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Application of Improved SVM Algorithm in Color Image De-Noising

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Abstract

*It cannot avoid the noise interference in image processing, whether it is image generation, or image transmission, among them, the most typical noise is salt and pepper noise and Gaussian noise. The salt and pepper noise will cause the image showing the random distribution of noise points, thus greatly reduce the image quality. The Gaussian noise affects the input, collection and output of the image processing. Gaussian noise will make the image blurred. Therefore, the image de-noising plays a very important role in image processing. It has direct influence on image segmentation, feature extraction and image recognition. As is known to all, the support vector machine has the advantages of solving the problem of nonlinear, high dimension and local minimum points. In this article, we use this advantage to propose an image de-noising method which is based on it. The method uses support vector regression to construct the filter for image de-noising. The feature extraction and training samples are designed to suppress different types of noise. Firstly, we use the noise pixel as the center of the 5*5 window, and generate the input vector of SVM from row to column. Secondly, we set the output of the support vector filter as an image that is not contaminated by noise. At this point, we get the training samples of SVM filter. In addition, the parameter selection of support vector machine has a great influence on the result of image de-noising. Therefore, the particle swarm optimization algorithm is proposed in this article to optimize the parameters of SVM. Finally, we adding the simulated salt and pepper noise and Gaussian noise in the original Lena image, and using several methods to carry out the de-noising experiment. From the experimental results we can see that the de-noising effect of filtering algorithm of this paper is very good for the two kinds of noise. It can effectively remove the noise, and better maintain the details and the color of the image.*

Keywords: *image processing technology, image de-noising, SVM, PSO*

1. Introduction

It cannot avoid the noise interference in image processing, whether it is image generation, or image transmission, among them, the most typical noise is salt and pepper noise and Gaussian noise. The salt and pepper noise will cause the image showing the random distribution of noise points, thus greatly reduce the image quality. The Gaussian noise affects the input, collection and output of the image processing. Gaussian noise will make the image blurred. Therefore, the image de-noising plays a very important role in image processing. It has direct influence on image segmentation, feature extraction and image recognition.

At present, there are mainly two methods to remove the noise, which are linear filter and nonlinear filter. With the extensive application of color image in the fields of biomedicine, computer vision and pattern recognition, color image processing has been paid more and more attention. Color image is different from the gray image, people generally can only distinguish dozens of gray levels, but can distinguish thousands of colors. Therefore, the color image contains more information, and how to de-noise is one

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of the most basic problems in the color image processing technology. In recent years, a large number of scholars and experts have proposed many filtering algorithms. Lin proposed a modified adaptive median filter with adaptive length [1]; Florencio proposed a median filter with local signal statistical characteristics [2]; Wang proposed a Min-max algorithm for median filter [3]; Wang proposed long-range correlation algorithm [4]; Li proposed a new adaptive algorithm for removing salt and pepper noise [5]. They improve the filtering performance to a certain extent, and make a useful exploration. But in practical applications, they have some limitations. Support vector machine [6-7] is a machine learning method based on statistical learning theory [8-9], VC dimension theory and structural risk minimization principle. It shows many special advantages in solving small sample, nonlinear and high dimensional pattern recognition problems. In addition, it overcomes the problem of "Curse of dimensionality" and "over learning". Therefore, it have been considerable development in the field of pattern recognition, regression analysis, function estimation, and time series prediction [10-14].

In this paper, we use advantage of SVM to propose an image de-noising method which is based on it. The method uses support vector regression to construct the filter for image de-noising. The feature extraction and training samples are designed to suppress different types of noise. Firstly, we use the noise pixel as the center of the 5*5 window, and generate the input vector of SVM from row to column. Secondly, we set the output of the support vector filter as an image that is not contaminated by noise. At this point, we get the training samples of SVM filter. In addition, the parameter selection of support vector machine has a great influence on the result of image de-noising. Therefore, the particle swarm optimization algorithm is proposed in this article to optimize the parameters of SVM. Finally, we adding the simulated salt and pepper noise and Gaussian noise in the original Lena image, and using several methods to carry out the de-noising experiment. From the experimental results we can see that the de-noising effect of filtering algorithm of this paper is very good for the two kinds of noise. It can effectively remove the noise, and better maintain the details and the color of the image.

