Jurnal Teknologi

Full paper

Adaptive Fuzzy Switching Noise Reduction Filter for Iris Pattern Recognition

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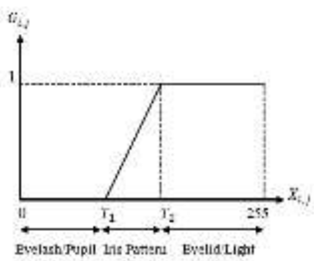
Article history

Received: 15 August 2014
Received in revised form:
5 November 2014
Accepted: 1 February 2015

Graphical abstract



Abstract

Noise reduction is a necessary procedure for the iris recognition systems. This paper proposes an adaptive fuzzy switching noise reduction (AFSNR) filter to reduce noise for iris pattern recognition. The proposed low complexity AFSNR filter removes noise pixels by fuzzy switching between an adaptive median filter and the filling method. The threshold values of AFSNR filter are calculated on the basis of the histogram statistics of eyelashes, pupils, eyelids, and light illumination. The experimental results on the CASIA V3.0 iris database, with genuine acceptance rate equals 99.72%, show the success of the proposed method.

Keywords: Iris pattern recognition, iris normalization, noise reduction, eyelash detection, fuzzy switching median, fuzzy weighted median.

Abstrak

Noise reduction is a necessary procedure for the iris recognition systems. This paper proposes an adaptive fuzzy switching noise reduction (AFSNR) filter to reduce noise for iris pattern recognition. The proposed low complexity AFSNR filter removes noise pixels by fuzzy switching between an adaptive median filter and the filling method. The threshold values of AFSNR filter are calculated on the basis of the histogram statistics of eyelashes, pupils, eyelids, and light illumination. The experimental results on the CASIA V3.0 iris database, with genuine acceptance rate equals 99.72%, show the success of the proposed method.

Kata kunci: Iris pattern recognition, iris normalization, noise reduction, eyelash detection, fuzzy switching median, fuzzy weighted median.

1.0 INTRODUCTION

Among all biometric modalities, such as fingerprint, face, iris, hand, and palm vein, iris is becoming more popular due to its high discrepancy power in recognizing or verifying individuals. Hence, iris recognition has been used in numerous fields, such as authentication of peoples at airports, immigration and border controls, banks, commercial buildings, ATM machines and e-commerce applications, and healthcare [1]. The interesting characteristics of the iris patterns are its uniqueness and stability for each individual over the lifetime [2].

Iris recognition system contains several procedures, such as image acquisition, image pre-processing, segmentation, region normalization, image enhancement, features extraction, and encoding and matching [1]. Although iris recognition system has high accuracy with very low false acceptance rate, the system performance can be affected by noise similar to other authentication system. In iris recognition, the textures, such as eyelashes and eyelids, or light reflections in the iris regions are considered as noise [3]. Very low intensity value of eyelash pixels or high intensity values of pixels corresponding to eyelids and light illumination in the iris image can cause inappropriate threshold value, and therefore, leads to poor iris region segmentation and feature extraction/encoding stage. Several methods have been proposed to remove and eliminate noise in the segmentation stage, and several noise reduction methods have also been proposed [3]-[7]. Kong and Zhang classified eyelash textures into multiple and separable eyelashes. They eliminated the eyelashes by applying the variance and 1D Gabor wavelet [3]. Huang et al. [4] removed the low intensity values of eyelash and pupil pixels with the fusion of the information of edge and region using the phase congruency. Tan et al. [5] applied a learned predicted method to detect the textures of eyelashes and shadows using the intensity statistics of iris patterns. Studies by Huang et al. [4] detected the noise region mask and removed noise region using filling method. Moreover, Masek [6] filled the noise pixels with the mean value of the iris pattern. Monemoto et al. [7] filled the noise pixels with a sample iris pattern from a partial iris region. Dehkordi et al. [8] detected noise region using multiple thresholding and filled the noise pixels with the iris pattern region's average value. In a separate approach, Aydi et al. [9] proposed a method to detect the eyelid and eyelashes. They detected the eyelids using the Radon transform and polynomial curve fitting and Least Squares Fitting method. The eyelash texture was detected using diagonal gradient and thresholding. Wang et al. [10] proposed an eyelash detection method based on expectation maximization (EM) and Gaussian Mixture Model (GMM). However, even though these proposed methods provide a better iris region extraction, the remaining pixels corresponding to the eyelash, pupil, eyelids, and light in the normalized iris image can cause poor feature encoding and iris code matching. Hence, the noise reduction procedure should be applied after the normalization stage.

