Enhanced convnet based Latent Finger Print Recognition

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Abstract – *Latent finger print recognition plays an important role in forensic, criminal cases etc. The latent images will not be recognised easily since they are impartial images, which find difficult to match with the registered database. Due to noisy images, it is very difficult for recognition. Autoencoder plays an important role in pre-processing the latent image. ConvNetbased method is an efficient approach used for latent image recognition. For each minutiae extraction, ConvNet descriptor is performed. Both minutiae and texture matcher is considered for comparison. This technique is compared with existing methods which shows, that the proposed method provides a higher accuracy than the existing methods like CNN, skeleton approach nonlinear mapping and product quantization. The proposed method provides an accuracy of 76.4%, 80.4% and 86.4% for rank1,5 and 10 respectively.*

Keywords: *convnet, autoencoder, texture template, minutiae extraction*

1. INTRODUCTION

Latent fingerprints, a kind of fingerprints which are taken from the finger skin impersonations at the criminality section, have been assumed to find distrusted convicts for a stretched time period. Real forensic cases, have greatly fewer sufficient result. Due to advanced technologies and experts, the difficulties present in recognition of finger prints is minimized. Quality of the image plays an important role in identification task. Latent prints are a minor section of entire finger print pattern. Latent images are taken from the surface using chemical reaction [2]. These latent prints, even if not of good quality, it is not possible for the expert to request the culprit for a clear print. Moreover, these latent prints are very much helpful in criminal investigations [6]. The fingerprint are captured using a camera from a distance. As a result, this fingerprint will be a zoomed image. It is necessary to enhance the image for further processing [20].

For enhancing the images, directional median filter [21] and an improved version called directional weighted median filter [22] is presented. Fourier transformation [23] is also used for enhancement. Hough transform [24] will provide the touchless technique of enhancing the image.
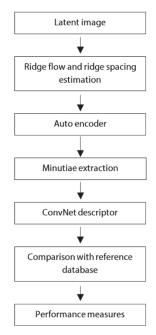
Latent recognition is done using physically pointed minutiae and region of interest [8]. The accuracy is improved using skeleton approach [9] and ridge flowing. But this technique consumes more time. Further the number of features used for mapping purpose is reduced and improvement is achieved using various techniques in [10], [11], [12]. A non-minutia latent fingerprint registration method, calculates the spatial transformation among two fingerprints [7]. Various feature extraction techniques are reviewed [5]. Latent fingerprint recognition algorithm uses Convolutional Neural Networks [4] to find out the templates for signifying the latent. Both rolled and slap images are taken and context switch is used for fusing the algorithms [1]. The physically marked structures [3], which consist of the Region of Interest (ROI), singular points, and minutiae is considered. Orientation field is calculated using the physically marked structures. Gabor filters plays an important role in enhancement. An approach using resemblance of learned demonstrations and interrelated patches is also provided. A deep learning network helps to study the optimized illustrations of latent im-

ages. CNN technique is used as a distance metric learning [13]. A round-robin technique [14] is used in examining the fingerprint data, resulting in good quality confidence scores.

From all the papers surveyed the following shortcomings are observed.

- Accuracy gets affected by more noise in images.

- The techniques consume more time.

- Accuracy will be affected when the patch size is varied.

- The contributions of the proposed work which overcomes these drawbacks are

- An auto encoder is used to improve the accuracy in extracting ridge flow and spacing.

- Minutiae template and ConvNet-based texture descriptor will increase the accuracy.

- Minutiae template and the texture descriptor are compared with the reference template which further reduces the computational complexity.

2. PROPOSED METHOD

The plan of the proposed latent fingerprint identification system is using an enhanced ConvNet based descriptor as shown in Fig. 1.
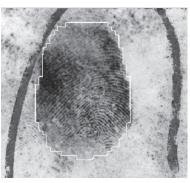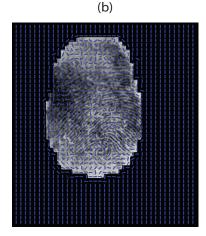

Fig. 1. Enhanced ConvNet based descriptor flow diagram

The latent image is subjected to ridge flow and ridge spacing estimation. The estimated ridge spacing is given to auto encoder. The output of auto encoder is subjected to minutiae extraction step. The extracted minutiae are given to ConvNet descriptor whose output is compared with reference database. Finally, the performance measures are estimated.

