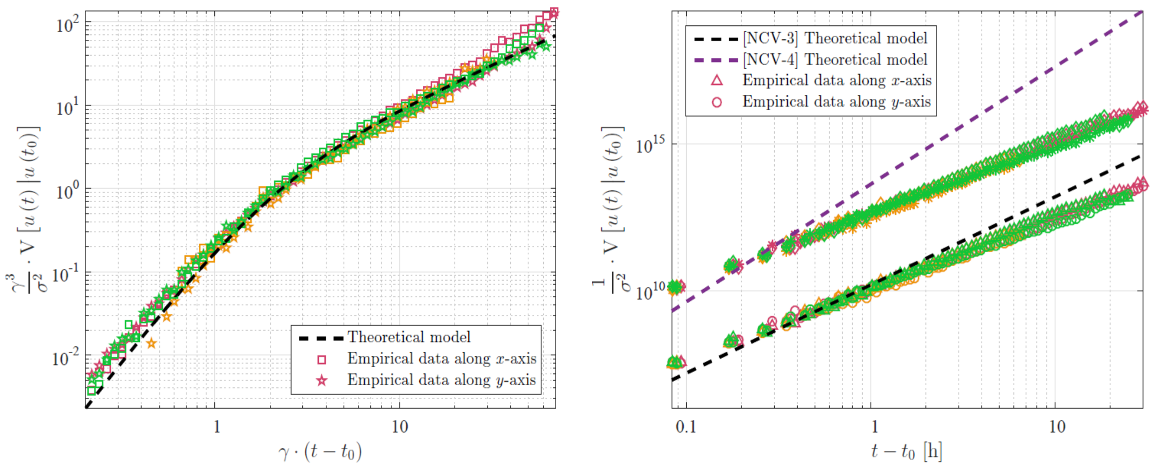

Figure 6: Normalized variance of the prediction error in the target position assuming the OU (left) and NCV (right) target motion models, for the three traffic categories: cargo (pink), tanker (green), and passenger (orange). Vessel position components along the x-axis and y-axis are identified using triangle and square markers, respectively.

5.0 CONCLUSIONS AND IMPLICATIONS FOR EXPLOITING SPACE-BASED ASSETS

In this paper the problem of issuing long term predictions of future vessel states has been studied, with specific focus on the modelling of the related uncertainty. That is, given a vessel motion model, the aim has been to derive an optimal prediction procedure and investigate its variance over the prediction horizon. However, unlike most of the literature in the tracking field, our efforts have been concentrated on the case of long- term target state prediction, where the prediction horizon is orders of magnitude above the refresh rate of the sensor issuing the observation, this case being much more plausible in the real-world problem of maritime traffic motion modelling.

Two different stochastic motion models have been hypothesized, the first being the well-known Nearly Constant Velocity (NCV) model, and the second the less commonly studied, at least in the tracking literature, Ornstein-Uhlenbeck (OU) mean-reverting stochastic model. Experimental results confirm that Ornstein-Uhlenbeck (OU) stochastic processes may be used to model the motion of non-maneuvering vessels while under way. Its major advantage over the more traditional NCV model is that the variance of the predicted position grows linearly with the prediction horizon, resulting in a prediction uncertainty that is orders of magnitude more contained at larger time scales.

The OU process applied to vessel state prediction can enable several scenarios relevant to NATO for which space-based assets can play a role. For example, in the task of satellite image acquisition, the reduction of uncertainty in vessel location enables more precise scheduling of the acquisition resources of the satellite, thus reducing the costs. Conversely, a tighter uncertainty area allows focusing the image acquisition, and enables the trade-off of lower resolution, higher coverage images with more targeted, higher resolution ones. In all cases, the interplay between the availability of the space-based assets and the algorithmic techniques is crucial to optimizing the allocation of resources, which can lead to more successful, but less costly, NATO operations.

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Title

Maritime situational awareness use cases enabled by space-borne sensors

Abstract

This paper discusses a technique for predicting a vessel's position over a long time horizon with much lower uncertainty than current methods. Lowering the uncertainty of long-range prediction is a key challenge in maritime situational awareness, and in particular for space-based systems can enable data fusion from sensors with different refresh rates, and help optimize the deployment and scheduling of the assets. These tasks are common to several practical scenarios: search and rescue and long-range vessel tracking in sparse data are two main ones. The proposed modelling is compared to one which is widely used in target tracking applications, using terrestrial and satellite Automatic Identification System (AIS) data, and the implications of the improved uncertainty for scenarios relevant to NATO are discussed.

Keywords

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