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An Unmanned Ship Navigation Environment Monitoring System Based on Millimeter Wave Radar

Qingzhou Yu
College of Electromechanical Engineering
Qingdao University of Science and Technology
Qingdao, China

Xiaoyuan Wang*
College of Electromechanical Engineering
Qingdao University of Science and Technology
Qingdao, China

Quanzheng Wang
College of Electromechanical Engineering
Qingdao University of Science and Technology
Qingdao, China

Wenzheng Yang
College of Electromechanical Engineering
Qingdao University of Science and Technology
Qingdao, China

Kaipeng Zhu
College of Electromechanical Engineering
Qingdao University of Science and Technology
Qingdao, China

Shihao Lian
College of Electromechanical Engineering
Qingdao University of Science and Technology
Qingdao, China

Abstract: With the rapid development of artificial intelligence, maritime technology is continuously advancing, and unmanned surface vessels (USV) are gaining significant attention as emerging waterborne transportation vehicles. Environmental monitoring during the navigation of USV is a critical component. This paper employs multiple millimeter-wave radars and utilizes a multi-hypothesis tracking algorithm to successfully achieve data association, data fusion, and target tracking for millimeter-wave radar data. Finally, the proposed method is validated through real ship experiments, providing a solid theoretical foundation for autonomous navigation of USV in the future.

Keywords: USV; Navigational Environment Monitoring; Millimeter-Wave Radar; Multi-Hypothesis Tracking Algorithm

1.Introduction

With the flourishing development of global economic globalization, maritime transportation plays a pivotal role in this process. Not only is the variety of vessels steadily increasing, but their numbers are also on a gradual rise, rendering maritime traffic increasingly complex. However, this trend is accompanied by a surge in maritime accidents, resulting in substantial economic losses and human casualties. Statistical data indicates that nearly 50% of maritime accidents are attributable to ship collisions.

n this context, with the continuous advancement of sensor technology and intelligent control technology, unmanned surface vehicle (USV) unmanned ship system technology has become a hot topic at present[1]. USV are capable of performing a variety of traditional maritime tasks, including maritime management, hydrological monitoring, underwater testing, and maritime search and rescue operations[2][3]. As they do not require onboard operators, USV are particularly well-suited for executing unconventional missions, especially in hazardous waters, without the need to consider human-related psychological and physiological factors. Leveraging advanced control systems, communication systems, and monitoring equipment, USV can conduct continuous, round-the-clock surveillance of specific water areas, such as polluted waters or ship accident scenes. Furthermore, USV offer advantages such as high safety, ease of operation, modularity of monitoring equipment, and intelligence. They can execute maximum tasks with minimal energy consumption, making them highly promising, especially in light of the rapid advancements in big data, cloud computing, neural networks, artificial intelligence, and modern control engineering.

However, achieving autonomous navigation on water for USV hinges on the swift and efficient autonomous path planning, which primarily depends on their precise environmental perception. Environmental perception serves as the cornerstone of this capability. Traditional methods rely on single sensors for data acquisition, each having its advantages and limitations, thereby falling short of meeting the comprehensive environmental data requirements for USV.

In previous research endeavors, RUIZ and colleagues[4] attempted to employ a five-line vertical scanning laser radar for environmental and obstacle detection. They initially preprocessed radar data, performed image segmentation based on jump points, and then utilized Kalman filtering to predict the positions of known obstacles. Finally, a clustering method was employed to unify fragments of the same obstacle, although it lacked effective differentiation between static and dynamic obstacles. Furthermore, Qiu Yiming[5] conducted research on surface target perception based on visible light, focusing on the "Huster-68" unmanned vessel. This study involved the processing of surface video to obtain information on water boundaries, surface target positions, and their motion speeds. In a similar vein, PENG Y and colleagues[6] proposed an obstacle detection algorithm and avoidance method based on 2D laser radar. They utilized filtering and clustering algorithms for point cloud data processing to extract obstacle positions. Additionally, Song H[7] introduced a collision avoidance system designed for safe navigation of unmanned vessels in dynamic environments. This system comprised a fuzzy controller based on laser radar sensors for obstacle detection.

But these approaches have their limitations. Therefore, this paper proposes an innovative method for monitoring the navigation environment of unmanned ships based on millimeter wave radar. The method uses three millimeter-wave radars, each of which covers a detection range of 120 degrees, and realizes 360-degree all-round monitoring of the ship through appropriate Angle arrangement, thus ensuring the safe navigation of the unmanned ship. These three millimeter-wave radars realize target correlation and tracking through multi-target tracking algorithm, providing an efficient and reliable solution for environmental monitoring of unmanned ships. The experiment proves that this system has important reference value in the practical application of unmanned ships, and provides solid theoretical support for the autonomous navigation of unmanned ships in the future.

