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Vessel Voyage Trajectory Extrapolation: Comparing the Performance of Kalman Filters

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***Abstract*—Effective management of port terminal operations and logistics requires efficient allocation of resources for arriving ships. Predicting vessel arrival times is crucial for optimizing the allocation of resources and ensuring smooth operations. To this end, the Automatic Identification System (AIS) has emerged as a valuable source of data for vessel tracking and voyage-related information retrieval. In this study, we investigate the performance of two popular filtering algorithms, Discrete Kalman Filter (DKF) and Unscented Kalman Filter (UKF), in extrapolating the short-term (2-minute) trajectory of vessels using a Constant Velocity (CV) model. This can be useful in providing missing information needed by a vessel arrival time prediction model. Our experimental results show that the UKF and DKF perform similarly in vessel trajectory extrapolation, suggesting that the additional computational cost of sigma point sampling and propagation in the UKF may not be necessary for this application. This finding has implications for the development of vessel arrival time prediction models that rely on vessel trajectory information.**

***Index Terms*—Automatic Identification System (AIS), Kalman Filter, Trajectory Extrapolation**

I. Introduction

Maritime commercial transportation accounts for over 80% of commercial transportation worldwide [1]. To ensure efficient delivery of essential items such as food, energy, and medicine, it is crucial to improve navigation security, port management, and logistics operations while minimizing potential disruptions.

Accurate information about a ship's position and speed is crucial for ensuring safe navigation and maneuvering in port, as well as for minimizing disruptions that could compromise the timely delivery of essential goods. The Global Positioning System (GPS) provides this information to ship officers, enabling them to chart the most secure and efficient routes. The Automatic Identification System (AIS), developed to enhance navigation safety, complements the GPS by allowing vessels to exchange low-granularity static and dynamic data with each other and with onshore Vessel Traffic Service (VTS) centers that are equipped with AIS receivers [2]. In addition to GPS, AIS gathers information from onboard sensors and transmits data via digital VHF radio communication technology. This system helps ship and port operators to plan their navigation and operations more effectively. The International Maritime Organization's International Convention for the Safety of Life at Sea requires *all ships of 300 gross tonnage and upwards engaged on international voyages, cargo ships of 500 gross tonnage and upwards not engaged on international voyages, and passenger ships irrespective of size to be fitted with an automatic identification system (AIS)* [3]. Today, more than 40,000 ships are equipped with AIS [2]. In addition to aiding collision avoidance, AIS data is also being used for other purposes, such as data mining and ship behavior analysis [4].

However, despite the benefits provided by AIS, there are limitations that must also be considered. One of the main limitations is the potential for human error in setting static information, leading to inconsistencies in variables such as "Vessel Type," "Length," and "Navigational Status." The "Navigational Status" variable, which identifies the vessel's current activity, is automatically emitted but can be manually changed by the officer of the watch (OOW). However, a study found that the "Navigational Status" was inconsistent 30% of the time for vessels leaving, approaching, and at anchor or alongside in Liverpool Bay port when compared to information from the port's VTS station database [5]. As a result, using this variable to identify ships' activities becomes unfeasible. Nevertheless, it could be helpful to split the trajectories of a single vessel in an offline dataset based on the "Navigational Status" when it is set to "moored."

Another limitation is the unavailability of updated data. The messages should be emitted with low granularity (i.e., seconds or minutes) [3], but larger gaps between consecutive samples, even of multiple hours, are present. These can be due to the turning off of the AIS by the ship's master judgment to not compromise the ship's security in regions of high risk for maritime criminal behavior [6]. It is essential to keep the information updated to improve navigation safety and provide potentially helpful information for port operations

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planning, e.g., improving berth planning with vessel arrival time prediction [7].

