Palmprint Images Enhancement Using Steerable Filters based Fuzzy Unsharp Masking*

YANXIA WANG AND QIUQI RUAN
Institute of Information Science
Beijing Jiaotong University
Beijing 100044, P.R.C.
E-mail: Wangyx_98_s@sohu.com

Palm lines include principal lines and wrinkles, which can uniquely describe an individual palmprint. On motive of palmprint image enhancement is to highlight palm lines. In this paper, a steerable filters based fuzzy unsharp masking algorithm is presented to enhance the contrast of a palmprint image. This method introduces the fuzzy set theory into the unsharp masking scheme. Moreover, in the method, we replace a highpass filter with steerable filters in unsharp masking scheme. In order to further enhance the contrast of wrinkles, a half open membership function is proposed to transform the output of steerable filters into fuzzy domain. The experimental results clearly show that our method not only improves the mage quality of palmprint wrinkles, but can get a better recognition performance.

Keywords: biometrics, palmprint image enhancement, steerable filters, unsharp masking, fuzzy set theory

1. INTRODUCTION

Palmprint recognition is a relatively new personal identification technique, which uses the features of palmprints, that is principal lines, wrinkles, ridges, minutiae points, singular points and texture *etc.* The principal lines and wrinkles in a palmprint convey a large amount of information that can uniquely identify a person. However, online palmprints images captured by a camera or a scanner are low-contrast images, which have a narrow dynamic range of gray levels. In addition, palm lines are irregular and have different directions, shapes and depths even in a same palm, increasing the difficulty of their extraction. Principal lines can be extracted easily, but are not sufficient to represent the uniqueness of each individual's palmprint because different people may have similar principal lines [1]. Moreover, it is difficult to extract wrinkles directly from online palmprint images. Thus, palmprint image enhancement becomes one of the most important tasks in palm-line extraction, which has made limited progress so far.

Contrast stretching is an effective method to increase the dynamic range of pixel gray levels [2]. It only makes principal lines observable, but for wrinkles, its role is limited. In order to extract more wrinkles, details in a palmprint image should be enhanced.

The popular unsharp masking (UM) technique is a simple and effective method, both computationally and conceptually, for emphasizing high frequency contents to en-

Received October 11, 2006; revised March 12, 2007; accepted May 2, 2007.
Communicated by Kuo-Chin Fan.
* This work was supported partly by the National Grand Fundamental Research 973 Program of China (No. 2004 CB318005) and the National Natural Science Foundations of China (No.60472033 and No. 60672062).

hance edges and other details in an image. Its basic idea is that a high-pass filtered and scaled version of an input image is added to itself and the enhanced image $y(m, n)$ is obtained from the input image $x(m, n)$ as

$$y(m, n) = x(m, n) \pm \lambda z(m, n) \tag{1}$$

where $z(m, n)$ is the output of a linear highpass filter, λ is a positive scaling factor that controls the gray level of the output image. If the center coefficient of the highpass filter operator is positive, the operator sign is plus in Eq. (1). Contrarily, it is subtraction sign.

The linear unsharp masking technique is used and works well in many applications. However, the linear high-pass filter is extremely sensitive to noise. In order to reduce the noise sensitivity of the UM technique, Lee and Park [3] used an order statistic (OS) Laplacian operator in the UM. They demonstrated that UMOS filter could amplify much less noise than the conventional UM filter. In addition, different nonlinear filters have been proposed to reduce the noise. Mitra *et al.* [4] replaced the Laplacian filter with a simple second-order Volterra filter. Strobel *et al.* [5] introduced a modified version of unsharp masking, in which they used a quadratic filter. A cubic unsharp masking (CUM) technique was presented by Ramponi and Giovanni [6] to suppress the effect of noise amplification. Polesel *et al.* [7] introduced a variation of the basic UM scheme that contained an adaptive filter in the correction path. Still, all previous unsharp masking methods suffer from another common drawback – they are not effective for low-contrast images. Therefore, before they are used to enhance the palm lines, the contrast of palmprint images is stretched. From the enhanced palmprint images, even though the principal lines and wrinkles are all emphasized, the wrinkles are enhanced much less than principal areas.

