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RESEARCH ARTICLE

Beam Scheduling of Maritime Multifunctional Radar Based on Binary Integration

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ABSTRACT This study developed a radar resource management (RRM) framework for maritime multi-functional radar (MFR) that performs surveillance and tracking of unknown targets. The proposed scheme consists of two stages: target prioritization based on fuzzy logic and a beam scheduling approach that transmits surveillance beam and tracking beams for each target appropriately. The proposed beam scheduling scheme also takes into account the imperfect detection of targets in real situation. A conventional heuristic beam scheduling approach was modified to incorporate binary integration in radar theory into the RRM strategy. The resulting scheme efficiently handles the complicated beam scheduling problem by considering the target priority as well as the imperfect detection of targets of a real maritime MFR. Simulation results based on a realistic maritime environment demonstrated that the proposed scheme not only determines the correct order of transmission beams according to the target priority but also maintains good tracking accuracy for the threatening target.

INDEX TERMS Radar resource management, multifunctional radar, beam scheduling, binary integration.

I. INTRODUCTION

In recent years, phased array radars (PAR) have been used to scan a beam in the desired direction in near real time by steering the beam electronically. Such radars can handle tasks much faster than conventional radars with mechanical beam steering. A single PAR system can secure sufficient time to simultaneously deal with multiple radar tasks, such as the surveillance, detection, and tracking of multiple targets. This PAR system with multiple missions is usually called a multifunctional radar (MFR) and has found widespread use in missile defense and aegis combat systems for battleships.

Combat systems based on MFR should respond to multiple targets as quickly as possible resulting in a deficiency of important radar resources in terms of time and energy [1]. Hence, in modern MFR systems, radar resource management (RRM) is essential for efficiently exploiting radar resources and improving the performance of various radar tasks, such as surveillance, detection, and tracking [2], [3], [4]. Generally, RRM comprises two components: target prioritization and beam scheduling [1]. Target prioritization determines the importance of the detected targets according to the situation, and it is crucial to measure the threat level of each target in a maritime MFR [5]. Through target prioritization, the threat levels of the detected targets can be classified into aircraft, anti-ship missiles (AShMs), and battleships,. Consequently, we can precisely track targets with high threat levels such as AShMs and aircraft, while simultaneously maintaininglong-range surveillance over those with low threat levels, such as battleships. Several target prioritization approaches such as those based on entropy, neural networks, and fuzzy logic [6], [7], [8], [9] have been addressed in previous studies.

The entropy-based methods in [6] and [9] first estimated the entropy (i.e., uncertainty) of the future state of the tracking filter. This approach minimizes the entropy for target prioritization, which is achieved based on the order of the confidence level of future information. However, this method determines the priority of a target based only on the certainty of detection; and, it does not take into account the threat level of an approaching target.

In the neural network-based method [7], priority considering the threat level can be achieved by various factors that are

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determined by the operator and mission. These factors may include the range, velocity, and altitude of a target, which are inputs to a neural network, with a supervised learning strategy. Using this neural network approach, the priority of an unknown target can be determined in real time. However, an extensive training dataset consisting of many different scenarios is required to guarantee robust performance of the neural network.

Similarly, the fuzzy-logic approach for RRM [8] uses information (i.e., the range, velocity, and altitude of a target) for target prioritization as fuzzy variables. It exploits a fuzzy inference system that measures the threat level of targets by designing reasonable membership functions (MFs), therefore, unlike the neural network approach, several training data sets are no longer needed for the fuzzy-logic approach. In this study, we adopted a fuzzy logic approach for efficient target prioritization.

The beam-scheduling process effectively arranges many task beams to which specific priorities are allocated. Since multiple beams cannot be emitted simultaneously, the beam scheduling process should determine the order and time instant of beam transmission during a single frame. In beam scheduling, the frame refers to the time it takes for the surveillance beam to scan all directions, that is, 360 °. As the frame time increases, the response to a newly appearing unknown target is delayed. In addition, surveillance and tracking beams should be transmitted to continuously acquire the information of new targets and maintain the tracking of detected targets. It is well known that when a Kalman filter approach is adopted for tracking, the tracking performance increases with a decrease in the measurement period [10]. The tracking performance is generally measured using the tracking error: however, if the tracking error is too high, it is nearly impossible for the Kalman filter to maintain tracking and immediately respond to the threatening target. Therefore, it is crucial to secure a tracking error of less than a certain level, which can be achieved by setting a high track update rate for threatening targets. Further, as the period for tracking a target is reduced to improve the tracking accuracy against numerous targets, the frame time increases significantly, resulting in a delayed response to new and threatening targets within the surveillance area. Therefore, it is important to find an efficient scheduling policy by adaptively controlling the trade-offs between high tracking accuracy, particularly against high-priority targets such as AShMs and a short frame time for immediate response to incoming targets [11].

Several studies have been conducted to optimize the track update rate of the Kalman filter for beam scheduling [2], [10], [11], [12]. In one such study [12], a radar load was defined by considering both the detection probability and load from frequent illumination. They suggested a criterion or algorithm to optimize the radar load for specific target models. However, these methods consider only a single target case, therefore, their extension to multiple target cases is not straightforward. In addition, the order of beam illumination of multiple targets has not been considered.

Similarly, the quality of service (QoS)-based resource allocation model (Q-RAM) [13] defines the track quality as a cost function for optimizing the track update rates of multiple targets with target-dependent parameters. Moreover, methods for allocating resources to new targets based on integrated probabilistic data association (IPDA) have also been studied [14], [15]. Although these approaches can be applied to multiple-target situations, they do not consider the order of beam transmission. Some studies provide beam scheduling that considers both tracking and surveillance through convex optimization: however, applying the threat level of the targets is still a challenge [16], [17].

The concept of a single-machine scheduling (SMS) problem can be adapted to allocate the surveillance and tracking beams of MFR in the correct order [18], [19]. Since MFR can process only a single beam at a time, the beam-scheduling process can be better explained by an SMS problem, which is a type of mixed-integer programming model that exploits a cost function, including the weights of the tasks and their constraints. When applying the same concept to the beam scheduling of MFR, a single beam to be transmitted to a target corresponds to each task, whereas the priority of the target corresponds to the weight of each task. Moreover, in an SMS problem, the optimization of the weighted cost functions including completion time, lateness, and tardiness is NP-hard [15]. Therefore, it is nearly impossible to find an analytical and optimal solution to the problem. Thus, a heuristic approach should be applied to beam-scheduling tasks.

