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A Maneuvering Target Detection in Time-Series Doppler Spectrums with Self-Organizing Model

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Abstract – **This paper presents a probability of detection enhancement technique for a maneuvering target with a low radar cross section in time-series Doppler spectrums. The target signal and a noise variance are estimated by the self-organizing model applied to the particle filter and the history of the particle information is used for the detection with a constant false alarm rate. A Monte Carlo simulation is carried out for the performance investigation. The results show that the probability is enhanced, even when a target has a high angular velocity.**

Index Terms — **Radar, CFAR, Self-organizing, Detection, Particle filter, Track-Before-Detect (TBD).**

1. Introduction

In a radar detection, the post detection integration (PDI) is used for a probability of detection (Pd) enhancement [1] and thus has a capability of low radar cross section (RCS) target detection. When the data processed in the PDI is time-series Doppler power spectrums of the fast Fourier transform (FFT), the integration is carried out in the same Doppler-bin and a moving target's Doppler spectrum can be detected. The PDI is an effective processing for an airplane detection.

However, if the target Doppler is changed due to a maneuvering, the PDI cannot work well. In this paper, a detection technique for a maneuvering target in the time-series Doppler spectrums is proposed. The technique is as the same approach as the Track-Before-Detect (TBD) [2],[3]. In the TBDs, however, the noise statistics, e.g., a variance, is assumed as known and detection with a constant false alarm rate (CFAR) is not discussed. Thus, these are hard to implement to actual radars. Meanwhile in the proposed technique, both of the signal and the noise statistics can be estimated by the self-organizing model applied to the particle filter and the CFAR detection is realized. The proposed technique thus can be readily to be implemented to actual radars.

In the following, the detection model and scheme is described in Sec. 2. The simulation results are given in Sec.3 and finally, Sec. 4 concludes this work.

2. Detection Technique

(1) Self-Organizing Model

The time-series spectrums is expressed as $\mathbf{Z}_1,...,\mathbf{Z}_K$, where $\mathbf{Z}_k=[Z_k(1)\ \ldots Z_k(X)]^T$ is the spectrum, k and x are an index of the time-series and the target Doppler-bin, respectively, and T is the vector transpose. It is assumed that the noise statistics, the target signal and its Doppler are unknown. The state sequence is defined by

$$V_k \sim IG(a_{k-1}, b_{k-1}), \tag{1}$$

$$S_k \sim U(0, S_{\max}), \tag{2}$$

$$x_k = 2x_{k-1} - x_{k-2} + w_{k-1}. \tag{3}$$

In Eq. (1), the variance V_k as the noise statistics is the random variable (RV) from the inverse Gamma distribution $IG(a, b)$ with a and b of a shape and scale parameters, i.e., hyper-parameters. The parameters are given by the estimated V_k. In Eq. (2), the signal S_k is the RV from the uniform distribution $U(0, Smax)$ with 0 to $Smax$. Eq. (3) stands for the target Doppler-bin changing, where w_k is a system noise given by Gaussian. When the target Doppler presents in x_k, the data model is given by

$$Z_k = S_k + N_k \tag{4}$$

where N_k is the noise whose distribution is the exponential with V_k of the mean (it is the variance in the complex Gaussian). The distribution of Z_k in Eq. (4) is thus given by the Rice. It is noted that the above model is nonlinear and the hyper-parameters are modeled in the state sequence. The model is thus the self-organizing one [4]. In this paper, the particle filter is applied for the online estimation, where the sampling importance re-sampling (*SIR*) [5] is used.

(2) CFAR Detection

To detect the signal after the estimation, the data integration using the particle history is processed. The test statistic t is then defined as

$$t = \max(C_1(i)/C_0(i)) \tag{5}$$

$$C_1(i) = \sum_{k=1}^{K} Z_k(\hat{x}_k(i)) \tag{6}$$

$$C_0(i) = \frac{1}{K(X-1)}\left(\sum_{k=1}^{K}\sum_{x=1}^{X} Z_k(x) - C_1(i)\right) \tag{7}$$

where i is a number of the particle. Eq. (6) gives an integration of the spectrum in the estimated Doppler-bin. Since the *SIR* is used, the i-th particle history from k=1 to K can be traced. By using the history, the target Doppler changing routes with the possibility are employed to the detection. Eq.(7) shows the mean of the noise.

When the target is absence in the data, and Eq. (6) and the numerator of Eq. (7) are the Gamma distribution with K and $K(X\text{-}1)$ of degree of freedom, respectively. Thus, the distribution of t is given as

$$P(t)=\frac{\Gamma(K+X)}{\Gamma(K)\Gamma(X)}\frac{(t/X)^{K-1}}{(1+t/X)^{K+X}}\frac{1}{X} \qquad (8)$$

where $\Gamma(\cdot)$ is the Gamma function. In Eq. (8), there are not any statistical parameters. Thus, the detector in Eq. (5) has the CFAR property.

