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Human identification using finger knuckle features

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Abstract

Many studies refer that the figure knuckle comprises unique features. Therefore, it can be utilized in a biometric system to distinguishing between the peoples. In this paper, a combined global and local features technique has been proposed based on two descriptors, namely: Chebyshev Fourier moments (CHFMs) and Scale Invariant Feature Transform (SIFT) descriptors. The CHFMs descriptor is used to gaining the global features, while the scale invariant feature transform descriptor is utilized to extract local features. Each one of these descriptors has its advantages; therefore, combining them together leads to produce distinct features. Many experiments have been carried out using IIT-Delhi knuckle database to assess the accuracy of the proposed approach. The analysis of the results of these extensive experiments implies that the suggested technique has gained 98% accuracy rate. Furthermore, the robustness against the noise has been evaluated. The results of these experiments lead to concluding that the proposed technique is robust against the noise variation.

Keywords: *finger knuckle, biometric system, Chebyshev Fourier moments, scale invariant feature transform, IIT-Delhi knuckle database.*

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1. Introduction

The person can be recognized based on three cases: first based on what he knows, second based on what he has, and third based on what he is. In the case of what he/she knows, e.g., PIN, password, and pattern, while in the case of what he/she has, e.g., smart card, and ATM card, finally based on what he/she is (biometric characteristics), e.g., finger knuckle print, face, and gait, etc [1, 2]. Biometrics is more secure, effective, and complicated compared to passwords, PINs, or cards. These technologies need protection against loss, stolen, or forgotten. Usually, we need to provide a different password or pin for different accounts or applications, but the same biometric can be used for most applications. Thus, biometrics can either replace or augment existing technologies, as the former offers various advantages over traditional non-biometric person authentication methods [3, 4]. Human being has a lot of unique biometric features that can be used to recognizing, distinguish or identify peoples. These features could be either physiological characteristics like the knuckle, faces, palm veins, fingerprints, DNA, iris, or behavioral characteristics like keystroke dynamics, mouse dynamics, gait, voice recognition, and retina [5, 6]. A biometric can be defined as a pattern recognition system (PRS) that detects and extracts biometric traits from humans. Additionally, the retrieved pattern information must be quantified in order to do a simple and automatic authentication of a person. [7]. The biometric features are invariant, acceptable, measurable, and permanence characteristics, so they are highly suitable for human identification. Since these features are easy to capture and scan, they have been increasingly investigated for many applications, like authentication, human surveillance, image forensics, etc. There are two ways to utilize biometric authentication; the first is an identification method, while the second is a recognition method. In verification mode, a human being is authenticated by executing one to many matching operations between the obtained pattern information and all of the system's registered pattern templates[8]. Biometric authentication approaches are divided into two different divisions hinge on the number of modalities used for biometric identification, recognition, or authentication, viz. A biometric authentication approaches could be either unimodal or multimodal. one of the most important features that could use biometric traits is the Finger knuckle print (FKP), a novel, unique and secure biometric characteristic that is not explored much for real-time implementation [9]. FKP is referring to the outer surface of the finger phalangeal joint[10]. In 2007 & 2009, Kumar et al. employed the Subspace analysis methods to extract finger back surface picture attributes for personal authentication. Subspace analysis is extensively employed in face recognition tasks because it has a strong, distinct, cheap computing cost, ease of implementation, and good separability. Nevertheless, it is unable to extract line characteristics, such as those found in FKP images[11, 12]. In 2019 Vidhyapriya and Lovelyn Rose present a secure biometrics authentication mechanism based on FKP. The Gabor with Exception-Maximization (EM) algorithm is used to extract texture patterns from finger knuckles, and the SIFT algorithm is used to extract feature vectors from these texture patterns[13]. A KFP authentication system using subspace techniques. The system includes three steps. The first step is to remove noise from the acquired image by applying a Gabor filter. The second step extracts the features using principal component analysis (PCA). The last step is Linear Discriminant Analysis (LDA) and Probabilistic Neural Networks (PNN) classifiers for matching purposes. Waghode and Manjare proposed this in 2017[14]. The main drawback of the aforementioned methods is that they are not rotation invariant as well as most of them are not evaluated under noise variation. Therefore, we presented a finger knuckle recognition technique based on combined global and local feature extraction technique. The presented technique consist of CHFMs and SIFT, CHFMs has utilized to provide global rotation invariant features while the SIFT has used to provide local rotation invariant features. The CHFMs has advantages namely it provides less redundant features and it rotation invariant as well as it has the robustness against the noise and image reconstruction error , from the other hand the SIFT is also rotation invariant and it more robust against the noise, therefor, combining them leads to exploits their advantages and produces effective pattern recognition technique.

