

A Cyber-Physical Traffic Signaling System for Controlled Waterway in Inland River Based on Edge-centric IoT

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Abstract—The controlled waterway in the upper reaches of the Yangtze River has become a bottleneck for shipping due to its curved, narrow and turbulent characteristics. The vessels passing through it must obey the signal revealed by the Intelligent Vessel Traffic Signaling System (IVTSS) to pass in one direction. The accuracy of signals is directly related to traffic safety and efficiency. However, the unreliability of vessel sensing sensors in these areas and the latency of transmission and computation of large amounts of sensing data may negatively impact IVTSS. Hence, more information from the physical world is needed to ensure the stable operation of the IVTSS, and we proposed an edge computing-centric sensing and execution system based on IoT architecture to enhance the reliability of IVTSS. We conducted experiments using plug-and-play methods, reducing command and recording error rates by 89.47% and 86.27%, respectively, achieving the goal of real-time perception control.

Index Terms—IoT, Multi-sensor, Data fusion, Traffic cyber-physical

I. INTRODUCTION

Yangtze River, the largest river in China, has been the world's busiest inland shipping channel. However, some narrow, curved, and turbulent sections in the upper Yangtze River still hinder the development of the inland waterway shipping industry [1]. As a result, the competent authorities must refer to these sections as restricted one-way waterways, such as the controlled waterway, to ensure safety. Vessels must follow the traffic signals issued by the signal stations to pass through these waterways.

Automatic Identification System (AIS)-based Intelligent Vessel Traffic Signaling System (IVTSS) [2] has been developed to provide suggested traffic signals, further confirmed by the manager who will issue the corresponding signals. IVTSS has significantly improved the safety and efficiency of vessel passage in the controlled waterway. A single AIS signal is not always reliable in complex waterways in mountainous areas, and it often experiences drift, time delay, and loss. In order to ensure the stable command of IVTSS and achieve more refined and intelligent services, a single AIS signal has been unable to meet the demand, and the IVTSS needs more information

about the physical world. Thus, the system needs more sensor data for deeper data mining and analysis, such as radar and Closed-Circuit Television (CCTV).

Wrong command or lack of command signal may lead to high-risk behaviors of vessels or even maritime accidents. Real-time, reliable and accurate perception of ship dynamics is fundamental for IVTSS. Thus, a stable communication network is necessary to ensure inland waterways' safe, efficient, and reliable passage. However, as the primary means of obtaining real-time information on inland vessel dynamics, AIS is not always effective and reliable due to the harsh conditions of limited visibility, lag, attrition, and faded areas in inland mountainous environments [3].

With the enormously growing level of traffic [4], the lower serviceability of IVTSS may lead to considerable congestion and safety risks in controlled waterways. Combining sensors with complementary characteristics can improve the perception system's performance while minimizing each sensor's shortcomings. On the other hand, signal stations are also used to set up traffic signals and signs due to the limitations of power and communication networks. Vessels waiting outside the boundary markers rely only on visually observing traffic signals or signs to enter the controlled waterway.

However, vessels from a greater distance cannot observe these visual signals set at the signal stations due to blocking trees or terrain, resulting in insufficient time for the downward vessels to make appropriate speed adjustments. In this case, the vessels will be forced to make a U-turn outside the upper boundary marking and wait for the downstream signal, which is a dangerous behavior. Obviously, this violated 1 of the two basic rules of passage commands. In addition, ensuring that the signal devices can reliably receive the remote control signal from IVTSS in harsh environments remains a challenge. Thus, adopting thriving wireless communication networks such as 5G and Long Range Radio (LoRa) can set up traffic signs at boundary markings for vessels to better observe in advance and offer machine-to-machine (M2M) links.

Owing to the blooming development of wireless networks and Artificial Intelligence (AI), Industry 4.0 technologies and Cyber-Physical Systems (CPS) have been identified as one of the current application trends for solving intelligent transportation problems in the inland river [5]. Internet of Things

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(IoT) has become one of the most effective ways to handle the above engineering challenges [6, 7]. The identification, recovery, prediction, and reconstruction of abnormal or error AIS data have been widely investigated [8, 9, 11]. However, data anomalies and loss problems still need to be solved. The combination of AIS, radar, and video can make the most of these three technologies, thus improving the detection speed and recognition accuracy.

This paper is an extension of our existing research results[12]. We establish an edge-centric IoT system with sensing and control functions whose architecture is based on Industrial CPS to improve the service quality of IVTSS. The proposed IoT system architecture includes five layers: 1) sensing and control layer; 2) edge computing layer; 3) network layer; 4) service layer; and 5) application layer. The proposed system integrates various sensors and multi-terminal remote control in the sensing and control layer. It adopts data processing techniques to process large amounts of dynamic, geographically distributed, and heterogeneous on-site data in the edge layer. In general, this paper investigates how to use industrial CPS to improve the high reliability and intelligence of the perception and control environment.

The contributions of this paper can be summarized as follows.

1) A multi-sensor fusion vessel perception system, including AISs, radars and cameras for controlled waterways, is proposed. The proposed perception system is centered on edge computing, and all the sensed data is aggregated at the edge center by wired or wireless means. Meanwhile, edge computing provides localized and instantaneous computation for low-latency and location-sensitive data, which can effectively guarantee the quality of sensory data required by IVTSS.

