Shore Identification and Navigation Route Modification Function for Autonomous Boats Used to Measure the Depth of Irrigation Ponds

Sho Nobumoto
Graduate School of Engineering and Science Master's
Shibaura Institute of Technology
Tokyo, Japan
email:al20109@shibaura-it.ac.jp

Tsuyosi Nakajima
College of Engineering
Shibaura Institute of Technology
Tokyo, Japan
email:tsnaka@shibaura-it.ac.jp

Kota Oshima
Graduate School of Engineering and Science Master's
Shibaura Institute of Technology
Tokyo, Japan
email:ma23039@shibaura-it.ac.jp

Yutaka Kaizu
Graduate School of Agricultural and Life Sciences
The University of Tokyo
Tokyo, Japan
email:kaizu@g.ecc.u-tokyo.ac.jp

***Abstract*—Many irrigation ponds are at high risk of collapse due to issues such as aging caused by insufficient management and sediment accumulation. The use of autonomous boats to measure water depth and estimate water storage capacity in these ponds has proven to be effective. However, there were some problems, such as discrepancies between the navigational map and actual conditions, which resulted in insufficient depth data collection near the water's edge or the boats running aground. In this study, we developed an autonomous boat system by improving the technology to utilize image recognition for identifying shoreline positions, allowing the boat to safely and adequately approach the water's edge. To achieve this, the boat's structure was modified by flattening the hull to reduce the risk of grounding. More importantly, three essential functions were also implemented: shoreline recognition, distance measurement from the boat, and route modification based on the collected data. These functions were evaluated in an actual irrigation pond, and it was verified that the distance estimation was accurate enough for the boat to safely navigate near the shoreline. However, several issues were identified, including the impact of boat sway and lighting conditions on recognition accuracy, as well as the need for improved recognition of obstacles along the route that are not part of the shoreline.**

Keywords-Irrigation ponds; Semantic segmentation; Distance measurement; Autonomous navigation.

I. INTRODUCTION

Irrigation ponds, known as "Tameike" in Japan, are artificially constructed reservoirs designed to store water for agricultural purposes. However, due to increasing labor shortages, the maintenance of many of these ponds has become insufficient, leading to their deterioration or, in some cases, complete abandonment. As these ponds age, the associated risks of disasters, including flooding and sediment outflow due to structural failure, have escalated. To mitigate these risks caused by aging irrigation ponds and to ensure adequate management in the face of labor shortages, large-scale interventions such as dredging or decommissioning may be required. However, informed decision-making on such measures necessitates regular monitoring of the ponds' water storage capacity, along with the accumulation of sediment and its temporal variations.

To address this need, a method for managing water storage by using autonomous boats to comprehensively measure water depth in irrigation ponds was proposed. However, because the route planning was based on map data, accurate depth measurement at the water's edge could not be achieved, resulting in significant estimation errors in the water storage capacity [1].

In this study, we propose a system that builds upon existing technology by modifying the route of the autonomous boat to enable accurate shoreline recognition. This enhancement allows for the collection of sufficient depth data and reducing estimation errors in water storage capacity. To achieve this, the boat's structure was modified by flattening the hull to reduce the risk of grounding. More importantly, three essential functions were also implemented: shoreline recognition, distance measurement from the boat, and route modification based on the collected data. The shoreline recognition function utilizes a semantic segmentation method to determine the shoreline position in camera images, and the distance measurement function employs a stereo matching method to calculate the distance to that position. The route modification function adjusts the boat's route based on the shoreline recognition results to ensure it can approach the shoreline safely and closely. These improvements not only address the issue of insufficient data collection near the water's edge but also mitigate the risk of grounding, ensuring safe and reliable data acquisition.

In this paper, Section 2 discusses previous research and its challenges, Section 3 presents the proposed system, Section 4 details the experiments and results, and Section 5 provides the conclusions.

II. PREVIOUS RESEARCH AND ITS CHALLENGES

To conduct high-accuracy depth measurements of irrigation ponds at low cost and within a short period of time, Kaizu et al. [1] developed a small autonomous boat equipped with navigation control and Global Navigation Satellite System (GNSS) sonar. The navigation control system utilizes open-source autopilot software originally designed for drones. With this navigation control, the boat autonomously follows along a route so as not to deviate from the planned navigation route based on the Global Positioning System (GPS) position information.

