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Efficient Vessel Tracking with Accuracy Guarantees

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Abstract. Safety and security are top concerns in maritime navigation, particularly as maritime traffic continues to grow and as crew sizes are reduced. The Automatic Identification System (AIS) plays a key role in regard to these concerns. This system, whose objective is in part to identify and locate vessels, transmits location-related information from vessels to ground stations that are part of a so-called Vessel Traffic Service (VTS), thus enabling these to track the movements of the vessels. This paper presents techniques that improve the existing AIS by offering better and guaranteed tracking accuracies at lower communication costs. The techniques employ movement predictions that are shared between vessels and the VTS. Empirical studies with a prototype implementation and real vessel data demonstrate that the techniques are capable of significantly improving the AIS.

Keywords: maritime navigation, tracking, trajectory prediction.

1 Introduction

Around eighty percent of all global interchange occurs via sea. One of the most successful systems used so far in maritime navigation is the Automatic Identification System (AIS), whose primary objectives are to identify and locate vessels at a distance. The AIS usually integrates a transceiver system as well as onboard GPS receivers and other navigational sensors such as gyrocompasses and rate of turn indicators. An onboard AIS transceiver operates in an autonomous and continuous mode, regularly broadcasting position reports according to the vessel's movement behavior. The reports are broadcast within a range of 35 miles to surrounding ships and Vessel Traffic Systems (i.e., maritime authorities) on the ground. The reports include the vessel's position, route, speed, and estimated arrival time at a port of call. The International Maritime Organization (IMO) has made the AIS a mandatory standard for the Safety of Life at Sea. As a result, passenger ships traveling internationally as well as cargo vessels with a gross tonnage above 300 tons are now equipped with AIS transponders.

In maritime areas with high densities of ships, the data volumes exchanged reach the inherent communication limits of the systems deployed, which entails losses of position reports that can adversely affect maritime safety. While solutions relying on increased numbers of communication bands have been proposed, the IMO is still asking for new approaches that can improve the performance of the AIS.

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This paper introduces tracking techniques based on shared predictions that aim to significantly reduce the amounts of position reports needed to accurately track vessels. The main principle is that a vessel and the surrounding infrastructure share a prediction of the vessel's near-future movement as well as a guaranteed accuracy. A Vessel Traffic Service then uses a vessel's prediction to determine the vessel's location, and the vessel transmits a new prediction as needed to ensure that the prediction never deviates from its actual location by more than the guaranteed accuracy. With good predictions, few position reports are needed.

The new techniques build on techniques previously developed for vehicles [1] and that follow recent advances in the development of logical models and physical structures for the efficient management of large volumes of location data (e.g., [4] [5] [6] [7] [8] [9] [12]). Other works in the field concern the introduction of novel algorithms to adjust incoming GPS data to route networks (e.g., [13] [14] [15]). Location data form trajectories that may be studied with purposes such as identifying emerging behaviors or reducing communication costs. The former includes the search for people displacements patterns at the local scale [10] [11] or even at the macro scale [16]. The latter is closely related to our study. Some solutions developed for vehicle tracking require a two-way communication between the server and the client. In contrast, our approach provides a solution to vessel tracking based on one-way client-to-server communication. The approach has been implemented and validated by a simulator that acts as a server in charge of vessels tracking. One of the key features of the algorithm presented is that it utilizes the best performing prediction technique among several alternatives, in accordance with the ship's behavior.

The reminder of the paper is organized as follows. Section 2 introduces the overall maritime tracking and prediction approach. Section 3 develops the principles of point-based and vector-based algorithms applied to maritime navigation and summarizes simulation results. Section 4 presents a decision tree along with optimization principles that identify the best prediction technique according to the ship's behavior. Finally, Section 5 draws conclusions.

2 Maritime Trajectory Prediction Principles

The AIS uses a VHF transceiver for automatically broadcasting position reports. The VHF signal is received by nearby ships and ground stations. The rate of transmission depends on the ship's current speed and maneuver, as illustrated in Table 1 [2].

