Ship-GAN: Generative Modeling Based Maritime Traffic Simulator

Demonstration Track

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ABSTRACT

Modeling vessel movement in a maritime environment is an extremely challenging task given the complex nature of vessel behavior. Several existing multiagent maritime decision making frameworks require access to an accurate traffic simulator. We develop a system using electronic navigation charts to generate realistic and high fidelity vessel traffic data using Generative Adversarial Networks (GANs). Our proposed Ship-GAN uses a conditional Wasserstein GAN to model a vessel's behavior. The generator can simulate the travel time of vessels across different maritime zones conditioned on vessels' speeds and traffic intensity. Furthermore, it can be used as an accurate simulator for prior decision making approaches for maritime traffic coordination, which used less accurate model than our approach. Experiments performed on the historical data from heavily trafficked Singapore strait show that our Ship-GAN system generates data whose statistical distribution is close to the real data distribution, and better fit than prior methods.

KEYWORDS

Generative Adversarial Networks; Maritime Traffic Simulation

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1 INTRODUCTION

Maritime traffic management in busy port waters such as Singapore strait and Tokyo bay is critical for improving safety of navigation. Given the increased traffic in geographically constrained ports such as Singapore's [6], safety of navigation gets adversely affected, endangering human lives and creating environmental issues such as oil and gas spills [9, 13]. To address vessel traffic coordination and improve navigation safety, several multiagent decision making approaches have been developed [1, 3, 10, 11, 14]. Of particular relevance to our work are reinforcement learning (RL) [12] based approaches [10, 11] that use a simulator to learn traffic control policies to reduce congestion and improve navigation safety. To learn effective traffic control policies that will work in a real world setting, it is crucial to develop a high fidelity maritime traffic simulator that can provide realistic feedback to RL algorithms about the impact of their proposed actions. Our Ship-GAN model addresses this important gap as the link between the RL algorithm and accurately simulating decision's impact in the real world. We show that our proposed data generator is more accurate than the estimation by simulators used in such previous RL methods for maritime traffic management [10, 11].

Our key contribution is to create a simulator of key aspects of maritime traffic that can model the vessel movements in a given area. This simulator is apt for training the policy of multiple agents which learn via reinforcement learning in order to optimize for congestion, collision risk and time to destination. Specifically, the simulation models the travel time distribution to cross a given zone in the sea conditioned on different aspects of the traffic such as vessels' current speeds and traffic intensity. The zones used in modeling have a correspondence to the real world in that these zones are also used by the Port Operations to manage the vessel traffic. The ship movements are a function of the type of these zones which will be captured by our simulator. Previous traffic simulation models, such as used in [10, 11], are unable to take into account various factors such as the speed and traffic intensity, and are thus less accurate than our proposed model (also validated empirically).

2 MARITIME TRAFFIC DOMAIN

Figure 1 shows the electronic navigation chart (ENC) of Singapore strait. The waterway is divided into multiple *zones*, which can be

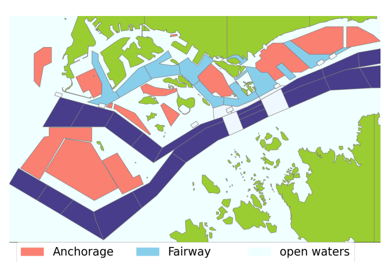

Figure 1: ENC Chart of Singapore strait. Different types of zones are denoted as polygons.

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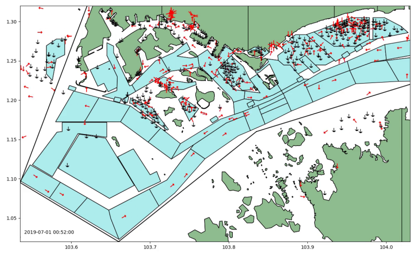

Figure 2: A screenshot from our simulator based on ENC.

of different types such as TSS, Anchorages among others, as color coded in Figure 1. A zone is a polygon, not necessarily convex, with its typical length around 5 km. The traffic separation scheme (TSS) zones are the *maritime highways* which allow traffic to enter Singapore port, or transit through. The anchorage zones are regions reserved for vessels that require anchoring for receiving services such as refueling, or maintenance. Fairway zones are regions which lead vessels to berths at the port terminal from TSS and vice-versa. By far, the bulk of the traffic is in TSS zones, and this is where dangerous traffic conditions can arise, sometimes leading to collisions. Therefore, our goal is to learn movement pattern of vessel in TSS zones. These are also the zones which have been used to regulate traffic in previous works [10]. Our traffic simulator (in Figure 2) is based on such geographical features present in the ENC.

