An Applied Method for Clustering Extended Targets With UHF Radar

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\section*{ABSTRACT}
In this paper, the application of coherent ultra-high frequency (UHF) Doppler radar for ship target detection over river is investigated. Due to the wide beam and high resolution of UHF radar, ship target echoes are usually significantly extended in both the range and Doppler dimensions of the radar Range-Doppler (R-D) spectrum. The range and radial velocity of the extended target are difficult to be determined using a constant false alarm rate (CFAR) detector, especially for the low-radial-velocity case in which the detection performance of CFAR detector is deteriorated due to strong river clutter. To solve this problem, an applied clustering method is proposed to detect and classify multiple targets and obtain corresponding target centers from the CFAR outputs. The target extension characteristics, which are used for clustering, are modeled and employed in segments for different range. The effectiveness of the proposed method is validated using both simulated and field data and the clustering method can classify extended targets without the need of knowing the number of targets beforehand.

\section*{INDEX TERMS}
UHF radar, extended target, target detection, constant false alarm rate (CFAR), clustering method.

\section*{I. INTRODUCTION}

Detecting and monitoring vessels on inland river are vital to improve efficiency and safety of inland navigation [1], [2]. Vessel detection over sea has been widely investigated [3]. The main sensors for non-cooperative targets detection include radar [4]–[6], optical imaging [7], video camera [8] and thermal infrared [9]. Compared to open sea, vessel detection on rivers is more challenging due to their complex background and various unregistered small vessels. In addition, the attenuation of electromagnetic wave in fresh water is significantly higher, which reduces the radar detection performance [10]. Song \textit{et al.} and Liu \textit{et al.} employed satellite-based optical images for ship detection on inland rivers [11], [12]. Robinette \textit{et al.} evaluated various sensors that can be used for vessel detection and classification in inland waterways [9]. These sensors include a marine radar (4 GHz), a Lidar (light detection and ranging), a stereovision camera and a thermal camera. Stateczny \textit{et al.} applied a microwave radar (24 GHz) for collision avoidance in inland waters [13], and also evaluated the performance (i.e., detection range, resolution and beam width) of several other types of radar systems which use different waveform parameters (i.e., pulse, continuous wave, and frequency-modulated continuous-wave) and operating frequency bands (i.e., S, X, 77 GHz and Lidar). Santi \textit{et al.} detected moving ships using Global Navigation Satellite System (GNSS)-based passive radar in three different scenarios (port, open area and river) [14]. Silvious and Tahmoush used the moving target indicator (MTI) of an X band radar to trigger a long-range camera for ship identification [15].

Ultra-high frequency (UHF) radar operating in the frequency band of 300 MHz to 1 GHz has been used for river surface velocity [16] and discharge measurement [17], [18]. Compared with microwave radar, the UHF radar has the advantage of lower attenuation in freshwater, thus achieving a longer detection range. Compared with video and image based monitoring, the UHF radar is inherently independent
of external illumination (e.g., daylight) and weather conditions (e.g., cloud, fog, rain and snow). In addition, as a shore based and non-contact sensor, the UHF radar is easy to install and maintain and not sensitive to water bodies, such as turbid water, drifting debris, water plants, etc. In this paper, the application of the UHF radar for ship detection and monitoring on natural rivers is investigated for the first time. However, due to the wide beam and high range resolution characters of UHF radar, ship echoes are no longer presented as a point target in the radar Range-Doppler (R-D) spectrum, but are extended in both range and Doppler dimensions, i.e., they are presented as an extended target or distributed target. Thus, multiple target points may be generated for each ship using a constant false alarm rate (CFAR) detector, which makes it difficult to determine the actual number of targets from the detected target point sets. In addition, the CFAR detector may not work effectively when the target appears in the river clutter area, resulting in false alarm or missed alarm. Moreover, the echoes of multiple targets may be partly overlapped with each other, making it more difficult to classify the targets correctly.