The table gives the maximum time between successive updates as a function of the vessel's behavior, and also reports the resulting accuracies. The positions transmitted by the AIS are obtained using embedded GPS. The accuracy guaranteed by the AIS is the largest distance a given vessel can cover between two updates (IMO assumes an accuracy of 10 m for embedded GPS). It can be noted that there are no upper bounds guaranteed on the accuracy for the last two kinds of vessel behavior.

Let us assume that a server (e.g., a VTS or a vessel at sea) and a mobile object (e.g., vessel at sea/underway) are both able to predict the next position of the given vessel with a shared algorithm: this is a shared prediction system. The prediction of

Table 1. AIS update frequencies

Vessel behavior	Time between updates	Accuracy (m)
Anchored	3 min	10
Speed between 0 and14 knots	12 s	10-95
Speed at 0-14 knots and changing course	4 s	10-40
Speed at 14-23 knots	6 s	55-80
Speed at 14-23 knots and changing course	2 s	25-35
Speed over 23 knots	3 s	45-
Speed over 23 knots and changing course	2 s	35-

the next positions of the vessel is based on several steps as illustrated in Figure 1. When the server receives the position information from the vessel, it stores this information locally. Until the reception of the next update, it will use the information for predicting the vessel's position.

Using the same algorithm as the server, the tracked vessel regularly compares its GPS position with the predicted one. The vessel monitors the distance between the predicted position and the GPS position. When this distance exceeds an agreed upon threshold, an update is issued to the server. This is illustrated in Figure 2.

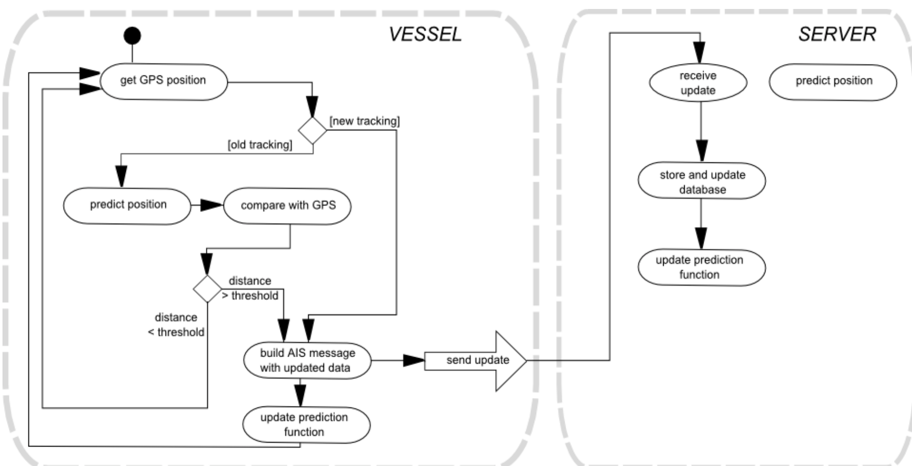
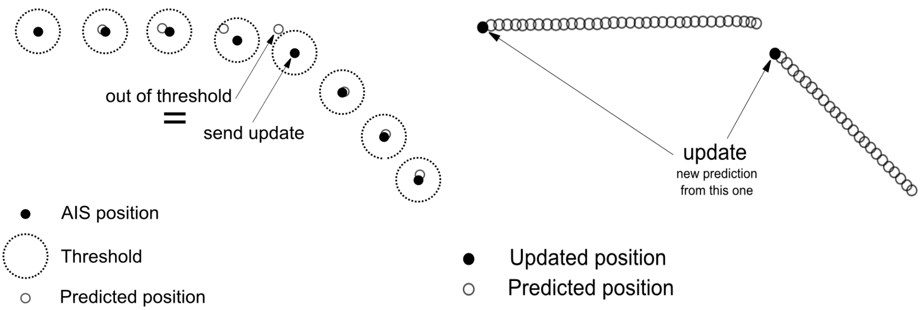


Fig. 1. Tracking principles

This approach to tracking is based on the assumption that client and server use the same prediction algorithm; however, the prediction algorithm can change in real-time as long as both sides work in concert and always use the same algorithm. The choice of which prediction algorithm to use should depend only on the data contained in an update. This data includes a GPS position, but it can also include heading, acceleration, and speed information. Given an update, the server and the vessel can then



(a) Tracking on the vessel side (b) Tracking on the server side

Fig. 2. Tracking mechanisms on the client and server sides

automatically switch to the same prediction algorithm (Figure 1). When the vessel receives the next GPS position, it makes a prediction from the last predicted or updated point using the newly selected algorithm. Similarly, the server uses its prediction algorithm continuously even if no GPS position has been transmitted by the vessel. In order to do so, the server uses (at least) the last reported position and the selected prediction algorithm.

