ISSN 2616-5767 Vol.8, Issue 2: 27-35, DOI: 10.25236/AJETS.2025.080204

Research on Target Micromotion Features Extraction Based on Wavelet Transform and Hilbert Transform

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Abstract: *Identification of low and slow small targets in multi-band radar requires high-precision micromotion features, while traditional data analysis provides methods with features that are not obvious and difficult to quantify. Aiming at this problem, two methods based on distance dimension transform are proposed to extract features from radar echo data, and the extracted parameters are compared and analyzed. The results show that the feature extraction accuracy of the Hilbert algorithm is better than that of the wavelet transform, and its information entropy is reduced by 6.31 bits, reduced by 91.31% compared to the wavelet transform; the signal-to-noise ratio is improved by 42.55 dB, which is about 10 times higher than that of the wavelet transform. In addition, these two feature extraction methods have the highest feature extraction accuracy for DJI Inspire 2 DJI Matrice 600 UAVs, which have been implemented in recent years, and their signal-to-noise ratios can reach up to 50.39dB.*

Keywords: *Low slow small targets; wavelet transform; Hilbert transform; micromotion features; extraction*

1. Introduction

Low slow small targets have the characteristics of low altitude flight, slow speed, small radar cross-section area, etc. They are widely used in the civil field for logistics and distribution, film and television shooting, environmental monitoring and agricultural plant protection, etc.; and in the military field, they are applied in reconnaissance and surveillance, electronic warfare and target training, etc. [1-4]. Micromotion feature extraction of targets is one of the key techniques in radar signal processing, which mainly identifies and extracts small but critical motion features from complex radar return wave data. This technique has a wide range of applications in several fields, especially in radar target identification of low slow small targets, and remote sensing monitoring. By accurately extracting these features, it is possible to gain a deeper understanding of the dynamic behavior of radar targets, thus optimizing the performance of the radar system and improving its reliability. In addition, micromotion feature extraction is essential to improve the resolution of radar data, enabling radar systems to achieve more accurate measurement and control in a variety of complex environments. The current major challenges for the identification of low slow small targets include noise interference in complex environments, difficulty in feature extraction due to the weak Doppler effect, and insufficient adaptation of conventional algorithms to non-stationary signals [5-7].

At present, many scholars at home and abroad have carried out extensive and in-depth research in the field of target micromotion feature extraction, and achieved a series of fruitful results. Among them, the algorithms with more applications mainly include: multi-scale wavelet analysis method, Hilbert transform method, adaptive feature extraction algorithm of wavelet transform, method combining Hilbert transform and time-frequency analysis techniques, etc. [8-17]. Literature [18] and [19] proposed an algorithm using wavelet transform-energy feature extraction, using multi-resolution analysis capability to effectively capture the characteristics of radar echo signals on different time scales, which can significantly improve the wavelet feature extraction accuracy of the signal, but the wavelet transform performance is highly dependent on the wavelet basis function selection, which is computationally large and more complex. Literature [20] and [21] use the Hilbert transform to obtain the time-frequency spectrum and marginal spectrum of the signal with high frequency resolution, which is suitable for the analysis of non-stationary signals, and can provide the instantaneous amplitude

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and phase of the signal, but it is prone to modal aliasing when dealing with multi-component signals, and it is less effective in dealing with high-frequency components, and may lose the important micromotion features. Therefore, how to choose a suitable feature extraction method or combine multiple methods to improve the accuracy and robustness of acquiring target micromotion features is still a hot and difficult issue in current research.

In order to achieve in-depth understanding and efficient application of two feature extraction methods, wavelet transform and Hilbert transform, it is necessary to carry out accuracy comparison. A systematic evaluation of the feature extraction accuracy of these two methods in different environments and under different signal characteristics can provide a key reference for the selection of feature extraction methods in practical application scenarios. This study focuses on comparing the feature extraction accuracies of wavelet transform and Hilbert transform, aiming to reveal the advantages and limitations of the two methods in micromotion feature extraction, and to explore feasible improvement paths to enhance the accuracy and effectiveness of feature extraction.

