Toward autonomous marine navigation in the near-shore: a GNN solution

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COMP5329

Deep Learning

Introduction

Over 70% of the earth's surface is covered by water and around 80% of global trade by volume and over 70% of global trade by value are carried by sea worldwide. Given the complexity of city traffic, marine autonomous navigation offers great value to research and commercialize. From all the different stages of marine navigation, the near-shore situation comes with the most complex water transportation environment. The Sealion Team under ACFR conducted various marine transportation research and water test based on the WAM-V and Kingfisher hardware. We proposed this novel visual navigation solution based on Graph theory in a near-shore environment. The algorithm has been proven for its agile training, robustness and convenience for deployment.

图 1. The world ' s first fully autonomous ferry in the waters of the Turku archipelago by Falco
Right: China's first Autonomous Cargo ship: Jindouyun 0

图 2. Left: Electric Propulsion Autonomous Container ship Yara Birkeland
UYSD autonomous navigation WAMV for water test

Different types of autonomous navigation boats in the world.

Near-shore sailing task description

The near-shore navigation usually requests boats to follow certain lanes formed by a specific buoy. In this task, the legal lane is formed by the red buoy and green buoy, and the boat shall neither get in contact with any buoy nor move beyond the buoy line.

The common situations would be too left or too right, which could be reflected by the angle of the color buoys.

Data Processing

The task set is to follow the water lane as the green buoy on the left and the red buoy on the right side. Two colors of the buoy would follow a lane for the boat to pass through. Video data were recorded at different times of the day in 2022 November in the Sydney International Regatta Center through the different cameras.

Data Processing

Frame rate 1 per second was set to pick samples of water lane during undertaking the task. We randomly selected 38 images which contain the water lane, either clear or not. Manually label them as 1 or 0 to represent the boat should turn left or right while facing that situation. An object detection to classify the red and green buoy left boat fork and right boat fork. Assign its centroid coordinate as its position and form a graph. The two forks of the boat are always static and the left fork extends to the closest green buoy and the right fork extends to the closest red buoy. Each buoy connects to the further next one with the same color.