Multiple studies have focused on improving AIS data availability. Particularly for short-term trajectory extrapolation, the Kalman Filter has been widely used [8]–[10]. The Discrete Kalman Filter (DKF) has been used with a Constant Acceleration and Turn Rate (CATR) motion model to fill missing data of a nearly linear real vessel trajectory with multiple step-ahead prediction, in order to maintain a 10 second interval between samples [9]. The Extended Kalman Filter (EKF) has been used with a Constant Velocity (CV) and a Constant Velocity and Turn Rate (CVTR) motion models, combining the best of both models with an Interacting Multiple Model (IMM) framework that merges the states of two EKF, each of them with one of the previous motion models, using a weighted sum of their estimates, where the weights are based on their likelihood of fitting the current system dynamics, according the the innovation measure of each [8]. Besides, the EKF has been tested for large scale vessel trajectory prediction for real-time applications, using distributed stream-processing systems, i.e., Apache Kafka and Flink [10].

In this work, a comparison between the Discrete Kalman Filter (DKF) and Unscented Kalman Filter (UKF) is done using real vessel trajertories of various shapes that were recorded during their voyages to the container terminal of the Port of Miami. This allows to provide insight into which filtering technique is better suited for vessel position extrapolation.

II. Methodology

In this work we first identify each vessel's trajectory and choose the appropriate trajectories to test the filters' capabilities. The filters are then used for position extrapolation, using a Constant Velocity (CV) model. Their performance is measured and compared.

A. Data

AIS data contains both static and dynamic information on vessels' characteristics and movement, with low granularity. The data used in this work comprises vessels arriving at the Port of Miami's container terminal between 2018 and March of 2021 [11] [7]. The original AIS data is available at the website of the National Oceanic and Atmospheric Administration (NOAA) Office for Coastal Management[1]. Even though the data has no missing values for the dynamic variables, the time between consecutive samples is inconsistent, as seen in Table I. This must be corrected, as Kalman Filters need equally spaced samples [12]. The variables used in this work are the latitude and longitude (LAT, LON), the Speed Over Ground (SOG), and the Course Over Ground (COG). COG is the direction/orientation of the vessel's movement in relation to the true North, which can differ from the direction it points to (i.e., Heading), particularly when there are adverse extreme weather conditions, such as high wind or current speed. Because of this, the Heading is not used in this work to formulate the vessels' movement.

[1] https://marinecadastre.gov/ais/

TABLE I
AIS Dynamic Data Structure.

	BaseDateTime	LAT	LON	SOG	COG	Heading
0	2021-02-18 19:49:02	22.90467	-78.91242	13.5	-88.3	319.0
1	2021-02-18 19:53:46	22.92118	-78.92096	14.1	-71.7	337.0
2	2021-02-18 20:00:45	22.94673	-78.93176	14.1	-72.3	337.0
3	2021-02-18 20:03:22	22.95611	-78.93592	14.0	-70.2	337.0
4	2021-02-18 20:05:10	22.96262	-78.93882	14.0	-72.9	337.0

The dataset is organized in CSV files, each corresponding to data from a single vessel. However, each vessel can have multiple voyages to the port, which must be identified and split. Voyages are split if there is a difference of 5 hours and 100 meters between two samples. Then, a polygon is defined around the port, and the AIS messages after the first within the polygon are removed since we only need data from the voyage to the port. The defined polygon is shown in Fig. 1.

As previously mentioned, the Kalman Filter requires equally spaced samples in time, but the dataset presents gaps of varying sizes between them. To address this issue, we computed the mean of each variable for every 2-minute interval, using a moving window with a step size of 2 minutes. If no values were available within a 2-minute interval, a row with missing values was added. Only voyages without missing rows were selected for the evaluation, to ensure that the filter's performance was compared to the original AIS measurements. Additionally, voyages with less than 100 samples were excluded. Out of the 13 remaining voyages, we selected four with different motion patterns to test the filters' performance, as illustrated in Fig. 2.

