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An Unmanned Traffic Command System for Controlled Waterway in Inland River: An Edge-centric IoT Approach*

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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. Consequently, the competent authorities must establish controlled one-way waterways and signal stations to ensure traffic safety. These signal stations are often located in remote and uninhabited mountainous areas, causing great difficulties in the living and working conditions for staff. Therefore, the trend has emerged towards unmanned and remoted traffic command at signal stations. 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.

Keywords: IoT; Multi-sensor; Data fusion; Traffic safety command.

1. Introduction

1.1. *Background*

Yangtze River, the largest river in China, has been the world's busiest inland shipping waterway. 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. These signal stations are often located in remote and uninhabited mountainous areas, causing great difficulties in the living and working conditions for staff. In order to provide employees with a better working environment and reduce work safety risks, intelligent unmanned signaling stations have become a necessary research.

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.

In experimental environment, ITVSS has successfully achieved unmanned command under ideal conditions. However, it has not yet addressed the data perception challenges faced by systems based on AIS for unmanned command. Therefore, when AIS information is abnormal, staff at the signal station need to use binoculars, Very High Frequency (VHF) voice communication, and other means such as telephone communication to conduct waterway traffic management. Thus, this paper proposes a model capable of supporting various tasks and an IoT architecture processing multimodal sensor data, which can provide a richer and more reliable data source for the IVTSS system, thereby enabling the practical implementation of Unmanned Remote IVTSS (UR-IVTSS).

A single AIS signal is not always reliable in complex waterways in mountainous areas, and it often experiences drift, time delay, and loss [3]. 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)

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[4].

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 UR-IVTSS. Therefore, integrating radar and surface visual recognition information [5] with the existing AIS data can significantly improve the vessel perception capabilities of the UR-IVTSS. Meanwhile, a stable communication network is necessary to ensure a safe, efficient, and reliable passage in internal waterways.

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 [6] [7]. Internet of Things (IoT) has become one of the most effective ways to handle the above engineering challenges [8].

1.2. *Related Works*

Several efforts have been made to improve the perception quality of vessels to overcome the poor performance of sensing reliability and data integrity. The identification, recovery, prediction, and reconstruction of abnormal or error AIS data have been widely investigated [9, 10]. However, data anomalies and loss problems still need to be solved.

Guo et al. designed an interpolation method based on vessel motion characteristics to reconstruct ship trajectories in order to overcome noise or missing data in AIS signals [11]. Liang et al. utilized Geohash and dynamic time warping algorithms to restore degraded ship trajectories that were affected by random noise and missing data [12]. El et al. employed Convolutional Neural Networks (CNN) with multi-spectral images (Red Green Blue (RGB) and Infra-Red (IR)) to enhance vessel perception and classification, improving the model's recognition accuracy under low visibility conditions [13]. These methods can mitigate system instability caused by unreliable data to some extent. However, single data source approaches face a significant challenge: when the quality of the data source deteriorates to a certain level or becomes unavailable for an extended period, there is no alternative information source to rely on, making it difficult to achieve reliable traffic management. Therefore, using multimodal data from multiple sensors for waterway traffic management is necessary.

Guo et al. proposed a method for asynchronously fusing AIS ship information with corresponding visual targets to enhance vessel detection capabilities under different weather conditions [14]. Habtemariam et al. proposed a joint probabilistic data association framework that combines AIS and radar information to achieve high-precision vessel target recognition [15]. Wu et al. employed three methodsradar tracking, AIS trajectory tracking, and video image trackingto generate trajectories simultaneously, and then fused these trajectories to enhance vessel detection [16]. These methods are quite similar to the approach proposed in this paper, as they use different information sources in a complementary manner to achieve high-precision vessel target detection under poor signal quality or adverse conditions. However, most research in this area focuses primarily on achieving high-precision target detection, without further applying the detected results.

The applications of maritime IoT based unmanned systems are mainly concentrated in the fields of marine monitoring, environment, and aquaculture [17]. We hope that through this research and practical application, we can extend unmanned intelligent systems into the field of waterway traffic control, providing a feasible IoT framework for smart channel construction and offering more intelligent and stable navigation services.

