Using the CGAN Model Extend Encounter Targets Image Training Set

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Abstract: A fully capable unmanned ship navigation requires full autonomous decision-making, large-scale decision model training data to answer for these conditions is essential. However, it is difficult to obtain enough scenes training data in a real sea navigation environment. In response to possible emergency situations even no shore-station support, this paper proposes a method using conditional generative adversarial networks (CGAN) to generate the most executable large-scale target ships image set, which can be used to training various sea conditions autonomous decision-making model. In practice, most of the current research on unmanned ships are based onshore remote control or monitoring. Nonetheless, in some extremely special circumstances, such as communication interruption, or if the ship cannot be guided or remotely controlled in real time on the shore, the unmanned ship must make an appropriate decision and form new plans according to the encounter targets and the whole current situation. The CGAN model is a novel means to generate the target ships to construct the whole encounter sea scenes situation. The generated targets training image set can be used to train decision models, and explore a new way to approach large-scale, fully autonomous navigation decisions.

1 INTRODUCTION

The equipment used in modern ocean-going vessels can be roughly divided into two types: navigation aids that help the crew to make the right decisions and control equipment that the seafarer's control. To reduce running costs and human factors in accidents, unmanned vessels with autonomous perception and decision-making are the future development direction. For this, a model or system is required to receive data from the navigation aids and make appropriate decisions for the obtained data through the control device to complete the autonomous navigation. The heavy sea environment may interrupt satellite communication and result in loss of remote-control capacity. To achieve long-distance and completely autonomous, unmanned merchant ship transportation, the system must be able to make its own [a] decisions at any time in response to emergencies, change the established strategy, and eliminate the danger.

As shown in Figure 1 on the following page, the ship is sailing along the coast, the target ship represented by T1~T3, and T* represents the fishing boat group that performs fishing operations in one area. Short-distance path replanning is possible, especially in extreme navigation environments, and without remote assistance from the shore, the unmanned ship must rely on the limited data information to make appropriate decisions (Liu and Bucknall, 2015). From the perspective of the bridge, the confirmation of the target ship and its trajectory are not easily presented in a three-dimensional manner. Furthermore, the relative positional relationship between the target ship and the ship is critical to the training of decision-making neural networks, so it is important to construct enough confrontation scenarios to train large-scale unsupervised decision models. Another problem of unsupervised learning is the determining of how to generate a new path for no-human participation in decision making; this problem sets high demands on the model.

First, the available models built using unsupervised methods are reviewed. The most straightforward idea is to estimate the sample distribution p(x) from the training set and sample p(x) to generate a new sample "similar to the training set".

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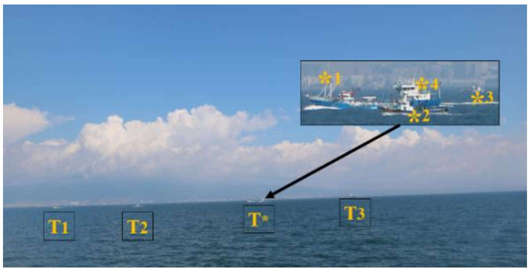

Figure 1: Real sea encounter environment.

For low-dimensional samples, a simple probabilistic model with only a few parameters (such as Gaussian) can be fitted to p(x), whereas high-dimensional samples (such as images) are difficult to implement. In the extreme navigation environment, the input of the sensing device may be encoding low-latitude information, or other high-latitude information such as images. A classic method is to construct an undirected graph by using the Restricted Boltzmann Machine (RBM). The energy values and node probability of the graph have an exponential relationship (Nair and Hinton, 2010). The training set is used to set the coefficients of nodes and edges in the graph to express the relationship between individual elements and connected elements in x. This method is cumbersome and computationally complex. The mixing speed of the Markov chain is very slow when sampling (Neal, 2000). Another method is the use of deep belief networks (DBNs), in which a single RBM and several directed layers are used to form a network. This method has the same computational complexity (Hinton et al., 2006). Another popular method is the use of convolutional neural networks (CNNs). Although CNNs show immediate results in supervised learning including classification and segmentation, how to conduct unsupervised learning has always been a problem (Wang and Gupta, 2015). Generative adversarial nets (GAN) can solve this problem systematically.

2 PREVIOUS WORK

2.1 Generative Adversarial Nets (GAN)

GAN is a new method of training the generation model proposed by Goodfellow et al., (2014); the method includes the generation and discrimination of two "adversarial" models. The generated model (G) is used to capture the data distribution, and the discriminant model (D) is used to estimate the probability that a sample is derived from real data rather than generating samples. Both the generator and discriminator are common convolutional networks as well as fully connected networks. The generator generates a sample from the random vector, and the discriminator discriminates between the generated sample and training set sample. Both train simultaneously as shown in equation (1):

When training the discriminator, discriminant model D is fixed, while the parameters of generator G are adjusted to minimize the expectation of $\log(1 - D(G(z)))$ as shown in equation (2):

where model G is fixedly generated and the parameters of the D are adjusted to maximize the expectation of $\log(D(X)) + \log(1 - D(G(z)))$. As shown in equation (3)

This optimization process can be attributed to a "two-player minimax game" problem. Both purposes can be achieved through a backpropagation method. A well-trained generation network can transform any noise vector into a sample similar to the training set. This noise can be seen as the encoding of the sample in a low dimensional space. The generator generates meaningful data based on random vectors. In contrast, the discriminator learns how to determine real and generated data, and then passes the learning experience to the generator, enabling the generator to generate more workable data based on random vectors. Such a trained generator can have many uses, one of them being environmental generation in automatic navigation. This paper proposes the feasibility of this method and applies it in image set generation to allow unmanned ships to achieve fully autonomous decision-making processes.