In previous studies [21], [22], [23], a mathematical framework was used to formulate an SMS problem, and heuristic approaches were suggested to address this problem. These approaches can determine not only the order of transmission beams according to the threat level of each target but also the track update rate for multiple target tracking, which is based on the time deadline for each beam transmission to maintain the tracking error below a certain level. As a result, heuristic scheduling methods can correctly determine the time instant for every beam transmission within a short computation time. However, in these methods, the targets are assumed to be always detected against every transmitted pulse (beam), and probability of detecting each target (P_{D1}) is assumed to be 100%. In a practical maritime environment, the detection of maritime targets usually interferes with sea clutter, in particular, in high sea states, the detection performance of MFR is significantly deteriorated by high sea spikes. In other words, the assumption that P_{D1} = 100% for every target is invalid in most cases. Imperfect target detection significantly degrades the performance of the tracking filter, thereby, increasing the tracking error. Therefore, previous heuristic approaches cannot reflect the actual tracking accuracy, resulting from imperfect detection in real-world scenario. Consequently, to design a more suitable beam scheduling process in a real environment, using heuristic methods, the imperfect detection of targets must be considered.

In this study, we adopted heuristic approaches, such as the apparent tardiness cost (ATC) and weighted modified due date (WMDD) algorithms for beam scheduling. These approaches determine the urgent task to be processed based on the priority and deadline of the task [24], [25]. Moreover, these algorithms are effective for optimizing the total weighted tardiness, which is one of the cost function of the SMS problem [18]. In addition, the detection probability of each tracked target is calculated using the Swerling model to model the imperfect detection of a target, leading to a realistic MFR operation scenario [26], [27]. Even if a target is illuminated by a tracking beam following the scheduling algorithm, missed detection may occur, and the corresponding detection probability is calculated using the Swerling Model II and a constant false alarm rate (CFAR) detector. Therefore, a loss of target information occurs, which in turn increases the tracking error of the Kalman filter, which better describes the actual tracking scenario. In this case, additional beams should be allocated to improve the tracking accuracy and achieve a tracking error below a predefined level. However, an excessive increase in the number of beams on a tracked target may reduce the time required for beam allocation to other important targets.

To allocate an appropriate number of beams to enhance tracking accuracy even with the imperfect detection of targets in an actual environment, we exploited binary integration (BI), which can guarantee the minimum number of detections during a single frame. BI is an approach used for combining multiple detection attempts to achieve a higher signal-to-noise ratio (SNR) and increase the detection probability compared to a single detection [28], [29]. This is also called M-of-N processing, and the success of the cumulative detection is declared if the number of successful single-pulse detections is equal to or greater than M when N pulses are transmitted. Although the original BI determines the cumulative probability of detection (CPD) for M detections out of N attempts, we use the concept of BI to determine the minimum number of beam transmissions (N) required to guarantee M detections with the desired high probability. In other words, if the desired tracking error is defined below a certain level, then M (i.e., the minimum number of detections for each target for the desired tracking accuracy) can be determined. Subsequently, N (i.e., the minimum number of beam transmissions for each target) can be easily determined using the BI framework mentioned above and the Swerling model. In addition, the frame time can be prevented from excessively increasing by setting the CPD according to the threat level of each target. For example, AShMs are lethal, therefore, a high CPD and tracking accuracy are required for countermeasures such as interception.

Consequently, the proposed beam-scheduling method based on a heuristic approach and BI is more efficient than the other approaches in terms of tracking accuracy. Unlike the traditional heuristic scheduling method, the proposed scheme enables us to maintain the tracking error below a predefined level against threatening targets and secure a high CPD within a reasonable frame time by incorporating the imperfect detection of targets in a real situation. Furthermore, the threat levels of each target and the order of beam transmission can be considered in the design of the beam scheduling strategy.

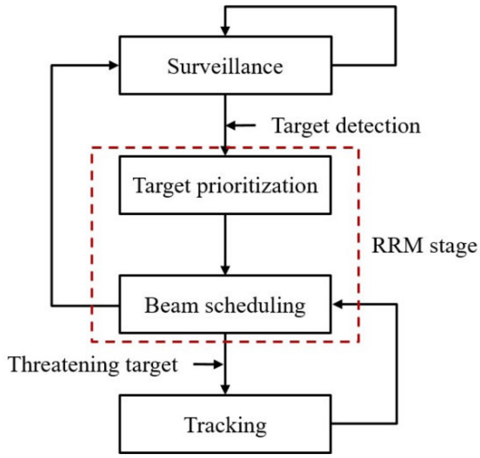

FIGURE 1. Overall flowchart of RRM for maritime MFR system.

We model a maritime MFR system to evaluate the proposed RRM scheme in a realistic environment. The modeled MFR system generates scattering centers of the targets and calculates echo signals from the target based on the Swerling radar cross-section (RCS) model. Moreover, clutter signal and noise, which deteriorate the detection probability, were added to the target signal enabling us to reflect on the detection scenario in a practical maritime environment.

The rest of this paper is organized as follows: First, the tasks of maritime MFR and the related RRM problem are defined in detail in Section II. In Section III, traditional target prioritization techniques, such as the fuzzy-logic approach and the heuristic beam scheduling method including WMDD and ATC algorithms, are discussed. In Section IV, we introduce a new beam scheduling methodology that efficiently combines a heuristic approach and BI. In Section V, experimental results based on realistic maritime scenarios are provided, are analyzed in terms of tracking accuracy and scheduling efficiency. Finally, conclusions are presented in Section VI.

II. BACKGROUND OF RRM FOR MARITIME MFR

Maritime MFR taskscan be categorized as surveillance, tracking, and RRM (Fig. 1). In maritime MFR, surveillance operations typically transmit a fan beam continuously over the entire range of azimuth angles to detect an unknown target. A fan beam usually has a narrow horizontal beamwidth and a wide vertical beamwidth, as shown in Fig. 2. If an unknown target is detected by the fan beam, the target prioritization module determines the approximate type and threat level of the target to track threatening targets. In the tracking stage, a pencil beam with very narrow horizontal and vertical

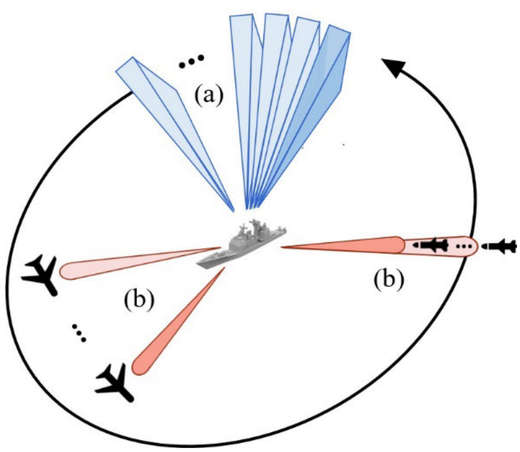

FIGURE 2. Illustration of beams operated by maritime MFR. (a) Surveillance beams. (b) Tracking beams.

beamwidth is typically employed to maintain precise tracking information. This pencil beam for tracking is transmitted periodically as long as the threatening target is within the surveillance region of the radar.

