

# Novel Ridge Orientation Based Approach for Fingerprint Identification Using Co-Occurrence Matrix

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**Abstract**—In this paper we use the property of co-occurrence matrix in finding parallel lines in binary pictures for fingerprint identification. In our proposed algorithm, we reduce the noise by filtering the fingerprint images and then transfer the fingerprint images to binary images using a proper threshold. Next, we divide the binary images into some regions having parallel lines in the same direction. The lines in each region have a specific angle that can be used for comparison. This method is simple, performs the comparison step quickly and has a good resistance in the presence of the noise.

**Keywords**—Parallel lines detection, co-occurrence matrix, fingerprint identification.

## I. INTRODUCTION

FINGERPRINT is considered as one of the most reliable biometric characteristics for human identification among other physical and behavioral characteristics, because of two elementary fingerprint properties, (1) persistence: i.e. basic fingerprint characteristics do not change with time, and (2) individuality: i.e. each person has a unique fingerprint. In fingerprint-based recognition system, the input fingerprint is compared with the images in the fingerprint database in order to find the best match.

There are many methods for fingerprint classification that can be generally divided into four groups. The first group includes the methods which are based on modeling fingerprint images. In these methods mathematical models are used for presenting fingerprint images. However, the exact mathematical model is difficult to determine because of the complexity of fingerprint images. In most of these methods [1] [2, the number and the positions of singular points are important characteristics to apply on]. The second group includes the methods in the frequency domain. In these methods first an image enhancement is applied and then the image is transformed into the frequency domain [3] and finally the frequency coefficients are used for comparison. The third group includes the methods based on the ridge structures. Some of these methods [4] [5] firstly find the

number and the positions of singular points, by using Poincare Index for different points. Then a fingerprint image is classified according to these singular points. The fourth group includes statistical methods. In these methods some points are considered as preliminary choices for singular points and then the real singular points are found statistically [6].

In this paper a new ridge orientation based method for fingerprint identification is proposed.

## II. PREPROCESSING AND IMAGE ENHANCEMENT

In most methods of fingerprint identification, preprocessing and image enhancement are inevitable [7]. These steps are as follows:

### A. Normalization

Generally the contrast of fingerprint images is low. Thus, image enhancement techniques are often employed so that the resulting image would have a fixed mean and contrast. The normalized image is defined as [8]:

$$N(x, y) = \begin{cases} M_0 + \sqrt{\frac{V_0(I(x, y) - M)^2}{V}} & \text{if } I(x, y) > M \\ M_0 - \sqrt{\frac{V_0(I(x, y) - M)^2}{V}} & \text{otherwise} \end{cases} \quad (1)$$

Where  $I(x, y)$ ,  $M$  and  $V$  are the gray level, mean and variance of the pixels in the original image respectively and  $N(x, y)$ ,  $M_0$  and  $V_0$  are the gray level, mean and variance of the pixels in the normalized image.

### B. Background Detection

In this step, the size of all the images is changed to the same size (256x256). Then they are divided into blocks of size of 16x16. And for each block the variance is computed. If the variance is less than a threshold, then the block is assigned to be a background region; otherwise, it is assigned to be a part of the foreground. In this method the threshold is defined locally resulting in better performance than a constant threshold for all blocks.

### C. Determination of Dominant Direction

Calculation of dominant directions is necessary for adjusting the filters at the filtering step (will be discussed later).

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To determine the directions, the Minimum Mean Square of the gradient is used in our proposed method [9].

To do so, the image is divided into blocks of size of 32x32. Then the local orientation of each block is estimated using:

$$V_x(i, j) = \sum_{u=i-\frac{w}{2}}^{i+\frac{w}{2}} \sum_{v=j-\frac{w}{2}}^{j+\frac{w}{2}} 2G_x(u, v)G_y(u, v) \quad (2)$$

$$V_y(i, j) = \sum_{u=i-\frac{w}{2}}^{i+\frac{w}{2}} \sum_{v=j-\frac{w}{2}}^{j+\frac{w}{2}} (G_x^2(u, v) - G_y^2(u, v)) \quad (3)$$

$$\theta(i, j) = \frac{1}{2} \tan^{-1} \left( \frac{V_x(i, j)}{V_y(i, j)} \right) \quad (4)$$

where  $G_y$  and  $G_x$  are the gradient vector elements in the x and y directions respectively.  $w$  has been chosen experimentally ( $w=5$ ).