2.Method

2.1 Millimeter Wave Radar Coordinate Conversion

According to the user manual of millimeter wave radar, the geometric center of the most prominent part of the front of the millimeter wave radar is the origin of the coordinate system of the millimeter wave radar sensor. Three millimeter wave radars are used in this system, which are radar No. 1, Radar No. 2 and radar No. 3. The installation positions of the three radars are shown in Figure 1:

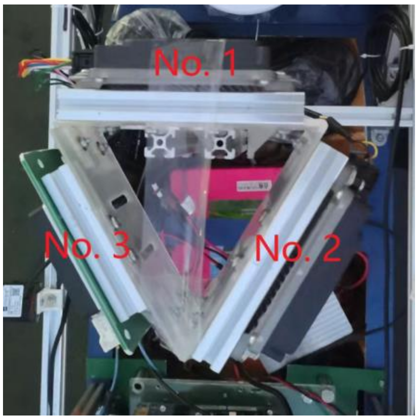

Figure 1. Millimeter wave radar installation

The x axis and y axis of the coordinate system of radar No. 1 are converted into the coordinate system of the ship, and the right hand coordinate system rule is also used to make the coordinate system of the millimeter wave radar coincide with the coordinate system of the ship.

When coordinate conversion is performed on the No. 2 and No. 3 Millimeter wave radars, the radar coordinate system needs to be rotated to a suitable position, and the coordinate conversion diagram is shown in Figure 2:

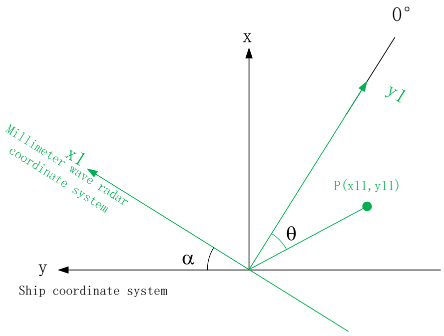

Figure 2. Coordinate system transformation diagram

The ship's coordinate system is established with the installation position as the center, and the coordinate system used by the millimeter wave radar for data measurement is also a rectangular coordinate system with the triangular center of gravity of the three millimeter wave radars as the origin, and the measurement results that the coordinate system of the millimeter wave radar needs to move 8 cm in the negative direction of the y axis. In Figure 2, the x-y coordinate system is the ship coordinate system, and x1-y1 is the millimeter wave radar coordinate system.

When the millimeter wave radar obtains data, the data of the target point is the distance in x direction, the distance in y direction, the relative acceleration in x direction, and the relative acceleration in y direction.

When the point p(x11, y11) is converted from the x1-y1 cartesian coordinate system to the x-y cartesian coordinate system, the coordinates of the converted point are p(x11z, y11z). When α is positive, the conversion formula is formula (1):

$$\begin{aligned} x11z &= (y11\text{-}0.08)\times\cos(\alpha)+x11\sin(\alpha) \\ y11z &= x11\cos(\alpha)\text{-}(y11\text{-}0.08)\times\sin(\alpha) \end{aligned} \tag{1}$$

When α is negative, the conversion formula is formula (2) :

$$\begin{aligned} x11z &= (y11\text{-}0.08)\times\cos(\alpha)\text{-}x11\sin(\alpha) \\ y11z &= x11\cos(\alpha)+(y11\text{-}0.08)\times\sin(\alpha) \end{aligned} \tag{2}$$

2.2 Millimeter wave radar multi-target correlation and tracking

The task of multi-object detection and tracking primarily involves detecting targets in complex and noisy environments while continuously estimating the motion parameters of these detected targets. In the context of ship navigation, a vessel's awareness of its surrounding environment is of paramount importance. This includes the detection of obstacles and the determination of operational parameters of other vessels, all of which occur within the operating range of the ship. Accurately determining the relative positions, headings, and speeds of other vessels in relation to one's own ship is crucial for collision prevention and ensuring safe navigation, especially in conditions of limited visibility. During ship navigation, functions such as collision warnings, collision avoidance, and route planning heavily rely on the effectiveness of environmental monitoring.

In the field of target tracking, there are typically several stages, including point acquisition, data association, tracking filtering, and track management. Figure 3 illustrates the target tracking process.