To prepare the data for use with Kalman filters, several unit

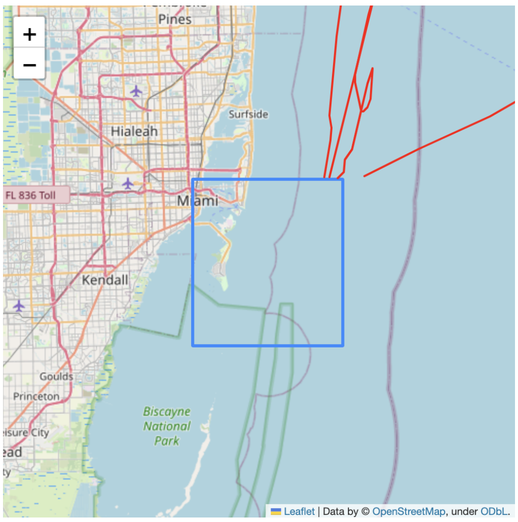


Fig. 1. Voyages from a single vessel (red lines) split by a 5-hour and 100-meter difference between consecutive samples (start of the next voyage) and by the first sample in a polygon (end of the current voyage) defined around the container terminal of the Port of Miami (blue square).

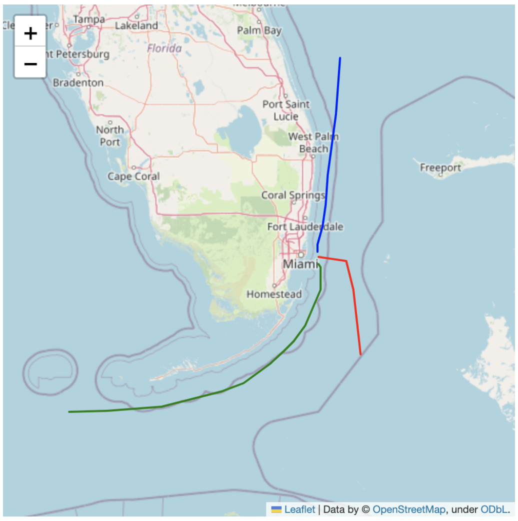


Fig. 2. Complete voyages obtained after applying a moving average of 2-minute window and step size to guarantee that samples are equally spaced in time. There is a "sharp turn" (red), a "curved" (green) and a "linear" (blue) trajectory.

conversions were performed. First, positions were projected from WGS-84 (EPSG:4326) to Pseudo-Mercator (EPSG:3857) using the GeoPandas library, converting coordinates from (longitude, latitude) in decimal degrees to (x, y) in meters. The SOG variable was converted from knots to meters per second using $v(m/s) = 0.51(4) * SOG(knots)$. Similarly, the COG variable was converted from degrees to radians using $\phi(radians) = COG(deg) * \pi/180$.

B. Estimation Filters

The Discrete Kalman Filter (DKF) recursively estimates a system's state using a mathematical model to describe its behavior over time (process model) and uses available external measurements to correct the prediction of the process model. Naturally, the process model simplifies the real behavior, and the external measurements have some associated noise, so the DKF takes that noise into account when calculating the uncertainty/covariance of the state estimate. The higher the covariance, the higher the Kalman Gain, which is used to scale the innovation (i.e., the difference between measurement and prediction), determining how much confidence we put in the measurement to update the estimate. If the Kalman Gain is 1 for every measured variable, the estimate is updated using the entire innovation, so all the confidence is in the measurement. For a more detailed explanation, refer to [13].

As the DKF assumes that the system's behavior and measurements are linear, it may provide inaccurate estimates in non-linear systems. The Extended Kalman Filter (EKF) allows extending the applicability of the DKF to non-linear systems by linearizing the model using a 1st-order Taylor-series approximation, calculating the Jacobian Matrices and using them in the prediction of the state estimate covariance and correction of the predictions. Besides the EKF, the Unscented Kalman Filter (UKF) can also be applied to non-linear systems that are not well approximated by a 1st-order Taylor series expansion since it takes a deterministic sampling approach to approximate the true covariance of the system, using a small number (usually $2N + 1$, where N is the dimension of the state) of sampled points, called sigma points.