Target detection using the UHF radar includes identifying the number of targets and determining the range, speed and direction of each target. It is very difficult to detect multiple non-cooperative extended targets. Moreover, the extension characteristics in range and Doppler dimension are time-varying and depend on the spatial structure (e.g., shape and size) [19] as well as the moving status (e.g., range and velocity) of the target. Clustering algorithms are commonly used for the classification of extended targets [20], [21]. Eryildirim and Guldogan proposed a method to track a single extended target based on Bernoulli filter [22], [23]. Schlichenmaier et al. identified two closely adjacent extended targets based on the analysis of target velocity profile [24]. By knowing the number of extended target, Lan and Li presented an approach for classifying extended object using random matrix and target size provided [25]. Magnant et al. proposed a method for classification of extended targets using target extent measurements [26]. For the case with unknown number of targets, Wu and Hu employed a probability hypothesis density (PHD) filter [27], [28]. Memarsadeghi et al. proposed a fast Iso-data clustering (ISOCLUS) algorithm to classify multiple extended targets [29]. Chi et al. distinguished extended targets based on clustering by fast search and find of density peaks (CFSFDP) [30], [31]. However, the aforementioned algorithms require additional user-supplied parameters to work effectively and they are not applicable to UHF radar. Thus, an applied method for clustering multiple extended targets without auxiliary data should be developed for UHF radar.

In this paper, a new clustering algorithm is proposed to detect extended ship targets from UHF radar data. The extension characteristics of target are statistically analyzed based on field data at first. It is found that the extension in both the range and Doppler dimensions is highly related to the target range. A range segmentation scheme is then proposed to select the thresholds for the clustering algorithm. The number of targets is estimated via preliminary clustering and updated via necessary mergence. The proposed clustering method can classify multiple targets without knowing the number of targets in advance. The target parameters such as range and radial velocity can also be estimated from the output of the clustering algorithm. In particular, such a method is able to detect and identify extended target in strong river clutter.

This paper is structured as follows: The extension characteristics of ship echoes are analyzed in Section II. In Section III, the proposed clustering method is introduced. The validation is then conducted using both simulated and field data in Section IV. The conclusions are made in Section V.

II. TARGET EXTENSION CHARACTERISTICS

Fig. 1 shows a typical UHF radar R-D spectrum collected from the Yangtze River, Yichang, China [32]. The y-axis represents detection range with a resolution of 15 m. The maximum range is 41 range bins (or range cells) or 615 m. The x-axis represents radial velocity with a resolution of 0.086 m/s. The maximum velocity is 128 Doppler bins or ± 5.5 m/s. The range area between the radial velocities of −1 and +1 m/s indicates the river clutter echoes, which have relatively high power value (dB). Two potential targets at different ranges are marked with oval boxes in Fig. 1(a).
Ship 1 is moving toward the radar (i.e., positive velocity) and ship 2 is moving away from the radar (i.e., negative velocity). The R-D spectrum at two minutes later is shown in Fig. 1(b), in which ship 1 has crossed over the front of the radar and is moving away from it and ship 2 moved out of the detection range of radar.

As shown in Fig. 1(a), the echoes of the two targets are both extended in both the range and Doppler dimensions. The target in the low-velocity region of the R-D spectrum (e.g., ship 1) is more heavily extended than that (e.g., ship 2) with large radial velocity and at long range. Generally, the echo power mainly depends on the radar scattering cross section (RCS) of the ship targets (i.e., the ship type and size), and decreases with range. However, since the ship on a river always moves straightly along the riverbank, the extension characteristics in the range and velocity dimensions are highly related to the target range. The radial velocity component of a target changes rapidly when it is near the radar. The closer the target distance is, the smaller the radial velocity is. Due to the wide beam (i.e., the beam width of the radar is $140^\circ$ [32]) and high range resolution of the UHF radar, the echoes of ship 1 span over multiple range cells and Doppler bins when it approached the radar and crossed over the front of radar within the coherent integration time (CIT), resulting in significant extension in range and Doppler dimension. Compared with the echoes of ship 1 in Fig. 1(a), those in Fig. 1(b) are less extended since it is at a longer range. In this paper, the level of extension is simply divided into four segments according to the ship target range. The three nearest range bins are taken as radar blind zone, and the two farthest bins are taken as fuzzy zone because the echoes from long range are relatively weak. The remaining 36 range bins are evenly divided into four regions with each having 9 bins, e.g., region I is from the 4th range bin to the 12th bin (see Fig. 1(a) in which the borders of the four regions are marked with black dotted lines).