3 Trajectory Tracking Strategies

Shared prediction-based tracking equipped with prediction algorithms that exploit the information broadcast by the AIS can significantly improve tracking accuracy while reducing communication. This section covers such prediction algorithms.

3.1 Point-Based Prediction

Point-based prediction algorithms predict that the current position of a vessel is the one contained in the most recent update. Thus, it is assumed that the vessel does not move. An update is sent by the vessel each time its GPS position differs from that of the last update by more than the current threshold. This prediction algorithm is expected to give good results for quite static objects. In a maritime context, this applies to moored or anchored vessels.

However, point-based prediction falls short when applied to objects with significant movement. In such settings, more sophisticated vector-based prediction is likely to perform better. This approach has to take advantage of additional location data contained in updates when forming predictions.

3.2 Vector-Based Prediction

With vector-based approach, predictions are linear functions of time. Considering the maritime domain and the AIS system, several specializations of the vector-based predictions used for vehicles are considered.

A first approach, called simply *vector-based*, computes a velocity vector using the last two reported positions (Figure 3): the predicted position is computed by a linear space-time function (assuming that the globe is locally plane) based on the positions in the two most recent updates (longitude, latitude, and time are required).

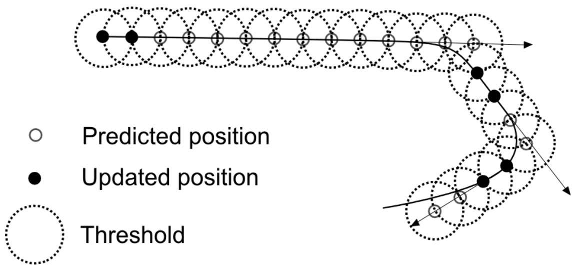


Fig. 3. Vector-based prediction

A second approach uses the vessel's *heading*. This relies on the ability of the AIS to report a ship's heading and speed in every update. This data comes from the vessel's compass and loch systems, and it enables derivation of a velocity vector with a single update. The prediction is represented by a 4-tuple: [longitude, latitude, speed (knots), heading (degrees)] [17].

A third variation that exploits the data provided by the AIS uses the *course over ground* (COG) of a vessel. The two previous approaches ignore the drifting of a vessel as the heading does not consider sea currents. Using the course over ground solves that problem. Most GPS receivers aboard vessels can calculate the COG. When this information is available, it is transmitted by the AIS and is thus useable by the prediction algorithm.

3.3 Non-Linear Prediction

The vector-based approach can also be improved by taking into account *acceleration* information when a vessel exhibits a uniform acceleration (fast variations are difficult to identify with the AIS). This method can be efficient for ships getting underway or in the vicinity of harbors. Given two position updates and their speeds, the acceleration vector is easily determined. The prediction of the next position can be computed using the last COG or heading received and improved using acceleration information [17].

Tracking ships that turn can be done using the *rate of turn*. The next location of a turning ship can be derived by considering the heading discrepancy between two updates. Indeed, if this value has changed between two reports, it may be turning. But one need to know how fast the rotation of the ship is, and this cannot be determined with only two updates which can be far apart. That is why prediction algorithms using a ship's turning rate as included in AIS updates might be more efficient.

Figure 4 illustrates a turning ship. When an update occurs, the rate of turn has to be evaluated (not all AIS installations send such information). If it has a significant value, the predicted position is computed using the turning rate. A position is then given using a five-tuple: [longitude, latitude, speed (knots), COG or heading (degrees), rate of turn (°.min^{-1})] [17]. The ship is assumed to turn endlessly until a new update occurs, resulting in new values (Figure 4, location B). If the ship's rate of turn is null, the vessel must have taken a new route.

