Wavelet Threshold Denoising of ACO Optical Lens Image

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Abstract. In the system of the image defect detection system, during image acquisition and transmission, the salt-and-pepper Noise will adversely affect the subsequent processing and recognition. To eliminate the salt-and-pepper noise effectively, a defect image denoising algorithm based on ant colony optimization wavelet threshold is improved in this paper. Firstly, the basic principle of wavelet denoising is analyzed theoretically, and a compromise threshold function and a GCV optimal threshold selection method are adopted. It uses ant colony algorithm to optimize the wavelet threshold, which greatly improves the speed and accuracy of the optimal threshold. Using standard soft threshold method, GCV threshold optimization method and the ant colony optimization wavelet threshold method, the defect image of the lens is denoised. The results of experiment indicate that the algorithm can remove the salt-and-pepper noise in the image of defective lenses more effectively than the other two algorithms, and improve the accuracy of the lens detection. This algorithm is also suitable for general image denoising.

Keywords: Lens defect image · Wavelet denoising
Ant colony optimization algorithm · Salt-and-pepper noise

1 Introduction

In recent years, Glasses industry have developed by leaps and bounds in our country. Many companies have fabricated optical les detecting system which based on machine vision. However, during the optical lens image capture and transmissing processing, it always brings some noise interference to some degree. It seriously affected the quality of the image because of the precision of the optical lens detection, the noise point that noise interference generate is easily mixed with optical lens' own defections, and submerges the optical lens' own characteristics. Therefore if's necessary to depress the noise processing.

The common ways of denosing can divided into airspace denoising and frequency domain denoising. The traditional airspace denoising way is use template to convolution or ranking to implementation and frequency domain way is usually according to the information of image shows different frequency combination in frequent space, with eliminating or restraining the high frequency part to implement the image

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denoising [1]. The traditional image denoising way could damage the image margin detail information when restrain the image noising, and image is blurry after denoising [2]. With the fast progress of the wavelet theory in recent years, wavelet has low entropy, multi-resolution, decor-relation and selection based flexible advantages. Which let wavelet conversion could realize the separation of signal and noise commendabiy, after Mallatt proposed the magnitude of the signal denoising, Donoho and some people proposed the wavelet threshold denoising which according to the multi-scale and the collecting ability of signal energy [3]. However, it is pivotal that using wavelet threshold denoising is to choose threshold function and threshold value. The traditional method of wavelet threshold denoising contains two kinds of ways, one of them is hard one and the other is soft. But the wavelet soft thresholding method has disadvantage, when the soft threshold are greater than the threshold, wavelet coefficients of the noise image will shrink. The hard threshold method can cause pseudo Gibbs phenomenon because the wavelet hard threshold denoising function is discontinuous at the threshold point [4]. Therefore, the reasonable choice of wavelet threshold and wavelet threshold function is very important to denoising effect.

In recent years, many intelligent algorithms have been applied to the threshold optimization of wavelet image denoising, and good results have been achieved. For example, Lin Jie et al. [5] proposed Wavelet Threshold Denoising Based on Particle Swarm Optimization Algorithm. The particle swarm algorithm is used to find the optimal threshold, and the particle fitness function is minimized, and the optimal threshold is obtained. But the algorithm will be caught in the local optimum answer easily and the search accuracy is not high. Zhang and Fang [6] proposed Multi-wavelet Based Adaptive Denoising Method and this algorithm has fast convergence speed and versatility, but it is easy to premature convergence.

In allusion to the problem of the lens defect image acquisition and transmission will generate the salt and pepper noise. The paper proposed a image denoising method which based on ant colony optimization wavelet thredhold. The method uses a compromise threshold function and combines ant colony optimization algorithm to optimize the wavelet threshold. The algorithm can effectively remove the noise in the lens defect image, and restore the characteristics of the defective image itself. It has very good denoising effect, and is beneficial to the post processing and recognition of the lens defects. The algorithm is also applicable to other image denoising.