A 6-hour field experiment in the daytime was carried out on the Yangtze River. Over 100 non-cooperative ships were manually recorded. In this work, when multiple targets are overlapped in the R-D spectrum, the corresponding data were eliminated. The extension characteristics of ship echoes are analyzed. Fig. 2(a) shows the statistics of ship extensions in different regions in the Doppler dimension. The ships in region I extend over 11 to 25 cells and most of their extension is less than 20 cells. In region II, the ships extend over 3 to 22 cells, whereas the majority of the extension is less than 16 cells. In region III, the extension of most of the ships is within 8 cells. As for the ships in region IV, the extension is between 2 and 7 cells. Fig. 2(b) depicts the statistics of ship extensions in different regions in the range dimension. Unlike the extension in the Doppler dimension, the ship extension is within 10 cells. Most of the ships in region I, II, and III extend over less than 8 cells, but for the ships in region IV, most of their extension is within 6 cells. In general, the extension of ships in different regions is relatively similar in the range dimension.

### III. CLUSTER ALGORITHM FOR EXTENDED TARGET

The main steps of the proposed clustering method are illustrated in Fig. 3. The initial target number is estimated via preliminary clustering, which is the input parameter of the $K$-Means clustering algorithm. The target number is finally determined via the merge program.

#### STEP 1. CFAR TARGET POINT DETECTION

The CFAR detector is implemented by combining the clutter map [33] and cell averaging (CA) CFAR method [34]. It scans $2H + 1$ orderly stored R-D spectra, numbered as $-H, \ldots, -1, 0, 1, \ldots, H$, in which No. 0 is the current R-D spectrum under test, and the spectrum of No. $-1$ and No. 1 are taken as the guard maps. Taking $P_k (v, R), k = -H, \ldots, -1, 0, 1, \ldots, H$, as the power of the cells in different R-D spectrum, where $v$ is the radial velocity and $R$ represents range, the power of the cell under test is $P_0 (v, R)$. The amplitude of the river clutter is assumed to follow the Weibull distribution [34], and the power of the river clutter is relatively stable over time.
The clutter and noise power \( P_c(v, R) \) can be written as
\[
P_c(v, R) = \frac{1}{2H - 2} \left( \sum_{k=-H}^{H} P_k(v, R) - \sum_{k=-1}^{1} P_k(v, R) \right)
\] (1)

The target cells with enough signal-to-clutter-and-noise ratio (SCNR) will be detected. The output of the CFAR detector is a set of points \( x_i(v, R_i) \) \((i = 1, 2, \ldots, M)\), where \( M \) represents the number of detected points.

**STEP 2. PRELIMINARY CLUSTERING**

Suppose the extended target centers are \( z_j(\bar{v}_j, \bar{R}_j) \) \((j = 1, \ldots, N)\), each target \( z_j \) contains one or more detected points. The preliminary clustering is done through the following steps.

i. Classify \( x_i \) as target \( z_1 \) directly. Start from \( j = 1, i = 2 \).

ii. Calculate the distance \( \Delta v_{ij}, \Delta R_{ij} \) between \( x_i \) and the center of the known target \( z_j \) according to (2) and (3).
\[
\Delta v_{ij} = |v_i - \bar{v}_j|, \quad (i = 1, 2, \ldots, M \& j = 1, \ldots, N) \quad (2)
\]
\[
\Delta R_{ij} = |R_i - \bar{R}_j|, \quad (i = 1, 2, \ldots, M \& j = 1, \ldots, N) \quad (3)
\]

where \( (\bar{v}_j, \bar{R}_j) \) is the two dimensional arithmetic mean of the detected points which have been classified as target \( z_j \).

iii. Determine target partition according to the range center of \( z_j \) (i.e., \( \bar{R}_j \)) and the corresponding clustering threshold. The threshold contains two-dimensional boundary value \( (v_{z_1}, R_{z_1}) \) and is shown in Table 1.

The thresholds are semi-empirical based on the statistics in Fig. 2. The thresholds set for preliminary clustering should contain more than 80% of the ship targets in each region.

iv. Point set classification through comparing \( (\Delta v_{ij}, \Delta R_{ij}) \) with the threshold \( (v_{z_1}, R_{z_1}) \). If both of the two distance \( (\Delta v_{ij}, \Delta R_{ij}) \) are less than the thresholds, then \( x_i \) is assigned to target \( z_j \). Otherwise, \( x_i \) does not belong to this target. Then continue to judge the relationship between the detected point \( x_i \) and the next target \( z_{j+1} \). If \( z_{j+1} \) is a null set, classify \( x_i \) as target \( z_{j+1} \) directly. If \( z_{j+1} \) is not a null set, return to step ii.

v. Process next detected point \( x_{i+1} \) after the current one is done and return to step ii, until all the \( M \) detected points have been classified. Then the cluster number \( N \) and preliminary clustering centers \( z_j(\bar{v}_j, \bar{R}_j) \) \((j = 1, \ldots, N)\) are determined.