1.3. *Contributions in This Works*

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 UR-IVTSS.

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

3) This study is the first work to apply the IoT that is based on an edge computing-centric sensing and control system to promote the service quality of IVTSS, successfully achieving unmanned remote applications of IVTSS.

4) With the deployment of the UR-IVTSS system, staff at signal stations no longer need to be stationed in remote, mountainous areas. By centralizing operations in urban areas, this approach not only improves the quality of life for staff and reduces the risk of accidents, but also significantly lowers the workload. In most cases, UR-IVTSS handles traffic command automatically, with human intervention only required during anomalies. Supervisory authorities can also allocate human resources more efficiently and gain a clearer understanding of the traffic conditions on each controlled waterway. This improvement provides valuable data support for the future development of the Yangtze River channel big data platform.

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 UR-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 UR-IVTSS for command.

2. Preliminaries

2.1. *Traffic Management in Controlled Waterways*

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 UR-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.

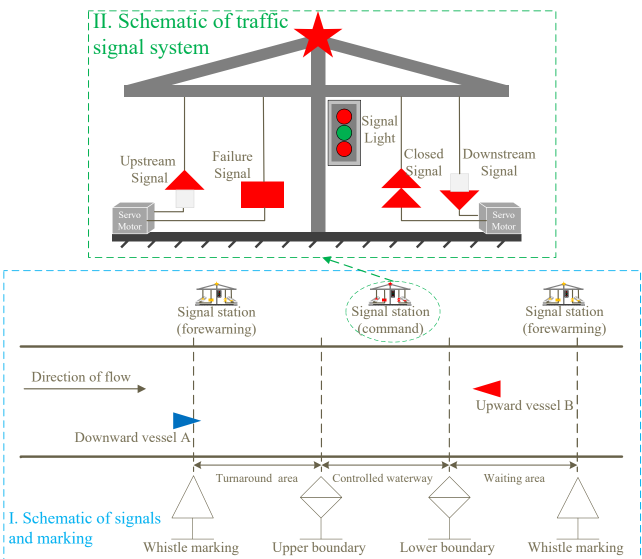


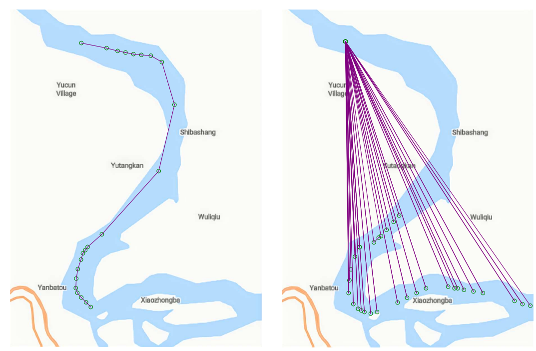
Fig. 1. Schematic of signals and markings in controlled waterway

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.

2.2. *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 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. 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 [18].

For example, there are three main categories of AIS anomalies commonly found in the Shenbeizui controlled waterway: 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)). In Fig. 2, the dots represent the location information contained in the received AIS data, and the purple lines connect the AIS points at two adjacent time points.



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

(c)Data loss

Fig. 2. Cases of abnormal AIS 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. 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.

Since the CCTV can provide direct visual images with details of vessels, it has been extensively used to monitor traffic in inland waterways, coastal waters and rivers [19]. CCTV have become an attractive option to support and supplement radar and AIS. If the CCTV, AIS and radar are employed together to exploit their respective advantages fully, the detection speed and identification accuracy of vessels can be dramatically improved.

3. Proposed Edge-centric IoT Architecture

In this section, the designed Iot framework is showed at first. This framework is capable of processing multi-modal data at the edge and then transmitting it to the cloud and human-computer interaction terminals, reducing the bandwidth required for data transmission and cloud computing resources in the command system. After that, we introduce the data flow of data sensing and control one by one. Finally, we extract all the sensor data required by considering the characteristics of various waterway traffic control scenarios. Combined with the cloud-edge-device IoT framework proposed in this paper and through data processing techniques, this approach enables intelligent remote unmanned command.