Among the targets to be detected by the MFR, AShMs and aircraft are generally regarded as more threatening as compared to battleships; therefore, tracking pencil beams are immediately assigned to these targets. According to the Swerling model for RCS fluctuations in [24], [25], and [26], AShMs and aircraft can be modeled as the sum of several independent scattering centers with nearly equal RCSs. Hence, the fluctuation model of Swerling case II can be used to describe the tracking operation (pulse-to-pulse independence), and the associated probability density function (PDF) for the RCS, σ, of these targets is given by [24]

$$p(\sigma) = \frac{1}{\sigma_{av}} \exp\left(-\frac{\sigma}{\sigma_{av}}\right), \quad \text{for } \sigma \geq 0, \tag{1}$$

where σ_{av} is the average value of the RCS.

A battleship, on the other hand, usually has a low speed and high RCSs, compared to AShMs and aircraft; thus, only a surveillance beam without tracking is sufficient to obtain precise information. Therefore, for the most part, battleships may be classified as less-threatening targets, and tracking operations are less necessary. In general, the RCSs of ships can be considered as the sum of a dominant scatterer and many small scatterers. Thus, the Swerling III model can be used to represent the RCS fluctuations of battleships in surveillance operations (independenct of scan) as follows:

$$p(\sigma) = \frac{4\sigma}{\sigma_{av}^2} \exp\left(-\frac{2\sigma}{\sigma_{av}}\right), \quad \text{for } \sigma \geq 0. \tag{2}$$

In the RRM of maritime MFR, it is crucial to consider both frame time and tracking error simultaneously. The frame time is given by

$$t_{frame} = \frac{2\pi}{\theta_s}\tau_s, \tag{3}$$

where θ_s is the horizontal (azimuth) beamwidth, and τ_s is the processing time of a single surveillance beam. However, once a threatening target is detected during surveillance, tracking must be performed within the frame. Since the pencil beam for tracking must be transmitted periodically, the frame time inevitably increases significantly. In particular, if there are many targets to be tracked and the frame time is excessively prolonged, the detection of a new threatening target in the surveillance area can be significantly delayed, resulting in a dangerous situation. Therefore, it is essential to ensure that the frame time does not exceed the predefined maximum frame time T_{frame} while allocating a sufficient number of tracking beams against multiple targets to maintain the tracking error below a predefined low level.

Since a pencil beam for tracking has a very narrow beamwidth, the tracking loop could be easily lost unless the tracking error between the position predicted by the tracking filter and the actual position is very small. The tracking error for each target *j*, e_j, is defined as follows:

$$e_j = \sqrt{\left(x-\hat{x}\right)^2 + \left(y-\hat{y}\right)^2 + \left(z-\hat{z}\right)^2}, \tag{4}$$

where (x, y, z) is the actual position of the target, and $(\hat{x}, \hat{y}, \hat{z})$ is the position predicted by the tracking filter. Furthermore, the tracking error is important for responding to a threatening target; notably, a target with a higher threat level requiring a smaller tracking error.

III. RADAR RESOURCE MANAGEMENT

A. TARGET PRIORITIZATION BASED ON FUZZY INGERENCE RULE

After an unknown target is detected using a surveillance beam, the MFR determines the threat level of the target to immediately initiate tracking against it. Therefore, target prioritization determines the degree of threat using information obtained from surveillance beams in real time. In general, AShMs and aircraft are critical targets for detectionin maritime MFR; thus, their threat levels should be set high.

In a target prioritization strategy based on fuzzy logic, the target information should be converted into fuzzy variables to determine the priority value of each target using the fuzzy inference rule [8]. These fuzzy input variables are typically selected as features that can distinguish each type of detected target. For example, AShMs and aircrafts are significantly faster than battleships. In addition, aircrafts are typically detected at high altitudes, whereas sea skimming AShMs and battleships are detected at very low altitudes. In other words, all three types of maritime targets can be distinguished using speed v, and altitude, h, information. Fig. 3 illustrates examples of fuzzy MFs for speed, and altitude including *fast* and *slow,* and, *high* and *low*, fuzzy subsets respectively.

As the outcome resulting from the target prioritization module is the priority value ω of each target,the fuzzy subsets for priority and their MFs corresponding to the combination of each input subset must be defined (Fig. 4). The fuzzy variables regarding priority include *AShM*, *aircraft*,

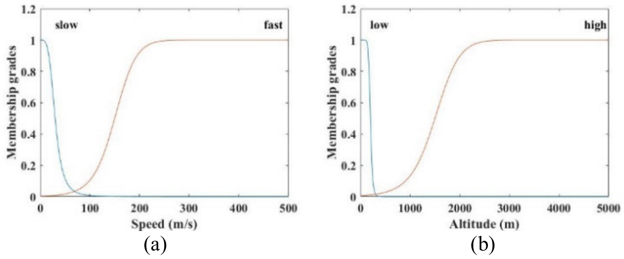

FIGURE 3. Membership functions of input fuzzy variables for target prioritization: (a) Speed. (b) Altitude.

