Rotor target recognition method based on radar echo time-frequency map feature

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Abstract. In order to realize the identification of different rotor targets, five typical rotor targets are selected as the research object. Five typical single-rotor or twin-rotor targets, AH-64 Apache helicopter, K-50 armed helicopter, K-MAX hoist helicopter, V-22 tilt-rotor aircraft, and WZ-9 armed helicopter, were selected as research objects. The echo signals are obtained according to the rotor target radar echo model in free space, and then the time-frequency image is obtained by short-time Fourier transform. According to the difference of the time-frequency images of five types of rotorcraft targets, two typical features that characterize the map differences, namely the histogram of oriented gradient feature and the gray level co-occurrence matrix feature, are extracted. Finally, the support vector machine (SVM) is used to realize the recognition of five types of rotor targets, and recognition accuracy reached 93.3%.

1. Introduction

The powerful combat performance of the rotorcraft makes it the "new darling" of modern warfare. If the identification of different rotorcraft targets can be achieved, it will help to win the war and even win. With the development and application of modern technologies such as electromagnetic camouflage and stealth materials, traditional target recognition methods based on non-moving features such as target shape and radar cross-sectional area have been difficult to meet the needs of rotor target attribute recognition. Since the introduction of the fretting concept into the radar field by V.C. Chen[1-2] of the US Naval Laboratory in 2000, the classification and recognition based on the unique micro-motion characteristics of the rotor target has become a research hotspot in the field of target detection and recognition. The micro-motion information generated by rotational modulation of the target rotor blade can accurately characterize its motion characteristics. If the effective features characterizing the target difference can be obtained, the recognition of the rotor target can be realized[3-6].

The existing micro-motion target classification and recognition methods generally extract the time domain, frequency domain or time-frequency domain features of the target echo, but the extracted features have limitations. In [7], the scintillation pulse width and period of the helicopter rotor echo are obtained by time domain detection and Hough transform, so as to realize the detection and identification of the Schwarzer 269C-1 helicopter and the Robinson R44 helicopter; the literature [8] extracts helicopters and jets. The variance and entropy of the time-domain echo peak function of the three types of aircraft and propeller aircraft, and then using the support vector machine to achieve a classification accuracy of 90.72%; the literature [9] based on the average time-frequency spectrum of the echo time-frequency diagram And image entropy characteristics, 94% of the recognition accuracy of the three types of aircraft targets; literature [10] by extracting the gray-scale co-occurrence matrix characteristics of the laser echo time-frequency diagram of the three types of aircraft targets, achieving
96.4% of the signal-to-noise ratio of 0dB. The classification accuracy rate, but the rotor target under the same attribute is not identified; the literature [11] reviewed the research status of the fretting target echo modelling, the fretting feature extraction and the classification and recognition of the radar target based on the micro-motion feature in recent years. It is pointed out that the use of micro-motion features for target classification and identification has broad application prospects.

The time-frequency diagram feature of the rotor target extracted in this paper can better characterize the difference between the target categories. In order to realize the identification of different rotor targets, this paper selects AH-64 Apache helicopter, K-50 armed helicopter, K-MAX. Five typical single-rotor or multi-rotor targets, such as hoisting helicopters, V-22 tilt-rotor aircraft, and WZ-9 gunships, are used as research objects, and echo signals are obtained from radar-echo models in free space according to rotor-type targets. The time-frequency diagram of the rotor target is then obtained by a short-time Fourier transform. According to the difference of the time-frequency images of these five types of rotor targets, the HOG and GLCM features are extracted to characterize the difference between the rotor targets. Finally, the SVM is used to identify the five types of rotor targets under seven different SNR.