**STEP 3. ADJUST WITH K-MEANS CLUSTERING**

The targets are roughly classified according to the thresholds in the preliminary clustering, but multiple targets may be merged partly with each other. The K-Means clustering algorithm [35] is used to adjust the classification results from previous step. The integer \( K \) indicates the initial number of clusters, herein, \( K = N \). The following two steps are iteratively repeated until convergence: first, it calculates the point set for which this center is the closest for each cluster center; next, the cluster center is replaced by the centroid of its new set. The average squared distortion \( D \) decreases with each step and the algorithm converges to a local minimum [36].

\[
D = \sum_{j=1}^{N} \sum_{x \in z_j} |x - z_j|^2
\] (4)

where \( x \) is the detected point which have been classified as target \( z_j \). The new clustering centers \( z_j(\bar{v}_j, \bar{R}_j) \) \((j = 1, \ldots, N)\) are updated after Step 3 is completed.

**STEP 4. MERGE PROGRAM**

Fig. 2 shows that some targets have large extensions in range dimension or Doppler dimension in the R-D spectrum, which may result in multiple clustering centers for a single target. In this case, mergence is necessary.

i. Compute the absolute distance of any two clustering centers in the range dimension and Doppler dimension, respectively. For instance, the absolute distance \( d_R \) of the \( p \)th and \( q \)th clustering centers in the range dimension is
\[
d_{pq}^R = |R_p - R_q|, \quad (p, q = 1, 2, \ldots, N) \quad (5)
\]

Similarly, the absolute distance \( d_D \) in the Doppler dimension is
\[
d_{pq}^D = |v_p - v_q|, \quad (p, q = 1, 2, \ldots, N) \quad (6)
\]

ii. Determine cluster center partition and boundary threshold for mergence. These thresholds are also semi-empirical and larger than those in Table 1. The merging thresholds \((v_{\theta}, R_{\theta})\) should contain all the ship targets in each region, as shown in Table 2.

 iii. Compare the absolute distance with the merging thresholds. If \( d_R \) and \( d_D \) are both less than the thresholds, then these two classes of detected points are merged, and the clustering centers are recalculated and updated. Meanwhile, the cluster number \( N \) is reduced by 1. Otherwise there is no need to merge.

**STEP 5. OUTPUT CLUSTERING RESULTS**

Repeat Step 3 and 4 till the cluster number \( N \) is not changed anymore, the clustering process is terminated. Output clustering results, including the updated target number \( N' \) and the target centers \( z_j(\bar{v}_j, \bar{R}_j) \) \((j = 1, \ldots, N')\).
IV. VERIFICATION ANALYSIS

A. SIMULATION VERIFICATION

Five simulated ship targets were used to validate the proposed clustering method, as shown in Fig. 4. The background data involving the river clutter comes from the UHF radar field data. The ship parameters are listed in Table 3. The 5 targets are distributed in four segments in the R-D spectrum and their extension level in range and Doppler dimensions are set according to the extension statistics in Fig. 2. Targets 1, 2, and 3 are located in the river clutter with low velocities, while Targets 4 and 5 are outside the clutter zone with high speeds. The signal power of the extended cells is increased randomly (meanwhile, the signal power near the target center is set to the maximum), and the mean of the increment is the corresponding value of SCNR.

By setting the false alarm probability \( P_{FA} \) as \( 1 \times 10^{-2} \), the output point sets of the CFAR detector are marked with ‘∗’ and shown in Fig. 4(a). It can be seen that some target points are partially overlapped or undetected (missed alarms), and some clutter points are detected as target points (false alarms) as shown in the zoom box. The point sets output by the CFAR detector are further processed by the proposed clustering method in this paper. The final clustering result is shown in Fig. 4(b). The clustering centers are marked with black ‘∗’. As can be seen, this method successfully determines the target number as 5. The comparisons between the clustering centers \((v', R')\) and the preset target centers \((v_0, R_0)\) are shown in Table 4. The error in the range dimension is \( \Delta R = |R - R_0| \), and the error in the Doppler dimension is \( \Delta v = |v - v_0| \). The maximum error in the range dimension is 10 m (Target 1) and is less than the range resolution of the radar (i.e., 15 m). The maximum velocity error is 0.15 m/s (Target 2), within two Doppler resolution cells of the radar. The error of Target 4 or 5 which is at long range is negligible, i.e., the clustering center is exactly the same as the target center. This indicates that the proposed clustering algorithm works perfectly for the low extension region and the clutter-free area. Targets 1, 2, and 3 are in the clutter region, where some missed alarms and false alarms from the CFAR detector are observed, hence the error is slightly larger. However, these 3 targets are also correctly classified in the end, the proposed clustering method works well even with river clutter.

