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ABSTRACT

This paper contributes a novel technique for reducing the interference of non-Gaussian texture noise from images. Since the inherent properties of texture noise are very different from those of Gaussian white noise, the basic assumption of conventional image denoising techniques is invalid. Here we present a spatial adaptive filtering scheme to remove non-Gaussian texture noise from textile images based on local and non-local similarities. In order to exploit the high correlations among pixels, pixels with uniform texture local regions are estimated differently from those pixels located near edges, that is, for points located in local uniform texture regions, Gaussian weighted averaging of their neighbors can achieve the adaptive effect of the human visual system, whereas for edge points, to find pixels with similar local statistics both in the vicinity and far away can produce a sufficient set of pixels for reasonable averaging. This filtering strategy is applied to textile images corrupted by texture noise and the performance is demonstrated to outperform current state-of-art image denoising techniques.

Index Terms **—** non-Gaussian, texture, non-local, adaptive, denoising

1. INTRODUCTION

Denoising is essential in many image processing applications, since the presence of noise in an image degrades its visual quality and decreases the performance of subsequent processing tasks.

Most of current research of image denoising addresses the removal of additive independent Gaussian noise while preserving important features, such as edges and fine-scale texture structures in images [1-5]. However in some applications texture do have negative effects in image processing, for example, in Fig.1 the uniformly distributed fabric texture structure named as "texture noise" [6,7] has a great influence on the colors' appearance. According to human observation there are about six dominant colors in the left image, but if the perceived uniform color regions within the red frames are enlarged, we will find that these perceived uniform color regions contain many other colors (the right enlarged images in Fig.1). This phenomenon is caused by the color halftoning techniques in textile printing.

Compared with Gaussian white noise, texture noise has many distinctive inherent properties. Fig.2 presents the histogram of the luminance component of a blue uniform texture region in Fig.1 (the right one), and the histogram of a Gaussian noise region generated with the same spatial size and variance. The PDF of texture noise is clearly non-Gaussian. Fig.3 shows the autocorrelation functions of texture noise and Gaussian white noise, we can find that texture noise is not independent as Gaussian white noise is but has high correlations among spatial neighbors.

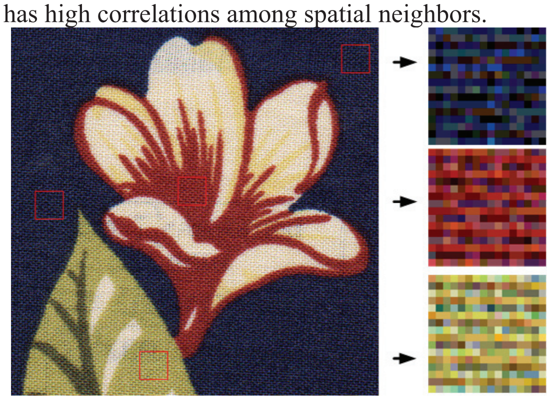


Fig.1 Example of texture noise

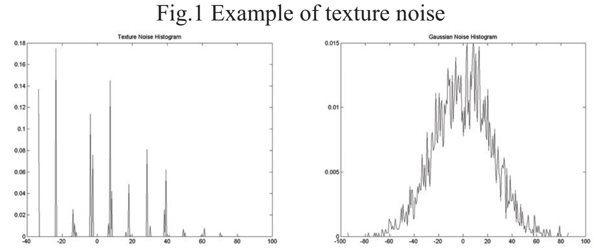


Fig.2 PDFs of texture noise and Gaussian noise

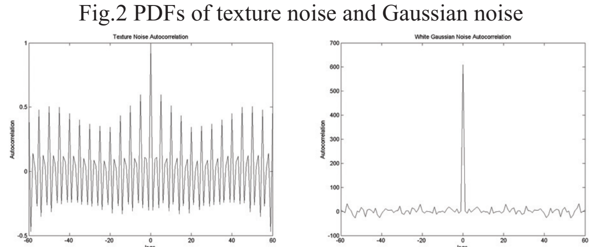


Fig.3 Autocorrelation functions of texture noise and Gaussian noise

So the basic assumption made in most of current image denoising algorithms [1-5] is not valid for texture noise anymore.