#### D. Filtering

The purpose of this step is to reduce the effect of the noise. In this paper the "two-dimensional Gabor" filter is used. This filter is a low pass filter for removing the noise. By adjusting the parameters of this filter for each block, we can obtain better performance according to the local properties of the fingerprint lines. The formula of this filter is:

$$G(x, y, \theta, f) = e^{-\frac{1}{2} \left( \frac{x_\theta^2}{\sigma_x^2} + \frac{y_\theta^2}{\sigma_y^2} \right)} \cdot \cos(2\pi f x_\theta) \quad (5)$$

$$x_\theta = x \cos(\theta) + y \sin(\theta)$$

$$y_\theta = -x \sin(\theta) + y \cos(\theta)$$

where  $\theta$  is the filter direction and  $f$  is the frequency of the cosine function.  $\sigma_x$  and  $\sigma_y$  represent the gaussian standard deviations in the  $x$  and  $y$  directions.  $x_\theta$  and  $y_\theta$  are the horizontal and vertical base vectors in the coordinate system of the filter. The frequency and direction of the Gabor filter is adjusted according to the frequency and local direction of fingerprint images respectively. Then, the filter is convolved with a fingerprint image in the space domain:

$$E(i, j) = \sum_{u=i-\frac{w_x}{2}}^{i+\frac{w_x}{2}} \sum_{v=j-\frac{w_y}{2}}^{j+\frac{w_y}{2}} G(u, v, O(i, j), f) N(i-u, j-v) \quad (6)$$

where  $O$ ,  $f$  and  $N$  are the image after determining the dominant directions, the frequency of the image and the

normalized image respectively.  $w_x$  and  $w_y$  represent the length and width of the Gabor mask respectively.

Fig. 1 shows an example of applying the preprocessing and image enhancement steps on a tested fingerprint image.

### III. PARALLEL LINE DETECTION BASED ON CO-OCCURRENCE MATRIX

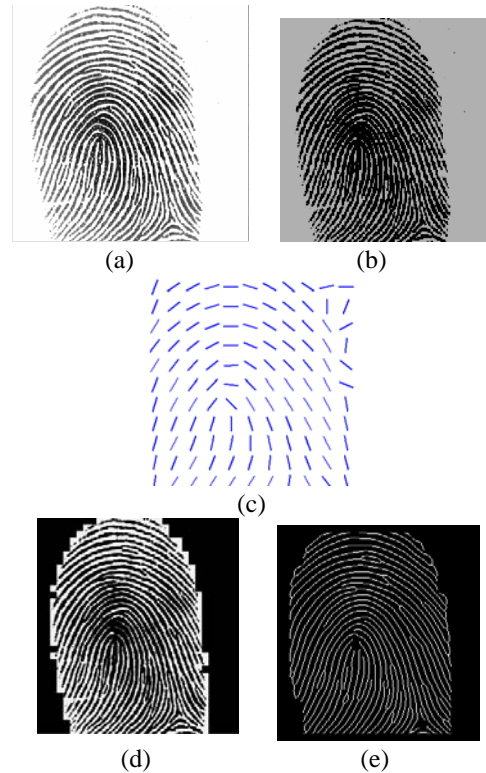


Fig. 1 Example of the preprocessing and image enhancement steps on a fingerprint image: (a) original image, (b) normalized image, (c) the dominant direction of ridges, (d) the image after Identifying the Background, (e) the image after using the Gabor filter

The proposed method is based on selecting 12 different classes in different angles from 0 to 180 degrees. For each angle a co-occurrence matrix indicating the neighborhoods of a pixel in the corresponding direction is specified. These angles and their corresponding angles are illustrated in Table I. The elements of each matrix in this table indicate the position of the pixels. Each row defines the coordinates of a neighborhood pixel. Finally, by connecting the pixels, the direction of the lines with their corresponding angle is determined.

### IV. FINGERPRINT IMAGE SEGMENTATION BASED ON CO-OCCURRENCE MATRIX

First, we divide the image into smaller blocks (32x32). This causes more lines in these blocks to be parallel. If small blocks are used, the number of pixels for testing is reduced and consequently the probability of error in the test of parallel lines is increased. On the other hand, if a large block is used, lines may have many directions. So it is hard to correctly find

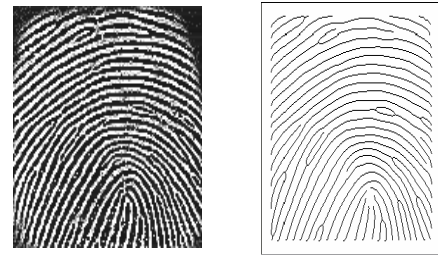
the dominant direction. Using a proper size for the image division is essential. In this paper the size of 32x32 is considered as the best choice for blocks.