2. Principles of Micromotion Feature Extraction Algorithm for Low Slow Small Targets under Multi-band Radar

2.1 Wavelet Transform Method

Wavelet transform [6,9,16] is a time-frequency transform method that progressively refines the signal at multiple scales by telescopic translation operations, which can decompose the signal into wavelet components at different frequencies, thus capturing the local feature information of the data. Its algorithm, as a fast algorithm for discrete wavelet transform, is to decompose and reconstruct the signal with the idea of multi-scale analysis. The energy limited signal $f(t)$ is decomposed as shown in equation (1):

$$f(t)=\sum_{k\in Z}c_{j,k}\cdot\varphi_{j,k}(t)+\sum_{m=1}^{j}\sum_{k\in Z}d_{m,k}\cdot\psi_{m,k}(t) \tag{1}$$

Where, $c_{j,k}$ denotes scale coefficients, $\varphi_{j,k}$ denotes scale space, $d_{m,k}$ denotes wavelet coefficients, $\psi_{m,k}(t)$ denotes wavelet space. The decomposition is expressed as:

$$\begin{cases} c_{j,k}=\sum_{k}h(m-2k)\cdot c_{j-1,m} \\ d_{j,k}=\sum_{k}g(m-2k)\cdot c_{j-1,m} \end{cases} \tag{1}$$

Where, $h(\cdot)$ and $g(\cdot)$ denote the low-pass and high-pass filters corresponding to the scale space and wavelet space decompositions, respectively. The scale and wavelet coefficients are thus derived.

The corresponding algorithmic reconstruction process of equation (2) is:

$$c_{j-1,m}=\sum_{k}c_{j,k}h(m-2k)+\sum_{k}d_{j,k}\cdot g(m-2k) \tag{2}$$

Wavelet basis function is the basis of wavelet transform and the key to wavelet analysis. The selection of the wavelet basis function has a great influence on the results of wavelet analysis, so a suitable wavelet basis function should be selected according to the characteristics of the target signal. Radar echo data has the characteristics of non-smooth and non-linear, it is necessary to choose a wavelet basis function with good tight support, high vanishing moment and strong orthogonality, and the commonly used wavelet basis functions are Meyer, Daubechies (dbN), Coiflets (coifN), Morlet, etc. Meyer and Morlet do not have tight support and Morlet do not have orthogonality, so these two wavelet basis functions are not suitable for wavelet analysis. So, these two basic functions are not suitable. Coiflets (coifN) has too large vanishing moments, poor localization accuracy, weak localization ability and high computational complexity. On the other hand, dbN wavelet has strong tight branching and orthogonality, which makes the signal decomposition and reconstruction with high resolution, good smoothing effect, and can avoid signal overlapping. In addition, the vanishing moment of dbN wavelet increases with the increase of order N, the stronger the localization ability of the signal, which is helpful for the feature extraction of dynamic non-smooth data. So, in this paper, we choose the dbN wavelet basis for wavelet decomposition, and the flow of micromotion feature extraction for low slow small targets using wavelet transform is shown in Figure 1.

