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Validation of the Ornstein-Uhlenbeck Route Propagation Model in the Mediterranean Sea

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***Abstract*—Traffic route analysis and prediction are both crucial to maritime security. The ability to predict a vessel position in the future is essential to provide information on upcoming events. However, accurate prediction along a route is a challenging task in the maritime domain, due to the complex nature and variability of traffic patterns.**

Based on the popular Ornstein-Uhlenbeck stochastic mean-reverting processes, a novel method has been recently presented that enables the accurate prediction of future positions of a vessel under the hypothesis that it is following an established traffic pattern in the area.

We present a large-scale extensive validation of the Ornstein-Uhlenbeck methodology applied to target predictions along routes in the maritime domain for several classes of vessel. This validation was done using a real-world dataset recorded in the Mediterranean Sea by a network of Automatic Identification System (AIS) receivers.

***Index Terms*—context-enhanced prediction, traffic route analysis, automatic identification system, maritime surveillance, real-word data**

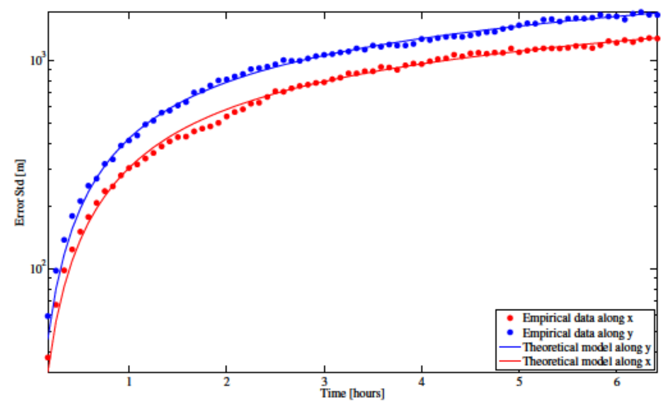


Fig. 1. Prediction error standard deviation along x and y for a cargo route in the Mediterranean Sea.

I. Introduction

Maritime transportation is the main conduit of international trade [1]. Consequently, ensuring maritime security is of crucial importance, and situational awareness is the crux of this requirement. Ship traffic monitoring represents one of the biggest challenges (*e.g.* in terms of law enforcement, search and rescue, environmental protection and resource management) and, in recent years, has led to intensive research activities in order to exploit new methodologies in support of maritime surveillance.

A key aspect of maritime safety and security is Maritime Situational Awareness (MSA), which is enabled through surveillance and tracking. As established by the International Maritime Organization's (IMO) International Convention for the Safety of Life at Sea (SOLAS) [2], Automatic Identification System (AIS) has to be fitted aboard international voyaging ships with gross tonnage (GT) of 300 or more and all passenger ships regardless of size. Therefore AIS, and cooperative vessel self-reporting systems in general, can provide a near real-time maritime traffic picture [2], [3]: each AIS transmitting vessel will report its position depending on factors such as its speed and manoeuvring status.

While the AIS system was originally conceived for collision avoidance, and the main use of the system is for local and real time applications, there are increasing possibilities for the use of AIS beyond this scope. For instance, AIS information can be collected over time and processed to identify recurrent patterns of behaviour. The amount of information reported by AIS providers is impressive, and for reference we report in Fig. 2 the density of traffic in the Mediterranean Sea computed using AIS data collected over six months by the NATO Science and Technology Organization Centre for Maritime Research and Experimentation (STO-CMRE).

Previous work for the automated learning of vessel traffic pattern behaviours [4]–[6] has shown that through the analysis of historical data, valuable knowledge about traffic patterns can be inferred. Recently, a method has been proposed [6] for predicting future vessel positions, based on the Ornstein-Uhlenbeck [7], [8] stochastic processes, whose parameters are estimated from real-world historical AIS data categorised into routes. These parameters are essential characteristics of recurrent routes, and can be exploited as prior knowledge in order to predict the position of vessels with a given confidence on the error estimates. Fig. 1 illustrates how the error variance of the prediction increases over the time and how the empirical data follows the theoretical model under the hypothesis that the motion of the vessel along its trajectory can be effectively described by an Ornstein-Uhlenbeck stochastic process [6].