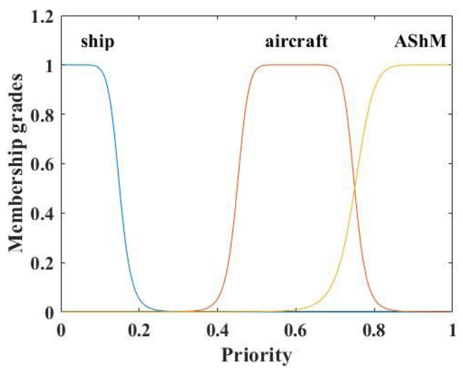

FIGURE 4. Membership functions for output priority, which is categorized by three types of targets: AShM, aircraft, and battleship.

and *battleship*, and each MF represents a relation connecting the two antecedents and an output. The MF of each relation can be calculated based on the Mamdani fuzzy inference system [30] as follows:

$$\begin{aligned}\mu_{AShM'}(\omega) &= \vee_{v,h}\left[\mu_{slow}(v)\wedge\mu_{high}(h)\right]\\ &\quad\wedge\left[\mu_{fast}(v)\wedge\mu_{low}(h)\wedge\mu_{AShM}(\omega)\right]\\ \mu_{aircraft'}(\omega) &= \vee_{v,h}\left[\mu_{slow}(v)\wedge\mu_{low}(h)\right]\\ &\quad\wedge\left[\mu_{fast}(v)\wedge\mu_{high}(h)\wedge\mu_{aircraft}(\omega)\right]\\ \mu_{ship'}(\omega) &= \vee_{v,h}\left[\mu_{fast}(v)\wedge\mu_{high}(h)\right]\\ &\quad\wedge\left[\mu_{slow}(v)\wedge\mu_{high}(h)\wedge\mu_{ship}(\omega)\right],\end{aligned}\tag{5}$$

where $\vee$ and $\wedge$ represent the maximum and minimum values, respectively. Then, the priority MF can be written as

$$\mu_{priority}(\omega) = \max\left(\mu_{AShM'}(\omega), \mu_{aircraft'}(\omega), \mu_{ship'}(\omega)\right).\tag{6}$$

Finally, the resulting priority output w is obtained by calculating the centroid of the MF area as follows:

$$w = \frac{\int_{\omega}\mu_{priority}(\omega)\,\omega d\omega}{\int_{\omega}\mu_{priority}(\omega)\,d\omega}.\tag{7}$$

B. BEAM SCHEDULING

In the beam-scheduling stage, the MFR determines the appropriate time to transmit both surveillance and tracking beams according to the priority of each target. Because the radar was assumed to transmit only a single beam at a time, the beam scheduling process can be regarded as an SMS problem. Fig. 5 shows that the SMS problem can be defined by five parameters: priority, w_j, deadline, d_j, starting time, s_j, completion time, c_j, and processing time, τ_j, for each task j, which includes the surveillance and tracking of each target. The tracking filter can set the deadline d_j for each task differently, and the starting time s_j of the beam transmission should be scheduled such that the completion time of each beam does not exceed the deadline.

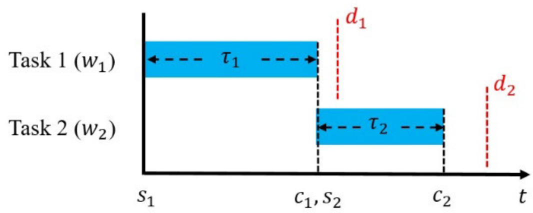

FIGURE 5. Example of scheduling over time for a single-machine scheduling problem with two tasks.

Several heuristic scheduling strategies exist to address the SMS problems. Among them, we adopted the ATC and WMDD algorithms that are suitable for minimizing the delay, namely $\max(0, c_j - d_j)$ while considering the priority of each task [14]. The ATC algorithm considers the target priority, processing time, and slack of the task, and calculates the degree of urgency of the j-th task, ATC_j, as follows [21]:

$$ATC_j = \frac{w_j}{\tau_j}\exp\left(-\frac{\max\left(d_j - \tau_j - t, 0\right)}{K\bar{\tau}}\right),\tag{8}$$

where K is a scaling parameter and $\bar{\tau}$ is the average processing time. The ATC algorithm updates all urgency values ATC_j for all tasks whenever a single task is completed and performs the task with the highest urgency value.

Meanwhile, WMDD algorithm determines the order of the tasks by comparing the deadline d_j and the expected completion time c_j of each task. The deadline of the j-th task reflecting the priority $WMDD_j$ is given as [25]

$$WMDD_j = \frac{\max\left(\tau_j, d_j - t\right)}{w_j}.\tag{9}$$

In other words, the WMDD algorithm begins with an urgent beam with the smallest $WMDD_j$.

IV. PROPOSED METHOD

Using the heuristic approach for the RRM described in Section III, it is possible to schedule beams against numerous targets with minimal computation. However, the beam-scheduling problem of MFR has several distinct differences from the SMS problem. For example, in a practical SMS problem, tasks are processed once and then terminated, whereas tracking in MFR can be continuously performed as long as the target is within the region of interest. In addition, a surveillance beam must be maintained to detect new threats in the region of interest. Therefore, each task should be reallocated as it is completed and, subsequently, its deadline should be updated. Meanwhile, because of the narrow beamwidth used for target tracking, the position of the target must be predicted in advance with an error below a certain level, ϵ, to maintain the track of the target. This tracking error is proportional to the tracking period p used in the Kalman filter for tracking radar systems [10]. The tracking period is the time taken to assign the next tracking beam to that target after the tracking beam has been transmitted to one target, also called the revisit time. If the tracking period is determined by the tracking filter, the deadline to be updated is calculated as:

$$d_{j,l+1} = c_{j,l} + p. \tag{10}$$

where $c_{j,l}$ is the completion time of the l-th tracking beam for target j, $d_{j,l+1}$ is the deadline of the next $l+1$-th tracking beam for target j, and p is the tracking period.

Even though p depends on the desired tracking error ϵ, it is nearly impossible to achieve a small ϵ in a practical situation owing to the imperfect detection of a target arising from MFR. Imperfect detection inevitably occurs not only because of sea clutter but also because ofthe RCS fluctuation of a target. However, most previous heuristic beam scheduling approaches have assumed that there is no imperfect detection, that is, a detection probability of 100% [21], [22]. Even though the Q-RAM [13] and Kalman filtering-based approaches [10], [11], [12], consider the imperfect detection of targets, the outcomes were only the optimal tracking period p for each tracking task (i.e., each target). For a successful RRM of maritime MFR, it is essential to find not only the optimal p but also the optimal order of beam scheduling (transmissions).

The proposed method adopts the Swerling model described in Section II, which considers the RCS fluctuations of a threatening target and calculates the related detection probability to be less than 100%, namely, imperfect detection. In addition, the proposed method uses BI to compensate for the imperfect detection and finds an appropriate tracking period p'_j, which depends on each tracking task (i.e., each target). Fig. 6 shows an example of the proposed scheduling results. Here, whenever each tracking task (blue box) is completed, a new tracking task for the target is assigned, and its deadline is determined based on the target-dependent tracking period, p'_j. Surveillance (green box) is continuously performed when the tracking beam is not transmitted.