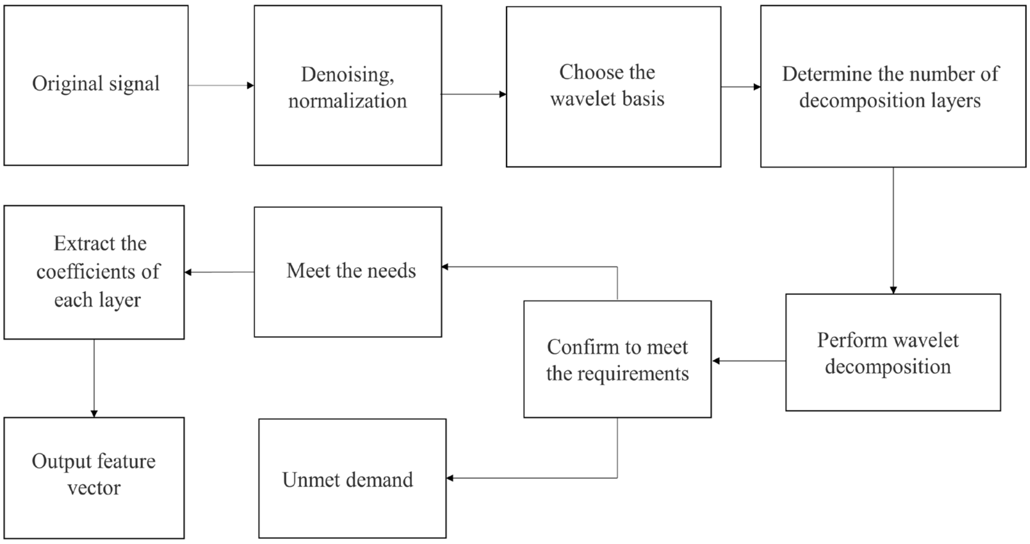

Figure 1: Wavelet transform feature extraction flowchart

2.2 Hilbert Transform Method

The Hilbert transform method [11,12,14] is a widely used tool in the field of feature extraction, which is mainly used to achieve an adaptive and accurate response to the pattern of frequency change over time. For a real-valued signal $x(t)$, its Hilbert transform $\hat{c}_i(t)$ is defined as:

$$\hat{c}_i(t) = H\left[c(t)\right] = \frac{1}{\pi} \cdot p \cdot v \cdot \int_{-\infty}^{\infty} \frac{x(\tau)}{t-\tau} \mathrm{d}\tau \tag{3}$$

Where, $x(\tau)$ denotes the signal over time, $p \cdot v \cdot$ denotes the Kersey principal value, and according to this definition $c_i(t)$ and $\hat{c}_i(t)$ form a complex conjugate pair to obtain an analytic signal $z_i(t)$:

$$z_i(t) = c_i(t) + j \cdot \hat{c}_i(t) = a_i(t) \cdot e^{j \cdot \theta_i(t)} \tag{4}$$

where

$$a_i(t) = \sqrt{c_i^2(t) + \hat{c}_i^2(t)}, \qquad \theta_i(t) = \arctan\left(\frac{\hat{c}_i(t)}{c_i(t)}\right) \tag{5}$$

Where, $a_i(t)$ is the instantaneous amplitude reflecting the change in energy of $c_i(t)$ with time, $\theta_i(t)$ is the instantaneous phase of $c_i(t)$. And the phase can be derived to obtain the instantaneous frequency, as shown in equation (7):

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$$\omega_i(t) = \frac{\mathrm{d}\theta_i(t)}{\mathrm{d}t} \tag{6}$$

The raw data $x(t)$ (without margins) can be expressed as:

$$x(t) = \mathrm{Re}\sum_{i=1}^{n} a_i(t) \cdot e^{j \cdot \int \omega_i(t)\mathrm{d}t} \tag{7}$$

The Hilbert amplitude spectrum $H(\omega,t)$ can be expressed as:

$$H(\omega,t) = \mathrm{Re}\sum_{i=1}^{n} a_i(t) \cdot e^{j \cdot \int \omega_i(t)\mathrm{d}t} \tag{8}$$

From the Hilbert amplitude spectrum $H(\omega,t)$, the marginal spectrum $h(\omega)$ and the instantaneous energy density level IE are obtained as follows:

$$h(\omega) = \int_0^T H(\omega,t)\mathrm{d}t \tag{9}$$

$$IE = \int_{\omega} H^2(\omega,t)\mathrm{d}\omega \tag{11}$$

The flow of micromotion feature extraction for low slow small targets using Hilbert transform is shown in Figure 2.