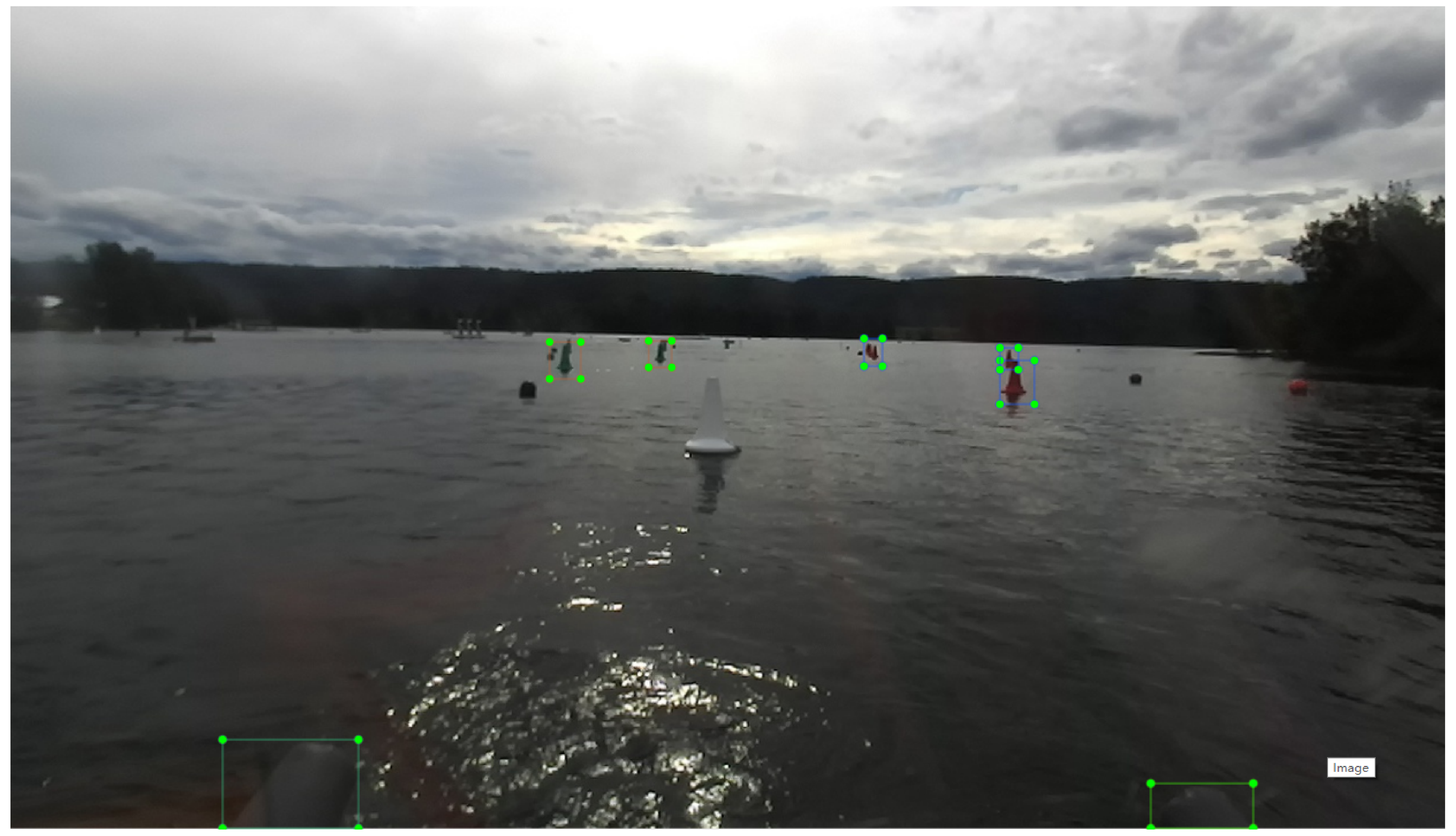

图 3. Common navigation graph

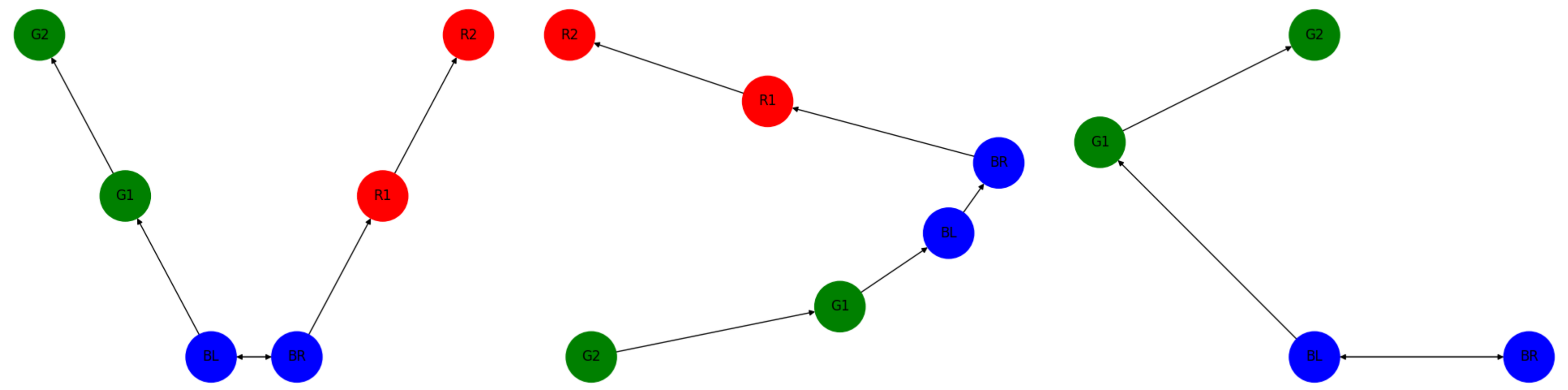

图 4. Ideal graph and less ideal and danger graph layout

After computing the angle between two connected edges, we annotate the angle data to a range of 20% and produced another 38 X 9 samples for a total of 380 samples feed for the Graph Neural Network training.

Innovation and highlights

First GNN solution for marine navigation There are many solutions proposed and this is the first proposal to solve autonomous navigation by GNN. Fast training: the whole training took less than 1 hour and was easy to deploy. Convenient to collect data and deploy: each manual operation turning left or right will accompany a timestamp and the front camera as the future training data. After one round, the new data will be immediately trained and ready for autonomous navigation. This provides us with a robust method to teach the real situation navigation on a real-time basis.

Model Training

Consider it as a binary classification task of GNN. A graph could be either classified as a left or a right turn. This batch data requires a manual label. The future data will automatically be labeled by the remote control operation. Hence the labeling problem would be resolved by the design of the mechanism. The model was trained on Colab default CPU with 12Gb RAM and typically last for 1 hour. Such a convenient setting will help us conduct instant training at any new water zone.

