Finding a Needle in a Haystack: Satellite Detection of Moving Objects in Marine Environments

(Extended Abstract)

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ABSTRACT

There is a growing need in maritime missions to monitor moving vessels with satellite sensors, in order to detect vessels that may mislead about their identity and transmit wrong identification parameters. In order to provide an efficient and cost-effective solution, vessel behavior prediction is a necessary ability. We present three models for vessel behavior prediction: Min-Max, Uniform-Walk and Normal-Walk. We use real marine traffic data (AIS, Automatic Identification System) to compare the performance of these models and their ability to predict vessel behavior in a time frame of 1–11 hours.

1. INTRODUCTION

In this paper, we focus on maritime missions, where the main goal is to monitor moving vessels with satellite sensors, in order to detect vessels that may mislead about their identity and transmit wrong identification parameters, for example their size and type. Satellite imagery is an expensive product, which covers a small area and can be acquired only at predefined acquisition opportunities. Thus, prediction of vessel behavior is a necessary ability in this domain, it will decrease the search area for the vessel and will lead to a much more economic solution.

Despite significant progress in vessel prediction in maritime domain, existing solutions do not yet account for long-term vessel behavior prediction, thus they are irrelevant in the space domain. We present three models for long-term vessel behavior prediction: Min-Max (Base model), Uniform-Walk and Normal-Walk (Multi-agent based models). We use real marine traffic data (AIS) to compare the performance of these models and their ability to predict vessel behavior in a time frame of 1–11 hours.

2. RELATED WORK

Recently there has been an increasing interest in maritime awareness [9, 8]. While most of the research concentrates on anomalous behavior detection or event recognition [5, 1, 6], predicting vessel behavior is still a big challenge for researchers. There are several approaches that were taken to tackle this challenge [3, 4, 10, 2], however, to the best of our knowledge, existing models do not yet account for long-term vessel behavior prediction.

Moreover, existing models [4] assume that the destination of the vessel is known based on AIS message. In reality, the destination field in AIS message is not always updated, and sometimes it is even falsely updated. Thus, in real application we cannot base our solution on reliability of the destination field in AIS signal. Our goal is to develop a real service that can be offered by an industrial company to its clients. Additionally, we would like to have the ability of prediction to work freely, without the constant need for destination knowledge.

3. VESSEL BEHAVIOR PREDICTION

Predicting vessel behavior is an important factor for detection of a moving vessel. Based on historical data of the vessel (AIS data), we create a behavioral model. We use Second Order Markov Chain to build a graph representing the historical behavior. Based on the built graph and the estimation of the current state, we enable the prediction of future vessel locations.

Figure 1 presents the movement of all vessels in a bounded area along seven days. The movement is received in the form of AIS data, and reflects 50,000 AIS samples. We can clearly observe the created lanes of vessel movement, which provide a motivation for using graph representation for vessel behavior prediction.

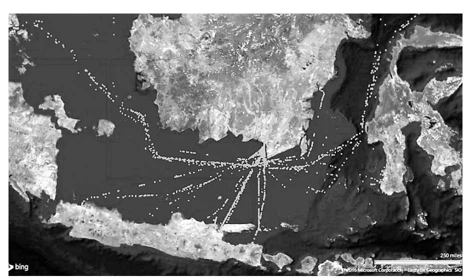

Figure 1: Actual vessels AIS samples over seven days.

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3.1 Behavioral Graph Creation

Each AIS message contains unique identification of the vessel, and static and dynamic properties. The AIS information may often be noisy and insufficiently frequent. It challenges the behavior modeling process, and thus requires a preprocessing stage. Therefore we interpolate data with spatial methods such as [7].

We divide the set of AIS signals into a leg segments, which corresponds to the vessels voyage as motion through straight lines. We transfer the set of leg segments into a directed Second Order Markov chain (graph). The nodes and edges are calculated based on clustering and merging of leg segments vertices. The probability of transition between nodes is calculated based on historical behavior of the vessel.

Due to unreliability of the destination field in the AIS signal, which is often not up-to-date, we use Second Order Markov Chain for vessel behavior prediction. To provide a more accurate prediction of the movement, the possible vessel velocities on each edge are partitioned into speed segments. Each velocity sample along the edge, that exceeds a velocity change threshold, defines a new speed segment. For each speed segment statistics are measured upon the distribution of the relevant velocity values of: minimum, maximum, mean and standard deviation of the vessel.

3.2 Behavior Prediction

Based on the historical graph and the initial vessel's location on the graph, we extract the possible paths of the vessel at different times. We compare between three models of vessels motion along the paths: Min-Max Walk, Uniform Walk and Normal Walk. All models produce sets of polygons along each path that represent the possible locations of the vessel at a given time. The output of the prediction is a set of ranked polygons which the vessel can reach at a given time. The rank of the polygon represents the confidence of the prediction.

The Min-Max Walk model extracts the polygons directly from the set of paths. We use this simplistic model as benchmark for evaluation: it clearly outperforms a simple prediction based on straight-line and last-velocity, as demonstrated in Figure 2. For each path, the extracted polygon starts from the location the vessel reaches when moving in the minimum speed, and ends on the location it reaches when moving at the maximum speed.