2) To avoid network link vulnerability, a dual-link redundant controller based on 5G/LoRa is developed to provide reliable M2M control for traffic signal systems.

3) To our best knowledge, although CPS-based online monitoring systems are widely used, the applications of maritime IoTs are mainly concentrated in the fields of marine monitoring, environment, and aquaculture [13–16]. Through an extensive literature review, this study is the first work to apply an edge computing-centric sensing and control system-based IoT to promote the service quality of IVTSS. All traffic management and command will be conducted at the traffic command center rather than separately controlled waterway sites.

This paper uses mature data fusion and target detection methods based on deep learning for verification, binds AIS data with other sensor data, and finally sends the fused data to IVTSS in an enhanced AIS data format. Firstly, the polar data of radar is converted into latitude and longitude data, and then the AIS and radar are fused by SAE. Then, the ship's current position is determined more intuitively by matching the AIS information of the vessel in CCTV with a series of electronic fences divided in CCTV. Finally, the enhanced AIS data is sent to IVTSS for command.

The rest of this paper is organized as follows. Section II introduces an overview of the traffic management of the controlled waterway from different perspectives. Section III

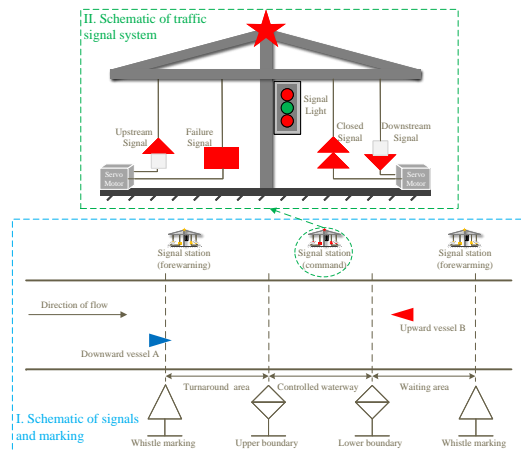


Fig. 1: Schematic of signals and markings in controlled waterway

presents the proposed framework and data fusion methods. In Section IV, a real application case study is carried out to validate the proposed approach. Finally, Section V draws the conclusions and research prospects. Section VI provides the code and model access link.

II. PRELIMINARIES

A. Traffic management in controlled waterways

Controlled waterways are usually narrow, curved, and turbulent sections in the upper Yangtze River [1]. To guarantee safety, only vessels from one direction can pass at a time, whether upstream or downstream. Therefore, the waterway authorities set up signal stations and signal signs at each controlled waterway to guide vessels through.

As shown in Fig. 1 part I, the infrastructure that serves the traffic management of the controlled waterway mainly includes stations, traffic flag/signal systems, and boundary markings. A controlled waterway includes at least one signal station and four signs, namely the upper whistle marking, the upper boundary marking, the lower boundary marking, and the lower whistle marks from upstream to downstream. In some controlled waterways with more complex terrain, only one signal station may not be able to observe vessels outside the whistle markings, and vessels may also be unable to observe the traffic signals. 2 to 3 signal stations must be set up for such controlled waterways. One of the signal stations is the command station, and the rest are defined as forewarning stations to inform the command station of the vessel's situation. The traffic flag/signal system (as shown in Fig. 1 part II) is set up at the signal station and is controlled by IVTSS so that the vessels can see the traffic signals before entering the controlled waterway. The traffic signal system can present four commands: during the day, signal flags present closed, fault, upstream and downstream signals. At night, the above four signals are indicated by a combination of red and green lights.

The basic traffic rules for passage on inland waterways can be summarized as: 1) Vessels should be given passage priority based on the order they arrive at a lock or other narrow

passage point. 2) Downward vessels should avoid turning around in narrow waterways during heavy traffic situations. U-turns mean delays and increased risk of collision and reefing, especially in some narrow waterways where U-turn conditions are unavailable.

B. IVTSS

IVTSS is a decision-making support system for traffic management on a controlled waterway. The basic operation procedures of IVTSS are: 1) receiving AIS data and visualizing it on an electronic river map; 2) calling algorithms to calculate the time when vessels arrive at each boundary line based on AIS data, and issuing recommended commands combined with the basic traffic rules of the controlled waterway to vessels allowed to pass through; 3) automatically executing commands, or executing the commands confirmed by the manager based on an evaluation of the dynamics of the vessel in the controlled waterway; 4) sending the control signals to the traffic signal system to present the corresponding signals; 5) returning the signal state to IVTSS.

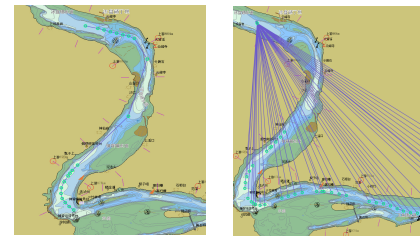
The real-time, correctness, and reliability of the received AIS data are essential for the operation of IVTSS. Therefore, the misjudgment of the traffic state of the waterway resulting from anomalies in AIS data can interfere with traffic management. Meanwhile, anomalies in AIS data can directly reduce the effectiveness of IVTSS. For example, preliminary statistics show that from December 2021 to February 2022, 868 vessels passed through the Shenbeizui controlled waterway, of which 425 were upward vessels and 443 were downward vessels. AIS data anomalies caused 70 misjudgments of IVTSS. Timely and accurate control commands are crucial for traffic safety, security, and operational efficiency. Even a single error is unacceptable. Unreliable vessel sensing data has also become a major obstacle to achieving unattended signal stations and remote control of traffic signal systems.