The rest of this paper has been prepared as the following: The CHFMs is discussed in Section 2. The overview of SIFT presented in Section 3. While section 4 is describing the distance measure which has used. Section 5 presented the proposed method. and finally, the details of the experimental was presented in section 6.

2. Chebyshev Fourier moments - CHFMs

Early presented by [17] then utilized in numerous applications like computer vision image processing, pattern analysis and. The CHFMs for two-dimensional image intensity function [15-20]:

$$f(x,y) = \sum_{q=0}^{M-1} ch_{pq}\ a_p(x)\ a_q(y) \quad (1)$$

Where q and p are the repetition and order of CHFMs, respectively, M is the maximum repetition of the CHFMs. The orthogonal property can be represented as:

$$P(i,M) = \frac{M(M^2-1)(M^2-2^2)\ldots\ldots\ldots(M^2-i^2)}{2n+1} = 0,\ldots\ldots\ldots M \quad (2)$$

for the image analysis CHFMs can be expressed as:

$$ch_{pq} = \frac{1}{\rho(p,M)\rho(q,M)} \sum_{x=0}^{M-1} \sum_{y=0}^{M-1} a_p(x) a_q f(x,y) \quad p,q = 0,1, \dots \dots \dots M-1 \quad (3)$$

Where

$$\rho(p,M) = \frac{M\left(1-\frac{1^2}{M^2}\right)\left(1-\frac{2^2}{M^2}\right) \dots \dots \dots \left(1-\frac{p^2}{M^2}\right)}{2p+1} \quad (4)$$

3. Scale invariant feature transform (SIFT)

The SIFT algorithm has distinct traits such as rotation, scaling, and translation invariant as well as a little bit of resistance to illumination changes. The SIFT algorithm was presented first by Lowe [21]as a feature extraction descriptor. The mechanism of SIFT descriptor to extract the features depend upon four stages [22] which can be explained as follows:

Scale space extrema detection: in this stage, the candidate keys, which are the locations of potential interest points, are detected by computing the difference of Gaussian function:

$$l(x,y,\sigma) = G(x,y,\sigma) * I(x,y) \quad (5)$$

where $I(x,y)$ refers to the image while the $*$ refer to the convolution operation

$$G(x,y,\sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{\sigma^2}} \quad (6)$$

This method has the ability to makes use of the scale space extrema in the difference of Gaussian function convolved with the image D(X, Y), which can be computed as:

$$D(x,y,\sigma) = \big(G(x,y,k\sigma) - G(x,y,\sigma)\big) * I(x,y) \;\; or \;\; D(x,y,\sigma) = L(x,y,k\sigma) - L(x,y,\sigma) \quad (7)$$

Where $L(x,y,\sigma)$refer to scale space and k is a constant multiplicative factor.

2. Keypoint localization: in this stage location and scale of each candidate location are determined by fitting the detailed model. Therefore, the distinct points are selected, and the point having poor contrast or weakly localization are discarded.

3. Assignment of orientation: The orientation of each keypoint is assigned by computing a gradient histogram in the neighborhood of the keypoint.

4. Keypoint descriptor: in the last stage, the local feature at each keypoint is computed based gradient transform and the orientation of keypoint in order to provide orientation invariance trait. The resulted local features used to construct the feature vector consist of 128 distinctively identifying the neighborhood sounding the keypoint. Fig. 1. shows the keypoints for one sample from the used database.

4. Distance Measure

The cosine distance similarity measure has been utilized in the classification stage. This measure estimates the distance between the values of the training and test knuckle image's feature vectors by computing the angles between them [23]. Then evaluate these angles, where the large angular value indicates to high similarity. The considered similarity distance measure can be defined as:

$$D = \frac{\sum_{j=0}^{N-1}(F_j(Te)\ X\ F_j(\mathrm{Tr}))}{\sqrt{\sum_{j=0}^{N-1}(F_j(Te)^2}\sqrt{\sum_{j=0}^{N-1}(F_j(\mathrm{Tr})^2}} \tag{8}$$

Where D is the computed distance, X is the cross product operator. $F_j(Te)$ and $F_j(Tr)$ are the features of test and training knuckle images, respectively.