The objective of this work is to validate the approach presented in [6] with a large-scale investigation based on an extensive dataset involving several typologies of sea lanes

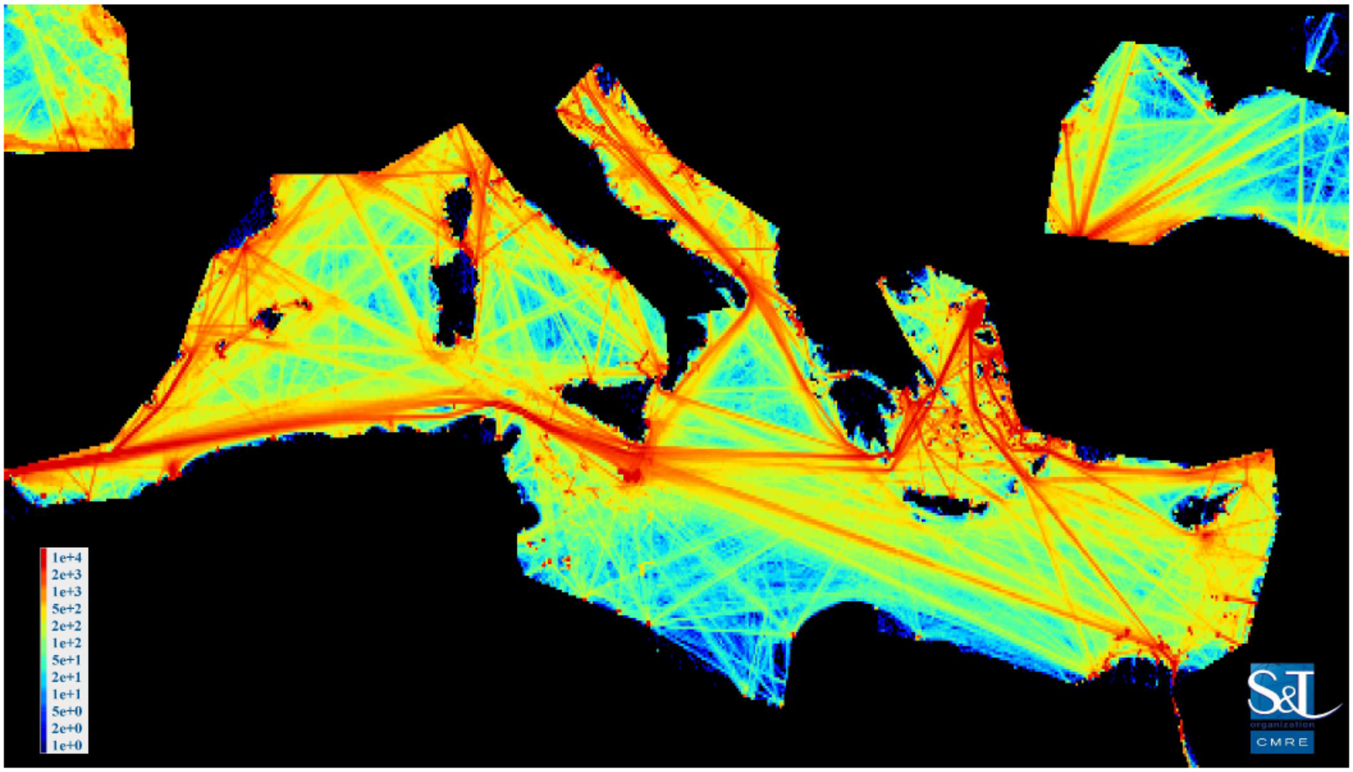


Fig. 2. Density of Automatic Identification System (AIS) messages collected from multiple AIS networks from April to September 2012. Each pixel covers a 4 nmi (one-fifteenth-degree) square on the ground and its colour is (logarithmically) proportional to the number of ships whose reported position fall within its footprint.

and vessel types. The hypothesis that the motion of vessels showing an established behavioural pattern is well described by Ornstein-Uhlenbeck processes is herein validated on a significant portion of the overall maritime traffic recorded in the Mediterranean Sea area during one month in 2014.