TABLE I  
 12 DIFFERENT CLASSES FOR DETERMINING THE DIRECTION OF FINGERPRINT LINES AND THEIR CORRESPONDING MATRICES

| class | Angle (degree)  | Co-occurrence matrix  | class | Angle (degree) | Co-occurrence matrix  |
|-------|-----------------|---|-------|----------------|---|
| 1     | 0, 10, 170, 180 | $\begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 2 & 0 \\ 3 & 0 \\ 4 & 0 \end{bmatrix}$ | 7     | 80, 90, 100    | $\begin{bmatrix} 0 & 0 \\ 0 & 1 \\ 0 & 2 \\ 0 & 3 \\ 0 & 4 \end{bmatrix}$               |
| 2     | 20              | $\begin{bmatrix} 0 & 0 \\ 1 & 1 \\ 2 & 1 \\ 3 & 1 \\ 4 & 2 \end{bmatrix}$ | 8     | 110            | $\begin{bmatrix} 0 & 0 \\ 1 & -1 \\ 1 & -2 \\ 1 & -3 \\ 2 & -4 \end{bmatrix}$           |
| 3     | 30              | $\begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 2 & 1 \\ 3 & 2 \\ 4 & 2 \end{bmatrix}$ | 9     | 120            | $\begin{bmatrix} 0 & 0 \\ 0 & -1 \\ 1 & -2 \\ 1 & -3 \\ 2 & -3 \\ 2 & -4 \end{bmatrix}$ |
| 4     | 40, 50          | $\begin{bmatrix} 0 & 0 \\ 1 & 1 \\ 2 & 2 \\ 3 & 3 \\ 4 & 4 \end{bmatrix}$ | 10    | 130, 140       | $\begin{bmatrix} 0 & 0 \\ 1 & -1 \\ 1 & -2 \\ 1 & -3 \\ 2 & -4 \end{bmatrix}$           |
| 5     | 60              | $\begin{bmatrix} 0 & 0 \\ 0 & 1 \\ 1 & 2 \\ 2 & 3 \\ 2 & 4 \end{bmatrix}$ | 11    | 150            | $\begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 2 & -1 \\ 2 & -1 \\ 3 & -2 \\ 4 & -2 \end{bmatrix}$  |
| 6     | 70              | $\begin{bmatrix} 0 & 0 \\ 1 & 1 \\ 1 & 2 \\ 1 & 3 \\ 2 & 4 \end{bmatrix}$ | 12    | 160            | $\begin{bmatrix} 0 & 0 \\ 1 & -1 \\ 2 & -1 \\ 3 & -1 \\ 4 & -2 \end{bmatrix}$           |

After dividing the image into blocks of size of 32x32, all the co-occurrence matrices (Table I) are applied on each block. The pixels (only pixels with the value of 1) along each line are examined. For each pixel on the lines we obtain a value from 0 to 6 according to the applied matrix. 0 indicates that none of the pixels with the value one and 6 (for the classes 3, 9, 11) and 5 (for the classes 1,2,4,5,6,7,8,10,12) indicate that all of the pixels with the value of one in the neighborhood of this pixel is in the assigned direction. Co-occurrence matrices examine six neighbors. Thus the result of applying each co-occurrence matrix of different classes (as in Table I) on a block of size of 32x32 is a matrix of size of 32x32 in which the values vary from 0 to 6. The more the count of 6's of this matrix (n) is, the nearer the lines are to the assigned direction. Thus the class with the maximum 'n' defines the dominant direction in this block. Finally as all the images are 256x256 and are divided into blocks of size of 32x32, there are 64 blocks with dominant directions corresponding to the classes of 1 to 12. Thus a matrix of size of 8x8 with values between 1 to 12 is obtained. This matrix is

used for comparing and matching an unknown fingerprint image in a database. Fig. 2 shows the results of applying the above steps on the tested image. It is interesting to see that a synthesized image created based on dominant directions (Fig. 2 (e)), is so similar to the filtered image (Fig. 2 (b)). It is confirmed the success of the proposed algorithm in determining dominant directions based on the co-occurrence matrices.