2. PSO-LS-SVM

Least squares support vector machine has the advantages of strong generalization and global optimization. Its training time is short and the result is more definite, so it is suitable for online application. At present, it has been widely used in the fields of signal processing, system identification and modeling, advanced control and soft measurement [15-18]. Least squares support vector machine algorithm is as follows:

Set the training sample set to (x_i, y_i) , $i = 1, 2, \cdots, n$, $x \in R^d, y \in R$, and the output function is $f(x) = w^T \varphi(x) + b$. At this point, the training of the model is transformed to minimize the structural risk.

$$R = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \xi_i^2 \tag{1}$$

It needs to satisfy the following constraints.

$$y_i = w^T \varphi(x_i) + b + \xi_i \text{ , } i = 1, 2, \cdots, n \tag{2}$$

The corresponding Lagrange functions are as follows:

$$L = (w, b, \xi, \alpha) = R - \sum_{i=1}^{n} \alpha_i (w^T \varphi(x_i) + b + \xi_i - y_i) \tag{3}$$

Among them, $\alpha = [\alpha_1, \alpha_2, \cdots, \alpha_n]$ is the Lagrange operator, w, b is the model parameter, C is the regularization parameter, and the ξ is the error vector of training set prediction.

According to KKT condition, we can get:

$$\frac{\partial L}{\partial w} = \frac{\partial L}{\partial b} = \frac{\partial L}{\partial \xi_i} = \frac{\partial L}{\partial \alpha_i} = 0 \tag{4}$$

$$\begin{cases} w = \sum_{i=1}^{n} \alpha_i \varphi(x_i) \\ \sum_{i=1}^{n} \alpha_i = 0 \\ 2C\xi_i = \alpha_i \end{cases} \tag{5}$$

According to Formula 2 and Formula 5, we can get:

$$\begin{bmatrix} 0 & 1 & 1 & \cdots & 1 \\ 1 & K(x_1, x_1) + \frac{1}{2c} & K(x_1, x_2) & \cdots & K(x_1, x_n) \\ 1 & K(x_2, x_1) & K(x_2, x_1) + \frac{1}{2c} & \cdots & K(x_2, x_n) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & K(x_n, x_1) & K(x_n, x_2) & \cdots & K(x_n, x_n) + \frac{1}{2c} \end{bmatrix} \tag{6}$$

$$\begin{bmatrix} b \\ \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{bmatrix} = \begin{bmatrix} 0 \\ y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}$$

In the Formula 6, the $K(x, x_i) =< \varphi(x), \varphi(x_i) >$ is the kernel function. According to the functional theory, as long as the function satisfies the Mercer condition, it can be used as the kernel function. The commonly used kernel functions are linear function, perception function and radial basis function. In view of the better performance of radial basis function [19], the radial basis function $K(x, x_i) = \exp(-\frac{\left\|x_i - x_j\right\|^2}{2\sigma^2})$ is selected as the kernel function of LS-SVM in this paper,.

The final decision function, as shown in the Formula 7:

$$f(x) = \sum_{i=1}^{n} \alpha_i K(x, x_i) + b \tag{7}$$

From the computation process of SVM, the different values of ξ in non-sensitive loss function, penalty coefficient C and σ^2 in radial basis function will lead to the different support vector regression model. Therefore, in this paper, we select approximate optimization of parameter sets (C, σ^2) based on PSO by controlling the value of ξ to construct image de-noising algorithm of PSO -SVM.

The core idea of parameter optimization in particle swarm optimization is treating the two-dimensional vector as the position of the particle and set a reasonable objective function at the same time. When each particle is searching by location, the purpose is to minimize or maximize the objective function and determine its historical best point in group or domain.

