Wind Turbine Clutter Mitigation for Weather Radar by Extreme Learning Machine (ELM) Method

Mingwei Shen[1(✉)], Xu Yao[1], Di Wu[2], and Daiyin Zhu[2]

[1] College of Computer and Information Engineering, Hohai University, Nanjing 211100, China
smw_hhu1981@163.com
[2] Key Laboratory of Radar Imagine and Microwave Photonics, Nanjing University of Aeronautics and Astronautics, Nanjing 210016, China

Abstract. Because of its overall performance, the Extreme Learning Machine (ELM) has been very concerned. This paper introduces the ELM algorithm into the clutter mitigation for weather radar, and proposes a wind turbine clutter mitigation method. Firstly, building training samples. Secondly, the model parameters for ELM are examined and optimized aim to improve its overall performance. Finally, the optimized ELM algorithm is used to recover the weather signal of the contaminated range bin. Simulation results show that the proposed algorithm can realize the precise recovery of the weather signal.

Keywords: Weather radar · Extreme Learning Machine · Clutter suppression

1 Introduction

Because of the importance of renewable energy, the use of wind farms is increasing. This continued growth seriously threatens the performance of most radar systems, especially the weather radar. The echo signal from the wind farm is called the wind turbine clutter (WTC) [1]. The focus of this paper is the mitigation of WTC on weather radar [2].

In recent years, many researchers have been dedicated to suppressing WTC and proposing some mitigation methods. The common method is spatial interpolation. Unfortunately, the weather data is the typical spatial-temporal data. The spatial interpolation only utilizes the spatial continuity in the range domain of the weather signal, but ignores the correlation in the Doppler domain.

In this paper, we creatively introduce the ELM into the mitigation of WTC. Compared with existing algorithms, ELM has two advantages: First, the recovery of the weather signal can be achieved with a small error; Second, ELM has low complexity and fast learning ability.

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2 Weather Radar Signal Model

Assume the lth range bin contains both WTC and the weather signal. The weather radar echo sampling in the n th pulse is expressed as

$$x_l(n) = w_l(n) + c_l(n) + s_l(n) + z_l(n),\ n = 1, 2, \ldots K \tag{1}$$

where K is the pulse number, $w_l(n)$ represents the wind turbine clutter, $c_l(n)$ is the ground clutter, $s_l(n)$ is the weather signal, $z_l(n)$ denotes the noise.

The weather signal is the distributed target, so the weather signal of a range bin is formed by the echo of multiple scattering particles [3]. Sum up the scattering particle echo vector of the lth range bin, then the weather signal return in the nth pulse can be expressed as

$$s_l(n) = \sum_{u=1}^{U} A_u e^{j(n-1)\omega_t} \tag{2}$$

where U is the number of scattering points in the lth range bin, A_u is the amplitude of the weather target particle u.

3 Wind Turbine Clutter Mitigation

3.1 Extreme Learning Machine for Weather Radar

For N different samples (t_i, y_i), the mathematical model of ELM can be expressed as

$$\sum_{j=1}^{L} \beta_j f(\omega_j \cdot t_i + b_j) = o_i, i = 1, \ldots, N \tag{3}$$

Where L is the number of hidden layer nodes, $f(x)$ is the activation function, β_j is the coefficient between the output layer node and the jth hidden layer node, ω_j is the coefficient between the input layer node and the jth hidden layer node, and b_j is the deviation of the jth hidden node. o_i is the network output of the ith sample. And there are

$$\sum_{j=1}^{L} ||o_j - y_j|| = 0 \tag{4}$$

There exist ω_j, b_j, β_j

$$\sum_{j=1}^{L} \beta_j f(\omega_j \cdot t_i + b_j) = y_i \tag{5}$$

Write the above formula in matrix form

$$H\beta = Y \tag{6}$$

Where

$$H = \begin{bmatrix} f(\omega_1 t_1 + b_1) & \dots & f(\omega_L t_1 + b_L) \\ \dots & \dots & \dots \\ f(\omega_1 t_N + b_1) & \dots & f(\omega_L t_N + b_L) \end{bmatrix} \tag{7}$$

$$\beta = [\beta_1^T, \dots, \beta_L^T]^T \tag{8}$$

$$Y = [y_1^T, \dots, y_N^T] \tag{9}$$

Where H is called the hidden layer output matrix. The ω_j and b_j can be randomly selected, and the β can be obtained

$$\beta = H^+ Y \tag{10}$$

Where H^+ is the Moore-Penrose generalized matrix inverse of the H.

3.2 Training Sample Design

The input of the network is as follows

$$\begin{bmatrix} 1 & R_1 & R_1^2 \\ 1 & R_2 & R_2^2 \\ \dots & \dots & \dots \\ 1 & R_i & R_i^2 \end{bmatrix} \quad i = 1, 2, \dots, N \tag{11}$$

Where R_i is the range of the ith sample.

In this paper, the radial velocity and spectral width estimation of the weather signal are respectively selected for prediction, and their outputs are shown as follows

$$[v_1, v_2, \dots, v_i] \tag{12}$$

$$[o_1, o_2, \dots, o_i] \tag{13}$$

Where v_i, o_i are respectively the radial velocity and spectral width estimation of the weather signal of the ith training sample.

4 Simulation Results and Performance Analyses

The validity of the proposed method is verified by computer simulation. Radar simulation parameters are shown in Table 1. We select the 25th range bin as the range bin contaminated by WTC and select the 15th–35th range bins as samples.

Table 1. Simulation parameters.