C. Sensors

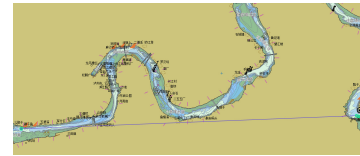
Although AIS, radar and cameras have been widely employed to monitor maritime situations, applying these three techniques to detect and identify vessels on inland waterways automatically can be highly sophisticated. AIS is a transceiver-based communication and reporting system for exchanging position, identification, heading, speed and other data to provide identification/location information to vessels and shore stations. AIS has several advantages over radar, such as providing more information and more accurate dynamic data. It is also considered a primary and low-cost tool for capturing real-time information on the movements of inland river vessels.

The China Maritime Safety Administration stipulates that vessels with 100 tons or more capacity on inland waterways must be equipped with AIS equipment. However, the primary drawback of AIS is the passivity of data collection. Although extensive research has been conducted to address AIS data anomalies, they are still inevitable.

For example, there are three main categories of AIS anomalies commonly found in the Shenbeizui controlled waterway:



(a) Excessively long AIS data transmission interval
(b) Abnormal longitude and latitude coordinates



(c) Data loss

Fig. 2: Examples of AIS data anomalies

1) excessively long AIS data transmission interval (shown in Fig. 2(a)), 2) abnormal longitude and latitude coordinates (shown in Fig. 2 (b)), and 3) data loss (shown in Fig. 2(c)). Only the longitude and latitude anomalies can be solved among the above sensor anomaly issues through data cleaning. The other two issues can be addressed using time series prediction approaches (such as ARIMA and LSTM) when the data missing is not severe. However, adding other sensors can only solve long-term and severely missing data.

Radar, characterized by a wide scanning range, was the first equipment employed to monitor vessels, but it cannot distinguish between different types of vessels. Radar is an active sensor that detects target signals within the scanning area and detects vessels with AIS equipment switched off. Additionally, the scanning cycle of radar is around 3 seconds, which is shorter than the update cycle of AIS. As a result, more precise position data of vessels can be obtained, objectively reflecting the actual trajectory of vessels before and after entering the controlled waterway. However, the quality of radar images and their ability to detect small targets depend mainly on the azimuth and range resolution of the radar. Due to the blind zones caused by surrounding obstructions, such as buildings and trees, the use of radar for monitoring the vessels on inland waterways in mountainous areas is quite limited. Therefore, a combination of radar and AIS networks is typically adopted to monitor maritime traffic.

Since the video monitoring system can provide direct visual images with details of vessels, it has been extensively used to monitor traffic in inland waterways, coastal waters and rivers [17]. With the rapid improvement of machine vision techniques, especially deep neural networks, image-based motion target detection and tracking techniques have triggered widespread attention [18]. Video monitoring systems have become an attractive option to support and supplement radar and AIS. If the camera, AIS and radar are employed together to exploit their respective advantages fully, the detection speed and identification accuracy of vessels can be dramatically

improved. In addition, the sensing device using active capture information is able to detect the vessel when the ship-born AIS device of the passing vessel is artificially switched off. Moreover, through more frequent information feedback for data mining, more quickly find the vessel into illegal or other risky behavior.

III. PROPOSED EDGE-CENTRIC IoT ARCHITECTURE

With the booming development of the e-navigation system and the IoT technology, the Internet of Vessels (IoV) or Internet of Ships (IoS) has been continuously developed to address the numerous difficulties faced by the maritime industry [7]. To significantly improve the safety, effectiveness, and environmental sustainability of the shipping industry, IoV/IoS has been developed, which is an interconnection network of all sensing objects related to vessels, including any physical infrastructure or equipment connected to vessels and ports [7].

IoT is essentially an application-driven network system [19]. Previous studies [20, 21] have presented a variety of IoT architectures aiming at different particular purposes, and these architectures apply to other application scenarios. Based on various IoT architectures adopted in the maritime industry [22, 23], a five layer comprehensive IoT architecture is developed in this study, including the sensing and control layer, heterogeneous network layer, edge computing layer, service layer and application layer.

A. Architecture

The basic requirements for intelligent traffic control in inland controlled waterways are reliable vessel sensing and traffic signal control. Therefore, we introduce IoT to achieve reliable and real-time vessel detection and signal control while considering the characteristics of striped mountainous waterways with limited communication and power resources. In this paper, an edge-centric computing perception and control system based on IoT is established to improve the service quality of IVTSS. There are similarities between the traditional IoT, the IoS, and the proposed IoT, such as the interconnection between intelligent devices and standard architecture components and services. Nevertheless, some key characteristics of the controlled waterways can only be handled through an edge-centric IoT approach. The functions of each layer (system) of the edge-centric IoT architecture are illustrated in Fig. 3. It can be seen from this figure that the proposed edge-centric IoT architecture consists of five layers: sensing and control layer, heterogeneous network layer, edge computing layer, service layer and application layer. Particularly, the sensing and control layer and edge computing layer are only for the controlled waterways. Each subsystem of the proposed system is described in detail as follows.

