A New Multi-Sensor Fusion Approach for Integrated Ship Motion Perception in Inland Waterways

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Abstract

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Full Text

Preamble

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Abstract: The ship motion perception approaches mainly use maritime radar, Automatic Identification System (AIS) and cameras. However, using either of these approaches alone may result in information inconsistency and insufficient data accuracy. Therefore, a multi-sensor fusion perception system is proposed in this study to monitor ship motion in inland waterways. Firstly, a hardware platform of multi-sensor fusion ship motion perception system composed of maritime radar, AIS, cameras and other accessories is constructed. Secondly, by utilizing the target detection and tracking algorithms, track association algorithms, the ship motion data collected from the three sensors are integrated. Finally, the performance of the ship motion perception system is verified by field experiments in day and night. The experimental results indicate that the integrated ship motion perception system with multiple sensors is able to improve the information consistency and data accuracy of ship motion apparently in inland waterway compared to other perception systems.

Keywords: motion perception; maritime radar; AIS; target detection and tracking; information fusion

1. Introduction

Ship motion perception is of great importance in maritime supervision and port traffic management. It is the fundamental procedure of analyzing maritime traffic conditions, supervising the illegal behavior of ships and ensuring the ship traffic flow and safety in port waterways. Hence, it has always been a hot topic in the field of maritime traffic engineering.

Ship motion perception data can benefit maritime study in many aspects. In legal applications, it can help legislators formulate ship traffic regulations scientifically and provide a reference for maritime regulators to judge the traffic status [1-3]. For crew members, it can provide empirical rules for ship navigation and manipulation, reducing the uncertainty of driver judgment regarding ship traffic state under encounter conditions [4]. For maritime regulators, it can be used to grasp the methods, characteristics and laws of ship manipulation and collision avoidance at the micro level, and identify existing problems [5]; it can provide theoretical and data support for the development of navigational aids and equipment [6]. From the perspective of ship operation, it can be used to predict sailing time and assist in port scheduling and operation [7]; it can be associated with ship emissions to formulate optimal sailing routes and navigation plans [8].

In this study, a multi-sensor fusion ship motion perception system based on radar, AIS data and cameras is proposed for inland waterways. Compared with traditional methods using a single type of sensor, the proposed system can overcome the poor performances of sensing reliability and data integrity that existed in the traditional methods, and can collect ship navigation data more comprehensively and accurately in real time. The rest of the paper is organized as follows: Section 2 reviews existing ship motion perception technology. Section 3 describes the configuration of the system from the perspectives of hardware and software in detail. Section 4 presents field experiments to evaluate and verify the performance of the system. Finally, Section 5 discusses the potential advantages and limitations of the system.

2. Related Work

Inland rivers and port channels have high traffic density, which leads to frequent ship encounters and collision avoidance decisions based on ship motion perception. The main facilities used in ship motion perception in inland rivers and port waters are maritime radar, AIS and cameras.

Among these facilities, maritime radar was the first to be used. One challenge of detecting ship targets using radar is solving the problem of clutter adaptive filtering in the procedure of signal processing [9]. The output format of maritime radar data is radar wave reflection images that contain massive irrelevant objects such as bridges, coastlines, islands and buoys, which significantly increases the difficulty of ship recognition. Ma et al. [10,11] proposed a radar target extraction method based on multi-evidence fusion by analyzing the inherent speed, heading and position laws of ships in motion to increase radar image recognition ability. He et al. [12] proposed a target recognition algorithm based on improved FCM according to ship motion characteristics and the shadow length of moving ships in radar images, which achieved higher recognition accuracy than traditional object detection algorithms. Nerea et al. [13] applied artificial intelligence technology to the detection of small and medium-sized ship targets in sea-clutter environments and designed a neural network training set for approaching Neyman-Pearson detector.

AIS is a maritime communication device using the very high frequency (VHF) radio broadcasting system, which is helpful for message transmission between ships and shore-based monitoring [14]. AIS data includes static information such as ship name, type, and size, as well as dynamic information such as ship position (longitude and latitude), speed and course. The transmission interval of dynamic information of shipborne AIS equipment changes according to the navigation status of the ship, which is usually 6 seconds (Class A) and 10 seconds (Class B). Due to its working mechanism, AIS information transmission is easily affected by terrain [15], transmission distance [16] and ship density [17], resulting in error, loss, or forgery of information [18]. Thus, it is necessary to carry out error data identification and repair work [19,20]. With rich information, AIS data has become the main data source for ship behavior research [21-23].