5. The proposed method

The proposed method is constructed based on two descriptors in order to provide hybrid feature vectors consist of global and local features. The CHFMs are used as a global descriptor to provide global features on the other hand; SIFT is utilized as a local descriptor to provide local features. Therefore the proposed method exploits the distinct traits of hybrid global and local features of the knuckle images. The proposed method can be clarified as follows:

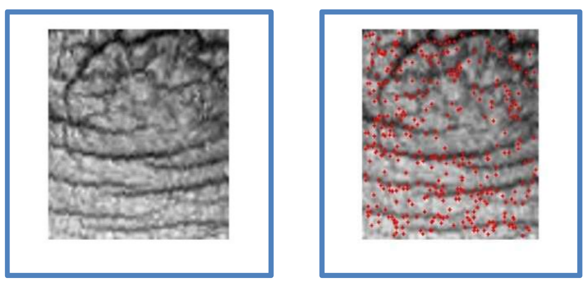
1. Extracting the Region Of Interest (ROI). The ROI contains the unique features of the knuckle; therefore, extracting this region led to increase in the recognition accuracy. In this work, we considered the method presented in [24]. Figure 1. Shows the original image and its segmented ROI.
2. Applying CHFMs descriptor in order to provide global features of ROI of knuckle images.
3. Computing the SIFT keypionts of the ROI of knuckle images, in order to extract local features. Figure 2 presented the ROI of the knuckle image and its SIFT keypoints.

4. Combining the extracted features using both descriptors together in the same feature vectors

Verify the query knuckle images by computing the distances between the combined global and local feature vectors of query and training knuckle images. For this purpose, the Cosine similarity measure has been utilized. The database is divided into test and training parts, the test knuckle images are not included in the training part. The accuracy is computed based on equation 9.

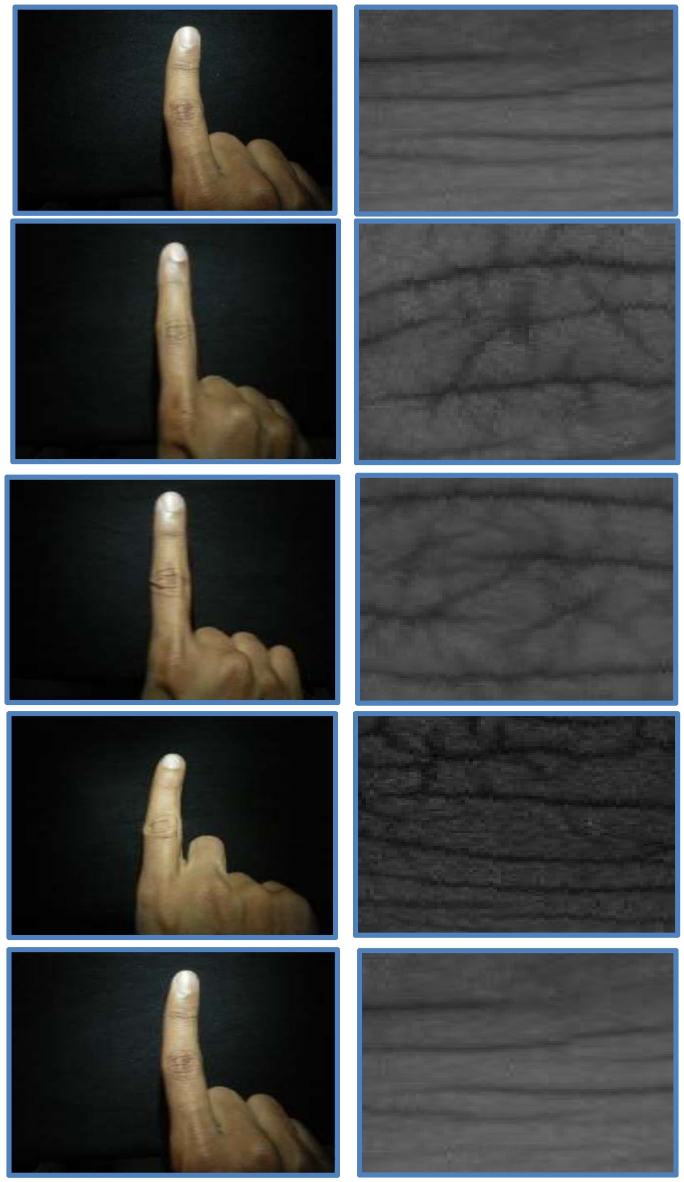
$$\text{Accuracy} = \text{number of recognized test knuckle images} / \text{total number of test knuckle images} * 100 \quad (9)$$

Figure 3 illustrate the block diagram of the above mentioned proposed method. As seen in this figure all the operations that performed on the test knuckle image are performed on the database knuckle images and both test and training knuckle images are feed into distance computation and classification stages.



