AN IMAGE DENOISING SCHEME FOR BASKETBALL VIDEO IMAGE

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ABSTRACT

In recent years, the wavelet-based image denoising techniques mainly focus on the case that uses a single wavelet base. In fact, different wavelet bases can often effectively represents different areas or features of an image. In this paper a new image denoising method using multiple wavelet bases is proposed. First, the noisy image is denoised by various wavelet bases and then a set of the denoised images are obtained. Next, the local character is computed in time domain of every denoised image. The variance, the mean and the gradient are selected to explain the local character of the denoised images. When the character is bigger, the recovery effect of the image is better, the pixel is picked up as a clear pixel to the final denoised image. Third, these multiple denoised images are fused into a final denoised image based on the local character. Experiments show that the simple fusion improves the visual quality of the recovery image.

Keywords: *Image Denoising, Bayes Thresholding, Local Character, Multiple Wavelet*

1. INTRODUCTION

With the rapid increasing of basketball video data, effective video analysis has become popular in multimedia research. So image processing has becoming one of the most research hotspots in sports video. The quality of the image can seriously affect the result of the analysis. As the pretreatment of image processing, image denoising is the key issue in video analysis.

When the background noises are white Gaussian noises, the classical method is using low passing filter. But this method blurs the image edges and textures while restrains the noise, namely, over-smoothing. Wavelet is effective in image denoising, which is used in non-stationary signal analysis. In an image, many characters such as the edge and texture, are non-stationary component, so the wavelet-based image denoising techniques can retain the detail information while remove the noise.

Wavelet is succeeded in this field due to those causes [1]: (1) low entropy, the 'large' wavelet coefficients are sparse and the entropy decreased. (2) multi-resolution, the structure can well describe the non-stationary character such as the edges, the pinnacles, the discontinue point, etc. (3) de-correlated, wavelet can well de-correlate the signal. (4) multi-bases, the wavelet transform can choose various wavelet bases and dispose different images and different areas of an image.

The essence of the wavelet-based image denoising techniques is that the noise is eliminated and the signal is restrained by all kinds of threshold due to the statistical character, which belongs to the transformative fields of the image and the noise. The threshold functions are those simply and effectively nonlinear functions such as hard threshold, soft threshold and etc. The estimate of threshold value [2] is the key of the denoising. And acquiring this threshold is often based on the statistical hypothesis, such as Universal threshold, Stein agonic threshold [2-3], Bayes threshold, Local Bayes threshold [4], Spatial adaptively threshold [5] and etc. From many experiments we know that Local Bayes threshold according with soft threshold function is one of the most effectively methods. The types of the wavelet bases are those such as orthogonal wavelet bases, biorthogonal wavelet bases, undecimated wavelet bases, M-band wavelet, and multi-wavelet etc. Unlike the traditional wavelet denoising, in this paper a wavelet-based image denoising method using multiple wavelet bases is proposed. Firstly, every wavelet base is employed to decompose, threshold with Local Bayes, and recover the image, and then a set of the denoised images are obtained. Next, these denoised images are fused into a clean image via local character. Comparing with other image denoising method, the method achieves the better

performance but its computation cost is less. And the selection of the wavelet bases is discussed from experiments.

2. THE MODEL OF IMAGE DENOISING BASED ON WAVELET SHRINKAGE[6]

The noise-corrupted image is obtained by an unknown image X plus the noise

$$Y(i,j) = X(i,j) + \varepsilon(i,j), \qquad (1)$$
$$i = 0, \cdots, M-1; j = 0, \cdots, N-1$$

Where $\varepsilon(i,j)$ is a zero-mean Gaussian white noise of variance σ^2, satisfy:

$$E\{\varepsilon(i,j)\} = 0, \qquad (2)$$
$$E\{\varepsilon(i,j)\varepsilon(i',j')\} = \sigma^2 \delta(i-i')\delta(j-j')$$

Let W denote an N × M orthogonal or biorthogonal wavelet transform matrix. In the wavelet domain, (1) becomes:

$$\mathbf{w} = W\mathbf{Y} = W\mathbf{X} + W\mathbf{e} \qquad (3)$$

After the decomposition, the energy of the image is compacted into a small number of large wavelet coefficients and lower solution scale coefficients, while the noise is remain equally scattered in all the wavelet coefficients and lower resolution scale coefficients. Thus a reasonable technique called the wavelet-based image denoising is to shrink the small coefficients while retain the large coefficients. The technique is a typical method based on no parameters and has good robustness, simple reputation, less former experimental information. The three important parts in the wavelet-based image denoising are the estimation of noise variance, the estimation of the threshold, and the selection of the threshold function. Then the three problems are as follows.

