Comparative Study of Tongue Image Denoising Methods

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Abstract—**Tongue diagnosis is one of the most important examinations in traditional Chinese medicine. Tongue images are often corrupted by various noises, but the subsequent diagnosis requires that the tongue images are clean, clear and noise-free. Thus, tongue image denoising is the vital preprocessing step in tongue diagnosis. A comparative study of tongue image denoising methods is given in this work, and four different methods, i.e. wavelet transform, wavelet packet transform, adaptive median filter and wiener filter are utilized to denoise the tongue images, and then the performance of these four methods is evaluated and compared. The experimental results show that wavelet transform-based method can effectively reduce Gaussian noise and speckle noise mixing in the tongue images and yields better results than the other three methods, and the adaptive median filter method gets the best result in removing salt & pepper noise. Moreover, the results also indicate that wavelet transform-based method outperforms wavelet packet transform-based method for the noise reduction of tongue images.**

Index Terms—**tongue image, traditional Chinese medicine, tongue diagnosis, noise reduction**

I. INTRODUCTION

The traditional Chinese medicine (TCM) is an important part of world medicine. With a long history of over twenty centuries, TCM has formed an complete medical system, and can diagnose, treats and prevents disease at an earlier stage. TCM causes little pain, has no injury and treats the human body as a whole, and is very effective in the treatments of some diseases, such as vital infections, chronic problems and cancers. It makes a great contribution to human health. However, due to being deficient in quantitative diagnostic standards, the accuracy of diagnosis completely depends on the doctor's experiences, and the diagnostic techniques are very hard to grasp. Therefore, it's very urgent to quantify TCM.

Tongue diagnosis is one of the most important examinations in TCM. Doctors diagnose the patient by inspecting the tongue color, tongue shape and tongue property. Tongue diagnosis is considered to be carrying very valuable information for some disease diagnosis, such as gastrosia. In recent years, with the development of computer science and technology, especially artificial intelligence and machine vision, the modernization of tongue diagnosis is paid more and more attention by researchers. Computerized tongue diagnosis is technology mainly includes tongue image preprocessing, feature extraction and tongue recognition [1].

This paper mainly focuses on the tongue image noise reduction in the preprocessing stage. Tongue images are obtained by a self-designed tongue image acquisition, which is shown in Fig. 1, in which a digital camera and standard illuminants are built in. Due to the influence of the light source and some uncontrollable movements of body and respiration, the obtained images can be easily contaminated by various noises. Therefore, it is essential to remove these noises. Common image noise usually include Gaussian noise, salt & pepper noise, multiplicative noise (for example, speckle noise), etc. Up to now, many methods have been developed to the noise reduction of tongue image [2-4]. However, the comparison research of tongue image noise elimination is not presented in these researches.

In this study, we applied four different algorithms to the tongue image noise reduction. The image denoising methods can be categorized into space domain and transform domain. Space domain methods are the data operation on the processing of image pixels grey value directly. Common space domain denoising methods include average filtering, median filtering [5] and wiener filtering [6], etc. Transform domain method deal with image in some transform domain, such as frequency domain and wavelet domain. It usually consists of four steps. Firstly, the image is converted from space domain to a transform domain. Then, the acquired coefficients are dealt with by some methods. Finally, the processed image is transformed inversely. Wavelet transform (WT) is a very useful denoising method, which is located in time and frequency, and can gain good sparsity for spatially localized details, such as edges and singularities [7]. Because such details carry significant information for subsequent analysis, in recent years, wavelet-based denoising methods has became important research direction of image denoising [8]. Meanwhile, wavelet-based denoising methods include WT denoising method, wavelet packet transform (WPT) denoising method, multi-wavelet denoising method, etc.

In order to compare the effectiveness of the tongue image noise reduction methods, we add Gaussian noise, salt & pepper noise and speckle noise into the tongue

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image, respectively. Then, WT, WPT, an adaptive median filter and wiener filter are employed to eliminate the noises that confused in the tongue images. Finally, the performances of these approaches are compared and some useful conclusions are given.

Figure 1. The tongue image acquisition instrument

II. Noise Type

Noise is undesired information, and the type of noises compounding in the image is usually unknown. In this study, to compare the effectiveness of noise reduction algorithms, we select several typical type images and add different types of noises into the images. Typical noises include Gaussian noise, salt & pepper noise and speckle noise, which is multiplicative in nature [9]. The characteristics of these noises are discussed in this section.