(A) (B)

Fig. 1. A: original knuckle image, B: the ORI of the original knuckle image.



(A) (B)

Fig. 2. Shows the SIFT keypionts for one sample, A: the ROI OF original knuckle image, B: the ROI of original knuckle image with keypoints.

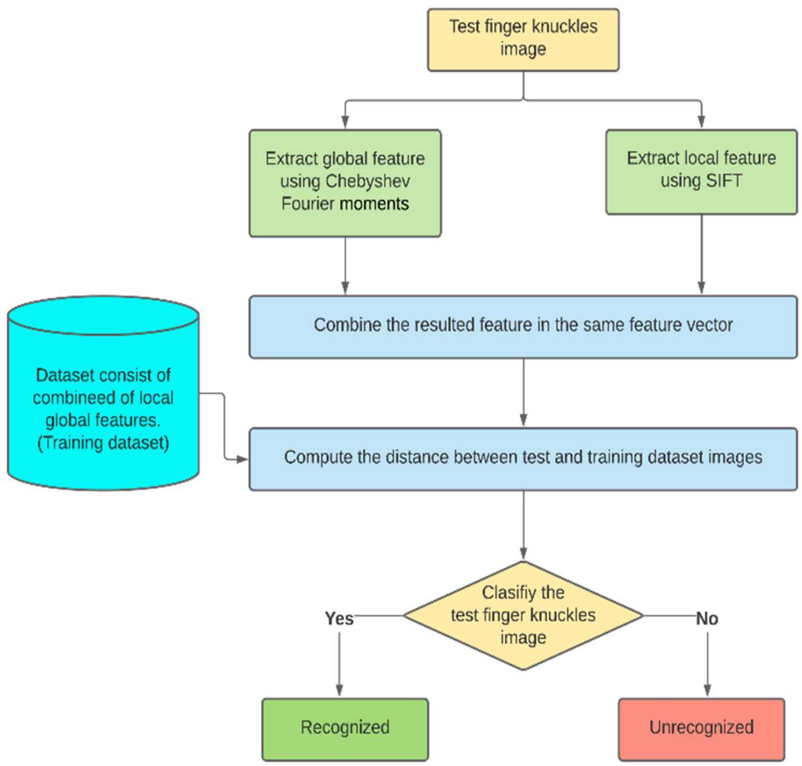


Fig. 3. Block diagram of the suggested technique.

6. Experimental analysis

In this section the accuracy of the suggested approach has been assessed by performed many experiments using IIT Delhi finger knuckle database. As well as we compare the performance of the proposed approach with its individual components namely CHFMs and SIFT. More experiments were performed to select the best maximum repetition and order of CHFMs descriptor that achieves high accuracy. Furthermore, we examine the robustness of the proposed approach against the presence of noise.

Experimental part is performed in Visual_C13 using processor: intel (R) core (TM) i7 – 85654 C. P. U. 1.8GHz 2.00 GHz and 16 GB RAM.

6.1 The utilized knuckle database

In this work the IIT-Delhi finger knuckle dataset [25] was used. This dataset includes the finger knuckle images for 158 subjects related to staff and students at IIT-Delhi with ages between 16-55 years. The images in this database are in bitmap (bmp) format with a resolution of 80 X 100 pixels. The total number of images in this database is 790. Figure 4. shows some images of the IIT Delhi finger knuckle database.