The boat autonomously navigates along a route set using the Mission Planner software. During navigation, the depth data from the sonar and time data are stored in the flight controller’s internal memory. Upon completion of autonomous navigation, the depth data are correlated with GPS information to determine the depth at specific pond locations. Spline interpolation is then applied to all depth measurements along the route to generate a map of the pond bed, enabling the estimation of the pond’s capacity.

However, in this study, the navigation route was designed using Mission Planner on a map of the pond obtained from Google Maps. Due to inaccuracies in the map and variations in water levels, significant errors often occurred in the shoreline positions. This led to issues, such as insufficient collection of depth data near the water’s edge or the boat running aground.

Figure 1 illustrates the distribution of estimation errors. The black line indicates the route taken by the autonomous boat, while the red, blue, and yellow areas on the water surface represent varying degrees of error. As shown in the figure, the central region allows for relatively accurate depth estimation, whereas the water’s edge exhibits significantly larger errors. This discrepancy is due to insufficient depth data collection, which causes deviations from the estimated values due to irregular depth changes in the lakebed near the shoreline.

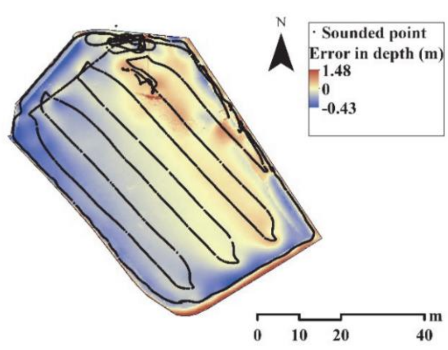

Figure 1. Distribution of Estimation Errors (reproduced from [1]).

To address this issue, it is essential to accurately determine the shoreline position during the boat’s navigation and to adjust the route based on this data. This approach enables the boat to safely approach the shoreline while avoiding the risk of grounding.

III. PROPOSED SYSTEM

A. Research Objective

The objective of this study is to address the challenges identified in the previous research and propose and evaluate a system that utilizes sensor data to recognize the shoreline and measure the distance to it. This system dynamically adjusts the navigation route to ensure safe and effective autonomous operation of the pond depth measurement boat.

B. Structure of the Prototype Boat

To conduct this research, we developed a new prototype boat. Figure 2 shows an image of the prototype boat.

Figure 2. Developed Experimental Boat.

In Figure 2, a bodyboard was used as the hull to facilitate navigation in shallow waters and minimize the risk of grounding. For shoreline recognition, two types of cameras were mounted at the front of the hull. One of these is a dual-lens 3D stereo synchronized USB camera module (ELP Co., Ltd.), which is used for autonomous navigation and shoreline detection. The other camera serves as a "visual aid" for manual remote control, with its video feed displayed in real-time on the controller's screen via telemetry.

Inside a waterproof case positioned at the center of the hull, the flight controller Pixhawk 6C (Holybro) and the Jetson Nano 2GB (NVIDIA), a development board equipped with a Graphics Processing Unit (GPU) for image processing, are installed. Four ducted fans were mounted on top of the waterproof case. These fans are controlled by the flight controller to manage the boat's movement. Additionally, a sonar system is attached to the rear of the hull to measure the depth of the pond.

The prototype boat performs autonomous navigation based on a route planned using Mission Planner and programmed into the Pixhawk 6C flight controller.

C. Functional Configuration

Figure 3 illustrates the functional configuration of the proposed system. The existing system configuration has been enhanced with three additional functions: shoreline recognition, distance measurement, and route modification.

In Figure 3, the camera mounted at the front of the boat periodically captures images. The shoreline recognition function uses the image data to estimate the position of the shoreline and outputs the coordinates of the shoreline within the image. Based on this shoreline position, the distance measurement function uses triangulation to calculate and output the distance to the shoreline. Then, the route modification function dynamically adjusts the navigation route using the measured distance.