Data Description: We have obtained the vessel data from the company Marinetraffic thus gaining access to the AIS (Automatic Identification System) data from vessel AIS calls. The data captures 2.5 million AIS calls from about 9000 vessels in the Singapore Straits for one month. A typical vessel broadcasts AIS information every 2 minutes when in transit. The data provides information about position of vessels, time stamp, speed, course, heading, and other features (e.g., destination, vessel size).

Problem Statement: We aim to simulate travel times of ships across zones. The travel time is stochastic and depends on many factors that are unknown. The goal is to learn this travel time distribution for each zone (marginalized over unknown factors) using deep generative models conditioned on the vessel's speed and the traffic ahead when entering a zone. The processed data is of the form $\langle \tau_r, \langle v_r, \mathrm{n}_t(z) \rangle \rangle$ where τ_r is the time taken to travel across the zone, v_r is the speed of vessel while entering the zone and $\mathrm{n}_t(z)$ the number of ships in zone z at the time of entry which denotes the traffic intensity.

3 GENERATIVE MODELING OF TRAVEL TIME

For each zone, we learn both unconditional and conditional travel time distribution using generative models. There are two popular techniques in deep generative models: generative adversarial networks (GANs) [5] and variational auto-encoders (VAEs) [8]; GANs performed best for us. We used Wasserstein GAN [2], an improved variant of the original GAN.

Evaluation Metric: GANs are notoriously challenging to evaluate quantitatively [4]. The The Kolmogorov-Smirnov (KS) distance provides a measure of difference between two univariate distributions [7]. Table 1 shows the average KS distance for the GAN, VAE and other baselines based on distributions such as Binomial and Gaussian (used in previous works [10, 11]). These results are also averaged over all the 19 zones we consider. Lower KS values indicate a better fit to the real data. These results clearly show that GANs are a better fit than other baselines.

Model	KS Distance (avg)
Gaussian	0.154 ± 0.036
Binomial	0.148 ± 0.037
VAE	0.155 ± 0.042
Ship-GAN	**0.141** ± 0.045

Table 1: Average KS distance between the real and fake distributions for unconditional modeling of travel times; lower is better

Model	Bucketed KS Distance
Conditional VAE	0.224 ± 0.023
Conditional Ship-GAN	**0.189 ± 0.021**

Table 2: Average KS distance between the real and fake distributions for conditional modeling of travel times (lower is better)

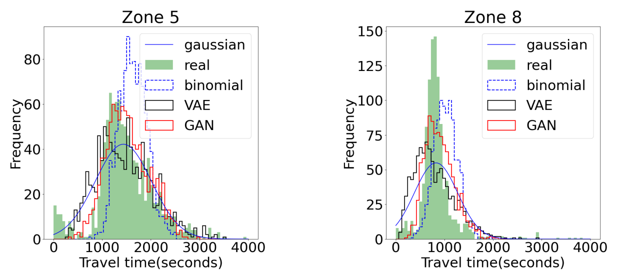

Figure 3: Unconditional fitting qualitative results

In Table 2, we extend the KS measure for the conditional generation of the data. The GAN and VAE take as input a vessel's speed as it enters a zone, and the current traffic conditions (count of vessels in the selected zone), and generates a travel time. Such capabilities are not considered in previous simulation models [10, 11] which can only simulate travel time without taking into account such conditions. These results also show that GANs provide a better fit for conditional modeling of the data than VAE.

Figure 3 provides a qualitative comparison of the distributions learned for the unconditional case for two zones for each of the four methods in the unconditional distribution fitting. The x-axis is the travel time, and y-axis shows how many vessels had the travel time within a particular interval on the x-axis. The results are shown using 1000 samples each for real and fake distribution. The results reveal visually that GAN matches the real distributions much better than fitting known distributions. Also, between GAN and VAE, GANs fits much better than VAE.

Conclusion: We demonstrated the superior performance of deep generative model based simulation of key aspects of ship traffic in a given area via quantitative KS metric and qualitative results. Our approach enables more realistic simulations for decision making models for maritime traffic management. Our demo video is at: https://youtu.be/xZVzr0WcefU

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