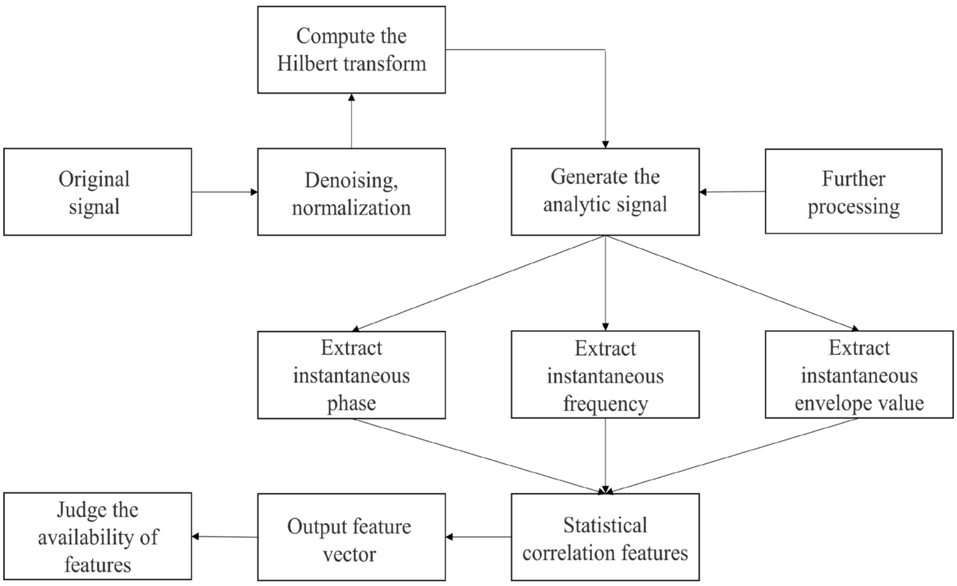

Figure 2: Hilbert transform feature extraction flowchart

3. Tests and Analysis

3.1 Sources of Experimental Data

In order to fully analyze the practical effects of the two micromotion feature extraction methods in this paper, the low slow small target detection dataset published by Radar Journal (https://radars.ac.cn/) is used for simulation and analysis, using target data with a modulation bandwidth of 100 MHz and a fixed modulation period of 0.3 ms under Ku+L band. There are five kinds of low slow small targets in this dataset, including DJI Mavic 2, DJI Phantom, DJI Inspire 2 and DJI Matrice 600.Considering that the rotor characteristics of DJI series UAVs are basically the same, and in order to provide some

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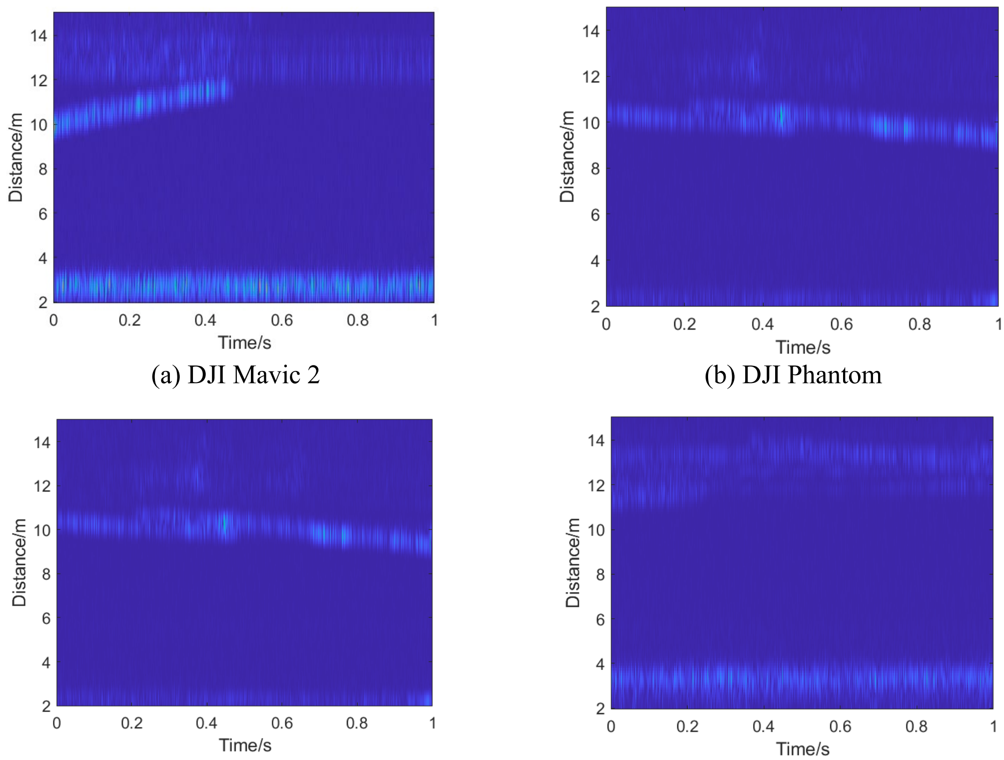
references for the tracking study of UAVs targets under multiband radar, the detection data of DJI Mavic 2, DJI Phantom, DJI Inspire 2 and DJI Matrice 600 are randomly selected in this study to conduct simulation experiments. The relevant information of the selected targets is shown in Table 1.

