Research on UAV image denoising effect based on improved Wavelet Threshold of BEMD

NIU Pingjuan1, MA Xueru2, MAO Run2, PAN Jie2 WANG Shan3, Shi Hao3 SHE Huanlin 4

1 School of Electrical Engineering & Automation, Engineering research center of high power solid state lighting application system, Ministry of education, TianGong University, 300387, China; 1162599582@qq.com

2 School of Electronics and Information Engineering, TianGong University, Tianjin, China 1181979673@qq.com

3 School of Mechanical Engineering, TianGong University, Tianjin 300387, China; 995922556@qq.com

4 Tianjin WanMao technology co. LTD, China

Abstract: Aiming at the noise generated by external or internal factors reduces the sharpness of unmanned aerial vehicle (UAV) images, an improved bi-dimensional empirical mode decomposition (BEMD) de-noising algorithm is proposed to solve the problem. Firstly, an intrinsic mode function (IMF) is obtained after BEMD decomposition of noisy image, and then the high frequency apply particle swarm optimization (PSO) after wavelet decomposition to the high-frequency IMF to obtain the optimal threshold filtering. As for the low frequency, it is filtered by the exponential attenuation threshold algorithm of wavelet semi-soft threshold. Finally, the filtered both high-frequency and low-frequency IMF are reconstructed after inverse wavelet transformation. This algorithm is applied to the processing of UAV images, and compared with the traditional UAV image denoising method and the advanced UAV image denoising method. Simulation results demonstrate that the proposed denoising method outperforms other de-noising methods in terms of peak signal-to-noise ratio and mean square error.

1. INTRODUCTION

The image acquisition and transmission by UAV are easily interfered by the surrounding environment, such as weather effects and jitters during shooting, which will decrease the quality of the received image and affect the subsequent image processing, making the de-noising processing of UAV images an indispensable part of UAV technology.

At present, there are plenty of methods for image de-noising, among which the commonly used filtering methods include median filtering, mean filtering and Vienna filtering[1]. The wavelet transform algorithm[2] can decompose and reconstruct the image to avoid the loss of image details caused by the filter. Yi-tan Hu proposed an improved median filter method using the physical gravity between pixels to determine the adaptive window and carry out the corresponding filtering[3]. Wang Jun developed a hybrid diffusion partial differential equation method[4]. Shen Chen put forward with a hybrid de-noising method for UAV images based on compressed sensing[5]. In 1990, Huang et al. from NASA stated
the Hilbert-Huang transform, which was composed of empirical modal decomposition (EMD) and Hilbert\cite{6}. In recent years, the bi-dimensional empirical mode decomposition (BEMD) has been an effective decomposition method for nonlinear nonstationary image analysis. In addition to maintain the characteristics of the signal itself, intrinsic mode function (IMF) has better time-frequency feature than the wavelet method. Moreover, Song Guo et al proposed an adaptive threshold de-noising method based on the energy estimation equation\cite{7} and a de-noising method based on IMF structure\cite{8} were prosed by Titijaroonroj, T et al. respectively. Also, Li Feng et al. raised a de-noising algorithm combining BEMD and wavelet transform\cite{9} while ignoring the noise in the low-frequency IMF, which means that the noise is not completely removed and able to affect image quality.

Based on the shortcomings of the above de-noising algorithm, this paper aims to filter the high-frequency IMF noise through PSO algorithm and optimize the threshold after wavelet transformation of the BEMD decomposed high-frequency IMF, as well filter the BEMD decomposed low-frequency IMF through exponential attenuation algorithm of wavelet semi-soft threshold after wavelet transformation.

2. BI-DIMENSIONAL EMPirical MODE DECOMPOSITION

Different from the empirical mode decomposition (EMD) as a multi-scale frequency analysis method, BEMD algorithm is an extension of EMD algorithm\cite{10} which is more suitable to nonlinear and complex signal analysis, even with certain similarities regarding decomposition between both. The steps for BEMD decomposition are listed as follows\cite{11}.

Input image set $f_{x,y}(x,y), k=1, j=1$, where $i$ represents the ith IMF, $K$ represents the Kth cycle of the ith IMF.