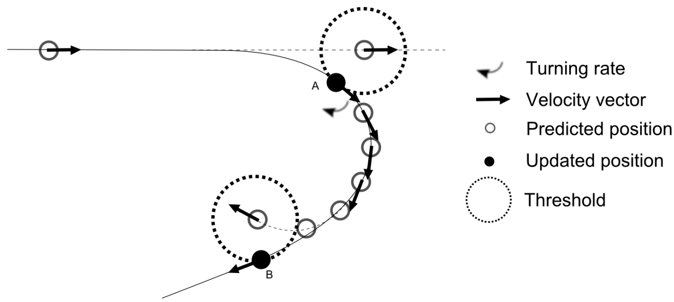


Fig. 4. Tracking of turning ships

3.4 Experimental Principles

The shared prediction approach and prediction algorithms have been prototyped. The simulation software relies on the *Poseidon platform* that gives access to a database of real-time AIS traffic data using Web-based services [3]. This database contains (1) vessels' static data such as the MMSI (international maritime identifier) and IMO identifiers, name, and ship type; (2) information about the journey such as destination, draught and estimated time of arrival; and (3) dynamic position reports that include time, longitude, latitude, heading, speed, course over ground, and rate of turn.

The simulation system allows the user to specify the relevant input parameters: the accuracy threshold to be used (based on the IMO assumption on intrinsic GPS accuracy, 10 m has been used in experiments), the specific AIS data to be used, and the prediction techniques to compare. The data used for the following experiments include speed, heading, course over ground, and rate of turn.

The time intervals between consecutive AIS reports exceed those of successive GPS reports. As the simulation system accesses broadcast AIS data located in the database, this means that the simulated vessel computes predicted position using AIS positions instead of using GPS data. Regarding a chosen threshold, this influences the accuracy and the detection mechanism to a smaller or larger degree. The results reported in the following section are nevertheless meaningful for comparing prediction techniques, although the results will be different when using GPS data. When embedding the algorithms in the AIS, they will obviously operate on GPS data.

3.5 Shared-Prediction Experiments

Empirical performance studies have been conducted on the point-based and vector-based prediction algorithms for different vessel behaviors: anchored, sailing straight, and changing speed and turning [17].

For anchored ships, the studies reveal that the algorithms perform similarly for small thresholds of 10 m (e.g., 10 m and an average update rate of 59% of that of the AIS). When the threshold is enlarged, point-based prediction performs better.

Regarding ships sailing straight, the studies show that point-based prediction is not appropriate, regardless of the speed. Heading-based and vector-based prediction perform well as far as drifting is minimized. When using a threshold of 57 m, they require only 4% and 7%, respectively, of the updates needed by the AIS. Cog-based prediction gives the best results and generates only 2% of the position updates needed by the AIS, assuming a 57 m threshold. It is worth to note that vector-based prediction is likely to give better results than heading-based prediction when updated positions are relatively close.

When the ship's speed is not constant, the studies show that cog-based and acceleration-based predictions are the best options. The factors that influence their relative performance are given by (1) the points selected for derivation of the acceleration, (2) how constant the acceleration is, (3) the type of trajectory of the ship (straight or curved), and (4) the threshold used.

Finally, when comparing the heading-based and cog-based predictions for turning ships, it has been found that even with large curves, cog-based prediction is best. This is because the AIS-based data influences the prediction mechanism by minimizing the number of locations taken into account, which is a problem for turning ships.

These studies show that the point-based and vector-based prediction algorithms take advantage of the availability of AIS data in many contexts. The policies are efficient within a given context and, overall, the findings can be summarized as follows:

- For ships anchored or docked, point-based prediction is the most efficient.
- When sailing straight, whatever the speed, vector-based predictions should be prioritized: first cog-based, then heading-based and finally vector-based technique.
- During accelerations and decelerations, the acceleration-based policy is efficient, but only when updated positions are available. Otherwise, the use of cog-based prediction should be retained.
- For ships changing their heading, no single type of prediction is a clear winner. Vector-based predictions such as heading-based and cog-based appear to be the most appropriate.