From the query latent image, the region of interest, ridge flow, ridge spacing are estimated as shown in Fig. 2.
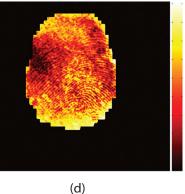

(a)

(b)

(c)

(d)

Fig. 2. Ridge quality, ridge flow and ridge spacing estimation (a) Latent finger print image, (b) RPI image (c) ridge flow and (d) ridge spacing shown as heat map

2.1 LATENT ENHANCEMENT VIA AUTOENCODER

First the latent image is enhanced to estimate ROI, ridge flow and ridge spacing accurately. The steps involved in latent enhancement is shown in Fig. 3. The ruined latent image is applied to encoder which has 5 convolutional layers, followed by decoder having 5 deconvolutional layer, resulting in enhanced finger print image.
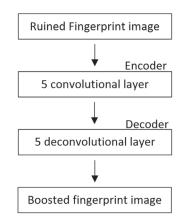

Fig. 3. A convolutional autoencoder for latent enhancement

From all the available latent finger print images the auto encoder will separate 3000 good quality fingerprint images (NFIQ 2.07 value > 70) for training purpose. Here the image is divided into overlapping patches each of size 128*128 pixels. Then Gaussian filtering is applied and finally enhanced image is obtained for training the auto encoder [16].

There are 5 layers of convolutional and deconvolutional layers in encoder and decoder respectively. Each layer is having a kernel window 4*4 and size 2. ReLU (Rectified linear Unit) is used in each layer except output layer. The rolled latent image does not provide good result while training the auto encoder. So, texture component of latent image is used in training phase of auto encoder [12]. Table 1 summarizes the architecture of the convolutional autoencoder.

Table 1. Summarizes the architecture of the convolutional autoencoder.

Layer	Size in	Size Out	Kernel
Input	128×128×1	-	4×4,2
Conv 1	128×128×1	64×64×16	4×4,2
Conv 2	64×64×16	32×32×32	4×4,2
Conv 3	32×32×32	16×16×64	4×4,2
Conv 4	16×16×16	8×8×128	4×4,2
Conv 5	8×8×128	4×4×256	4×4,2
DeConv 1	4×4×256	8×8×128	4×4,2
DeConv 2	8×8×128	16×16×64	4×4,2
DeConv 3	16×16×64	32×32×32	4×4,2
DeConv 4	32×32×32	64×64×16	4×4,2
DeConv 5	64×64×16	128×128×1	4×4,2

The boosted latents have expressively advanced ridge clarity than initial images

2.2 ESTIMATION OF RIDGE FLOW AND SPACING

In dictionary technique, entries of dictionary have various orientations and spacing. For calculating the ridge flow with ridge spacing, the output of the autoencoder is split into 32*32 with overlap of 16*16 pixels. The similarity S_i and element D_{iis} computed as $S_i = p.D_i \|p\| + \alpha$ for every patch. In this the value of α is obtained as 200 which is the regularisation function. The dictionary entry which has the highest value of similarity S_m is taken and its orientation and spacing are considered. The ridge quality is the summation of S_{mand} the similarities between the patch with highest similarity and the patch whose ridge quality is to be estimated. The patch with larger ridge quality greater than 0.35 is taken as valid fingerprint patch.

2.3 MINUTIAE DETECTION VIA AUTOENCODER

In minutiae detection approach, two minutiae extractor models MinuNet reference and MinuNet Latent are trained. A set of reference minutiae is required to train the network for minutiae extraction. This is a challenging task in poor quality images. Experts can perform the minutiae markup easily. The editing involves, insert, delete and reposition of markup points.