Several researchers have proposed the noise reduction approaches applied on the normalized iris region. Min and Park [11] separated the eyelash region by applying the parabolic Hough transform and Otsu's method to the normalized iris image. In another approach, Zhang et al. [12] applied the 5 x 5 median filter on the neighboring pixels in the direction of the eyelashes using the perpendicular axis. However, the iris pattern around the eyelash region became slightly blurred.

The high contrast of eyelids/light illumination and eyelash/pupil is similar to characteristics of salt-and-pepper noise, which is a type of impulse noise. There are some studies proposed for removing salt-and-pepper and impulse noises, such as Chen and Wu [13], who proposed adaptive impulse detector with center-weighted median filter (ACWM), and Zhang and Karim [14], who proposed Laplacian switching-median filter, that could not filter high levels of salt-and-paper noises. Srinivasan and Ebenezer [15] proposed the decision-based algorithm (DBA) filter and Deng et al. [16] proposed the open-close sequence (OCS) filter based on mathematical morphology [16], which filter high-density salt-and-pepper noises but have high computational times [17]. Russo [18] presented the fuzzy inference ruled by else-action (FIRE) filter; his method was based on fuzzy rules and fuzzy sets. Recently, fuzzy set theory is employed more for noise reduction in image processing, such as fuzzy filter proposed by Luo [19]. Toh et al. [20] proposed a fuzzy switching median (FSM) filter. Their proposed filter contains two parts the salt-and-pepper noise detection and fuzzy noise cancelation. The fuzzy set employed in this method does not required tuning of parameters and training scheme. Toh and Isa [21] proposed a new type of salt-and-pepper noise filter called the noise adaptive fuzzy switching median (NAFSM) filter. The NAFSM filter is a combination of the simple adaptive median filter proposed by Ibrahim et al. [22] and their previous study: fuzzy switching median filter presented in [20].

In this paper, we proposed an adaptive fuzzy switching noise reduction (AFSNR) filter. The method modifies the NAFSM filter proposed in [21] combined with the filling method proposed in [8]. Our proposed method is a combination of fuzzy switching, adaptive median filter, and filling method. The adaptive size of the filtering window speeds up the system and filters high-density noise. Fuzzy switching behavior enables the filling method to perform noise reduction when the adaptive median filter fails to reduce the noise. The filling method is suitable for high density of noise such eyelids, light illumination and pupil region and thick eyelashes however, filling method fails to remove low density of noise. Therefore, we provide a fuzzy switching combination of two methods [21] , [8] to remove the fuzzy distribution of noise. This combination provides better noise reduction, while speeding up the procedure. Computation of threshold values and detection of noise pixels for pupil/eyelash and eyelid/light illumination is based on the intensity values and histogram statistics of iris patterns and noise pixels.

The contents of this paper are outlined as follows: section two explains the proposed method, which computes the threshold value corresponding to eyelash, pupil, eyelids, and light illumination using their histogram statistics. This section provides the explanation about the proposed AFSNR filter. Section three presents the experimental results of the proposed method, and the last section is devoted to the conclusion.

2.0 NOISE REDUCTION FOR IRIS RECOGNITION

This section will give detailed accounts for each stage in iris recognition system. In particular, we will focus on the pre-processing stage, segmentation, normalization, and reduction stages. Fig. 1 shows the flowchart of the iris recognition system and proposed method.