2. Rotor target modelling and data set construction

2.1 Rotor target micro-motion model

The integral model of the rotor blade echo [1] is shown in Figure 1. Let the radar coordinate system be \((U,V,W)\), the origin is \(O\); the reference coordinate system \((X,Y,Z)\) is parallel to the radar coordinate system, and it is the same as the origin of the target coordinate system, and is recorded as \(O'\). The distance between the center of the rotor \(O'\) and the center of the radar \(O\) is \(R\), and the azimuth and elevation angles are \(\alpha\) and \(\beta\) respectively, \(0 \leq \beta \leq 90\), without loss of generality. It is assumed here that the radar main beam \(\alpha = 0\) is the illumination target at the time.

![Figure 1. Three-dimensional model of helicopter rotor blades.](image)

When studying the flight state of a rotorcraft, the Euler angle \((\gamma,\phi,\varphi)\) [2] is generally used to express the spatial attitude change of the target rotor blade, the angle between the target coordinate system \((X',Y',Z')\) and the reference coordinate system \((X,Y,Z)\) is \((\gamma,\phi,\varphi)\). After the change of the spatial attitude, the coordinates of any point on the rotor blade in the target coordinate system \((X',Y',Z')\) are transformed into the reference coordinate system through the rotation matrix \(R\). Rotation matrix is

\[
R = \begin{bmatrix}
    r_{11} & r_{12} & r_{13} \\
    r_{21} & r_{22} & r_{23} \\
    r_{31} & r_{32} & r_{33}
\end{bmatrix}
\]
among them

\[ \begin{align*}
  r_{11} & = \cos \phi \cos \varphi \\
  r_{12} & = -\sin \phi \\
  r_{13} & = \cos \psi \sin \phi + \sin \psi \sin \varphi \\
  r_{14} & = \cos \psi \cos \phi \\
  r_{31} & = \cos \phi \cos \varphi \\
  r_{32} & = -\sin \phi \\
  r_{33} & = \cos \psi \sin \phi + \sin \psi \sin \varphi \\
  r_{34} & = \cos \psi \cos \phi
\end{align*} \tag{2} \]

On the target coordinate system \((X',Y',Z')\), it is assumed that the target rotor blade rotates around the center of the rotor \(O'\), the angular velocity is \(\omega = 2\pi f_{\text{rot}}\), and the rotation frequency is \(f_{\text{rot}}\). The initial rotation angle of the first rotor blade is \(\theta_i\), where the distance from one scattering point \(P_i\) to the center of the rotor is \(x_i\) \((0 \leq x_i \leq L\), \(L\) is the length of the blade), and the angle of rotation becomes \(\theta_i = \theta_i + 2\pi f_{\text{rot}} t\) \(t\) after the elapse of time \(t\). At this time, if the coordinates of the point \(P_i\) in the target coordinate system \((X',Y',Z')\) are \(\mathbf{r}_0 = [x_i\cos \theta_i, x_i\sin \theta_i, 0]^T\), the coordinates converted to the reference coordinate system \((X,Y,Z)\) are \(\mathbf{g}\mathbf{r}_0\)

\[
\mathbf{g}\mathbf{r}_0 = \begin{bmatrix}
  r_{11}x_i \cos \theta_i + r_{12}x_i \sin \theta_i \\
  r_{21}x_i \cos \theta_i + r_{22}x_i \sin \theta_i \\
  r_{31}x_i \cos \theta_i + r_{32}x_i \sin \theta_i 
\end{bmatrix} = \begin{bmatrix}
  x \\
  y \\
  z
\end{bmatrix} \tag{4}
\]

Assume that the single carrier frequency signal transmitted by the radar is \(u_i(t) = \exp(j2\pi f_i t)\), where the wavelength is \(\lambda = c/f_c\). Assuming the target is in the far field, the distance between \(P_i\) and the radar is

\[
R_i(t) = [(O'P_i)^2 + (P_iP_i')^2]^{1/2} = R + x\cos \beta + z\sin \beta = R + x_i f_1(t) \tag{5}
\]

where \(f_1(t)\) is the angle information of the first blade, and the expression is

\[
f_i(t) = \cos \beta(r_{11} \cos \theta_i + r_{12} \sin \theta_i) + \sin \beta(r_{21} \cos \theta_i + r_{22} \sin \theta_i) \tag{6}
\]