Video monitoring cameras can collect images within 1 km and are often used as a supplement for monitoring key water areas. They can reduce the on-site patrol frequency of maritime supervisors and save response time after danger, but staff on duty need to stare at video screens 24 hours. With the development of image processing technology, more image processing technologies have been used for ship target tracking and recognition in video images [24,25]. Cao et al. [26] proposed a ship recognition method based on Morphological Watershed Image Segmentation and Zernike moment. In marine ship target detection, a large number of clutters in the video background significantly impact the detection effect. Chen et al. [27] used the characteristics of Gaussian mixture model (GMM) to judge whether new pixels in the video belong to the foreground and used background subtraction for moving ship detection. With the advance of deep neural networks in image recognition, their application in ship target recognition is also becoming more popular. Huang et al. [28] proposed an image target detection method based on YOLOv3, and the model was trained and verified with the ship dataset. Ren et al. [29] proposed a ship recognition method based on Hu invariant moment and convolutional neural network (CNN) by using the characteristics of Hu invariant moment of image. In ship motion perception systems, not only must targets be detected, but they must also be tracked. There are two kinds of traditional target tracking approaches: generative-based method and discriminative-based method. Common generative-based tracking algorithms include particle filter [30], mean shift [31], Kalman filter [32] and feature-based tracking. However, in the process of target tracking, target features are usually similar to the background, and only modeling the tracking target can no longer meet the requirement of the target tracking task. Wang Naiyan proposed the DLT [33] algorithm based on deep learning technology in the field of target tracking, which showed that deep learning technology can achieve more accurate results than traditional methods in target tracking. Ma et al. [34] proposed a target tracking method that combines deep learning and correlation filtering and achieved remarkable results; David adopted a deep learning framework in 2016, which is the first time that deep learning-based target tracking has achieved over 100 frames per second [35].

Although maritime radar, AIS and video monitoring cameras mentioned above have many applications, the accuracy and content integrity of ship navigation dynamic data sensed by only one of them is still insufficient. It is hard to distinguish moving objects with sailing ships via radar images and AIS can be interfered by broadcast radio or buildings nearby the inland channel. In contrast, using an integrated ship motion perception system with multiple sensing facilities can obtain more accurate and consistent data based on information fusion. Radar and AIS can work together very well because their information complements each other. Habtemariam et al. [36] analyzed the characteristics of AIS and radar sensor data and proposed a measurement level fusion algorithm of radar and AIS information based on Joint Probabilistic Data Association (JPDA) framework, which solved the uncertainty in AIS target tracking allocation through Bayesian inference. Liu et al. [37] proposed a data association algorithm based on multi-factor fuzzy judgment and grey correlation analysis to improve the correct correlation between AIS system and radar target. Cao et al. [38] used standard deviation to normalize the preselected data, then used a backpropagation (BP) algorithm to adjust the weight and threshold of trajectory correlation cost function; the proposed methods can improve the accuracy of AIS system and radar tracking. However, these two kinds of sensor data are not as intuitive as video surveillance images, and the verifiability of fusion results is not good either.

The ship motion perception system has evolved from the most primitive manual method to the current AIS system, radar, electronic chart and other technical methods, which greatly improves the safety of ships and the level of collaborative management of ships. Recently, the ship motion perception system based on computer vision is an effective supplement to the existing system. However, existing research is mostly based on the SAR ship dataset, which is different from the application scenarios of ship motion perception. Target tracking is a vital part of ship motion perception. The method has developed from traditional Kalman filtering, Mean shift, etc. to correlation filtering and deep learning methods. For ship target tracking, the sea surface conditions are complex, and there are problems regarding target occlusion and ambiguity, which are difficult to solve by traditional methods. Additionally, there are relatively few researches on the fusion of vision and other ship motion perception, and research on information fusion of AIS, radar, and electronic chart is still the mainstream. How to associate, match and fuse the multi-target information of visual perception with radar and AIS-perceived multi-target information still needs to be further explored.