A. Gaussian Noise

Gaussian noise is distributed over the image evenly which means that each pixel in the noise image is the sum of the original pixel value and a random Gaussian distribution noise value. Namely, this type of noise has a Gaussian distribution and it's probability distribution function is given by

$$F(g) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-(g-m)^2}{2\sigma^2}} , \quad (1)$$

where g represents the gray level, m is the mean of the noise, and σ is the standard deviation of the noise.

B. Salt & Pepper Noise

Salt & pepper noise is a typical noise type commonly confusing in images. It is an impulse type of noise and caused generally by malfunctioning of pixel elements in the camera sensors, faulty memory locations, or timing errors in the digitization process [9]. An image was corrupted by salt & pepper noise usually has dark pixels in bright regions and bright pixels in dark regions. As it has only two possible values, the corrupted pixels are set alternatively to the minimum or to the maximum value, which makes the image look like “salt and pepper”.

C. Speckle Noise

Speckle noise is a kind of multiplicative noise which presents in almost all coherent imaging systems such as laser, acoustics and synthetic aperture radar (SAR) imagery [9]. It can reduces the image picture quality and seriously affect the subsequent image processing such as automatic segmentation, classification, target detection, and other quantitative analysis of image contents.

III. Noise Reduction Methods

A. WT

At the end of 1980s, wavelet analysis started to become a hot research field. The wavelet analysis method is a very effective method of time-frequency analysis, which has been applied in many fields, such as signal process, speech analysis and pattern recognition. WT is adept in dealing with signals on short time intervals for high frequency components and long time intervals for low frequency components. At large scale, low frequency part of signal can be come out by WT, while at small scale; high frequency information could be revealed. Therefore, WT is called math microscope. WT can be categorized into continuous and discrete. Continuous wavelet transform (CWT) is defined by

$$\mathrm{CWT}(a,b) = \int_{-\infty}^{+\infty} x(t)\psi_{a,b}^{*}(t) , \quad (2)$$

where x (t) represents the analyzed signal, a and b represent the scaling factor (compression coefficient) and translation along with time axis (shifting coefficient). The superscript asterisk means the complex conjugation. $\psi_{a,\, b}$ (t) is expressed by scaling the wavelet at time b and scale a:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right) , \quad (3)$$

where ψ (t) represents the wavelet.

Usually, an image consists of useful signals and noises. The useful signals often presents in the low-frequency part while noises and edge details generally present in the high-frequency part. The denoising methods based on WT generally filter out noises by setting thresholds. WT is good at energy compaction. Usually, small coefficients are considered to be produced by noise while large coefficients are corresponding to the useful image information. Hence, these small coefficients can be abandoned without affecting the significant image features.

The threshold method was the most frequently used one among the wavelet-based denoising methods which is simple and effective. Determining threshold is focal task in the wavelet threshold denoising method. The threshold value influences the quality of the processed image directly. Smaller threshold means that more wavelet coefficients will be retained, namely, more image information will be remain. However, more noises also will survive. Reversely, if a larger threshold is set, noise will be eliminated, and at the same time, some useful high frequency information of the image may be missed. The selection of thresholds can be classified into two categories, i.e. hard threshold and soft threshold. In hard threshold method, the wavelet coefficients are set to zero if their value is smaller than a certain threshold λ, which is given as

$$W_\lambda = \begin{cases} w, & |w| \ge \lambda \\ 0, & |w| < \lambda \end{cases} . \quad (4)$$

While in soft threshold method, the wavelet coefficients which are less than a threshold are set to zero

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and others would be subtracted the value of the threshold, as given by (5).

$$W_\lambda = \begin{cases} [\mathrm{sign}(w)](|w| - \lambda), & |w| \ge \lambda \\ 0, & |w| < \lambda \end{cases}, \quad (5)$$

where sign () is signum function. Hard threshold can maintain some local characteristics, such as image edges, but it is prone to produce visual distortions such as ringing, pseudo-Gibbs effect [10]. Thus, soft threshold method is employed in this paper. Soft threshold methods can be divided into global soft threshold and local soft threshold. Global threshold means that a same threshold is employed for the high-frequency wavelet coefficients in all decomposition layers, while local soft threshold method utilizes different thresholds in each layer, which can achieve better performance in most situations. Hence, local soft threshold method is utilized. In this paper, we use the NormalShrink [11] method to select the wavelet thresholds.

