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Automatic target recognition combining angular diversity and time diversity for multistatic passive radar

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Dear editor,

The radar cross section-based (RCS-based) method is an important research direction in the field of automatic target recognition (ATR) of passive radars [1–5]. Due to the unknown transmitting parameters in the passive radar, it is impossible to extract the true target RCS from the echo power. As a result of this, researchers use a biased RCS which has an unknown parameter to realize the RCS-based ATR in passive radar [1, 2]. However, the average correct recognition rates (ACRRs) of their methods are not good. Apart from those using the measured biased RCS, the other studies only employ simulated RCS to verify their ATR methods [3–5]. Although good ACRRs are obtained in their work, there is no evidence to prove the effectiveness of their methods in the actual scene.

In this article, we propose an ATR method combining angular diversity and time diversity to improve the performance of ATR in passive radar and to facilitate its application in actual scenes. The proposed method takes advantage of the amplitude of the measured quasi-RCS in angular subspace to recognize targets. In each angular subspace, we build a sub-recognizer. All the sub-recognizers together form the proposed recognizer. In each angular subspace, the sub-recognizer can be well trained with less amount of training data compared with the situation without angular space division. In addition, we propose a successive voting (SV) strategy to automatically output the recognition result with corresponding correct prediction probability (CPP).

Method design. Figure 1(a) shows the block diagram of the proposed ATR method. It consists of fuzzy recognizers built in all angular subspaces that are obtained by dividing the angular space of the target coordinate system. We call each fuzzy recognizer in an angular subspace a sub-recognizer. At each time point, each receiving station calls a sub-recognizer to do the preliminary recognition on the unknown target and outputs a preliminary decision separately. Then these preliminary decisions are sent to the station fusion module to make station fusion. The station fusion module employs the voting strategy to fuse the preliminary decisions and outputs a secondary decision about the unknown target. The secondary decision is then sent to the decision container to wait for time fusion. When M (the expected value) secondary decisions are input, the time fusion module fuses them and outputs a final decision. The final decision is then sent to the decision module to determine the class of the unknown target.

In the decision module, an SV strategy is proposed to estimate the CPP of the recognition result. The SV strategy estimates the CPP according to the total probability theorem as follows:

$$P(B) = \sum\nolimits_{i=1}^{\gamma} P(A_i)P(B|A_i), \tag{1}$$

where γ is the current number of fused final decisions, $A_i, i = 1, 2, \ldots, \gamma$ denotes the event that the recognizer correctly recognizes the target i times in γ final decisions, and B denotes the event that the recognizer correctly recognizes the unknown target with fusing γ final decisions. $P(B)$ is the probability of event B happening, i.e., the CPP, $P(A_i)$ is the probability of event A_i happening, and $P(B|A_i)$ is the conditional probability of event B happening conditioned on event A_i. The probability $P(A_i)$ is expressed as

$$P(A_i) = \sum\nolimits_{s=1}^{C_\gamma^i} \xi_s, \tag{2}$$

where $C_\gamma^i = \frac{\gamma!}{i!(\gamma-i)!}$ is the number of possible situations of event A_i happening, $\xi_s = \prod_{d=1}^{i} p_d \prod_{g=1}^{\gamma-i}(1-p_g)$ is the probability of the sth situation happening among C_γ^i situations corresponding to the event A_i, where p_d is the correct probability of each final decision among i correct final decisions, $(1-p_g)$ is the wrong probability of each final decision among $(\gamma-i)$ wrong final decisions. p_d and p_g are the prior

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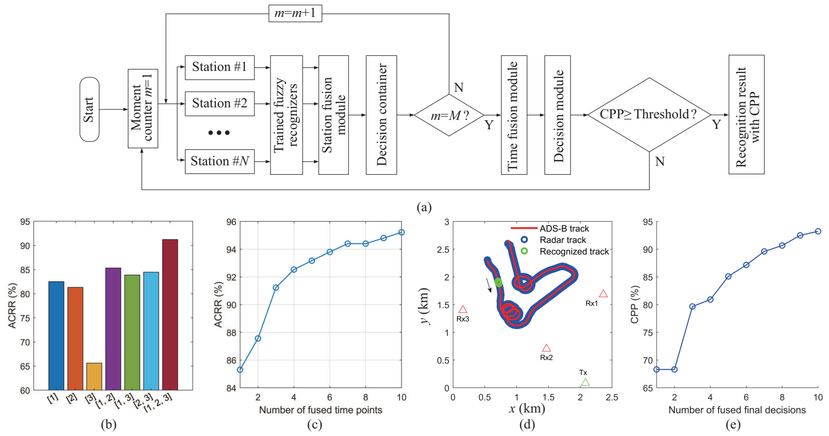