Aiming at the demands of ship motion perception in inland river and port waters, this research adds camera as an information source on the basis of radar and AIS data. The addition of cameras can provide new continuous tracking information of ship targets for supervisors. Moreover, by utilizing the target detection and tracking algorithms, the ship motion data collected from the three sensors are integrated to strengthen the accuracy of information fusion, which is helpful for supervisors of inland waterways to verify the type of ship, construct a closed-loop of tracking and make decisions.

3. System Configuration

The configuration of multi-sensor information fusion system is described in two parts: hardware and software. Hardware including AIS, Radar and Cameras modules are introduced in Section 3.1. Software algorithms using for ship motion recognizing, tracking and fusion on the basis of above hardware module are illustrated in Section 3.2.

3.1. Hardware

As shown in Figure 1 [Figure 1: see original paper], the multi-sensor ship motion perception system proposed in this paper mainly consists of a CWFM Solid-state Radar (SIMRAD, 4G), an AIS terminal (ZYE, ZY-1000), a camera (Hikvision, DS-2CD6A64), an industrial computer for data processing and so on. Among them, the radar obtains the radar echo image data of the surrounding navigation environment and ships in real-time. The AIS receiver receives the AIS message broadcast by surrounding ships and obtains navigation information such as the positioning, speed and navigation of the sailing ship. The camera collects video information of nearby ships to identify ship type, azimuth, distance, etc. The computer is responsible for collecting, processing and fusing the data output by radar, AIS, video camera and other sensors. The modules of radar, AIS and camera are introduced in detail as follows.

Radar module: The system uses a SIMRAD 4G FM CW Solid-state Radar, and its detection range is between 1/32 to 36 nm. Doppler beam sharpening is used to improve the radar resolution. At the same time, FM continuous wave technology is also used to improve the accuracy of distance information measurement. Finally, high-precision perception and recognition are achieved for the range, azimuth, motion speed and other parameters of ship targets within the monitoring area. The data output format of radar is picture, and the data interval is 2 seconds.

AIS module: The AIS mode used in the system meets the relevant standards of AIS Class B. It can receive data related to ship navigation safety in real-time, and provide relevant AIS data for port and shore management, ship warning, collision avoidance, and ship supervision. The data output format of AIS equipment is text, and the data interval is from 30 seconds to 3 minutes.

Camera module: The system adopts Hikvision 24 million ring eagle eye DS-2CD6A64 series camera. The camera consists of four horizontally spliced camera modules, forming a viewing angle of 180° in horizontal and 80° in vertical. The four camera modules are hoisted at the lower end of the holder, which can rotate with the holder in the horizontal direction of -90°~90°, and swing with the holder in the vertical direction of -45°~90°. Due to the ultra-wide viewing angle, the camera is precisely suitable for image monitoring in a wide water area. The data output format of the camera is video frame, and the frame interval is 1/60 seconds.

3.2. Software

The software algorithm of the multi-sensor information fusion method adopts a distributed architecture shown in Figure 2 [Figure 2: see original paper]. The algorithm is mainly composed of four modules. The first is the image recognition and tracking module, which recognizes and classifies the ship image, tracks it, and outputs the image target features. The second is AIS data processing module, which analyzes and denoises the ship' s AIS information, subcontracts the data according to MMSI code, and outputs the AIS target motion characteristics. The third is the radar target recognition and tracking module, which outputs the target characteristics of radar images. The fourth part is the target information fusion module, which outputs the target fusion features after data registration, fuzzy evaluation and track correlation. Software algorithms are demonstrated in detail as follows.

3.2.1. Target Recognition The target recognition system is described in two parts: ship image recognition and radar image recognition.