In order to solve the above problem, this paper proposes an improved UM scheme, steerable filters based fuzzy unsharp masking algorithm. It not only introduces the fuzzy set theory into the unsharp masking method, but also replaces a highpass filter with steerable filters in UM scheme. The steerable filters at different orientations can effectively give prominence to line structure in a palmprint image. The finial summation of filtered images includes three parts: low, medium and high response parts. Since wrinkles are shallower than principal lines in a palmprint, the response of steerable filters to the former is weaker than that to the latter. Thus, the responses to principal lines, wrinkles and smooth areas belong to high, medium and low response, respectively. To enhance the response to wrinkles, a half open fuzzy membership function is designed. It enables the response to wrinkles to stand out. The membership function is illuminated in section 3.

The rest of the paper is organized as follows: A brief descriptions of steerable filters is given in section 2. The fuzzy set theory is given in section 3. Section 4 describes the steerable filters based fuzzy unsharp masking algorithm. Section 5 reports the experimental results and analysis. Finally, the conclusion is given in section 6.

2. STEERABLE FILTERS

Steerable filters belong to oriented filters, *i.e.*, filters with response in orientation. The coined term "*steerable filter*" was proposed to describe a class of filters in which a filter of arbitrary orientation is synthesized as a linear combination of a set of "basis filters" by Freeman and Adeison [8]. Steerable filters were applied successfully in a great deal of areas such as image denoising [9], color image segmentation [10] and feature detection [11].

A function $g(x, y)$ has steerability, when it can be written as a linear sum of rotated versions of itself. The steering constraint is

$$g^{\theta}(x, y) = \sum_{i=1}^{M} k_i(\theta) g^{\theta_i}(x, y) \tag{2}$$

where $g(x, y)$ is an arbitrary isotropic window function. $k_i(\theta)$ are the interpolation functions. M is the number of basis functions required to steer a function $g^{\theta}(x, y)$.

In order to work better, let g be any function $g(r, \phi)$ that can be expressed as a Fourier series in polar coordinates $r = \sqrt{x^2 + y^2}$ and $\phi = \arg(x, y)$:

$$g(r, \phi) = \sum_{n=-N}^{N} a_n(r) e^{jn\phi}. \tag{3}$$

Then $g^{\theta}(x, y)$ can be expressed as

$$g^{\theta}(r, \phi) = \sum_{i=1}^{M} k_i(\theta) g^{\theta_i}(r, \phi). \tag{4}$$

The interpolation function $k_i(\theta)$and the minimum number of basis function required to steer a particular function $g(r, \phi)$ can be got by the following theorems [8]:

Theorem 1 The steering condition Eq. (2) holds for functions expandable in the form of Eq. (3) if and only if the interpolation functions $k_i(\theta)$ are the solution of

$$\begin{pmatrix} 1 \\ e^{j\theta} \\ \vdots \\ e^{jN\theta} \end{pmatrix} = \begin{pmatrix} 1 & 1 & \cdots & 1 \\ e^{j\theta_1} & e^{j\theta_2} & \cdots & e^{j\theta_M} \\ \vdots & \vdots & \cdots & \vdots \\ e^{jN\theta_1} & e^{jN\theta_2} & \cdots & e^{jN\theta_M} \end{pmatrix} \begin{pmatrix} k_1(\theta) \\ k_2(\theta) \\ \vdots \\ k_M(\theta) \end{pmatrix}. \tag{5}$$

The orientations of the $n + 1$ basis functions were assumed to be evenly spaced between 0 and π, *i.e.*, $\theta_j = (j - 1)\pi/(n + 1)$, where $j = 1, 2, \ldots, n + 1$. According to Eq. (5), we can get

$$k_j(\theta) = \begin{cases} (1 + h_1(\theta))/(P + 1), & P \in \text{even} \\ h_2(\theta)/(P + 1), & P \in \text{odd} \end{cases} \tag{6}$$

where $h_1(\theta) = \sum_{l=0}^{Q} 2\cos(2l(\theta - \theta_j))$, $h_2(\theta) = \sum_{m=0}^{Q} 2\cos((2m+1)(\theta - \theta_j))$, $P = n + 1$ and Q is the integer part of $(P/2 + 0.5)$.

Theorem 2 Let T be the number of nonzero coefficients $a_n(r)$ for a function $g(r, \phi)$ expandable in the form of Eq. (3). Then, the minimum number of basis functions sufficient to steer $g(r, \phi)$ by Eq. (4) is T, *i.e.*, M in Eq. (4) must be greater than or equal to T.

Theorem 2 does not point to how to find the minimum number of basis functions that can steer a filter. To steer a filter, more basis functions are required than the minimum number given by Theorem 2. For instance, $2N + 1$ basis functions are sufficient to steer any Nth polynomial, whereas a complete set of 2-D polynomial basis functions would require $(N + 1)(N + 2)/2$ basis functions.