Through observation and computation of power spectrums of local uniform texture regions at different locations in color textile images, we find that there exist quasi-repetitive patterns both in local and non-local ranges.

In this paper we study an unsupervised spatial adaptive filtering scheme to reduce the interference of uniformly distributed texture structure from images based on these inherent properties of textile images.

In order to remove non-Gaussian texture noise efficiently, we have to utilize the correlations among pixels both in local and non-local range, and at different scales as well. Since self-similarity exists in uniform texture regions, first we classify pixels into uniform or edge types based on a self-similarity measurement of the local region of each pixel.

For pixels with uniform local regions, Gaussian weighted averaging of their neighbors can improve the reliability of denoising (since averaging neighboring pixels can lessen the disturbance of textured appearance of the fabric), while for those pixels located at boundary areas, we have to smaller the radius of local regions to reduce the possibility of including pixels belonging to other different regions, and to look for pixels with similar neighbor statistics in a large search window at the same time for a sufficient averaging set.

The rest of paper is organized as follows. In Section 2 first we analysis the limitations of current image denoising techniques for removing correlated non-Gaussian texture noise. Then we introduce a spatial adaptive filtering scheme including a multiscale uniform pixel estimator and an adaptive edge pixel estimator for images corrupted by uniformly distributed texture structure. In Section 3 the performance of the spatial adaptive filter is compared with those of currently well-known image denoising techniques for smoothing texture noise. Conclusions are presented in Section 4.

2. ADAPTIVE SMOOTHING SCHEME FOR NON-GAUSSIAN TEXTURE NOISE

Most of current denoising techniques assume that the additive noise is independent Gaussian noise. But the objective of this paper is to remove uniformly distributed texture structure from images.

Shrinkage wavelet transform based techniques [1-2] are demonstrated to have the ability to remove Gaussian noise efficiently. However for color textile images, it is difficult to tell the singularities caused by genuine image edges from the singularities caused by texture noise.

Recently a class of image denoising filters [3-5] that adaptively takes into account intensity or color information from more distant locations became widespread. Rather than considering only the central pixel in the similarity of two points as in the bilateral filter [3], the UINTA filter [4] and the NL-means filter [5] use a distance that considers not only the similarity of the central pixel, but the similarity of its neighborhood also.

For images corrupted by texture noise, there exist high correlations among neighbor pixels especially in uniform texture regions, but these semi-local filters don't take the correlated neighbors into consideration during denoising.

Besides two $s \times s$ patches centered at $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$ ($i \neq j$) though seemed to be very similar in a color textile image (for example, the two uniform blue texture regions in Fig.1), the distance based on the Euclidean metric between $\vec{u}_i = \left(u_i^{(1)} \quad \cdots \quad u_i^{(s^2)}\right)^T$ and $\vec{u}_j = \left(u_j^{(1)} \quad \cdots \quad u_j^{(s^2)}\right)^T$ may be large. So we have to turn to a local statistical distance to measure the similarity between two patches.

Based on the above analysis and study, we propose a spatial adaptive filtering scheme for smoothing non-Gaussian texture noise: first we apply a multiscale uniform pixel estimator based on the self-similarity property of uniform texture regions, and this estimator is to mimic the adaptation of the human vision system to perceive colors depends on surrounding pixels. And for those pixels located at edge strips, we look for pixels with similar small local statistics in a large search window to avoid the risk of including pixels belonging to other different regions and to improve the reliability of denoising of edge pixels simultaneously.

2.1. Multiscale Uniform Pixel Estimator

Since there exist self-similarity in uniform texture regions, we can expect that the differences between the mean color of a uniform texture region and the mean colors of its four inner sub-windows: left, right, up and down, will be small.