Ship image target recognition: The ship image target recognition is responsible for obtaining the pixel position, area size, target reliability and target classification of ship image target, and it adopts Darknet network model based on YOLOv3 deep learning framework algorithm. Darknet deep learning framework is an open-source neural network framework proposed by Joseph Redmon, and YOLO (You Only Look Once) is the core target detection algorithm for this framework. In the YOLO algorithm, the object detection problem is treated as a regression problem. The bounding box and the probability of category can be directly predicted from the input image with a convolutional neural network structure. This method improves the basic classification network structure and the two classification prediction method of targets in traditional deep learning, and realizes ship tracking and ship type recognition. The real-time ship tracking and recognition algorithm based on Darknet network and YOLOv3 algorithm achieves the balance of speed and accuracy. The flow chart of the algorithm is shown in Figure 3 [Figure 3: see original paper].

Ship radar target recognition: The radar target recognition module in inland river and port waters firstly sets the capture area, eliminates the coastline and navigation buildings, and retains only the accessible area of ships. When the position of the target falls into the capture area, the moving target ship is detected by image processing methods such as background difference method, image morphological processing and median filtering. The process of target acquisition is an essential part of the process of track initiation. The track initiation algorithm based on M/N logic shown in Figure 4 [Figure 4: see original paper] is adopted. In N consecutive scanning cycles, when the number of detections meeting the threshold conditions in the time window reaches a specific value M, the track initiation is successful; otherwise, keep the number of time windows unchanged and move one scanning time in the direction of time increases.

3.2.2. Target Tracking The target tracking process is composed of ship AIS trajectory tracking, ship radar track tracking, and ship image target tracking, with details presented as follows.

Ship AIS trajectory tracking: According to Maritime Mobile Service Identities (MMSI), the navigation track data of the same ship should be subcontracted. For discontinuous navigation ships such as ferries and official ships, the tracks of the same MMSI code with a time interval greater than a certain threshold value shall be segmented to ensure the continuous and stable navigation data of each ship section. Finally, the single-day ship trajectory data can be extracted.

Ship radar track tracking: Ship radar target tracking mode mainly includes target acquisition, track correlation, and filtering, with its specific process shown in Figure 5 [Figure 5: see original paper]. By analyzing radar image, the current GPS coordinate position of the radar and the inertial navigation information of the current radar can be established. The information of radar targets is also extracted, which includes the heading and speed of the target relative to the radar, the position information of the target and the size estimation information of the target. With the target tracking, the radar image data is acquired. The nearest neighbor method is adopted in the process of radar tracking. By judging the predicted value of the target output by the filter, the wave gate is established with the predicted value as the center, and the target is collected within the wave gate range to judge whether the target and track are related. Under special circumstances such as target intersection, bridge crossing and being blocked by navigation buildings, it is difficult to identify the radar target. Therefore, the position and velocity state of the target at the next time are calculated through the motion equation.

Ship image target tracking: The Kalman filter and Hungarian matching algorithm are adopted in ship image target tracking. Through the tracking of ship image target, the track correlation of continuous multi-frame image target is carried out to obtain the continuous track of ship image target. The main steps of the algorithm are as follows: Creation of tracker. Detect the ship image at the beginning, initialize the detected target, create a new tracker to track it, and mark the serial number of the target. Target matching. The target frame obtained from the initial frame detection can be used to obtain covariance prediction and state prediction through Kalman filter. Taking the intersection over union (IOU) as the matching basis, the IOU value of the prediction of all targets and the detection frame was calculated at first; then, the maximum and unique matching through the Hungarian algorithm was obtained; finally, the matching pair whose matching value is less than the threshold was deleted. Status update. For the target without matching, a new tracker is established, and the target detection frame of this frame is used to update the Kalman filter. The updated contents include Kalman gain, state matrix and covariance matrix. The tracking frame of this frame is the state update value.

3.2.3. Data Fusion In the Integrated Ship Motion Perception system of ship navigation in inland river and port waters, the main perception method will still be AIS and radar. Benefiting from their large-scale perception abilities and having a variety of perception means, using data fusion technology and integrating a variety of perception technologies can complement and expand each other. In this paper, AIS, radar and camera are integrated to dynamically perceive the ship navigation status. The specific model is as shown in Figure 6 [Figure 6: see original paper].