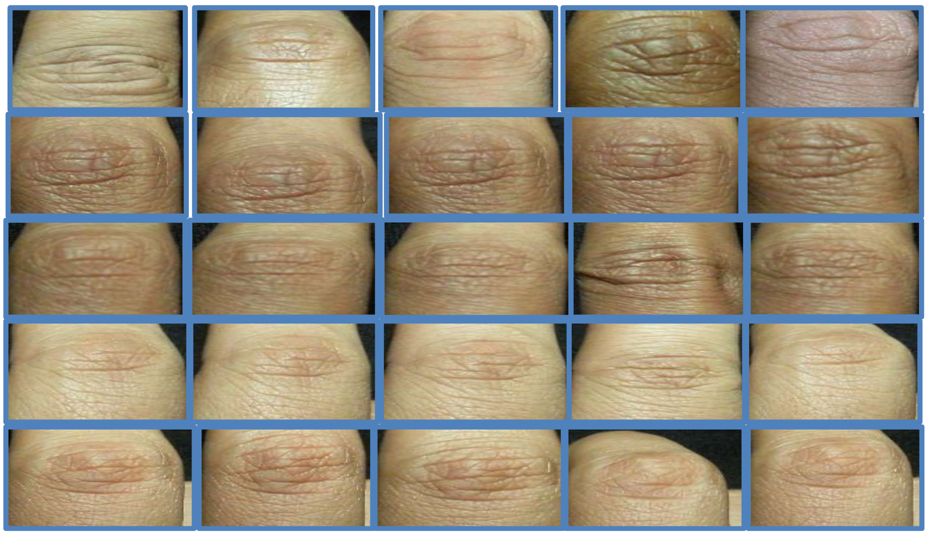


Fig. 4. Some samples of IIT- Delhi finger knuckle database

6.2 The evaluation of the accuracy for the proposed approach

The accuracy of the suggested approach and its individual parts was evaluated and compared. For this purpose, two experiments are achieved over IIT- Delhi knuckle database. In the first experiment one knuckle image randomly selected utilized for test while the remaining four knuckle images were utilized for training for each class. Therefore the total numbers of knuckle images used for test and training are 158 and 632, respectively. In the second experiment, two knuckle images were randomly selected used for the test and the remaining three knuckle images were used for training so that the numbers of test and training knuckle images are 316 and 474, respectively. Figure 5. shows some samples of test and training knuckle images used in the above mentioned experiments.

Table 1 presented the accuracy results of the above mentioned experiments. The presented results indicate that the accuracy of the suggested approach outperforms the accuracy of its individual part (CHFMs and SIFT), this because of that, the proposed approach exploits the inherent traits of both SIFT and CHFMs. It is seen also that the accuracy of the features provided by SIFT descriptor is slightly better than the recognition accuracy of the features extracted by CHFMs. In order to select best maximum order and repetition of CHFMs, that achieves better recognition accuracy, we performed experiment used the same dataset of the first experiment.

The result of this experiment is shown by Fig. 6. It is clear that the best maximum

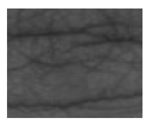
The used method	Accuracy % of First experiment	Accuracy % of second experiment
Chebshive moments	93.3	92
SIFT	94	93.6
Proposed method (SIFT + Chebshive moments)	98	97.2

order and repetition is 12; therefore, it is utilized in all experiments.

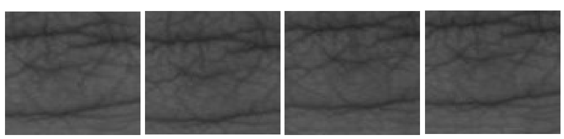
Table 1. The accuracy results of the first and second experiments

6.3 Evaluation the robustness against the noise variation

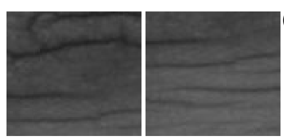
The noise image is an challenge to the accuracy of the biometric system, therefore the robustness against the noise was evaluated. For this purpose, we add salt-and-pepper impulsive noise

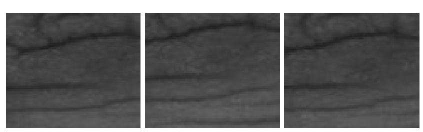


(a)



(b)





(d)

Fig 5. Some samples of the first and second excrements, (a) test image for first experiment, (b) training images for first experiment, (c) test images for second experiment, (d) training images for second experiment.

with a density of 0.05 to the test knuckle images used in the above mentioned first and second experiments, while the training knuckle images are taken without noise. Figure 7 shows the original image and its noised image. The results of evaluation of the proposed approach in presence of the noise variation presented in table 2. It is observed that the accuracy of the proposed approach is slightly affected by noise variation. Furthermore, it is also seen that the SIFT descriptor is outperform CHFMs.