Suppose a $(2n+1)\times(2n+1)$ (n is an integer) sliding window centered at pixel (i,j), the mean color $\bar{\mathbf{c}}(i,j)$ of the sliding window can be estimated as:

$$\bar{\mathbf{c}}(i,j) = \frac{1}{(2n+1)^2} \sum_{k=i-n}^{i+n} \sum_{l=j-n}^{j+n} \mathbf{c}(k,l) \qquad (1)$$

The mean colors of its four sub-windows: left, right, up and down, are estimated as following:

$$\bar{\mathbf{c}}_l(i,j) = \frac{1}{(2n+1)(n+1)} \sum_{k=i-n}^{i+n} \sum_{l=j-n}^{j} \mathbf{c}(k,l) \qquad (2)$$

$$\bar{\mathbf{c}}_r(i,j) = \frac{1}{(2n+1)(n+1)} \sum_{k=i-n}^{i+n} \sum_{l=j}^{j+n} \mathbf{c}(k,l) \qquad (3)$$

$$\bar{\mathbf{c}}_u(i,j) = \frac{1}{(2n+1)(n+1)} \sum_{k=i-n}^{i} \sum_{l=j-n}^{j+n} \mathbf{c}(k,l) \qquad (4)$$

$$\bar{\mathbf{c}}_d(i,j) = \frac{1}{(2n+1)(n+1)} \sum_{k=i}^{i+n} \sum_{l=j-n}^{j+n} \mathbf{c}(k,l) \qquad (5)$$

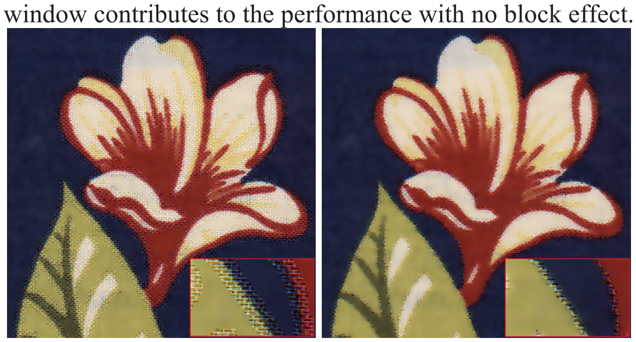
If the maximum color difference between the mean color $\bar{\mathbf{c}}(i,j)$ and the four mean colors $\bar{\mathbf{c}}_l(i,j)$, $\bar{\mathbf{c}}_r(i,j)$, $\bar{\mathbf{c}}_u(i,j)$, $\bar{\mathbf{c}}_d(i,j)$ of its four sub-windows is less than a threshold, then the local region of the central pixel (i,j) is considered as uniform, otherwise the local region of the central pixel (i,j) is non-uniform.

The estimated color of pixel (i,j) located in an uniform local region will be the Gaussian weighted sum of all pixels in the window *(2n+1)×(2n+1)* to mimic the adaptation of the human visual system:

$$\bar{\mathbf{c}}_{filt}(i,j)=\sum_{k=i-n}^{i+n}\sum_{l=j-n}^{j+n}\mathbf{c}(k,l)\frac{\exp(-((k-i)^2+(l-j)^2)/2n)}{\sum_{y=-n}^{n}\sum_{x=-n}^{n}\exp(-(y^2+x^2)/2n)} \quad (6)$$

When the sliding window moves to pixels near edge areas, the uniform neighbor regions of these pixels will become smaller to avoid the risk of including pixels from other regions. Here a multiscale sliding window is used to circumvent the conflict between boundary localization and the tendency to utilize as more neighbor statistics to reduce the interference of texture noise as possible.

In our implementation, the sliding window with *n= 7* and *5* are applied sequentially to textile images. Fig.4 presents the progressive outputs of the multiscale uniform pixel estimators. We can see that the uniform areas are penetrated gradually into boundary areas when reducing the size of the sliding window, and the overlapping sliding window contributes to the performance with no block effect.



