Data Diven Based Extraction and Recognition of Space Target’s Radar Micromotion Features

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Abstract. The micromotion features of the space target is an important information source of radar target recognition. Multiple micromotions due to certain complex features can further characterize the specific targets and then improve the accuracy of the target recognition. With regard to the extraction and recognition of space target complex micromotion features, the data-driven method was used to conduct effective extraction and training recognition. On the one hand, the EMD method was used to effectively separate the complex micromotion components of the space target, and then the motion parameters of the target are estimated with high precision. On the other hand, we take the motion parameters of the target in various forms of micromotion as input and learn typical object movement characteristics by a machine learning algorithm, thus improve the precision and accuracy of target detection. The simulation results show that EMD method can accurately extract various motion parameters of space complex micromotion targets, and the neural network model can complete the target classification and recognition task with high accuracy.

1. Introduction
The traditional radar target recognition technology relies on the usage of various features. In recent years, with the development of electromagnetic camouflage and stealth materials, the traditional target recognition effect is affected in a complex electromagnetic environment. As a result, the accuracy and robustness of traditional radar target recognition technology face great challenges. Meanwhile, it also has difficulties in the library construction due to heavy workload, which limits the engineering application to some extent.

Nowadays, machine learning technology can automatically learn the essential characteristics of the target, and the end-to-end learning mode can greatly improve the accuracy and robustness of target recognition. The mainstream algorithms of machine learning mainly include decision tree algorithm, Naive Bayes algorithm, support vector machine algorithm, artificial neural network algorithm, random forest algorithm, etc. Aiming at the problems existing in the traditional radar target recognition, some literatures have carried out researches on the analysis and extraction of micro-Doppler characteristics of space target.

In [3], they study the separation method of multicomponent Sinusoidal FM Signal for the Empirical Mode Decomposition algorithm, obtaining the instantaneous frequency of each intrinsic mode function through the short-time Fourier transform, and then extracting the micromotion characteristics like precession period and precession angle of the space vertebral object; Reference[4] studied the target electromagnetic scattering area sequence measured by radar, adopting deep neural network model to identify space flight target. However, these works are analyzed on the basis of the artificial
extraction of target characteristics. There are some problems in target feature extraction, such as high computation cost and large reconstruction error.

The extraction and recognition technology of data-driven space target radar micromotion features are still in the initial stage. In the earlier studies, the EMD method has achieved great recognition rate for extraction of space target features, and machine learning has also realized certain applications in radar target recognition. However, there is a lack of combing EMD method and machine learning algorithms. This paper presents a method of target recognition based on a data-driven framework, extracting the features of simulated radar echoes by means of the EMD method and using machine learning for recognition. After an appropriate training, a high recognition rate can be achieved in a wide range of SNR.

2. Feature extraction of the spatial object based on the EMD method

2.1. The simulation of radar echo signal

Given warheads and decoys in the space, which are generally cone shape. The received signal can be modeled approximately by a sum of signals received from some dominant and discrete scattering points on the target. The radar echo signal is as follow:

\[ S_{rx}(t) = \exp(j2\pi f_0 t) \]

Where \( f_0 \) is the radar frequency. The general received signal can be written as:

\[ S_{rx}(t) = \sum_{i=0}^{N_s-1} \mu_i(t) \exp(j2\pi f_0 (t - \tau_i(t))) \]

The warheads and decoys are generally the same shapes. Our RCS is calculated based on the vertebral body scattering model. Where \( N_s \) is the number of scattered points, \( \mu_i(t) \) is the propagation delay and scattering intensity of RCS scattering points. It usually depends on the angle of, which is the angle between the radar LOS and the symmetry axis of the target. When there is a scattering LOS, the value is 1 and the others are 0. The propagation delay of the universe point is:

\[ \tau_i(t) = \frac{2\rho_i(t)}{c} \]

Which \( c = 3 \times 10^8 m/s \) represents the speed of light. \( \rho_i(t) = ||r_i^{radar}|| = ||r_i^{radar} + \mathbf{r}_i(t)|| \) and \( r_i = (X_i, Y_i, Z_i) = T_m \mathbf{r}_i^{local} - r_i^{local} \) are the microscopic motion matrix of the cone. For the conical warhead, the matrix \( T_m \) is represented by the product of precession value, spin value, and nutation value, that is \( T_m = R_p R_s R_n \).