In Decompose the image, the subbands (K is the largest level) are as follows:

$$c_K(m,n), w_{LH}^{(k)}(m,n), w_{HL}^{(k)}(m,n), w_{HH}^{(k)}(m,n), \qquad (4)$$
$$k = 1, 2, \cdots, K$$

where $c_K(m,n)$ represents the low scale coefficient, HL, LH and HH respectively represent the horizontal detail, vertical detail, diagonal detail of the same level, and the superscript is the decomposition level.

The standard variance of the noise is estimated from the subband HH_1 by the robust median estimator,

$$\hat{\sigma} = MAD(|w_{HH}^{(1)}(m,n)|) / 0.6745 \qquad (5)$$

Because there is few signal component in the subband HH1, and large wavelet coefficient is sparse. And the estimation is much robust.

Now we can estimate the threshold and select the thresholding (or shrinkage) function. The soft thresholding function is a double input and single output nonlinear function, as follows:

$$\hat{w}(m,n) = \text{soft\_T}(w(m,n), \lambda(m,n))$$
$$= \begin{cases} sign\{w(m,n)\}(|w(m,n)| - \lambda(m,n)), & |w(m,n)| \geq \lambda(m,n) \\ 0, & |w(m,n)| < \lambda(m,n) \end{cases}$$
$$(6)$$

where $\hat{w}(m,n), w(m,n), \lambda(m,n)$ are respectively denote estimated wavelet coefficient, noise wavelet coefficient and threshold. In the shrinking processing we often deal with the detail coefficient and not with the low scale coefficients. To simplify notation, the superscript and the subscript are ignored in the follows.

Except the soft-threshold function, there are hard-threshold function, semisoft-threshold function and empirical-wiener filtering etc. The selection of the threshold is the key part of the wavelet-based image denoising. The universal threshold [7] only depends on the number of subband-coefficient and the noise variance, the SURE threshold [8] depends on the energy of the subband-coefficient and the noise variance. And the local Bayes threshold [9], the spatially adaptive wavelet thresholding have appeared, every time the new method achieves much high performance. The combination of local Bayes threshold and soft thresholding function is one of the most effectively methods based on experiments. The local Bayes threshold is a spatially adaptive wavelet thresholding for image denoising, which is employed by the cluster property of the coefficients, that is to say: the coefficients in wavelet domain are not even, and the large coefficients which are represent the edges and the textures of an image often get together. In the edges we wish to use small threshold to keep the detail character, while in the smooth area, we use large threshold to remove some of the noise and preserve most of the signal due to the little difference between the signal and the noise. That is to say we use the averaged energy in the local area of the wavelet domain to estimate the signal energy. For example, we use the window 7×7, the point $w(m,n)$'s neighboring field is:

$$B(m,n) = \begin{bmatrix} w(m-3,n-3) & \cdots & w(m-3,n+3) \\ \vdots & w(m,n) & \vdots \\ w(m+3,n-3) & \cdots & w(m+3,n+3) \end{bmatrix} \quad (7)$$

The estimated energy including noise of this point is:

$$\hat{\sigma}_y^{\;2}(m,n) = \frac{1}{7 \times 7} \sum_{w(i,j) \in B(m,n)} w^2(i,j) \quad (8)$$

the estimated energy of the signal is:

$$\hat{\sigma}_x^2(m,n) = \hat{\sigma}_y^2(m,n) - \hat{\sigma}^2 \quad (9)$$

So according to Bayes rule, the threshold of this point is:

$$\lambda(m,n) = \begin{cases} \dfrac{\hat{\sigma}^2}{\hat{\sigma}_x}, & \hat{\sigma}_x > 0 \\ |w(m,n)|, & \hat{\sigma}_x \le 0 \end{cases} \quad (10)$$

Obviously, when the signal is much stranger than the noise, the threshold is chosen to be small in order to preserve most of the signal and remove the some of the noise; vice versa, when the noise dominate and the normalized threshold is chosen to be large to remove the noise which has overwhelmed the signal. In this paper we use local Bayes threshold to all the wavelet bases, and the neighboring field is square field of 7×7.