In this work, the Constant Velocity (CV) motion model is used. The state of the system is represented by:

$$\mathbf{x}_t = [x_t, v_{x,t}, y_t, v_{y,t}], \tag{1}$$

where the position of the vessel is (x_t, y_t) and the velocity for each corresponding axis is $(v_{x,t}, v_{y,t})$. The state is initialized from the first AIS message of the trajectory. The velocities are initialized using the velocity (v) and orientation (ϕ):

$$\begin{aligned} v_{x,0} &= v_0 \times \sin(\phi) \\ v_{y,0} &= v_0 \times \cos(\phi). \end{aligned} \tag{2}$$

The transition matrix $\mathbf{F}$ for the motion model corresponds to:

$$\mathbf{F} = \begin{bmatrix} 1 & \Delta t & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \Delta t \\ 0 & 0 & 0 & 1 \end{bmatrix}. \tag{3}$$

There is no external control input in the motion model. The process and measurement noise covariance matrices are defined as:

$$\mathbf{Q} = \begin{bmatrix} \frac{\Delta t^4}{4} & \frac{\Delta t^3}{2} & 0 & 0 \\ \frac{\Delta t^3}{2} & \Delta t^2 & 0 & 0 \\ 0 & 0 & \frac{\Delta t^4}{4} & \frac{\Delta t^3}{2} \\ 0 & 0 & \frac{\Delta t^3}{2} & \Delta t^2 \end{bmatrix} \sigma_a^2 \tag{4}$$

$$\mathbf{R} = \begin{bmatrix} 10^2 & 0 \\ 0 & 10^2 \end{bmatrix}, \tag{5}$$

where σ_a^2 corresponds to the acceleration that is not considered in the CV motion model. In this study, the movements in both axis are considered independent, so the covariance between the axis in the Q matrix is set to 0. The measurement noise covariance matrix R is a diagonal matrix with the values defined as the performance standards defined by IMO for GPS receivers equipped with differential receivers [14]. As the initial state is the same as the first AIS measurement for the trajectory, the initial state estimate covariance error matrix P_0 is set with small values:

$$P_0 = \mathbf{I} \cdot 0.01. \tag{6}$$

The measurement model matrix H is defined as:

$$\mathbf{H} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}. \tag{7}$$

The use of the EKF was not considered, since the Jacobian matrices would be similiar to F and H, so the results would be the equivalent to the DKF. The UKF utilizes $2 \cdot N+1$ sigma points, and the parameters $\alpha = 0.001$, $k = 0$, and $\beta = 2$ are set based on [15].

C. Evaluation Metrics

In this work, two performance metrics, built for regression problems, are used to evaluate the estimated measurements against the actual ones from the AIS data: Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). RMSE applies the root to the Mean Squared Error (MSE), so the final value is in the same units as the target variables. This way, the RMSE is more interpretable than MSE and still emphasizes larger errors. The formula of the RMSE is as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{8}$$

The MAE measures the actual deviations of the estimated values against the target values, so it doesn't emphasize large errors. The formula of MAE is as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{9}$$

When comparing the results of two estimation methods, if one has a larger RMSE but a lower MAE, it indicates that overall, the deviations from the target values are lower, but there are enough larger deviations that contribute to the larger RMSE.

Besides these performance metrics, the execution time of each filter to estimate a single position is also calculated as the mean time it takes in the prediction and correction steps for the whole trajectory.

III. Results

This section evaluates the two tested methods using the RMSE and MAE performance metrics, for different values of acceleration considered for the Q matrix and the best values obtained for each trajectory.

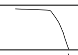
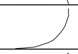
The MAE and RMSE are similar between the DKF and UKF, as can be seen in Fig. 3 and Fig. 4. The estimation execution time of the DKF is significantly lower that the UKF, since the latter needs to perform more computations to sample and propagate the sigma points which is not worth the computational cost according to the obtained results. The acceleration values considered in matrix Q (σ_a) that provided the best results for the sharp turn, curved and linear trajectories where 0.001, 0.0001, and 0.0001, respectively.

The best results were achieved for the "linear" trajectory on the x axis and the "curved" trajectory on the y axis, with the latter showing more balanced results between both axis, as shown in Table III. On the "sharp turn" trajectory, the RMSE values differ the most from the MAE values, while on the "linear" trajectory they differ the least. This is because the filters are more adapted to changes in the vessel's Course Over Ground (COG), which are more significant on the "sharp turn" trajectory than on the "linear" trajectory, resulting in larger errors in those situations.