For training MinuNet reference, around 400 fingerprint pairs involving both high and poor quality are taken from the MSP longitudinal fingerprint database [17]. A finger can be selected such that

$$(R_h - R_l) > 70 \qquad (1)$$

Where R_h is the highest NFIQ 2.0 value and R_l is the lowest NFIQ 2.0 value. It is observed that from the same finger both low and high-quality image is obtained. To obtain the initial minutiae and its resemblance with the selected fingerprint image pairs, COTS SDK is used.
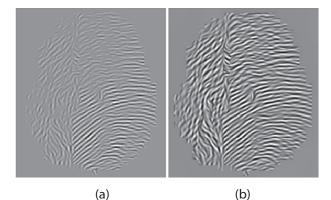

(a)   (b)

Fig. 4. Latent Image processing: (a) STFT result (b) Autoencoder result

A minutia point M is usually denoted as a triplet $M = (X, Y, p)$, where X and Y denote its location, and p is its

orientation respectively. Using minutia cylinder-code [18], a minutiae set is encoded as a channel heat map and position the extraction of minutiae as a regression problem. For each point (I, J, K) response value m (I, J, K) calculated as $M(I,J,K) = \sum_{t=1}^{n} c_s\left((X_t,Y_t),(I,J)\right) \cdot c_o(p_t, \frac{2k\pi}{12})$ where first and the second term are the spatial and orientation of minutia respectively.

The Euclidean distance between (X_t, Y_t), (I, J) is given by

$$c_s\left((X_t,Y_t),(I,J)\right) = \exp\left(-\frac{\|(X_t,Y_t)-(I,J)\|^2}{2w_s^2}\right) \quad (2)$$

Here w_s denotes the width of Gaussian. The function of difference in orientation value is given by

$$c_o\left(p_t, \frac{2k\pi}{12}\right) = \exp\left(\frac{-D\emptyset\left(p_t,\frac{2k\pi}{12}\right)}{2w_s^2}\right) \quad (3)$$

If $\emptyset_1$ and $\emptyset_2$ are two angles, then orientation difference between them is given as

$$D\emptyset(\emptyset_1,\emptyset_2) = |\emptyset_1 - \emptyset_2| \, if -\pi \leq \emptyset_1 - \emptyset_2 < \pi \quad (4)$$

$$D\emptyset(\emptyset_1,\emptyset_2) = 2\pi - |\emptyset_1 - \emptyset_2| \, otherwise \quad (5)$$

The autoencoder applied for minutiae recognition and latent improvement are similar. The MinuNet reference and Latent, are trained for both the reference and latent images. In case of reference images and latent finger print images, the unprocessed fingerprint and short-time Fourier transform (STFT) are respectively used for training purpose. The model MinuNet Latent is a fine-tuned edition of the form MinuNet reference. Fig. 4. shows the latent image processing result.

Take an image of size $W \times H$ in the inference stage, a $W \times H \times 12$ minutiae map N is obtained from a minutiae detection model. For each location (I, J, K) in N, if $N(I, J, K)$ is larger than threshold value and if in its neighbouring it is local maximum a minutia is marked at this location. Minutiae orientation is calculated as

$$F(k-1).\frac{\pi}{6} = N(I,J,(K-1)\%12), F(c).\frac{\pi}{6} = N(I,J,K) \quad (6)$$

$$F(k+1).\frac{\pi}{6} = N(I,J,(K+1)\%12) \quad (7)$$

Where c%d represents c modulo d. Fig. 5. shows the minutiae detection result.

Fig. 5. Minutiae detection

2.4 MINUTIAE DESCRIPTOR

Based on the image features of neighbours there are numerous attributes in the descriptor. Conv net-based descriptor is used to train the fingerprint patches. Training a set of ConvNets using numerous image patches at changed scales and areas can knowingly increase the recognition performance. Numerous occurrences of areas take out for the same minutia are used to train 14 different ConvNets. Using bilinear interpolation all the patches are resized to 160* 160 pixels. For each and every ConvNet, output of the last layer which is 128-dimension has to be taken as a feature vector. Final descriptor output will be the concatenation of the all the feature vectors [15].

Here in case of training the patches, only the minutiae which have eight or more impressions from the same finger can be considered. The patches which are found locally to these minutiae is considered for ConvNet training. From all the 20 patches, the smaller patch can be resized to 160*160 pixels. In training certain shift and rotation pattern is selected in a random manner. From, the final layer a feature vector of 128-dimension is obtained. Thus, from all the 20 patches, 20 feature vector each of size 128 dimension is taken. The minutiae similarity is given as

$$S_{minutiae} = \sum_{I=1}^{N} De\ S(I_1,I_2) \quad (8)$$

Where DeS() is the descriptor similarity between two descriptors. Fig. 6. shows the minutiae descriptor result.
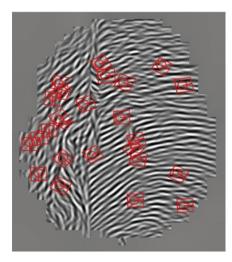

Fig. 6. ConvNet Minutiae descriptors

2.5 COMPARISON OF LATENT WITH ROLLED

Three comparison algorithms are framed:

(i) Algorithm for minutiae correspondence

(ii) Algorithm for power iteration in eigen value problem

(iii) Method to confirm one to one mapping

The detailed explanation of the algorithms is provided in section 3.