II. Stochastic Model

In this section we describe the stochastic model of the vessel kinematics. The generic term *target* will be adopted instead of *vessel*, in order to conform with the related tracking literature. The target-to-route association process is not addressed in the paper; it is, however, widely studied in literature [5], [9]–[12], especially in the context of ground target tracking, where of particular interest is the Variable Structure Interactive Multiple Model (VS-IMM) mechanism [9], [10], that is used to handle the on/off-road transitions and the change from one road to another. Transition probabilities for the routes are used in [5], where the probability has been shown to be well described by a Weibull distribution.

Let us assume that a target is following a given route, i.e. it is showing a behaviour that is recognised as an established traffic pattern. The objective is then to describe how its state can be propagated along the route and how the uncertainty of its estimated position evolves over time. The target state at time $t \in \mathbb{R}$ is indicated with

$$\boldsymbol{x}(t) = [x_1(t),\, x_2(t),\, \dot{x}_1(t),\, \dot{x}_2(t)]^T\,, \tag{1}$$

where the two coordinates and the corresponding velocities are

$$\boldsymbol{x}_p(t) \stackrel{def}{=} [x_1(t),\, x_2(t)]^T \tag{2}$$

$$\dot{\boldsymbol{x}}_p(t) \stackrel{def}{=} [\dot{x}_1(t),\, \dot{x}_2(t)]^T\,. \tag{3}$$

The coordinates $x_{1,2}$ and the corresponding velocities $\dot{x}_{1,2}$ are here intended to be in a two-dimensional Cartesian (x_1, x_2) reference system.

It is assumed that the target dynamics are given by a set of linear stochastic differential equation (SDE) of the form [6]:

$$d\boldsymbol{x}(t) = \boldsymbol{A}\ (\boldsymbol{x}(t) - \boldsymbol{m})\ dt + \boldsymbol{B}\, d\boldsymbol{w}(t), \tag{4}$$

where $\boldsymbol{m} = \left[0, 0, \boldsymbol{v}^T\right]$, and $\boldsymbol{w}(t)$ is a standard bi-dimensional Wiener process. The matrices $\boldsymbol{A}$ and $\boldsymbol{B}$ are defined as:

$$\boldsymbol{A} = \begin{bmatrix} \boldsymbol{0} & \boldsymbol{I} \\ \boldsymbol{0} & -\gamma \boldsymbol{I} \end{bmatrix}, \quad \boldsymbol{B} = \begin{bmatrix} \boldsymbol{0} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{C} \end{bmatrix}, \tag{5}$$

where $\boldsymbol{0}$ is bi-dimensional matrix of null elements, $\boldsymbol{I}$ is the identity matrix, $\boldsymbol{\gamma} = [\gamma_1, \gamma_2]^T$ is a vector whose elements are positive values, and $\boldsymbol{C}$ is a bi-dimensional matrix.

Equation (4) has the form of a Langevin dynamic [13] and can be solved in closed form by using Itô calculus [14]. The $\dot{\boldsymbol{x}}_p(t)$ process is then said to be of Ornstein-Uhlenbeck type [7], [8] and correspondingly, we say that $\boldsymbol{x}(t)$ is an integrated Ornstein-Uhlenbeck process [8].

Ornstein-Uhlenbeck processes are very popular in several areas of research: finance [8], [15], physics [7], [13], [14] and network control [16]. These processes, or mostly the corresponding versions in discrete time steps t_k, are occasionally used also in the target tracking community to model the autocorrelation of acceleration [17]–[23]. However, due to the inherently asynchronous nature of AIS information, here we consider the Ornstein-Uhlenbeck process in its continuous-time formulation.