The threshold value is T_N is defined as

$$T_N = \frac{\beta \hat{\sigma}^2}{\hat{\sigma}_y} \quad (6)$$

where the scale parameter β is computed once for each scale using the following equation:

$$\beta = \sqrt{\log(\frac{L_k}{J})} \quad (7)$$

L_k is the length of the subband at k^{th} scale, J is decomposition level. $\hat{\sigma}^2$ is the noise variance, which can be estimated from the subband HH_1, HH_1 is diagonal direction component of high-frequency at the first scale, $\hat{\sigma}^2$ can be denoted as

$$\hat{\sigma}^2 = [\frac{\mathrm{mdian}(|Y_{ij}|)}{0.6475}]^2, \; Y_{ij} \in \text{subband } HH_1 \quad (8)$$

and $\hat{\sigma}_y$ is the standard deviation of the subband under consideration.

Currently, common wavelet basis function mainly includes orthogonal wavelet, semi-orthogonal wavelet and biorthogonal wavelet. Different wavelets have different time-frequency features, using different wavelets to denoise image can get different effects. Therefore, the selection of wavelet basis function is also one important issue and required to be considered carefully. According to [12], if the noise intensity is comparatively low, low threshold is needed. If the same threshold is set, the high frequency coefficients remained by the filtering method based on orthogonal wavelet transform can get better reconstruction result than that based on biorthogonal wavelet transform. Oppositely, when the noise intensity is comparatively high, due to the range of the coefficients obtained by biorthogonal wavelet transform is larger than orthogonal WT, there would be more energy of the original image in the remained coefficients if bigger threshold is set. However, as usual, the conditions of the images are complex, and this strategy is not suitable to select appropriate wavelet basis. We utilizes the emulation experiment to ascertain the best wavelet basis and its decomposition scale based on SNR and MSE, which will be introduced in the following sections.

In sum, the procedure of tongue image denoising method based on WT is illustrated as follows.

1. Choose one wavelet function and decomposition layer, apply WT to the noisy tongue images and get the wavelet coefficient.
2. Select the thresholds according to (6) at each decomposition layer and assign zero to the detail coefficients whose values are smaller than the selected thresholds.
3. Use the inverse WT and reconstruct the denoised image from the wavelet coefficients.
4. Compute the signal to noise ratio (SNR) and mean square error (MSE), which shown in (16) and (17), to guide the choice of the wavelet function and decomposition layer. Repeat step 1, 2 and 3, record the denoising results when get the maximal SNR or Minimal MSE.

B. WPT

Wavelet packet analysis is extended from wavelet analysis and makes signal information decompose more meticulous. The wavelet packet performs the recursive decomposition of the frequency bands obtained by the recursive binary tree. These sequences are then sub-sampled by a factor of two [13]. In the WPT, a pair of low pass and high pass filters is used. The two wavelet orthogonal bases generated from a parent node are defined as

$$\psi_{j+1}^{2p}(k) = \sum_{n=-\infty}^{\infty} h[n]\psi_j^p(k - 2^j n) \quad (9)$$

$$\psi_{j+1}^{2p+1}(k) = \sum_{n=-\infty}^{\infty} g[n]\psi_j^p(k - 2^j n) \;, \quad (10)$$

where $h[n]$ is the lowpass filter, $g[n]$ is the highpass filter and $\psi[n]$ is the wavelet function. In the $\psi_j^p(k - 2^j n)$, j is the depth of decomposition, p is the number of nodes to the left of the parent node.

As shown in Fig. 2, WPT can be viewed as a tree. The root of the tree denotes the original data set. The next level of the tree is the result of one step of WT. Similarly, the inverse wavelet packet can reconstruct the original image from the wavelet packet decomposition spectrum. Note that, the wavelet basis function cannot be changed during the construction.

The original image is decomposed gradually into some sub-images with different scales by two-dimensional WT. After the first decomposition, the original image is divided into four parts. The first part is the low frequency component reserving the most important information of the original image. The second part is the high frequency horizontal component. The other two are the high frequency vertical component and the high frequency diagonal direction component. The high frequency part includes the information of edge details and noise. WT only decomposes the low frequency component at the second decomposition, while WPT decomposes both the

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low frequency component and the high frequency component.

Just as WT, using WPT to denoise the corrupted tongue image also needs to set thresholds. In order to convenient for comparing the different methods, we also use the Normal Shrink method to select thresholds in the WPT based denoising method.

