Feature-level fusion of major and minor dorsal finger knuckle patterns for person authentication

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Abstract

The identification of individuals by their finger dorsal patterns has become a very active area of research in recent years. In this paper, we present a multimodal biometric personal identification system that combines the information extracted from the finger dorsal surface image with the major and minor knuckle pattern regions. In particular, first the features are extracted from each single region by BSIF (binarized statistical image features) technique. Then, extracted information is fused at feature level. Fusion is followed by dimensionality reduction step using PCA (principal component analysis) + LDA (linear discriminant analysis) scheme in order to improve its discriminatory power. Finally, in the matching stage, the cosine Mahalanobis distance has been employed. Experiments were conducted on publicly available database for minor and major finger knuckle images, which was collected from 503 different subjects. Reported experimental results show that feature-level fusion leads to improved performance over single modality approaches, as well as over previously proposed methods in the literature.

Keywords Finger dorsal patterns · BSIF · PCA + LDA · Feature-level fusion

1 Introduction

The principal idea of biometrics is replacing person recognition via human experts with machine learning-based automated identity verification system in different applications such as national identity card, driver's license, social security, border control, passport control and mobile user authentication [1]. Broadly, biometric systems can be divided into categories: unimodal (i.e., using only single biometric source of information to establish the identity) and multibiometric system (i.e., using multiple biometric sources of information) [2]. However, the unimodal biometric systems suffer from several defects such as high error rate, low usability, the possibility of the intrusion of these systems and other problems (e.g., aging) [3, 4]. Multibiometrics is an alternative solution that merges information from multiple biometric sources [5–7]. The information sources can be different instances of the same modality, different biometric modalities, numerous prototypes of same modality from different sensors or several feature extraction algorithms for the same single modality. There exist ample of theoretical and experimental studies that demonstrate the efficacy of the multimodal biometric systems that improve performance compared to unimodal systems [8–10]. Therefore, not only research on but also practical adoption of [10] multibiometric systems is getting much more momentum now, including on mobile platforms.

The main realistic reasons for investigating and combining different biometric modalities are to enhance the recognition rates. The use of finger knuckle images for multibiometric systems is relatively new and has taken recently a considerable attention in the literature. For instance, Woodard and Flynn [11] have been efficiently showed the benefit of using 3D finger dorsal images for personal identification. The authors have developed a curvature-based recognition method that employs 3D finger surface captured by a 3D sensor. Kumar et al. [12] have introduced an online system based on hand dorsal surface images, which utilizes the finger knuckle patterns from the multiple fingers and geometrical shape attributes with subspace-based methods using principal component analysis (PCA), independent compo-

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nent analysis (ICA) and linear discriminant analysis (LDA). Ravikanth and Kumar [13] have investigated the likelihood of employing minor finger knuckle patterns for person identification. The proposed coarse-to-fine segmentation approach in [9] was capable to reach a better matching accuracy. Kumar in [14] as well studied biometric identification capability of minor finger knuckle images by developing an algorithm for the automated segmentation of ROI including image normalization, enhancement and robust matching to accommodate inherent image variations. The local binary patterns (LBP) with log-Gabor filters have been employed for feature extraction. However, in another work [11], Kumar used band-limited phase-only correlation (BLPOC) for feature extraction, while Aoyama et al. [15] proposed a new algorithm for finger-knuckle-print (FKP)-based individual recognition that also utilizes BLPOC-based local block features matching.

Sonawane and Dhanokar [16] investigated major and minor knuckle surfaces imaging for personal authentication. In turn, Usha and Ezhilarasan [17] proposed a method for personal recognition using finger knuckle print, which uses texture, geometric and shape-oriented features. Kumar and Zhihuan [18] explored the possibility of using second minor finger knuckle images for the personal recognition. Authors employed local spatial features, BLPOC, local radon transform (LRT) and ordinal representations for feature extractions. Likewise, Kusanagi et al. [19] devised personal authentication using second minor finger knuckles (i.e., metacarpophalangeal (MCP) joints) for door security. The BLPOC with phase-based correspondence matching is used to calculate matching scores.