The parameters v_1 and v_2, in $\boldsymbol{v} = [v_1, v_2]^T$, play a key role in the proposed model because they represent the *typical* velocities, along x_1 and x_2 respectively, of the route under consideration. These velocities can be empirically estimated by using historical routes, which provide a reference mean transit speed, as shown in the Sec. III-A. Assuming that the target is associated to the route at the time t_0, then its expected position follows the model

$$\begin{aligned} &\mathrm{E}\left[\boldsymbol{x}_p(t) \middle| \boldsymbol{x}_p(t_0)\right. \\ &\quad = \boldsymbol{x}_p(t_0) + t\,\boldsymbol{v} + (\dot{\boldsymbol{x}}_p(t_0) - \boldsymbol{v})\,\frac{1 - e^{-\gamma t}}{\gamma}. \end{aligned} \tag{6}$$

Similarly, assuming that the target is associated to a route at the time t_0, we can expect its velocity evolves accordingly to

$$\mathrm{E}\left[\dot{\boldsymbol{x}}_p(t) \middle| \dot{\boldsymbol{x}}_p(t_0)\right. = \boldsymbol{v} + (\dot{\boldsymbol{x}}_p(t_0) - \boldsymbol{v})\,e^{-\gamma t}. \tag{7}$$

An approximation of (6)–(7) can be derived if the initial transitory phase (vanishing exponentially in t) is neglected. The target's expected position is then propagated at constant velocity $\boldsymbol{v}$, so we can write as in [8], [14]:

$$\mathrm{E}\left[\boldsymbol{x}_p(t) \middle| \boldsymbol{x}_p(t_0)\right. \approx \boldsymbol{x}_p(t_0) + t\,\boldsymbol{v} \tag{8}$$

$$\mathrm{E}\left[\dot{\boldsymbol{x}}_p(t) \middle| \dot{\boldsymbol{x}}_p(t_0)\right. \approx \boldsymbol{v}. \tag{9}$$

With the time window defined as $t^* = t - t_0$, the related variances are then given by:

$$\mathrm{Var}\left[x_1(t) \middle| \boldsymbol{x}(t_0)\right. = \frac{\sigma_1^2}{2\gamma_1^3}\left(2\gamma_1 t^* + 4e^{-\gamma_1 t^*} - e^{-2\gamma_1 t^*} - 3\right) \tag{10}$$

$$\mathrm{Var}\left[x_2(t) \middle| \boldsymbol{x}(t_0)\right. = \frac{\sigma_2^2}{2\gamma_2^3}\left(2\gamma_2 t^* + 4e^{-\gamma_2 t^*} - e^{-2\gamma_2 t^*} - 3\right) \tag{11}$$

$$\mathrm{Var}\left[\dot{x}_1(t) \middle| \boldsymbol{x}(t_0)\right. = \frac{\sigma_1^2}{2\gamma_1}\left(1 - e^{-2\gamma_1 t^*}\right) \tag{12}$$

$$\mathrm{Var}\left[\dot{y}_2(t) \middle| \boldsymbol{x}(t_0)\right. = \frac{\sigma_2^2}{2\gamma_2}\left(1 - e^{-2\gamma_2 t^*}\right) \tag{13}$$

where σ_1^2 and σ_2^2 are the entry elements of $\mathrm{diag}\left(\boldsymbol{C}\boldsymbol{C}^T\right)$.

The parameters $\boldsymbol{v}$, γ and $\sigma_{1,2}$ fully characterise the statistical properties of the route under consideration. In particular, assuming that we observe the target state at a given time t_0, we can predict its position and velocity with (6), whose uncertainty is given by (10)–(13).

A distinctive element of this model for the vessel's dynamics over the common models adopted in the tracking literature (as for instance in [9]) is that the variance of the target position grows linearly with time, i.e. $\sim t\left(\sigma_{1,2}^2/\gamma_{1,2}^2\right.$, as reported in (10) and (11).

In the popular *near constant velocity* model (see [19]), the target position variance grows faster, i.e. $\sim \tilde{\sigma}^2\, t^n$ with $n \geq 3$. Clearly, in most tracking applications this is not a problem because the data rate is quite large and the predictions are over shorter time spans (e.g., in sonar systems, less than a minute [24]) compared to our case in which we aim at providing an estimated vessel prediction of several hours. In the following sections, evidence that the correct scaling law of the variance is linear, is provided.