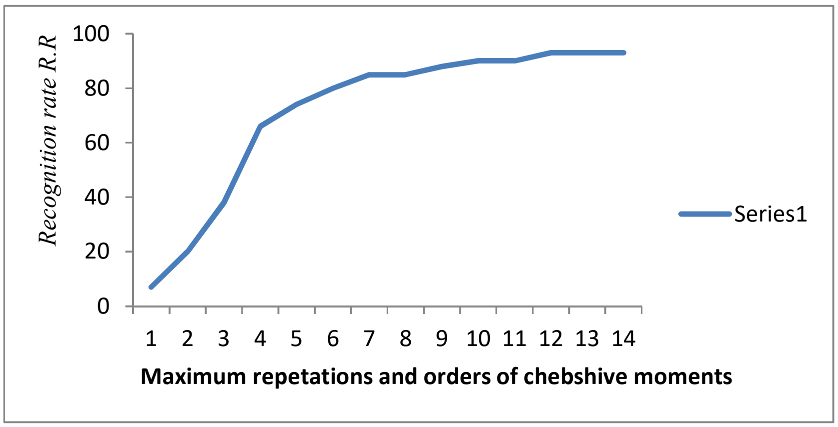
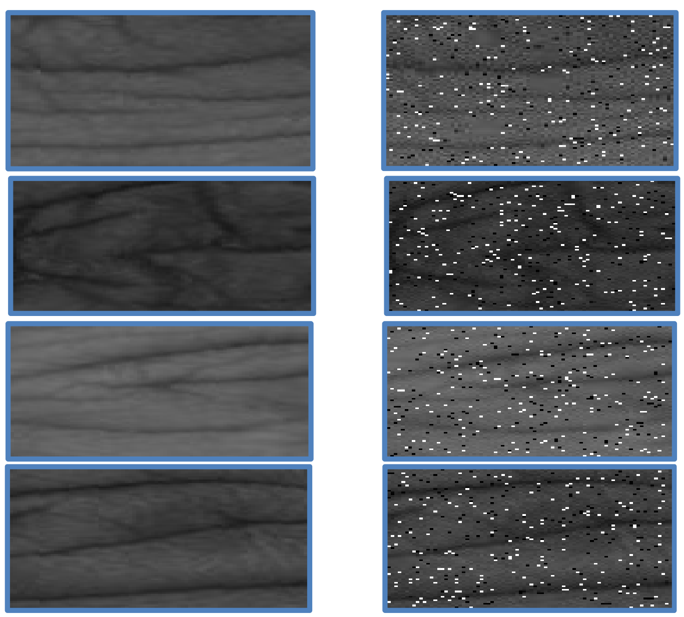


Fig 6. The maximum order and repetition of CHFMs and its accuracy



(A) (B)

Figure 7. Some original knuckle image and their noised image: A: original knuckle images, B: original image after added 0.05 density salt-and-pepper noise.

Table 2. the accuracy results of the first and second experiments under noise variation

The used method	Accuracy % of First experiment		Accuracy % of second experiment	
	Before additive noise	After additive noise	Before additive noise	After additive noise
CHFMs descriptor	93.3	91.5	92	90.7
SIFT descriptor	94	93.12	93.6	92.81
Proposed method (SIFT + CHFMs)	98	97.1	9 7.2	96.6

6.4 Comparing the proposed technique with some similar techniques

The accuracy of the presented technique has been compared with the accuracy of some other techniques in the same domain. The results of this comparison that presented in table 3 indicated that the proposed technique gained better recognition rate than the recognition rate achieved by compared methods,

Table 3: the results of the comparison between the proposed method and other methods

Method	Accuracy %
Angular distance [10]	97
PCA [26]	96
Correlation Coefficient [27]	91
Gabor +CNN [28]	94.6
Proposed technique	98

7. CONCLUSION

In this work a combined approach for human identification based on finger knuckle image recognition has been proposed. The proposed approach utilized two effective descriptors: namely SIFT descriptor and CHFMs descriptor. The evaluation of the proposed method under the standard knuckle image database indicated that the proposed method achieved high recognition accuracy (%98). Furthermore, the proposed combined method is robust against noise. This is because that the proposed combined method exploited the advantages of its individual parts. The analysis of the performance for the individual parts of the proposed method refers that the SIFT descriptor is slightly better than CHFMs descriptor. The experiments indicated that the best maximum order and repetition of CHFMs is 12 therefore it considered in all other experiments of the experimental part of this paper. It is also noticed that the SIFT descriptor is more robust against the noise than CHFMs descriptor.

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