An Integrated De-noise and enhancement Method for Ancient Chinese Tablet Images

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Abstract—Image noise can severely affect Chinese tablet image comprehension. In this paper, a novel integrated de-noising and enhancement method for Chinese tablet images is proposed. The method consists of three stages: first, granular bright spots are smoothed by convoluting input Chinese tablet images with the bilateral filter. For obtaining more clear edge detail image, contrast enhancement between the foreground and background of the Chinese tablet image is followed by Top-Hat and Bottom-Hat transformations. Next, a mixture of run-length statistics and connected region techniques is employed to remove the random block noises in the images. Then, two mathematical morphological operators, erosion and dilation, are used to remove small holes and linear noises. Experimental results show that the proposed method can effectively remove most image noise (including block noise, and linear noise) and preserve characters better than existing methods.

Keywords—Chinese tablet images; integrated de-noising; bilateral filter; run-length; erosion; dilation;

I. INTRODUCTION

The tablet is important for preserving ancient Chinese calligraphy, and digital tablet images provide a convenient way to study and reproduce ancient rubbing calligraphy techniques. However, image noise greatly affects post-processing of digital tablet images [1]. Therefore, it is important to remove image noise without damaging the intricate details of Chinese calligraphy. In general, there are five basic strokes in Chinese characters: Dian (dot stroke), Heng (horizontal stroke), Shu (vertical stroke), Pie (left-falling stroke) and Na (right-falling stroke) [2](Figure 1). These traditional basic strokes are used to make all other compound strokes or complex strokes. All these strokes have distinct orientations and variant widths in a continuous manner (Figure 1). While image noise is usually randomly distributed in isolation with irregular shapes and sizes, and the size of image noise is usually not bigger than the width of the stroke in most cases. In order to reduce the noise influence, a novel integrated de-noising and enhancement method for Chinese tablet images is proposed in this study. First, an input tablet image is smoothed using a bilateral filter. Next, the contrast between the foreground and background of the Chinese tablet image is enhanced using the Top-Hat and Bottom-Hat transformations. Finally, the image binarization is performed using the Otsu thresholding method. A mixture of run-length statistics and connected region is employed to remove most of the random and block noise from the images. To the best of our knowledge, our work is the first to apply a mixture method to tablet image de-noising. Compared to existing de-noising methods, the proposed method can more effectively remove image noise from tablet images, enhance text details, and achieve ideal visual effects.

Figure 1. The five basic Chinese character strokes and their directions

The primary contributions of the work are summarized as follows:

(1) A three-stage de-noising method for Chinese tablet images is proposed.

(2) A mixture of run-length statistics and connected
region for tablet image de-noising is proposed based on the differences in shape, size, and distribution between Chinese characters and image noise.

(3) Contrast enhancement between the foreground and background of the Chinese tablet image is followed by Top-Hat and Bottom-Hat transformations.

The remainder of this paper is organized as follows: First, related work is discussed in Section 2. Second, the proposed method is described in Section 3. Experiment results are presented and discussed in Section 4. Finally, conclusions and further discussion are provided in Section 5.

II. RELATED WORKS

Removing image noises from digital Chinese tablet images without damaging the characters has seen an increasing interest in recent years, and various methods have been proposed, such as anisotropic smoothing de-noising, median filtering [3], mean filtering [4], and so on [5] [6] [7]. However, because of the randomness of noises in shape, size and distribution, the above mentioned method are usually not very effective. Sometimes, these methods even destroy the shape of Chinese characters. For example, strokes of the pen tip and the angles formed by the folding strokes are easy to be blurred. And as a result, the characteristics of characters are missing. In order to solve these problems, Wang [8] proposed an anisotropic diffusion algorithm to filter document images firstly, and then combined Otsu thresholding method to remove the random noise. However, the case, in which the smoothing may lead to the formation of blocky noise which is very similar to the stroke in size, will make the tablet image more difficult to be processed. Zhang [9] et al proposed a run-length statistics based de-noising algorithm. Although this method can remove the most massive noise in tablet images, there are still some isolated point noises, linear noises, and the incomplete strokes.

III. PROPOSED METHOD

The basic framework of the proposed method begins by enhancing a Chinese tablet image (image smoothing using the bilateral filter, contrast enhancement using the Top-Hat and Bottom-Hat transformations). The enhanced image is then binarized using the Otsu thresholding method. Finally, the block noise is removed using a mixture of run-length statistics and image connected region technique (Figure 2). Details of each step are described as bellows.