Since the parameters $\sigma_{1,2}$ and $\gamma_{1,2}$ completely characterise the statistical properties of the trajectory under consideration, in order to possibly validate the correctness of the model against trajectories from multiple and various routes, let us rewrite (10)–(13) in the form

$$\mathrm{Var}\left[x_1(t) \middle| \boldsymbol{x}(t_0)\right. = \frac{\sigma_1^2}{\gamma_1^3}\, f\left(\gamma_1 t^*\right) \tag{14}$$

$$\mathrm{Var}\left[x_2(t) \middle| \boldsymbol{x}(t_0)\right. = \frac{\sigma_2^2}{\gamma_2^3}\, f\left(\gamma_2 t^*\right) \tag{15}$$

$$\mathrm{Var}\left[\dot{x}_1(t) \middle| \boldsymbol{x}(t_0)\right. = \frac{\sigma_1^2}{\gamma_1}\, g\left(\gamma_1 t^*\right) \tag{16}$$

$$\mathrm{Var}\left[\dot{y}_2(t) \middle| \boldsymbol{x}(t_0)\right. = \frac{\sigma_2^2}{\gamma_2}\, g\left(\gamma_2 t^*\right) \tag{17}$$

where $f(t)$ and $g(t)$ are the prediction position and velocity error *normalised* variance, defined as

$$f\left(t\right) \stackrel{def}{=} \frac{1}{2}\left(2t + 4e^{-t} - e^{-2t} - 3\right. \tag{18}$$

$$g\left(t\right) \stackrel{def}{=} \frac{1}{2}\left(1 - e^{-2t}\right. . \tag{19}$$

Equations (14)–(17) describe how the variance of the prediction error changes over the time, suggesting that the aforementioned variance is proportional to a *normalised* model, evaluated on a time axis scaled by $\gamma_{1,2}$, through constants that depend only on the ratio between $\sigma_{1,2}^2$ and $\gamma_{1,2}^3$. Therefore, (18) and (19) can be used to test extensively the correctness of the model against a heterogeneous dataset of routes.

III. Real-world Experimental Results

The STO-CMRE collects unclassified AIS data from near real-time collection and distribution networks and uses this data for research purposes. Satellite and terrestrial AIS data collected in the Mediterranean Sea have been herein used to validate the model presented in Sec. II.

A. Traffic Route Extraction

Comprehensive knowledge of recurrent vessel patterns in an area under investigation is valuable information to support accurate vessel predictions. However, the increasing quantity of historic AIS reports poses new challenges in the related fields of data mining and machine learning techniques when applied within the context of big data and MSA. The large amount of vessel movement data collected by terrestrial networks and satellite constellations of AIS receivers requires the aid of automatic processing techniques to fully exploit this data, since the initial amount of raw information can overwhelm human operators. Also, the learning process should be robust with respect to number of sensors, their coverage and refresh rate, and scale of the area of interest. Thus, it is desirable to base the traffic route extraction process on incremental learning which can be applied both in real-time or batch fashion.

Within this context, traffic route extraction and prediction in an unsupervised way, based on historical knowledge of maritime traffic, is an essential first step. It implies that raw maritime data can be translated into information. Although AIS data reliably depicts the traffic related primarily to large vessels, it can be effectively used to infer different levels of contextual information, spanning from the characterisation of ports and off-shore platforms to spatial and temporal distributions of routes. The proposed methodology exploits the knowledge about the traffic patterns in the area of interest derived using the STO-CMRE Traffic Route Extraction for Anomaly Detection (TREAD) tool. This tool automatically learns a synthetic representation of maritime traffic patterns from low-level AIS data in an unsupervised way. More details about the TREAD tool can be found in [4], [5], [25].

The knowledge achieved via TREAD about the traffic scene is shaped in a compact form via three mutually dependent classes of objects: *vessels*, *way-points* and *routes*. These objects are generated by incremental processing of raw data where meaningful events are generated in the vessel state vector sequences, including events like a break in observation updates. Specifically, the recurrent patterns of life are derived by clustering these meaningful events based on the vessel behaviour, enabling the creation of way-points of interest which can be classified as either *stationary areas*, *entry points* and *exit points* within the selected bounding box. *Routes* are then created by connecting such *way-points* and are then statistically characterised.