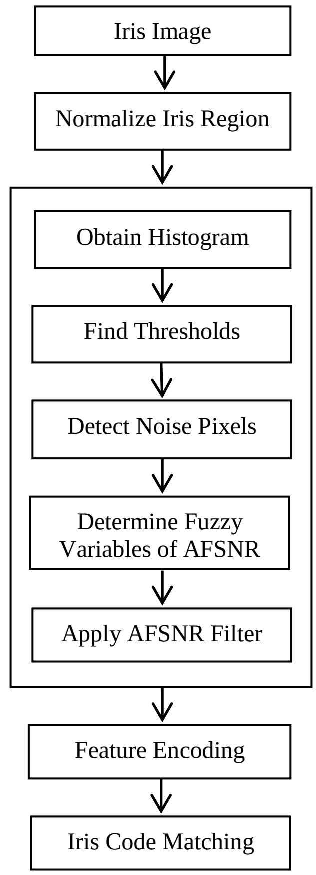


Figure 1 Flowchart of System

In the iris segmentation stage, the iris and pupil are first localized. Then, the circular iris region is extracted within the eye image. In this work, we apply Canny edge detection, followed by circular Hough transform function that is proposed by Wildes [23]. Next, we map the extracted iris region from a ring shape to rectangular shape by mapping the Cartesian coordinates to normalized polar coordinates using Daugman's rubber sheet model (see Fig. 2) [1]. The normalization mapping [1] is shown as follow:

$$I\big(x(r,\theta), y(r,\theta)\big) \rightarrow I(r,\theta) \qquad (1)$$

where $I(x, y)$ is the circular iris image, $I(r, \theta)$ is the normalized iris image, θ belongs to the interval of [0, 2π], and $x = r\cos(\theta)$, $y = r\sin(\theta)$ [1].

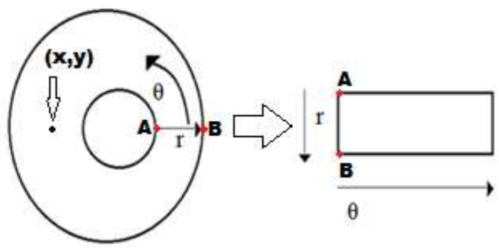


Figure 2 Daugman's Rubber sheet model for the normalization of the iris region

The proposed method performs the noise intensities detection and computes the eyelash/pupil and eyelid/light illumination thresholds and finds the location of the "noise pixels." When a pixel is detected as noise, the proposed AFSNR filter is applied on it. Otherwise, a pixel is classified as "iris pattern," and it will be preserved.

We utilize the normalized iris image histogram to obtain threshold values corresponding to eyelash/pupil and eyelid/light illumination noise. In the histogram of the normalized iris image, pixels corresponding to eyelash and pupil are concentrated in the low intensity values, whereas, eyelids and light illumination pixels have very high intensity values, which are almost located at the high intensity values of the image's dynamic range. We denote this histogram as $h(s_k) = n_k$, where k indicates the k^{th} gray level $k = (1,2,\ldots,255)$, s_k is the intensity value, n_k is number of pixels for the k^{th} gray level, and n is the total number of pixels within the normalized iris region [24].

Fig. 3 shows an example of a histogram for a normalized iris image. We classify the histogram $h(s_k)$ into 3 classes: pupil/eyelash, iris pattern, and eyelids/light illumination. Note that *A* is the threshold value corresponding to the pupil region, *B* is the threshold value for the eyelash region, and *E* is the thresholds value for the eyelid/light reflections region. Points labeled *C* and *D* indicate the values at $h(s_B)$ and $h(s_E)$, respectively. The calculation of the threshold values corresponding to each class starts from the peak of the histogram labeled as *Peak* with intensity value of s_{Peak}.

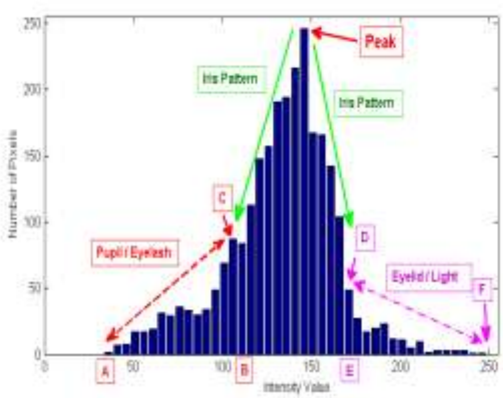


Figure 3 The classification of the noise and iris patterns in the normalized iris image's histogram