At this time, the baseband echo of the scattering point \(P_i\) received by the radar \([2]\) can be expressed as

\[
s_{i}(t) = \sigma \exp(-j4\pi R_i(t)/\lambda) \tag{7}
\]

Where \(\sigma\) is the scattering coefficient and \(\Phi_i(t) = 4\pi R_i(t)/\lambda\) is the phase function, which is related to the state of the rotor blade in three-dimensional space.

Based on the fact that all scattering points of the rotor blades generate echoes: from the mechanism of electromagnetic scattering, the blade echoes are essentially the vector sum of the echoes of all the scattering points on the blade in the direction of the radar line of sight, which is theoretically equivalent. In order to integrate equation (7), the scattering point integral model echo on the first blade can be expressed as

\[
s(t) = \int_0^1 s_i(t) \, dt = \sigma \exp(-j4\pi R / \lambda) \exp(-j2\pi f_i(t) / \lambda) \text{sinc}[2f_i(t) / \lambda] \tag{8}
\]

Since the initial rotation angles of the \(N\) blades on the rotor are different, the initial rotation angle of the \(n\)th blade is \(\theta_n = \theta_1 + (n-1)2\pi / N\), and then the rotation angle is \(\theta_n = \theta_1 + (n-1)2\pi / N\) \(t\) at this time, the rotation angle \(\theta_i = \theta_i + 2\pi f_{\text{rot}} t\), the angle information is \(f_n(t)\), and \(f_n(t)\) is compared with \(f_i(t)\), and only the initial rotation angle \(\theta_n\) contained in \(\theta_i\) is increased by \(2\pi(n-1) / N\). At this point, considering the initial rotation angle and the number of blades, the total echo can be expressed as

\[
s_n(t) = \sum_{n=1}^{N} s_n(t) = \sum_{n=1}^{N} \sigma i \exp(-j4\pi R / \lambda) \exp(-j2\pi f_n(t) / \lambda) \text{sinc}[2f_n(t) / \lambda] \tag{9}
\]
Equation (9) is the radar echo model of the rotor in three-dimensional space.

Under radar observation conditions, the rotor blade can only contain the micro-Doppler information in the radar echo when the distance difference is generated in the radar line of sight (LOS), while the rotational component of the vertical radar in the direction of the line of sight is slightly moving to the target. No effect. The rotation of the rotor blade can be decomposed into two rotational components in the direction of the line of sight of the radar and the direction of the vertical radar, while the motion of the rotor in free space can be equivalent to the combined motion in the direction of roll, pitch and yaw. The motion in three directions will cause the rotation component of the rotor blade to change along the radar line of sight, thus affecting the fretting characteristics of the rotor. This paper establishes the rotor target data set based on the changes of the three attitude angles and the elevation angle.

2.2 Construction of five types of rotor target data sets

In this paper, the five types of single-rotor or double-rotor targets of AH-64, K-50, K-MAX, V-22 and WZ-9 are studied and identified.

Since the distance between the two main rotors of the dual-rotor target is much smaller than the distance between the two main rotors, it can be considered that the two main rotors are in the same position, and the total rotor target total echo is the superimposed value of the two rotors. According to the above analysis, this paper constructs the radar echo time-frequency diagram of the three types of twin-rotor targets K-50, K-MAX and V-22 in free space. Since the tail of the AH-64 helicopter can be observed by the radar, The tail of the WZ-9 helicopter was occluded, so only the tail echo of the AH-64 helicopter was considered in the simulation below. The simulation parameters are as follows: scattering coefficient: $\sigma = 1$ azimuth: $\alpha = 0$ the initial rotation angle of the rotor blade: $\theta_i = 0$, initial distance: $R = 15$km, observation time: $T = 1s$, pulse repetition frequency: $PRF = 4000$Hz. Among them $M$ is the number of rotors, $l$ is the rotor blade length, $f$ is the rotor blade rotation frequency, $N$ is the number of blades. The parameter settings are shown in Table 1. The time-frequency diagram of the rotor target is obtained by short-time Fourier transform.