As a comparison, the classical K-Means algorithm is also implemented to the simulated data. The initial number of clusters is set to be 5, and the initial centers of the 5 clusters are chosen by searching 5 local peaks in the CFAR output point sets. As shown in Table 4, the errors in the range dimension and Doppler dimension between the cluster center \((v', R')\) and the target center \((v_0, R_0)\) are \( \Delta R' = |R' - R_0| \) and \( \Delta v' = |v' - v_0| \), respectively. The errors are quite small, indicating that the clustering center is close to the target center. However, selecting different input parameters for the K-Means algorithm will produce different results. For example, if the target number is set to be 4, then wrong clustering results will be obtained. As shown in Fig. 5, Targets 4 and 5 are clustered as one ship, resulting in missed alarm of one ship and incorrect parameters estimation for the other ship. Thus, the K-Means algorithm is significantly dependent on prior information about the target, whereas the method proposed

| Target | Target center \((v_0, R_0)\) | Range extension \(\Delta R\) | Doppler extension \(\Delta v\) | SCNR (dB) |
|--------|-----------------------------|-----------------------------|-----------------------------|-----------|
| 1      | (-0.94,261)                | 6                          | 16                          | 21        |
| 2      | (0.17,200)                 | 5                          | 19                          | 22        |
| 3      | (0.94,100)                 | 6                          | 23                          | 20        |
| 4      | (2.6,500)                  | 4                          | 2                           | 25        |
| 5      | (2.9,462)                  | 3                          | 3                           | 27        |

The unit of \( v_0 \) is m/s, the unit of \( R_0 \) is m. The range (Doppler) extension means the number of extended cells in Range (Doppler) dimension.

| No. | \((v_0, R_0)\) | \((v', R')\) | \(\Delta v\) | \(\Delta R\) |
|-----|---------------|---------------|--------------|--------------|
| 1   | (-0.94,261)   | (-0.92,251)   | 0.02         | -0.98,256    | 0.04,5     |
| 2   | (0.17,200)    | (0.32,199)    | 0.15         | 0.27,189     | 0.10,11    |
| 3   | (0.94,100)    | (0.827,98)    | 0.113,2      | 1.02,103     | 0.08,3     |
| 4   | (2.6,500)     | (2.6,500)     | 0.0          | 2.6,500      | 0.0        |
| 5   | (2.9,462)     | (2.9,463)     | 0.1          | 2.9,463      | 0.1        |

The unit of \( v \) is m/s, the unit of \( R \) is m.
FIGURE 5. The clustering results from simulated data using the K-Means algorithm with initial number of targets set to be 4.

FIGURE 6. (a) Relative errors versus $P_{FA}$ for SCNR = 20 dB. (b) Relative errors versus SCNR for $P_{FA} = 1 \times 10^{-2}$.

in this paper does not have this limitation and it can cluster accurately without knowing the number of targets in advance.

Fig. 6 shows the detection performance of Target 3 for the proposed clustering method under different $P_{FA}$ and SCNR. Herein, Fig. 6(a) shows the relative errors between the clustering center ($v, R$) and the target center ($v_0, R_0$) (i.e., $(R-R_0)/R_0$ and $(v-v_0)/v_0$) under SCNR = 20 dB with different $P_{FA}$. No target point is detected when $P_{FA}$ is less than $2 \times 10^{-4}$, meanwhile there will be many false alarms leading to more than one clustering center when $P_{FA}$ is larger than $6 \times 10^{-2}$. The range error is negligible, whereas the velocity error fluctuates slightly, with the maximum error being 0.31 m/s. Fig. 6(b) shows the relative differences under $P_{FA} = 1 \times 10^{-2}$ with varying SCNR. No target point is detected when SCNR is less than 12 dB, whereas more and more target points will be detected with the increase of SCNR. When SCNR is larger than 25 dB, the relative differences of both the range and the radial velocity approach zero.