3. ALGORITHM

Algorithm 3.1: Algorithm for minutiae correspondence

Step 1: Latent and reference minutiae template having m_l andm_rminutiae respectively are obtained as inputs

Step 2: Minutiae correspondences are obtained as output.

Step 3: Estimate minutiae similarity matrix using below equation

$$sim(I1, I2) = \frac{1}{\sum_{p \in P} 1} \sum_{p \in P} \frac{DI1(p) - DI2(p)}{\|DI1(p)\|.\|DI2(p)\|} \quad (9)$$

Where $DI_1(p)$, $DI_2(p)$ is calculated based on the cosine function of the distance.

Step 4: Find out the top N minutiae correspondence from the matrix and design h^2

Step 5: Follow algorithm 2 and 4 and remove the false values and again construct h^3

Step 6: Once again remove the false correspondences and finally at the end show the minutiae correspondences.

Algorithm 3.2: Algorithm for power iteration in eigen value problem

Step 1: Provide h^2 value as input

Step 2: Principal eigen vector y, of h^2 is obtained as output.

Step 3: Initialize y

Step 4: Until convergence, perform the below rules,

$$y \leftarrow hy$$
$$y \leftarrow \frac{1}{\|y\|_2} y \quad (10)$$

Step5: Finally find the power iteration for the third order eigen value problem.

$$y_i = \sum_{j,k} h^3{}_{i,j,k} y_j y_k \quad (11)$$

Algorithm 3.3: Method to confirm one to one mapping

Step 1: The eigen vector obtained from the above algorithm is given as input.

Step 2: Initialize threshold and minutiae pair.

Step3: Minutiae correspondence is taken as the output.

Step 4: Set flag as zero

Step 5: If maximum value of y is greater than threshold then flag is set as one and the loop continues.

Step 6: If the above condition is not satisfied then c. append= (I1, I2)

Texture template similarity

The algorithm used for minutiae comparison is used for texture template comparison. The texture template similarity is obtained by multiplying minutiae similarity with ridge flow similarity. A texture template for reference prints is presented in similar method as that for latent. The ROI is explained as the value of the gradient

and the orientation each having a block size of 16×16 pixels. The block size can be preferred as 4×4, 8×8 and 16×16. But every block size will not provide good results for every quality of images. Preferably block size 16×16 will provide good results for even less quality of images. Only square shaped template is preferred since there is no loss in information. The intensity of the block is same as the intensity of image. The virtual minutiae nearby the mask boundary are left out. A 96-dimensional descriptor is first achieved and then lowered to 16 dimensions using product quantization.

Similarity Score Fusion

From the minutiae and texture template only one from each is taken as reference point. The similarity score is calculated as

$$S = \lambda_1 S_{minutiae1} + \lambda_2 S_{minutiae2} + \lambda_3 S_T$$
$$(12)$$

where λ_1, λ_2, λ_3 are the weights. S_T is the texture template similarity.

4. EXPERIMENTAL RESULTS

In this paper, NIST SD27 [19] latent database is used to verify the performance of proposed method with existing method. This database has 258 latent finger print images and their reference images. For fingerprint of database manually marked ROI is used, but Finger net is applied for rolled ones. If background is clear, the Otsu's method [41] and morphological operations are used to obtain the ROI of each fingerprint. ROI is obtained by automatic cropping by providing boundary for the finger print in a query latent. The experiment is tested by varying the dimension of the descriptor as 100,80,30 for various ranks like 1,5,10 and accuracy of recognition is noted. Further the proposed technique is tested for various quantization factor such as 10,14,18 etc. Moreover, the technique has applied to two qualities of images like good and poor. Table2 shows the performance of proposed ConvNet method with the existing method like CNN, skeleton approach nonlinear mapping and product quantization for various ranks 1,5, and 10. The proposed ConvNet method provides an accuracy of 76.4%,80.4% and 82.4% respectively. The least performance is observed for nonlinear mapping which has an accuracy of 53.4%,62.2% and 73.2% for rank1, rank5 and rank10 respectively.