3.1. *Architecture*

In this paper, an edge-centric computing perception and control system based on IoT is established to improve the service quality of UR-IVTSS. There are similarities between the traditional IoT 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.

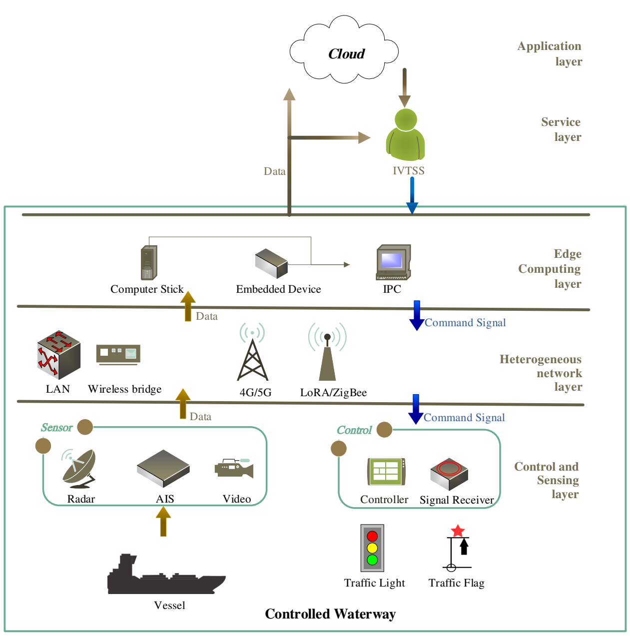


Fig. 3. Overall architecture of edge-centric IoT serving UR-IVTSS

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.

3.2. *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 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.

MQTT is a message subscribe/publish protocol based on the ISO/IEC PRF 20922 standard. It works on the TCP/IP protocol. MQTT is designed for remote devices in low hardware performance and poor network conditions, and is widely used in the Internet of Things due to its lightweight, simplicity, openness, and ease of implementation [20]. In this study, there are self-developed embedded software and host computer software that will select different programming languages due to the varying performance and requirements. The communication between different software relies on standard communication protocols. To use analogous means to simply illustrate this, the information that needs to be passed between different devices is the goods that need to be transported; 4G/5G, ZigBee or LoRA transport networks are equivalent to a road; MQTT is equivalent to a truck transporting the goods.

Each controlled waterway is equipped with an edge computing device, a signal flag system and three traffic flights, 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 UR-IVTSS are transmitted to the traffic lights and signal flag systems using the 5G-based UR-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.

3.3. *Edge 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 UR-IVTSS. (as shown in Fig. 5).

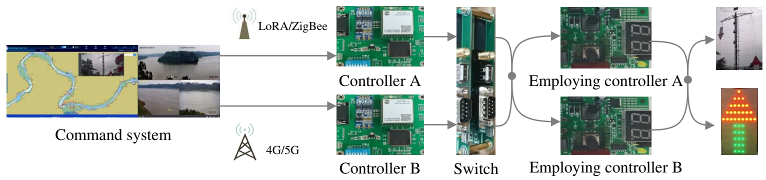


Fig. 4. Schematic of dual-link redundant signal control of traffic signal system

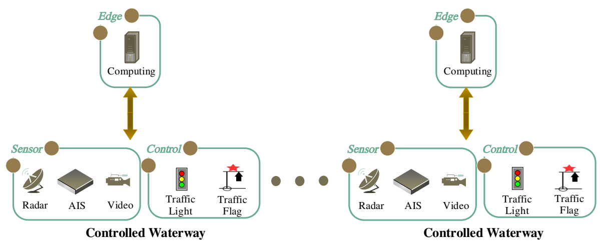


Fig. 5. Edge computing devices are deployed near controlled waterway

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.