3. JOINT IMAGE DENOISING METHOD VIA MULTIPLE WAVELET BASES

Differing from the Fourier transform, the wavelet transform has various wavelet bases. Different wavelet bases can often represent different areas and features of an image due to their different time-frequent character. For example, short support wavelet bases, such as Haar, with better local time character, can effectively represent the suddenly changes of the signal, especially the odd point. While other wavelet bases which have high regularity and high vanishing moment can effectively represent the smooth area of a signal. Most images consist of regions, smoothness, edges and textures. As for the smoothness, the smooth wavelet with high regularity and high vanishing moment can achieve the better effect. That's to say, the energy is central in some big wavelet coefficients. While for the sharp region, the longer the support of the wavelet base, the stranger the Gibbs-like ringing, and the energy of the signal is scatter on many small wavelet coefficients. It is harm to the image denoising. However the wavelet with short support is not well in the smooth area but in the sharp transition. Traditionally only one single wavelet is used to denoise the image. Often the

wavelet base is high regularity and high vanishing moment. But this method leads to over-smooth phenomena in the edges and textures. The base with high regularity and high vanishing moment can often achieve more signal-to-noise improvement than short support wavelet. That is because the most areas of the image are smooth.

3.1 The Joint Denoising Method based on Local Character and Multiple Wavelets

The traditional method is difficult to benefit from both the smooth area and the sharp area only with one single wavelet. So a joint denoising method via multiple wavelet bases is proposed. Firstly, various wavelet bases are employed to decompose, threshold, and recover the image, then a set of denoised images are obtained. Next, the local character of every pixel in denoised images is computed by the square window. Third, the multi-denoised images are fused into one final image based on local character. The flow chart of the method is as follows:
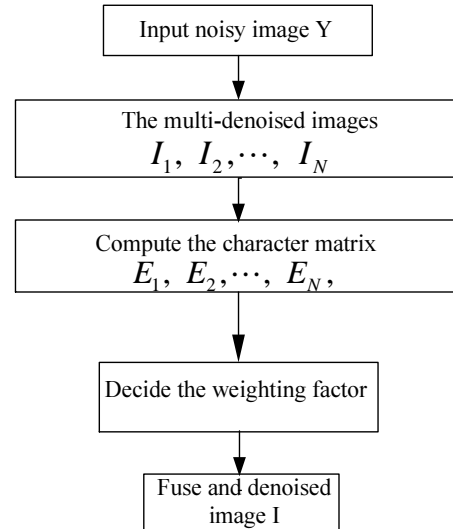
Input noisy image Y

The multi-denoised images $I_1, I_2, \cdots, I_N$

Compute the character matrix $E_1, E_2, \cdots, E_N,$

Decide the weighting factor

Fuse and denoised image I

Figure. 1 The Flow Chart Of The Proposed Algorithm

3.2 The Local Character

The denoised images have little noise and better visual quality, the local character in time domain can explicit the effect of the images. The variance, the mean and the gradient are selected to explain the local character of the denoised images. When the character is bigger, the recovery effect of the image is better, the pixel is picked up as a clear pixel to the final denoised image.

To compute the character of pixel $I(i, j)$, a square window is selected and the window central

is $I(i,j)$, then the character of $I(i,j)$ is computed by the average of the pixel energy inside the window. The formula is as follows:

$$V(i,j) = \frac{1}{d} \sum_{m=i-k}^{i+k} \sum_{n=j-k}^{j+k} \left[I(m,n) - \overline{I}(m,n) \right]^2 \qquad (11)$$

$$G(i,j) = \frac{1}{d} \sum_{m=i-k}^{i+k} \sum_{n=j-k}^{j+k} \left[G_x^2(m,n) + G_y^2(m,n) \right]^{1/2}$$

$$M(i,j) = \frac{1}{d} \sum_{m=i-k}^{i+k} \sum_{n=j-k}^{j+k} \left| I(m,n) - \overline{I}(m,n) \right|$$

Where, d is the pixel number of window $(2k+1)\times(2k+1)$. $\overline{I}(i,j)$ is the mean of the pixels in the window:

$$\overline{I}(i,j) = \frac{1}{d} \sum_{m=i-k}^{i+k} \sum_{n=j-k}^{j+k} I(m,n) \qquad (12)$$

$G_x(m,n)$ and $G_y(m,n)$ are respectively denote the first order derivate of horizontal and vertical in pixel (m,n).