2 The Basic Theory of Wavelet Denoising for the Lens Defect Image

2.1 The Principle of Wavelet Denoising

The idea of multi-resolution analysis (MRA) was proposed by Mallat in 1988 and the fast algorithm of wavelet analysis and reconstruction was later proposed. It allows us to de-noise noisy images, that is, Mallat algorithm [7]. The principle of the algorithm is that:

If $f(t)$ is the original signal and f_k is the discrete sampling data, and $f_k = c_{0,k},$ then the decomposition formula of the orthogonal wavelet transform of the signal $f(t)$ is:

$$\begin{cases} c_{j,k} = \sum_n c_{j-1,n} h_{n-2k} \\ d_{j,k} = \sum_n d_{j-1,n} g_{n-2k} \end{cases} (k = 0, 1, \cdots N-1) \tag{1}$$

$g_{j,k}$ is the scaling factor, and $h_{j,k}$ is the wavelet coefficient, and *l, m* is Quandrature Mirror Filter (QMF), and *J* is the decomposition layer number, and *N* is the discrete sampling point. The reconstruction of wavelet transform is the inverse process of decomposition, and its reconstruction formula is as follows:

$$c_{j-1,n} = \sum_n c_{j,n} h_{k-2n} + \sum_n d_{j,n} g_{k-2n} \tag{2}$$

After the wavelet decomposition of the noisy signal, the energy of the signal mainly spread in the wavelet range with larger wavelet coefficients, while the energy of the noise spread in the whole wavelet range. Therefore, the amplitude of wavelet coefficients is greater than the amplitude of noise coefficients. It can be said that the wavelet coefficients with larger amplitudes are usually dominated by signals, and the smaller are the noise signals to a large extent. According to the threshold value we set in advance, all wavelet coefficients whose amplitudes are smaller than the threshold are all set to zero, while the wavelet coefficients whose amplitudes are greater than the threshold are retained or properly reduced. Finally, the corresponding wavelet coefficients are transformed into inverse wavelet transform. We can get the de-noised image. The process of wavelet denoising is shown in the following Fig. 1:

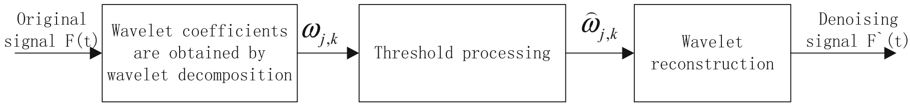


Fig. 1. Flow chart of wavelet denoising

The multi-resolution characteristics of wavelet can decompose signals at different scales, and decompose the signals into different sub signals, so that the signals can be processed by frequency bands. A two-dimensional image with noise is $p(x, y) = b(x, y) + kd(x, y)$. $p(x, y)$ is the noise signal, $b(x, y)$ is the real signal, and $d(x, y)$ is the noise signal. Wavelet denoising is to handle the wavelet coefficients by decomposing the wavelet coefficients, and then suppress the noise signals and restore the real signals.

2.2 Wavelet Threshold Function and GCV Threshold

Using threshold function to deal with the wavelet coefficients, the chosen of wavelet threshold T will influence the denoising effect directly. If the threshold is too small, the de-noised image still has noise, but if the selection is too large, the feature information of the image will be filtered out, which will lead to bias. Therefore, we need to select the appropriate threshold *T*, and use the threshold function to process the wavelet coefficients and reconstruct the image. In the wavelet analysis proposed by Donoho, the formulas of hard threshold and soft threshold function [8] as:

(1) Hard threshold

$$\omega_{j,k} = \begin{cases} \omega_{j,k} & |\omega_{j,k}| \geq T \\ 0 & |\omega_{j,k}| < T \end{cases} \tag{3}$$

(2) Soft threshold

$$\omega_{j,k} = \begin{cases} \mathrm{sgn}(\omega_{j,k})(|\omega_{j,k}| - T) & |\omega_{j,k}| \geq T \\ 0 & |\omega_{j,k}| < T \end{cases} \tag{4}$$

$\omega_{j,k}$ is the discrete wavelet transform operator, T is the threshold, and *sgn(.)* is the symbolic function. If the wavelet coefficients are less-than threshold T, it will be represented by zero, and the wavelet coefficients greater than T are reduced by $\omega_{j,k}$.

In the wavelet analysis proposed by Donoho, there are some defects in the hard threshold and the soft threshold. In the hard threshold, because of the discontinuities at T and $-T$, the reconstructed image may suffer from visual anamorphose such as ringing and pseudo Gibbs effect. Although the continuity and smoothness of the soft threshold are good, when $|\omega_{j,k}| \geq T$, the constant deviation between the $\omega_{j,k}$ and $\acute{\omega}_{j,k}$ will lead to the blurring of the reconstructed image.