To find the threshold values corresponding to eyelash/pupil and eyelid/light illumination, we find the maximum of histogram distribution in the particular intervals in contrast with [21], which finds the local maximum or the histogram peak. Note that the maximum of the histogram in a particular interval is different with a local maximum or the peak of the histogram (see Fig. 3). To find the threshold value of eyelash/pupil T_1, we start a search in intensity values less than $s_{peak} - \sigma^2$ in small intervals for a size of l. Here, l is 25% of the variance of the histogram distribution σ^2. By finding $s_k, (k = s_{peak} - \sigma^2 - l, \ldots, s_{peak} - \sigma^2)$, through the maximum value of $h(s_k)$ which should be less than $h(s_{peak} - \sigma^2)$ and greater than the local maximum of the eyelash region, the threshold value of the eyelash/pupil, T_1 is evaluated. Similarly, the threshold value of eyelid/light, T_2 is calculated by obtaining s_k through the maximum value $h(s_k)$ for $k = s_{peak} + \sigma^2, \ldots, s_{peak} + \sigma^2 + l$.

Once the threshold values are found, we can detect the possible "noise pixels" in the image. Next, the detected "noise pixels" are represented in a bitwise mask $N(i,j)$ as follows:

$$N(i,j) = \begin{cases} 1, X(i,j) < T_1 \ or \ X(i,j) > T_2 \\ 0, \ otherwise \end{cases} \qquad (2)$$

Where $X(i,j)$ represents the pixel with intensity value X at location (i,j). $N(i,j) = 1$ represents "noise pixels" to be removed from the iris image using next filtering stage, while $N(i,j) = 0$ represents the "iris pattern" to be preserved. Therefore, the criterion of method can be given by:

$$y_{i,j} = \begin{cases} g_{i,j}: & N_{i,j} = 1 \\ X_{i,j}: & otherwise \end{cases} \qquad (3)$$

Here, $g_{i,j}$ represents the AFSNR filter output, and $y_{i,j}$ is the corrected image after noise reduction. The AFSNR filter has an adaptive square filtering window with odd $(2r+1) \times (2r+1)$ size. The number of "noise pixels," $D_{i,j}$ in the AFSNR filtering window is calculated as follows:

$$D_{i,j} = \sum_{m,n \in (-r,\ldots,0,\ldots,r)} N(i+m, j+n) \qquad (4)$$

If the number of noise pixels $D_{i,j}$ in the window reaches its maximum (i.e., $D_{i,j} = (2r+1) \times (2r+1)$), then the AFSNR window will expand by one pixel on each side (i.e., $r \leftarrow r+1$). The method continues expanding the window until the criterion of $0 < D_{i,j} < (2r+1) \times (2r+1)$ halts the procedure. For each "noise pixel," the initial size of the window is 3 × 3 (i.e., r = 1) and the maximum size of the window is 7 × 7. In contrast with [21], which selects "noise free pixels" for the median filter, we use "noise pixels" to avoid blurring the "iris patterns."

The AFSNR filtering is based on fuzzy switching between the adaptive median filter and filling method. When the median filter is not able to perform corrections on "noise pixels," the Fuzzy switching mechanism switched the adaptive median filter to the filling method. The value of filling method, *w*, is given as follows:

$$w = \begin{cases} w2: & \mathrm{T}_2 \leq X_{i,j} \leq 255 \\ w3: & \mathrm{T}_1 \leq X_{i,j} < \mathrm{T}_2 \\ w1: & 0 \leq X_{i,j} < \mathrm{T}_1 \end{cases} \qquad (5)$$

Where parameters w_1, w_2, and w_3 are average values corresponding to eyelash/pupil, eyelid/light, and iris patterns, respectively. The values of filling method can be computed as follows:

$$w_1 = \frac{\sum_{k=0}^{T_1} h(s_k) \times s_k}{\sum_{k=0}^{T_1} h(s_k)} \qquad (6)$$

$$w_2 = \frac{\sum_{k=T_2}^{255} h(s_k) \times s_k}{\sum_{k=T_2}^{255} h(s_k)} \qquad (7)$$

$$w_3 = \frac{\sum_{k=T_1}^{T_2} h(s_k)\times s_k}{\sum_{k=T_1}^{T_2} h(s_k)} \tag{8}$$

By applying the filling method, the eyelash/pupil pixels will be replaced by $w1$, and the eyelid/light pixels will be replaced by $w2$.