Data space and time registration: As shown in Figure 6, the output data of the radar, AIS and camera have different data formats and coordinates. The radar targets are expressed by polar coordinates, the AIS data uses latitude and longitude coordinate system, and the camera uses pixel coordinates. In data space registration: AIS and video image fusion need a unified position coordinate system. In this paper, AIS coordinates and radar polar coordinates are converted into camera pixel coordinates through coordinate conversion to unify with the ship image target in the same coordinate system for track correlation. The ideal AIS ship image coordinates are calculated by using the ideal pinhole imaging model. However, the lens of the optical camera is distorted (geometric distortion of the image), so the ideal AIS ship image coordinates were converted into the image coordinates in the real distorted image after calculation. The polar coordinate system is adopted for the radar coordinates, and the radar data is inversely transformed by three-dimensional coordinates to complete the spatial matching between the target information and the visual image. In terms of data time registration: since the sending time interval of ship AIS data ranges from 10 seconds to 3 minutes and the update frequency of image data is 25 Hz, it is necessary to predict the AIS space-time trajectory during space-time registration, so as to align the time of ship AIS data involved in fusion with image data. In this paper, the AIS ship is assumed to move at a uniform speed. Using the characteristic values of longitude, latitude, speed, heading and steering rate of AIS ship target and taking 1 second as the cycle, the cubic spline interpolation method is used to predict the AIS space-time trajectory in a short time.

Track correlation: In this paper, the comprehensive factor fuzzy evaluation method is used to determine the correlation between AIS, radar and image target tracking, so as to determine the correlation of each sensor target, which mainly includes three parts: coarse correlation, fine correlation and comprehensive judgment. The track correlation framework of comprehensive factor fuzzy evaluation is shown in Figure 7 [Figure 7: see original paper].

Coarse correlation: Coarse correlation is to find the target subset satisfying Eq. (1) in the current AIS and radar target set according to the pixel coordinates of the midpoint at the bottom of the target in the ship image. The coarse correlation conditions are determined based on the relative angle and distance of image targets, where pixel coordinate thresholds are applied to filter potential matches.

Fine correlation: The ship image target, AIS data and radar target meeting the condition of rough correlation are smoothly correlated by a comprehensive factor fuzzy evaluation algorithm. Smooth correlation mainly includes determining fuzzy factor set, constructing membership function model, comprehensive evaluation and calculating compactness.

Fuzzy factor set: In this paper, pixel abscissa, pixel abscissa change rate and pixel ordinate are selected as the fuzzy factor set. These factors are calculated based on the target pixel position, optical center, camera focal length, pixel physical size, camera installation height, target angle and distance.

Membership function: In this paper, the probability density is estimated by using the training sample data of U1, U2 and U3. The probability density functions corresponding to membership functions S1, S2 and S3 are obtained, and then the probability density function is normalized. First, as shown in Figure 8 [Figure 8: see original paper], the probability density functions of S1 and S3 adopt semi-normal distribution, and the probability density function is estimated according to the data samples of U1 and U3, while the probability density function of S2 adopts exponential distribution to estimate the probability density of U2. Secondly, the probability density functions of S1, S2 and S3 are normalized to the range [0,1], where 0 indicates relevance and 1 indicates irrelevance.

Comprehensive evaluation: Firstly, the judgment matrix used in this paper is constructed based on the membership grades calculated according to the membership functions Si. The weighting coefficients are determined by the membership degree calculated by the training set samples. According to the statistics of training samples, the weights are determined as a1 = 0.374, a2 = 0.267, and a3 = 0.359. Secondly, the continuous multiple frames of the ship image target and the corresponding single AIS target are averaged. Then, the tightness coefficient takes the maximum value of multiple different AIS targets at the same time. The correlation decision threshold is taken as 0.6.

3.2.4 Quality Management The track correlation quality is expressed as a confidence metric where the correlation strength between tracks is evaluated. When the correlation quality exceeds a predefined threshold, the two tracks are considered fixedly correlated.

3.2.5 Target Information Fusion In the process of radar and AIS data fusion, due to the high accuracy requirement of radar, the coordinate information is calculated based on the radar measurement data and the correlation between longitude, latitude and distance. The fusion of AIS and radar targets is realized after the process of weighted combination and validation.

For the related target, the information is fused to obtain the fused target. AIS target information, radar target information and target information after fusion are shown in Table 1 .

Table 1. Target information fusion of AIS and radar.