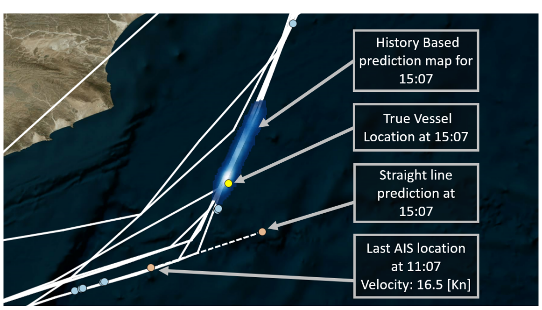

Figure 2: Predicted location after 4h: simple straight-line vs. historical data-based prediction, demonstrating the irrelevance of the simple straight-line prediction.

Uniform-Walk and Normal-Walk models are simulation-based models, where each agent represents a possible vessel motion on each path. To provide more accurate prediction we create agents that simulate the possible movements on the extracted paths. Each agent gets the movement path based on path's probability, thus the higher the probability - the more agents will move on this path. Each agent draws different velocities according to the speed segment, based on the chosen statistical model. In Uniform-Walk model an agent chooses velocity based on uniform distribution of velocities on each speed segment, while in the Normal-Walk model an agent chooses its velocity based on Gaussian distribution. Figure 3 presents the agents move on the created graph based on the historic statistics using Normal-Walk model.

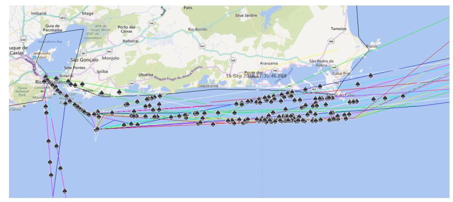

Figure 3: Using multi agent simulation for vessel behavior prediction.

4. VESSEL PREDICTION RESULTS

We randomly selected a set of vessels in different locations in the world. AIS data of 13 months was collected for each vessel, where the first 12 months data was used for the extraction of historical graph model, and the additional 1 month was used for prediction validation. The experiment was carried out using 27 vessels, for each vessel 10 different validation tests, in total 270 test-subsets for prediction validation.

Figure 4 displays the comparison of the models on Hit-Miss parameter, which represents successful prediction rate. The x-axis represent the prediction time (1–11 hours) and the y-axis represent the percentage of successful prediction. The results show that Normal-Walk model has much higher number of successful predictions than Uniform-Walk and Min-Max models. Moreover, the Normal-Walk model was found to be significantly higher in Hit-Miss parameter than Uniform-Walk and Min-Max models, with p-value < 0.01 (in both cases).

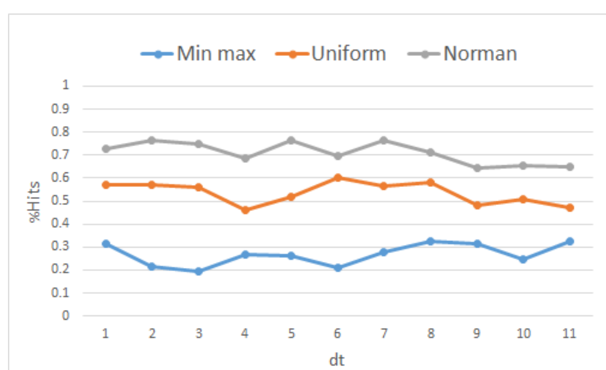

Figure 4: Hit-Miss results.

REFERENCES

[1] R. O. Lane, D. A. Nevell, S. D. Hayward, and T. W. Beaney. Maritime anomaly detection and threat assessment. In *In Proceedings of the 13th Conference on Information Fusion (FUSION)*, pages 1–8. IEEE, 2010.

[2] G. Pallotta, M. Vespe, and K. Bryan. Vessel pattern knowledge discovery from ais data: A framework for anomaly detection and route prediction. *Entropy*, 15(6):2218–2245, 2013.

[3] B. J. Rhodes, N. A. Bomberger, and M. Zandipour. Probabilistic associative learning of vessel motion patterns at multiple spatial scales for maritime situation awareness. In *Information Fusion*, 2007.

[4] B. Ristic, B. La Scala, M. Morelande, and N. Gordon. Statistical analysis of motion patterns in ais data: Anomaly detection and motion prediction. In *Information Fusion*, pages 1–7. IEEE, 2008.

[5] M. Riveiro, G. Falkman, T. Ziemke, and T. Kronhamn. Reasoning about anomalies: a study of the analytical process of detecting and identifying anomalous behavior in maritime traffic data. In *SPIE Defense, Security, and Sensing*, pages 73460A–73460A. International Society for Optics and Photonics, 2009.

[6] J. Roy. Automated reasoning for maritime anomaly detection. In *In Proceedings of the NATO Workshop on Data Fusion and Anomaly Detection for Maritime Situational Awareness (MSA 2009), NATO Undersea Research Centre (NURC), La Spezia, Italy*, pages 15–17, 2009.

[7] K. Shoemake. Animating rotation with quaternion curves. In *ACM SIGGRAPH computer graphics*, volume 19, pages 245–254. ACM, 1985.

[8] L. Snidaro, I. Visentini, and K. Bryan. Fusing uncertain knowledge and evidence for maritime situational awareness via markov logic networks. *Information Fusion*, 21:159–172, 2015.

[9] G. Thomas. Maritime domain awareness. *Coast Guard Journal of Safety & Security at Sea, Proceedings of the Marine Safety & Security Council*, 63(1), 2006.

[10] M. H. Tun, G. S. Chambers, T. Tan, and T. Ly. Maritime port intelligence using ais data. *Recent advances in security technology*, page 33, 2007.