A. Granular bright noises using the bilateral filter

Chinese tablet images usually contain noise made by granular bright spots because ancient Chinese characters are primarily inscribed on rocks [9]. Smoothing with a median filter is a common method used to remove granular bright spot noise in Chinese tablet images [3]. However, due to the high concentration of small points and lines, the median filter cannot accurately account for all of the detail.

In order to solve this problem, a bilateral filter was employed in the study to smooth the input image. The bilateral filter is a nonlinear, edge-preserving smoothing
filter [10], and can be defined as:

$$B_x = \frac{1}{k(x)} \sum_{\xi \in \Omega} c(\xi, x)s(I_\xi, I_{x})$$

Where $B_x$ is the output bilateral filter result, $\Omega$ denotes the neighboring pixel locations, which includes the current location $x$; $c(\xi, x)$ and $s(I_\xi, I_{x})$ are Gaussian functions that measure the geometric closeness and photometric similarity between the neighborhood center $x$ and a nearby point $\xi$; $I_\xi$ represents the intensity value of $\xi$, and $k(x)$ is a normalized factor defined by:

$$k(x) = \sum_{\xi \in \Omega} c(\xi, x)s(I_\xi, I_{x})$$

Figure 3 shows some results for comparison of bilateral filter with medium filter and Gauss filter. From figure 3, it can be seen that the bilateral filter can well smooth the images while preserving edges. Whereas other filters failed to preserve details of edges.

B. Contrast enhancement with Top-hat-bottom-hat transformation

Due to environmental effects, the contrast between the background and the foreground of the Chinese tablet image is usually very low, and make the discrimination of noises and image details difficult. For this reason, the image contrast must be enhanced. This paper enhances the image contrast using the mathematical morphological Top-Hat (TH) and Bottom-Hat (BH) transformation

The TH and the BH transformation are two fundamental operations in morphological processing. Given a 2D image $I(m,n)$ and a 2D structuring element $S(i,j)$, formally, the TH operation and BH operation of image $I$ by a structuring element $S$ are defined as follows:

$$TH = I - (I \circ S)$$

$$BH = (I \bullet S) - I$$

Where

$$(I \circ S) = (I \otimes S) \oplus S$$

$$(I \bullet S) = (I \oplus S) \odot S$$

Termed as opening and closing, the opening of image $I$ by a structuring element $S$ is defined as erosion followed by dilation, while closing has the opposite order of these operations. The dilation and the erosion of a 2D image $I(i,j)$, by a 2D structuring element $S(i,j)$, are defined as

$$Dilation \quad (I \oplus S)(m,n) = max\{I(m-i,n-j)\}$$

$$Erosion \quad (I \odot S)(m,n) = min\{I(m+i,n+j)\}$$

Where $I(m-i,n-j)$ and $I(m+i,n+j)$ belong to $DI(i,j)$ and $DS(i,j)$. $DI$ and $DS$ describe the domains of $I$ and $S$ respectively.

As a consequence, with opening operation, one can remove bright details that are not bigger than the structuring element. Both bright and dark details that are larger than the structuring element remain nearly unchanged. Conversely, closing operation removes dark details that are not bigger than the structuring element. For reasons discussed above, by combining opening and closing, small bright details from a non-uniform background can be enhanced using TH, and dark features from a brighter background can be extracted using BH. Therefore, by adding an original image to the difference between TH and BH operated image, local contrast enhancement can be achieved, as described as

$$I_{enhancement} = I + (TH - BH)$$

Figure 4 shows part results for comparison of TH and BH based method with histogram equalization and Multi-scale Retinex which both are commonly used methods for image enhancement. From figure 4, it can be seen that the TH and BH processing methods significantly enhance the contrast between the Chinese character fonts and the background, and improve the clarity of the text. However, both histogram equalization and Multi-scale Retinex not only enhance the contrast between the Chinese character fonts and the background but also amplify the noises.