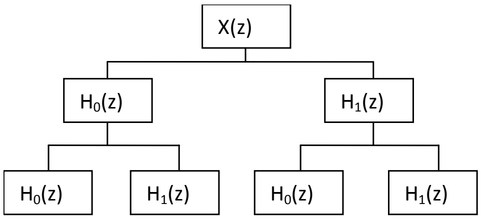

Figure 2. Wavelet packet tree.

We can adopt many kinds of wavelet packet bases when apply WPT to denoise an image. Not all wavelet basis function can be suitable for noise reduction. Therefore, we need select the best wavelet packet basis [14]. Entropy is the frequently-used standard for selecting the best basis.

The procedure of WPT based denosing method for tongue images is listed as follows.

1. Choose the suitable wavelet basis function and decomposition level and apply WPT to decompose the tongue images.
2. Appoint shannon entropy and calculate optimum tree to determine the best wavelet packet basis.
3. Select threshold limit T_N using NormalShrink at each level and apply soft thresholding to remove the noises.
4. Utilize inverse WPT to obtain the denoised images.

C. Adaptive Median Filter

Median filter was proposed by Tuckey in 1971 and currently extensively applied to signal analysis and image processing. Median filter is a nonlinear filtering and the output is estimated minimum of a distribution center of observation samples. The median filter deals with each pixel in the image in turn and looks at its nearby neighbors to decide whether or not it represents its surroundings. Substitute for simply replacing the pixel value with the mean of neighboring pixel values, median filer replaces it with the median of those values. The median is computed by first sorting all the pixel values from the surrounding neighborhood into numerical order and then replacing the pixel being considered with the middle pixel value [15].

Suppose f (x, y) be the gray value of pixel (x, y), filtering window is S, then median filter of two dimension can be defined as

$$f^{'}(x,y) = \mathrm{med}\{f(x+s, y+t), (s,t) \in S(x,y)\} \quad (11)$$

Shape and size of the filtering window have an great effect on filtering result. The bigger the window size is, the more loss of the detail image information. Conversely, the smaller the window size is, the less power of the median filter to denoise. Therefore, it is essential to select a suitable filtering window size for removing tongue image noise.

There are many ways to select a suitable filing window, such as fixed window size and adaptively adjusted window size. Adaptive median filter is better in preserving the details of image than fixed size strategy. Thus, in order to keep the useful details of the tongue image, an adaptive median filter was proposed in our previous work [16].The most significant characteristic of the method is that it takes the maintenance of the image edge details into consideration. To preserve the tongue image details, edge detection is employed to regulate the median filter window size. Consider that edge detection based on wavelet modulus maximum can locate the edges precisely, hence, the proposed adaptive median filter applies it to keep the edge information sufficiently.

Assume that g (x, y) denotes the final output gray value of pixel (x, y), f (x, y) is the gray value of pixel (x, y) in the original image and m (x, y) is the processed gray value using the improved adaptive median filter to replace the original gray value of pixel (x, y), then the relation among them could be written as [16]:

$$g(x,y) = \begin{cases} f(x,y), \ (x,y) \text{ is noise free pixel} \\ m(x,y), \ (x,y) \text{ is noise pixel} \end{cases} \quad (12)$$

The procedure of the proposed adaptive median filter is listed as follows [15].

1. Detect the edge of the original tongue images using wavelet modulus maximum method.
2. Both length and width of the adaptive median filter is initialized to W=2R+1, where R is a small positive integer value.
3. Compute the number of noise-free pixels contained in the contextual area defined by this W×W filter.
4. If the number of noise-free pixels is less than eight and the center of the filter window is not located in the edge of the original image, extend the size of the window by two (i.e. W=W+2), then go back to step 3; If the number of noise-free pixels is less than eight but the center of the filter window is on the edge of the original image, the window size of will stay unchanged and go to step 5 directly.
5. Compute the median gray value of all the noise-free pixels contained in the window and set m (x, y) as the calculated median value.
6. Update the value of g (x, y) using (12).

D. Wiener Filter

The Wiener filter is a filter proposed by Norbert Wiener during the 1940s. Assume that the inputs of the linear filter are the sum of useful signal and noise and the inputs are stationary. According to minimum mean-square error criterion, Wiener achieved the best linear filter parameters [17].This filter is called wiener filter.