The dpsip, dtheta and dphi respectively represent the initial precession angle, initial nutation angle, and initial rotation angle. During the movement of warhead and decoy, respectively Table 1 shows the parameters of each group of tests.

| Table 1. Parameter setting of warhead and decoy |
|-----------------|----------|--------|
| angle           | warhead  | decoy  |
| First group     |          |        |
| dpsip           | Pi       | 0      |
| dtheta          | 0        | pi     |
| dphi            | 3*pi     | 0      |
| Second group    |          |        |
| dpsip           | pi       | 0      |
| dtheta          | 0        | pi/2   |
| dphi            | 4*pi     | 0      |
We conducted 20 simulation tests and take four of them as examples in this paper to explore the Doppler differences of warhead and decoy. After changing the initial motion parameters, the warhead and decoy operating forms under different parameters were simulated. The Doppler signatures are shown in Figure 1:

| Third group | dpsi | p | 0 |
|-------------|------|---|---|
| dtheta      | 0    |   | pi/3 |
| dphi        | 5*pi |   | 0  |

| Fourth group | dpsi | p | 0 |
|--------------|------|---|---|
| dtheta       | 0    |   | pi/4 |
| dphi         | 6*pi |   | 0  |
Figure 1. micro doppler characteristics of warhead and decoy

Figure 1 indicates that the warhead movement is relatively stable while the doppler frequency changes less than the decoy and the movement speed is fast so that the period is relatively short. The decoy is light in weight and mainly involves tumbling motion, that is why the doppler period increase when we set the initial tumble angular velocity to change from large to small, The period of radar echo receiving is long. Since the received echo is a multi-component signal, we adopt the EMD method to decompose the Doppler signal for extracting finer information and obtain a single component signal used to extract target features and classify target types.

2.2. EMD target feature extraction

One of the stop conditions of EMD adopted in this paper is also known as the Cauchy type of convergence criterion, which can be formulated as:

\[ \| c_n(t) - 1(i) \| \leq \frac{1}{2} \| c_n(t) \| \]

In the i-th iteration, EMD algorithm stops when the default value is 0.2. Performing the EMD decomposition the on the doppler maps obtained from the four groups and the IMFs obtained was shown in Figure 2 and Figure 3:

Figure 2. The results of warhead signal
From Figure 3, we can find that the micromotion of warhead mainly contains spin, precession, and nutation movements, among which spin is the motion with the highest frequency and the main motion form, while the decoy mainly involves tumble motion.

3. Experimental results and analysis

The numerical simulation experiments in this section implement the target recognition for warhead and decoy. The mass center location of the warhead is 0.563m, and the mass center location of the decoy is 0.4m.

Doppler time series measured by radar use EMD decomposition to obtain IMF data training classification network, and then use the test data, check the effect of the classification network to identify the target.

Due to the difference in initial motion parameters, IMF obtained by EMD decomposition by Doppler is an N*5000 matrix (The magnitude of N varies with different motion parameters). Since the Doppler signals obtained are multi-component, the IMF signals obtained after EMD decomposition are single-component. Thus, signals are constructed in the time domain by using the matrix obtained from the IMF, then the characteristics of these signals are extracted, and finally compared and classified.

This experiment adopts 50 groups of training data and two models of target recognition first, then select 50 identification test samples for each type of target. These 100 groups of test samples are used to verify the effect of target recognition.

The numerical experimental results are shown in Table 2.

|                      | warhead (target1) | decoy (target2) |
|----------------------|-------------------|-----------------|
| Test 10 groups       | 0.9               | 0.9             |
| recognition rate     |                   |                 |
| Test 50 groups       | 0.98              | 0.94            |
| recognition rate     |                   |                 |
In [5], the authors show that when EMD method was used to extract features of the spatial vertebral target radar micromotion, the average recognition error is over 15%.

4. Conclusion
This paper proposed a data-driven method for extracting and identifying micro-motion features of space target radar. Different from traditional methods, this method avoids the construction of template libraries, features extraction, and so on. The target Doppler information not only reflects the structure, size, and other information of the target but also contains some micromotion information of the target. IMF was obtained after EMD decomposition of radar doppler echo, the SVM algorithm commonly used in machine learning is selected for classification and recognition. Experimental results show that this method can effectively extract stable and valid features from doppler signals. After multiple trials, the average recognition accuracy is over 94%.

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