| Rotor target type | $M$ | $l$/m | $N$ | $f$/Hz |
|------------------|-----|-------|-----|--------|
| AH-64            | 2   | 7.315/1.395 | 4   | 3/6    |
| K-50             | 2   | 7.25   | 3   | 5      |
| K-MAX            | 2   | 7.365  | 2   | 6      |
| V-22             | 2   | 5.79   | 3   | 4      |
| WZ-9             | 1   | 5.97   | 4   | 5.8    |

In order to make the construction of the rotor target data set more realistic, that is, to simulate the change of the flight state of the rotor target in the real environment, by changing the pitch angle of the rotor center of the five different types of rotor targets, the space attitude angle of the helicopter rotor blade (rolling angle). The four angles of pitch angle and yaw angle increase the diversity of data. The parameter settings are shown in Table 2. Among them, “0~20°” means that the pitch angle is randomly generated between 0 and 20°, and other angles are set in the same way.

| Angle setting | elevation angle $\beta$ | roll angle $\psi$ | pitch angle $\theta$ | yaw angle $\varphi$ |
|---------------|-------------------------|------------------|---------------------|---------------------|
| variation range | 0~20°                   | 0~40°            | 0~60°               | 0~60°               |

The four angles of the rotor target are randomly generated at the same time, that is, the four angle simulation conditions of each type of target time-frequency map are not completely consistent. For example, the four angles of the AH-64 rotor helicopter are randomly changed 50 times at the same time, and 50 sheets can be obtained. A target time-frequency diagram with inconsistent angle simula-
tion conditions. In order to analyze the influence of noise on the target recognition effect of the rotor, complex Gaussian white noise is added to the target echo, and then the time-frequency map is obtained by time-frequency transform. When the signal-to-noise ratio is 30dB, AH-64, K-50, A typical time-frequency diagram of the five types of rotor targets K-MAX, V-22, and WZ-9 is shown in Figure 2.

![Time-frequency diagram examples](image)

- (a) AH-64
- (b) K-50
- (c) K-MAX
- (d) V-22
- (e) WZ-9

Figure 2. Example of five types of target time-frequency diagrams when SNR=30dB.

The simulation data set for the five types of rotor targets is: at 0, 5, 10, 15, 20, 25, and 30 dB SNR, 800 time-frequency maps are generated for each type of target, of which 500 are used for training and 300 are used. For testing, it consisted of 17500 training sets and 10500 test sets.
3. Rotor target modelling and data set construction

3.1 Histogram of Oriented Gradient

The Histogram of Oriented Gradient (HOG) is a feature proposed by French researcher Dalal for pedestrian detection and has achieved good results [12]. The HOG feature constitutes a feature by calculating and counting a gradient direction histogram of a local region of the image. Because the time-frequency curve and the blinking time in the radar echo time-frequency diagram of different rotor targets are different, the gradient amplitude and direction of the pixel points in the image are different. Therefore, the HOG feature can be extracted to realize the recognition of the rotor target. A flow chart in which the HOG feature is extracted is shown in Figure 3.

![Flow chart for extracting HOG features](image)

Figure 3. Flow chart for extracting HOG features.

The specific steps for extracting the HOG feature are as follows:

1) Normalize the graphics. The input RGB three-channel color time-frequency image is first converted into a grayscale image, and then the uneven image is normalized by a gamma correction method.

