Data-driven Trajectory Prediction and Spatial Variability of Prediction Performance in Maritime Location Based Services

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Abstract. Location-based services in the maritime domain aim to improve efficiency and safety of vessel operations. Predictive functionality can increase the value of these services beyond ordinary visualizations of the current operational picture. Trajectory prediction aims to forecast the future path of vessels and can thus help improve logistics as well as help predict potentially dangerous situations. This paper presents ongoing work on data-driven trajectory prediction that leverages information of past vessel movements to improve prediction results. Preliminary results show that data-driven prediction outperforms baseline approaches, particularly in complex situations. However, results also show a large spatial variability in prediction performance. This indicates that it is impossible to compare the performance of different prediction methods by relying solely on the error statistics reported in publications since every research group uses different data samples from different geographic regions.

Keywords. Computational movement analysis, trajectory prediction, Automatic Identification System

1. Introduction

Methods for extracting useful information from increasingly massive movement data are lagging behind the tracking technology that generates these datasets (Long & Nelson 2013). Frameworks and predictive models for movement data in GIScience therefore are an important research avenue towards understanding, simulating, and predicting movement (Dodge et al. 2016).

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In the maritime sector, for example, all vessels of a certain size are tracked since they are required to carry Automatic Identification System (AIS) receivers. They have to broadcast their information (including location and status) to other vessels and AIS base stations in their vicinity. The resulting AIS data is an important input for location-based services, such as vessel traffic services (VTS).

This work focuses on data-driven vessel trajectory prediction, also known as route estimation (Tu et al. 2018) or future location prediction (Georgiou et al. 2018). In contrast to other moving objects, such as land vehicles and aircraft, ships typically exhibit slow parabolic maneuvers. They cannot stop, turn or reverse abruptly and their movement occurs on a two dimensional plane (Tu et al. 2018). Vessel trajectory prediction methods come in three main classes: physical model-based methods, data-driven methods, and hybrid methods (Tu et al. 2018). Physical model-based methods include linear and kinematic prediction but, particularly kinematic prediction is mostly used in the context of trajectory interpolation rather than prediction (Long 2016, Sang et al. 2016). Data-driven methods are increasingly popular and vary considerably in their approaches and complexity. One type of data-driven methods are map-based approaches using attracting and repelling forces (Vespe et al. 2008). Approaches that are trained using previously observed movement include, for example, Hebbian learning of location changes between grid cells (Bomberger et al. 2006), Ornstein–Uhlenbeck (OU) processes (Vivone et al. 2017), perceptrons and multi-layer perceptrons (MLP) (Zorbas et al. 2015, Valsamis et al. 2017), and neural networks (Gao et al. 2018). The prediction errors reported for different prediction approaches vary significantly. For example, error values range from 153m to 1314m (Valsamis et al. 2017) for 4-minute predictions to 7km (Zorbas et al. 2015) for 1-hour predictions, as listed in Table 1. To the best of our knowledge though, existing approaches (Table 1) all base their evaluations on different regions and do not take into account spatial variability within and between regions.

Paper	Method	Prediction:	4min	5min	10min	15min	20min	30min	60min
Valsamis	Linear		890		2,186		4,256	6,477	
Graser	Linear			520	1,247	1,923			
Wijaya	Similar trajectory				900 [a]				
Graser	Similar trajectory			436	919	1,344			
Graser	Gaussian mixture			582	1,029	1,522			
Zorbas	Perceptron							3,000	7,000
Valsamis	Multi-layer perceptron		153		652		983	1,721	
Valsamis	MLP time series		1,314		1,896		2,102	4,613	

Table 1. Trajectory prediction errors (mean distance error in meters) ([a] median error)

Most works measure prediction error using distance error, that is the distance between predicted position and observed position. Other less common error metrics include cross-track error and along-track error as illustrated in Figure 1. Cross-track error measures the distance between predicted position and the observed trajectory. It thus provides information about how well the prediction reflects the true movement direction. In contrast, along-track error measures the error along the observed trajectory and thus provides information about how well the prediction reflects the true speed.

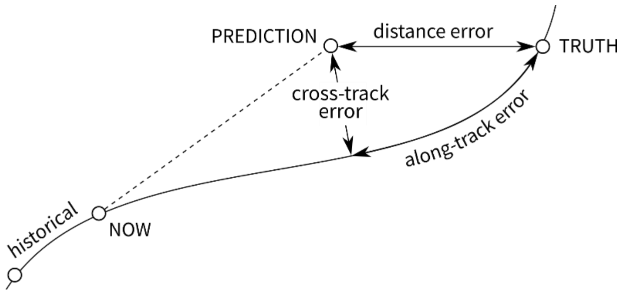


Figure 1. Prediction error measures

The rest of this paper is structured as follows: Section 2 presents preliminary results of our ongoing work on data-driven trajectory prediction with a specific focus on the spatial variability of prediction performance. Finally, Section 3 provides an outlook towards planned future work.