3.3.1. *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. [21] 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

$$\begin{cases} cosu_1 = \frac{cosB_1}{\sqrt{1-e^2 sin^2\varphi_1}} \\ cot\sigma_1 = \frac{cosu_1 cosA_1}{sinu_1} \end{cases} \tag{1}$$

where measure $e^2 = 6.69342 \cdot 10^{-3}$ [22].

Then, the spherical distance can be calculated as:

$$\begin{cases} g = S - (B + Ccos2\sigma_1)sin2\sigma_1 \\ \sigma_0 = g/A \end{cases} \tag{2}$$

where A, B, C are the fixed coefficients can be expressed as $A = 6356863.0189 + (10708.97 - 13.531cos^2A_0)cos^2A_0$, $B = (5354.485 - 9.020cos^2A_0)cos^2A_0$, $C = (2.255cos^2A_0)cos^2A_0 + 0.006$, and the A_0 is defined as $sinA_0 = cosu_1 sinA_1$. 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

$$\begin{cases} S' = \sqrt{S^2 - h^2} \\ g = S' - (B + Ccos2\sigma_1)sin2\sigma_1 \end{cases} \tag{3}$$

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 UR-IVTSS to determine whether the vessel has violated regulations or entered the dock.

Then, the spherical length can be calculated as

$$\begin{cases} \sigma = \sigma_0 - (B + 5C \cdot cos2(\sigma_0 + \sigma_1))\frac{sin2(\sigma_0+\sigma_1)}{A} \\ \sigma^0 = \frac{g}{A}\rho^0 \end{cases} \tag{4}$$

where $\rho^0 = 57.295779513$ is a measurement, the formula derivation of e and ρ^0 can be referred to [22].

Next, an intermediate variable u_2 need to be calculated

$$sinu_2 = sinu_1 cos\sigma + cosu_1 cosA_1 sin\sigma \tag{5}$$

The latitude of the target coordinates can be expressed as

$$B_2 = arctan[\frac{sinu_2}{\sqrt{1-e^2}\sqrt{1-sin^2u_2}}] \tag{6}$$

Adopting the method proposed by Shi et al. to get the following equation

$$A_2 = \begin{cases} arccos(\frac{sinu_1}{sin\sigma_1}) & (sinA_2 \leq 0) \\ 2\pi - arccos(\frac{sinu_1}{sin\sigma_1}) & (sinA_2 < 0) \end{cases} \tag{7}$$

Improve by (7), the Bessel's geodetic algorithm can be simplified by not considering the coordinate quadrant.

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

$$L_2 = L_1 + \{\alpha\sigma + \beta[sin2(\sigma_0 + \sigma_1) - sin2\sigma_1]\}sinA_0 \tag{8}$$

where α, β are as follows

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

The above-mentioned (B_2, L_2) are the latitude and longitude coordinates of the target captured by the radar.

3.3.2. *AIS Data Processing*

AIS, as the most widely used data source in the field of water transportation [23], is also the most crucial data source for inland waterway traffic control. In this paper, we have performed a certain level of preprocessing on AIS data. A deep learning model is used to address issues such as AIS data loss, anomalies in vessel speed, and irregularities in the latitude and longitude data. Additionally, the original AIS signals from non-stationary, irregular sequence signals is converted into non-stationary, irregular time series signals to facilitate model training [18].

The preprocessing steps for AIS data during the training process can be described as follows:

Step 1: Assuming we have a complete AIS trajectory, denoted as N = n1, n2,..., nn, and the Deep Temporal Clustering (DTC) block [24] is applied to process this trajectory. The principle of the DTC block involves using convolutional transformations to extract semantic features from the data, introducing non-linear changes through an activation function, and finally mapping and outputting the data via a linear layer. These blocks are stackable, but in this paper, we utilize a single-layer DTC block constructed with 1D convolution, a Rectified Linear Unit (ReLU) activation function, and a single linear layer. Given the complexity of the transformation process, we represent the transformation performed by the DTC block as $DTC()$. The preliminary transformation using the DTC block can be described as

$$N' = DTC(N) \tag{10}$$

Step 2: The output of this model consists of multiple adjacent sliding window datasets. Each dataset is connected to the final dataset to compute the Kullback-Leibler (KL) divergence. The purpose of calculating the KL divergence is to conveniently understand changes in navigation states and identify boundaries of state transitions. To express this mathematically

$$C_{boundary} = KL(N') \tag{11}$$

where $C_{boundary}$ is a sequence. Each element in the sequence contains information about the AIS data belonging to that category, computed based on the KL divergence.