2) Calculate the gradient value of the image. The one-dimensional discrete differential template \([-1,0,1]\) and its transposition are used to convolve the normalized image to obtain the gradient components in both horizontal and vertical directions.

\[
F_x(x, y) = H(x + 1, y) - H(x - 1, y)
\]

\[
F_y(x, y) = H(x, y + 1) - H(x, y - 1)
\]

Where \(H(x, y)\) represents the pixel value of the current pixel. Then the amplitude amplitude \(F(x, y)\) and gradient direction of the image \(\alpha(x, y)\) are

\[
F(x, y) = \sqrt{F_x(x, y)^2 + F_y(x, y)^2}
\]

\[
\alpha(x, y) = \arctan\left(\frac{F_y(x, y)}{F_x(x, y)}\right)
\]

3) Construct a gradient direction histogram for each cell unit. The input image is preprocessed, and it is uniformly converted into a 256×256 pixel size, and the image is divided into 16×16 cell units, that is, each cell unit is a 16×16 pixel size. The gradient direction of the cell unit is limited to \([0,180^\circ]\), and is equally divided into nine sections at intervals of 20°. Firstly, the gradient direction of all the pixels in the cell unit is found, and then the weighted projection is performed in the histogram according to the range corresponding to the gradient direction. The size of the histogram is to sum the gradient amplitudes of all the pixels projected in the interval, so that the difference is different. Each of the range intervals obtains a value, thereby obtaining an array of size 9, that is, each cell unit corresponds to a 9-dimensional feature vector.

4) Combine a plurality of cell units into blocks, and normalize the blocks to obtain a gradient histogram. In this paper, adjacent 2×2 cell units are combined into one block, and each block corresponds to a 36-dimensional feature vector. In order to avoid excessive variation of the gradient amplitude within the block, the 36-dimensional feature vector in the block is normalized. as follows

\[
V = v / \| v \|_2
\]

Among them, the feature vector \(v\) that is not normalized, \(\| v \|_2\) is the 2 norm.

5) Obtain the HOG feature. As shown in Figure 4, the input image is scanned by a block, wherein the scanning step is a cell, and 15 positions can be obtained in the horizontal and vertical directions, so that a total of 225 blocks can be obtained, and the features corresponding to all the blocks are obtained.
The vector connection gets the $1 \times 8100$ dimension feature vector.

$$\text{Figure 4. Schematic diagram of the cell unit.}$$

3.2 gray level co-occurrence matrix features

The gray level co-occurrence matrix (GLCM) feature reflects the texture features of the image by describing the direction, variation amplitude and adjacent interval of the gray level of the image. This paper extracts the gray level symbiosis of the time-frequency map. Matrix features are used to identify the five types of rotor targets.

Set a preprocessed image to have a size of $M \times N$ and a grayscale (pixel) level of $K$. The essence of the gray level co-occurrence matrix feature is to find the pixel point coordinates of the pixel point $A$ with the pixel size $A$, and the pixel point coordinates with the relative distance of the pixel coordinates $C$, the direction $D$, and the pixel size $E$. The pair of pixels of $F$ and $G$ counts the number of occurrences of the pair of pixels, thereby forming a gray level co-occurrence matrix. In the case where the distance is $H$ and the directions of $0^\circ$, $45^\circ$, $90^\circ$, and $135^\circ$ are taken, the gray level co-occurrence matrix $J$ is

The essence of the gray level co-occurrence matrix feature is to find the pixel point coordinate from the pixel point coordinate $(x, y)$ with the pixel size $i$ in the image, and find the pixel point coordinate $(x_1, y_1)$ with the relative distance of the pixel coordinate $d$, the direction $\theta$, and the pixel size $j$. For the pair of pixels of $i$ and $j$, the number of occurrences of the pair of pixels is counted to form a gray level co-occurrence matrix. In the case where the distances $d$ and $\theta$ are in the four directions of $0^\circ$, $45^\circ$, $90^\circ$, and $135^\circ$, the gray level co-occurrence matrix $G(m, n, d, \theta)$ is