The input to the Wiener filter is assumed to be a image signal s (t), corrupted by noise n (t). The output □ (□) is computed by means of a filter g (t) by using the following convolution [17]:

$$\hat{s}(t) = g(t) * [s(t) + n(t)] \quad (13)$$

where g (t) is the Wiener filter's impulse response. The error is defined as

$$e(t) = s(t) - \hat{s}(t) \quad (14)$$

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So the minimum mean-square error is defined as

$$E[e^2(t)]_{\min} = E\left\{\left[s(t)-\hat{s}(t)\right]^2\right\} \tag{15}$$

From the above definitions, we conclude that the smaller mean-square error means the better denoising result. In order to get the mean-square error minimum, it is the key to seek the Wiener filter's impulse response. If the impulse response meet the Wiener-hopf equation, the filtering would be the best. Wiener filter process can be shown in Fig. 3. In this paper, the traditional wiener filter is employed. In order to achieve a better result, we adopt several filter windows which size are different, then the best filter window is selected by comparing the values of SNR.

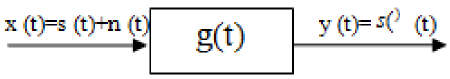


Figure 3. Wiener filter flow chart.

IV. EXPERIMENTS AND DISCUSSION

This section draws the comparisons of the different denoising techniques, namely, wavelet based denoising, and wavelet packet based denoising, an adaptive median filter and wiener filter. The signal to noise ratio (SNR) and mean square error (MSE) are selected as quantitative standards for comparison. MSE indicates how close the estimated image is to the original one.

Usually, the higher SNR of the output image means the better denoising effect. As for MSE, the smaller means the better. Suppose that $s(x, y)$ denotes the original image and $\hat{s}(x,y)$ denotes the processed image, then

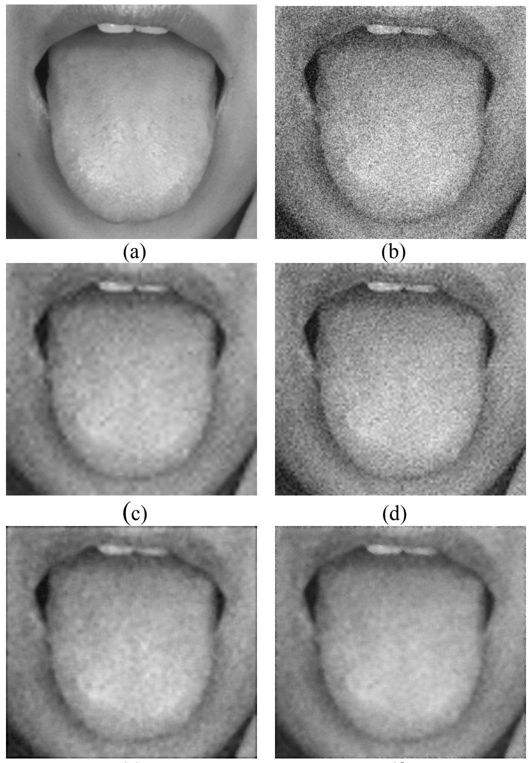
$$\mathrm{MSE} = \frac{\sum_{x=1}^{N_x}\sum_{y=1}^{N_y}(\hat{s}(x,y)-s(x,y))^2}{N_x \times N_y} \tag{16}$$

$$\mathrm{SNR} = 10\log_{10}\frac{\sum_{x=1}^{N_x}\sum_{y=1}^{N_y}(s(x,y))^2}{N_x \times N_y \times \mathrm{MSE}}\,, \tag{17}$$

where the size of the image is N_x-by-N_y pixels.

To display the effectiveness of the denoising methods, we select two typical tongue image samples from database with size 429×400, which are clean and not corrupted by noises. We add Gaussian noise, salt & pepper noise and speckle noise to the tongue images respectively. One sample is collected from a health volunteer,

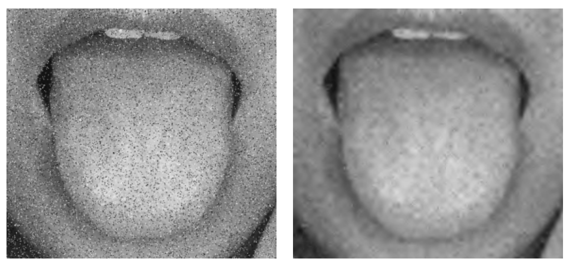
To select the window size of the wiener filter, we adopt windows with size 3×3, 5×5, 7×7, 9×9, 11×11 and 13×13 to denoise the tongue images and compare their effects. Table I shows the denoising results using different wiener filter windows. We select the filter windows which get the highest SNR. According to the simulation results, we use the 11×11, 11×11 and 9×9 filter windows to remove Gaussian noise, salt & pepper noise and speckle noise, respectively.