For example, derivatives of Gaussians of all orders are steerable, because each one can be expressed as a polynomial times a radically symmetric window function. Therefore, in the paper, a second derivative of a Gaussian function is used to design steerable filters. We use three basis filters to create steerable filters along to arbitrary angle θ:

$$G_2^{\theta} = k_1(\theta)G_2^{0^\circ} + k_2(\theta)G_2^{60^\circ} + k_3(\theta)G_2^{120^\circ} \tag{7}$$

where $G_2^{0^\circ} = (4x^2 - 2)e^{-(x^2+y^2)}$, $G_2^{60^\circ}$ and $G_2^{120^\circ}$ can be not by rotating $G_2^{0^\circ}$. $k_j(\theta)$ can be computed by Eq. (6). Fig. 1 shows three basis filters in the directions of 0°, 60° and 120° and three arbitrarily synthesized filters along the directions of 30°, 75° and 165°.

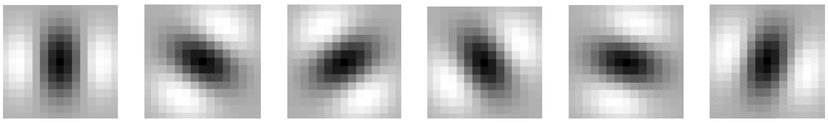


Fig. 1. Three basis filters and three synthesized filters.

3. FUZZY SET THEORY AND FUZZY MEMBERSHIP FUNCTION

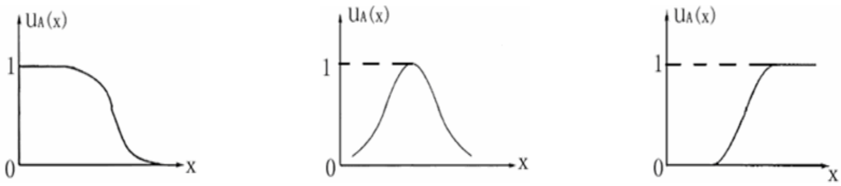
3.1 Fuzzy Set Theory

Fuzzy set theory is a useful mathematical tool for handling ambiguous situations, particularly for the vagueness in human languages and reasoning. It has advanced in a variety of way and applied in many disciplines. The application of the theory can be found, for example, in artificial intelligence, computer science, control engineering, decision theory, expert systems, logic, management science, operations research, pattern recognition, and robotics [12]. While many branches of mathematics are dichotomous regarding truth and falsehood, the fuzzy set theory provides a systematic way to study human factors with all its vagueness of perception, subjectivity, attitudes, goals and conceptions. The fuzzy set theory is an extension of the conventional set theory. By introducing vagueness and linguistics, fuzzy set theory becomes more robust and flexible than the classical dichotomous set theory.

A membership function describes the fuzziness of a fuzzy set. Determining a suitable membership function is a basic task [13].

Let the universe be $X = \{x_1, x_2, \ldots, x_n\}$. A fuzzy set A on X is a set defined by a membership function μ_A representing a mapping, $\mu_A : X \rightarrow [0, 1]$, here the value of $\mu_A(x)$

for the fuzzy set A is called the membership value or the membership degree of $x \in X$. The membership value represents the degree of x belonging to the fuzzy set A. The membership value of a fuzzy set can be an arbitrary real value between 0 and 1. The closer the value of $\mu_A(x)$ to 1 is, the higher the membership degree of the element x in fuzzy set A. If $\mu_A(x) = 1$, the element x completely belongs to the fuzzy set A. If $\mu_A(x) = 0$, the element x does not belong to A at all. According to the shape of a membership function, commonly used membership functions are classified into three classes: downtrend, central limit and uptrend, which are shown in Fig. 2, respectively.



(a) A downtrend membership function. (b) A central limit membership function. (c) An uptrend membership.

Fig. 2. Three membership functions.

3.2 Half Open Fuzzy Membership Function

The fuzzy set theory has been successfully applied in image enhancement [14-18]. Image fuzzification is an important and necessary process for fuzzy enhancement. It uses a member function to map all the gray levels of an image into real numbers in [0, 1]. The most commonly used membership function for gray levels is the standard S-function. For example, a standard S-function is used to transform a function image from the intensity domain into the fuzzy domain in [14]. Hsieh [15] had extended the standard S-function by combining S-function and the Z-function.