Next, we determine the fuzzy variable, $d_{i,j}$. In contrast to [21], in which the fuzzy input variable is the maximum value of the absolute gradient (luminance difference) in the filtering window, we determine the total number of "noise pixels" per window size as the fuzzy input variable given by

$$d_{i,j} = \frac{D_{i,j}}{(2r+1)^2} \tag{9}$$

Fig. 4 shows the fuzzy set $f_{i,j}$, and the fuzzy input variable $d_{i,j}$. The fuzzy set $f_{i,j}$ is represented as follows:

$$f_{i,j} = \begin{cases} 0: 0 \le d_{i,j} < L_1 \\ \frac{d_{i,j}-L_1}{L_2-L_1}: L_1 \le d_{i,j} < L_2 \\ 1: \quad otherwise \end{cases} \tag{10}$$

Where $L_1 = 0.3$ and $L_2 = 0.5$ are the threshold of the fuzzy set to perform fuzzy switching between the adaptive median filter and filling method (see Fig. 4). Upper threshold L_2 indicates that if more than half of the filtering window contains noise pixels, the adaptive median filter should be switched to the filling method. Lower threshold L_1 indicates that if the total number of noise pixels in the window does not reach 0.3 of the window size, the AFSNR filter switches the filling method to the adaptive median filter.

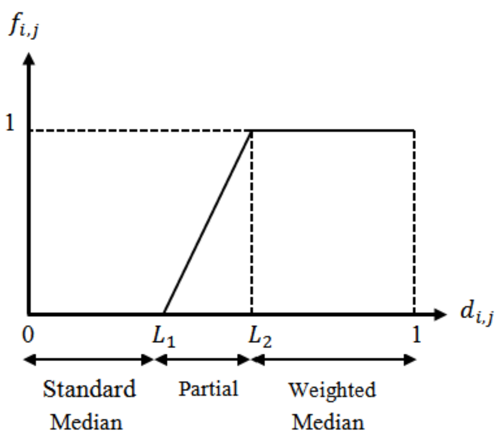


Figure 4 Fuzzy set adopted by fuzzy switching weighted median filter

To perform AFSNR filtering between eyelid/light and eyelash/pupil "noise pixels," we determine the intensity values of "noise pixels," with $X_{i,j}$ as the fuzzy input variable. Fig. 5 shows the fuzzy set $G_{i,j}$ and the fuzzy input variable $X_{i,j}$. The fuzzy set $G_{i,j}$ is represented as follows:

$$G_{i,j} = \begin{cases} 0: 0 \le X_{i,j} < T_1 \\ \frac{X_{i,j}-T_1}{T_2-T_1}: T_1 \le X_{i,j} < T_2 \\ 1: \quad otherwise \end{cases} \tag{11}$$

Where T_1 and T_2 are the threshold values of eyelash/pupil and eyelid/light, respectively.

For the output of the AFSNR filter, $g_{i,j}$ is the modification to include the correction terms to works presented in [19-21]. The correction term $g_{i,j}$ adopted by the proposed AFSNR filter is presented in (12).

$$g_{i,j} = (1 - f_{i,j})m_{i,j} + f_{i,j}w \quad with\ N(i,j) = 1 \tag{12}$$

Where $m_{i,j}$ represents the median filter of pixels in the $(2r+1) \times (2r+1)$ window given in (13), and w represents the filling filter of pixels in the $(2r+1) \times (2r+1)$ window given in (5).

$$m_{i,j} = median\{X_{i+m,j+n}\},\ with\ m,n \in (-r,.,0,\dots,r)\ and\ N\_(i,j) = 1 \tag{13}$$

The correction term $g_{i,j}$ is the combination of median filter $m_{i,j}$ and filling method filter w. The fuzzy membership value $f_{i,j}$ indicates whether the "noise pixels" replaced by the output of the median filter or by the average value corresponding to that noise or the combination of both filters.