Step 3: This step includes using cubic spline interpolation within the same category of AIS data and organizing the interpolated values back into the format used for the original AIS data.

During the inference process, we apply a traditional threshold-based method to filter the AIS data based on vessel speed and position. No additional data processing was performed; the filtered data was directly fed into the fusion model for application.

3.3.3. *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 [25]. The algorithm steps are summarized as follows. The working principle of the model is shown in Fig. 6.

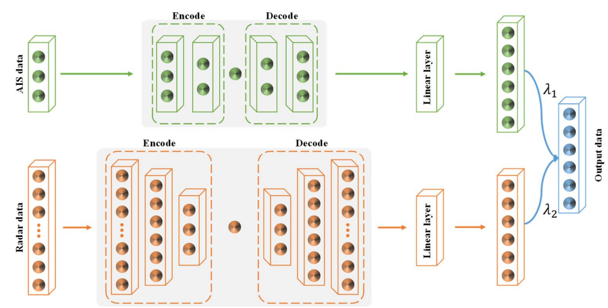


Fig. 6. Principle of SAE

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

$$\begin{aligned} v = \{&A_{Cog}, A_{Sog}, A_{Lon}, A_{Lat}, A_{Len}, A_{Wid}, A_{Typ}, \\ &R_{Cog}, R_{Sog}, R_{Lon}, R_{Lat}, \\ &W_v, W_w, W_f, W_{wl}, W_{wth}, W_l, W_{ss}\} \end{aligned} \tag{12}$$

where the input data A_* and R_* are AIS and radar data, the input data W_* are waterways information.

Step 2: Establishing the SAE model. The SAE is composed of an encoding part and a decoding part. Suppose that the input is x, the encoder output is y, and the decoder output is x', and then the SAE can be expressed as

$$\begin{cases} y = f(x) = A_e(w_1x + b_1) \\ x' = g(y) = A_d(w_xy + b_2) \end{cases} \tag{13}$$

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.

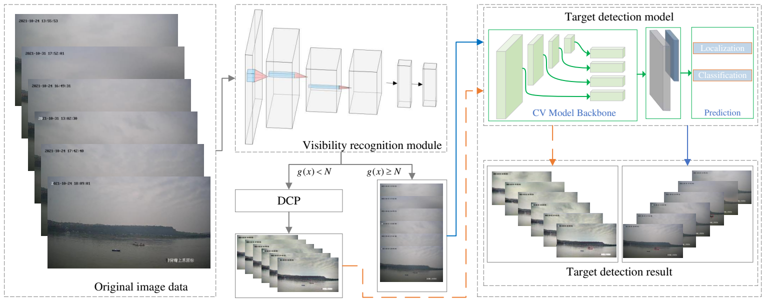


Fig. 7. Proposed target detection process

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.

3.3.4. *Video information processing*

This paper proposes an image-based pre-training module for visibility recognition. Through this model, it aims to eliminate the negative impact of heavy fog on video quality, achieving more ideal recognition 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 [26]. Subsequently, images with low and high visibility are input into target detection models with and without the Dark Channel Prior (DCP) [27], respectively. This principle can be summarized as

$$J^{dark}(x) = min_{y\in\Omega(x)}(min_{c\in r,g,b}J^{c}(y)), J^{dark} \to 0 \tag{14}$$

where J^{dark} represents the dark channel. The images can be optimized for target detection through fog removal. The complete image processing workflow can be expressed as

$$y(x) = \begin{cases} f(x), g(x) \geq N \\ f(J^{dark}(x)), else \end{cases} \tag{15}$$

where $g(\cdot)$ is the process of visibility recognition, N represents the preset visibility threshold, $f(\cdot)$ stands for the target detection process, and $y(\cdot)$ represents the result.