For vessel prediction purposes, route objects can be considered, representing a directed path of the vessels which started their journey from, and travelling towards specific way-points. Therefore, each route can be thought as a cluster of vessel trajectories that have shown similar behaviours.

Hence, routes represent a natural starting point for our validation analysis, since they inherently provide a set of homogeneous motion models against which the Ornstein-Uhlenbeck approach can be effectively applied. Information from the derived routes, such as the vessel type, mean velocity or the series of route points provided by previous transits, represent a set of constraints that can be used to characterise the behaviour of specific classes of vessels along the route.

To this aim, each route embeds the temporal distribution of the kinematic features (i.e. geographical position, Course Over Ground (COG) and Speed Over Ground (SOG)) of the vessels associated to its cluster distinguished by ship type.

In the remainder of this section, the traffic routes and the corresponding feature clusters will be used in the prediction of vessel positions with the aid of non-linear filtering techniques. Specifically, these key concepts will be fed into the proposed context-based tracking model based on Ornstein-Uhlenbeck stochastic processes to evaluate the utility to predict vessel positions in the future.

B. Large-scale model validation

The entire batch of terrestrial and satellite AIS messages collected by a global sensor network has been used to validate the model presented in Sec. II. The dataset spans a time-frame from the 1st to the 30th of September 2014. This historic dataset has been used to extract the recurrent Patterns Of Life (POL) using the TREAD methodology.

Unlike the original study [6], the whole dataset has been divided into three smaller datasets, comprising messages broadcast only by cargo, tanker and passenger vessels, enabling the analysis of more homogeneous behaviours.

Latitude and longitude coordinates were converted in a two-dimensional Cartesian (x, y) coordinate system, but due to the different refresh rates of the AIS information, in order to provide a good estimate of the Ornstein-Uhlenbeck process parameters, data was also interpolated along trajectories at fixed time intervals between subsequent data points. After this initial preprocessing phase, the datasets were ready for the testing against the proposed model.

Considering that each route in the knowledge base corresponds to a typical motion behaviour between two given way-points, it can be used as the input motion information for the vessel kinematics. With the objective of verifying the model, each route has then been further segmented into piece-wise continuous linear trajectories of the vessels which transited along it.

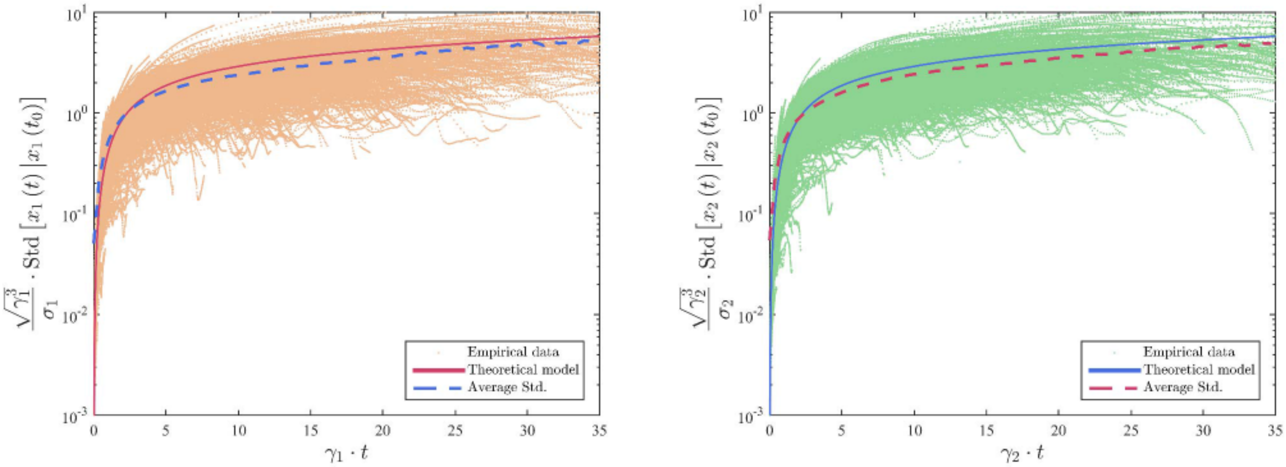
These piece-wise continuous trajectories were used to validate the proposed approach in the prediction of vessels' future positions, in terms of *prediction error*, defined as the displacement of an observed state $x(t)$, with respect to its prediction $\hat{x}(t)\,|x(t_0)$, given a time interval $t^* = t - t_0$. Unlike in [6], where the prediction was carried out using the approximation in (8) and (9), in this work we first estimate the parameters of the Ornstein-Uhlenbeck stochastic process and afterwards we use the exact formulas in (6) and (7) to compute the prediction. The parameters of the aforementioned stochastic process are inferred using a Maximum Likelihood (ML) estimator from the velocity samples.