B. Sensing and control

The sensing subsystem architecture comprises different sensors for measuring the characteristics of different targets. These sensors include vessel dynamic sensors (AIS, radar, and camera), waterway elements sensors (water depth, flow

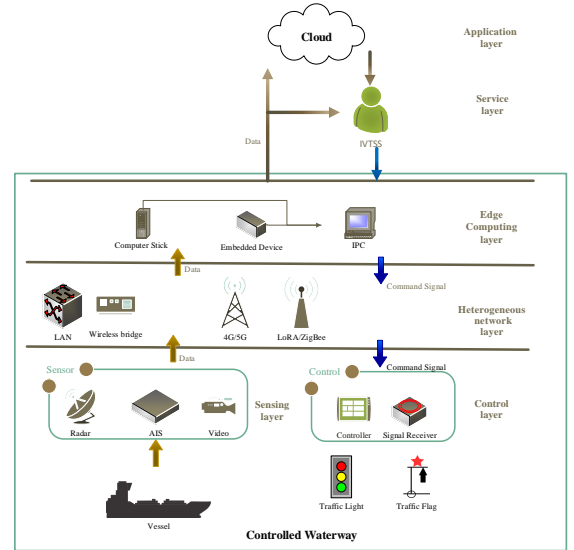


Fig. 3: Overall architecture of edge-centric IoT serving IVTSS

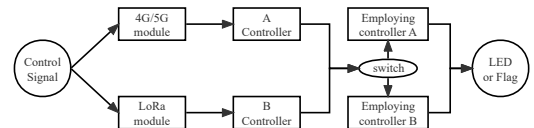


Fig. 4: Schematic of dual-link redundant signal control of traffic signal system

speed, and flow direction), environmental sensors (wind speed, wind direction, visibility, and light intensity), and device health sensors (current and voltage). Most sensors are connected to a low-power embedded processor to capture and decode raw data. The sensor data is transmitted by wired and wireless based on the Message Queuing Telecommunications Transport (MQTT) protocol.

Video monitoring systems usually comprise multiple cameras to provide visual images of the controlled waterway. A wired network or network bridge transfers the video stream to an edge computing device for moving object detection. A large amount of time-sensitive and dynamic data from vessels is first sent to edge computing devices (such as IPC) for fusion analysis, and then, the results will be sent to the Cloud and IVTSS.

Each controlled waterway is equipped with an edge computing device, a signal flag system and three traffic lights, two of which are set at upper whistle and boundary markings respectively to command downward vessels, and one of which is set at lower boundary marking to command upward vessels. Moreover, each traffic light is equipped with a remote control unit. In the signal control subsystem, the control commands from the IVTSS are transmitted to the traffic lights and signal flag systems using the 5G-based IVTSS-to-light loop and the redundant loop using the edge computing device as the LoRa base station, respectively. The schematic of 5G+LoRa dual-link redundant signal control is depicted in Fig. 4.

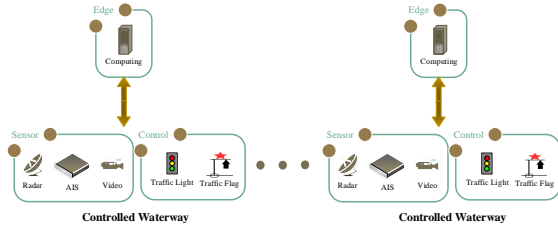


Fig. 5: Edge computing devices are deployed near controlled waterway

C. Edge Computing

In implementing intelligent traffic management, all time-sensitive data and tasks are transmitted between IVTSS and the vessel sensing and control subsystem through the edge computing layer. The edge computing layer can complete the analysis and fusion of multi-sensor data at the edge, thus reducing the cost of data transmission and the pressure of cloud computing. We propose an edge-computing architecture with sensors and actuators placed near the controlled waterways. The edge computing device should have the following functions: 1) it can process real-time dynamic sensor data (position, direction and speed) of the vessel and fusion data obtained by using artificial intelligence (AI) techniques to fuse various sensor data; 2) it can control the traffic signal lights and flag according to the commands of IVTSS (as shown in Fig. 5).

In this study, edge computing is mainly adopted to convert radar data from a polar coordinate system to a geographic coordinate system, fuse radar and AIS data, and process CCTV data. The model chosen for validation in this paper considers more on the infrastructure for deploying projects in production environments. In practical applications, the IPC configuration commonly used by signal stations is a medium performance CPU (Intel Core I5/I7 or AMD Ryzen R5/R7) and an entry-level GPU. If experiments are conducted for scientific research purposes, larger and better performing models can be used, such as using Vivit [24] and Swin transformer [25] in target detection, adding some object tracking algorithms based on these object detection models, such as KCF [26] and SiamMask [27]; Or directly use video processing models, such as Timesformer [28], IDT [29]; In multidimensional data fusion tasks, models with perform better but are larger and require more computing power support can be used, such as Deepsense [30], STGCN [31].

1) *Radar Coordinate System Conversion*: The radar data is converted into longitude and latitude data to fuse with AIS data for trajectory fusion. Many researchers have favored Bessel's geodetic algorithm in surveying and mapping. Its principle is to project the geodesic line of an ellipsoid onto a sphere, forming a large circle. The azimuth angle, arc, and size of any point on the geodesic sphere are equal to the corresponding reduced latitude on the ellipsoid.

Shi et al. [32] discovered that the introduction of the Spherical Sine Theorem to calculate the geodetic key azimuth can achieve higher accuracy. In this method, if the longitude φ_1 , latitude α_1 and geodetic azimuth δ of one point is known,

the longitude φ_2 , latitude α_2 and geodetic azimuth λ of another point can be calculated accordingly. Compared with the original algorithm, the improvement of Shi's method can eliminate the correlation between the accuracy of Bessel's geodetic algorithm and the distance length. Meanwhile, iterative calculation is not required using this method.