In general, BI is a method for achieving specific probabilities of detection and false alarms by combining multiple single detections [29]. In the proposed method, BI is used to calculate the number of detection attempts that can guarantee the required number of successful detections within a frame. The CPD in BI is expressed as follows [31]:

$$P_D = \sum_{k=M}^{N} C_{k,N} P_{D1}^{k} \left(1 - P_{D1}\right)^{N-k}, \tag{11}$$

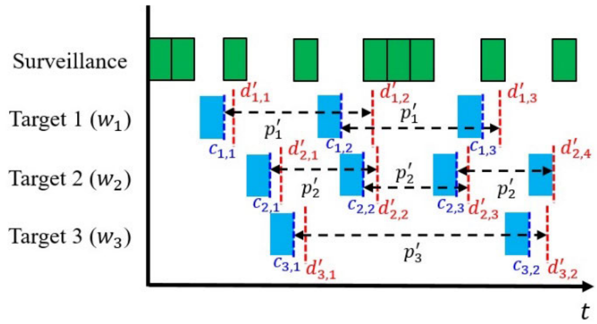

FIGURE 6. Example of scheduling table for multiple-target beam scheduling problem.

where P_{D1} is the single-trial detection probability, N is the number of independent detection trials, M is the minimum number of successful detections required, and $C_{k,N}$ is a binomial coefficient.

$$C_{k,N} = \frac{N!}{k!\,(N-k)!}. \tag{12}$$

Therefore, among N detection attempts, the probability that the number of successful detections is at least M can be calculated using (11).

The primary targets to be tracked by 4 maritime MFR are typically aircraft and AShMs, and their PDF is known as the Swerling II model, as in (1). Therefore, the single-trial detection probability of Swerling II targets is given by [27]

$$P_{D1} = 1 - \Gamma_I \left(\frac{V_T}{1 + SNR}, n_p \right), \tag{13}$$

where Γ_I is the incomplete gamma function, V_T is the threshold determined from the false alarm rate, SNR is the signal-to-noise ratio, and n_p is the number of integrated pulses. The SNR can be obtained using the following radar equation [32]:

$$SNR = \frac{P_t G^2 \lambda^2 \sigma}{(4\pi)^3\, k_B T_0 BFLR^4}, \tag{14}$$

where P_t is the peak power, G is the antenna gain, λ is the wavelength, T_0 is the Kalvin temperature, B is the bandwidth, F is the noise figure, L is the radar loss of the MFR, k_B is Boltzmann's constant, and R is the range between the target and MFR, respectively. The single-trial detection probability of each target can then be obtained according to the specifications of the MFR and the measured range of the target.

Meanwhile, the required minimum number of successful detections of target j, M_j, is determined by the tracking period p_j of the tracking filter and the desired tracking error ϵ in the single frame as follows:

$$M_j = \frac{T_{frame}}{p_j}. \tag{15}$$

p_j is given as the maximum tracking period required to guarantee a tracking error less than ϵ when the extended Kalman filter (EKF) tracks a circularly maneuvering target that constantly changes its direction. Subsequently, by substituting M_j into (14) and setting the desired minimum P_D depending

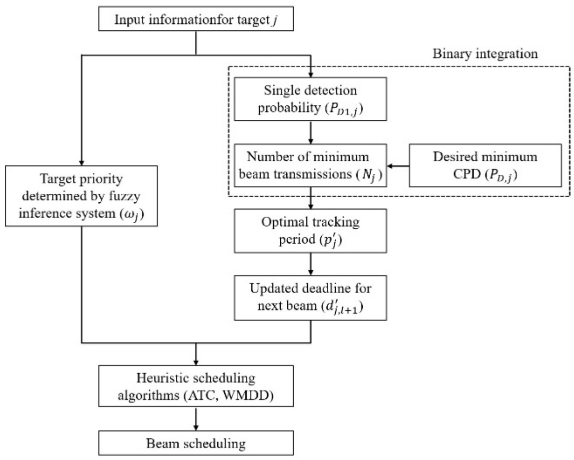

FIGURE 7. Flowchart of the proposed RRM scheme consisting of fuzzy-based prioritization, BI, and heuristic scheduling problem.

on each target type (target priority), the number of required tracking attempts (beam transmissions), N_j can be determined through an exhaustive search. The optimal tracking period of target j, p'_j, can, therefore, be obtained as follows:

$$p'_j = \frac{T_{frame}}{N_j}. \tag{16}$$

In addition, the resulting deadline for each target can be obtained as in (10); and is expressed as

$$d'_{j,l+1} = c_{j,l} + p'_j, \tag{17}$$

where $d'_{j,l+1}$ is the updated deadline for the next beam of the l-th tracking of target j. Therefore, the required tracking accuracy ϵ and the minimum CPD, P_D, can be maintained by using ATC and WMDD with new deadlines $d'_{j,l+1}$. Moreover, by setting P_D for CPD differently according to the priority of the target, higher tracking accuracies can be secured for a more threatening target, such as an AShM, among the targets to be tracked by the MFR. The overall process of the proposed method is shown in Fig. 7.

V. SIMULATION RESULTS

A. SIMULATION SETUP

To verify the proposed RRM scheme, we modeled a maritime MFR system that can perform both surveillance and tracking tasks. The specifications of the MFR are listed in Table 1. In addition, we modeled an echo signal as the sum of the reflected signal from the target, noise, echoes from sea clutter, and multi-path signals, which caused imperfect detection. The echo signal was further processed using the pulse compression and a CFAR detector to provide information on the presence of a target as well as its range. The received signal $s(t)$ based on the linear chirp signal is expressed as follows:

$$s(t) = \sqrt{P}rect\left(t - \frac{2R}{c}\right) \times \exp\left(j2\pi\beta\left(t - \frac{2R}{c}\right) + j\pi\frac{B}{T_p}\left(t - \frac{2R}{c}\right)^2\right), \tag{18}$$

TABLE 1. Radar specifications.