Results

After 300 epochs of training, the classification result reached:

Accuracy: 0.7105263157894737

F1 Score: 0.699840248693925

Confusion Matrix: [[210 40] [70 60]]

The loss is rendered as below chart.

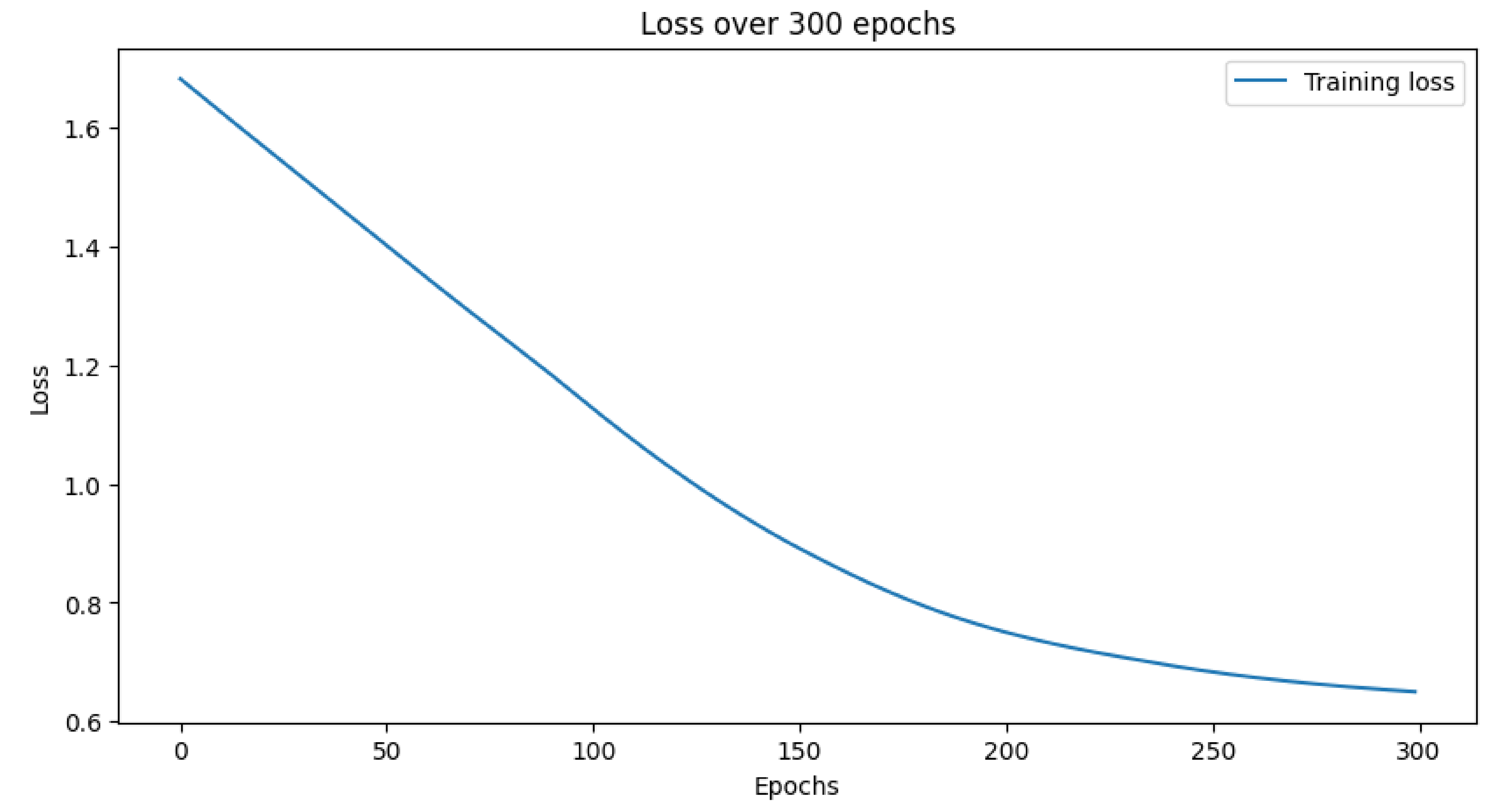

图 5. Loss Curve 300

Discussion

The graph design filtered out unnecessary information in the water transportation task. Infinite image possibilities were converted to a limited graph layout. It provides a robust mechanism to resolve the water lane following. The graph could easily extend to more different types of nodes to cover more possibilities.

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