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A New Adaptive Threshold Image-Denoising Method Based on Edge Detection

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Abstract

In image processing, removal of noise without blurring the image edges is a difficult problem. Aiming at orthogonal wavelet transform and traditional threshold's shortage, a new wavelet packet transform adaptive threshold image de-noising method which is based on edge detection is proposed. By edge detection method, the wavelet packet coefficients corresponding to edge which is detected and other non-edge wavelet packet coefficients are treated by different threshold. Using the relativity among wavelet packet coefficients and neighbor dependency relation, at the same time, adopting the new variance neighbor estimate method and then the adaptive threshold is produced. From the experiment result, we see that compared with traditional methods, this method can not only effectively eliminate noise, but can also well keep original image's information and the quality after image de-noising is very well.

***Keywords**: image denoising, wavelet packet transform, edge detection, neighbor dependency adaptive threshold*

1. Introduction

Wavelet transform is an effective signal denosing tool, it has shown mass application prospect in image processing, pattern recognition etc. Wavelet transform has multi-resolution analysis capability as well as time-frequency domain analysis of signal at the same time [1]. Recently, main image denosing algorithm based on wavelet is still staying on image decomposition of wavelet basis, however, image decomposition of wavelet basis only decompose low frequency part of information, high frequency part of information can't be got refinement handling, this way causes undetected loss phenomenon in information of high frequency part, wavelet packet basis can overcome such shortage to get better analysis ability [2]: Low frequency part and high frequency part can be decomposed at the same time, thus more high frequency part of information can be saved and got refinement handling.

The most widely used wavelet denosing method is nonlinear wavelet transform threshold shrink method proposed by Donoho et al [3]. Wavelet threshold shrink method calculates orthogonal wavelet transform of noise image, however, general threshold $T=\sigma_n\sqrt{2\log n^2}$ has "excessive killing" tendency trend to wavelet coefficient, it will cause oscillation located in vicinity of discontinuity point and quick change place for denoised image called Gibbs phenomenon. Thus, a new wavelet packet transform adaptive threshold image de-noising method which is based on edge detection is proposed. Based on the edge information which is effectively detected by this method, wavelet packet is chosen to decompose the image. Using large amount of redundant information which is produced by wavelet packet decomposition and this kind of redundant information is useful to find the dependency relationship of wavelet coefficients between intra-scale and inter-scale, the coefficient variance estimation accuracy based on wavelet coefficient neighbor is greatly improved. Meanwhile, the wavelet packet coefficients are divided into two categories, which are corresponding to edge and non-edge wavelet packet coefficients. These two kinds of coefficients are treated by different adaptive threshold. This method can save the original image information well and denoise effectively; in addition, it is very useful to do further image processing.

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2. Wavelet Packet Principle

In short, the wavelet packet is a family of functions. The canonical orthogonal basis library of $L^2(R)$ is constructed by this family of functions. Form this library, many groups of canonical orthogonal basis of $L^2(R)$ can be chosen and wavelet orthogonal basis is only one group of them.

When the signal is decomposed by wavelet packet, many kinds of wavelet packet basis can be adopted. According to the demand of signal and noise, the best basis should be chosen from them [4]. Nowadays, Shannon entropy is used more to search the best basis. Threshold is the key of wavelet packet denoising and the adaptive threshold which is based on edge detection is adopted by this paper.

3. Edge Detection Algorithm

For an arbitrary image pixel $P(i, j)$, the wavelet packet transform values of horizontal and vertical direction are got respectively, they are $w_1(i, j)$, $w_2(i, j)$. So its modulus is:

$$M(i, j) = \sqrt{w_1(i, j)^2 + w_2(i, j)^2} \quad (1)$$

Argument direction of image pixel is gradient direction, argument $A(i, j)$ can be got from arc tangent of $w_2(i, j)/w_1(i, j)$, and the expression is:

$$A(i, j) = \arctan\left(\frac{w_2(i, j)}{w_1(i, j)}\right) \quad (2)$$

Argument $P_0(i, j)$ and modulus $M(i, j)$ of arbitrary image pixel is given, image pixel pointed by its gradient direction can be got from argument $A(i, j)$, firstly, image pixel point P_0 is lighten, then set the point pointed by argument direction of image pixel P_0 as P_1, compare modulus of two points, lighten P_1 and extinguish P_0 if the modulus of P_1 is larger. Continue doing the same handling to P_1 until modulus of next point is larger than or equal to this point. After traversing all image pixels, maximum value image of local modulus is consist of all light points.