2. Data-driven Vessel Trajectory Prediction

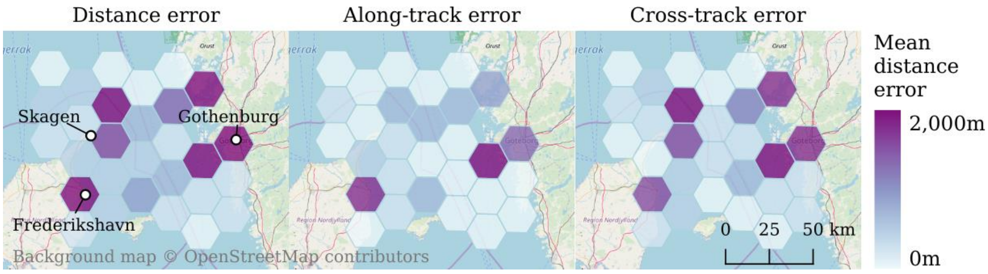
The data-driven prediction approach presented in this work is inspired by Wijaya & Nakamura (2013). It is based on the concept that historical trajectory data provides a sample of potential paths that objects can travel. To predict future locations, we search the historical data for moving objects that were moving along a similar path. While different distance metrics are conceivable to determine similarity, this approach relies on selecting past trajectories of vessels of the same type, located in the same region, and moving in the same direction at similar speeds. Then we determine the locations of those vessels after the defined prediction time frame. The complete algorithm can be summarized as follows:

1. Find n similar trajectories: for a given observed track, identify up to *n* similar trajectory segments that move in the same direction (direction tolerance α_{max}), at similar speed (speed tolerance v_{max} and are at most d_{max} (distance tolerance) meters from the observed track
2. Identify potential future locations: for each identified segment determine where the moving object was located after the given prediction time frame

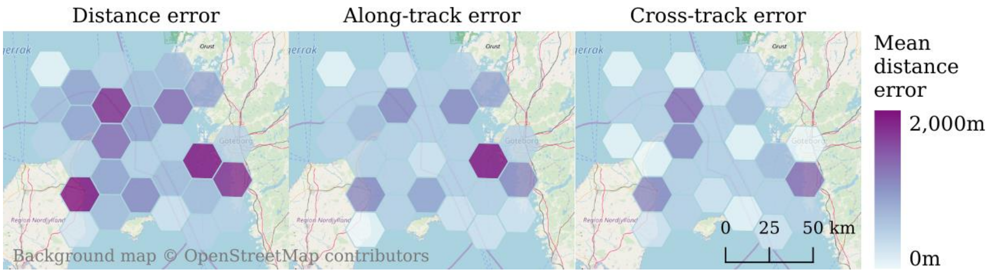
3. Compute the final prediction given the set of potential future locations

If no similar trajectories are found in the historical database, the method falls back to linear prediction. This mostly happens in open areas where vessels do not need to follow shipping lanes and it is therefore less likely to find a trajectory within the distance tolerance.

Linear trajectory prediction is a commonly used base line for comparison (Graser et al. 2018, Valsamis et al. 2017). It is based on the assumption that vessel movements will continue with the last observed direction and speed. Direction and speed can be instantaneous values that are provided by the input data, or alternatively, direction and speed can be computed from consecutive data records.



(a) Linear trajectory prediction errors are highest in coastal regions near Frederikshavn, Skagen, and particularly Gothenburg.



(b) Similar trajectory prediction error distributions show improvements where linear prediction suffers from large cross-track errors.
Figure 2. Spatial distribution of 20 minute trajectory prediction errors based on 3 minutes observations for cargo vessels

Figure 2 shows the cargo vessel trajectory prediction performance for 20-minute predictions in the sea between Denmark and Sweden, near Gothenburg. The largest linear prediction errors (Figure 2a) are observed in coastal regions, particularly near Frederikshavn (Denmark), Skagen (Denmark), and Gothenburg (Sweden). Similar trajectory prediction error distributions (Figure 2b) most notably show improvements where linear prediction suffers from large cross-track errors, indicating that this data-driven prediction method manages to better capture vessel movement directions.