In this paper, we define a half open fuzzy membership function:

$$\mu_A = \begin{cases} 0, & x < a_1 \\ 0.5 + 0.5\sin\left(\dfrac{\pi\left(x - \dfrac{a_1 + a_2}{2}\right)}{a_2 - a_1}\right), & a_1 \le x < a_2 \\ 1 - 0.25\left(\dfrac{x - a_2}{a_3 - a_2}\right)^2, & a_2 \le x < a_3 \\ 0.5 + 0.25\left(\dfrac{a_4 - x}{a_4 - a_3}\right)^2, & a_3 \le x < a_4 \end{cases} \tag{8}$$

where x is a variable in the real domain, and a_1, a_2, a_3 and a_4 are the parameters which determine the shape of the half open membership function. These parameters can be determined by some statistic values of x. Fig. 3 shows a half open membership function. The function can enhance the overall influence of the variable with the medial values and halve the influence of the biggish values. Thus it can not only enhance the influence of the medial values, but also balance the influence between the medial values and biggish values.

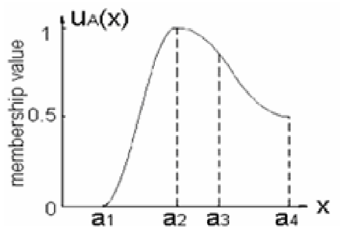


Fig. 3. A half open membership function.

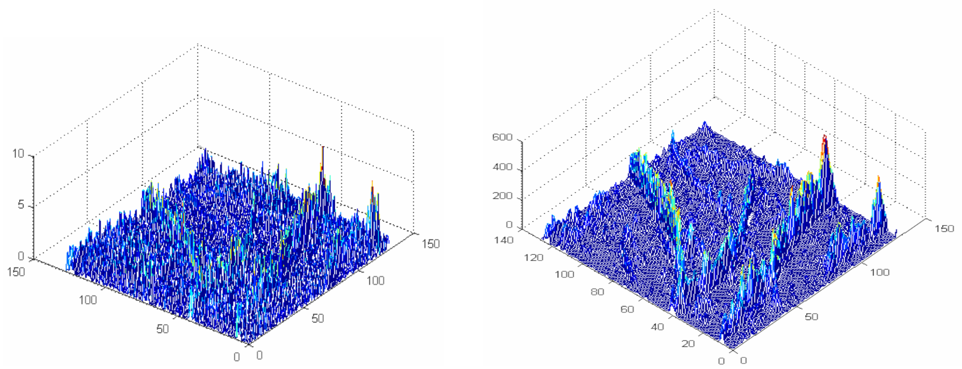
4. STEERABLE FILTERS BASED FUZZY UNSHARP MASKING ALGORITHM

4.1 Basic Idea

By analyzing palmprint images, it can be found that a palmprint image has four characters:

(a) The intensity values of palm lines are lower than palm surface.
(b) The gray levels of wrinkles are higher than principal lines. Furthermore, wrinkles are blurry, even some of them can not be made out.
(c) Palm lines are irregular and have various directions and depths.
(d) Because the recessed part in the palm deviates from the glass plate of the scanner, there is a shadow area in the center of the palmprint image, which can be called shadow effect.

In the palmprint image, palm lines are very important information, and they are just what we want. The UM method uses a highpass filter, such as Laplacian filter, to obtain the high frequency components and effectively highlight them. But it is extremely sensitive to noise. Thus, to decrease noise, in our method, the high frequency components in original image are obtained by steerable filters at different directions not by a Laplacian filter. Fig. 4 shows the outputs of a Laplacian filter and steerable filters, respectively.



(a) The output of a Laplacian filter. (b) The output of steerable filters.

Fig. 4. Comparison of the outputs of different filters.

Here the negative values of the responses of both filters are ignored. From Fig. 4 (a), it can be found that the output of the Laplacian filter contains a great amount of noise, and part of high frequency components are faded away in the noise. In comparison with the result of the Laplacian filter, there is only relatively little noise in the output of steerable filters, and the high frequency components are still clear. Thus using steerable filters to obtain high frequency information is a better choice in the UM method.

Though the noise can be reduced, the degree of enhancement of wrinkles is far from satisfactory. It is because the degree of enhancement varies with the response of filters. From Fig. 4 (b), we can find the responses of principal lines are stronger than that of wrinkles. Thus, to a certain extant, we can distinguish them and control their degree of enhancement. To increase the degree of enhancement of wrinkles, a half open fuzzy membership function is designed for fuzzification of the response of steerable filters. By the fuzzy membership function, the medial responses, that is the response of wrinkles of steerable filters, are mapped into the maximum value, and the stronger responses are weakened. In the way, the degree of enhancement of wrinkles is increased and the degrees of enhancement of palmlines are balanced.