The maximum and minimum points of the input image $r_{x,y}(x,y)$ are calculated by neighborhood comparison method.

Triangulation method is used to obtain the sum of upper surfaces $E_{max}(x,y)$ and lower envelope surfaces $E_{min}(x,y)$ for the extremum points, and its mean value is calculated as $E_{mean}(x,y)$

$$E_{mean}(x,y) = \frac{E_{max}(x,y) + E_{min}(x,y)}{2} \quad (1)$$

Let $h_{x,y}(x,y) = r_{x,y}(x,y) - E_{max}(x,y)$

Calculate the value of SD to determine whether the constraint conditions are met.

$$SD = \sum_{x=0}^{w-1} \sum_{y=0}^{h-1} \frac{|r_{x,y}(x,y) - h_{x,y}(x,y)|}{r_{x,y}(x,y)} \quad (3)$$

Experimental results show that the range of SD is about 0.2-0.3, and SD is assumed as 0.2 in this paper. If yes, let $h_{x,y}(x,y) = IMF$. Otherwise, make $r_{x,y}(x,y) = h_{x,y}(x,y), k = k + 1$, return to step (2) and repeat the above steps until the signal meets the above conditions after K sieving.

After N level decomposition, BEMD is expressed as

$$f(x,y) = \sum_{i=1}^{N} IMF_i + r(x,y) \quad (4)$$

3. IMPROVED BEMD THRESHOLD DE-NOISING ALGORITHM

Most of UAV images are more complex and belong to nonlinear image signal. Now commonly used BEMD image denoising is to remove the noise in the high frequency by excluding the first levels of low-frequency functions according to the feature of noise distribution concentrated in low-frequency functions. This method is simple, but ignores the small amount of detailed information containing in the low-frequency IMF. To improve the shortcomings existed in the above commonly used methods, this paper presents a wavelet threshold de-noising algorithm based on BEMD. After decomposition of noisy UAV images by BEMD, it obtains the IMF with various frequency from high to low and residual of energy. Dividing the obtained IMF into two parts, one part is IMF containing both noise and image information, and the other is IMF with only a small amount of image information. In order to minimize the noise of the image, after decomposing the high-frequency IMF by wavelet, the PSO algorithm is
adopted to optimize the threshold value of each decomposed layer, and the low-frequency IMF and residual are filtered employing exponential attenuation threshold method of wavelet semi-soft threshold. Finally, the last stage is to reconstruct processed IMF and residual.

3.1 High-frequency IMF de-noising based on PSO optimized wavelet threshold

The traditional wavelet de-noising algorithm deals with wavelet coefficients by soft threshold[12] and hard threshold[13] de-noising methods proposed by Donoho. Aiming at the defects of hard threshold and soft threshold, the method presented in this paper improves the setting of threshold and adopts an adaptive threshold method for high-frequency IMF. This method is between the hard threshold and the soft threshold with strong flexibility and capability to make adjustments at any time depends on different image information and noise intensity. According to the correlation of wavelet coefficients, the neighborhood coefficient should be considered when setting the threshold value of the image after wavelet decomposition, and the coefficients of each layer should be extracted and processed respectively in the horizontal, vertical and diagonal directions to avoid the loss of some image information[14]. The threshold function is expressed as follows.

$$d_{jk} = \begin{cases} d_{jk} \left(1 - \alpha \frac{\lambda^2}{s_{jk}^2} \right), & s_{jk}^2 \geq \beta \lambda^2 \\ 0, & \text{else} \end{cases}$$

(5)

Where, R is the size of the domain window and wavelet coefficient set is $d_{jk}$. The size of $\alpha$ is between 0 and 1. The wavelet coefficient of each layer sub-band is $d_{m,n}$. The wavelet decomposition energy of each layer sub-band is $s_{jk}^2$. The expression is as follows.

$$s_{jk}^2 = 1 \sum_{d=1}^{D} \sum_{s=1}^{S} d_{m,n}^2$$

(6)

In order to threshold the wavelet coefficient, the contraction method of the neighborhood windows is applied by calculating the average value of neighborhood windows, whose expression is as follows.

$$\beta_{jk} = (1 - N^2 \lambda^2 / s_{jk}^2)$$

(7)

Where, the threshold value is

$$\lambda = (\sigma, \sqrt{2\log(R)})$$

(8)

In the formula, the threshold value of each layer is different. According to the image surface features of each layer decomposition, PSO is adopted to optimize the threshold value to obtain a higher PSNR. The standard noise difference expression is as follows.

$$\sigma = \frac{\text{median}[|d_{jk}|]}{0.6475}$$

(9)

Where, median is an operation command for calculating median in MATLAB, and j is the wavelet decomposition scale.