Table 1: Information on selected low slow small targets

Drone type and number	Modulation bandwidth/MHz	Modulation period/ms	Distance range/m	Radar band Ku/L
DJI Mavic 2	100	0.3/1.024	5~12	Ku+L
DJI Phantom	100	0.3/1.024	5~ 12	Ku+L
DJI Inspire 2	100	0.3/1.024	5~ 12	Ku+L
DJI Matrice 600	100	0.3/1.024	5~ 12	Ku/L

These five types of low slow small targets use a high base, and the detected radar echo data are clear and complete, and fully representative. The waveforms of the data processed by de-direction and distance dimension are shown in Figure 3:



(a) DJI Mavic 2 (b) DJI Phantom

(c) DJI Inspire 2 (d) DJI Matrice 600

Figure 3: Data processing diagram of DJI Mavic 2, DJI Phantom, DJI Inspire 2 and DJI Matrice 600

3.2 Results and Analysis

In order to fully analyse the accuracy and performance of the method in this paper, the first radar echo data in the four low slow small target detection data sets is selected, and the wavelet transform model and the Hilbert transform model are established to perform feature extraction on the radar echo data with a modulation bandwidth of 100 MHz, a modulation period of 0.3 ms, and in the Ku+L band. Subsequently, the extracted feature maps are compared and analysed in terms of accuracy so that the accuracy difference between the models can be calculated.

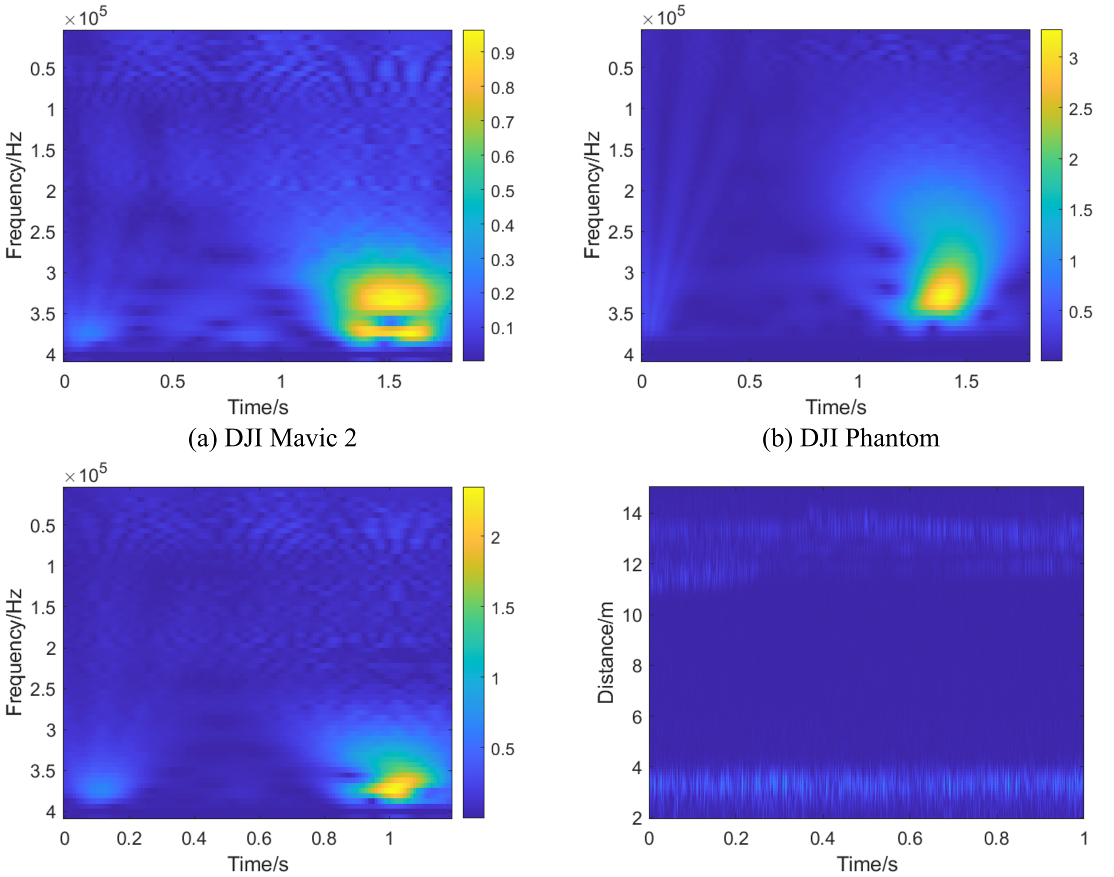
In this experiment, Information Entropy (IE) and Signal-to-Noise Ratio (SNR) are used as evaluation indexes (see equation (12) and equation (13) for the specific calculation formula) to evaluate the feature extraction effect of wavelet transform and Hilbert transform models. IE is used to quantify the concentration of information, the lower its value, the better the feature extraction effect and the higher the concentration of features. The SNR is used to measure the quality of the signal, and the higher its value, the better the extraction effect and the higher the accuracy accordingly. By comparing the size of these two indexes, the accuracy of the model under different types of errors can be evaluated more comprehensively.