(a) (b) (c) (d) (e) (f)

Figure 4. (a) Clean tongue image sample I. (b) image corrupted by Gaussian noise with square error 0.04 (SNR=9.502, MSE=0.03671), (c) Result from denoising by wavelet sym4 with layer 3 (SNR=24.543, MSE= 0.00114), (d) Result from WPT with wavelet sym4 and layer 3 (SNR=20.947, MSE=0.00263), (e) Result from adaptive median filter (SNR=21.622, MSE=0.00227), (f) Result from common wiener filter with fixed window size 11×11 (SNR=22.570, MSE=0.00180).

Fig. 4 is the denoising comparison results for Gaussian noises. Fig. 4 (a) is a clean tongue image sampling from a healthy volunteer. Fig. 4 (b) shows the image corrupted by Gaussian noise with 9.502 SNR. Fig. 4 (c) is the result denoised by WT. We found that the highest SNR can be achieved by selecting sym4 as the wavelet basis function, and setting decomposition layer to three. It can be seen that most of the noises are eliminated. Fig. 4 (d) is the denoising result based on WPT. When SNR gets the maximum, some noises still remain in the image. The noise reduction result using the adaptive median filter is presented in Fig. 4 (e). It illustrates that the noises are eliminated effectively and at the same time, some useful details are preserved well, such as the tongue edges and indentation. Fig. 4 (f) is the wiener filter denoising result. Compared with the former three methods, more image useful details are filtered out.



(a) (b)

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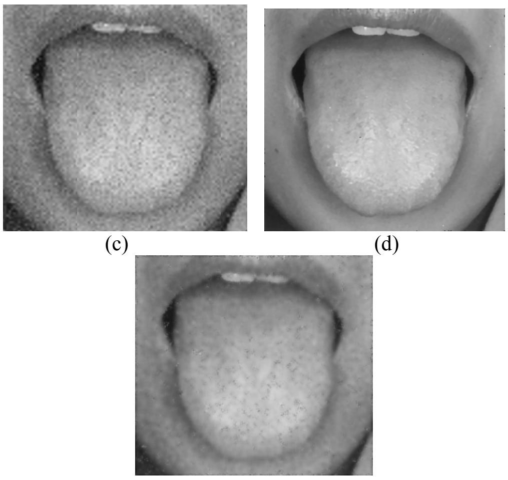
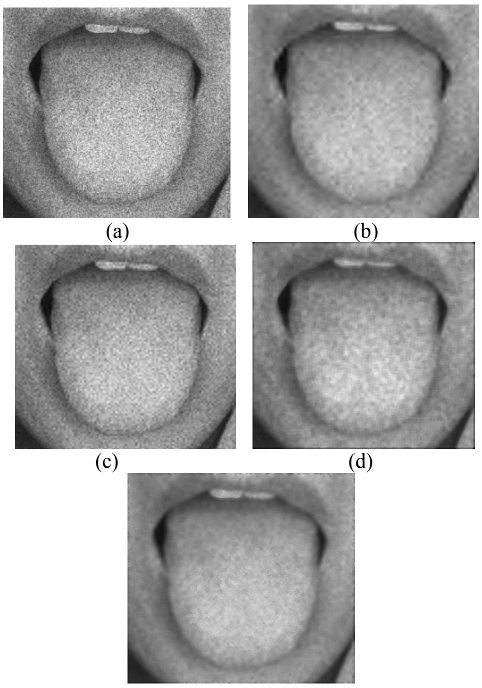


(c) (d)

(e)

Figure 5. (a) Tongue image corrupted by salt & pepper noise with density 0.1 (SNR=10.701, MSE=0.02733), (b) WT, coif3 wavelet and layer 3 (SNR=24.394, MSE=0.00136), (c) WPT, coif3 wavelet and layer 3 (SNR=21.642, MSE=0.00220), (d) Adaptive median filter (SNR=31.623, MSE=0.00024), (e) Common wiener filter with fixed window size 11×11 (SNR=21.537, MSE=0.00230)