The empirical results might in some cases overestimate the "true" results. This is because relatively infrequent AIS data is used instead of data that is sampled frequently, e.g., each second. Overestimation occurs when the tracking threshold is exceeded before the time of the next AIS position. This affects experiments with small thresholds the most. For example, if the average time between two AIS positions is 10s, the curves may be overestimated by 10s in the worst case. If the average time between two updates is 500s, the error would be less than 2%. But if the average time between two updates is 30s, the error can reach 33%.

4 Combined Shared Prediction-Based Tracking

Based on findings of from the study covered in the previous section, we introduce a combined shared prediction-based approach that is capable of using different prediction algorithms in response to the movement behavior of a vessel. The objective of this approach is to determine in real time which prediction algorithm is best and then use that one, so that low cost (few updates) is achieved.

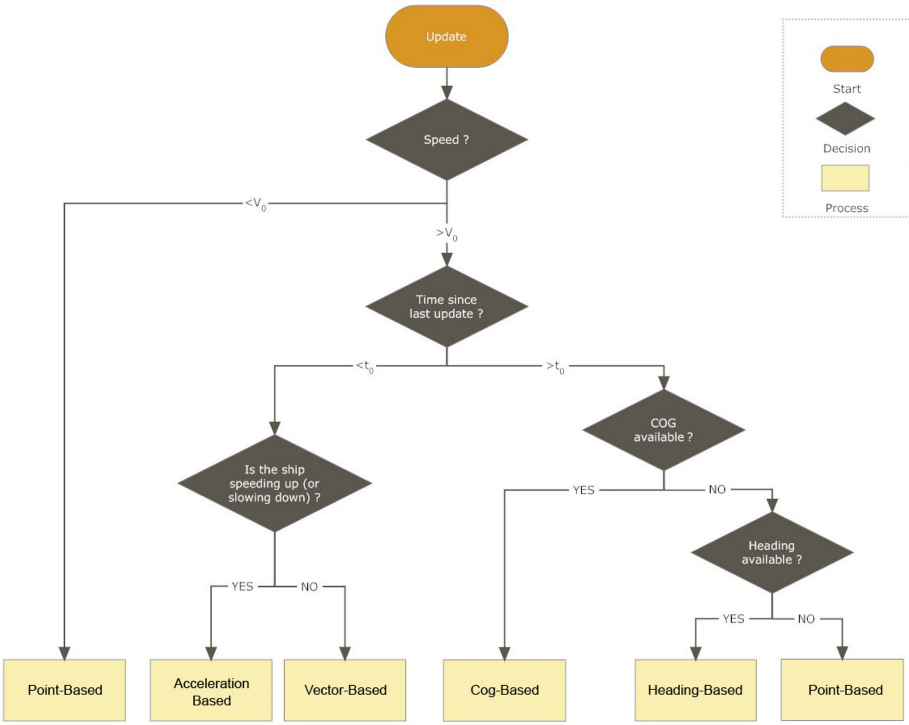


Fig. 5. Decision tree

This algorithm, illustrated in Figure 5, is based on the following variables:

- V_0: when a ship's velocity is below the value of this variable, the ship is considered to be moored or anchored. This velocity is set at 0.2 knots based on findings from the empirical studies.
- T_0: when the duration between the two most recent updates is below the value of this variable, either acceleration-based or vector-based prediction is activated. It is not straightforward to find an appropriate value for this variable, as the best value is likely to fluctuate even between AIS locations. Based on findings from the empirical studies, T_0 is set at 25 seconds.

The overall algorithm first evaluates the speed of the ship and then chooses either the vector-based or point-based approaches. Then it compares the time since the last update with T_0. When updates are close in time, we take that to indicate that the prediction algorithm used is inefficient. This means that the ship has accelerated, decelerated, or transmitted wrong data (e.g., the course over ground or heading). When two updates occur close in time, the overall algorithm will use acceleration-based or vector-based predictions. If not and if COG and heading values are available, a choice is made among cog-based, heading-based, and point-based prediction.

The combined algorithm has been compared to vector-based predictions using AIS data from the passenger ship *Enez Eussa 3*. This ship has been chosen as its trajectory embodies several mobility patterns. First, the ship is anchored, then it leaves Brest harbor accelerating and maneuvering; finally the ship sails straight and heads towards the Atlantic sea. Data from *Enez Eussa 3* incorporates each a range of possible errors, e.g., a speed of 0.1 knot when anchored, a course over ground that is not always available, and a heading that is at times unreliable.