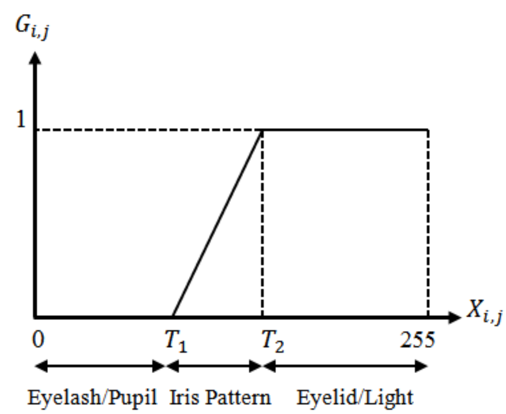


Figure 5 Fuzzy set adopted by fuzzy switching weighted median filter

The fuzzy rule base of AFSNR filter comprises five conditional IF–THEN–ELSE statements. The algorithm for choosing the maximum operator for $d_{i,j}$ in fuzzy rule base is taken from [20].

IF ($d_{i,j}$ is high) AND ($G_{i,j}$ is large)
THEN ($f_{i,j}$ is large) AND (w is small)
IF ($d_{i,j}$ is high) AND ($G_{i,j}$ is small)
THEN ($f_{i,j}$ is large) AND (w is large)
IF ($d_{i,j}$ is medium) AND ($G_{i,j}$ is large)
THEN ($f_{i,j}$ is medium) AND (w is small)
IF ($d_{i,j}$ is medium) AND ($G_{i,j}$ is small)
THEN ($f_{i,j}$ is medium) AND (w is large)
IF ($d_{i,j}$ is small)
THEN ($f_{i,j}$ is small) AND (w is medium)
ELSE ($f_{i,j}$ is zero) (14)

The first rule is to fill eyelid/light pixels. ($f_{i,j}$ is large) means that standard median filter is switched to weighted median filter. The second rule aims to remove the high occlusions by pupil pixels or tick eyelashes. Second rule provide noise reduction for pixels with low intensity values. The third rule aims to filter moderate occlusions with eyelid/light pixels. The fourth rule aims to filter the moderate occlusions with eyelash/pupil pixels. The fifth rule process the median filtering for small occlusions. When $f_{i,j}$ is zero, the AFSNR filter processes the adaptive median filter to remove the noise pixels.

For extracting and encoding the iris features of the iris pattern information, the 2D Gabor wavelet filters as proposed by Daugman [1] is applied. The corresponding equation is reproduced as follows:

$$G(x,y) = e^{-\pi\left[\frac{(x-x0)^2}{\alpha^2}+\frac{(y-y0)^2}{\beta^2}\right]} e^{-2\pi[u0(x-x0)+v0(y-y0)]} \quad (15)$$

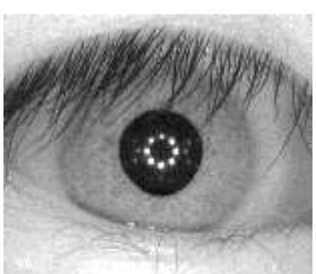
Finally, the produced bitwise iris code (*codeA*) and the enrolled bitwise iris code (*codeB*) are compared in the matching stage using the Hamming distance [1]. The one that gives the minimum disagreement distance will be chosen as the identified person. The Hamming distance operator obtained from [1] is reproduced as follows:

$$HD = \frac{\|(codeA \otimes codeB) \cap (maskA \cap maskB)\|}{\|(maskA \cap maskB)\|} \quad (16)$$

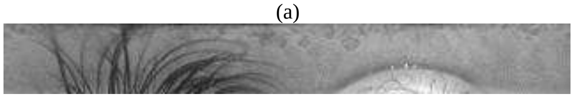
3.0 EXPERIMENTAL

Experiments using the proposed method were performed on the CASIA V3.0 iris database from the Institute of Automation, Chinese Academy of Sciences, which contain more than 22000 iris images from the more than 700 individuals. CASIA V3.0 iris image data base contains 3 subsets; an indoor subset with 395 classes and 2639 images, an indoor with lamp subset with 819 classes and 16213 iris images and an outdoor subset with 400 classes and 3183 iris images. All images are stored in a 8 bit-gray level JPEG format [25]. In the following experiments, we chose S1090R01, S1109L03, S1175L01, and S1001L01 iris images from the database, as shown in Figs. 6, 7, 8, and 9, respectively. In each of the following figures, the first row depicts the original input image. The second row shows the normalized iris region. The third row shows the results of applying the standard 5 x 5 median filter. The fourth row shows the results of applying the filling method. The last row shows the results of applying our proposed method.