After the process of fuzzification, the scheme of the unsharp masking is generalized into fuzzy field. The enhancement performed in the fuzzy field can be described as:

$$g(m, n) = \gamma(m, n) - \lambda w(m, n) \tag{9}$$

where $g(m, n)$ is the enhanced image in fuzzy domain, $\gamma(m, n)$ is the normalized input image, $w(m, n)$ is the fuzzification of the response of steerable filters, λ is the positive scaling factor. The block diagram of steerable filters based fuzzy unsharp masking approach is shown in Fig. 5.

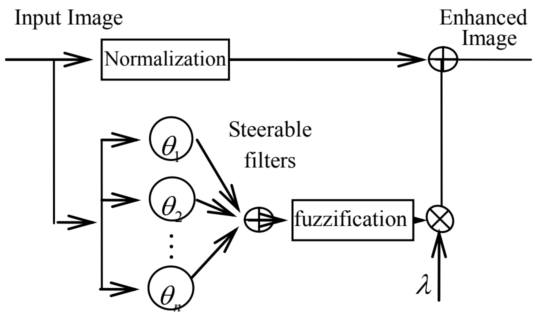


Fig. 5. The block diagram of steerable filters based fuzzy UM.

4.2 Implementation of the Proposed Method

Suppose that $x(m, n)$ is the intensity value of the pixel at (m, n) the input palmprint image. In order to implement Eq. (9), the value of $w(m, n)$ should be calculated first. The steerable filters based fuzzy unsharp masking algorithm consists of the following steps:

Step 1: Use steerable filters, like Eq. (7), to get the high frequency components of the original image.

We chose five synthesized filters $G_2^{\theta_i}$ along θ_i, here $\theta_i = 20° + i * 40°$, $i = 1, 2, \ldots, 5$. The response of every filter is $Z_i = G_2^{\theta_i} * x$. The final output of steerable filters is $Z(m, n) = \sum_{i=1}^{5} Z_i(m, n)$. The output of steerable filters $Z(m, n)$ consists of positive and negative values. If $Z(m, n)$ is positive, the pixel at (m, n) in the original image maybe is a high frequency component; otherwise, the pixel at (m, n) does not belong to high frequency component. In addition, the larger the absolute value of $Z(m, n)$ is, the higher the probability that the pixel at (m, n) has a high frequency component. Since we are only interested in palm lines and their intensity values are lower than other areas, we modify the result of Z to z to make the palm lines stand out:

$$z(m, n) = \begin{cases} Z(m, n) & Z(m, n) \\ 0 & \text{otherwise} \end{cases}. \tag{10}$$

Step 2: Fuzzification.

Using Eq. (8) maps the final output of steerable filters $z(m, n)$ into fuzzy field and gets $w(m, n)$. The parameters of the membership function directly affect the result of fuzzification. In our algorithm, the parameters depend on the mean and variance of the final output of steerable filters.

$$\begin{cases} a_1 = m - \delta/2 & a_3 = m + 5\delta/2 \\ a_2 = m + 3\delta/2 & a_4 = z_{\max} \end{cases} \tag{11}$$

where m and δ are the mean and standard deviation of the final output of steerable filters, z, respectively. $z_{\max}$ is the maximum value of z.

Step 3: Normalization.

Because the output of fuzzification is mapped into [0, 1], we normalize the original palmprint image by the following function:

$$\gamma = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{12}$$

where x is the gray level of the original palmprint image, $x_{\min}$ and $x_{\max}$ are the minimum and maximum gray levels of the palmprint image. If the function γ is considered as a fuzzy membership function, the normalized image can also be seen a fuzzification image.

Step 4: Calculate the values of $g(m, n)$.

Using Eq. (9) calculates the value $g(m, n)$ and implements the image enhancement in the fuzzy domain.

Step 5: Map into the image filed.

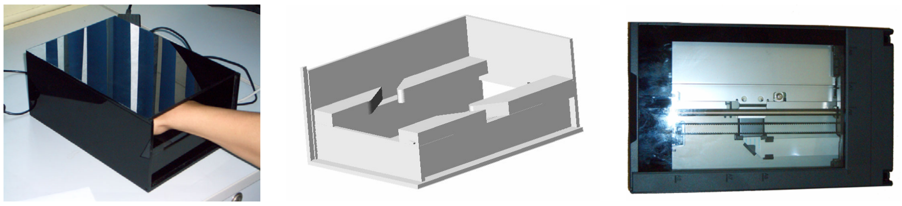
The enhanced image in fuzzy field should be mapped to gray levels:

$$y(m, n) = \frac{L(g(m, n) - g_{\min})}{g_{\max} - g_{\min}} \tag{13}$$

where $y(m, n)$ is the enhanced image pixel gray level, g_{max} and g_{min} are the maximum and minimum values of $g(x, y)$, respectively. L is the maximum gray level of the enhanced image, and it means that the dynamic range of the enhanced image is in $[0, L]$.