Maximum point of local modulus of image is linked as maximum chain; the principle is that maximum point of two modulus is adjoin, tangent line direction is approximate at one line, tangent line direction is vertical direction of gradient, and use threshold to wipe off short maximum value link, in this way, image $P(m, n)$ is margin of original image.

4. Adaptive Threshold Image Denosing Based on Wavelet Packet Transform and Neighbor Dependency

4.1. Adaptive Threshold Based on Bayesian Estimation [5]

Threshold determination is very important segment in threshold image denosing. Chang et al use Generalized Gaussian Distribution (GGD) as prior model of wavelet coefficient distribution, by minimum Bayes risk, to get adaptive threshold of digital drive in Bayes framework.

Set:

$$y_{i,j} = x_{i,j} + \varepsilon_{i,j} \quad (3)$$

$i, j = 1, 2, ..., N$, $y_{i,j}$, $x_{i,j}$ and $\varepsilon_{i,j}$ mean observed noise image, true image and independent identically distributed Gaussian noise, $\varepsilon_{i,j}$ obeys $N(0, \sigma_n^2)$ distribution. Set $Y_{i,j} = X_{i,j} + V_{i,j}$ as corresponding wavelet coefficient. Suppose if X and Y as Gaussian distribution, that is $X \sim (0, \sigma_x^2)$, $Y/X \sim (X, \sigma_x^2)$

Generalized Gaussian distribution expression is listed as follows:

$$GG_{\sigma_X, \beta}(x) = C(\sigma_X, \beta) \exp\{-[\alpha(\sigma_X, \beta)\,|x|]^{\beta}\} . \quad (4)$$

$-\infty < x < \infty$, $\sigma_X > 0$, $\beta > 0$

$$\alpha(\sigma_X, \beta) = \sigma_X^{-1}[\frac{\Gamma(3/\beta)}{\Gamma(1/\beta)}]^{1/2} . \quad (5)$$

$$C(\sigma_X, \beta) = \frac{\beta \cdot \alpha(\sigma_X, \beta)}{2\Gamma(\frac{1}{\beta})} . \quad (6)$$

$\Gamma(t) = \int_0^{\infty} e^{-u} u^{t-1} du$ is gamma function, parameter σ_X is standard variance, β is formal parameter. Then Bayes risk is defined as:

$$r(T) = E(\hat{X} - X)^2 = E_X E_{Y|X}(\hat{X} - X)^2 = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} (\eta_T(y) - x)^2 p(y|x) dy dx \cdot \quad (7)$$

As to given parameter, the target is to find the best threshold T^* that can get the minimum Bayes risk:

$$T^*(\sigma_X, \beta) = \arg\min_T r(T) . \quad (8)$$

We can get approximate optimal formulas of T^* by derivation [5]:

$$T_B(\sigma_X) = \frac{\sigma_n^2}{\sigma_X} . \quad (9)$$

σ_X is standard variance of X , σ_n^2 is standard variance of noise. This threshold is Bayes Shrink threshold.