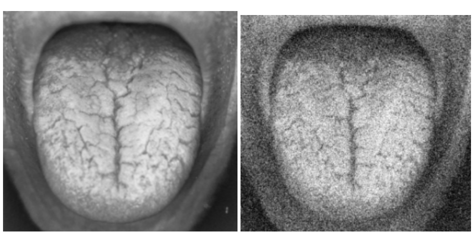


(a) (b)

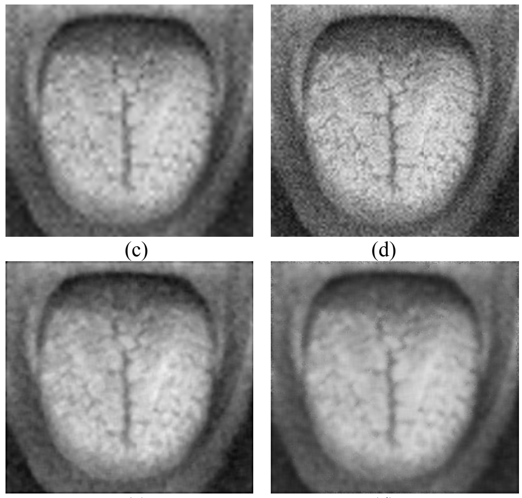
(c) (d)

(e)

Figure. 6 (a) Tongue image corrupted by speckle noise with variance 0.1 (SNR=10.283, MSE=0.03101), (b) WT, db3 wavelet and layer 3 (SNR=24.680, MSE=0.00102), (c) WPT, db3 wavelet and layer 3 (SNR=21.545, MSE=0.00237), (d) Adaptive median filter (SNR=20.971, MSE=0.00265), (e) Common wiener filter with fixed window size 9×9 (SNR=21.246, MSE=0.00242).



(a) (b)



(c) (d)

(c) (d)

Figure. 7 (a) Clean tongue image sample II, (b) The image corrupted by Gaussian noise with square error 0.04 (SNR=9.005, MSE=0.03522), (c) WT, sym4 wavelet and layer 3 (SNR=22.263 MSE=0.00166), (d) WPT, sym4 wavelet and layer 3 (SNR=20.190, MSE=0.00268), (e) Adaptive median filter (SNR=20.425, MSE=0.00254), (f) Common wiener filter with fixed window size 11×11 (SNR=20.956, MSE=0.00224) .

Fig. 5 gives the noise reduction results for salt & pepper noise. It can be seen that WPT and wiener filter cannot eliminate the noises effectively here and some noises survive, which are shown in Fig. 5 (c) and (e). In Fig. 5 (d), it should be noted that the salt & pepper noise is removed perfectly by using the adaptive median filter. Meanwhile, due to utilizing edge detection to regulate the size of the median filter window, the edges of the tongue image are also protected very well. As shown in Fig. 5 (b), WT based denoising method also can eliminate the noises effectively, but the image is blurred simultaneously. Fig. 6 sketches the results for speckle noises. It seems that the method based on WT obtains the best result, which can filter out the noise effectively and retains some useful details. In order to display the effectiveness of protecting edge and texture of tongue image, we select a tongue image which is not corrupted by noise and has obvious cracks.

Fig. 7 gives the other tongue image example, which sampled from a patient volunteer. There are many cracks in the tongue image, which are also important diagnostic information. We mix the image with the Gaussian noise with 0 mean and 0.04 square. It can be seen that the edges and textures of the tongue images become blurred, especially for the denoised result obtained by the wiener filter. The large crack in the middle place of the tongue image can be preserve well, but some small cracks are missed.

The methods based on WT and the adaptive median filters seem better, which are shown in Fig. 7 (c) and (e), the noises are reduced effectively and part of small cracks is also preserved. All the above results are presented in terms of the visual appearance, and at the same time the corresponding SNR and MSE values are given.

In order to further validate the denoising effectiveness, we give the SNR comparisons, which are described in Fig. 8-10 and Table II.