Information Type	Attributes
AIS target	position, UTC time, speed, heading, steering rate, longitude and latitude
Radar target	distance, relative orientation, track direction, relative ship speed
Fusion target	distance, track direction, relative ship speed, relative orientation, speed, heading, steering rate, longitude and latitude

The fusion result of video tracking target information and radar AIS target information is shown in Table 2 .

Table 2. Video target information fusion.

Information Type	Attributes
Video target	relative orientation, target detection box, target category
Fusion target	distance, relative orientation, speed, relative ship speed, longitude and latitude, steering rate, track direction

In the matching process, the image target has the highest priority. When there is only one image target, the target is retained. At the same time, the image is helpful to judge the absence of AIS target. Ship image information includes relative azimuth, relative distance, target frame coordinates, size and other information; AIS information includes ship name, MMSI, longitude and latitude, speed, heading, steering rate, etc.; the target information after merging includes the target ship name, MMSI, longitude and latitude, speed, heading, steering rate, relative azimuth, relative distance, target frame coordinates and size, etc. After fusion, the data with more information is acquired, so the positioning accuracy is improved.

4. System Verification

The system verification of multi-sensor information fusion system is conducted by field experiments in this section. Firstly, the overall design of ship motion perception system software in inland river is demonstrated in Section 4.1. Then, effect of image fusion and radar fusion is verified separately in Section 4.2 and

4.3. Lastly, on contrast, multi-source fusion verification is carried out under various practical scenes.

4.1. System Demonstrator

The overall design of ship motion perception system software is demonstrated in Figure 9 [Figure 9: see original paper]. As indicated in the function architecture shown in Figure 9(a), the software consists of three parts: control and acquisition, perception and information display. The main function design follows the content of demand analysis. The perception part mainly implements the algorithm content studied in this paper. The information display part is designed for video preview, which is used to show the real-time perception effect of images. The interface of the information display is presented in Figure 9(b). The electronic River map can display AIS targets, superimpose the radar map, and show the fusion perception effect of radar and AIS targets.

Figure 9. Ship motion perception system software. The interfaces of each part of the software are as follows: (1) AIS module: The AIS message information is displayed at the center of the interface. The AIS message contains dynamic information such as ship position, heading, speed, longitude and latitude, steering rate and static information such as ship name, call sign and ship type. (2) Radar module: The main operation interface is divided into several different functional areas. The user can connect the radar, set the frequency of image storage and perform other operations. (3) Camera module: The camera module is set to control the connection of the camera and the storage of images and videos. At the same time, it can preview the video and display the target list.

4.2. Image Fusion Verification

Optimized YOLOv3 network structure description and algorithm evaluation: The dataset used for the accuracy verification of ship target detection is verified by 10-fold cross-validation. At the same time, the mean average precision (mAP) commonly used in target detection task is adopted as the evaluation index of detection. The test set is tested and the average value is taken after ten times. Generally, when evaluating the performance of the target detector, it is qualified if IOU between the detection frame and the actual target frame is greater than 0.5. The overall mAP of the target detection and verification result of the system reaches about 93.04%. Considering the high demand for target positioning in environment aware applications, the mAP values based on different IOU thresholds were tested and compared before and after improvement.

Figure 10. Comparison of evaluation results. As it can be seen from Figure 10, the system optimized and adjusted the original loss function and network super parameters of YOLOv3, which improved the positioning accuracy. With the improvement of the positioning accuracy requirements, the mAP value

decreases accordingly. When the IOU is increased to about 0.6, the algorithm can still yield an mAP value of about 0.9, while the improved YOLOv3 is slightly improved in terms of the mAP value in general.

Continuous evaluation of ship target tracking: The system uses the optimized YOLOv3 model as the detector. By introducing the depth feature and cascade matching algorithm, the tracking algorithm performed very well in the tracking continuity of ship images. After introducing the depth feature information, the tracker can still track the target correctly under occlusion for a long time, so as to reduce the occurrence of ID switching. In order to reduce the false alarm caused by YOLOv3 detector, the detection confidence threshold was appropriately adjusted, and the final tracking result performance was greatly improved.