In order to test the denoising results of various characters, some experiments are designed. Two images are selected in basketball video, and changed to gray image. The Gaussian noise with zero mean and 15 variance is added to original image. After the denoising flow of section 3.1, the experimental results are shown in Table 1.

Table 1．The Experimental Results Of Various Characters (ISNR: Db)

The group of wavelet bases	character	PSNR
Im1.jpg		
Haar+Bior4.4+Sym8	variance	29.02
Haar+Bior4.4+Sym8	mean	29.03
Haar+Bior4.4+Sym8	gradient	29.02
shoot.jpg		
Haar+Bior4.4+Sym8	variance	31.08
Haar+Bior4.4+Sym8	mean	31.08
Haar+Bior4.4+Sym8	gradient	31.08

3.3 The Selection of The Wavelet Bases

In an image there are some smoothness and sharp transition (edge and texture). In the smoothness, we use high regularity and high vanishing moment smooth wavelet system, for example, the least asymmetric wavelet Sym8 (the filter coefficients are 16 and the vanishing moment is 8) and the symmetric wavelet Bior4.4.also named 9/7 wavelet (biorthogonal, the filter coefficients are 9 and 7, the vanishing moment is 4), and the wavelet Db10[10]. All the wavelets can process the different smoothness properties. While in the sharp transition, we use the compact-support wavelet bases such as Haar, Db2, Db3, which are good in

dealing with discontinue point. In this paper, we use the multiple wavelets in the processing. Instinct, the more different in time-frequent field, the preferable result are achieved.

Table 2 presents the results of different sets. From that we can see the first set (Haar+Bior4.4+Sym8) is the best, which include the compact-support wavelet (Haar), the middling-length but good time-frequent wavelet (Bior4.4), and the smooth wavelet (Sym8).

Table 2 The Performance Of Denoised Image σ=15, (PSNR: Db)

wavelet base	Im1.jpg	Im2.jpg	shoot.jpg	dribble.jpg
Haar	28.20	29.00	30.53	29.46
Db2	28.23	29.03	30.62	29.39
Db3	28.20	28.98	30.10	29.43
Db10	27.70	28.31	29.92	28.71
Bior4.4	28.25	28.99	30.61	29.53
Sym8	28.08	28.82	30.39	29.29
Haar+Bior4.4+Sym8	29.02	29.62	31.08	30.12
Sym8+Db10+Bior4.4	28.51	29.48	30.86	29.93
Haar+Db2+Db3	28.02	29.10	30.71	29.61

4. THE EXPERIMENTAL RESULTS

The test images are from the basketball video, and changed to gray image. The Gaussian noise with zero mean and 15 variance is added to original image. In the denoising experiment, we apply the three-level decomposition and local Bayes threshold with soft threshold function. The local character is variance and the group of wavelet base is Haar, Bior4.4 and Sym8.

There are some measurement to evaluate the denoised images, such as mean square error (MSE), signal-noise-ratio (SNR), and peak signal-noise-ratio (PSNR). In this paper, PSNR is used. Suppose $f(m,n)$ is a clean image, $\hat{f}(m,n)$ is the denoised image, the maximum gray is $f_{\max} = \max\{f(i,j)\}$, so, the PSNR of denoised image is defined as follows: (dB)

$$PSNR = 10 \times \log_{10} \left[\frac{f_{\max}^2 \cdot M \cdot N}{\sum_{m=0}^{M-1} \sum_{n=0}^{N-1} [f(m,n) - \hat{f}(m,n)]^2} \right] \qquad (11)$$

The more PSNR, the better the denoised result is.

From Figure 2, we can see the denoised images have a better visual result.