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TABLE I
SNR OBTAINED BY WIENER FILTER USING DIFFERENT FILTER WINDOWS

Noise type	3×3, SNR	5×5, SNR	7×7, SNR	9×9, SNR	11×11, SNR	13×13, SNR
Gaussian	16.932	20.432	22.014	22.571	**22.628**	22.440
Salt & pepper	15.103	18.322	21.104	21.059	**21.531**	21.125
Speckle	17.443	18.855	20.419	**20.975**	20.936	20.738

TABLE II
IMAGE QUALITY METRICS OBTAINED BY VARIOUS METHODS FOR VARIOUS NOISES

Noise type and variance	Input SNR	Input MSE	Output SNR	Output MSE	Denosing Methods
Salt &pepper noise, 0.1	10.701	0.02733	24.394	0.00136	WT
	10.701	0.02733	21.642	0.00220	WPT
	10.701	0.02733	**31.623**	**0.00024**	Adaptive median filter
	10.701	0.02733	21.537	0.00230	Wiener filter
Gaussian noise, 0.01	15.145	0.01018	**27.100**	**0.00064**	WT
	15.145	0.01018	25.519	0.00092	WPT
	15.145	0.01018	25.187	0.00193	Adaptive median filter
	15.145	0.01018	25.971	0.00181	Wiener filter
Speckle noise , 0.1	10.283	0.03101	**24.680**	**0.00102**	WT
	10.283	0.03101	21.545	0.00237	WPT
	10.283	0.03101	20.971	0.00265	Adaptive median filter
	10.283	0.03101	21.246	0.00242	Wiener filter

These results illustrate which methods are more suitable for the three different noises. Fig. 8-10 sketches the relationship of the input SNR and the output SNR, in which method1-4 denote WT, WPT, the adaptive median filter and the wiener filter respectively.

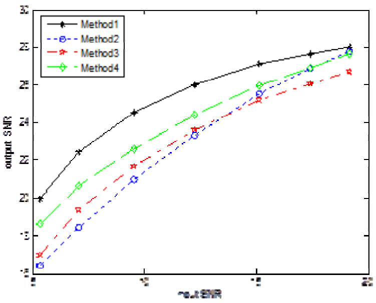

Figure 8. The performance comparison of the four denoising methods for Gaussian noise.

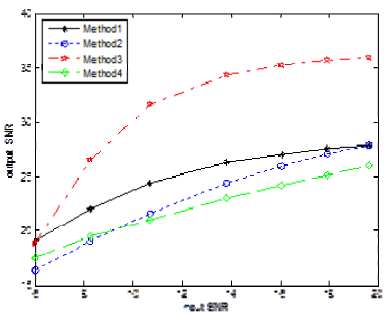

Figure 9. The performance comparing of the four denoising methods for salt & pepper noise.

According to Fig. 4 and Fig. 8, we can see that WT is more suitable to remove the Gaussian noise for the corrupted tongue image. However, it seems that the edge of the tongue image become blurred, as shown in Fig. 4 (c). From the results of Fig. 5 and Fig. 9, it is obvious that the adaptive median filter achieves the best effectiveness for salt & pepper noise. For speckle noise, WT is a better choice, as shown in Fig. 6 and Fig. 10.

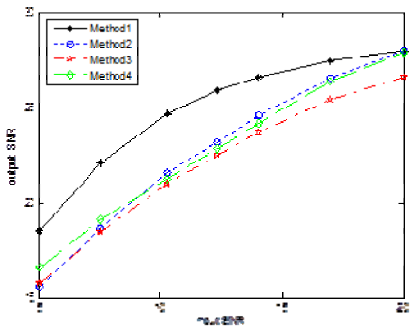

Figure 10. The performance comparing of the four denoising methods for speckle noise.

By this experiment, we can also note an interesting phenomenon: for tongue images noise reduction, WT is superior to WPT for all the three types of noises.

V. CONCLUSION

Noise reduction is one of the important tasks in the tongue image pre-processing procedure, which is a vital step for the subsequent tongue diagnosis. In this paper, the comparison research for the tongue image denoising methods is given. We simulate the corrupted tongue images by adding three types of noises to the clean tongue images, and then utilize four denoising methods to denoise them. According to the experiment results, we conclude that WT is better than the other three methods in removing Gaussian noise and speckle noise for tongue images, and for the noise reduction of salt & pepper noise, the adaptive median filter is the best choice. Note that, in terms of the denoising results, WT is better than WPT for tongue images. However, for tongue image, WT is not very perfect for removing Gaussian noise and speckle noise. Because some noises still remain in the tongue images and the edge and texture of the tongue images are blurred. The filter window size of the wiener filter is selected when SNR gets the maximum. However, this

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strategy may make the edge and texture of the image become inconspicuous if the filter window is too big. Hence, if the tongue images are contaminated by Gaussian noise and speckle noise, new methods should be developed, which can eliminate the unknown noises and at the same time preserve the useful details for diagnosis, such as cracks, indentation and other textures.

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