|   |   |   |   |   |    |    |    |     |     |     |     |     |      |      |      |
|---|---|---|---|---|----|----|----|-----|-----|-----|-----|-----|------|------|------|
| 2 | 2 | 1 | 1 | 1 | 1  | 1  | 10 | 20° | 20° | 10° | 10° | 0°  | 0°   | 170° | 130° |
| 2 | 1 | 2 | 2 | 1 | 1  | 1  | 1  | 20° | 10° | 20° | 20° | 0°  | 0°   | 170° | 170° |
| 2 | 1 | 1 | 2 | 1 | 1  | 1  | 1  | 20° | 20° | 10° | 20° | 0°  | 0°   | 170° | 170° |
| 2 | 1 | 1 | 2 | 1 | 1  | 1  | 10 | 20° | 20° | 10° | 20° | 0°  | 0°   | 170° | 130° |
| 4 | 4 | 4 | 4 | 1 | 1  | 10 | 10 | 40° | 40° | 40° | 40° | 0°  | 0°   | 130° | 130° |
| 4 | 4 | 4 | 4 | 1 | 10 | 10 | 10 | 40° | 70° | 40° | 40° | 0°  | 130° | 130° | 130° |
| 6 | 4 | 4 | 4 | 4 | 8  | 9  | 8  | 70° | 40° | 40° | 40° | 40° | 110° | 120° | 110° |
| 6 | 6 | 6 | 6 | 9 | 7  | 8  | 8  | 70° | 70° | 70° | 70° | 70° | 90°  | 110° | 110° |

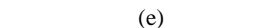
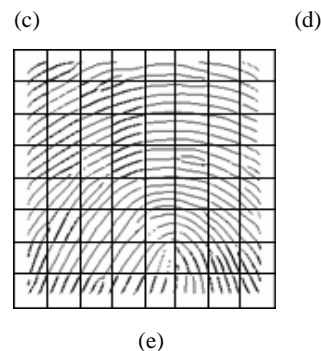


Fig. 2 Results of applying the different steps of the proposed algorithm: (a) original image, (b) filtered image after enhancement stages, (c) dominant direction classes, (d) corresponding angles to the defined classes, (e) synthesized image, created with dominant directions

### V. FINGERPRINT IDENTIFICATION

Result of applying the algorithm in the previous section is a matrix of size of 8x8 that its elements indicate the dominant directions in each block. The element of this matrix can be 1, 2, ..., 12.

Table I shows the classes and their corresponding angles. For identifying a fingerprint image in a database, first, the matrix of the dominant directions is computed for the fingerprint image under test and for all fingerprint images of the database. Then, the matrix of dominant directions of the tested fingerprint image is compared with those in the database to find the best match which has the same dominant

directions in corresponding blocks of two matrices.

## VI. EXPERIMENTAL RESULTS

The proposed method has been applied on databases including 75 and 80 fingerprints which obtained from the reference [10]. Fig. 3 shows two examples of fingerprint images in the selected databases.

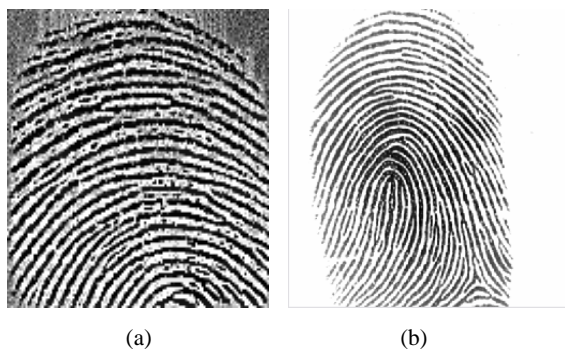


Fig. 3 Two examples of fingerprint images in the selected databases

For evaluating the results, we define a threshold and only the images with the similarity percentage more than this threshold are considered as acceptable images. Among the acceptable images, an image with the maximum similarity percentage is accepted as the final match. If this image is correctly matched, it is considered as 'True acceptance', otherwise it is considered as 'False Acceptance'. If the maximum similarity percentage is less than the threshold, the image is considered as 'Rejection'. If the threshold is low, we reduce the chance of rejection rate and increase the acceptance rate, but simultaneously the risk of false acceptance will be increased. In contrary, if we choose a high threshold, few images are considered as true or false acceptance, but the risk of rejection rate will be augmented. So, we should select a proper threshold to tradeoff between acceptance and rejection rates.