4.2. Spatial Adaptive Threshold for Edge Wavelet Packet Coefficients

This paper uses spatial adaptive method to determine adaptive threshold for each wavelet coefficient, thus each coefficient threshold is:

$$T_B(i, j) = \frac{\sigma_n^2}{\sigma_X(i, j)} \quad (10)$$

Noise variance σ_n^2 determined by noise type, according to robustness median estimation proposed by Donoho [6], that is, σ_n^2 is estimated by subband HH_1 :

$$\hat{\sigma}_n = \frac{Median(|Y_{ij}|)}{0.6745}, \quad Y_{ij} \in HH_1 \tag{11}$$

For the edge pixel, the edge pixels which are adjacent have spatial relation. Therefore, one edge pixel's variance estimated by its adjacent edge pixels is more accurate than the method estimated by its N neighbor pixels. Let $\sigma_{Y_P}[i, j]$ represents the wavelet packet coefficient related to edge pixel $P(i, j)$, so its variance can be got by the following formula:

$$\sigma_{Y_P}^2[i, j] = \frac{1}{2L+1}\sum \sigma_{Y_P}^2[t, v] \tag{12}$$

$P(t, v)$ is the adjacent edge pixel of edge pixel $P(i, j)$. For the given edge pixel, its variance is estimated by its two sides adjacent L edge pixels respectively, that is 2L+1 edge pixels in all. Generally speaking, different value of L can produce similar result. However, it will destroy the regional when L is too large and it will affect the calculation accuracy when L is too small. L is usually chosen $\max(50, 0.02*M^2)$ to ensure adequate pixels to estimate its variance. $\sigma_{X_P}^2[i, j]$ is estimated as follows:

$$\sigma_{X_P}^2[i, j] = \max\left(\frac{1}{2L+1}\sum_{[t,v]\in B(i,j)} \sigma_{Y_P}^2[t, v] - \sigma_n^2, 0\right) \tag{13}$$

$B(i, j)$ is the set of 2L adjacent edge pixels of $[i, j]$.

4.3. Neighbor Dependency Adaptive Threshold for Non-edge Wavelet Packet Coefficients

During the variance estimation of non-edge noisy coefficients, this paper considers not only intra-subband but also inter-scale dependency relativity of wavelet packet coefficients which is different from past variant neighbor estimation. That is the relativity between child and father/brother coefficient. In scale s and direction o, the father coefficient of one coefficient $Y^{(s,o)}[i, j]$ is defined as $Y^{(s+1,o)}[i, j]$ in scale s+1, same direction o and same spatial location, $s = 1, 2, \cdots, J$; $O \in \{HL, LH, HH\}$. The brother coefficient of $Y^{(s,o)}[i, j]$ is defined as same scale s, different direction o' and same spatial location. So:

$$\hat{\sigma}_Y^{2\,(s,o_1)}(i,j) = \frac{1}{N\times N}\sum_{(k,l)\in win_{i,j}} Y^{2\,(s,o_1)}[k,l] + Y^{2\,(s+1,o_1)}[i,j] + Y^{2\,(s,o_2)}[i,j] + Y^{2\,(s,o_3)}[i,j] \tag{14}$$

$win_{i,j}$ is square neighbor window centering wavelet coefficient $Y^{(s,o)}[i, j]$, window size is $N \times N$, N is positive odd number. The corresponding item of above formulas will be eliminated if there is coefficient that exceeds the range of wavelet subband. The windows size will affect the estimation result of variance; undersized window can't utilize neighbor dependency relativity well, overlarge window will impact the effect of denosing. This paper uses size 3×3 neighbor window [7].

Thus $\sigma_X(i, j)$ is estimated as:

$$\hat{\sigma}_X(i,j) = \sqrt{\max(\hat{\sigma}_Y^2(i,j) - \hat{\sigma}_n^2, 0)} \quad (15)$$

4.4. Wavelet Packet Adaptive Threshold Algorithm which is Based on Edge Detection

In conclusion, the procedure of this algorithm is listed as follows:

(1) Decomposition of wavelet packet of image. Select a kind of wavelet and determine layer N of wavelet decomposition, then decompose wavelet packet of N layer for image; Determine optimal wavelet packet basis. Calculate optimal wavelet packet basis by given Shannon entropy standard.