Figures 3, 4 and 5 illustrate the outcome of the validation study for cargo, tanker and passenger vessels, respectively. In all the three cases, it is apparent how the observed error prediction average variance over time closely follows the curve of the theoretical (normalised) model, as defined in (18) and (19).

IV. Conclusion

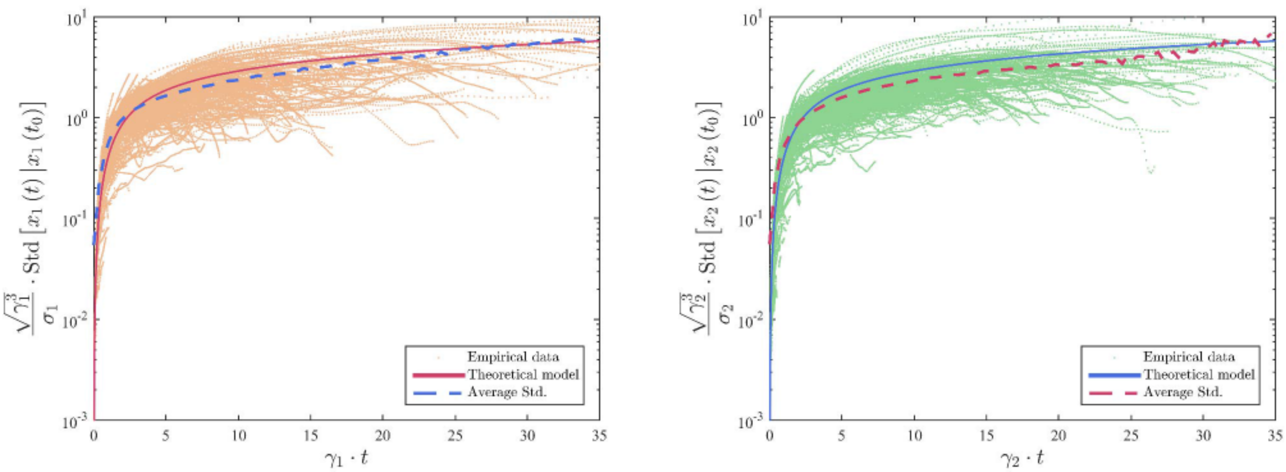
The current work deals with the problem of predicting the position of a vessel in the future, based on a methodology that increases the accuracy of the prediction under the assumption that the target motion model is well represented by Ornstein-Uhlenbeck mean-reverting stochastic processes.

An extensive validation study has been presented, and the related results suggest that Ornstein-Uhlenbeck processes may



(a) x-axis (b) y-axis

Fig. 3. Prediction error normalised variance for cargo vessels. The time axes are scaled by the route-specific $\gamma_{1,2}$ coefficients. The analysis comprises data points from 386 recognised routes of cargo vessels in the entire Mediterranean Sea from September, 1st to 30th, 2014. Trajectories were segmented and segments lasting less than 4 hours were ignored, leading to a working dataset of 5218 quasi-rectilinear vessel sub-trajectories.