Therefore, we choose a compromise threshold function:

$$\omega_{j,k} = \begin{cases} \mathrm{sgn}(\omega_{j,k})(|\omega_{j,k}| - \alpha T) & |\omega_{j,k}| > T \\ 0 & |\omega_{j,k}| \leq T \end{cases} \tag{5}$$

Formula: a is a real number. When $0 < a < 1$, the $\omega_{j,k}$ obtained by this method is between the soft and hard threshold. Therefore, we adjust the size of the a and the noisy image is more resemble to the original image. We can get better denoising effect. Usually, $a = 0.5$.

During image acquisition and transmission, the image noise is unstable, the noise is unknown and can not estimate the noise energy. Therefore, the threshold method based on GCV quasi side is selected in this paper [9]. The function expression as:

$$GCV(T_j) = \frac{\frac{1}{N_j}\left|\left|\omega_j - \omega_{j,T}\right|\right|^2}{\left[\frac{N_{j0}}{N_j}\right]^2} \tag{6}$$

Formula: N is the number of wavelet coefficients. N_0 is the threshold. The number of wavelet coefficients is zero after the contraction. j is the number of wavelet decomposition.

3 The Application of Ant Colony Optimization Wavelet Threshold (ACOTE) in Image Denoising

3.1 The Basic Theory of Ant Colony Algorithm

Ant colony optimization algorithm, called ant colony algorithm, is an advanced simulated bionic algorithm based on the foraging of ants in nature [10]. Ants can release pheromones when they are foraging, and their companions can sense the presence and intensity of pheromones. Since the beginning of the ant behavior always is random and the number of individuals in the colony is huge. So some ants can always find food, and find the base answer between the nest and the food. Because the path is short, the ants leave more pheromones per unit time, and other ants will choose the shortest path by perceiving the pheromone concentration. Thus, more and more pheromones are added to the path and establish positive feedback, and finally the ant colony is concentrated on the shortest path, and finally the optimal solution is obtained.

Ant colony algorithm (ACO) is a parallel algorithm with strong robustness, few parameter settings and simple setting. It can easily apply to combinatorial optimization problems [11]. The main operation process of ant algorithm in solving the problem is shown below [12]: Suppose that in the t iteration, the probability of ant K from the city i to the city j is $P_{ij}^{k}(t)$:

$$P_{ij}^{k}(t) = \begin{cases} \frac{\tau_{ij}^{\alpha}\eta_{ij}^{\beta}(t)}{\sum\limits_{s \in allowd_k} \tau_{ij}^{\alpha}\eta_{ij}^{\beta}(t)} & j \in allowd_k \\ 0 & otherwise \end{cases} \tag{7}$$

Formula: $\mathrm{allowd}_{\mathrm{k}}$ is allowed mobile table for the ant K. ι_{ij} is pheromone concentrations of the t iteration on the i and the j. a is the heuristic factor, used to characterize the importance of information, $\eta_{ij} = 1/d_{ij}$. d_{ij} is the distance between two points. β is the expected factor, used to indicate the importance of the i and the j.

When the global ant completes a traversal, the pheromone is updated:

$$\tau_{ij}(t+1) = (1-\rho) \times \tau_{ij}(t) + \Delta\tau_{ij} \tag{8}$$

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \tag{9}$$

Formula: ρ is the pheromone residual coefficient, $0 \leqslant \rho \leqslant 1$, $\varDelta T_{ij}$ represents the pheromone remain by the ant K in the path between the t iteration and the $t + n$ iteration between the i and the j. The formula used in the ant-cycle model is generally used $\varDelta T_{ij}^{k}$ [13]:

$$\Delta\tau_{ij}^{k} = \begin{cases} Q/L_k, When\ the\ ant\ K\ passes\ through\ the\ city\ (i,j)\ at\ T\ and\ T+1 \\ 0, \quad otherwise \end{cases} \tag{10}$$

Formula: Q is pheromone intensity, which affects convergence speed; L_k is the path taken by the ant K in this cycle.