$$G(m, n, d, 0) = \text{card}\{A(x, y), A(x_1, y_1) | x_1 - x = 0, y_1 - y = d\}$$

$$G(m, n, d, 45) = \text{card}\{A(x, y), A(x_1, y_1) | x_1 - x = -d, y_1 - y = d\}$$

$$G(m, n, d, 90) = \text{card}\{A(x, y), A(x_1, y_1) | x_1 - x = -d, y_1 - y = 0\}$$

$$G(m, n, d, 135) = \text{card}\{A(x, y), A(x_1, y_1) | x_1 - x = -d, y_1 - y = -d\}$$

In the equations (15) to (18), $A(x, y) = i$, $A(x_1, y_1) = j$, $\text{card}\{\}$ represents the sum of the number of occurrences of pixel pairs in which the pixel points are $i$ and $j$ in the corresponding distance and direction. The normalization of the gray level co-occurrence matrix is

$$P(m, n, d, \theta) = G(m, n, d, \theta) / \sum_{m,n=1}^{K} G(m, n, d, \theta)$$

Literature [13] defines 14 different texture feature parameters of GLCM. The literature [14] proves that four of them are not only unrelated, but also have high classification accuracy. To this end, this paper uses the four characteristics of GLCM to extract the feature of the time-frequency diagram of the rotor target.

1) Angular Second Moment (ASM) energy: reflects the uniformity of the grayscale distribution of the image.

$$\text{ASM}(d, \theta) = \sum_{m,n=1}^{K} [P(m, n, d, \theta)]^2$$
2) Contrast: Reflects the clarity of the image and the depth of the texture groove.
\[
\text{CON}(d, \theta) = \sum_{m,n=1}^{K} \left[ \left| m - n \right| \right] P(m,n,d,\theta)
\]  
(21)

3) Inverse moment difference: measures the local variation of the image texture, reflecting the homogeneity of the image.
\[
\text{HOM}(d, \theta) = \sum_{m,n=1}^{K} \left[ P(m,n,d,\theta) / (1 + |m - n|) \right]
\]  
(22)

4) Relevance: reflects the consistency of the texture.
\[
\text{COR}(d, \theta) = \sum_{m,n=1}^{K} \left[ (m - \mu_1)(n - \mu_2)P(m,n,d,\theta) / (\sigma_1\sigma_2) \right]
\]  
(23)

Where \(\mu_1\), \(\mu_2\), \(\sigma_1\), and \(\sigma_2\) are defined as
\[
\mu_1 = \sum_{m,n=1}^{K} mp(m,n,d,\theta)
\]  
(24)
\[
\mu_2 = \sum_{m,n=1}^{K} np(m,n,d,\theta)
\]  
(25)
\[
\sigma_1 = \left[ \sum_{m,n=1}^{K} (m - \mu_1)^2 P(m,n,d,\theta) \right]^{1/2}
\]  
(26)
\[
\sigma_2 = \left[ \sum_{m,n=1}^{K} (n - \mu_2)^2 P(m,n,d,\theta) \right]^{1/2}
\]  
(27)

When extracting the GLCM features of the rotor target time-frequency map, the set distance is changed from 1 to 10 at intervals 1. At the same distance, the ASM energy, contrast, and inverse are obtained at directions equal to 0°, 45°, 90°, and 135°, respectively. The four characteristics of the moment difference and the correlation are respectively calculated, and then the mean and standard deviation of the four features in different directions are respectively calculated, thereby converting a rotor target time-frequency map into an \(180 \times 1\)-dimensional feature vector. When the distance \(d = 10\) is selected, 100 time-frequency maps are randomly selected from each type of target of the training set, and the average values of the mean and standard deviation of the four features of the GLCM in different directions of the five types of targets are shown in Table 3.