Table 2. Performance measure of proposed method in NIST SD database with CNN, skeleton approach, nonlinear mapping and product quantization

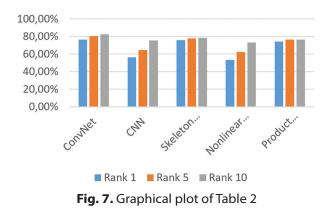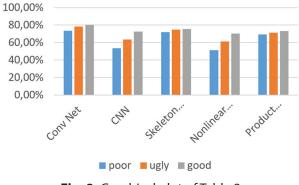| Techniques	Rank 1	Rank 5	Rank 10
ConvNet	76.4%	80.4%	82.4%
CNN	56.4%	64.4%	75.4%
Skeleton approach	75.8%	77.8%	78.5%
Nonlinear mapping	53.4%	62.2%	73.2%
Product quantization	74.3%	76.4%	76.3%

Fig. 7. Graphical plot of Table 2

Fig. 7. shows the performance plot of proposed method for various ranks compared with existing method as given in Table 2. From Fig. 7. it is observed that ConvNet provides good results in rank 1, rank 5 and rank10.Table 3shows that the technique is analysed with various quality of images like good, ugly, poor in rank 10. This proposed technique gives higher accuracy than the existing techniques like CNN, skeleton approach and local and global matching. Fig. 8. shows the graphical plot of Table 3. In poor quality image ConvNet provides an accuracy of 73.4% whereas least performance is nonlinear mapping which has an accuracy of 51.4%. For ugly image the ConvNet has an accuracy of 78.4% whereas nonlinear mapping has 61.2%. In good quality image higher and lower performance is for conv net and nonlinear mapping respectively. From Fig. 8., it is observed that ConvNet has good results for all the three types of images such as poor, ugly and good latent images.

Table 3. Comparison of proposed method with CNN, skeleton approach, nonlinear mapping and product quantization for various types of images in rank 10.

Techniques	poor	ugly	good
Conv Net	73.4%	78.4%	80.4%
CNN	53.4%	63.4%	72.4%
Skeleton approach	71.8%	74.8%	75.5%
Nonlinear mapping	51.4%	61.2%	70.2%
Product quantization	69.3%	71.2%	73.1%

Fig. 8. Graphical plot of Table 3

5. CONCLUSION

Latent fingerprints comprise significant and broadly used sources of forensic data in forensic investigations. In midst of this plan and assemble accurate, robust, and entirely programmed latent fingerprint recognition systems have been restricted. In this paper latent image recognition is done using ConvNet method. Here minutiae template and texture template can be utilized, so that matching information can be obtained. Even though this latent image is not of good quality, it provides higher accuracy for various rank such as rank1, rank5 and rank10 for the NIST SD27 database compared to existing methods like CNN, skeleton approach nonlinear mapping and product quantization. In future work techniques has to be improved to enhance the speed of execution even after training large datasets.

6. REFERENCES:

[1] Sankaran, T. I. Dhamecha, M. Vatsa, R. Singh, "On Matching Latent to Latent Fingerprints", Proceedings of the 2011 International Joint Conference on Biometrics, Washington, DC, USA, 29 December 2011, pp. 1-6.

[2] D. Maltoni, D. Maio, A. K. Jain, S. Prabhakar, "Fingerprint Matching", Handbook of Fingerprint Recognition, pp. 131-171, Springer, New York, NY, 2003.

[3] A. A. Paulino, A. K. Jain, J. Feng, "Latent Fingerprint Matching: Fusion of Manually Marked and Derived Minutiae", Proceedings of the 23rd SIBGRAPI Conference on Graphics, Patterns and Images, Gramado, Brazil, 30 August - 3 September 2010, pp. 63-70.

[4] K. Cao, A. K. Jain, "Automated Latent Fingerprint Recognition", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 41, No. 4, 2019, pp. 788-800.

[5] D. Valdes-Ramirez, M. A. Medina-Pérez, R. Monroy, O. Loyola-González, J. Rodríguez-Ruiz, A. Morales, F. Herrera, "A Review of Fingerprint Feature Representations and Their Applications for Latent Fingerprint Identification: Trends and Evaluation", IEEE Access, Vol. 7, No. 1, 2019, pp. 48484-48499.