(2) Use local modulus maximum value method to extract the image edge information;

(3) Threshold quantization of wavelet packet decomposition coefficient. For the wavelet packet coefficients related to edge, spatial adaptive threshold is chosen to deal with; for the wavelet packet coefficients related to homogeneous regions, neighbor dependency adaptive threshold is chosen to deal with.

(4) Wavelet packet reconstruction. Wavelet packet reconstruction of image is done according to wavelet packet decomposition coefficients of Nth layer and the coefficients after the quantization handling.

5. Experiment Result and Analysis

Based on the image denosing algorithm mentioned above, we use MATLAB 6.5 to do the simulation experiment. As to size 512×512's boat image with zero mean Gaussian white noise, we use Winner2 method, wavelet packet method and the method proposed in this paper to do simulation experiment. We can get Winner2 function from MATLAB image processing tools box, 3×3 window is used in this paper. This experiment selects haar wavelet to do image decomposition of 3 layers. As to different Gaussian white noise, we use PSNR (Peak Signal to Noise Ratio) of image as benchmark of denosing performance, it is defined as:

$$PSNR = -10\log_{10} \frac{\sum_{i,j}(B(i,j) - A(i,j))^2}{n^2 256^2} \quad (16)$$

B is denoised image; A is original noise-free image.

PSNR (dB) of boat image is shown in Table 1 in different noise intensity and different de-nosing method. The optimal result is emphasized in bold.

Result figure of different denosing method of boat image is shown in Figure 1 while noise variance $\sigma_n = 25$.

Table 1. PSNR (dB) of Noisy Boat Image Using Different Denoising Method

Method / σ_n	Noisy image	Winner2	Wavelet packet	Proposed by this paper
$\sigma_n = 15$	24.3892	28.1743	30.3059	33.2671
$\sigma_n = 20$	22.5016	26.7738	29.0127	31.8376
$\sigma_n = 25$	20.4733	24.5942	26.9548	29.7902

From experiment result, we see that this method can still effectively eliminate noise while noise variance is big and noise pollution is heavy. Denoised image has clear margin. This method overmatches traditional methods from PSNR and visual effect.

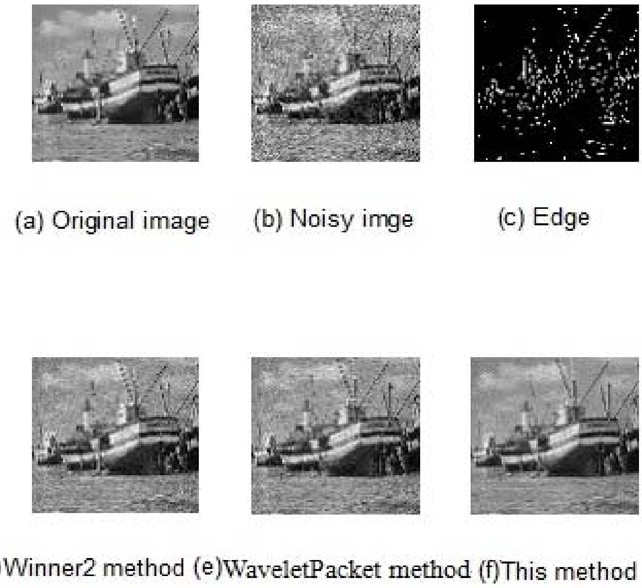

Figure 1. Image Denoising by Using Different Methods on a Noisy Boat Image while $\sigma_n = 25$

6. Conclusion

Low frequency part and high frequency part can be decomposed at length by wavelet packet transform that avoid the shortage of wavelet transform. The expression of image is redundant in the domain of wavelet packet transform, decomposition coefficient is relative. This paper uses local modulus maximum value method to extract image edge information and treats the wavelet coefficients which are related to edge and homogeneous regions differently. They are treated by different adaptive threshold. Meanwhile, the dependency relationship of wavelet coefficients between intra-scale and inter-scale is considered adequately and then a new image denoising method is proposed. Experiment result indicates that this method can not only denoise effectively, but can also gain clear image margin.

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