Recently, Chlaoua et al. [20] have investigated a principal component analysis network (PCANet) in feature extraction for FKP trait. The PCANet is based on simple deep learning topology. In particular, PCANet has been used to learn two-stage of filter banks; then, a simple binary hashing and block histograms for clustering at feature vectors are used. Finally, a linear multiclass support vector machine (SVM) has been employed for classification step. Also, Chalabi et al. [21] designed a system based on score level fusion of minor and major finger knuckle with PCANet-SVM method. Jaswal and Nath [1] designed a novel finger-knuckle-print-based biometric system that first extracted the ROI of finger knuckle image. Then, the ROI image has been enhanced and transformed by the invented bubble ordinal pattern (BOP), STAR ordinal pattern (SOP) algorithms and image ray transform (IRT)-based locally adapted method. In the matching process, a novel deep matching technique has been used. Similarly, Kim et al. [22] investigated an analytic projection-based line feature projection (LFP) method for finger-knuckle-print verification. Effectively, the both horizontal and vertical line features (H-LFP and V-LFP) have been extracted. Then, the system applied fusion of H-LFP and V-LFP at score level. Distance and deep matching have been utilized in the matching module.

Qian et al. [23] proposed a novel biometric image feature representation technique for FKP, known as deep gradient information (DGI). Lalithamani et al. [24] introduced a new biometric authentication system based on major finger knuckle patterns by employing convolution neural networks (CNNs). The back-propagation algorithm with stochastic gradient descent and mini-batch learning has been used to train the CNNs, whereas Zhai et al. [25] presented a new batch-normalized CNNs architecture for FKP recognition. The data augmentation techniques of random histogram equalization and dropout layers were implemented to prevent over fitting during training of the proposed scheme. Joshi et al. [26] proposed a personal recognition system-based FKP using a Siamese neural network. Also, Thapar et al. [27] designed a deep learning scheme for personal recognition system using the full finger dorsal texture. The method used new Siamese-based CNNs matching framework named finger-knuckle-image matching network (FKIMNet).

Despite current progress, the state of the art in FKP-based person recognition is nascent. Inspired by recent convolution neural networks success, this work aims to use convolution filters that are designed via a set of natural image patches and ICA, which eradicates the requirement for manual tuning of filter parameters and maximizes the statistical independence between the learned filters ensuring effective information encoding. In addition, the use of pre-learned filters removes the need for dataset or application specific learning. Table 1 summarizes the prior works on FKP recognition systems.

Especially, in this paper, a simple and fast multibiometrics system based on feature-level fusion of minor, major and dorsal finger knuckle has been presented. Experimental results on public dataset show the efficacy of the proposed method compared to prior techniques in the literature. Moreover, we can state that main advantages of the proposed system are: (1) this method presents the use of the finger knuckle print, which is considered rich in texture and unique features and can be considered a good alternative of the traditional overused traits such as face and iris; (2) the ability to use a different modality such as dorsal finger knuckle patterns with different regions like minor and major knuckle; (3) the presented system is a new approach that has not been applied before on a biometric system; (4) also, for simplicity, the proposed method provides a reasonable small sized template(s) that represent an individual by combine three different.

The rest of paper is organized as follows. Section 2 describes the proposed multibiometric system. Section 3 explains the database and evaluation metrics. Section 4 presents the experimental results. The conclusions and future work are given in the conclusion section.