If a model has a large value of IE and a small value of SNR, it reflects that the model has a lower concentration of features but performs poorly in signal noise processing. On the contrary, if the SNR value of a model is larger and the IE value is smaller, it reflects that the model has more concentrated features and performs well in signal noise processing. Therefore, based on these two indicators, the feature extraction effects of the two models can be effectively compared and analysed to provide reference for further experimental research.

$$H\left(X\right)=-\sum_{i=1}^{n}n\cdot P\left(x_i\right)\cdot lbP\left(x_i\right) \tag{12}$$

$$SNR=\frac{\mu^2}{\sigma^2} \tag{13}$$

The wavelet transform and the Hilbert transform are applied to the four low slow small target data, and the results are shown in Figures 4 and 5.



(a) DJI Mavic 2 (b) DJI Phantom

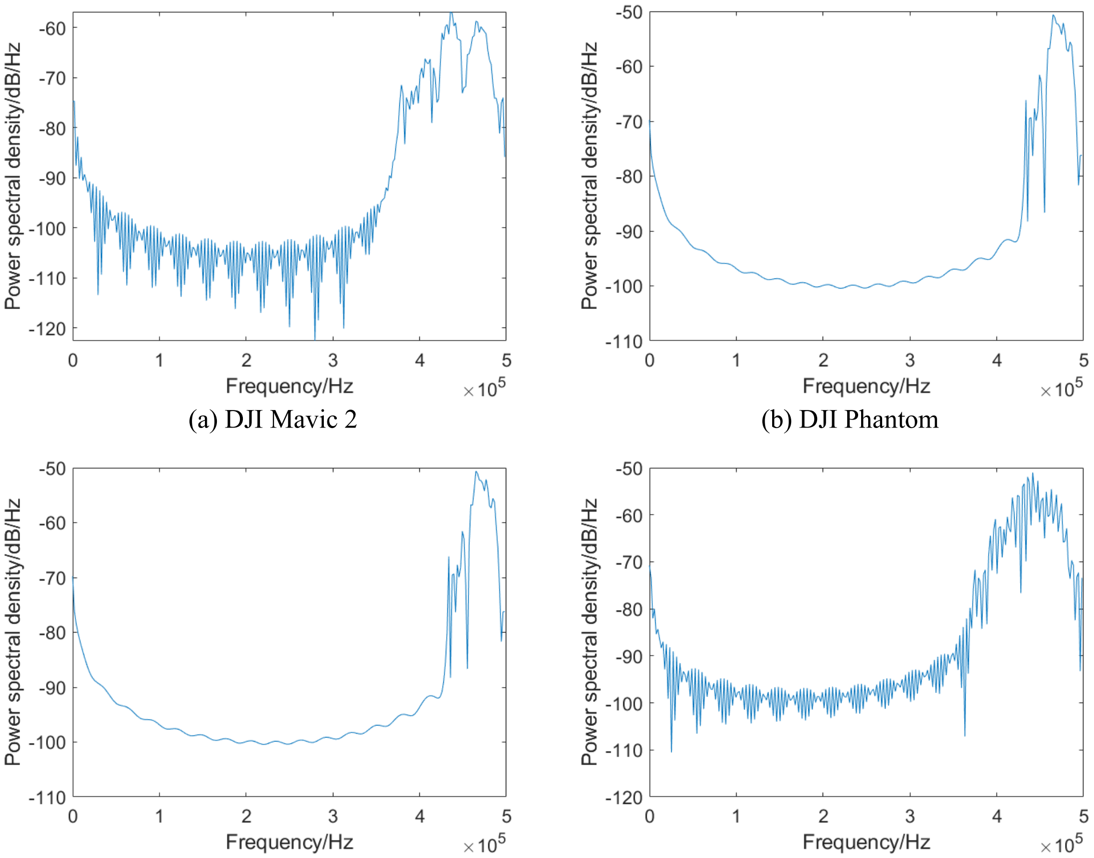
(c) DJI Inspire 2 (d) DJI Matrice 600

Figure 4: Wavelet transform energy distribution of DJI Mavic 2, DJI Phantom, DJI Inspire 2 and DJI Matrice 600