TABLE II
EXECUTION TIME OF EACH FILTER FOR A SINGLE ESTIMATION (PREDICTION + CORRECTION).

Trajectory	Filter	Execution Time (s)
	DKF	$6.4e-5$
	UKF	0.001
	DKF	$6.11e-5$
	UKF	0.001
	DKF	$6.51e-5$
	UKF	0.001

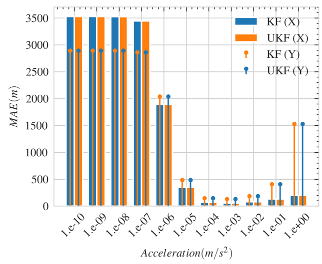
TABLE III
BEST PERFORMANCE BY THE DISCRETE KALMAN FILTER.

	RMSE (m)		MAE (m)	
Trajectory	X	Y	X	Y
	106.90	219.52	63.75	150.51
	81.54	58.16	63.46	40.23
	18.10	110.85	14.17	101.91

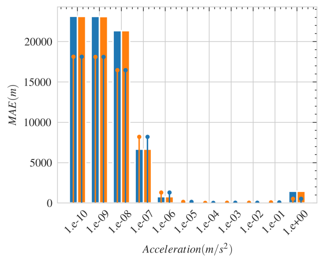
IV. Conclusions

This study compared the performance of the Discrete Kalman Filter (DKF) and Unscented Kalman Filter (UKF) filtering methods for estimating vessel positions based on three different trajectories derived from AIS data of vessels arriving at the Port of Miami container terminal. The results showed that both filters performed similarly for all three trajectories. This suggests that the UKF's sigma points sampling approach, which requires additional computations to sample and propagate the sampled points, does not provide significant improvements over the DKF. Furthermore, the best results were obtained using relatively low acceleration values, as considered in the matrix Q.

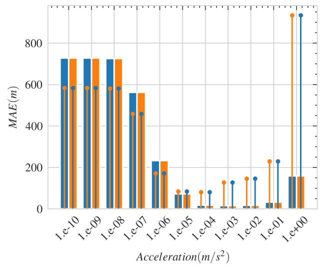
There are several potential avenues for future research. For example, tests can be conducted using adaptive filtering for the Q matrix in the Kalman Filters, which may improve the filters' performance [16]. Additionally, incorporating more data, such as the Rate of Turn (ROT) from AIS data and vessel acceleration calculated from velocity, ROT, and orientation, may further enhance the accuracy of the process model. In addition to improving accuracy, it is important to consider the execution time of each method, particularly for real-time applications. Therefore, future research could focus on evaluating the performance of both filters in terms of their execution time.



(a) Sharp turn Trajectory

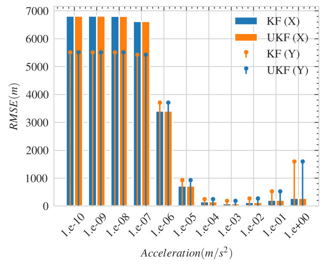


(b) Curved Trajectory

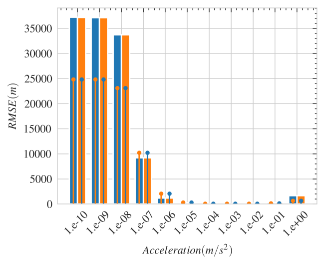


(c) Linear Trajectory

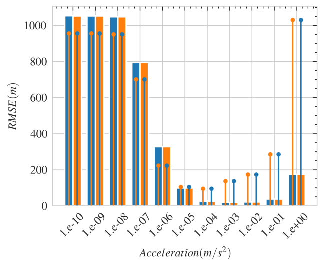
Fig. 3. MAE values for different acceleration values considered in the process noise covariance matrix Q.



(a) Sharp turn Trajectory



(b) Curved Trajectory



(c) Linear Trajectory

Fig. 4. RMSE values for different acceleration values considered for in the process noise covariance matrix Q.

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