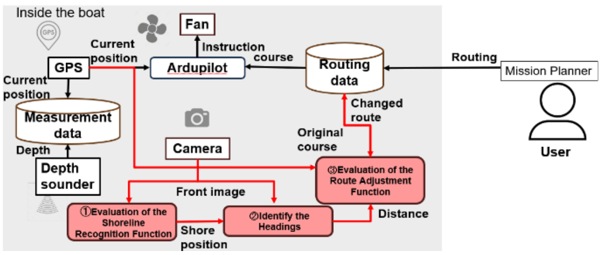

Figure 3. Functional Configuration of the Proposed System.

This series of functions is executed by the Jetson Nano 2GB installed on the boat. The Jetson Nano 2GB is connected to the dual-lens 3D stereo synchronized USB camera module, which manages the timing of the image capture and performs the necessary computational processing for each function. The route modification function communicates with the flight controller Pixhawk 6C via a wired connection, enabling real-time navigation commands and control.

IV. EXPERIMENT AND RESULTS

The performance of each added function was evaluated through a series of experiments. The purpose, method, and results of these experiments are outlined below.

A. *Shoreline Recognition Function*

(1) Purpose and Method

This function represents the initial step of the proposed system, and it is crucial that it can recognize the shoreline in captured images with accuracy comparable to that of a human determining the shoreline through a camera.

To evaluate this accuracy, we tested the inference performance of semantic segmentation[2]. In this experiment, images of shorelines taken from various distances were input into the shoreline recognition function, and performance was assessed. Multiple models with different training parameters, such as the number of epochs and batch sizes, were developed for semantic segmentation, and a comparison was made to select the optimal model.

(2) Results

The system successfully recognized both the water surface and the shoreline with a visually identifiable level of accuracy across various distances.

Figure 4 provides an example of the output from the shoreline recognition function. In this figure, the shoreline is distinctly identified. The image on the right shows how the system classifies the white areas as water (navigable) and the black areas as land (non-navigable).

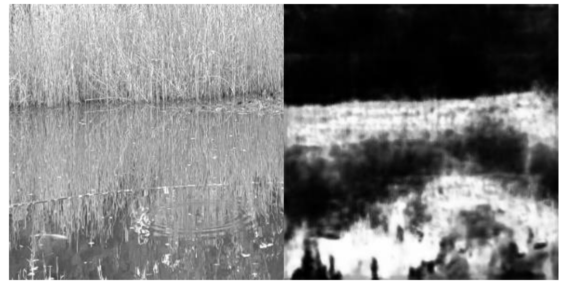

Figure 4. Example of Output from the Shoreline Recognition Function.

The shoreline recognition function utilizes semantic segmentation. The performance of the trained model was evaluated using a confusion matrix, and metrics including the accuracy, precision, recall, and F1 score [3]. The evaluation results for the trained model are shown in Figure 5. As indicated in Figure 5, accuracy exceeded 90%, suggesting that the data volume and number of training epochs were adequate. Although there were a few cases of misdetection in localized areas, such as reflections, the system successfully classified the water and land and recognize the shoreline in most areas.

Accuracy	0.95415149
Precision	0.92114224
Recall	0.91336736
Specificity	0.969868
F1score	0.91723832

Figure 5. Evaluation Scores.

Additionally, for performance comparison, several models were created with varying combinations of batch size (4, 8) and number of epochs (100, 200). Table 1 presents the accuracy metrics for these different hyperparameter settings.

TABLE I. ACCURACY BY HYPERPARAMETER.

epochs	batch size	accuracy
100	4	0.956
	8	0.946
200	4	0.972
	8	0.964

From Table 1, it can be observed that, even with the same data volume, models with more epochs achieved higher accuracy, while smaller batch sizes resulted in slightly better accuracy.

However, a challenge of the shoreline recognition function is the presence of obstacles other than the shoreline. Obstacles such as fences, plants, and rocks can hinder the boat's movement, and thus must be detected and avoided during autonomous navigation. Since the method in this study focuses specifically on shoreline recognition, it is unable to detect such obstacles. To address this issue, it is necessary to develop a function to detect obstacles separately from the shoreline and relay this information to the route modification function.