Fusion accuracy evaluation: After the system detects and tracks the ship target, it will finally fuse with other multi-source information. An output result of the ship target fusion experiment is shown in Figure 11 [Figure 11: see original paper]. The nine-digit code of MMSI, speed and heading information of the ship are displayed on the picture, and the historical fusion track of the ship is also displayed at the same time.

Figure 11. Effect of ship target recognition, tracking and fusion. After fusion, the output data of the system is described in the following table: ID is the identification number of the system to the ship, and each new identification target ID value is added by 1. The size of the target identification frame is marked as BBOX, and the abscissa and ordinate of the midpoint pixel at the bottom of the target identification frame are marked as BCX and BCY, respectively.

Table 3. Ship image target data.

ID	BBOX
103	[280,547,153,49]
103	[273,546,166,49]
103	[304,555,132,41]
103	[314,554,132,41]
103	[325,554,132,41]
103	[335,554,132,41]
103	[349,544,159,47]
103	[360,543,170,48]
103	[374,542,170,48]
103	[381,540,167,46]
103	[382,541,175,47]
103	[456,540,120,45]
103	[433,538,160,46]
103	[373,541,269,44]
103	[477,538,126,46]

The final video fusion accuracy of the system is shown in Figure 12 [Figure 12: see original paper]. When the threshold which applied to compared spatial difference between ships in AIS and image is around 2°, the accuracy tends to be the largest, and the overall variation range with the threshold is small, mainly because the image is less sensitive to orientation. The maximum error rate is about 3%, which is mainly limited by the accuracy of image recognition, and the whole is still at a low level. The result of video perception is relatively accurate, but the target will still be lost due to occlusion during ship meeting; after fusion, the perception result is good, but there are still few targets that cannot be perceived due to occlusion.

Figure 12. Video fusion effect.

4.3. Radar Fusion Verification

Data introduction: Figure 13 [Figure 13: see original paper] presents the original radar and AIS data acquired on the Yangtze River, Wuhan, China. The radar can form a 1024 × 1024 pixel image in 2.5 seconds. The coastline in the radar image was removed. The AIS data was irregular in time, so it needed interpolation.

Figure 13. Original data sample. In the actual application of the equipment, the visible range of the radar is taken as the sensing range. When a target passes through the sensing range, if the target is correctly identified and the effective tracking time reaches more than 80%, it is considered that the target is correctly perceived. In contrast, all the perceived targets except for the correct ones are considered as misperceived targets. To evaluate the performance of the perception algorithm, Accuracy and ErrorRate are designated as the evaluation parameters of the experimental results, and their expressions are given as follows:

$$\text{Accuracy} = \frac{T}{M}$$

$$\text{ErrorRate} = \frac{E}{M}$$

where T represents the number of correctly perceived targets, E represents the number of incorrectly perceived targets, and M represents all actual targets. In the experiment, if there are many missed detections, the number of perceived targets will be less than the actual number, so the sum of accuracy and error rate will be less than 1; if there are many false detections, the perceived target number will be more than the actual target number, which leads to the sum of accuracy and error rate greater than 1.

Experimental results: By adjusting the threshold value of AIS data and radar fusion, the changing trend of Accuracy and ErrorRate are shown in Figure 14

[Figure 14: see original paper]. When the threshold is about 100m, the accuracy reaches its maximum, indicating that most matching pairs are within 100m. The maximum value of accuracy is about 93%. When the threshold is set less than 50m, the effect is poor with small accuracy values, which denotes that the coordinate error between AIS and radar target detection is relatively large, so it is difficult to match the target with a small threshold. It is observed that the errorRate increases with the increase of the threshold, and its maximum value is about 7%, which is mainly due to the matching between some drifting AIS targets and radar jamming targets when the threshold is too large. After data fusion, the target detection effect is shown in Figure 15 [Figure 15: see original paper]. The triangles are the AIS detection targets, the circles are the radar detection targets, and the squares are the fused targets. It is seen that the target match rate between AIS and radar has been greatly improved after fusion.

Figure 14. Fusion effect of AIS and radar.
Figure 15. AIS and radar data fusion.

4.4 Multi-source Fusion Verification

In this section, the evaluation of the accuracy of the multi-source fusion algorithm under single-target and multi-target scenes are presented, respectively.