As shown in Figs. 6 and 7, when the iris region is occluded by thick eyelash textures, the standard median filter is not able to remove them (see Figs. 6c and 7c). Meanwhile, the filling method is not able to remove the ends of eyelash lines and thin eyelashes (see Figs. 6d and 7d). Results of the proposed AFSNR filter are shown in Figs. 6e and 7e. The adaptive behavior of our proposed filter generates better results of the reduction of thin or single eyelash lines compared with the standard median filter, while switching the behavior of the proposed filter avoids blurring or the loss of iris patterns and performs better reduction of eyelash/pupil and eyelids/light textures.

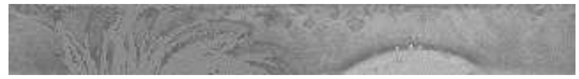


(a)



(b)

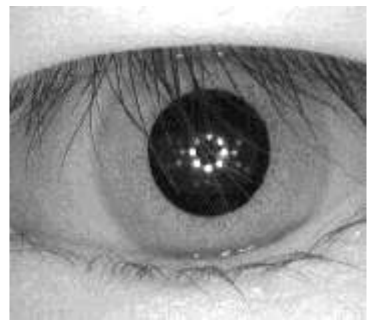
(c)



(d)

(e)

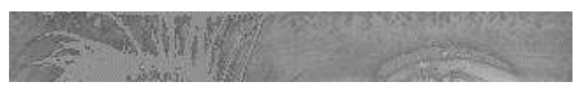
Figure 6 (a) Original Image (S1090R01), (b) normalized iris image, (c) results of the reduction of eyelash/pupil obtained by the standard median filter [12], (d) results of the reduction of eyelash/pupil and eyelid/light obtained by the filling method [8], (e) results of the reduction of eyelash/pupil and eyelid/light by applying our proposed AFSNR filter.



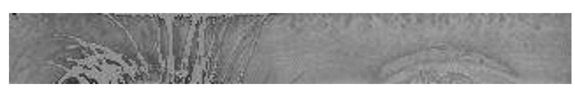
(a)

(b)

(c)



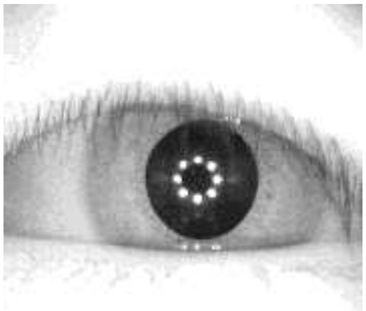
(d)



(e)

Figure 7 (a) Original image (S1109L03), (b) normalized iris image, (c) results of the reduction of eyelash/pupil obtained by the standard median filter [12], (d) results of the reduction of eyelash/pupil and eyelid/light obtained by the filling method [8], (e) results of the reduction of eyelash/pupil and eyelid/light by applying our proposed AFSNR filter.

Fig. 8 shows the experiment where the iris region is occluded by multiple eyelash lines and eyelids. Fig. 8c shows that the standard median filter failed to remove eyelashes in the eyelid area and the multiple eyelash lines on the top of normalized iris image. From Fig. 8d it can be observed that the filling method has failed to preserve the iris patterns between the eyelash pixels. Fig. 8e shows that our proposed method was able to preserve the iris patterns between the eyelash lines and remove the eyelashes in the eyelid area. As shown in Fig. 9, the standard median filter was able to remove separate eyelash lines, but it failed to remove multiple eyelash lines in the eyelid region (see Fig. 9c). In addition, it can be observed that the filling method is not able to remove thin separate eyelash lines, while the standard median filter perform better reduction of these lines (Fig. 9d). Fig. 9e shows that by adaptive fuzzy switching between the median filter and filling method, the proposed AFSNR method has performed better noise reduction.