In the n-dimensional search space, the total number of particles is m, and the population is $X = \{x_1, x_2, \cdots, x_n\}$. The position and velocity of the ith particle are expressed as $x_i = (x_{i1}, x_{i2}, \cdots, x_{in})^T$, whose velocity is $v_i = (v_{i1}, v_{i2}, \cdots, v_{in})^T$. The optimal position of the particle and the population are respectively $p_i = (p_{i1}, p_{i2}, \cdots, p_{in})^T$ and $p_s = (s_{11}, s_{21}, \cdots, s_{in})^T$. The particle and population quantity velocity position update formula[16] is

$$v_{i(t+1)} = v_{i(t)} + c_1 \xi_i (p_{i(t)} - x_{i(t)}) + c_2 \xi_c (p_{s(t)} - x_{i(t)})$$

(10)

Where d = 1, 2, ..., N, I = 1, 2, ..., m, the current iteration number is t. The $\xi_i$ and $\xi_c$ are random numbers between [0,1], $c_1$ and $c_2$ are acceleration constants. For better control the exploration and development capacity, Shi et al[17] introduced the inertia weight, which can be expressed as

$$w(t) = (w_{init} - w_{end})/(T_{max} - t) + w_{end}$$

(11)

$T_{max}$ is the maximum number of iterations. The initial inertia weight and the maximum iterative inertia
weight are respectively $\omega_u$ and $\omega_w$. In this paper, the $\omega_u$ and $\omega_w$ are assumed as 0.9 and 0.4. Update the velocity and position of particles in Eq. (10) and Eq. (11). And in accordance to modelled on the GCV criterion of $GVC = \frac{1}{\bar{N}} \| \omega - \omega^* \|$, set the target function of PSO as deviation $T_i$ between $\omega_{j,k}$ and $\omega_{j,k}^\wedge$, that is, the minimum deviation before and after thresholding of wavelet coefficient as the optimal solution, which can be expressed to be:

$$T_i = \min \left| \omega_{j,k} - \omega_{j,k}^\wedge \right| \quad (12)$$

3.2 Low-frequency IMF de-noising based on exponential attenuation threshold of wavelet semi-soft threshold

Due to the non-ignorable and relatively smooth noise in low-frequency IMF and residual, a relatively smooth threshold should be selected for de-noising. The Wavelet semi-soft threshold function method is between soft threshold and hard threshold. When $\lambda < |w_{j,k}| \leq \lambda_1$, it is close to the soft threshold function; otherwise is close to the hard threshold function when $|w_{j,k}| > \lambda_2$. When $\lambda = \lambda_2$ it can be considered as a hard threshold function, and the situation of $\lambda_1 = \infty$ makes it the soft threshold function. The formula is as follows.

$$\hat{w}_{j,k} = \begin{cases} 0 & |w_{j,k}| \leq \lambda_1 \\ \text{sign}(w_{j,k})(\frac{\lambda_1}{\lambda_2 - \lambda_1} |w_{j,k}| - \lambda_1) & \lambda_1 \leq |w_{j,k}| \leq \lambda_2 \\ |w_{j,k}| & |w_{j,k}| > \lambda_2 \end{cases} \quad (13)$$

Adding exponential decay method is to smooth the threshold by transforming the linear processing mode of $w_{j,k}$ between $\lambda_1$ and $\lambda_2$ into exponential, preventing not only noise but also the loss of certain characteristic in images, and the formula is as follows.