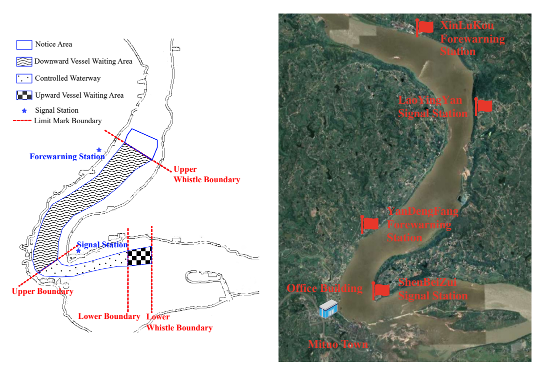
In this paper, the target detection model is only representative of the later-stage detector that other target detectors can replace. To ensure the validity of our experiments, we selected representative models based on CNN (faster RCNN [28]), darkNet (YOLOv5s [29], YOLOX [30]), Transformer (DDQ-DETR [31]), some difficult-to-categorize methods (TOOD [32]) and peer comparison (Lightweight Ship Detection Model (LSDM) [33]) to conduct the experiments in this paper. 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 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 will undoubtedly be better.

4. 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 UR-IVTSS is compared with that of the original AIS-based UR-IVTSS.

4.1. *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 UR-IVTSS scheme, both signal stations are equipped with AIS, signal control systems, and VHF radios, while UR-IVTSS is only installed at the Shenbeizui signal station.



(a)Regional division of controlled waterway (b)Locations of signal stations and the new office

Fig. 8. Example of controlled waterway

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 (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 UR-IVTSS were relocated to a command center far from the waterway.

(a)Radar

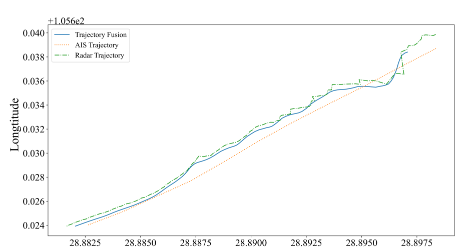
(b)CCTV

Fig. 9. Installation sites of radar and camera

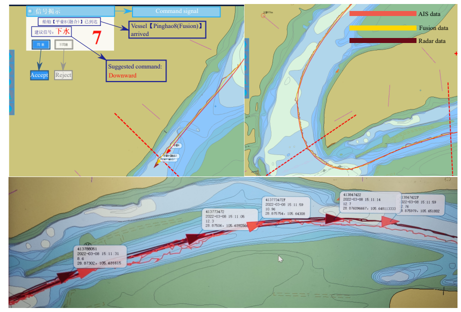
4.2. *Multi-sensors Data Fusion*

The data fusion of AIS and radar has been extensively applied in navigation, mainly for target detection and tracking [34]. 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 [15] 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.



(a)Data Fusion Experiment



(b)Actual machine results of trajectory fusion

Fig. 10. Effect of AIS and radar data fusion

Fig. 10(a) illustrates the data fusion effect in an experimental environment, while Fig. 10(b) demonstrates the data fusion effect in an actual machine system. In Fig. 10(b), the upper left image shows the effect of traffic command using fused signals, the upper right image represents the result of trajectory fusion, and the lower image displays the data fusion results during real-time tracking. Please note that in the upper left image of Fig. 10(b), the system is in an unmanned automatic command mode, hence the red digital countdown displayed. When the countdown reaches zero and there is no manual intervention, the system will automatically send the recommended command signal.