5. EXPERIMENTAL RESULTS AND DISCUSSION

In this paper, we develop a scanner-based device to capture palm images. The scanner is a Fujitsu fi-60F high speed flatbed scanner, and it is enclosed in an organic glass box. The whole device is shown in Fig. 6 (a), and its internal structure and the fi-60F scanner are shown in Figs. 6 (b) and (c), respectively. The device is used to capture images of both hands from 80 individuals. The device has not fixed pegs to restrict the palm movement, rotation and stretch. It only uses four bars and a groove between the two bars in each side to avoid the hand removing the scanning area.



(a) (b) (c)

Fig. 6. Palmprint images capture device.

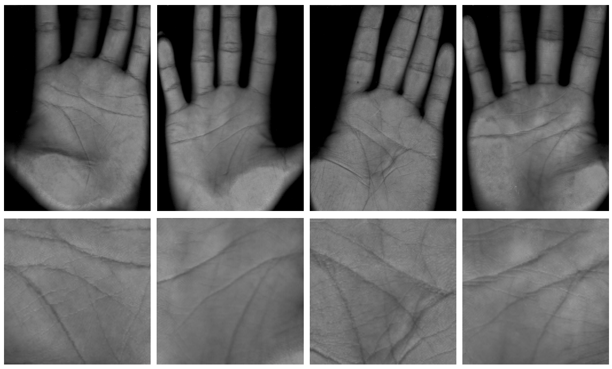
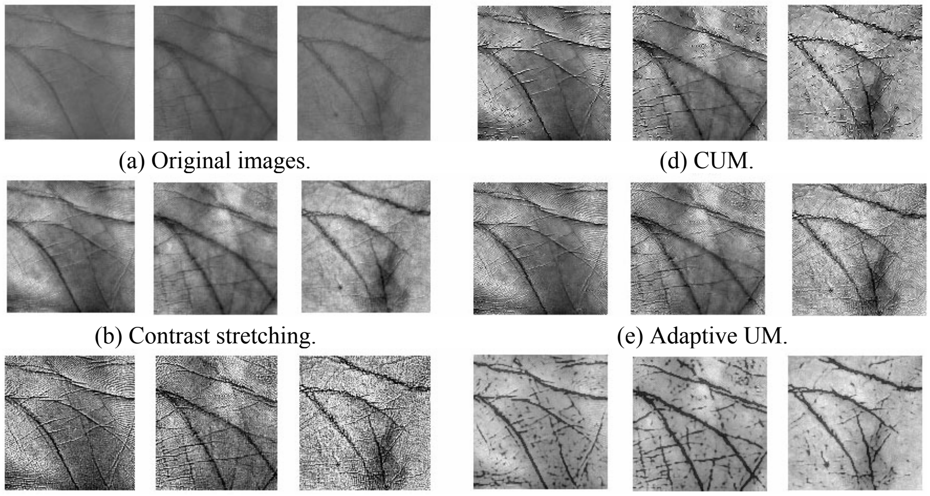


Fig. 7. Hand images and palmprint images in our database.

Ten images are captured from each hand of a person. The palm images are 292 × 413 pixels with the resolution of 72 dpi in 8-bit gray levels. A preprocessing method proposed by W. X. Li [19] is used to set up the coordinate systems for each palm image and align them. The center part of each palm is extracted and stored as palmprint images of size 128 × 128. A total of 1600 images (80 × 2 × 10) form a palmprint database. Fig. 7 shows four palm images and palmprint images in our database.



(a) Original images. (d) CUM.

(b) Contrast stretching. (e) Adaptive UM.

(c) LUM. (f) Our method.

Fig. 8. Comparison among different enhancement approaches.

Table 1. Parameters employed in different algorithms.