$$\hat{w}_{j,k} = \begin{cases} 0 & |w_{j,k}| \leq \lambda_1 \\ \text{sign}(w_{j,k})(\lambda_1 e^{-x_0} + x_0 e^{-x_0} - 1) \frac{\lambda_1}{\lambda_2 - \lambda_1} |w_{j,k}| - \lambda_1 & |w_{j,k}| \leq \lambda_2 \\ |w_{j,k}| & |w_{j,k}| > \lambda_2 \end{cases} \quad (14)$$

3.3 The algorithm steps

The high-frequency IMF obtained by decomposing noise images through BEMD contains a large amount of image information and most of noise, comparing to low frequency IMF and residual with less image information and noise. In this paper, PSO optimized wavelet adaptive threshold method is adopted to filter high-frequency IMF, and exponential attenuation threshold filter of wavelet semi-soft threshold is adopted to filter low-frequency IMF. The flow chart of image de-noising algorithm in this paper is shown in Figure 1, and the algorithm is described as follows:

Step 1: Input a 512*512 UAV image of $I(x,y)$ with Gaussian white noise up to $\sigma = 0.005$, and then the noisy image $I(x,y)$ using BEMD to obtain four IMF and residual.

Step 2: The wavelet basis of $db5$ is selected to perform wavelet transformation on high-frequency IMF$_1$ and IMF$_2$.

Step 3: Make $R = 5, \alpha = 0.1, \beta = 0.3$, and calculate the energy, noise variance around the wavelet coefficient and wavelet coefficient in Eq. (5), Eq. (6) and Eq. (9).

Step 4: Initialize $n=4, m=20, T_{max} = 50, \omega_u = 0.9$ and $\omega_w = 0.4$, and apply PSO according to different energy and frequency in each layer of the image to optimizes adaptive thresholds $\lambda$.

Step 5: Set the minimum deviation before and after thresholding of the wavelet coefficients of the
objective function as the optimal solution $T_i$.

Step 6: Comparing with the fitness function before the particle, the minimum value is p-best. The optimal value of each particle is compared with the global optimal value to determine the minimum value as g-best.

Step 7: If $t = T_{\text{max}}$, stop iterating; otherwise, continue to optimize.

Step 8: After de-noising the noisy images at each layer which have been processed with wavelet decomposition using the optimal threshold obtained above, wavelet inverse transformation is employed to reconstruct images.

Step 9: The low-frequency IMF is denoising by exponential attenuation of wavelet semi-soft threshold.

Step 10: The denoisingd IMF and residuals are reconstructed.

Figure 1. Image de-noising algorithm flow chart

3.4 Objective Evaluation Criteria
In this work, MATLAB R 2017 environment has been selected and applied to simulate multiple de-noising methods for comparative tests in order to prove the effectiveness of this method in dealing with nonlinear and complex UAV images. The mean square error (MSE) and peak signal-to-noise ratio (PSNR) are adopted to evaluate the de-noising effect of the method in this paper. The expressions of mean square error (MSE) and peak signal-to-noise ratio (PSNR) are as follows.

1) mean square error (MSE):

$$MSE = \frac{1}{m \times n} \sum_{x=1}^{m} \sum_{y=1}^{n} (I(x, y) - \hat{I}(x, y))^2$$

(15)

$m$ and $n$ are the size of the image, the original image and the de-noising image are expressed respectively.
as $I(x, y)$ and $I'(x, y)$. The smaller the mean square error is, the better the de-noising effect is.

2) peak signal-to-noise ratio (PSNR):

$$PSNR = 10 \log_{10} \frac{R^2}{MSE}$$  \hspace{1cm} (16)

Where, $R$ is the grayscale of the image, and higher PSNR indicates better image de-noising effect.

4. EXPERIMENTAL RESULTS AND ANALYSIS

In this work, Lena and UAV images are used to evaluate the performance of the proposed images de-noising method. In order to study the performance of this method extensively, we evaluate its robustness in Gaussian white noise environment. And then the proposed algorithm is compared with the most advanced de-noising method to show that the improved method has good de-noising performance.