3. Performance Analysis

In order to discuss the proposed technique, a Monte Carlo simulation is carried out. One of the results is presented here. Fig. 1 shows the time-series Doppler spectrums, where a signal to noise ratio (defined as mean of signal spectrum to that of the noise one, *SNR*) is 8dB and the target signal is a constant. The target turns with 1.2rad/s of an angular velocity. The target Doppler changing route is then expressed as a curved line, but it is hard to be found in this figure.

Fig. 2 shows the estimated target Doppler-bin changing, where the simulation conditions are as the same as that in Fig. 1 and a probability of false alarm rate (Pfa) is given as 10e-2. We can see that the estimate is correspondence to the truth within one or two Doppler-bin difference.

Fig. 3 shows the performance comparison with the PDI for various angular velocities. The Pd is calculated both from the target detection and the estimation of the Doppler-bin changing points of view. Here, if the Doppler-bin difference between the proposed and the truth in the route is one or less, then the estimation is regarded as a success. In the figure, it is found that the Pd of the PDI is higher than that of the proposed in the small angular velocity, such as 0.8rad/s. Meanwhile, the Pd of the proposed is considerably higher in the large velocity, more than 1.5rad/s. The proposed technique is enhanced the Pd and useful to a maneuvering target detection.

4. Conclusions

This paper presents maneuvering target detection, where the self-organizing model applied to the particle filter is used. From the results of a Monte Carlo simulation, it is found that the proposed technique is superior to the PDI and the Pd is enhanced by the proposed, when a target has a high angular velocity.

References

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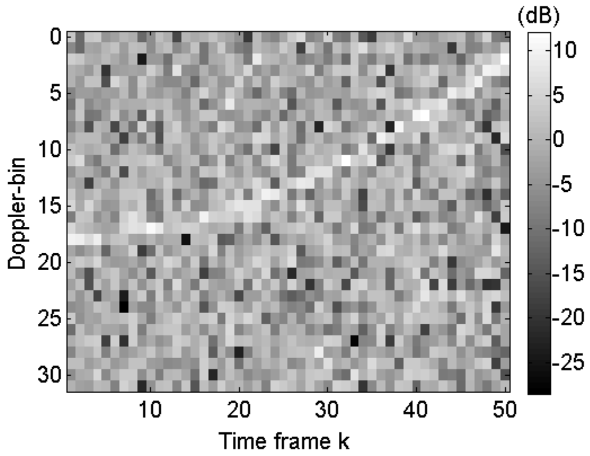

Fig. 1 Time-series Doppler spectrums; *SNR*=8dB.

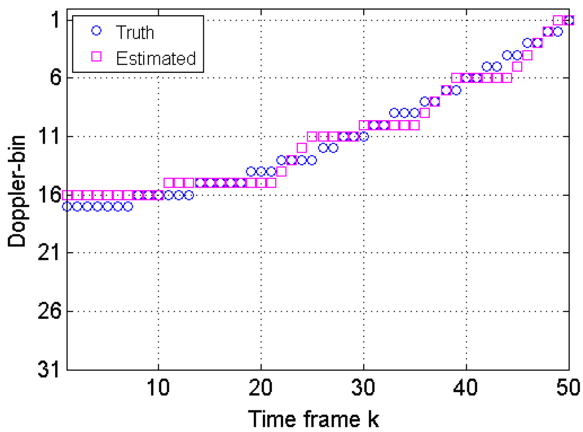

Fig. 2 Estimated target Doppler-bin changing.

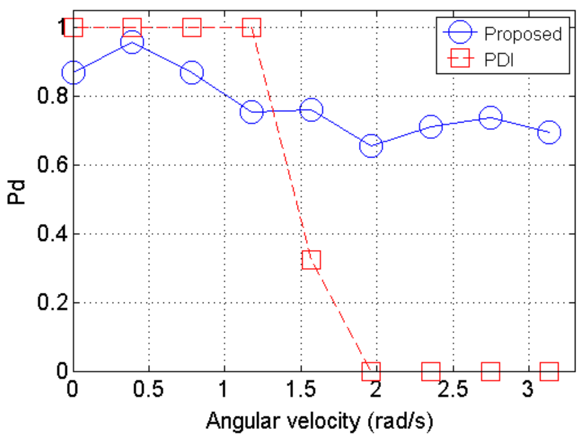

Fig. 3 Performance comparison; Pfa = 10e-2, *SNR*=8dB.