Figure 6 illustrates the performance of the different predictions when using several thresholds. As expected, the best results (i.e., longest average time between updates) are obtained by the combined algorithm (i.e., using all prediction algorithms).

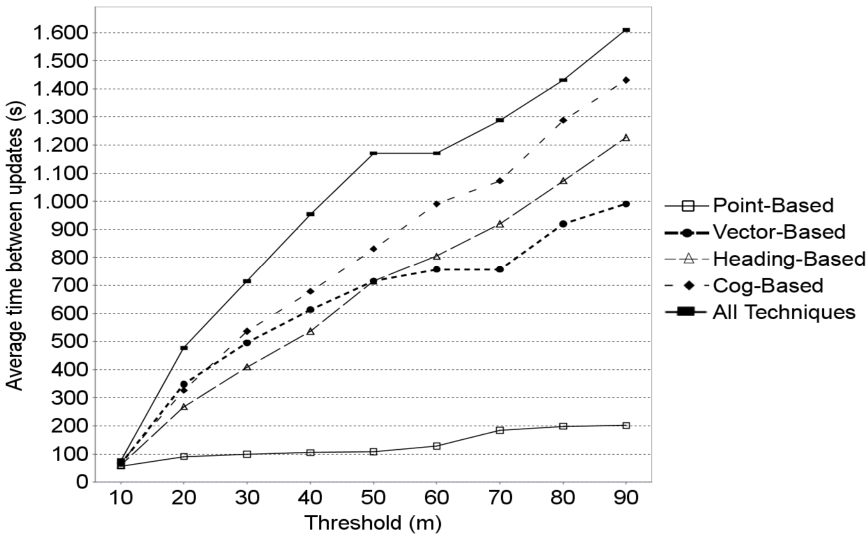


Fig. 6. Comparison of tracking algorithms for *ENEZ EUSSA 3* from 2007/05/18, 00:07:17 to 2007/05/18, 07:16:48

Table 2 shows the performance of the different tracking algorithms when applied to *Enez Eussa 3* (again from 2007/05/18 at 00:07:17 to 2007/05/18 at 07:16:48). The combined approach always yields the best results for threshold set to 10, 20, 40, and 80 m.

Table 2. Comparison of tracking algorithms (average durations between updates)

Threshold (m) / Algorithm	**10**	**20**	**40**	**80**
Point-based	57s	91s	105s	198s
Vector-based	66s	348s	613s	920s
Heading-based	68s	268s	536s	1073s
Cog-based	69s	326s	678s	1288s
All combined	77s	477s	954s	1431s

The route followed by the *Enez Eussa 3* was analyzed in order to determine where the different prediction algorithms were used. Figure 7 represents the path followed by the ship when it left Brest harbor (fast-changing direction and low speed). The anchored position corresponds to the part identified by a square; here, point-based prediction was used. One can remark that during the first ship maneuvers, the combined algorithm mainly uses heading-based and vector-based predictions. Finally, while approaching the exit of the harbor, the algorithm started to favor cog-based prediction.