Table 3. Mean and standard deviation of four characteristics of the five-class rotor target GLCM.

| Rotor target type | ASM energy | Contrast | Inverse moment difference | Relevance |
|-------------------|------------|----------|---------------------------|-----------|
|                   | Mean       | Standard deviation | Mean | Standard deviation | Mean | Standard deviation | Mean | Standard deviation |
| AH-64             | 1.4410     | 0.4368    | 0.1637 | 0.7529    | 0.3566 | 0.1380     | 0.0208 | 0.0297       |
| K-50              | 2.5861     | 0.4514    | 0.1088 | 0.6633    | 0.6540 | 0.1389     | 0.0198 | 0.0391       |
| K-MAX             | 1.7653     | 0.4381    | 0.1457 | 0.7266    | 0.4805 | 0.1494     | 0.0207 | 0.0334       |
| V-22              | 1.9777     | 0.4446    | 0.1312 | 0.7068    | 0.4688 | 0.1305     | 0.0201 | 0.0326       |
| WZ-9              | 2.2464     | 0.5042    | 0.1126 | 0.6781    | 0.5594 | 0.1230     | 0.0198 | 0.0370       |

It can be seen from Table 3 that the mean and standard deviations of the four characteristics of the GLCM of the five different types of rotor target time-frequency diagrams of AH-64, K-50, K-MAX, V-22, and WZ9 are different, so the rotor target has good separability.

### 3.3 SVM recognition process based on HOG features and GLCM features

In this paper, five different types of rotor targets are identified by Support Vector Machine (SVM). The specific steps are shown in Figure 5. Firstly, the training set and test set of five different rotor targets
are constructed, and then the features of all time-frequency maps are extracted by methods 1–3 respectively. Finally, the classification results of test sets under different SNR are obtained by SVM classifier.

4. Results

4.1 Feature Visualization
In this paper, the extracted high-dimensional feature vectors are dimensioned and visualized to show the separability of the extracted HOG features, GLCM features and HOG+GLCM combination features, so as to further verify the quality of the extracted features. The following are randomly selected from the training set of the data set to randomly select the features extracted from the 1500 time-frequency maps of the five types of targets. The results are shown in Figure 6, where 1 represents the AH-64 rotorcraft and 2 represents the K-50 rotor Helicopter, 3 for the K-MAX rotorcraft, 4 for the V-22 rotor helicopter, and 5 for the WZ-9 rotorcraft.

![Visualization of different feature distributions](image)

It can be seen from Fig. 6 that the HOG features and GLCM features extracted from the time-frequency diagrams of the five types of rotor targets have good separability, and the separability of HOG features is better than that of GLCM features, and HOG+GLCM combination feature has the best separability effect.

4.2 Identification performance analysis
In order to analyze the recognition performance of different features, under the same simulation conditions, compared with the recognition results of the time domain features extracted in [8], the average recognition rate of the five types of rotor targets with the signal-to-noise ratio is shown in Fig. 7. Show.

![Average recognition rate as a function of signal-to-noise ratio](image)

It can be seen from Fig. 7 that the recognition rate of the extracted time domain feature method is the lowest according to the literature [8], and the average recognition rate of the extracted HOG fea-
ture and the HOG+GLCM combination feature increases with the increase of the signal to noise ratio, but the extracted GLCM. The average recognition rate of the feature has little relationship with the signal-to-noise ratio, and does not keep increasing. It shows that the GLCM feature is not sensitive to noise and can not well characterize the difference of the noise environment where the rotor target is located. Among them, when the signal-to-noise ratio is 30dB, the average recognition rate of the five types of rotor targets is up to 97%.

At the same time, the recognition rates under different signal-to-noise ratios are averaged, and the overall recognition rate of the five types of rotor targets is shown in Table 4.