The objective function is set to the mean square error function:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \quad (8)$$

Then writing C as $x = (x_1, x_2)$. It consists of particles in groups. Then the position of particle i can be expressed as $x_i = (x_{i1}, x_{i2})$, velocity of particle i is $v_i = (v_{i1}, v_{i2})$. Its historical best point can be written as $p_i = (p_{i1}, p_{i2})$ and the whole best point can be written as $p_g = (p_{g1}, p_{g2})$. Then the position and velocity of the particle will change with the following equation:

$$v_{ij}^{(t+1)} = wv_{ij}^{(t)} + c_1\delta_1(p_{ij}^{(t)} - x_{ij}^{(t)}) + c_2\delta_2(p_{gj}^{(t)} - x_{ij}^{(t)})$$

$$x_{ij}^{(t+1)} = x_{ij}^{(t)} + v_{ij}^{(t+1)}, \quad j = 1, 2$$

Among them, c_1 and c_2 are known as learning factors and always equal to 2. δ_1 and δ_2 are pseudo random number whose interval is $[0,1]$, and the w is the inertia weight. We make the value of the time-varying as weights and hypothesis $w \in [w_{\min}, w_{\max}]$, $Iter\_\max$ is maximum number of iterations.

$$w_i = w_{\max} - \frac{w_{\max} - w_{\min}}{Iter\_\max} * i$$

Among them $[w_{\min}, w_{\max}] = [0.1, 0.9]$.

Now we use the idea of cross validation to optimize the PSO-SVM model in order to find a more reasonable set of parameter (C, σ^2), so the model's error is smaller.

3. Noise Filter

Assumed that the $I(i, j, k)$ is RGB image which is not contaminated, the noise of the image is $\varepsilon(i, j, k)$, and $I^{'}(i, j, k)$ is the image which is filtered by the support vector.

$$I^{'}(i, j, k) = I(i, j, k) + \varepsilon(i, j, k) \quad (9)$$

Support vector image filtering process can be expressed as follows:

$$f(\bullet) = f(u(i, j, k)) = I^{''}(i, j, k) \quad (10)$$

Among them, $f(\bullet)$ is the filter, $u(i, j, k)$ is the filter input vector of pixel (i, j, k), and $I^{''}(i, j, k)$ is the filtered image. Firstly, we use the noise pixel (i, j, k) as the center of the 5*5 window, and generate 25 pixel values from row to column which are expressed as $I(i, j, k)$. Then, the $u(i, j, k)$ are used as the filter input vector, and the output of the support vector filter is set to $I(i, j, k)$. At this point, we define $\{u(i, j, k), I(i, j, k)\}$ as a sample point $\{x_i, y_i\}$ in support vector regression.

4. The Simulation and Result Analysis

Experiment A: The de-noising of the salt and pepper noise.

In this paper, we test and analyze the Lena image (24 bit RGB images, the size of 256*256). First, we make the Figure 1, as the target output samples, and add the simulated salt and pepper noise in Figure 1. The noise probability is 1%-30%. Then, we have obtained the Figure 2. After that, we record the pixel value $u(i, j, k)$ in the 5*5 window, and assume that each component is equal to the intensity of the noise pollution. In order to test the performance of PSO-SVM filtering algorithm, this paper compared with the commonly used Gaussian filter and median filter to filter the Figure 2, and quantitatively analyzes the results of filtering. In the experiment, using Matlab as a tool to construct support vector regression network, the parameter (C, σ^2) in support vector regression is determined by particle swarm optimization.

Figure 1. Original Image of Lena

Figure 2. Adding the Salt and Pepper Noise

Next, this paper uses the Gaussian filter, median filter and PSO-SVM filter to test the filtering effect of the Lena image, the experimental results are shown in Figure 3-5. At this point, we only give one effect chart that the noise pollution is 30%, and in the rest of the de-noising results of the noise probability, we are given by Figure 6 and Figure 7.