C. Binarization using the Otsu thresholding method

The Chinese characters in tablet images usually have poor quality, and this leads the grayscale values of characters and noises in tablet document images very similar. In order
to reduce the affect of grayscale to de-noise, the tablet image should be converted into a binary image. In this work, the Otsu thresholding method [11] was used. The Otsu thresholding method searches for the threshold that minimizes the intra-class variance, defined as a weighted sum of variances of the two classes:

$$\sigma^2 = \omega_1(t)\sigma_1^2(t) + \omega_2(t)\sigma_2^2(t)$$  \hspace{1cm} (10)

Weights $\omega_i$ are the probabilities of the two classes separated by a threshold $t$ and variances of these classes. The Otsu thresholding method shows that minimizing the intra-class variance is the same as maximizing intra-class variance [3].

$$\sigma_b^2 = \sigma^2 - \sigma_i^2(t) = \omega_1(t)(\omega_2(t)[\mu_1(t) - \mu_2(t)]^2$$  \hspace{1cm} (11)

Which is expressed in terms of class probabilities $\omega_i$ and class means $\mu_i$. The class probability $\omega_1(t)$ is computed from the histogram as:

$$\omega_1(t) = \sum_{i=1}^{t} p(i)$$  \hspace{1cm} (12)

While the class mean is:

$$\mu_1(t) = \left[ \sum_{i=1}^{t} p(i)x(i) \right]/\omega_1$$  \hspace{1cm} (13)

Where $x(i)$ is the value at the center of the $i$th histogram bin. The class probabilities and class means can be computed iteratively. This idea yields an effective algorithm.

$$\omega_1(t) = \sum_{i=1}^{t} p(i)$$  \hspace{1cm} (12)

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Where $p_{1_{Hr}}$, $p_{2_{Hr}}$ and $p_{3_{Hr}}$ are the three point for equally dividing the horizontal run length $p_{[i,j]}$.

To determine whether a pixel belongs to a stroke or noise in the calligraphy image, the run-lengths of the pixel are computed in directions of the angle 0, 45, 90 and 135, respectively. If any of the run-lengths is not bigger than the estimated stroke width, the pixel belongs to image noises.

Figure 7. Method to avoid influence of horizontal stroke on horizontal scan

Though with run-length statistics, the block noise in the calligraphy image could be effectively removed, some characters might be destroyed and appear as a saw-tooth shape, as shown in Fig.8. In order to solve this problem, connected region was used. The connected region is described as:

$$ C = \{ p(i,j) | r_{l_{p(i,j)}} > T \} $$  \hspace{0.5cm} (18)

Where $p(i+1,j) = 1$ or $p(i-1,j) = 1$ or $p(i,j+1) = 1$ or $p(i,j-1) = 1$

The pixel saved in set $D$ is

$$ D = \{ p(i,j) | r_{l_{p(i,j)}} > T \} $$  \hspace{0.5cm} (19)

Where $p(i,j)$ is from set $C$, $r_{l_{p(i,j)}}$ is the run-length of pixel $p(i,j)$, $T$ is the threshold which distinguish the noise from the stroke.

$$ T = \frac{\mu_1 + \mu_2}{2} + \frac{\sigma^2}{\mu_1 - \mu_2} * ln a_1 a_2 $$  \hspace{0.5cm} (20)

Where $\mu_1$ and $\mu_1$ are Means of Gauss distribution of noise and stroke respectively. $\sigma$ is Standard deviation of noise and stroke. $a_1$ is the probability density of noise, $a_2$ is the probability density of stroke.

If the ratio between set $C$ and set $D$ is larger than the stroke width $t(1.0-3.0)$, we determine that it is noise and the pixel and its connected region should be set to zero.

Finally, the erosion and dilation morphological operators were employed for removing the isolated points. With above discussed method, the noise in the tablet image can be removed without disturbing the character boundaries, and the image clarity is greatly improved (Fig. 9).

Figure 8. The result after traditional run-length method. (a) The original image (b) The image after improved run-length method

The pixel saved in set $D$ is

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Where $\mu_1$ and $\mu_1$ are Means of Gauss distribution of noise and stroke respectively. $\sigma$ is Standard deviation of noise and stroke. $a_1$ is the probability density of noise, $a_2$ is the probability density of stroke.

IV. EXPERIMENTS

To demonstrate the advantages of the proposed method in practice, we implement it with Matlab R2010b and compare it with median filter [12], gauss filter [13], and Zhang's run-length de-noising algorithm [9], also with histogram equalization and Multi-scale Retinex. The test images are selected from ancient calligraphy masterpieces, written by well-known calligraphers, which have been preserved over 1000 years. For tablet type, the selected images have damages with different degree made by natural or man-made mishaps. Totally 100 images are selected in this study. All experiments are run on a 2.8GHz Pentium Dual with 2.0GB of RAM.