When the tested image was selected from the database and no noise was added, 100 percent for the true acceptance rate was obtained. Table II shows the result of using the proposed method for the two databases and choosing an image from the own database as the tested image. All images in the database have been tested. Note that for all selected thresholds the successful results were obtained. Table III shows the results when the tested image was selected from out of the database. For this experiment, all images of other database used as the tested images. As can be seen for the threshold of 60% and more, the exterior image is considered as having no match in the database.

TABLE II

RESULTS OF APPLYING THE PROPOSED METHOD ON THE TWO DATABASE GROUPS (THE TESTED IMAGES HAVE BEEN CHOSEN FROM OWN GROUP)

| Thresh. % | True Acceptance Rate (%) |         | False Acceptance Rate (%) |         | Rejection Rate (%) |         |
|-----------|--------------------------|---------|---------------------------|---------|--------------------|---------|
|           | Group 1                  | Group 2 | Group 1                   | Group 2 | Group 1            | Group 2 |
|           | 50                       | 100     | 100                       | 0       | 0                  | 0       |
| 55        | 100                      | 100     | 0                         | 0       | 0                  | 0       |
| 60        | 100                      | 100     | 0                         | 0       | 0                  | 0       |
| 65        | 100                      | 100     | 0                         | 0       | 0                  | 0       |
| 70        | 100                      | 100     | 0                         | 0       | 0                  | 0       |

TABLE III

RESULTS OF APPLYING THE PROPOSED METHOD ON THE TWO DATABASE GROUPS (THE TESTED IMAGES HAVE BEEN CHOSEN OUT OF OWN GROUP)

| Thresh. % | True Acceptance Rate (%) |         | False Acceptance Rate (%) |         | Rejection Rate (%) |         |
|-----------|--------------------------|---------|---------------------------|---------|--------------------|---------|
|           | Group 1                  | Group 2 | Group 1                   | Group 2 | Group 1            | Group 2 |
|           | 50                       | 0       | 0                         | 2.5     | 10                 | 97.5    |
| 55        | 0                        | 0       | 2                         | 7.5     | 98                 | 92.5    |
| 60        | 0                        | 0       | 0                         | 0       | 100                | 100     |
| 65        | 0                        | 0       | 0                         | 0       | 100                | 100     |
| 70        | 0                        | 0       | 0                         | 0       | 100                | 100     |

### A. Effect of the Noise

In this step four different noises (Poisson, Speckle, Gaussian and Salt & Pepper) have been applied on the fingerprint images. Fig. 4 shows the example of a fingerprint image on which these noises have been applied.

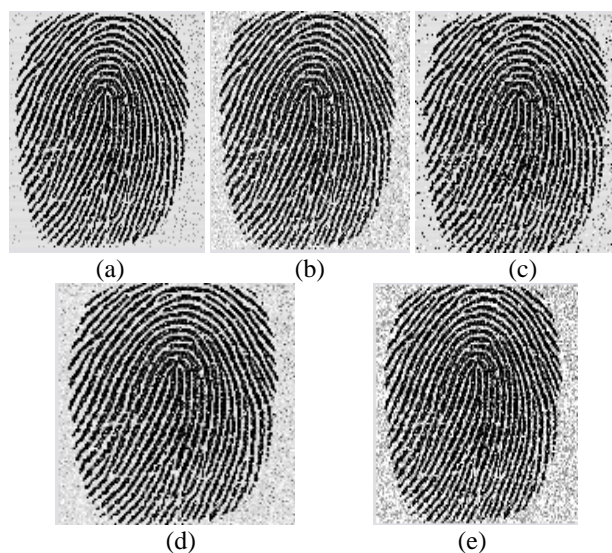


Fig. 4 Example of fingerprint image after applying different noises: (a) original image, (b) applying Gaussian noise (mean: 0 and variance: 0.01), (c) applying Salt & Pepper noise (density: 0.05), (d) applying Poisson noise, (e) applying Speckle noise (mean: 0 and variance: 0.04)

All of these noises have been applied on the tested image in each step, and the results have been compared with the original database. The results with thresholds 50%, 55%, 60%, 65% and 70% for different noises and for two databases are presented in Tables IV to VII.

As shown in the tables, true acceptance, false acceptance and rejection rates vary with thresholds. In fact the less the threshold is, the better an identification will be obtained. Note that with a less threshold external images are also considered as acceptable images. Thus a suitable and global threshold should be chosen. For the proposed method the threshold of 60% is convenient.