(a) lm1.ipg

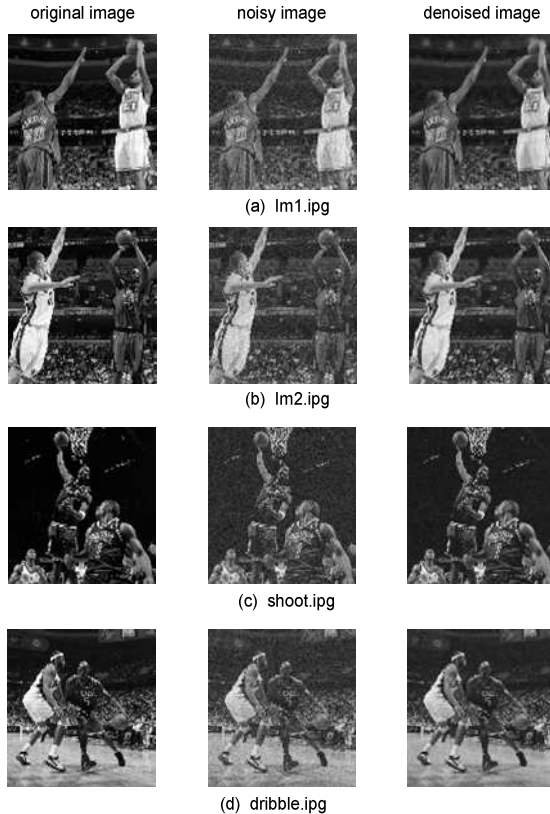(b) lm2.ipg

(c) shoot.ipg

(d) dribble.ipg

Figure 2 The Visual Result Of Denoised Image

5.   CONLUSION

In this paper, we proposed a simple and effective joint image denoising method via multiple wavelet bases. The method fuses some pieces of images into one by pixel weight. In fact, considering the space localization property, we may first divide the image into smooth area and the edges (texture), then various weighted coefficients is made to various domain or various points. The performance may be improved. In addition, we simply consider two-band wavelet, in fact, all these wavelets are little different in their filter figure except for their vanishing moment. We also select M-band wavelet, multi-wavelet, and the result maybe well than ever.

REFERENCES:

[1] S. G. Mallat, "A theory for multiresolution signal decomposition: the wavelet representation", *IEEE Transactions on Pattern Analysis and Machine Intelligence*. Vol. 11, No. 7, 1989, pp. 674-693.

[2] A. Chambolle, R. A. DeVore, N. Lee, and etc., "Nonlinear wavelet image processing: Variational problems, compression, and noise removal through wavelet shrinkage", *IEEE Transctions on Image Processing*, Vol. 7, No.3, 1998, pp. 319–335.

[3] S. Grace Chang, Bin Yu and M.Vetterli, "Adaptive wavelet thresholding for image denoising and compression", *IEEE Transactions on Image Processing*, Vol.9, No.9, 2000, pp. 1532-1546.

[4] F. Abramovich, T. Sapatinas, and B.W. Silverman, "Wavelet thresholding via a Bayesian approach", Journal of the Royal Statistical Society Series B-Statistical Methodology, Vol. 1, No. 2, 1998, pp. 725-749.

[5] S. Grace Chang, Bin Yu and Martin Vetterli, "Spatially adaptive wavelet thresholding with context modeling for image denoising", *IEEE Transactions on Image Processing*, Vol.9, No.9, 2000, pp. 1522-1531.

[6] M. K. Mihcaak, I.Kozintsev, K. Ramchandran, and etc., "Low-complexity image denoising based on statistical modeling of wavelet coefficients", *IEEE Signal Processing Letters*, Vol.6, No.12, 1999, pp. 300-303.

[7] D. L. Donoho, "De-noising by soft-thresholding ", *IEEE Transactions on Information Theory*, Vol.41, No.3, 1995, pp.613-627.

[8] M.S.Charles, "Estimation of the mean of a multivariate normal distribution", Annals of Statistics, Vol.9, No.6, 1981, pp.1135-1151.

[9] G.M. Shi, F.D. Li, " Image denoising with optimized subband threshold", ICCIMA 2003, 7: 27-30.

[10] W. H. Liu, P. L. Shui, "Denoising joint image method via multiple wavelet bases", Xi Tong Gong Cheng Yu Dian Zi Ji Shu, Vol.27, No.9, 2005, pp.1511-1514.