B. PRACTICAL APPLICATION

Next, the proposed clustering method is applied to UHF radar field data. Fig. 7(a) shows the target point sets (marked with ‘*’) of the CFAR detector and Fig. 7(b) shows the clustering results of the targets (marked with black ‘★’). Two targets are successfully detected: the nearby target at range $R = 283.8$ m and radial velocity $v = 1.84$ m/s; the farther target at $R = 500.7$ m, $v = -3.68$ m/s. However, it can also be seen that some points of the nearby target are submerged in the clutter as shown in Fig. 7(a), resulting in the deviation of the clustering center from the geometric center of the target.

The movement of a ship travelling on a straight river channel can be treated as uniform rectilinear motion. As shown in Fig. 8, suppose a ship travels along the straight shipping lane with a speed of $v_s$, the distance from the lane to the riverbank is $R_0$, which can be estimated when the ship moves across the radar normal line (i.e., the radial velocity $v = 0$) and used to determine the shipping lane. At some point the distance of the ship from the radar is $R$, the radial velocity is $v$, and the direction of arrival (DOA) is $\theta$, thus the ship speed $v_s$ can be calculated as

$$v_s = v / \cos \theta \quad (7)$$
The track of a target consists of the sequence of the target clustering centers detected. Fig. 9 shows the tracks of the other two targets. ‘SanB’ is the UHF radar site; the black line crossed the river shows the radar normal direction. The nearby target (ship 1) moved upstream from east to west along the red shipping lane, and the detected target positions p1 to p13 (the interval between adjacent positions is 21 s) are marked with red stars. The farther target (ship 2) moved downstream from west to east along the white shipping lane, and the detected positions q1 to q10 are marked with white stars. Corresponding target parameters are shown in Table 5.

The absolute values of both the radial velocity (i.e., $v$) and range (i.e., $R$) of ship 1 (or ship 2) decrease first, with a minimum value near the radar normal line (i.e., p6, q6) and then gradually increase. This change is associated with a ship crossing the front of the radar. It is worth noting that positions p5 to p8 and q4 to q7 are detected when the targets are in the clutter of the R-D spectrum, hence the detection errors may be a little bit larger, which accounts for the uneven target positions and low ship speeds at these positions: it illustrates the impact of the river clutter on target detection. The measured ship speeds at the positions free of clutter (i.e., p1-4, p9-13, q1-3, and q8-10) are more uniform, hence can be taken as the real speed of the ship, i.e., the speeds of ship 1 and ship 2 are about 3 m/s and 4 m/s, respectively. In addition, the travelling distance from p1 to p13 is about 775 m over an interval of 252 s (i.e., 21 × 12 s).

Thus, the average speed of ship 1 can be calculated as about 3.08 m/s. The distance from q1 to q10 is about 750 m over an interval of 189 s (i.e., 21 × 9 s), thus, the average speed of ship 2 is 3.97 m/s. Both the average speeds agree well with the measured data. In general, it shows that our detection and classification are feasible and effective, especially in the area free of river clutter.

### V. CONCLUSION

In this paper, the application of using a UHF radar for detecting ship targets in the Yangtze River of China is investigated. Due to its high resolution, the ship echoes are significantly extended in both the range and Doppler dimensions of the R-D spectrum. The target extension characteristics are firstly analyzed in terms of the target range, and then an applied clustering method is proposed. To verify the effectiveness of the proposed method, both simulated and field data were used. The results showed that the number of targets can be estimated correctly, and the change of the target center including range and radial velocity can be tracked with decent precision.

Since the detection threshold of the proposed clustering method is semi-empirical based on the statistics of limited data, more field measurements and ground truth data are required for further analysis. Moreover, ship detection in strong clutter with low SCNR is challenging but necessary. As we know, river clutter will affect the detection performance. Since the river clutter in our data is relatively stable over time, a simple cell averaging (CA) CFAR method was used to detect ship targets and it proved to be effective. Further study of how river clutter will affect the detection performance should also be conducted. In addition, it should note that the ship type and size have not been considered in the characteristics and threshold determination since the ship information is not available. In the future, the effect of such information on the detection performance could be investigated.
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