Figure 10 gives the comparison of the proposed method with median filter, gauss filter, and Zhang's run-length de-noising algorithm for image de-noising. The contrast of the original image is generally low, and the fonts in the image are dim because image noise covers the characters (Figure

Figure 9. Comparison of the traditional run-length method and the improved run-length method. (a) The result after traditional run-length method (b) The result after improved run-length method.
The images were processed using median filtering, mean filtering, gauss filtering and the methods in this paper are all improved, but block noise is still remained and the image is not clear. Comparison of images reveals that the methods used in this study are the most efficient in image restoration.

Figure 11 gives the comparison of the proposed method with histogram equalization [14] and Multi-scale Retinex [15] in image contrast enhancement. As can be seen that the proposed method can not only significantly enhance the contrast between the Chinese character fonts and the background, but also significantly suppress image noises, and having obtaining the clarity of the text. However, both histogram equalization and Multi-scale Retinex not only enhance the contrast between the Chinese character fonts and the background but also amplify the noises.

This paper also selects average gradient, signal to noise ratio, information entropy and mean variance to gain the quantitative analysis and evaluation of the performance of the proposed method in de-noising and contrast enhancement. As shown in Table 1, average gradient represents the clarity of the image and reflects the rate of change in the subtle details [16]. Average gradient is an important index to measure the expression ability of image detail contrast. Larger average gradient values mean a clearer image. Average gradient is defined as follows:

\[
g = \frac{1}{(M-1)(N-1)} \times \sum_{i=1}^{M-1} \sum_{j=1}^{N-1} \sqrt{\left( F(i, j) - F(i+1, j) \right)^2 + \left( F(i, j) - F(i, j+1) \right)^2}
\]

(21)

Where \( F(i, j) \) is the gray value of point \((i, j)\), \( M \) is the total number of rows, \( N \) is the total number of columns. Information entropy is another important tool for measuring the richness of the information, and can reflect the detail performance of the image. The information entropy is defined as follows:

\[
EN = - \sum_{g=0}^{L-1} p(g) \log_2 p(g)
\]

(22)

Where \( p(g) \) is the distribution probability of grayscale, and \( L \) is gray level.

The signal to noise ratio (often abbreviated as SNR) describes the possible maximum power [15]. There is less image noise when the signal to noise ratio is larger, and it means that there is a greater de-noising ability. The SNR is defined as follows:

\[
SNR = 10 \cdot \log_{10} \left( \frac{MAX_f^2}{MSE} \right) = 20 \cdot \log_{10} \left( \frac{MAX_f}{MSE} \right)
\]

(23)

Where \( MAX_f \) is the largest numerical value of image color. \( MSE \) is defined as follows:

\[
MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} |I(i,j) - K(i,j)|^2
\]

(24)

Where \( m, n \) is the size of image, \( I(i,j) \) and \( K(i,j) \) is the original image and the de-noising image.

From Table 1, it can be seen that compared to the original image, the values of average gradient, information entropy and mean variance are reduced after the process of the mean filtering and Gauss filtering, while only the values of the median filtering and the algorithm proposed in this paper are increased (Table 1). The information entropy, average gradient, SNR, and mean variance of our method are significantly higher than that of the others, showing clearer images, higher retention of edge information, and more efficient de-noising.

![Figure 10. Comparison of a variety of techniques](image-url)
Table I
QUALITY EVALUATION ON DIFFERENT HAZE REMOVAL METHODS

<table>
<thead>
<tr>
<th>Index</th>
<th>Input image</th>
<th>Medium filtering</th>
<th>Gauss filtering</th>
<th>Zhang’s run-length</th>
<th>Our method</th>
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<td>3.0584</td>
<td>0.8024</td>
<td>2.3350</td>
<td>2.4560</td>
</tr>
</tbody>
</table>

Figure 11. Comparison of a variety of techniques. (a) the original image; (b) histogram equalization; (c) Multi-scale Retinex; (d) the algorithm in this paper

V. CONCLUSIONS

This paper proposes an integrated de-noise method for Chinese calligraphy based on different shapes and distributions between strokes and image noise in tablet images. The experimental results show that, compared with classical de-noising algorithms, the proposed method can more effectively eliminate noise and enhance text detail. However, some linear noise remains and future research will aim at the removing of this noise.

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