The known $X - Y$ rectangular coordinate data of radar can be converted into the longitude and latitude coordinates required in this paper. Suppose the radar coordinates (B_1, L_1) , the current radar azimuth A_1 , and the Geodetic distance S are known. Then, the target coordinates (B_2, L_2) can be obtained through the following radar coordinate transformation formula.

First, the reduced latitude u_1 and the intermediate variable σ_1 can be calculated as

$$\begin{cases} \cos u_1 = \frac{\cos B_1}{\sqrt{1 - e^2 \sin^2 \varphi_1}} \\ \cot \sigma_1 = \frac{\cos u_1 \cos A_1}{\sin u_1} \end{cases} \quad (1)$$

where measure $e^2 = 6.69342 \cdot 10^{-3}$ [33].

Then, the spherical distance can be calculated as:

$$\begin{cases} g = S - (B + C \cos 2\sigma_1) \sin 2\sigma_1 \\ \sigma_0 = g/A \end{cases} \quad (2)$$

where A, B, C are the fixed coefficients can be expressed as $A = 6356863.0189 + (10708.97 - 13.531 \cos^2 A_0) \cos^2 A_0$, $B = (5354.485 - 9.020 \cos^2 A_0) \cos^2 A_0$, $C = (2.255 \cos^2 A_0) \cos^2 A_0 + 0.006$, and the A_0 is defined as $\sin A_0 = \cos u_1 \sin A_1$. The intersection of the extension lines of A_1 and A_2 at the equator is the vertex, and the angle formed by the connection between this vertex and the pole and the extension lines of A_1 and A_2 is A_0 .

Since only medium and long distances are considered in Bessel's geodetic algorithm, the radar installation height can be negligible. This paper assumes that the geodetic distance between the radar and the target is S , and the vertical distance between the radar and the river surface is h . The accuracy improvement method proposed in this study can be rewritten to

$$\begin{cases} S' = \sqrt{S^2 - h^2} \\ g = S' - (B + C \cos 2\sigma_1) \sin 2\sigma_1 \end{cases} \quad (3)$$

When the radar scanning range is $[0, 4,000]$ m, the accuracy can be increased by $[0.0782, 1.5687]$ m after employing (3). This correction value increases as the vessel approaches the radar. High-precision positioning is beneficial for IVTSS to determine whether the vessel has violated regulations or entered the dock.

Then, the spherical length can be calculated as

$$\begin{cases} \sigma = \sigma_0 - (B + 5C \cos 2(\sigma_0 + \sigma_1)) \frac{\sin 2(\sigma_0 + \sigma_1)}{A} \\ \sigma^0 = \frac{g}{A} \rho^0 \end{cases} \quad (4)$$

where $\rho^0 = 57.295779513$ is a measure, the derivations of ρ^0 can be referred to reference [33].

Next, an intermediate variable u_2 needs to be calculated

$$\sin u_2 = \sin u_1 \cos \sigma + \sin A_0 \sin \sigma \quad (5)$$

The latitude of the target coordinates can be expressed as

$$B_2 = \arctan \left[\frac{\sin u_2}{\sqrt{1 - e^2} \sqrt{1 - \sin^2 u_2}} \right] \quad (6)$$

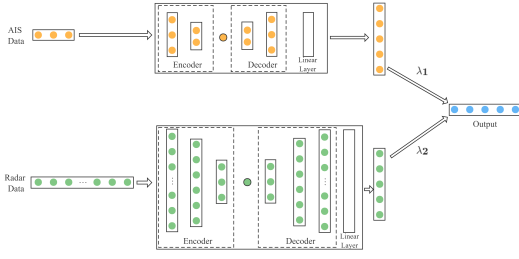


Fig. 6: Principle of SAE

Adopting the method proposed by [32] to get

$$A_2 = \begin{cases} \arccos(\frac{\sin u_1}{\sin \sigma_1}), & (\sin A_2 \geq 0) \\ 2\pi - \arccos(\frac{\sin u_1}{\sin \sigma_1}), & (\sin A_2 < 0) \end{cases} \quad (7)$$

Improved by (7), Bessel's geodetic algorithm can be simplified by not considering coordinate quadrants.

Finally, the longitude of the target coordinates can be written as

$$L_2 = L_1 + \{\alpha\sigma + \beta[\sin 2(\sigma_0 + \sigma_1) - \sin 2\sigma_1]\} \sin A_0 \quad (8)$$

where α, β are as

$$\begin{cases} \alpha = [33523299 - (28189 - 70\cos^2 A_0)\cos^2 A_0] \times 10^{-10} \\ \beta = 14094.3 - 46.8\cos^2 A_0 \times 10^{-10} \end{cases} \quad (9)$$

The abovementioned (B_2, L_2) are the latitude and longitude coordinates of the target captured by the radar, respectively.

2) Trajectory Fusion of AIS Data and Radar Data:

Through a comprehensive method comparison, it is considered that the Stacking Auto-Encoder (SAE) approach can be adopted for data fusion in this study [34]. The algorithm steps are summarized as follows. The working principle of the model is shown in Fig. 6.