Peak power	P_t	5 MW
Antenna gain	G	45 dB
Carrier frequency	f_0	3 GHz
Wavelength	λ	0.1 m
Bandwidth	B	3 MHz
System loss	L	6 dB
Noise figure	F	3 dB
False alarm rate	P_{fa}	10^{-3}
Number of integrated pulses	n_p	1
Temperature	T_0	300 K
Azimuth beamwidth of surveillance beam	θ_s	2°
Task processing time	τ_s, τ_j	10 ms
Desired tracking error	ϵ	30 m
Maximum frame time	T_{frame}	2 s

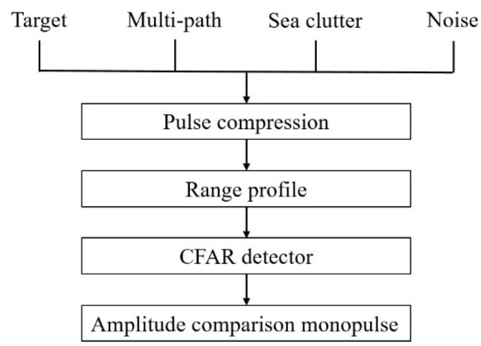

FIGURE 8. Signal processing procedure for the received signal from the tracking beam of the MFR.

where β is the carrier frequency and T_p is the pulse width. P is the power of the received signal, calculated as

$$P = \frac{P_t G^2 \lambda^2 \sigma \rho}{(4\pi)^3 R^4 L}, \tag{19}$$

where ρ is the pulse compression ratio. The angle information of the target was obtained using the amplitude comparison monopulse technique. The overall signal processing procedure is illustrated in Fig. 8.

B. TRACKING PERIOD DETERMINATION FOR IDEAL TRACKING

We adopted the EKF to track a threatening target and observed that the error in the Kalman filter decreased with a decrease in the tracking period, p_j [10]. Therefore, it is necessary to figure out the required tracking period p_j to achieve the desired tracking accuracy ϵ. The tracking accuracy is defined as the difference in distance between the actual position of the target and the position of the target measured by the radar. We measured a reference target maneuvering along a circular path and tracked the target using the EKF to determine the appropriate tracking period p_j. The speed of the target was set to 340 m/s, and the radius of the path was set to 20 km.

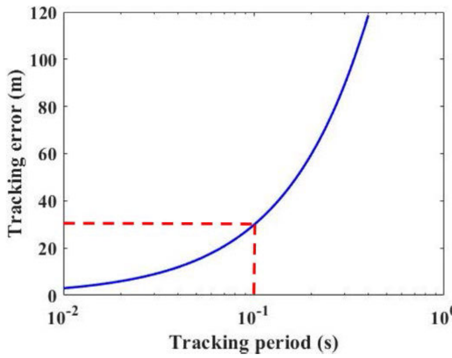

FIGURE 9. Tracking error according to tracking period of a reference target maneuvering at 340 m/s in a circular trajectory with a radius of 10 km.

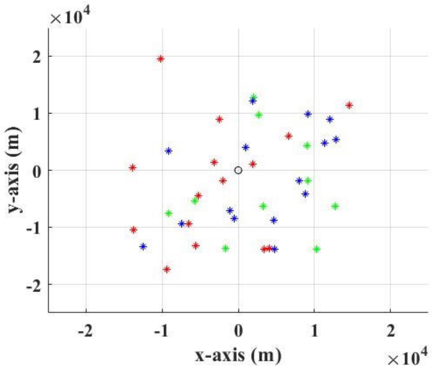

FIGURE 10. Distribution of the target in the x-y plane. AShMs are shown in red, aircraft in blue, and battleships in green.

The tracking error based on the tracking period is shown in Fig. 9. According to the measurement result for the reference target, the information on the target must be updated at least every 0.101 s to satisfy $\epsilon = 30$ m. The circularly maneuvering reference target constantly changes its direction and causes a relatively large tracking error compared to realistic targets when tracked using the EKF. Therefore, it is reasonable to set the required tracking period p_j, under the assumption of perfect detection, to 0.101 s for the targets.

C. EXPERIMENT 1

A scenario, including multiple targets was used to evaluate the performance of the proposed scheme. The scenario consisted of 40 targets, that is, 15 AShMs, 15 aircraft, and 10 battleships, which were distributed randomly inside a 40 km × 40 km rectangular area when the MFR was at the origin (see Fig. 10). In this scenario, three types of targets were assumed to maneuver in a straight or circular path, with randomly chosen parameters such as speed, altitude, and average RCS, as shown in Table 2.

In the proposed scheme, the MFR scans in all directions using a surveillance beam and determines the priority of the detected target. The MFs for the fuzzy input variables, speed, and altitude are shown in Fig. 3, and those for the output

TABLE 2. Target parameters.

	AShM	Aircraft	Battleship
Speed (m/s)	200 ~ 350	200 ~ 500	10 ~ 50
Altitude (m)	10	500 ~ 5000	10
Average RCS (m^2)	0.1~0.4	2~4	1000
Swerling model	II	II	III

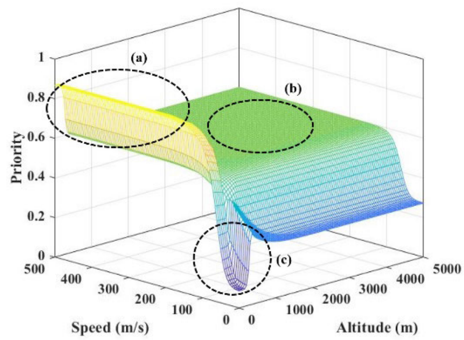

FIGURE 11. Priority map according to speed and altitude. (a) Priority region of AShM. (b) Priority region of aircraft. (c) Priority region of battleship.

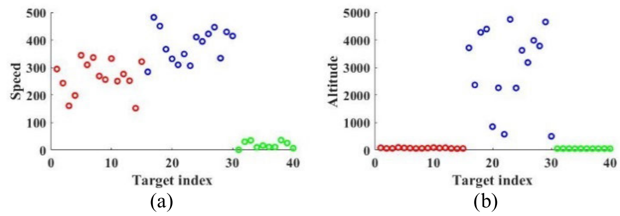

FIGURE 12. Initial speed and altitude of targets in Experiment 1. AShMs are shown in red, aircraft in blue, and battleships in green. (a) Speed of targets. (b) Altitude of targets.

priority are shown in Fig. 4. Using prioritization based on the fuzzy inference rule, the resulting priority map is illustrated in Fig. 11. From Fig. 11 it is also seen that a target with both low speed and altitude has the lowest priority, one with both high speed and altitude has medium-level priority, and one with high speed and low altitude has the highest priority. Therefore, the MFR can determine the priority of the detected target in real time using the obtained target information and priority map.