## VII. CONCLUSION

In this paper a new method for the fingerprint identification has been presented. The steps of the method are as follows. The first step is the preprocessing and enhancement which include normalization, identification of the background, calculation of dominant directions and filtering with the Gabor filter. Then the dominant direction of fingerprint lines in different fingerprint blocks is determined by using co-occurrence matrix. The algorithm of identifying a fingerprint image consists of comparing an 8x8 matrix (including the classes of defined directions) with the matrices of the fingerprint images in the database. This method has a good resistance to different noises and performs the comparison step quickly.

TABLE IV

RESULTS OF APPLYING THE PROPOSED METHOD ON THE TWO DATABASES IN THE PRESENCE OF GAUSSIAN NOISE

| Thresh.<br>% | True<br>Acceptance<br>Rate (%) |            | False<br>Acceptance<br>Rate (%) |            | Rejection Rate<br>(%) |            |
|--------------|--------------------------------|------------|---------------------------------|------------|-----------------------|------------|
|              | Group<br>1                     | Group<br>2 | Group<br>1                      | Group<br>2 | Group<br>1            | Group<br>2 |
|              | 50                             | 100        | 97                              | 0          | 3                     | 0          |
| 55           | 100                            | 96         | 0                               | 3          | 0                     | 1          |
| 60           | 100                            | 96         | 0                               | 1.5        | 0                     | 2.5        |
| 65           | 100                            | 92         | 0                               | 1          | 0                     | 7          |
| 70           | 100                            | 89         | 0                               | 1          | 0                     | 10         |

TABLE V

RESULTS OF APPLYING THE PROPOSED METHOD ON THE TWO DATABASES IN THE PRESENCE OF SALT & PEPPER NOISE

| Thresh.<br>% | True<br>Acceptance<br>Rate (%) |            | False<br>Acceptance<br>Rate (%) |            | Rejection Rate<br>(%) |            |
|--------------|--------------------------------|------------|---------------------------------|------------|-----------------------|------------|
|              | Group<br>1                     | Group<br>2 | Group<br>1                      | Group<br>2 | Group<br>1            | Group<br>2 |
|              | 50                             | 100        | 95                              | 0          | 5                     | 0          |
| 55           | 100                            | 93         | 0                               | 5          | 0                     | 2          |
| 60           | 98                             | 92         | 0                               | 2.5        | 2                     | 5.5        |
| 65           | 98                             | 86         | 0                               | 1.5        | 2                     | 12.5       |
| 70           | 98                             | 71         | 0                               | 1          | 2                     | 28         |

TABLE VI

RESULTS OF APPLYING THE PROPOSED METHOD ON THE TWO DATABASES IN THE PRESENCE OF POISSON NOISE

| Thresh.<br>% | True<br>Acceptance<br>Rate (%) |            | False<br>Acceptance<br>Rate (%) |            | Rejection Rate<br>(%) |            |
|--------------|--------------------------------|------------|---------------------------------|------------|-----------------------|------------|
|              | Group<br>1                     | Group<br>2 | Group<br>1                      | Group<br>2 | Group<br>1            | Group<br>2 |
|              | 50                             | 100        | 98                              | 0          | 2                     | 0          |
| 55           | 100                            | 98         | 0                               | 2          | 0                     | 0          |
| 60           | 100                            | 98         | 0                               | 2          | 0                     | 0          |
| 65           | 100                            | 87         | 0                               | 0          | 0                     | 13         |
| 70           | 100                            | 90         | 0                               | 0          | 0                     | 10         |

TABLE VII

RESULTS OF APPLYING THE PROPOSED METHOD ON TWO DATABASES IN THE PRESENCE OF SPECKLE NOISE

| Thresh.<br>% | True<br>Acceptance<br>Rate (%) |            | False<br>Acceptance<br>Rate (%) |            | Rejection Rate<br>(%) |            |
|--------------|--------------------------------|------------|---------------------------------|------------|-----------------------|------------|
|              | Group<br>1                     | Group<br>2 | Group<br>1                      | Group<br>2 | Group<br>1            | Group<br>2 |
|              | 50                             | 98         | 93                              | 0          | 7                     | 2          |
| 55           | 98                             | 91         | 0                               | 5          | 2                     | 4          |
| 60           | 98                             | 91         | 0                               | 0          | 2                     | 9          |
| 65           | 98                             | 86         | 0                               | 0          | 2                     | 14         |
| 70           | 98                             | 77         | 0                               | 0          | 2                     | 23         |

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