3.2 Wavelet Threshold Denoising Method Based on Ant Colony Optimization

The ant colony optimization wavelet threshold denoising method is as follows:

(1) The wavelet transform and the three-layer decomposition of the image are obtained, and the coefficients of wavelet decomposition are obtained.
(2) The initialization of the ant colony is to assign the initial urban location T_k and initial pheromone concentration τ_{ij} of each ant in the population and to reset the tabu list.
(3) The GCV(T_j) threshold is calculated for each ant in the population using the corresponding wavelet coefficients. When GCV(T_j) is the minimum, the threshold T_j can be considered as the best threshold.
(4) According to formula (7), the transfer probability of each ant is calculated and the ants move according to the calculated probability of movement. Each move adds

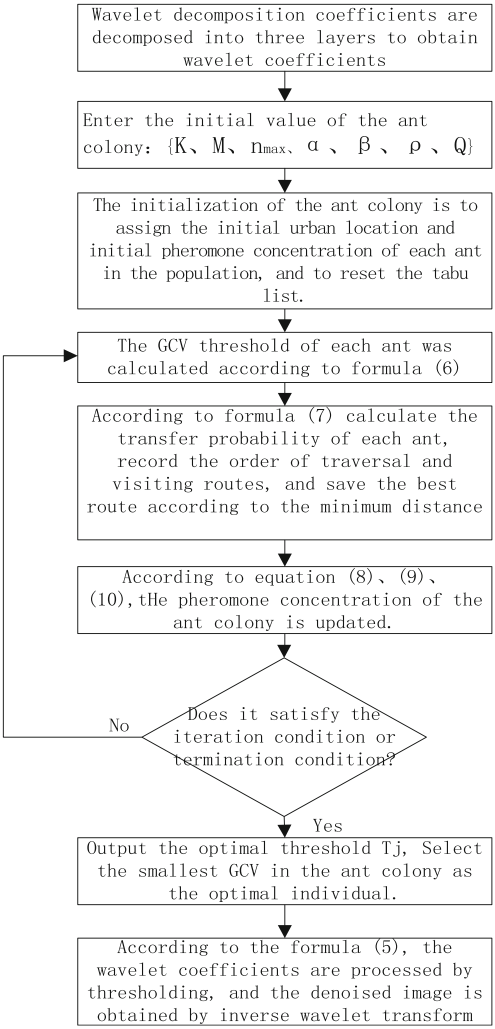


Fig. 2. Low chart of wavelet threshold denoising process based on ant colony optimization

the moving city to the tabu list until the ant has completed its traversal of all the cities. We record the traversal order and the visiting route, and keep the best route according to the minimum distance.

(5) Pheromone concentrations of ants are updated by formula (8), (9) and (10).

(6) The GCV threshold of the ants is calculated again and to determine whether the condition is satisfied. If the condition is satisfied, the optimal solution T_j is output, or else it returns to step 3. The optimal path is obtained and the optimal solution T_j is output until the maximum iterations are reached.

(7) The optimal threshold is used to denoise the image, and then the denoised signal is reconstructed by wavelet transform to get the denoised image.
The parameters of the ant colony algorithm are set as follows: Ant population: $K = 40$, City quantity: $M = 50$, Maximum iterations: $n_{max} = 100$. The flow chart of removing the noise in the optical lens by the wavelet threshold of ant colony optimization is shown in Fig. 2.

4 The Image Denoising Results of the Lens Defect Image

4.1 The Noise Generation and Characteristics of Lens Defect Image

In the detection system of optical lens, the image acquisition of lens general select the method of Dark Field Imaging [14] and the lens defect shows a brighter point in the image. Because of the interference from the outside of the system and the image sensor, the images collected by the CCD camera will have different levels of Salt-and-pepper Noise. Salt-and-pepper Noise is the black and white light dark noise. For optical lenses, filtering not only does not destroy the contours of the image edge, but also needs to make the image clear, which is conducive to subsequent processing. The Salt-and-pepper Noise that appears randomly in the optical image is shown below (Fig. 3).

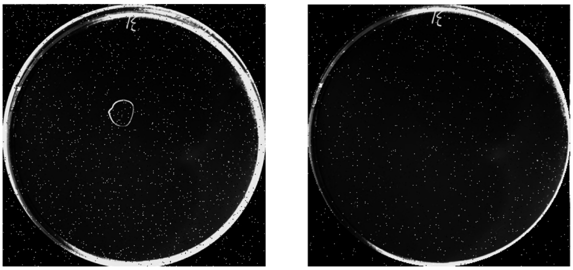


Fig. 3. Random noise of salt-and-pepper in the lens defect image

4.2 Evaluation Criterion of the Lens Defect Image

The experimental environment of this experiment is Matlab R2010b and subjective and objective methods are used in evaluation criteria. The subjective standard is the sharpness of the image and the smoothness of detail, and the objective standard is Peak Signal Noise Ratio (PSNR) and the run time of algorithm as the criterion. The calculation method of PSNR [15] as:

$$PSNR = 10\lg\frac{\delta^2(i,j)}{MSE}$$

$\delta^2(i, j)$ is the variance of the gray value of the denoised image, and MSE is the minimum mean square deviation of the denoised image.