(a) The first stage output (b) The second stage output

Fig.4 Outputs of the multiscale uniform pixel estimator

2.2. Adaptive Edge Pixel Estimator

In order to cope with the edge pixels after the multiscale uniform pixel estimator, we have to turn to smaller local windows because a large local window risks including pixels from other different regions. Since there exist long-range correlations in images corrupted by texture noise, we compare the similarity of small local patches around two pixels, and the search window is much larger than the size of the local patch to improve the reliability of estimating the true values of edge points.

We select the size of the local patch to be 3×3 to compute the similarity between the local patch centered at an edge pixel and patches located at other pixels. First we compute the mean and variance of the luminance component of each pixel within a 3×3 window. The similarity between two patches $\vec{u}_i$ and $\vec{u}_j$ centered at $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$ is computed as:

$$dist(\vec{u}_i,\vec{u}_j)=\frac{1}{2}\{\frac{(m_i-m_j)^2}{\sigma_i^2}+\frac{(m_j-m_i)^2}{\sigma_j^2}\} \quad (7)$$

Where m_i and m_j are the mean values, and σ_i^2 and σ_j^2 are the variances of the luminance component at pixel $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$, respectively.

We use this symmetric distance to test both the hypotheses that $\boldsymbol{x}_j$ belongs to the local region centered at $\boldsymbol{x}_i$ and $\boldsymbol{x}_i$ belongs to the local region centered at $\boldsymbol{x}_j$ at the same time. Accordingly the hypothesis $\vec{u}_i$ and $\vec{u}_j$ are similar, is accepted if the distance is small, i.e. $dist(\vec{u}_i,\vec{u}_j)\le\lambda_\alpha$. In our implementation, the parameter $\lambda_\alpha\in R^+$ is chosen as a quantile of a $\chi^2_{s^2,1-\alpha}$ distribution with s^2=9 degrees of freedom (since we use a 3×3 local window to compute the mean and variance at each pixel), and controls the probability of type I error for the hypothesis of two points have similar local neighbor

$$P\{dist(\vec{u}_i,\vec{u}_j)\le\lambda_\alpha\}=1-\alpha \quad (8)$$

In the experiment, we suggest to use a *1−α=0.99* quantile. If $dist(\vec{u}_i,\vec{u}_j)$ exceeds this critical threshold λ_α, then there is a significant different between $\vec{u}_i$ and $\vec{u}_j$, and we reject the hypothesis that $\vec{u}_i$ and $\vec{u}_j$ are similar, and the color of pixel at $\boldsymbol{x}_j$ will not contribute to the average filtering at pixel $\boldsymbol{x}_i$. The search window size is much larger than the matching window size. For the filtering results presented in Section 4, the search window size is set to *15×15*.

After searching all of the pixels with similar neighbor statistics in the search window, the following weight function is used

$$\pi_{i\sim j\in\aleph_i}=\frac{K(\lambda_\alpha^{-1}dist(\vec{u}_i,\vec{u}_j))}{\sum_{\mathbf{x}_k\in\aleph_i}K(\lambda_\alpha^{-1}dist(\vec{u}_i,\vec{u}_k))} \quad (9)$$

With K(·) denoting a monotone decreasing function, e.g., a kernel K(*z*) = exp(-*z*/2) and $\aleph_i$ is the set of similar pixels of the pixel centered at $\boldsymbol{x}_i$.

3. EXPERIMENTAL RESULTS

Here we apply the spatial adaptive filter scheme introduced above to textile images, and compare the performance with those of current state-of-art image denoising techniques. Fig. 5 shows the experimental results of smoothing texture noise to two textile images by using different filter schemes.

BLS-GSM algorithm [1] is one of the most efficient image denoising techniques up to now. In they program the variance of noise in image is supposed to be known, so we extract a uniform texture region from input image and the variance of its luminance component is used as the variance of texture noise. We can see that BLS-GSM cannot smooth texture noise efficiently.