Figure 3. The De-Noising of Gaussian Filter

Figure 4. The De-Noising of Median Filter

Figure 5. The De-Noising of PSO-SVM Filter

In order to quantitatively evaluate the performance of various algorithms, we use mean square error (MSE), normalized mean square error (NMSE) and peak signal to noise ratio (PSNR) as the comprehensive evaluation index of filtering performance. Among them, the PSNR value is the average value of running 20 times. Table 1, is the comparison results of quantitative performance of the standard Gaussian filter (GF), median filter (MF), and PSO-SVM filtering.

Among them, the mean square error (MSE), normalized mean square error (NMSE) and peak signal to noise ratio (PSNR) calculation method as shown in Formula 11-13.

$$PSNR = 10\log_{10}\frac{3*255^2}{\frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}(I(i,j,k),I^{'}(i,j,k))^2} \tag{11}$$

$$MSE = \frac{\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\left\|I(i,j,k),I^{'}(i,j,k)\right\|^2}{3mn} \tag{12}$$

$$NMSE = \frac{\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\left\|I(i,j,k),I^{'}(i,j,k)\right\|^2}{\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\left\|I(i,j,k)\right\|^2} \tag{13}$$

From the above three formulas we can see that only by calculating the results of PSNR, MSE and NMSE in R, G, and B component, we can calculate the PSNR, MSE and NMSE values of the overall color image. Next, we give trend of the PSNR value of three algorithms that the salt and pepper noise pollution between 1% and 30% in Figure 6, and Figure 7. Where, $I^{'}(i,j,k)$ and $I(i,j,k)$ are the pixel values of noise image and the original image, m and n are the number of rows and columns of the image.

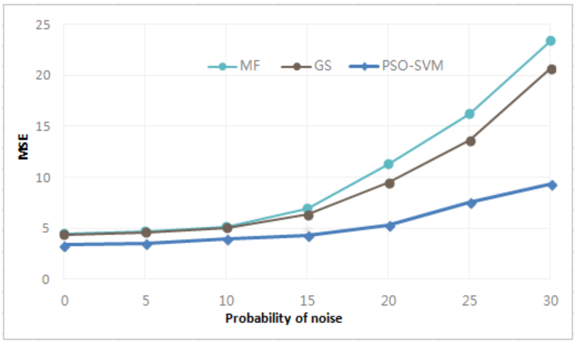

Figure 6. The Comprehensive Evaluation Criteria of MSE

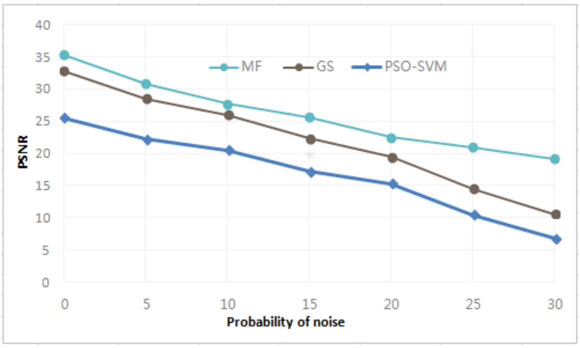

Figure 7. The Comprehensive Evaluation Criteria PSNR

For the filter performance evaluation criteria, the smaller the value of RMSE or the greater of PSNR value, the better the filter filtering effect. It can be clearly seen from the two graphs that the filtering performance of PSO-SVM filter is obviously better than Gaussian filter and median filter.

Experiment B: The de-noising of the Gaussian noise.

First, we add the simulated Gaussian noise in Figure 1. Its mean value is 0, and the variance is 0.001. Then, we get the Figure 8.