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 UR-IVTSS 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 experiments conducted in this study were all based on the recommended hyper-parameters and pre-trained model (utilizing ResNet50 [35] as the backbone, LSDM use DarkNet53 [36]) by the authors of the original paper, and without the adjustment of hyperparameters. The comparison results of target detection parameters are summarized in TABLE 1, all models exhibit significant growth in the "mAP 50" metric. YOLO v5s appears to outperform other models due to the targeted hyperparameter tuning conducted specifically for it during previous submission rounds. In the "mAP 50:90" metric, the TOOD model experiences a decline. Upon a detailed examination of the test outputs on a per-sample basis, we discovered that this decline is attributed to the TOOD model's higher tendency to misclassify the riverbank area as ships compared to other models.

The video detection effects of the models in ours study with and without DCP 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

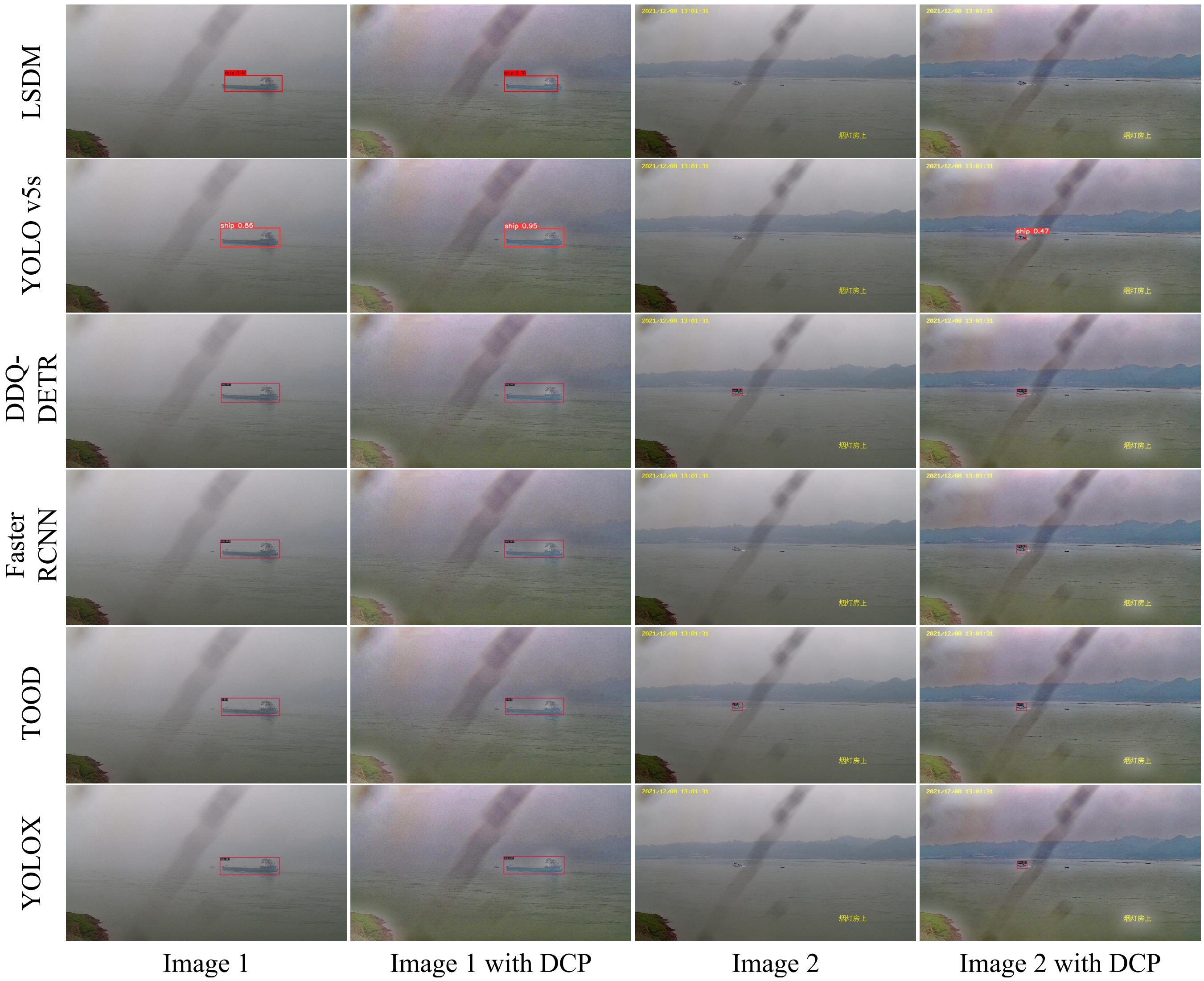


Fig. 11. Target detection effects

will enhance the video data. Subsequently, the enhanced video data will be transmitted to UR-IVTSS.

Table 1. Comparative Effectiveness of Target Detection Models

	Original image		Image preprocessing with ours methond	
	mAP 50	mAP 50:95	mAP 50	mAP 50:95
LSDM [33]	0.872	0.594	0.883	0.624
YOLO v5s [29]	**0.982**	**0.756**	**0.990**	**0.765**
DDQ-DETR [31]	0.939	0.744	0.973	0.756
Faster RCNN [28]	0.930	0.710	0.933	0.730
TOOD [32]	0.927	0.735	0.937	0.725
YOLOX [30]	0.945	0.660	0.959	0.708

4.3. *Results*

In this study, we conducted a simulation analysis using UR-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 2.

As shown in TABLE 2, there were 70 misjudgments of UR-IVTSS caused by AIS data anomalies during the UR-IVTSS 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.

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

Table 2. 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%

the waiting area without entering the controlled waterway, but UR-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 UR-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 2, 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.

In summary, the edge-centric IoT architecture proposed in this paper is capable of accommodating multiple artificial intelligence models for different tasks. By utilizing data obtained during the trial runs for replay and simulation, it addresses most of the issues encountered in the traffic control process on the upper reaches of the Yangtze River, such as erroneous commands, incorrect recording of entry/departure times, and unresponsive command instructions.

5. Discussion