4.1 High-frequency IMF de-noising analysis

The 512*512 Lena image with $\sigma = 0.005$ white Gaussian noise is decomposed by BEMD. Both the traditional de-noising method and the paper-proposed method are used to filter the high frequency IMF, respectively. Figure 2 presents the result of experimental simulation with the traditional de-noising method and de-noising method proposed in the paper. Figure 3 shows the objective evaluation criteria with both methods. The experimental simulation results and objective evaluation criteria of high-frequency IMF1 and IMF2 by traditional de-noising methods and the paper method are shown in Figure 4 and Figure 5.

Figure 2. high-frequency IMF1 de-noising image: (a) high-frequency IMF1 de-noising image (b) soft threshold de-noising (c) hard threshold de-noising (d) paper methods

Figure 3. comparison of experimental results between the traditional method and the method in this paper

Figure 4. high-frequency IMF1 and IMF2 de-noising images: (a) high-frequency IMF1 and IMF2 de-noising images; (b) soft threshold de-noising; (c) hard threshold de-noising; (d) The paper method
Figure 5. Comparison of experimental results between the traditional method and the method in this paper.

The above experimental results show that it is better to remove the noise of IMF1 and IMF2 simultaneously. Compared with the traditional method, the proposed method in this paper is more effective in removing high-frequency IMF noise.

4.2 Low-frequency IMF de-noising analysis

The 512*512 Lena image with $\sigma = 0.05$ white Gaussian noise is decomposed by BEMD. And the eight energy diagrams of IMF $i$ are shown in Figure 6. The BEMD decomposition of the pre-noise and post-noise UAV images is shown in Figure 7. Although there are more noise energy in the high-frequency IMF, the noise in the low-frequency IMF also cannot be ignored.

4.3 Experimental analysis of UAV image de-noising

In the experiment, the white Gaussian noises of $\sigma = 0.005$, $\sigma = 0.01$, $\sigma = 0.05$ and $\sigma = 0.1$ are added to UAV image respectively and compared with six different methods including median filtering, mean filtering, wavelet hard threshold filtering, wavelet soft threshold filtering, BEMD-wavelet semi-soft threshold of exponential decay threshold by de-noising high frequency IMF1 and BEMD-wavelet adaptive threshold by de-noising high frequency IMF1. In addition to comparing traditional methods, the paper method is compared with the improved median filter method proposed by Yi-tan Hu[3], the mixed diffusion partial differential equation method proposed by Wang Jun[4], and a compression sensing based de-noising method proposed by Shen Chen[5]. Figure 8 shows the simulation results of UAV image filtering with $\sigma = 0.05$ white Gaussian noise by the above method.
4.3.1 Analysis of the PSNR

The simulation results of filtering the UAV image with Gaussian noise using the above method are shown in Figure 9. Comparing with other de-noising methods in low noise situation, the PSNR of the paper algorithm is about 16.7%-19.6% higher than that of median filtering and mean value filtering. Comparing with the wavelet hard threshold filtering method and the soft threshold filtering method, the PSNR of this method is increased about 12.5% to 21.5%. In addition, comparing with the BEMD-wavelet semi-soft threshold of exponential decay threshold algorithm filtering method and the BEMD-wavelet self-adaptive threshold filtering method which only deal with the high-frequency IMF, the PSNR is improved by 5.7%-7.4%.

In contrast, other denoising methods in high noise situation, the PSNR of the paper algorithm is about 6.0%-13.8% higher than that of median filtering and mean value filtering. Comparing with the wavelet hard threshold filtering method and the soft threshold filtering method, the PSNR of this method is increased about 4.3% to 17.7%. What's more, comparing with the BEMD-wavelet semi-soft threshold of exponential decay threshold algorithm filtering method and the BEMD-wavelet self-adaptive threshold filtering method which only deal with the high-frequency IMF, the PSNR is improved by 7.2%-16.2%.

Figure 9. PSNR of various methods

Figure 10 shows the PSNR adopted with more advanced filtering methods in recent years. In a low
noise situation, comparing with the improved median filter method, the mixed diffusion partial differential equation method and the compression sensing based de-noising method, the PSRN of the proposed method are increased respectively by about 7.3%-11.1%, 7.3%-8.6% and 1.4%-2.5%. As well as in high noise situation, comparing with the improved median filter method, the mixed diffusion partial differential equation method and the compression sensing based de-noising method the PSRN of the proposed method is increased respectively by about 3.0%-5.1%, 4.7%-5.1% and 0.5%-0.7%.