The energy micromotion distribution characteristics of the four Unmanned Aerial Vehicle (UAV) under wavelet transform are shown in Figure 4, and the energy of the four UAVs under wavelet transform gradually increases with time. The energy of DJI Mavic 2 is mainly concentrated in the region of 1.20~1.60 seconds in the time axis and 3×10^5~4×10^5Hz in the frequency axis 1.2~1.6 seconds, significantly enhanced and formed a concentrated region, the energy concentration area lasts longer, but the frequency band is wider, indicating that the wavelet transform has limited ability to discriminate high frequencies. Since DJI Mavic 2 adopts the folded rotor design with a single vibration mode and significant high-frequency vibration characteristics, the wavelet transform can capture its regular vibration, but the energy distribution is wide and there is low-frequency noise interference. The DJI Phantom energy mainly gathers in the region of about 1.2~1.5 seconds in the time axis and about 2.5×10^5~3.5×10^5Hz in the frequency axis. As the time advances to 1~1.2 seconds, the energy starts to

ISSN 2616-5767 Vol.8, Issue 2: 27-35, DOI: 10.25236/AJETS.2025.080204

gather to the specific frequency region, and at 1.2~1.5 seconds, the energy in the frequency band of 2.5×10^5~3.5×10^5Hz is significantly enhanced, forming an obvious energy concentration region, the DJI Phantom series UAVs adopt the traditional fixed-blade design, with low rotor rotational speeds and vibration. The frequency is dispersed, and the energy is gradually focused with time, but the frequency band span is large, reflecting the insufficient adaptability of the wavelet basis function to low-frequency signals. The DJI Inspire 2 energy is mainly concentrated in the region of about 0.8~1seconds in the time axis and 3.5×10^5~4×10^5Hz in the frequency axis. An obvious energy concentration area is formed at 0.8~1seconds. The energy concentration area is shorter and narrower in frequency band, but the overall SNR is low and the feature extraction accuracy is the weakest. DJI Inspire 2 early brushless motor technology stability is poor, the body frame is heavier, and the low-frequency noise is significant, resulting in redundant energy distribution. There are two major energy concentration areas in the DJI Matrice 600. One is in the region around 0~0.2 seconds in the time axis and 3.5×10^5~4×10^5Hz in the frequency axis; and the other is in the region around 1.2~1.5 seconds in the time axis and the same frequency axis of about 3.5×10^5~4×10^5Hz. At 0~0.2 seconds, there is a significant energy build-up in the high frequency band (3.5×10^5~4×10^5Hz). This is followed by a more uniform and lower energy distribution across the frequency range during 0.2~1.2 s. The energy distribution is more uniform and lower in the frequency range. By 1.2~1.5 seconds, the energy concentration phenomenon is again seen in the high-frequency band, which shows the characteristic of stage concentration. DJI Matrice 600 is equipped with a six-axis power system, and the motor cooperative control is complicated, which makes the energy gather in part of the invalid frequency band, leading to the confusion of the correspondence between the energy distribution and the actual effective features, which in turn results in the discrepancy of the energy distribution during feature extraction.



(a) DJI Mavic 2 (b) DJI Phantom

(c) DJI Inspire 2 (d) DJI Matrice 600

Figure 5: Hilbert transform energy distribution of DJI Mavic 2, DJI Phantom, DJI Inspire 2 and DJI Matrice 600

The difference in the energy distribution of the four UAVs under the Hilbert transform is demonstrated in Figure 5, and the energy of the four UAVs is mainly concentrated in the interval of frequencies from about 3.50×10^5Hz to 4. 50×10^5Hz.The energy of DJI Mavic 2 is highly concentrated in the energy peak of about -60Hz, and the transient frequency fluctuation is large with the existence of