As illustrated in Fig. 6, the advantage of SAE is that its fusion process can ignore differences in data timestamps and output data with the same timestamps through corresponding automatic encoder networks and linear layers.

Step 1: The input data can be expressed as

$$v = \{A_{Cog}, A_{Sog}, A_{Lon}, A_{Lat}, A_{Len}, A_{Wid}, A_{Typ}, R_{Cog}, R_{Sog}, R_{Cpa}, R_{Dis}, W_v, W_w, W_f, W_{wl}, W_{wth}, W_l, W_{ss}\} \quad (10)$$

where the input data A_* and R_* represent AIS data and radar data respectively, and the input data W_* is the waterway information. Based on previous laboratory research results, visibility can be determined using a Convolutional Neural Network (CNN) and camera data [35]. Besides, our system can get more information. The SAE model uses the AIS, radar, and other valuable conditions to determine the weight parameters λ_1, λ_2 of SAE fusion outputs.

Step 2: Establishing the SAE model. Generally, the SAE model consists of three layers, including the input layer, hidden layer and reconstruction layer, and it has been proved to be a greedy hierarchical unsupervised model [36]. The SAE is composed of an encoding part and a decoding part. Suppose

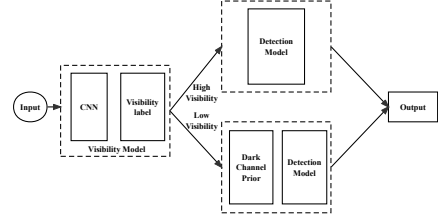


Fig. 7: Proposed video detection process

that the input is x , the encoder output is y , and the decoder output is x' , and then the SAE can be expressed as

$$\begin{cases} y = f(x) = A_e(w_1 x + b_1) \\ x' = g(y) = A_d(w_2 y + b_2) \end{cases} \quad (11)$$

where $f(x)$ represents encoding process, and $g(y)$ is decoding process. w_1, w_2 are the weighted parameter matrixes, b_1, b_2 are bias terms, and A_e, A_d are the activation functions for encoding part and decoding part respectively.

Step 3: Since the alignment of data timestamps is required in this study, we replace the softmax layer with a linear regression layer as the backward stage of SAE.

3) *Video information processing*: The speed of vessels on the inland waterway is about 1-20 knots, and the visual field of monitoring video is more than 200 meters on the river surface. Consequently, even if the vessel is moving downstream at a fast speed, it can still be exposed in the camera's visual field for 20 seconds.

In addition, the monitoring videos can provide users with more intuitive visual observation and identify and track vessels in the video stream through deep learning. The YOLO model has been widely used for video target identification and tracking. It typically includes a set of residual modules, each consisting of several convolutional layers and one residual layer. Reference [37] proposed a Lightweight Ship Detection Model (LSDM) based on YOLO v3 and employed a pyramid network to reduce the number of network parameters. In the present paper, a video detection process based on the YOLO v5 simplified model (YOLO v5s) is proposed to eliminate the negative impact of foggy weather on video quality and achieve more desirable identification and tracking results (shown in Fig. 7).

In the video detection process, according to the visibility identification model proposed in our previous research, the input images are first labeled with visibility level labels [35]. Subsequently, images with low and high visibility are input into target detection models with and without the dark channel prior [38], respectively. This principle can be summarized as

$$J^{dark}(x) = \min_{y \in \Omega(x)} (\min_{c \in r, g, b} J^c(y)), J^{dark} \rightarrow 0 \quad (12)$$

where J^{dark} represents the dark channel. The images can be optimized for target detection through fog removal.

In this paper, the target detection model of the YOLO series is only representative of the later-stage detector that other target detectors can replace. The focus of this paper is to utilize the camera to estimate the visibility of the current section of the river, and accordingly select a dehazing method based on the current visibility. The aim is to improve the edge detection

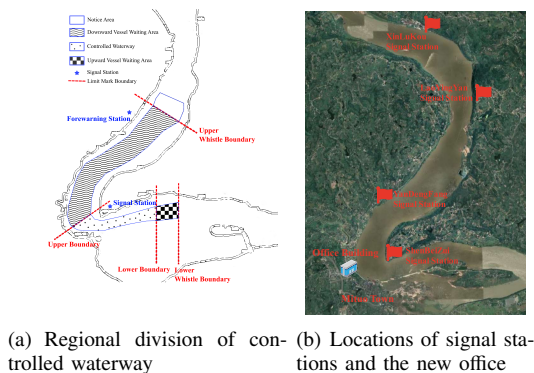


Fig. 8: Example of controlled waterway

architecture of the target detection model. Suppose the IPC computing power can support a larger model. In that case, replacing it with more advanced target detection models such as ViviT [24], DeiT [39] and others will undoubtedly be better.

D. Cloud and IVTSS

The Cloud can provide storage and computing capabilities to handle historical big data transmitted from vessel sensing subsystems and IVTSS. A machine learning model driven by historical data can pressure databases significantly. Data Lakehouse is a new data storage structure that supports synchronous processing of hot and cold data, real-time queries, and using hot data for statistics. It updates models with cold data during the idle time of the server.

To address the issue of data diversity, Data Lakehouse can support mainstream data formats such as XML, JSON, CSV, and binary. Additionally, to store and process a large amount of obtained data, Data Lakehouse typically has API interfaces for big data platforms such as Hadoop, Spark, Kafka, Hive, and TDengine. Moreover, the edge computing layer can provide vessel images, AIS-Radar fusion data and other information to IVTSS.