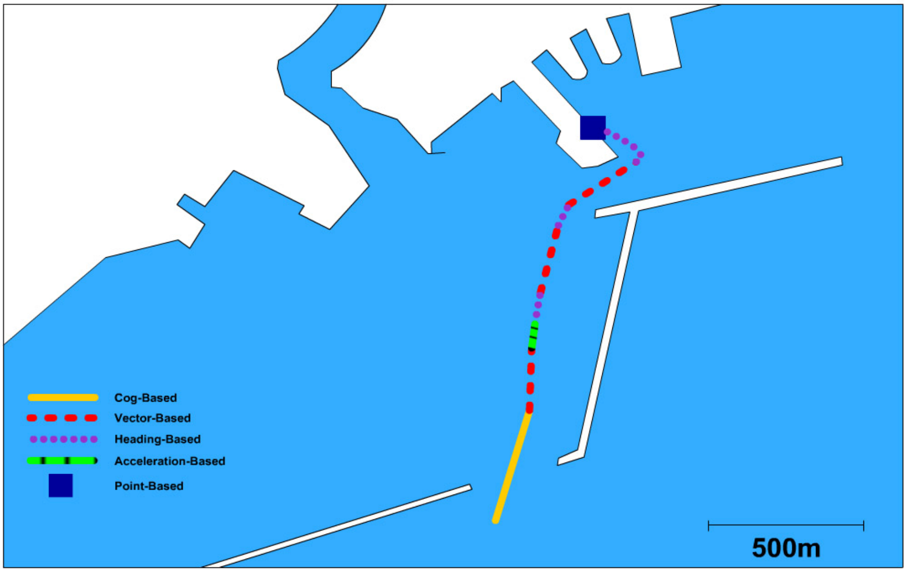


Fig. 7. Course of *Enez Eussa3* inside the harbor and prediction algorithms used

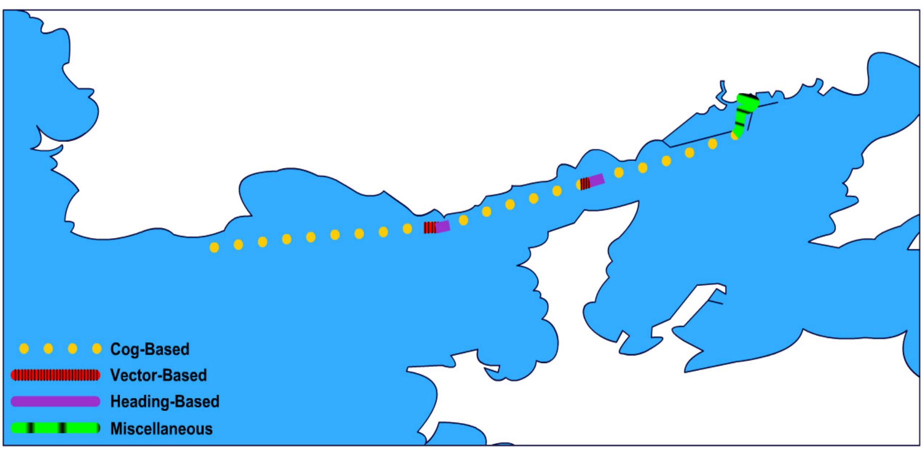


Fig. 8. Course of Enez Eussa 3 and policies used

Figure 8 illustrates the path of the ship and the techniques used from Brest harbor to the Atlantic sea. One can remark the uses of heading-based prediction for short periods of time. This comes from either a wrong heading being received or from drifting. In this navigation context (i.e., straight line and high speed), mainly cog-based tracking is used. When it is not used, this is due to the course over ground not being available.

Acceleration-based prediction is used only once. This is due to the fact that when considering an accelerating ship between two updates, the speed increases or decreases by more than 1 knot. This ship accelerates only slowly. Using a value below 1 knot may result in this type of prediction being overused, at the expense of vector-based prediction.

5 Conclusion

This paper introduces an efficient vessel tracking approach customized for the maritime environment, where vessels can be located using the international Automatic Identification System (AIS). The approach relies on several vessel position prediction algorithms that take advantage of the location data contained in AIS messages. By sharing predictions between the vessels and an on-ground Vessel Traffic Service, it is possible to save on the transmissions of position data. Empirical studies using real AIS data and simulated data show that point-based and vector-based predictions are efficient in different settings. A combined, context-aware algorithm is proposed that selects the best prediction algorithm according to the ship's movement behavior. The studies offer evidence that the amount of data transmitted by the AIS can be reduced very substantially, in many cases by more than 98%.

The combined algorithm can be extended, e.g., by considering the type and usual behavior of a ship and by using learning techniques. Trajectory patterns exhibited by common maritime routes and constraints derived from navigation rules may also be exploited for improving the tracking efficiency. Additional experimental studies are also in order. Current work is underway in the Brest harbor using the AIS system connected to mobile appliances and wireless communication (e.g., WIFI or ISM communications). The objective of these experiments is to evaluate update frequencies and appropriate thresholds in real contexts.

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