The formula is as follows:

$$MSE = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}[f(i,j) - f_0(i,j)]^2$$

M and N is the number of rows and columns of the image, and $f(i, j)$ is the denoised image function, and $f_0(i, j)$ is the original image function.

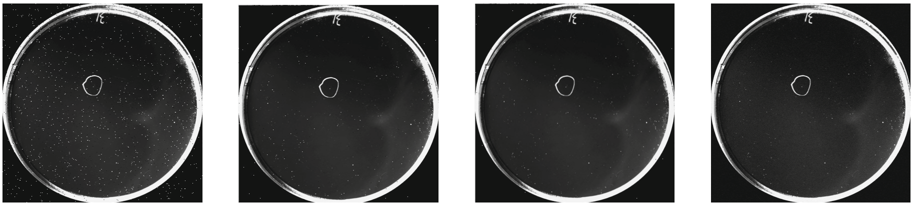
The object of this experiment is the lens defect image (400 × 400) taken by camera. First, The Salt-and-pepper Noise of 20%–40% is added to the image, and Wavelet base select sym4. We use standard soft threshold denoising (STE), GCV threshold method (GCVTE) and ant colony optimization wavelet threshold algorithm (ACOTE) to denoise and we can get the following experimental data:

Table 1. PSNR of the lens defect image under different intensity noises

Method	Intensity									
	20%		25%		30%		35%		40%	
	PSNR	Time	PSNR	Time	PSNR	Time	PSNR	Time	PSNR	Time
STE	34.042	0.82	34.876	1.14	34.564	1.22	34.345	1.43	34.045	1.66
GCVTE	36.652	6.21	36.045	6.61	35.896	7.01	35.601	7.31	35.454	7.81
ACOTE	39.452	2.21	38.945	2.61	38.696	2.91	38.401	3.21	38.154	3.61

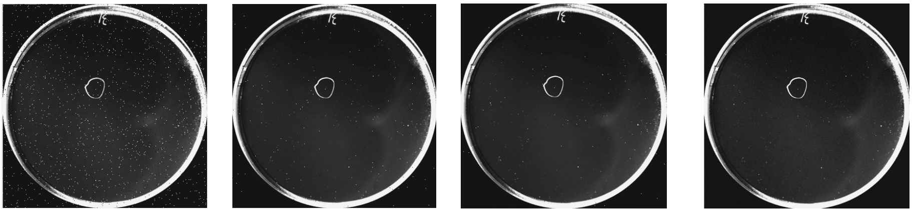
There are the treatment of lens defect image under different strength in the Table 1. The results of experiment indicate that, with the increase of noise intensity, the PSNR decreases gradually, and the processing time increases gradually. Under the same noise, the PSNR processed by ACOTE algorithm is significantly higher than the GCVTE algorithm and the STE algorithm. The GCV method takes a long time in the calculation process, while the ACOTE algorithm reduces the optimization time of wavelet threshold.

It shows the result of adding 25% and 40% salt-and-pepper noise to the lens defect image in the Figs. 4 and 5. The results of experiment indicate that, the ACOTE algorithm and the GCVTE algorithm can effectively remove the salt-and-pepper noise in the image. The STE algorithm is not effective in removing salt-and-pepper noise, so it is difficult to distinguish the salt-and-pepper noise and the defects of the lens itself.



The image with noise 25% STE GCVTE ACOTE

Fig. 4. The treatment result of 25% noise in optical lens



The image with noise 40% STE GCVTE ACOTE

Fig. 5. The treatment result of 40% noise in optical lens

5 Conclusion

Based on a compromise threshold function, combined with ant colony optimization algorithm, the optimal wavelet threshold of image denoising is achieved in this paper. The standard soft thresholding method, the GCV criterion denoising method and the ant colony optimization wavelet threshold algorithm are used to denoise the defective image. The experimental results show that the ant colony optimization wavelet threshold algorithm and the GCV criterion denoising method can remove the salt-and-pepper noise in the defective image more effectively than the standard soft thresholding method, and retain the defect information in the lens image. Ant colony optimization algorithm reduces the optimization time of wavelet threshold, and is beneficial to the post processing recognition of lens defect image.

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