However, not all regions exhibit improvements from data-driven prediction. This is due to the behavior of cargo vessels which tend to travel on straight courses at constant speeds if there are no specific reasons to do otherwise. This behavior is well represented by linear trajectory prediction. It is therefore hard to beat linear prediction performance in these regions.

Particularly in coastal regions, however, there are external reasons for vessels to change course and speed. Therefore, switching from linear to similar trajectory prediction results in better predictions in these areas. In our example, seven regions fall into this category. Replacing linear trajectory prediction with similar trajectory prediction in these regions improves the results for five out of seven regions. The largest improvement is observed near Gothenburg with a mean distance error reduction by 2,252m. The mean improvement over all seven regions is 769m.

3. Conclusions and Outlook

Our work on data-driven vessel trajectory prediction for maritime LBS is still ongoing. The preliminary findings presented here show that even comparatively simple data-driven prediction approaches outperform basic linear prediction in areas of complex movement. Furthermore, our results show how prediction performance varies across different geographic regions. This considerably impacts the interpretation of existing vessel trajectory prediction publications, as well as their potential to inform the selection of prediction methods for future applications. Comparing trajectory prediction errors found in the literature is meaningless without access to the same evaluation data.

In the future, we plan to improve on the data-driven trajectory prediction presented in this paper. In particular, we envision data-driven trajectory prediction methods that make use of movement patterns that can be extracted from massive movement datasets. Depending on the area of interest, vessel movement patterns are furthermore influenced by other factors, such as tides, current, and visibility. Finally, since nearby vessels influence each other's movement, future prediction methods should also take the surrounding traffic situation into account.

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References

Bomberger NA, Rhodes BJ, Seibert M, Waxman AM (2006) Associative learning of vessel motion patterns for maritime situation awareness. In: Information Fusion, 2006 9th International Conference on, pp. 1–8. IEEE

Dodge S, Weibel R, Ahearn SC, Buchin M, Miller JA (2016) Analysis of movement data. International Journal of Geographical Information Science 30(5), 825–834

Gao M, Shi G, Li S (2018) Online Prediction of Ship Behavior with Automatic Identification System Sensor Data Using Bidirectional Long Short-Term Memory Recurrent Neural Network. Sensors 18(12), 4211

Georgiou H, Karagiorgou S, Kontoulis Y, Pelekis N, Petrou P, Scarlatti D, Theodoridis Y (2018) Moving Objects Analytics: Survey on Future Location & Trajectory Prediction Methods. arXiv:1807.04639 [cs, stat]

Graser A, Schmidt J, Widhalm P (2018) Predicting trajectories with probabilistic time geography and massive unconstrained movement data. In: Workshop on Analysis of Movement Data AMD2018 in conjunction with GIScience 2018. Melbourne, Australia

Long JA (2016) Kinematic interpolation of movement data. International Journal of Geographical Information Science 30(5), 854–868

Long JA, Nelson TA (2013) A review of quantitative methods for movement data. International Journal of Geographical Information Science 27(2), 292–318

Sang Lz, Yan X, Wall A, Wang J, Mao Z (2016) CPA Calculation Method based on AIS Position Prediction. Journal of Navigation 69(6), 1409–1426

Tu E, Zhang G, Rachmawati L, Rajabally E, Huang G (2018) Exploiting AIS Data for Intelligent Maritime Navigation: A Comprehensive Survey From Data to Methodology. IEEE Transactions on Intelligent Transportation Systems 19(5), 1559–1582

Valsamis A, Tserpes K, Zissis D, Anagnostopoulos D, Varvarigou T (2017) Employing traditional machine learning algorithms for big data streams analysis: The case of object trajectory prediction. Journal of Systems and Software 127, 249–257

Vespe M, Sciotti M, Burro F, Battistello G, Sorge S (2008) Maritime multi-sensor data association based on geographic and navigational knowledge. In: Radar Conference, 2008. RADAR'08. IEEE, pp. 1–6

Vivone G, Millefiori LM, Braca P, Willett P (2017) Performance Assessment of Vessel Dynamic Models for Long-Term Prediction Using Heterogeneous Data. IEEE Transactions on Geoscience and Remote Sensing 55(11), 6533–6546

Wijaya WM, Nakamura Y (2013) Predicting ship behavior navigating through heavily trafficked fairways by analyzing AIS data on apache HBase. In: computing and networking (CANDAR), 2013 first international symposium on, pp. 220–226. IEEE

Zorbas N, Zissis D, Tserpes K, Anagnostopoulos D (2015) Predicting object trajectories from high-speed streaming data. In: Trustcom/BigDataSE/ISPA, 2015 IEEE, vol. 2, pp. 229–234