Figs. 12 and 13 show the prioritization results according to the speed and altitude of the generated targets. AShMs are indexed from 1 to 15, aircrafts from 16 to 30, and battleships from 31 to 40. Although each target had a different speedand altitude, targets of the same type were assigned similar priorities (i.e., AShMs > 0.8, aircraft ≈ 0.6, and battleships < 0.2), as shown in Fig. 13. Moreover, the priority of each target was successfully assigned using fuzzy inference rule-based target prioritization, thus, the threat level of each target type was correctly reflected. Beam scheduling can then be performed

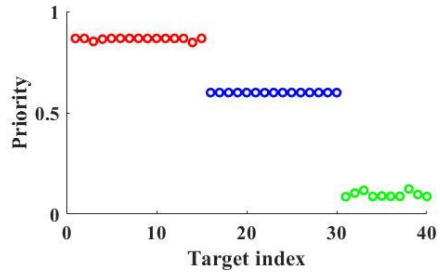

FIGURE 13. Resulting priority value of each target in Experiment 1. AShMs are shown in red, aircraft in blue, and battleships in green.

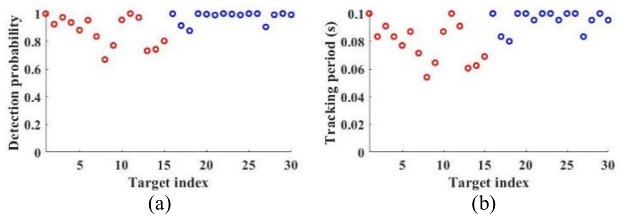

FIGURE 14. Single detection probabilities and corresponding optimal tracking periods of the targets to be tracked. AShMs are shown in red and aircraft in blue. (a) Single-trial detection probabilities. (b) Optimal tracking periods.

based on the assigned priorities w_j. For example, if the threat level of the detected target belongs to AShMs or aircraft (priority greater than 0.5), MFR immediately assigns a tracking task to the detected target. In addition, by setting the priority of the surveillance task between 0.2 and 0.5 (i.e., priorities of aircraft and battleships), when scheduling the beam with the ATC or WMDD algorithm, there is no allocation of the tracking beam for the target with the lowest priority (battleship), leading to a significant reduction in the frame time.

The proposed beam scheduling scheme was performed for the targets in Fig. 8 based on the priority w_j in Fig. 13, and the initial tracking period $p_j = 0.101$ s. For both the ATC and WMDD algorithms, we assumed that the scaling parameter for the ATC algorithm was $K = 0.1$, the required CPD of the AShM was $P_{D,AShM} = 0.95$, and the required CPD of the aircraft was $P_{D,aircraft} = 0.90$.

The total operation time of the MFR in each trial was 30 s, and we performed the RRM experiments using four different beam scheduling methods (ATC, ATC+BI, WMDD, and WMDD+BI) based on 10 Monte Carlo simulations. ATC and WMDD determine the order of beams with a fixed tracking period $p_j = 0.101$ s, whereas the ATC+BI and WMDD+BI adopt the adaptive p'_j determined by the proposed BI-based approach. Then, the average frame time and average tracking error for each type (AShMs and aircraft) of tracked target were measured in each trial.

Fig. 14 shows the single-detection probability of each target $P_{D1,j}$ and the optimal tracking period obtained through BI. $P_{D1,j}$ was calculated based on the Swerling model and the radar equation, as shown in (13) and (14). Owing to the low RCS of AShM, its single detection probability is usually lower than that of other types of targets. Additionally, targets far from the MFR have poor $P_{D1,j}$ owing to their low SNRs. Fig. 14 shows that a target with a low single-detection probability was assigned a shorter tracking period by the BI to ensure a predefined CPD and tracking accuracy within a limited frame time.

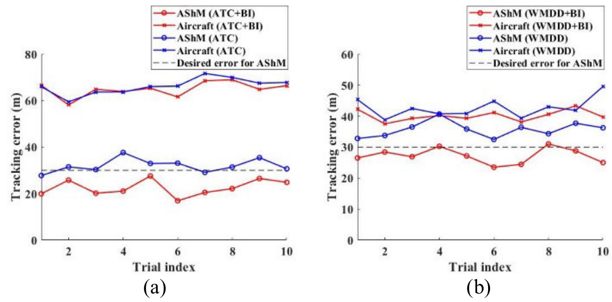

FIGURE 15. Measured tracking errors depending on the type of targets and the scheduling method in each trial of Experiment 1. (a) Tracking errors resulted by ATC algorithm. (b) Tracking errors resulted by WMDD algorithm.

After the optimal tracking period p'_j for all the targets is obtained through BI, the updated deadline $d'_{j,l+1}$ can be determined by substituting p'_j in (17). Then, the order of the beams can be determined by calculating ATC_j and $WMDD_j$ as in (8) and (9) using the priority w_j and updated deadline $d'_{j,l+1}$ of each target. Fig. 15 shows the tracking error for each type of target, and Fig. 16 shows the resulting frame time, which was scheduled by the heuristic algorithms as well as the proposed approach. When the beams were scheduled using the ATC algorithm (see Fig. 15(a)), the tracking errors of the aircraft were significantly higher than those of AShM. Because the ATC algorithm considers the weight of the task, the AShM with higher priority is given a higher urgency, although the required tracking period of both targets is 0.101 s. Instead of allocating the same number of beams to all targets, assigning more beams to AShMs is efficient as it can reduce the tracking error for critical AShMs and save frame time. However, even if the tracking period necessary to achieve the desired tracking error ($\epsilon = 30$) for AShMs was set, the tracking errors in most of the trials without BI were higher than the desired tracking error due to imperfect detection. The average tracking error in all the trials was 31.9754, which was also higher than the desired tracking error ϵ. However, in the case of the proposed ATC+BI algorithm, the tracking errors were lower than the desired error in all trials, because it was scheduled using the updated tracking period while considering imperfect detection. The average tracking error was 22.5253, which enabled the MFR to respond to the threats of AShMs. However, the frame time of the ATC+BI algorithm increased owing to the additional allocation of tracking beams for AShMs to compensate for imperfect detection, however it was still lower than the maximum frame time $T_{frame} = 2$ s (Fig. 16(a)).

Similarly, when the targets were scheduled using the WMDD algorithm, the tracking errors for the aircraft were

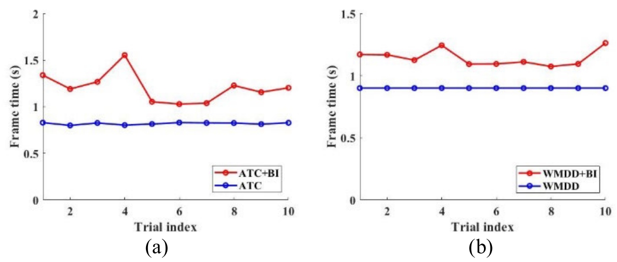

FIGURE 16. Frame time depending on the type of targets and the scheduling method in each trial of Experiment 1. (a) Frame time of ATC algorithm. (b) Frame time of WMDD algorithm.