Figure 1 (Color online) (a) Block diagram of the proposed ATR method; (b) ACRR of the proposed method obtained with different receiving stations; (c) ACRR of the proposed method as a function of the number of fused time points; (d) the real-life target track used in the recognition experiment; (e) CPP of the recognition results corresponding to the track segment in (d).

probabilities. $P(B|A_i)$ is calculated as

$$P(B|A_i) = \begin{cases} 0, & i < \frac{\gamma}{Q}, \\ \sum_{j=1}^{C_{\gamma-i+Q-2}^{Q-2}} \frac{p'_j}{C_{\gamma-i+Q-2}^{Q-2}}, & \gamma/Q \leqslant i \leqslant \gamma/2, \\ 1, & i > \frac{\gamma}{2}, \end{cases} \tag{3}$$

where Q denotes the number of target classes in the standard target database, p'_j denotes the probability that the jth voting result among $C_{\gamma-i+Q-2}^{Q-2}$ possible voting results is the correct recognition.

The sketch map of the angular subspace can be found in Appendix A. The time fusion module and decision module can be found in Appendix B. The detailed derivation of CPP can be found in Appendix C.

Experimental results and analyses. The proposed ATR method is evaluated with the real-life data. The experimental scene configuration and the measured raw data can be found in Appendix D. Figure 1(b) shows the ACRRs of the proposed ATR method obtained with different receiving stations. The x-tick labels denote the indices of the receiving stations used in the recognition experiments. We can see from the figure that the ACRR obtained with fusing multiple receiving stations is better than the ACRRs obtained without station fusion. Moreover, it also shows that the ACRR obtained with fusing three receiving stations is higher than the ACRRs obtained with fusing two receiving stations. These results indicate that the more the receiving stations used for fusion are, the better the performance of the method is.

Figure 1(c) shows the results of ACRR as a function of the number of fused time points. It shows that the ACRR of the recognizer increases as the number of fused time points increases. As can be seen from the figure that the ACRR of recognizer can be improved from about 85% to more than 91% with only fusing secondary decisions from three time points, which demonstrates that the ACRR could be effectively improved with less sacrifice of the real-time performance of the recognizer by combing station fusion and time fusion in the ATR method.

A recognition experiment is also conducted with the real radar track to validate the SV strategy. Figure 1(d) shows the measured target track. Figure 1(e) shows the CPP of recognition result obtained with the recognized track in Figure 1(d). It shows that the CPP of recognition result increases when more final decisions are fused. As can be seen from Figure 1(e), the CPP of recognition result increases from about 68% to around 90% with fusing 7 final decisions. These results indicate that the recognition result becomes more credible after the recognizer employing more final decisions to recognize the target, which is consistent with the actual situation and validates the effectiveness of the proposed SV strategy.

More analyses of the proposed method can be found in Appendixes E and F.

Conclusion. To tackle the target recognition problem in multistatic passive radar, we propose an ATR method combining station fusion and time fusion. The proposed method first fuses preliminary decisions from all receiving stations and then further fuses the secondary decisions to obtain more credible results. An SV strategy is finally employed to decide whether the final decision satisfies the requirement. Recognition results validate the effectiveness of the proposed method and show a promising application prospect of the method in real situations.

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Supporting information Appendixes A–F. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

References

1 Ptak P, Hartikka J, Ritola M, et al. Aircraft classification based on radar cross section of long-range trajectories. IEEE Trans Aerosp Electron Syst, 2015, 51: 3099–3106
2 Pisane J, Azarian S, Lesturgie M, et al. Automatic target recognition for passive radar. IEEE Trans Aerosp Electron Syst, 2014, 50: 371–392
3 Ehrman L M, Lanterman A D. Incorporation of aircraft orientation into automatic target recognition using passive radar. IET Radar Sonar Nav, 2020, 14: 1079–1087
4 Hinostroza I, Ren C, Letertre T, et al. Analysis of airplane signatures using passive VHF radar for recognition perspectives. In: Proceedings of International Radar Conference, Toulon, 2019. 1–4
5 Fix J, Ren C, Lopes A C, et al. Deep learning for aircraft classification from VHF radar signatures. IET Radar Sonar Nav, 2021, 15: 697–707