Algorithm	Linear UM	CUM	Adaptive UM	Our method
Parameters	$\lambda = 0.5$	$\lambda = 0.00035$	$\tau_1 = 45$, $\tau_2 = 150$, $\alpha_{dh} = 4$, $\alpha_{dh} = 3$, $\alpha_b = 1$, $\mu = 0.1$, $\beta = 0.5$	$\lambda = 0.45$, $L = 255$

In order to test the performance of the proposed algorithm, our method, contrast stretching and other unsharp masking methods (the linear UM, the cubic UM and the adaptive UM techniques) are used to enhance all palmprint images in our database, respectively. Three enhanced palmprint images by each method are selected arbitrarily to demonstrate their performance. Fig. 8 shows the results.

In Fig. 8, (a) shows the original images; (b) shows the results of contrast stretching; (c) shows the results of linear unsharp masking (LUM); (d) shows the results of cubic unsharp masking (CUM); (e) shows the results of adaptive unsharp masking (adaptive UM) and (f) shows the results of our method, respectively. Table 1 displays the parameters employed to obtain above results. In Table 1, parameters not defined in this paper are the same as in the references describing corresponding work.

In Figs. 8 (b-e), the contrast of principal lines have been enhanced, but the wrinkles still are indistinct, and there are black areas in the center part of the palm. All of these will affect the extraction of wrinkles and crotches of the principal lines. Linear unsharp masking algorithm can enhance effectively the principal lines and wrinkles, but an amount of the background noise is amplified and visible in the smooth areas, which can be demonstrated by Fig. 8 (c). On the other hand, the results of CUM and adaptive UM techniques are very similar. In both methods, a large number of noisy background pixels are restrained, but it is at the expense of weakening the medium-contrast information, which is critical for the personal identification. Comparing the results of our algorithm with that of other methods, there is less noise in homogeneous areas than linear UM method. In addition, our method not only enhances the contrast of principal lines and wrinkles, but also removes black areas in the center part of palm. From Fig. 8 (f), the wrinkles are more clear-cut, specially the wrinkles in the second enhanced palmprint image. Moreover, the shadow effect is almost eliminated and the line structures in the shadow become evident in our results. The experimental results show that our method not only reduces noise, but also effectively enhances the contrast of wrinkles in palmprint images.

From the above comparative experiment, our method demonstrates evident enhancement on the wrinkles of palmprint image. But these are only some visual results. In order to prove the effectiveness of the proposed method with respect to palmprint recognition, the palm-line detection palmprint recognition algorithm [20] is used for enhanced palmprint images in our database by each previously mention enhancement methods, respectively. The recognition results are shown in the Table 2. Because contrast stretching method is the commonly used enhancement method in palmprint recognition, the results of other methods are compared with its results.

Table 2. Comparison of recognition performance of different enhancement methods.

Recognition Rate	Contrast stretching	LUM	CUM	Adaptive UM	Our method
Palm-line detector[20]	93.75%	92.5%	94.75%	95%	97.125%

From Table 2, it can be found that the recognition rate of using LUM method to enhance palmprint images is lower than that of using contrast stretching method. It is because that a lot of amplified background noise causes a confused disturbance for the operation of the brightness comparison in a local area of palm-line detector. Moreover, the recognition rates of using CUM and Adaptive UM methods are higher than that of using contrast stretching method, but they are lower than that of using our method to enhance palmprint images. That is because our method effectively enhanced the contrast of palm lines, especially wrinkles, and less noise in homogeneous areas.

6. CONCLUSIONS

In this paper, a steerable filters based fuzzy unsharp masking method is proposed for palmprint image enhancement by introducing steerable filters and the fuzzy set theory into the unsharp masking scheme. A half open membership function is designed to highlight the intermediate frequency components of the output of steerable filters so as to enhance the contrast of wrinkles, which is significantly propitious for extracting line features. The experimental results demonstrate that the proposed approach can not only effectively enhance the contrast of principal lines and wrinkles in the palmprint image visually, but also obtain better recognition rate. In summary, the steerable filters based fuzzy unsharp masking method is simple and effective enhancement approach of the palmprint images for palmprint recognition.