Figure 10. PSNR of more advanced filtering methods

4.3.2 Analysis of the MSE
The filtering mean square error (MSE) of the above method is shown in Figure 11 and Figure 12, and Figure 11 is the MSE of the image without noise.

In comparison other de-noising methods in low noise situation, the MSE decreases by about 19.5% to 38.3% than median filtering and mean value filtering. There is another point comparing with the wavelet hard threshold filtering method and the soft threshold filtering method, the MSE decreased by about 25.8% to 38.3%. Comparing with the BEMD-wavelet semi-soft threshold of exponential decay threshold algorithm filtering method and the BEMD-wavelet self-adaptive threshold filtering method only dealing with the high-frequency IMF, the MSE is reduced by 20.8%-38.3% after comparison.

In contrast these de-noising methods in high noise situation, the MSE decreases by about 2.4-8.9% than median filtering and mean value filtering. Comparing with the wavelet hard threshold filtering method and the soft threshold filtering method, the MSE decreased by about -0.1% to 1.4%. Comparing with the BEMD-wavelet semi-soft threshold of exponential decay threshold algorithm filtering method and the BEMD-wavelet self-adaptive threshold filtering method which only deal with the high-frequency IMF, the MSE is reduced by 0%-1.2%. Therefore, all above facts indicate a higher suitability of the proposed method in removing low-noise UAV images.

Figure 11. MSE of various method
To summarize objectively and subjectively, the median filtering, mean filtering and the images listed in the report have a little fuzzy. The PSRN of image denoising by wavelet hard threshold is better, but some Gibbs effect appears. The wavelet soft threshold de-noising image looks very smooth, however the PSRN is lower and lead to the loss of some high-frequency information. BEMD decomposes the image into different scales from high-frequency to low-frequency IMF, which can maintain the characteristics of the signal itself. Comparing with wavelet transform, BEMD has better time-frequency characteristics and is more suitable for nonlinear and impetuous signal analysis and processing. Combining with two methods not only make up the deficiency of wavelet decomposition, but also filter the image decomposed by BEMD and multiple threshold methods of wavelet. And then the BEMD-wavelet semi-soft threshold of exponential decay threshold and BEMD-wavelet adaptive threshold filtering method have better processing effect. The PSNR of this method is relatively high, and the cutting error is negligible. However, the noise cannot be completely removed through just de-noising high-frequency IMF and still have noise in the low-frequency IMF, which cannot be ignored. The improved median filter processes all the pixels in the image, but the unpolluted pixels also is destroyed. The mixed diffusion partial differential equation method preserves the edge information of the UAV images. The based on compression sensing de-noising method improves the PSNR and visual quality of the denoisingd images.
However, the paper-proposed method in this work can not only effectively deal with the noise in high frequency IMF, but also smoothly remove the noise in low frequency IMF, which is superior in terms of visual effect. PSRN and MSE, especially in low noise environment.

5. CONCLUSION
To solve the problem of noise pollution in UAV images. In the paper, a filtering method based on BEMD decomposition is proposed to optimize the wavelet threshold of high-frequency IMF by PSO and the low-frequency IMF by wavelet semi-soft threshold of exponential decay threshold. The algorithm can decompose the UAV image into IMF images of different scales. The high-frequency IMF uses PSO to optimize the threshold value. At the same time, the wavelet semi-soft threshold of exponential decay threshold to de-noising the low-frequency IMF. The method applied in this paper can filter the high-frequency IMF optimally and avoid the influence of low frequency IMF and RES noise on the UAV image. The algorithm is applied to UAV image processing and comparison with median filtering, mean filtering, wavelet soft threshold filtering, wavelet hard threshold filtering, the BEMD-wavelet semi-soft threshold of exponential decay threshold, BEMD-wavelet adaptive threshold that only de-noising high-frequency IMF, improved median filter method, as well as mixed diffusion partial differential equation method and based on compression sensing de-noising method. The PSNR of this algorithm will increase by 10.6%-12.2% and the mean square error will decrease by 20.0%-38.3% on average. In high noise situation, the PSNR will increase by 7.4%-9.0% and the mean square error will decrease by 1.6%-1.9% on average. The experiment results is show the effectiveness of the method on UAV image in low noise situation.