(a) x-axis (b) y-axis

Fig. 4. Prediction error normalised variance for tanker vessels. The time axes are scaled by the route-specific $\gamma_{1,2}$ coefficients. The analysis comprises data points from 105 recognised routes of tanker vessels in the entire Mediterranean Sea from September, 1st to 30th, 2014. Trajectories were segmented and segments lasting less than 4 hours were ignored, leading to a working dataset of 1074 quasi-rectilinear vessel sub-trajectories.

be appropriate to model the motion of vessels that exhibit typical behaviours between established way-points.

For such vessels, evidence was presented that the uncertainty –i.e. the variance– of the prediction grows linearly with the time. In other terms, it has been shown that contextual information can be effectively exploited to achieve better accuracy in predicting future vessel positions.

A future extension of the presented approach is to model of the probability of switching between subsequent paths in proximity of way-points and forks.

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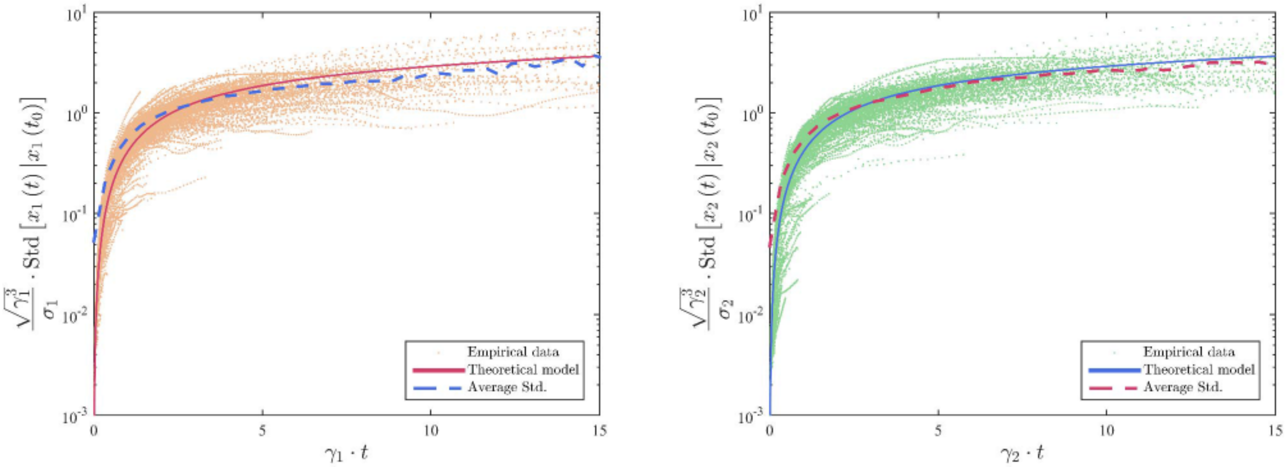

(a) x-axis (b) y-axis

Fig. 5. Prediction error normalised variance for passenger vessels. The time axes are scaled by the route-specific $\gamma_{1,2}$ coefficients. The analysis comprises data points from 368 routes of passenger vessels in the entire Mediterranean Sea from September, 1st to 30th, 2014. Trajectories were segmented and segments lasting less than 4 hours were ignored, leading to a working dataset of 1197 quasi-rectilinear vessel sub-trajectories.

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Title

Validation of the Ornstein-Uhlenbeck route propagation model in the Mediterranean Sea

Abstract

Traffic route analysis and prediction are both crucial to maritime security. The ability to predict a vessel position in the future is essential to provide information on upcoming events. However, accurate prediction along a route is a challenging task in the maritime domain, due to the complex nature and variability of traffic patterns. Based on the popular Ornstein-Uhlenbeck stochastic mean-reverting processes, a novel method has been recently presented that enables the accurate prediction of future positions of a vessel under the hypothesis that it is following an established traffic pattern in the area. We present a large-scale extensive validation of the Ornstein-Uhlenbeck methodology applied to target predictions along routes in the maritime domain for several classes of vessel. This validation was done using a real-world dataset recorded in the Mediterranean Sea by a network of Automatic Identification System (AIS) receivers.

Keywords

Context-enhanced prediction, traffic route analysis, automatic identification system, maritime surveillance, real-world data

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