REFERENCES

1. D. Zhang, W. K. Kong, J. You, and M. Wong, "Online palmprint identification," *Pattern Analysis and Machine Intelligence*, Vol. 25, 2003, pp. 1041-1050.
2. R. C. Gonzales and R. E. Woods, *Digital Image Processing*, 2nd ed., Prentice-Hall, New Jersey, 2002,
3. Y. H. Lee and S. Y. Park, "A study of convex/concave edges and edge-enhancing operators based on the Laplacian," *IEEE Transactions on Circuits and Systems*, Vol. 37, 1990, pp. 940-946.
4. S. K. Mitra, H. Li, I. S. Lin, and T. H. Yu, "A new class of nonlinear filters for image enhancement," in *Proceedings of International Conference on Acoustics*, *Speech*, *and Signal Processing*, Vol. 4, 1991, pp. 2525-2528.
5. N. Strobel and S. K. Mitra, "Quadratic filters for image contrast enhancement," in *Proceedings of the 28th Asilomar Conference on Signals*, *Systems and Computers*, Vol. 1, 1994, pp. 208-212.
6. G. Ramponi, "A cubic unsharp masking technique for contrast enhancement," *Signal Processing*, Vol. 67, 1998, pp. 211-222.
7. A. Polesel, G. V. Ramponi, and J. Mathews, "Image enhancement via adaptive unsharp masking," *IEEE Transactions on Image Processing*, Vol. 9, 2000, pp. 505-510.
8. W. T. Freeman and E. H. Adelson, "The design and use of steerable filters," in *Proceedings of IEEE International Conference on Pattern Analysis and Machine Intelligence*, Vol. 13, 1991, pp. 891-906.
9. A. F. Laine and C. M. Chang, "De-noising via wavelet transforms using steerable filters," in *Proceedings of IEEE International Symposium on Circuits and Systems*, Vol. 3, 1995, pp. 1956-1959.
10. C. Burlacu and G. Burlacu, "Color image segmentation using steerable filters," in *Proceedings of International Symposium on Circuits and Systems*, Vol. 1, 2005, pp. 347-350.
11. M. Jacob and M. Unser, "Design of steerable filters for feature detection using canny-like criteria," in *Proceedings of IEEE International Conference on Pattern Analysis and Machine Intelligence*, Vol. 26, 2004, pp. 1007-1019.
12. H. J. Zimmermann, *Fuzzy Set Theory and Its Applications*, 4th ed., Kluwer Academic Publishers, Boston/Dordrecht/London, 2001.
13. Y. J. Lai and C. L. Hwang, *Fuzzy Mathematical Programming: Methods and Applications*, Springer-Verlag, Berlin Heidelberg, 1992.
14. H. D. Cheng, Y. H. Chen, and Y. Sun, "A novel fuzzy entropy approach to image enhancement and thresholding," *Signal Processing*, Vol. 75, 1999, pp. 277-301.
15. J. Hsieh, "Image enhancement with a fuzzy logic approach," *Electronics Letters*, Vol. 31, 1995, pp. 708-710.
16. Y. S. Choi and R. Krishnapuram, "A robust approach to image enhancement based on fuzzy logic," *IEEE Transactions on Image Processing*, Vol. 6, 1997, pp. 808-825.
17. F. Farbiz, M. B. Menhaj, S. A. Motamedi, and M. T. Hagan, "A new fuzzy logic filter for image enhancement," *IEEE Transactions on Systems*, *Man and Cybernetics – Part B*, Vol. 30, 2000, pp. 110-119.
18. G. J. Liu, J. H. Huang, X. L. Tang, and J. F. Liu, "A novel fuzzy wavelet approach to contrast enhancement," *Machine Learning and Cybernetics*, Vol. 7, 2004, pp. 4325-

4330.
19. W. X. Li, D. Zhang, *et al.*, "Texture-based approach to palmprint retrieval for personal identification," in *Proceedings of Multimedia Storage and Retrieval*, Vol. 4315, 2000, pp. 415-424.
20. L. Liu and D. Zhang, "Palm-line detection," in *Proceedings of IEEE International Conference on Image Processing*, Vol. 3, 2005, pp. 269-272.

Yanxia Wang (王艳霞) was born in Liaoning, China in 1977. She received the B.S. degree and M.S. degree form Dalin Polytechnic University, Dalian, China in 1999 and 2003 respectively. She is currently working on the Ph.D. degree at the Institute of Information Science, Beijing Jiaotong University, Beijing, China. Her research interests include image processing, palmprint recognition, *etc.*

Qiuqi Ruan (阮秋琦) was born in 1944. He received the B.S. and M.S. degrees from Beijing Jiaotong University, China in 1969 and 1981 respectively. From January 1987 to May 1990, he was a visiting scholar in the University of Pittsburgh, and the University of Cincinnati. Subsequently, he has been a visiting professor in USA for several times. Now he is a professor, doctorate supervisor and the head of the school of computer and information technology, Northern Jiaotong University. He is also the head of the institute of information science and the school of software, Northern Jiaotong University. He is a senior member of IEEE. His main research interests include digital signal processing, computer vision, pattern recognition, and virtual reality, *etc.*