During the trial operation phase of the project, we also discovered some additional conclusions. We found that radar and CCTV are almost complementary data sources. This is because, under high load conditions, upward vessels move very slowly. The radar scanning accuracy used in this paper is low under the condition of the limited budget, which often leads to the fact that the radar misjudges the upward vessel as a stone or a floating object in the river. During the trial operation of the system, we also tested a kind of high-precision radar, which are quite expensive. These radar effectively addressed the issue of radar misidentification of slow-moving vessels. However, its high cost is nearly equivalent to the entire budget for the complete system. Additionally, these radars cannot resolve the scanning blind spots caused by obstructions such as mountains and trees.

Slow-moving vessels are exposed to the CCTV field of view for a longer duration. Consequently, this results in bigger opportunities for the model to detect and identify the vessel, thereby increasing the probability of accurate vessel recognition. Indeed, the installation method of CCTV cameras also has a significant impact. Currently, to achieve a wider field of view, cameras are often angled towards the river. Ideally, cameras should be positioned perpendicular to the river. Angling the cameras towards the river can make vessels appear smaller in the field of view, which may somewhat reduce the models recognition performance.

Regarding the command mistakes caused by certain vessel abnormal behaviors, after consulting with five staff members who have over three years of experience in controlling river traffic, and tracking the trial operation for over three months, we have summarized some potential handling methods and future research directions. Generally, vessels are aware that their abnormal operations can pose traffic risks. Therefore, in most cases, vessels use VHF radio to communicate with signal stations when performing risky maneuvers. If the UR-IVTSS system were equipped with speech recognition capabilities, it could quickly and accurately identify imminent abnormal operations from voice information. This might provide a faster and more reliable method for detecting vessel anomalies compared to using AIS, radar, and CCTV data.

6. 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 vessel motion perception and unmanned traffic signal control system based on edge-centric IoT. 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 UR-IVTSS and AIS-based UR-IVTSS. The results demonstrate that the UR-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 UR-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 UR-IVTSS.

7. 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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