2.2 Generated Image Set Data

The acquiring of real data on critical sea conditions is difficult; therefore, acquiring data similar to real scenes is important, especially when data is scarce. When acquiring data for training the automatic driving system, according to the concept used in this study, the use of GAN can be extended to replace the real image according to the virtual image generated

$$\min_{G}\max_{D} V(D,G) = E_{x\sim Pdata(x)}\left[\log\left(D(X)\right)\right] + E_{z\sim Pz(z)}[\log(1 - D(G(z)))] \tag{1}$$

$$\max_{D} V(D,G) = E_{x\sim Pdata(x)}\left[\log\left(D(X)\right)\right] + E_{z\sim Pz(z)}[\log(1 - D(G(z)))] \tag{2}$$

$$\min_{G} V(D,G) = E_{z\sim Pz(z)}[\log(1 - D(G(z)))] \tag{3}$$

from the generator. (Yang et al., 2018) used an opposing concept, in which the scene image obtained was directly acquired through real driving by using unsupervised learning to remove the details unrelated to the prediction of driving behavior. It was simplified to the refinement specification representation in the virtual domain. Accordingly, the ship-driving instructions were predicted to form a new training program that is more efficient and accurate.

Unmanned surface navigation involves a type of driverless navigation. The deep Q-network (DQN) algorithm can be used to train the unmanned ship navigation model (Mnih et al., 2015); this is the embodiment of the wider application of GAN. Goodwin (Goodwin 1975) derived, training data from sensory data collected by the ship's real navigation, and real navigation seafarers inevitably maintained sufficient safety distance. Therefore, when an unmanned ship encounters a dangerous situation, the experience replay utilized is actually not sufficient. This is because adopting appropriate decision-making and behavioral judgment based on the previous data-training results is difficult when the unmanned ship actually encounters a sea state that is different from typical sea conditions (Schaul et al., 2015).

The purpose of the present study involves generating data containing more similar critical sea conditions through the GAN model by using a small number of maritime-navigation real data in critical situations. The aforementioned data potentially corresponds to pre-collision scenes encountered by two ships [including pictures, Automatic identification system (AIS) data, and radar data]. For example, the data can also correspond to a scene that occurred prior to when a ship is stranded in the waters with insufficient water depth (the most important factor corresponds to the water-depth data). The problem for which the DQN algorithm does not learn from experience in the case of the aforementioned data sparseness is solved using the GAN algorithm.

3 VIRTUAL TRAINING IMAGE SET GENERATION MODEL

3. 1 Conditional GANs

Conditional GANs (CGAN) is an extension of the original GAN, in which both the generator and discriminator add additional information y to the condition. Here, y can be any information, such as category information or any other modality information data as shown equation (4). (Mirza and Osindero, 2014). If condition variable y is a category label, CGAN can be considered as an improved supervised model of the pure unsupervised GAN. This simple and straightforward improvement has proven to be very effective and widely used in subsequent related work (Denton et al, 2015; Radford et al., 2015).

The conditional GAN is achieved by feeding additional information y to the discriminator and generator models as part of the input layer. In the generator model, the input a priori noise p(z) and condition information y are combined to form a joint hidden-layer representation. The adversarial training framework is relatively flexible in terms of the composition of the hidden-layer representation. Similarly, the objective function of conditional GAN is a "Conditional two-player minimax game."

3.2 The Process of CGAN in Sea-Scene-Environment Construction

The specific process to obtain various sea-condition scenarios is shown in Figure 2. First, condition information Y is entered into the generator and discriminator, and then a few random vectors are input to the generator network, and fake data are subsequently generated by the generator. These fake data can correspond to a few ship-state pictures or a few other navigation data, such as AIS data of nearby

$$\min_{G}\max_{D} V(D,G) = E_{x\sim Pdata(x)}[\log(\mathrm{D}(\mathrm{x}|\mathrm{y}))] + E_{z\sim Pz(z)}[\log(1 - \mathrm{D}(\mathrm{G}(\mathrm{z}|\mathrm{y})))] \quad (4)$$

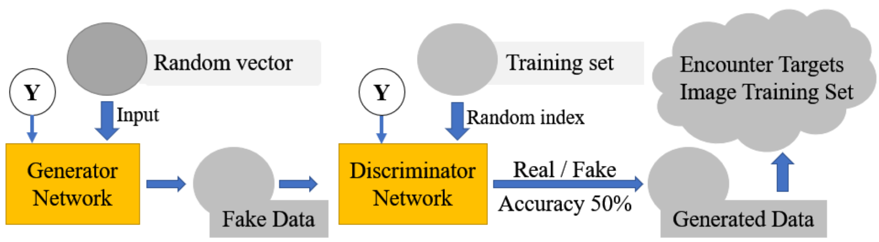

Figure 2: Applying CGAN algorithm to generate encounter targets image training set.