[6] X. Huang, P. Qian, M. Liu, "Latent Fingerprint Image Enhancement Based on Progressive Generative Adversarial Network", Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, China,14-19 June 2020, pp. 800-801.

[7] S. Gu, J. Feng, J. Lu, J. Zhou, "Latent Fingerprint Registration via Matching Densely Sampled Points", IEEE Transactions on Information Forensics and Security, Vol. 16, 2021, pp. 1231-1244.

[8] A. K. Jain, Jianjiang Feng, A. Nagar, K. Nandakumar, "On matching latent fingerprints", Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops, Anchorage, AK, USA, 23-28 June 2008, pp. 1-8.

[9] A. K. Jain, J. Feng, "Latent Fingerprint Matching", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 33, No. 1, 2011, pp. 88-100.

[10] H. Choi, M. Boaventura, I. A. G. Boaventura, A. K. Jain, "Automatic Segmentation of Latent Fingerprints", Proceedings of the IEEE Fifth International Conference on Biometrics: Theory, Applications and Systems, Arlington, VA, USA, 23-27 September 2012, pp. 303-310.

[11] J. Zhang, R. Lai, C. J. Kuo, "Adaptive Directional Total-Variation Model for Latent Fingerprint Segmentation", IEEE Transactions on Information Forensics and Security, Vol. 8, No. 8, 2013, pp. 1261-1273.

[12] K. Cao, E. Liu, A. K. Jain, "Segmentation and Enhancement of Latent Fingerprints: A Coarse to Fine Ridge Structure Dictionary", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 36, No. 9, 2014, pp. 1847-1859.

[13] J. Ezeobiejesi, B. Bhanu, "Patch Based Latent Fingerprint Matching Using Deep Learning", Proceedings of the 25th IEEE International Conference on Image Processing, Athens, Greece, 7-10 October 2018, pp. 2017-2021.

[14] H. Guan, P. Lee, A. Dienstfrey, M. Theofanos, C. Lamp, B. Stanton, M. T. Schwarz, "Analysis, Comparison, and Assessment of Latent Fingerprint Image Preprocessing", Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, Hawai, USA, 21-26 July 2017, pp. 126-133.

[15] K. Cao, A. K. Jain, "Automated Latent Fingerprint Recognition", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 41, No. 4, 2019, pp. 788-800.

[16] K. Cao, D. L. Nguyen, C. Tymoszek, A. K. Jain, "End-to-End Latent Fingerprint Search", IEEE Transactions on Information Forensics and Security, Vol. 15, 2020, pp. 880-894.

[17] S. Yoon, A. K. Jain, "Longitudinal Study of Fingerprint Recognition", Proceedings of the National Academy of Sciences, Vol. 112, No. 28, 2015, pp. 8555-8560.

[18] R. Cappelli, M. Ferrara, D. Maltoni, "Minutia Cylinder-Code: A New Representation and Matching Technique for Fingerprint Recognition", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 32, No. 12, 2010, pp. 2128-2141.

[19] NIST Special Database 27, http://www.nist.gov/srd/nistsd27.cfm (accessed: 2018)

[20] V. Jain, A. K. Singh, R. Kumar, "An Efficient Approach for Latent Fingerprint Recognition," Proceedings of the Second International Conference on Computational Intelligence & Communication Technology, Ghaziabad, India, 12-13 February, 2016, pp. 70-75.

[21] C. Wu, Z. Shi, V. Govindaraju, "Fingerprint image enhancement method using directional median filter", Biometric Technology for Human Identification, Vol. 5404, pp. 66-75.

[22] Y. Dong, S. Xu, "A New Directional Weighted Median Filter for Removal of Random-Valued Impulse Noise", IEEE Signal Processing Letters, Vol. 14, No. 3, 2007, pp. 193-196.

[23] A. M. Raičević, B. M. Popović, "An effective and robust fingerprint enhancement by adaptive filtering in frequency domain", Facta universitatis-series: Electronics and Energetics, Vol. 22, No. 1, 2009, pp. 91-104.

[24] A. Amrata, Khindre, V. A. More, "An Approach to Touchless Fingerprint Recognition Using Matlab," International Journal of Emerging Trends & Technology in Computer Science, Vol. 3, 2014, p. 4.