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multiple side flaps. The rotor speed is stable, and the Hilbert transform accurately extracts the high-frequency fundamental frequency by parsing the signal, with strong noise immunity and significantly improved feature concentration. The main peak of DJI Phantom is about -50Hz, but there are some side flaps. The DJI Phantom series signal is more concise in the Hilbert transform, but the distribution fluctuation is still large. The DJI Inspire 2 energy peak is concentrated around -52Hz, but the sidelobe becomes smaller, and the instantaneous frequency cycle volatility is smaller. The vibration signal contains low-frequency interference, and the Hilbert transform retains the effective fundamental frequency components through time-frequency spectral analysis to improve the SNR. The main peak of DJI Matrice 600 is located at about -50Hz, complex motor control introduces multi-component signals, the Hilbert transform decomposition ability is better, combined with the Ku band high resolution, the energy distribution is more focused. The extraction effect is analysed and judged by extracting the metrics of its micromotion features, and the results are shown in Table 2.

Table 2: Statistical results of model indicators

Method	Evaluations norm	DJI Mavic 2	DJI Phantom	DJI Inspire 2	DJI Matrice 600
Wavelet transform	IE/bit	6.90	6.91	6.90	6.91
	SNR/dB	3.38	2.55	3.91	4.26
Hilbert transform	IE/bit	0.49	0.77	0.50	0.58
	SNR/dB	46.69	46.53	50.39	40.86

According to the analysis results in Figures 4-5 and the statistical results in Table 2, it can be seen that the IE of the four types of targets of the wavelet transform are all high, which is about 6.91bit, and its SNR is about 3.50dB on average. It shows that the algorithm has insufficient suppression of low-frequency noise, which leads to poor concentration of the features, and thus fails to achieve its contribution to the model, and cannot effectively distinguish between certain specific values of the take. The noise interference in the signal is serious, and the effective features are submerged, which cannot meet the high accuracy requirements. In contrast, the Hilbert transform exhibits lower IE in micromotion feature extraction for four low slow small targets, with an average of about 0.59 bit, and its SNR is significantly improved to an average of about 46.05 dB. Lower IE indicates a significant improvement in feature concentration, and the algorithm is able to filter out the redundant noise and focus on the core frequency band effectively. The higher SNR means that the algorithm is verified to be able to accurately capture high-frequency vibration signals, with better discriminative ability and more usable information. In addition, through the Hilbert transform, the IE is reduced by about 6.31 bits, which is about 91.31% compared with that of the wavelet transform; the SNR is improved by about 42.55 dB, which is more than ten times from 3.50 dB in the wavelet transform to 46.05 dB in the Hilbert transform.

4. Conclusions

In order to effectively improve the accuracy and stability of micromotion feature extraction for low slow small targets, this paper carries out an in-depth investigation based on the low slow small dataset released by the Radar Journal, and applies two methods based on the distance-dimensional transformation to carry out high-efficiency feature extraction on radar echo data. The signal processing and feature extraction process is optimized by cleverly converting the data space. After systematic algorithm design, the comparative analysis of the extracted parameters is achieved. The experimental results show that the Hilbert transform algorithm performs more excellent in feature extraction accuracy, and is more accurate and stable compared with the wavelet transform algorithm. When dealing with all kinds of UAV signals, the Hilbert transform algorithm can keenly capture the subtle changes in motion and extract finer feature information. At the same time, the algorithm is more reliable when dealing with noise, significantly reducing the false alarm rate and leakage rate, and enhancing the overall credibility of feature extraction. For the DJI Inspire 2 and DJI Matrice 600 UAVs, which have been widely used in recent years, both feature extraction algorithms show high accuracy, good adaptability and sensitivity. Comparative analysis reveals that the earlier-launched DJI Phantom UAVs also work well in feature extraction, while the earlier DJI Inspire 2 UAVs, due to technological limitations, have a relatively low feature extraction accuracy, but can still provide information of some value.

ISSN 2616-5767 Vol.8, Issue 2: 27-35, DOI: 10.25236/AJETS.2025.080204

Acknowledgements

This work is supported by the National Natural Science Foundation of China (No. 12403080), China Postdoctoral Science Foundation Funded Project (No.2024M764304), Postdoctoral Fellowship Program of CPSF (No. GZC20233565), Natural Science Basic Research Program in Shaanxi Province of China (No.2023-JC-QN-0027) and the Youth Fund of PLA Rocket Force University of Engineering (No.2021QN-B007).

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