Figure 3: Generated lifeboat from submarine by Big-GAN.

ship or the path planning data after the ship route is updated. We inputted the fake data to the discriminator, which determines whether the input data are real or generated by the generator based on a random comparison with the real data. The similarity between the data by the generator and the real data from the discriminator progressively increases, thus increasing the discriminating ability required by the discriminator. Additionally, the generator and discriminator share a mutually competitive and adversarial relationship. The generated data are considered to sufficiently mirror real data when the fake data input by the generator appears sufficiently realistic, and the accuracy of the discriminator at this time is approximately 50%. This corresponds to the sea-scene data required in critical sea situations.

3.3 A Case Study for Generated Image

CGAN model image generation as shown in figure3. This section mainly demonstrates how to generate a lifeboat using images of submarines taken from different angles using the Big-GAN model. Big-GAN model proposed by Andrew Brock from Heriot-Watt University (Brock et al., 2018). The authors proposed a model (Big-GAN) with modifications focused on the following three aspects: a. improving conditioning by applying orthogonal regularization to the generator; b. The orthogonal regularization applied to the generator makes the model amenable to the "truncation trick" so that fine control of the trade-offs between fidelity and variety is possible by truncating the latent space; c. stability is very significant for large-scale image generate.

Figure 4: Generate lifeboat images by Big-GAN model.

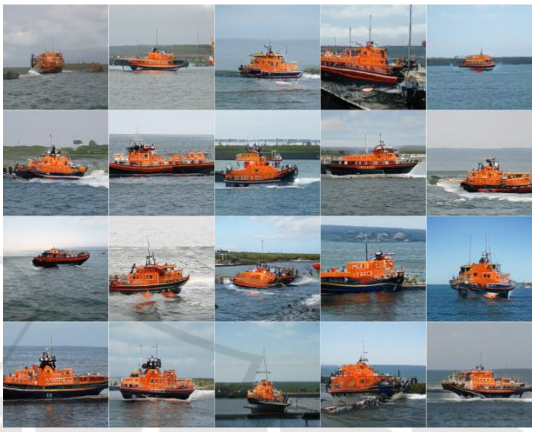

Figure 5: A portion of the generated lifeboat image set.

Figure 6: A portion of the generated ocean liner image set.

We can input different random vectors and combine the real data input by the discriminator to get a large number of Real enough image data sets. This study, we input random vectors are submarine. As shown in Figure 4, we get three different types of lifeboats, more importantly, the different background environments of lifeboats can also achieve various changes. It can be provided a large amount of training data for our unsupervised decision model. It is much richer than the target ship data collected from real sea environment.

4 APPLICATION

4.1 Generated Target Image Set

The most important part of this study is to obtain a data set of the target ship with sufficient quality and quantity. As shown in Figure 5, a portion of the entire large-scale lifeboat target image data set is shown. These images were not taken by the camera and were generated entirely from our GAN model. Using our model, we can generate various situations at sea scenes and the various forms that the own ship may encounter; even various types of accidents, such as collisions, stranding, fire, loss of goods, etc. Not only the training data set for lifeboats, but also the ocean liner data set shown in Figure 6, as well as data sets for various other types of marine moving targets.

4.2 Generated Data for Unsupervised Decision Model Training

GAN is easy to embed into the framework of reinforcement learning. For example, when using Deep Q-Network to solve collision avoidance problems, GAN can be used to learn the conditional probability distribution of an action. The agent can select reasonable images based on the response of the generated model to different actions.

In the training of image recognition models of convolutional neural networks and the training of decision models such as deep reinforcement learning, the quality of the input data greatly affects the effect of the training results. The target image dataset generated by CGAN has the same image size and the same image density, which can easily solve the problem of inconsistent input data during the training process. In addition, the CGAN model solves many of the scene data that are difficult to obtain in a real navigation environment, making it possible to use large-scale data input for deep learning.

5 CONCLUSIONS

This paper using the Conditional Generative Adversarial Networks to generate image set of the available target ships and improve the quantity and quality of training data. The surrounding environment data of the own ship obtained by the sensors, mainly includes AIS data, radar data, and image data. Small vessels, especially those in some areas, do not have AIS data, radar data is greatly affected by the weather. Therefore, training automatic driving unmanned ships are inseparable from the support of image data sets, especially the image data of small ships in various states. This paper uses the image data of target ship as a sample, which obtained from the perspective of the ship's bridge, using the CGAN algorithm to generate more, and the same type of the target ship image data to support model training. According to different condition information, through the CGAN model, it is possible to generate more different environmental states, such as different near-shore backgrounds, different city lighting pollution, different weather conditions, and even different seasons, new images of different ocean wave levels. This method can greatly expand the quantity and quality of the training data set, therefore, easy for completing the construction of a better autonomous unsupervised decision model.

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