Table 4. Overall recognition rate of rotor targets (%).

| Feature type | HOG  | GLCM | HOG+GLCM | Time domain feature |
|--------------|------|------|-----------|--------------------|
| Recognition rate/% | 86.29 | 78.78 | 93.30 | 70.6 |

It can be seen from Table 4 that the HOG+GLCM combination feature has the best recognition effect, and its overall recognition rate reaches 93.3%, which is better than the extraction time domain feature recognition. The validity of the proposed method is verified.

5. Conclusion

In order to realize the identification of different types of rotor targets in the real combat environment, this paper selects five typical rotor targets AH-64, K-50, K-MAX, V-22, WZ-9 as research objects, according to the rotor class target. The radar echo model in free flight state obtains the echo signal of the target, and then obtains the time-frequency graph data set of the five types of targets under different simulation conditions by short-time Fourier transform. According to the difference of time-frequency diagrams of these five different rotor targets, two typical features that characterize image differences, namely HOG features and GLCM features, are extracted. The support vector machine (SVM) is used to realize five types of rotor targets under different SNR. The simulation results show that the HOG+GLCM combination feature extracted from this paper has a good overall recognition effect on the rotor target, and the overall recognition rate in the data set constructed in this paper reaches 93.3%.

References

[1] Chen V C, Li F, Ho S S, et al. (2006) Micro-Doppler effect in radar: phenomenon, model, and simulation study. IEEE Transactions on Aerospace and Electronic Systems, 42(1):2-21.
[2] Chen V C, Ebrary I. (2011) The micro-doppler effect in radar. Artech House Publishers. Fitchburg.
[3] Praveen, N., & Valarmathi, J. (2017). Modelling and extraction technique for micro-doppler signature of aircraft rotor blades. IOP Conference Series Materials Science and Engineering, 263.
[4] Samczyński, Piotr, Kulpa K, Misurewicz J, et al. (2015) Micro-Doppler signatures of helicopters in multistatic passive radars. IET Radar, Sonar & Navigation. Hangzhou. pp. 1-8.
[5] Zhang L, Huang G Q. (2011) Extracting of Micro Doppler Parameter of Helicopter Rotor Based on Time-Frequency Analysis. J. Applied Mechanics and Materials, 130-134:2696-2700.
[6] Guang-Feng C, Lin-Rang Z, Gao-Gao L. (2012) Parameter Estimation of Helicopter Blade Based on Micro-doppler Analysis. J. Computer Engineering, 38(17):249-253.
[7] Hu R, Wu L Y. (2017) Research on Detection Method Based on Helicopter Main Rotor Echo. J. Electronic Science and Technology, 6:96-98.
[8] Du L, Li L S, Li W, Wang B S, Shi R R. (2015) A Method of Aircraft Target Classification Based on Time Domain Echo Correlation Feature. J. Journal of Radar, 4(06):621-629.
[9] Jiang Y, Fan J P, Guo L T, Deng G J. (2016) Aircraft Target Feature Extraction Algorithm Based on Time-Frequency Map. J. Modern Radar,38(04):38-41.
[10] Wang Y P, Hu Y H, Lei W H et al. (2017) Aircraft Target Classification Method Based on Texture Characteristics of Laser Echo Time-Frequency Map. J. Acta Optica Sinica, 11: 348-357.
[11] Zhang Q, Hu J, Luo Y, et al. (2018) Research progress on feature extraction, imaging and recognition of fretting target radar. J. Journal of Radar, 7(05):5-21.

[12] Dalal N, Triggs B. (2005) Histograms of Oriented Gradients for Human Detection. Computer Vision and Pattern Recognition, Computer Society Conference on IEEE, San Diego. pp:886-893.

[13] Haralick R M, Shanmugam K, Dinstein I. (1973) Textural Features for Image Classification. J. Systems Man & Cybernetics IEEE Transactions on, smc-3(6):610-621.

[14] Ulaby FT, Kouyate F, Brisco0. B, et al. (1986) Textural information in SAR Images. J. IEEE Transactions on Geoscience and Remote Sensing, 24(2):235-245.