Single-target scene: A ferry ship named Jiangcheng No.5 ship was chosen as the single-track target. The ship travelled from Wuhanguan wharf to Zhonghua Road wharf in Wuhan, China, and its real track is recorded by a high-precision differential GPS device (decimeter level) equipped on the ship. As shown in Figure 16 [Figure 16: see original paper], the recorded real track of the ship is composed of two turns and three stages of constant speed and a relatively stable course. It is noted that the X and Y axials in the figure denote longitude and latitude, respectively.

Figure 16. Real track of ferry ship. The tracking performances of the methods, including AIS track, radar track, video and radar fusion track, and the fusion track of the proposed multi-sensor fusion ship motion perception system, were evaluated. After aligning the time points of data acquired by all the tracking methods and converting the coordinates of the data to the geodetic coordinate system, the performances of all the track methods were compared, as shown in Figure 17 [Figure 17: see original paper]. In which lines with different colors denote the ship’ s trajectory tracked by various sensor separately and integrally.

Figure 17. Various sensor tracks and fusion tracks. The camera is accurate for angle measurement, but its performance in distance measurement is poor, hence this paper uses radar to measure distance and camera to measure angle information to realise a multi-source fusion track. The final fusion track is closer to the real track of the ship target than other tracks, which can prove that the target fusion algorithm is effective in Figure 18 [Figure 18: see original

paper]. The relative errors of all track methods in terms of longitude and latitude in a sampling period of 120 s are presented in Figure 18. It is observed that the data of fusion has much smaller errors than other track methods, indicating the advantage of the target fusion algorithm.

Figure 18. Fusion error diagram.

Multi-target scene: In order to verify the detection and tracking effect of the system in the multi-target ship scene, tests were carried out in different scenes during the day and night. The test environment is shown in Figure 19 [Figure 19: see original paper]. Two data groups lasting one hour acquired during the day and night respectively were analyzed, and the comparison of ship recognition and tracking performance of single sensor and multi-sensor data fusion methods are compared in Table 4. Table 4 reveals that, given a period of 1 h, the total number of ships at night and day is 443 and 1368 relatively. It is found that the day and night have little impact on radar which detection rate is 70.32% and 69.30% respectively. However, the perception ability of video ship targets at night decreases greatly, and the recognition rate decreases from 68.34% to 57.33%; among the three sensing methods, the fusion sensing target recognition rate is the highest, reaching 72.15%.

(a) Daytime (b) Night
Figure 19. Multi-objective test environment.

Table 4. Ship identification rate.

Environment	Total Ships	Radar (%)	Video (%)	Fusion (%)
Night	443	69.30	57.33	72.15
Day	1368	70.32	68.34	72.15

5. Conclusion and Discussions

This paper designed an integrated ship motion perception system based on multi-sensors information fusion. In order to evaluate the reliability, consistency and accuracy of the system, a pilot test was carried out in Wuhan waterway of the Yangtze River. Compared with the existing ship motion perception methods, it has the following main advantages.

In terms of hardware, the system proposed and designed in this paper forms a three-layer monitoring mode which can cover inland waterways within 1.5 nautical miles. The accurate trajectory of the ship in the waters is obtained through the information fusion of radar and AIS, and the video image is used to verify the ship motion and ship type. Consequently, the system has better robustness and reliability in ship motion perception.

In terms of software, the system integrates three ship motion perception techniques: radar, AIS and camera. In the fusion of radar, AIS and camera, the spatial registration of three kinds of sensor data is realized through coordinate transformation. Then, the track correlation between AIS, radar and image target are carried out by using the comprehensive factor fuzzy evaluation method. After the track correlation is completed, the redundant information in the three-sensor data is eliminated to realize the comprehensive, consistent, accurate and real-time monitoring of ship motion.

The ship motion perception system can also be deployed and applied to the smart ships. Although the system has been preliminarily verified, the wide application of the device is still in the early stage. The next research work will focus on improving its performance in various experimental and practical environments. The structural design will be optimized considering the factors of waterproof and dustproof. Moreover, by introducing the correction device of longitude and latitude position and attitude, the system can also be deployed on the intelligent ship as the situation awareness sensing system.

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