(a)

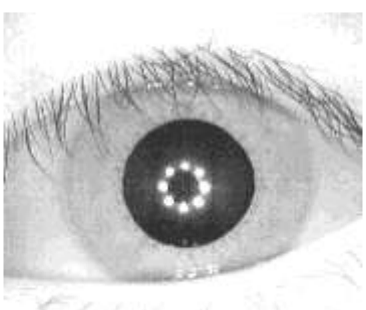
(b)

(c)

(d)

(e)

Figure 8 (a) Original image (S1175L01), (b) normalized iris image, (c) results of the reduction of eyelash/pupil obtained by the standard median filter [12], (d) results of the reduction of eyelash/pupil and eyelid/light obtained by the filling method [8], (e) results of the reduction of eyelash/pupil and eyelid/light by applying our proposed AFSNR filter.



(a)

(b)

(c)

(d)

(e)

Figure 9 (a) Original image (S1001L01), (b) normalized iris image, (c) results of the reduction of eyelash/pupil obtained by the standard median filter [12], (d) results of the reduction of eyelash/pupil and eyelid/light obtained by the filling method [8], (e) results of the reduction of eyelash/pupil and eyelid/light by applying our proposed AFSNR filter.

■4.0 RESULTS AND DISCUSSION

Since the proposed AFSNR was designed based on characteristics of salt and pepper noise and impulse noise, the advantage of the proposed AFSNR filter is the ability to remove two types of noise; eyelash/pupil and light/eyelids in contrast with other works which are presented to eliminate only one type of noise [3], [10], [12]. Another advantage of the proposed AFSNR filter is its adaptive window size. The adaptive behavior of the filter perform a better noise reduction for different noise densities compared with a method with a constant window size [12] (see Figs. 6-9). The proposed method applies some modification to the NAFSM filter presented in [21] and combined it with the filling method proposed in [8] using fuzzy switching. While a standard median filter alone is not able to remove the high noise density [12] and filling method fails to remove low density noise such as narrow eyelash lines [8], by switching between filling method and the adaptive median filter, the proposed AFSNR filter is able to remove whether high or low density noise. The fuzzy switching behavior of the proposed filter avoids blurring the iris patterns between the eyelash lines within noisy regions. (see Figs. 6-9). Comparison of system performance between method proposed in [8] with GAR = 99.6% and our proposed method in this paper with GAR = 99.72 % shows the success of method.

In our experiments, a computer PC with Intel® core™2 Duo CPU and 2.00 GHz processor was used, and the average processing time of the proposed AFSNR filter was 4.3 *ms*. Fig. 10 shows the receiver operating curves (ROC) for the proposed method in terms of the false rejection rate (FAR) and genuine acceptance rate (GAR). It can be observed that the proposed method with GAR = 100% - FRR = 99.72% has better filtering results than the standard median filter and filling method.

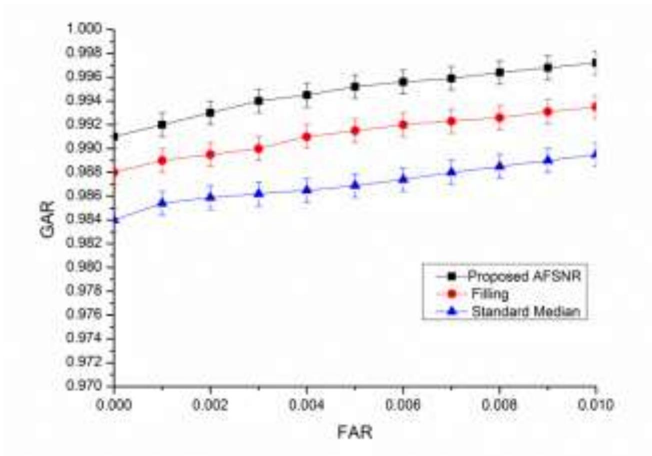


Figure 10 Receiver operating curves (ROC) of our proposed method

■5.0 CONCLUSION

In this study, we proposed an AFSNR filter to reduce noise in the iris normalization stage. The low complexity AFSNR filter with adaptive window size is aimed to remove noise with different densities by employing fuzzy switching between adaptive median filter and filling method. The threshold values of AFSNR filter corresponding to eyelash/pupil and eyelid/light pixels are evaluated using the histogram statistics of the normalized iris image. The experimental results of our proposed system shows that the GAR = 99.72%, which shows the success of the proposed method.

Acknowledgement

The authors would like to thank the Ministry of Higher Education (MOHE) and Universiti Technologi Malaysia for supporting this research under MIS scholarship.

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