Parameters	Values
Carrier frequency f_0	5.5 GHz
Pulse repetition frequency	1000 Hz
Radar height	1000 m
Wind turbine height	880 m
Wind turbine rotate speed	15 r/min
Wind turbine blade length	26 m

We compare the radial velocity estimation and spectrum width estimation before and after applying the proposed method. We choose two-dimensional joint interpolation for comparison. In order to make the experimental results more accurate, we conduct 100 independent Monte Carlo experiments.

Figure 1 and Fig. 2 respectively show the radial velocity and spectral width estimation before and after the application of ELM algorithm. As shown in Fig. 1 and Fig. 2, ELM algorithm can greatly reduce the error of radial velocity and spectral width estimation caused by WTC contamination. It further shows that ELM algorithm is suitable for clutter suppression of wind turbine for weather radar.

Figure 3 and Fig. 4 respectively show MAE in radial velocity and spectral width estimation in different SNR. From Fig. 3, we note that the MAE of ELM algorithm is less than two - dimensional joint interpolation, When the SNR is 20 dB, the MAE of ELM algorithm is 0.01 m/s, and the two-dimensional joint interpolation is 0.03 m/s, which reduced by 0.02 m/s. And in the Fig. 4, when the SNR is 10 dB, the MAE of ELM algorithm is 0.2 m/s, and the two-dimensional joint interpolation is 1.9 m/s, which reduced by 1.7 m/s.

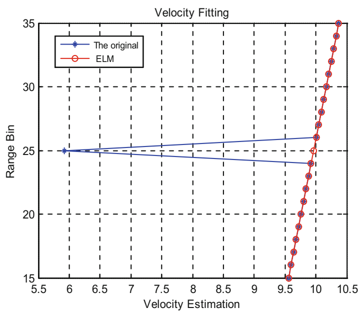

Fig. 1. The radial velocity estimation before and after the application of ELM

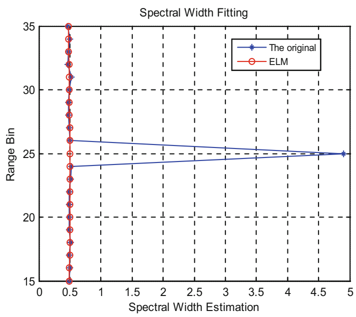

Fig. 2. The spectral width estimation before and after the application of ELM

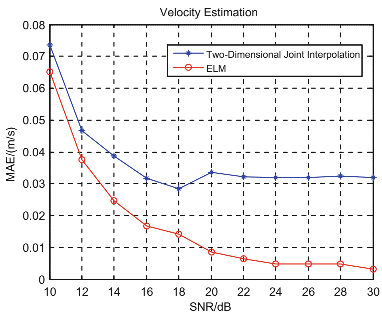

Fig. 3. MAE in radial velocity estimation in different SNR

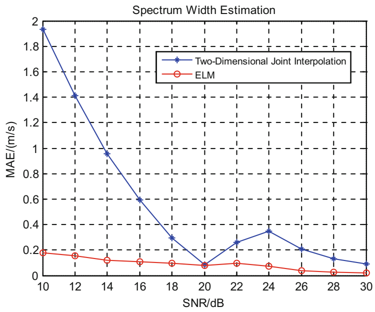

Fig. 4. MAE in spectral width estimation in different SNR

Figure 5 and Fig. 6 respectively show the mean values of radial velocity and spectral width estimation in different SNR. From Fig. 5, we note that the mean value of radial velocity estimation is sensitive to noise. And we can see that the radial velocity estimation of the ELM algorithm has a small deviation from the truth value. From Fig. 6 that the MAE in spectral width estimation of the ELM is small and finally converges to the truth value.

We analyze the complexity of two-dimensional joint interpolation and ELM. The computational complexity of the two-dimensional joint interpolation in range-Doppler domain is $O(N(N_f + K)n)$, while the ELM is $O(Nn)$. Under the simulation parameters, the number of selected range bins is $N = 21$, the selected Doppler frequency bins is $N_f = 22$, the number of experiments is $n = 100$. Calculation results show that computational complexity of the ELM is greatly reduced compared with the two-dimensional joint interpolation, which confirms the proposed algorithm is suitable for engineering application.

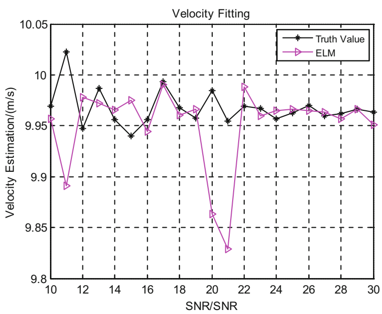

Fig. 5. Mean values of radial velocity estimation in different SNR

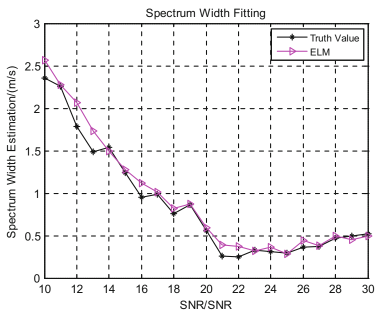

Fig. 6. Mean values of spectral width estimation in different SNR

5 Conclusion

This paper proposes a WTC suppression method for weather radar based on the ELM. Through the network training, the weather signal prediction model is constructed. Simulation results illustrate the proposed method can effectively suppress the WTC and realize the precise recovery of the weather signal. Increasing the efficiency and precision of ELM will be further explored in future works by improving the optimization algorithm.

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