We apply the bilateral filter [3] to the RGB color channels independently. Due to the texture noise disturbance, it is difficult to measure the similarity just based on the color information of a single pixel only. The filtering results are almost the same to the input ones (Fig.5 (a) and (b)).

Since the NL-means filter [5] is very time-consuming, here we set the search window as 15×15, and the similarity between two patches is computed within a 5×5 window on their luminance components. Although these semi-local filters consider both the similarity of the center pixel and the similarity of its neighbors, the correlation among neighbor pixels is not utilized sufficiently during the filtering, and the matching window cannot be adapted to boundary areas. The filtering result of the NL-means algorithm is also unsatisfied.

In order to show the filtering results clearly, we enlarge the red frame in each output image. Due to the lack of the ground true of these textile images, the objective evaluation metric for denoising techniques, such as PSNR cannot be given here. And this will be one of our future research works.

Many other denoising results based on some recent new image denoising techniques cannot be presented here due to the limitation of space. From Fig.5, we can find that the proposed spatial adaptive filter scheme can utilize the local and non-local correlations in textile images, and help to remove uniformly distributed texture structure, but to some degree blur edges at the same time. To improve the accuracy of boundary localization needs further research.

4. CONCLUSION

In this paper we study the properties of non-Gaussian texture noise, and propose a spatial adaptive filtering scheme to reduce the interference of texture noise based on local and non-local correlations among pixels. The performance of this filter scheme demonstrates its capability of smoothing non-Gaussian texture noise.

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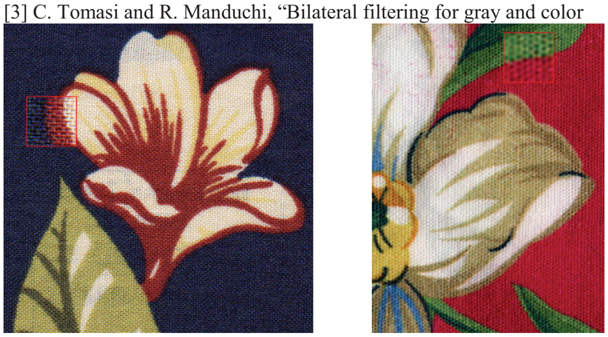
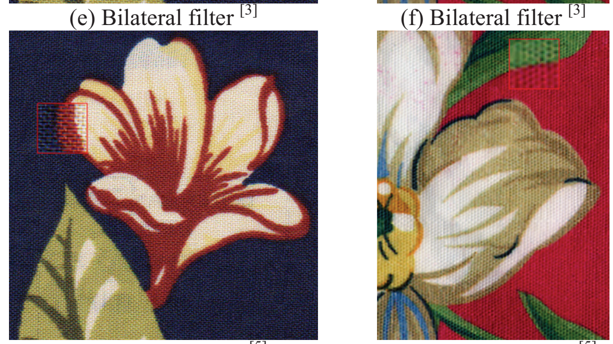


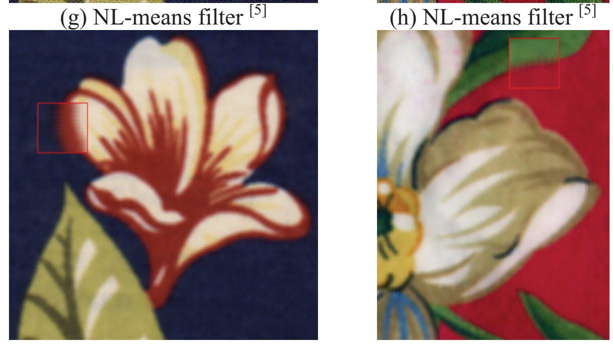
(a) Textile image 1 corrupted by texture noise (b) Textile image 2 corrupted by texture noise

(c) BLS-GSM [1] (d) BLS-GSM [1]

(e) Bilateral filter [3] (f) Bilateral filter [3]



(g) NL-means filter [5] (h) NL-means filter [5]



(i) Spatial adaptive filtering (j) Spatial adaptive filtering

Fig.5 Comparison of denoising results of different filters