TABLE 3. Frame time and tracking error according to scheduling method.

	VKB [2]	White [9]	ATC +BI	WMDD +BI
Frame time (ms)	1.8556	1.7675	1.2059	1.1439
Error-AShM (m)	49.9133	39.6523	22.5253	27.1808
Error-aircraft (m)	33.3131	30.0669	31.9754	35.6379

higher than those for AShMs (Fig. 15(b)). Furthermore, when the WMDD algorithm was applied without considering imperfect detection, the tracking errors were higher than the desired error for AShMs ϵ in all the trials. Conversely, using the proposed WMDD+BI algorithm, the tracking errors for AShMs were lower than the desired errors in most trials. The average tracking errors in these cases were 35.6379 and 27.1808, respectively. As shown in Fig. 16(b), similar to the ATC algorithm, BI increased the frame time of WMDD scheduling, but it was lower than T_{frame}.

In addition, scheduling was performed under the same conditions using the existing RRM method to compare the performance of the proposed method. Table 3 shows the frame time and tracking errors when applying the approach used by van Keuk and Blackman (VKB) [2] and the approach used by White [9] to Experiment 1, as well as the proposed method (ATC+BI, WMDD+BI). According to Table 2, when the proposed methods are used, the frame time is reduced compared to conventional methods, thereby improving the surveillance performance. In addition, scheduling the beam using conventional methods results in a higher tracking error of the AShM compared to the tracking error of the aircraft, whereas the proposed method can guarantee a lower tracking error of the more threatening AShM. For conventional methods, the priority of the target is not considered, and it tends to allocate more tracking beams to aircraft with higher detection probabilities owing to the high RCS. In contrast, the proposed method enables more reasonable beam scheduling in tactical situations by considering both, the priority of the target and detection probability.

D. EXPERIMENT 2

Experiment 2 also consisted of 40 targets, that is, no AShM, 35 aircraft, and 5 battleships; the other settings were the same as in Experiment 1. Fig. 17 shows the prioritization results based on the speed and altitude of the targets generated in Experiment 2. The aircrafts were indexed from 1 to 35, and the battleships were indexed from 36 to 40. In Figure 17(c), it can be seen that the priorities of the aircraft and battleships are distinguished.

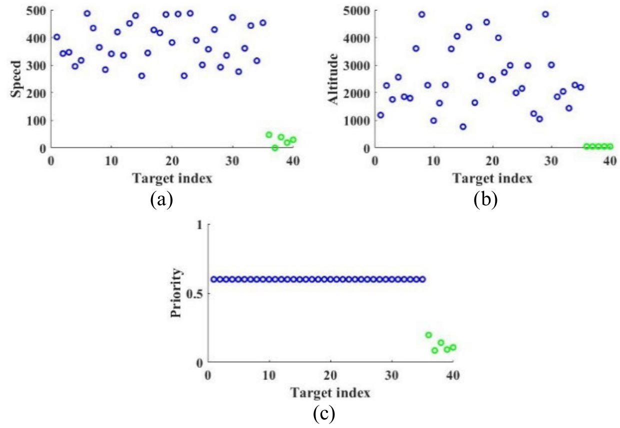

FIGURE 17. Initial parameters and resulting priority value of each target in Experiment 2. Aircraft in blue and battleships in green. (a) Speed of targets. (b) Altitude of targets. (c) Priority of targets.

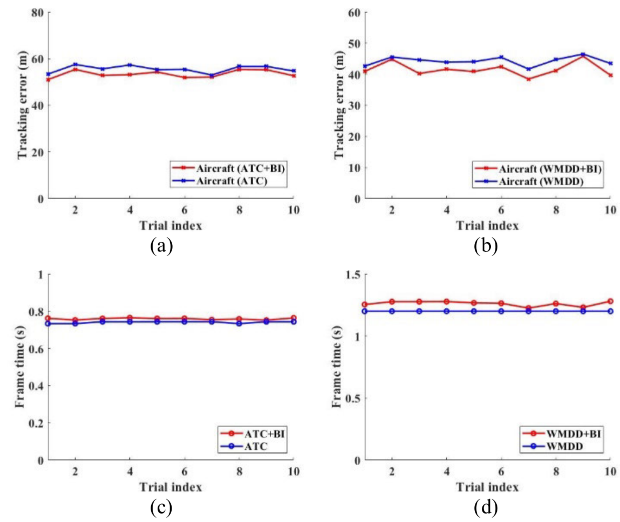

FIGURE 18. Measured tracking errors and frame time depending on the type of targets and the scheduling method. (a) Tracking errors of ATC algorithm. (b) Tracking errors of WMDD algorithm. (c) Frame time of ATC algorithm. (d) Frame time of WMDD algorithm.

Because the targets in Experiment 2 consist of aircraft and battleships without the AShM, only the aircraft were tracked. Furthermore, as shown in Fig. 18(a) and (b), when beam scheduling was performed using both ATC and WMDD algorithms, the tracking errors for aircraft were always higher than the desired error ϵ. Moreover, the tracking errors of the proposed methods did not change significantly, because there was no time-critical threatening target, namely the AShMs. This, in turn, leads to a zero increase in the frame time, which is a valuable resource in RRM. In conclusion, the proposed approach can be automatically adapted following the priority of threatening targets by controlling the trade-off between the tracking accuracy and frame time.

VI. CONCLUSION

This study presented a novel RRM strategy for maritime MFR that performs both surveillance and tracking, especially for targets with high threat levels such as AShMs. The proposed scheme consists of two stages: target prioritization based on fuzzy logic and a new beam-scheduling approach that accounts for the imperfect detection of targets in a real situation. We presented a BI-based heuristic beam scheduling approach that can efficiently adjust the order of beam transmissions to handle target priority as well as the imperfect detection of targets.

To demonstrate the proposed scheme, we modeled a maritime MFR system and associated signals, consisting of noise, clutter, and multipath signals, as well as the targets of interest. According to simulation results based on a realistic maritime environment, the proposed RRM can maintain the tracking error of the AShM below a predefined threshold, derived from the desired minimum CPD at the expense of a slight increase in frame time. Moreover, the frame time increases only when AShM exists within the surveillance area; thus, there is no noticeable increase as long as there is no highly threatening target such as AShM.

This study incorporated realistic detection issues of MFR into the RRM strategy to improvetracking accuracy and also has the potential for further improvement by linking the original RRM theory to radar engineering.

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