IV. EXPERIMENTS

In this section, to further demonstrate the proposed system's superiority and engineering application potential, a case study is carried out based on a real application scenario of the Shenbeizui controlled waterway. First, an edge computing-centric sensing and control system is established. Then, the performance of the IoT-based IVTSS is compared with that of the original AIS-based IVTSS.

A. Deployment of Sensors and Actuators

Shenbeizui controlled waterway, a typical waterway in the upper Yangtze River, is jointly commanded by the Shenbeizui signal station and the Yangdengfang signal station, which are the command station and the forecasting station respectively (shown in Fig. 8). In the original AIS-based IVTSS scheme, both signal stations are equipped with AIS, signal control systems, and Very High Frequency (VHF) radios, while IVTSS is only installed at the Shenbeizui signal station.



Fig. 9: Installation sites of radar and camera

Since the office building is higher than the Shenbeizui signal station, the AIS and VHF radios originally deployed at the signal station have been moved to the top of the office building to get a better view. Moreover, a radar (Quantum 2 Solid-state Radar, shown in Fig. 9(a)), an edge computing device and a LoRa-based station are installed at the office building as well.

Additionally, three traffic lights are installed at the upper whistle, upper, and lower boundary. Furthermore, there are four cameras deployed along the controlled waterway. Specifically, one camera deployed at the upper whistle boundary is used to monitor the upstream of the upper whistle boundary (shown in Fig. 1(b)), two cameras deployed on the top of the office building are used to monitor the waterway within the upper and lower boundaries, and another camera deployed at the lower whistle boundary is used to monitor the downstream of the lower whistle boundary. In particular, all staff and IVTSS were relocated to a command center far from the waterway.

B. Multi-sensors Data Fusion

The data fusion of AIS and radar has been extensively applied in navigation, mainly for target detection and tracking [40]. In this study, the Quantum 2 Solid-state Radar produced by Raymarine company has a scanning radius of 4km, covering the Yangtze River waterway mileage line from 878km to 871km centered on the radar installation site. Based on two algorithms [41, 42] improved by this paper, radar echo signals are analyzed and converted into position, distance, speed, heading and other data by edge computing device for fusion with AIS data.

Fusing the latitude and longitude coordinate data scanned by radar with AIS data can improve the density of AIS data. As illustrated in Fig. 10, to exhibit the superiority of the trajectory fusion, we carried out a case study based on a downward vessel sailing from the upper whistle boundary to the upper boundary. This case study has 14 pieces of AIS data and 130 pieces of radar data.

In Fig. 10, the solid blue line represents the result of the trajectory fusion. It is worth mentioning that the proposed fusion model also has certain drawbacks. For instance, if a set of input data used for fusion cannot meet the output requirements, the model will wait until the output requirements are met, resulting in data lag. Meanwhile, this fusion model also can process data without timestamps. The superiorities of the AIS and radar data fusion can be summarized as: 1) it can provide a more reliable data source for the IVTSS

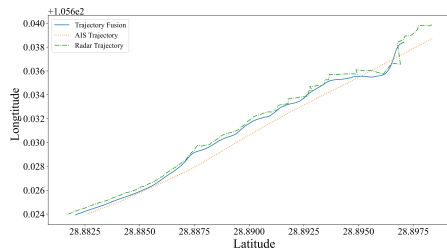


Fig. 10: Effect of AIS and radar data fusion

algorithm module; 2) the AIS and radar data fusion can significantly increase the receiving frequency of data, resulting in a smoother display on the electronic inland waterway chart.

More than 20,000 pieces of data on passing vessels and waterways were collected by manual photography and CCTV, and 3,100 was selected for model training and testing. The comparison results of YOLO v3d and YOLO parameters are summarized in TABLE I.

TABLE I: Comparison of model parameters

	YOLO v3d[37]	YOLO v3d with dark channel prior	YOLO v5s	YOLO v5s with dark channel prior
mAP	0.872	0.883	0.982	0.99
Model size	234MB	236MB	23.8MB	27.1MB
RAM usage	3GB	3GB	140MB	150MB
FPS(CPU)	\	\	5	5
FPS(GPU)	6	6	100	90

In this study, the Graphics Processing Unit (GPU) is 1660TI, and the Central Processing Unit (CPU) is I7-9700. From TABLE I, the number of Frames Per Second (FPS) on the GPU of YOLO v3d is the same as that of YOLO v3d with the dark channel prior, since the average detection speed of each picture increases from 160 ms to 162 ms after adding dark channels to YOLO v3d. The FPS on the CPU of YOLO v5s has a similar situation. Moreover, YOLO v3d cannot run on a separate CPU.

It can be seen from TABLE I that the size of the YOLO v5s model is smaller than that of the YOLO v3d model, and its inference speed of GPU is remarkably higher than that of the YOLO v3d model. The results indicate that YOLO v5s can run without a GPU and consume fewer hardware resources, outperforming YOLO v3d in cost-effectiveness and energy consumption. The video detection effects of the two models with and without dark channel prior are shown in Fig. 11.

As depicted in Fig. 11, when the camera detects vessels entering or leaving the controlled waterway, fusing with AIS data will enhance the video data. Subsequently, the enhanced video data will be transmitted to IVTSS.