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REFERENCES

[1] Li Chen-xin. Research on image de-noising technology based on MATLAB three filtering algorithms [J]. Communications world,2018(06):283-284.
[2] Yan R M, Shao L, Liu Y. Nonlocal hierarchical dictionary learning using wavelets for image de-noising[J]. IEEE Transactions on Image Processing, 2013, 22(12): 4689-4698.
[3] Hu Yi-tan, Cao Jie, Liu Wei. Image de-noising algorithm for UAV visual landing [J]. Computer application research,2016,33(02):629-631.
[4] Wang Jun, Yang Cheng long. Model of UAV image de-noising based on hybrid diffusion [J]. Fire and command control, 2008,43(12):55-58.
[5] Shen Chen, Zhang Min. Combined de-noising method of UAV image based on compressed sensing [J]. Fire and command control, 2008,43(06):11-15+20.
[6] Huang N E, Shen Z, Long S R, et al. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis[J]. Proceedings of the Royal Society A, 1998, 454(1971): 903-995.
[7] Song Guo, Luan F, Song X et al. Self-adaptive image de-noising based on bi-dimensional empirical mode decomposition (BEMD)[J]. Bio-medical materials and engineering, 2014, 24(6):3215-22.
[8] Titijarooraj, T. Woraratpanya, K. Image De-noising Based on Structural BIMF[J]. ICSEC 2017 - 21st International Computer Science and Engineering Conference 2017, Proceeding, p 35-39, August 21, 2018.
[9] Li Feng, Lu hui. MRI medical image de-noising based on BEMD and wavelet threshold [J]. Chinese journal of image and graphics,2009,14(10):1972-1977
[10] Taravichet K, Kantpong W. Iteration-Free Bi-Dimensional Empirical Mode Decomposition and Its Application[J]. IEE-ICE Transactions on Information and Systems, 2017, E100.D(9):2183-2196.
[11] Cui M, Wu Y, Wang C. et. al. Salt and Pepper Noise Removal for Image Using Adaptive Pulse-Coupled Neural Network Optimized by Grey Wolf Optimization and Bi-dimensional Empirical Mode Decomposition[J]. Applied Sciences, 2018, 8(10).
[12] Donoho, D. L. De-noising by soft-thresholding[J]. IEEE Transactions on Information Theory, 1995, 41(3):613-627
[13] Xiao Q. Wang J, Jiang Y, et al. An Improved Wavelet Threshold De-Noising Method and Its Application[C]/ Control
and Decision Conference. IEEE, 2012.

[14] Chen G Y, Bui T D, Krzyzak A. Image de-noising using n-neighbouring wavelet coefficients [C]// Proc of IEEE International Conference on Acoustics, Speech and Signal Processing. Piscataway, NJ: IEEE Press, 2004.

[15] Alireza A. particle swarm optimization (PSO) algorithm with adaptive mutation and inertia weight and its application in dynamic system parameter estimation [J]. Acta Automatica Sinica, 2011, 37(5):541-549.

[16] Shi Y, Eberhart R C Empirical study of particle swarm optimization[M]. 2002.

[17] Wang Chao, Zhu Hong-ping. Study on wavelet de-noising method based on GCV criterion and improved threshold function [J]. World bridge,2015,43(06):47-50+57.

[18] Zhen Long-xin, Wang Yun-long, Deng Xiao-yan, et al. Wavelet semi-soft threshold noise reduction based on set empirical mode [J]. Journal of detection and control, 2018, 40(05):55-59.

[19] Hu Yi-tan, Cao Jie, Liu Wei. Image de-noising algorithm for UAV visual landing [J]. Computer application research,2016,33(02):629-631.

[20] Wang Jun, Yang Cheng long. Model of UAV image de-noising based on hybrid diffusion [J]. Fire and command control, 2008,43(12):55-58.

[21] Shen Chen, Zhang Min. Combined de-noising method of UAV image based on compressed sensing [J]. Fire and command control, 2008,43(06):11-15+20.