B. *Distance measurement function*

(1) Purpose and Method

The distance measurement function calculates the distance from the boat's current position to the coordinates of the shoreline identified by the shoreline recognition function using the stereo matching method [4]. For the boat to adjust its route effectively while navigating, not only is measurement accuracy important, but real-time computation is also required. Additionally, since the boat needs time to alter its course, it is necessary to measure the distance from a point far enough to allow for this adjustment. Therefore, it is important to understand how the distance to the shoreline affects the accuracy of the distance estimation.

To evaluate this, the accuracy of the distance measurement function is assessed by calculating the difference between the measured distance and the actual distance as an error, and then dividing this error by the actual distance.

(2) Results

Figure 6 presents the results of the experiment. The data demonstrate that the distance measurement function accurately measured distances up to 10 meters with an error margin of less than 5% when the boat was stationary. Given that the distance to the shoreline when the boat initiates deceleration is 5 meters, and the error at this distance was less than 0.1 meters (within 1%), the function is confirmed to be sufficiently accurate for practical applications.

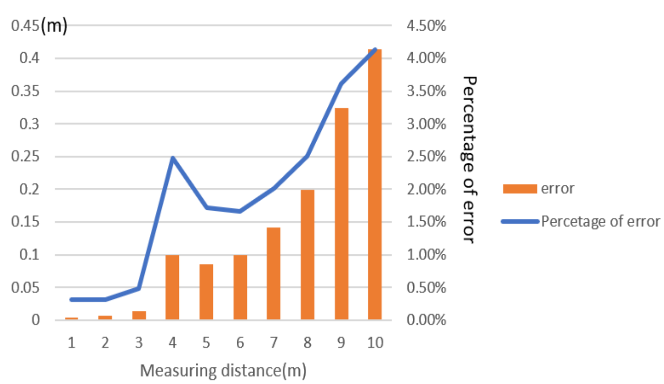

Figure 6. Experiment Results.

However, the camera used in this study had issues when the boat was shaking, causing the captured images to blur and making it impossible to detect distances in some cases. Therefore, for the distance measurement function to operate properly, it is necessary to use a camera capable of capturing clearer images in cases of significant shaking caused by wind, for example.

C. *Route Adjustment Function*

(1) Purpose and Method

The route modification function prioritizes collision avoidance and the prevention of grounding to ensure safety before making any changes to the navigation route. In this experiment, we evaluated the boat's ability to halt its movement upon approaching the shoreline and to successfully modify its course afterward.

To achieve this, we tested whether the boat could safely navigate while modifying its course.

(2) Results

Figure 7 illustrates the pre-configured route (yellow line) set in Mission Planner, as well as the actual route followed by the boat (red line).

Figure 7. Pre-configured route and the actual route followed by the boat.

The results are as follows:

The boat successfully altered its course to navigate safely before reaching the shoreline. During the experiment, the boat approached the shoreline 25 times along the pre-configured route, but in 8 instances, the route modification function did not perform adequately. The details are as follows:

- At points 2 and 5, the boat ran aground and became inoperable.
- At points 3, 7, 11, 15, 19, and 23, the boat collided with obstacles, requiring manual operation.

The causes of these route adjustment failures are as follows:

- Unclear images due to boat shaking: 4 incidents.
- Unclear images in shaded areas: 3 incidents.
- Collision with obstacles such as fences: 1 incident, where the shoreline recognition function detected these as shorelines.

To address these issues, the following improvements to the shoreline recognition and distance measurement functions are recommended:

- Shoreline recognition function: Enhance the ability to detect obstacles in addition to the shoreline.
- Distance measurement function: Use of higher-resolution cameras to estimate distances with consistent accuracy, regardless of lighting conditions or boat movement.

V. CONCLUSION

To address the issue of depth measurement errors due to insufficient data in the waterfront areas, we developed a new prototype boat and incorporated three functions to it: shoreline recognition, distance measurement, and route modification. Through experiments, we verified the effectiveness of these functions. The shoreline recognition function achieved over 90% accuracy in its evaluation metrics, the distance measurement function maintained an error of less than 4.5% at a distance of 10 meters, and the route modification function successfully avoided collisions in two-thirds of the cases.

Moving forward, it is crucial to enhance the functionality and accuracy of each component to ensure the system's practicality and facilitate its application to real-world pond depth measurements.

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