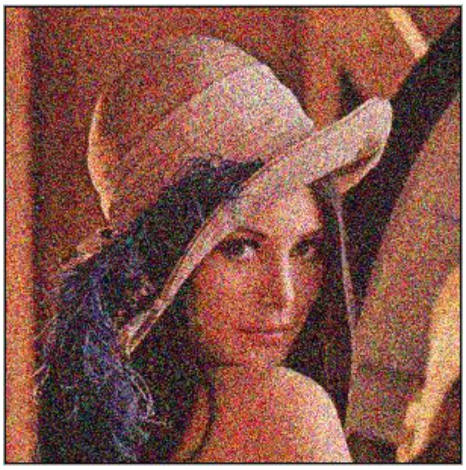

Figure 8. Adding the Gaussian Noise

Next, this paper uses the Gaussian filter, median filter and PSO-SVM filter to test the filtering effect of the Lena image, the experimental results are shown in Figure 9-11.

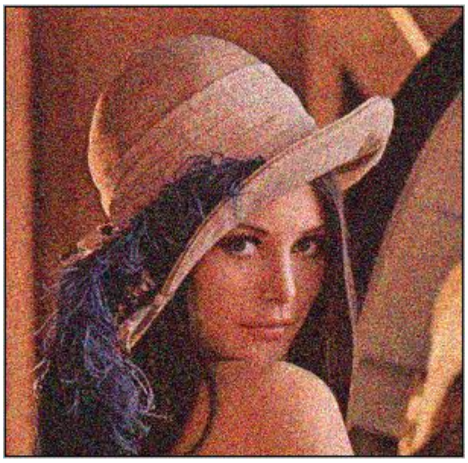

Figure 9. The De-Noising of Gaussian Filter

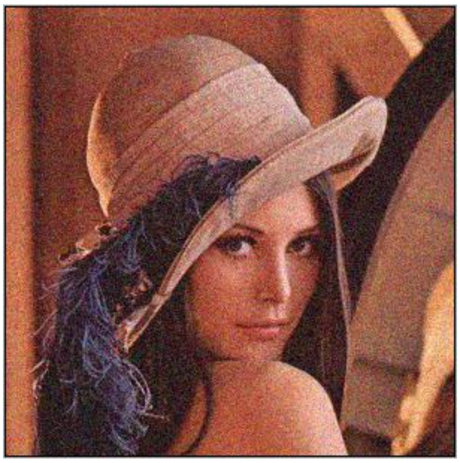

Figure 10. The De-Noising of Median Filter

Figure 11. The De-Noising of PSO-SVM Filter

From Figure 9-11, we can see that the best de-noising effect is the support vector regression filtering, the Gaussian filtering effect is slightly worse, and the median filtering effect is the worst. Compared with the support vector regression filter, the median filter leaves more spots, which shows that it is ineffective to protect the details. It can be seen that the support vector regression filter has obvious advantage to the de-noising of Gaussian noise.

Finally, we give PSNR table of three algorithms in the de-noising of Gaussian noise.

Table 1. The Average PSNR Value of Each Algorithm in De-Noising of Gaussian Noise

	PSNR(dB)	MSE	NMSE(10^{-4})
MF	27.34	8.92	25.47
GS	31.16	7.35	21.18
PSO-SVM	39.29	4.89	13.33

5. Conclusion

In this paper, we use advantage of SVM to propose an image de-noising method which is based on it. The method uses support vector regression to construct the filter for image de-noising. The feature extraction and training samples are designed to suppress different types of noise. Firstly, we use the noise pixel as the center of the 5*5 window, and generate the input vector of SVM from row to column. Secondly, we set the output of the support vector filter as an image that is not contaminated by noise. At this point, we get the training samples of SVM filter. In addition, the parameter selection of support vector machine has a great influence on the result of image de-noising. Therefore, the particle swarm optimization algorithm is proposed in this article to optimize the parameters of SVM. Finally, we adding the simulated salt and pepper noise and Gaussian noise in the original Lena image, and using several methods to carry out the de-noising experiment. From the experimental results we can see that the de-noising effect of filtering algorithm of this paper is very good for the two kinds of noise. It can effectively remove the noise, and better maintain the details and the color of the image.