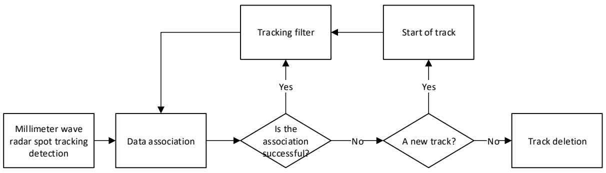

Figure 3. Target tracking flow chart

Multiple Hypothesis Tracking (MHT) is an advanced algorithm used to solve complex target tracking problems. It was first proposed by D.B. eid at the end of 1980s[8]. The algorithm mainly includes: cluster formation, hypothesis generation, probability calculation of each hypothesis and hypothesis reduction. Under ideal conditions, MHT is considered to be the optimal method for dealing with data interconnection[9].

(1) Hypothesis generation

Suppose the interconnection hypothesis set at time t is J^t, then from J^{t-1} and the latest measurement set, the J^t set is obtained, as follows:

$$\text{S(t)}=\{S_n(t), n=1,2,...,N_t\} \tag{3}$$

The first $S_n(t)$ is obtained by the interconnection of $J^{\text{t-1}}$, and then extended by $S_2(t)$ to all sets to form a new hypothesis.

Where $S_t=\{S(1),S(2),...,S(t)\}$ represents cumulative measurements from the beginning to the current moment.

There are three possible state definitions for each hypothesis: ① the goal is an existing goal. ② This goal is a new goal. ③ The target is false alarm. Each target can be connected to at most one current time measurement, and that measurement must fall into its confirmation region.

(2) Calculation of probability

P_i^k is the probability of hypothesis J_i^k, $P_i^t=(J_i^t \mid S_\text{t})$.

Among them, J_i^t can be regarded as the joint hypothesis of $S_{\text{t-1}}$ and the correlation hypothesis Ψ_h of the current number data measurement. According to literature [8], it can be obtained:

$$P_i^t=(J_i^t \mid S_\text{t})=\frac{1}{\text{c}}P(S(t)\mid J_g^{t-1},\Psi_h,S_{t-1}) \times P(\Psi_h \mid J_g^{t-1}, S_{t-1})P_g^{t-1} \tag{4}$$

Where c is the normalization factor, as follows:

$$P(S(t)\mid J_g^{t-1},\Psi_h,Z_{t-1})=\prod_{n=1}^{N_t} f(n) \tag{5}$$

If the n measure comes from false alarm or noise, $f(n)=1/v$; If the measurement comes from the target, $f(n)=M(S_n(t);\hat{S}_n(t\mid t-1),D_n(t))$, the compliance expectation is $\hat{S}(t\mid t-1)$ and the variance is the information covariance matrix $D_n(t)$.

It is assumed that N_{DT}, N_{FT} and N_{NT} represents the number of current measurement data belonging to existing tracks, the number of false alarms, and the number from new targets respectively. According to reference[10], the second item in the formula can be obtained as follows:

$$P(\Psi_h \mid J_g^{t-1},S_{t-1})=\frac{N_{FT}!N_{NT}!}{N_t}\times\prod_b P_{Db}^{\delta_b}(1-P_{Db})^{1-\delta_b} \times P_{N_{FT}}(\beta_{FT}V)P_{N_{NT}}(\beta_{NT}V) \tag{6}$$

Put formula (6) into formula (4) to get the formula for calculating the hypothesis probability:

$$P_i^t=\frac{1}{c}\frac{N_{FT}!N_{NT}!}{N_t}\times V^{-N_{FT}-N_{NT}}\prod_{n-1}^{N_t}\{S_n(t);\hat{S}_n(t\mid t-1),D_n(t)\} \prod_b P_{Db}^{\delta_b}(1-P_{Db})^{1-\delta_b}\times P_{N_{FT}}(\beta_{FT}V)P_{N_{NT}}(\beta_{NT}V)\times P_g^{t-1} \tag{7}$$

(3) Hypothetical reduction

Hypothesis generation is a primary factor affecting the complexity of the Multiple Hypothesis Tracking (MHT) algorithm. Therefore, simplifying and pruning hypotheses have become crucial directions for algorithm improvement. Typically, methods like low-probability hypothesis removal and hypothesis merging are employed for hypothesis simplification and pruning. This study adopts the K-best optimal hypothesis generation and N-scan pruning methods to facilitate the engineering implementation of the MHT algorithm.