C. Results

In this study, we conducted a simulation analysis using IVTSS based on all AIS, radar, and monitoring camera data collected from December 2021 to February 2022. The final simulation results are shown in Table II.

As shown in TABLE II, there were 70 misjudgments of IVTSS caused by AIS data anomalies during the IVTSS

TABLE II: Simulation results

Error type	Command misjudgment	Notification/entry/departure time recording error	Command signal loss
Real system (AIS base) error number	19	51	1
Real system error ratio	2.1889%	2.3600%	0.1152%
System with Radar error number	8	22	0
System with Radar error ratio	0.9217%	1.0180%	0%
System with CCTV error number	10	26	0
System with CCTV error ratio	1.1521%	1.2031%	0%
Our method error number	2	7	0
Our method error ratio	0.2304%	0.3239%	0%

trial run, including 19 and 51 misjudgments resulting from command errors and record errors, respectively. When using our method for simulation, except for two command misjudgments, almost all judgment errors can be eliminated by multi-sensors data fusion. In the experiment, we found that radar and CCTV are almost complementary because the speed of the upward vessel is slow under high load. The radar scanning accuracy used in this paper is low under the condition of the limited budget, which will often lead to the radar misjudging the upward vessel as a stone or a floating object in the river. However, the slow-moving vessel will have a longer time when passing through the CCTV field of view so that the model can have more time and recognition times to identify the vessel, improving the probability of identifying the vessel. Of course, the installation method of the camera also has a specific impact. To obtain a wider field of view of the CCTV, it is suggested tilting the camera angle towards the river direction (ideally, the camera angle should be perpendicular to the river), which causes the ships in the field of view to appear smaller and may to some extent reduce the recognition performance of the model.

It needs to be clarified that these two command misjudgments resulted from the abnormal behavior of the vessel. One abnormal behavior is that a downward vessel stays overnight in the waiting area without entering the controlled waterway, but IVTSS still sends a downward command. Another abnormal behavior is that an upward vessel crosses the lower boundary while waiting for the downward vessel to pass through the controlled waterway, and IVTSS judges that the upward vessel violates the regulations without sending an upward command to the upward vessel. Furthermore, the command-sending mode based on dual-link redundant communication can solve the issue that commands cannot be sent due to the fluctuation of the network. As shown in TABLE II, the multi-sensor perception system composed of radar, AIS, and camera can effectively reduce command misjudgments and time recording errors caused by data source anomalies.

V. DISCUSSION AND CONCLUSION

Online monitoring in maritime supervision and water traffic management is crucial for providing real-time, accurate, and reliable data on channel conditions and vessel motion status for the Traffic Management Center. Furthermore, online monitoring can contribute to improving the service quality of the intelligent transportation system. This paper presents a

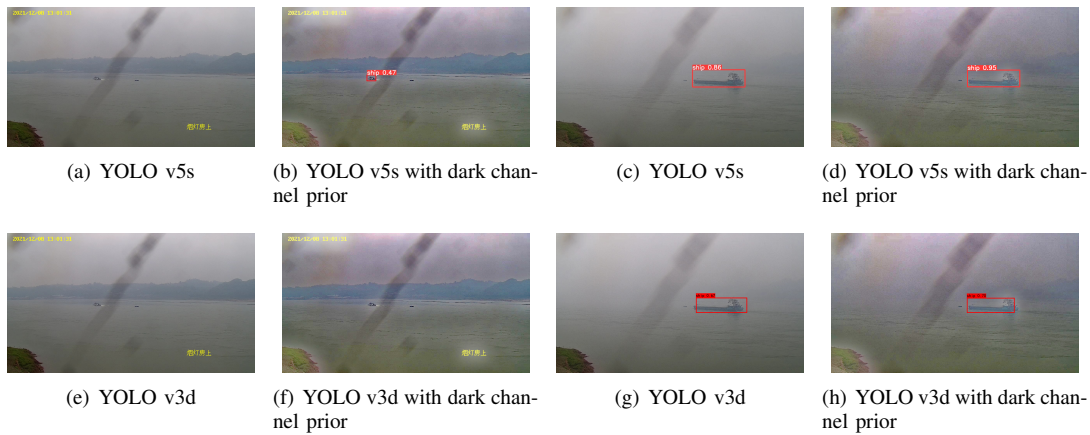


Fig. 11: Video detection effects

vessel motion perception and traffic signal control IoT system based on industrial CPS. The proposed framework innovatively introduces an edge computing-centric perception and control system architecture, multi-sensors data fusion technology, and the dual-link redundant controller. Many dynamic, geographically distributed, and heterogeneous field data are processed at the edge of the data origin.

A case study based on a real application scenario of the Shenbeizui controlled waterway is conducted to compare the performance of IoT-based IVTSS and AIS-based IVTSS. The results demonstrate that the IVTSS based on the proposed IoT architecture reduces the command misjudgment rate and recording error rate by 89% and 86.27%, respectively. The proposed system architecture provides a sufficient real-time and reliability guarantee for the IVTSS's sensing and control requirements. This technology can be well applied to all controlled waterways in the upper Yangtze River to achieve unattended signal stations and intelligent traffic control. In the future, we intend to apply mobile Internet and Big Data analysis technologies to further improve the functionality and performance of IVTSS.

VI. APPENDIX

The code without waterway information and all models adopted in this paper can be accessed through the following link:

<https://gitee.com/LiZeChen-Git/isc-inland-waterway-multi-sensor>

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