References

[1] H. M. LIN and A. N. WILLSON, "Median filters with adaptive length", .IEEE Trans on Circuits and Systems, vol. 35, no. 6, **(1988)**, pp. 675-690.

[2] D. A. F. FLORENCIO and R. W. SCHAFER, "Decision-based median filter using local signal statistics", Proc of SPIE Symposium on Visual Communications Image Processing. Chicago, **(1994)**, pp. 268-275.

[3] J. Wang and L. LIN, "Improved median filter using min-max algorithm for image processing", Electronics Letters, vol. 33, no. 16, **(1997)**, pp. 1362-1363.

[4] Z. Wang and D. ZHANG. "Restoration impulse noise corrupted images using long-range correlation", IEEE Signal Processing Letters, vol. 5, no. 1, **(1998)**, pp. 4-7.

[5] Y. Wang and S. Li, "Non-Linear Adaptive Removal of Salt and Pepper Noise from Images", Journal of Image and Graphics, vol. 5, no. 12, **(2000)**, pp. 999-1001.

[6] N. CRISTIANINI and J. S. TAYLOR, "An introduction to support vector machines and other kernel-based learning methods", Publishing House of Electronics Industry, Beijing, **(2004)**.

[7] X. G. ZHANG, "Statistical learning theory and support vector machines", Acta Automatic Sinica, vol. 26, no. 1, **(2000)**, pp. 32-41.

[8] V. N. VAPNIK, "The nature of statistical learning theory", Tsinghua University Press, Beijing, **(2000)**.

[9] V. N. VAPNIK, "Statistical Learning Theory", Publishing House of Electronics Industry, Beijing, **(2004)**.

[10] X. L. Liu and S. F. Ding, "Appropriateness in applying SVMs to text classification", Computer Engineering and Science, vol. 32, no. 6, (**2010**), pp. 106-108.

[11] K. B. Lin and Z. J. Wang, "The method of fax receiver's name recognition based on SVM", Computer Engineering and Applications, vol. 42, no. 7, **(2006)**, pp. 156-158.

[12] S. Xie, F. Shen and X. QIU, "Face recognition using support vector machines", Computer Engineering, vol. 35, no. 16, **(2009)**, pp. 186-188.

[13] Y. Li and X. G. RUAN, "Feature selection for cancer classification based on support vector machine", Journal of Computer Research and Development, vol. 42, no. 10, **(2005)**, pp. 1796-1801.

[14] G. Wei and W. Ning, "Prediction of shallow-water reverberation time series using support vector machine", Computer Engineering, vol. 34, no. 6, **(2008)**, pp. 25-27.

[15] Y. Weiwu, Z. Hongdong and S. Huih, "Soft sensor modeling based on support vector machines", Journal of System Simulation, vol. 15, no. 10, **(2003)**, pp. 1494-1496.

[16] J. A. K. Suykens and J. Vandewalle, "Recurrent least squares support vector machines", IEEE transactions on circuits and systems-I: Fundamental theory and applications, vol. 47, no. 7, **(2000)**, pp. 1109-1114.

[17] X. Zhiming, W. Xiaoqiang, S. Yuanyuan, X. Zhiming, W. Xiaoqiang and S. Yuanyuan, "State prediction of slogging on coal-fired boilers based on least squares-support vector machine for regression Xu Zhiming, Wen Xiaoqiang, Sun Yuanyuan, State prediction of slogging on coal-fired boilers based on least squares-support vector machine for regression", Proceedings of the CSEE, vol. 29, no. 17, **(2009)**, pp. 8-13.

[18] M. Chen and D. Liu, "Multi objective optimization of coal-fired boiler combustion based on LS-SVM and SPEA2", East China Eclectic Power, vol. 34, no. 3, **(2006)**, pp. 50-54.

[19] S. S. Keerthi and C. J. Lin, "Asymptotic behaviors of support vector machines with Gaussian kernel", Neural Computation, vol. 15, no. 7, **(2003)**, pp. 1667-1689.