The K-best optimal hypothesis generation method is a technique that enumerates K hypotheses with the highest confidence without exhaustively considering all possible scenarios. It constructs a cluster-based assignment matrix, with measurements as rows and tracks, new tracks, and false alarms as columns. Elements in the assignment matrix represent the negative logarithm of the likelihood probability between measurements and tracks or the negative logarithm of the probability that a measurement comes from a new track or a false alarm. Based on this assignment matrix, we employ the algorithm proposed by Murty [11]. Initially, a queue containing all possible assignments is constructed, and then the Hungarian algorithm is used to find the best linear assignment in each iteration. Subsequently, this best assignment is removed from the assignment queue, and the process continues to find the next best assignment. This loop is repeated K times to identify K hypotheses with the highest confidence and probability.

The N-scan pruning method is a technique that controls the number of hypotheses by restricting the depth of the track tree[12]. When the depth of the track tree exceeds N, the N-scan pruning method searches for the leaf node with the highest confidence in the current track tree. It retains the branch with the root node where the highest-confidence leaf node resides while eliminating the other branches.

In summary, hypothesis generation significantly impacts the complexity of the MHT algorithm, making hypothesis simplification and pruning key directions for algorithm enhancement. This study employs the K-best optimal hypothesis generation and N-scan pruning methods to advance the engineering implementation of the MHT algorithm.

3.Experiment

3.1 Pool experiment

Before conducting experiments in this study, an artificial water tank (as shown in Figure 4) was set up to assess the environmental detection capabilities of the millimeter-wave radar.

Figure 4 Artificial water tank

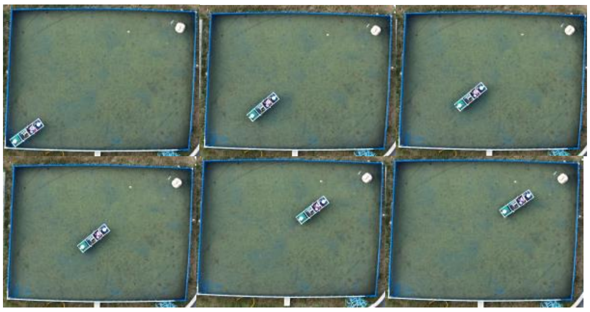

Figure 5 Millimeter-wave radar environmental detection experiment

In the artificial water tank, experiments were conducted using multiple millimeter-wave radars for object recognition and tracking, as depicted in Figure 5. The system provided detection results for the buoys placed throughout the entire autonomous navigation process of the unmanned surface vehicle, as shown in the figure.

The relative position diagram of the unmanned ship and obstacles is shown in Figure 6, which shows the relative position of obstacles relative to the coordinate system of the unmanned ship during navigation.

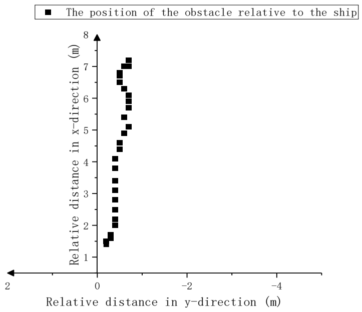

Figure 6 Map of the relative position of unmanned ships and obstacles

Figure 7 shows the relative distance between an unmanned boat and an obstacle detected during navigation.

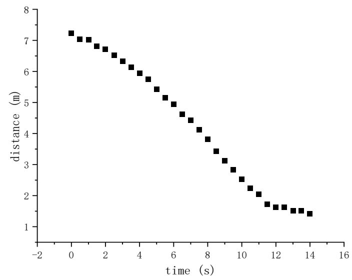

Figure 7 Relative distance between unmanned ships and obstacles

As shown in Figure 8, the relative velocity between the unmanned boat and the detected obstacle during navigation

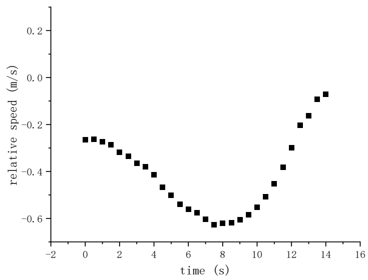

Figure 8 Relative speed between unmanned ships and obstacles

4.Conclusion

This paper discusses the current state of environmental perception in unmanned surface vessels (USV). Addressing the shortcomings of existing approaches, a navigation monitoring system for intelligent ships is proposed, which relies on millimeter-wave radar technology. The system is constructed using three millimeter-wave radars. In this system, the radars are initially installed at specific angles, and the data collected by these radars undergoes processing using a multi-hypothesis tracking algorithm. This processing includes data of a system for monitoring the navigation environment of intelligent small vessels using millimeter-wave radar. The reliability and accuracy of this system are validated through real ship experiments. However, it's worth noting that during actual navigation, the size of the waves can affect millimeter-wave radar navigation monitoring. Therefore, future research will focus on mitigating interference caused by water surface ripples to continually optimize the construction of this control platform.

6.References

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