Table 1 Summary of conventional based on finger-knuckle-print recognition systems

Authors	Traits	Features	Similarity/matching
Woodard and Flynn [11]	3D knuckle	Surface curvature	NCC
Kumar and Ravikanth [12]	FKP	Textures with PCA, ICA and LDA	Sum, product
Kumar [14]	Major and minor knuckle	LBP, Log-Gabor filters	Distance
Aoyama et al. [15]	FKP	BLPOC-based local block matching	Correlation
Kumar [28]	Minor knuckle	LBP,1D-Log-Gabor filters	BLPOC
Sonawane and Dhanokar [16]	Major and minor knuckle	LBP	Distance
Usha and Ezhilarasan [17]	FKP	New approaches based on geometric and texture analyses	Distance
Kumar and Zhihuan [15]	Minor finger knuckle	Local Feature Descriptor, BLPOC and LRT	Hamming distance
Jaswal and Nath [1]	FKP	BOP, SOP	Deep matching
Kusanagi et al. [19]	Minor finger knuckles	BLPOC	Correlation
Chlaoua et al. [20]	FKP	PCANet	SVM
Kim et al. [18]	FKP	H-LFP and V-LFP	Distance and deep matching
Chalabi et al. [21]	Major and minor knuckle	PCANet	SVM
Qian et al. [23]	FKP	DGI	Distance
Lalithamani et al. [24]	Major knuckle	CNN	SVM
Zhai et al. [25]	FKP	Batch-normalized CNN	Distance
Joshi et al. [26]	FKP	Siamese CNN	Distance
Thapar et al. [27]	Major and minor knuckle	FKIMNet	Distance

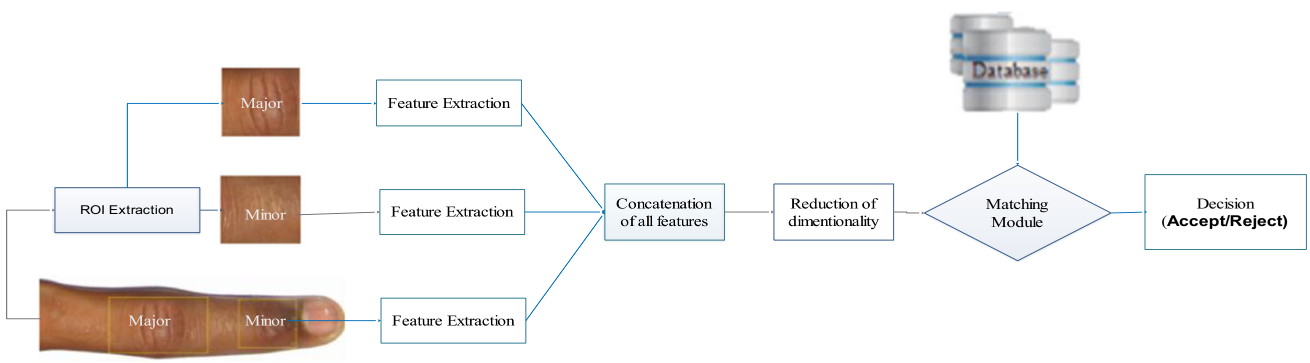

Fig. 1 Block diagram of dorsal finger knuckle, major and minor regions of personal identification

2 Proposed dorsal finger-knuckle-patterns-based system

Figure 1 depicts the block diagram of the proposed dorsal finger-knuckle-patterns-based person recognition system. The proposed scheme consists of five stages: (1) ROI extraction that is explained in details in Sect. 2.1, (2) features extraction using BSIF method, then the top performing extracted features (histograms) are concatenated to form large feature vector, (3) PCA + LDA dimensionality reduction technique discussed in Sect. 2.3 is used in order to obtain concise feature representation, (4) dimensionality reduction is presented in Sect. 2.4, and (5) decision-making classifier to determine the identity of the person is explained in Sect. 2.5

Decision-making classifier to determine the identity of the person is explained in Sect. 2.2

2.1 Finger knuckle and regions of interest

Here, we describe the finger knuckle and the region of interest (ROI) extraction.

2.1.1 Finger knuckle

As illustrated in Fig. 2, every finger excluding thumb has two joints and three bones known as the proximal, middle and the distal phalanges. The major knuckle is the part that joints the proximal phalange and middle phalange, while the minor knuckle is the area which joints between middle phalange

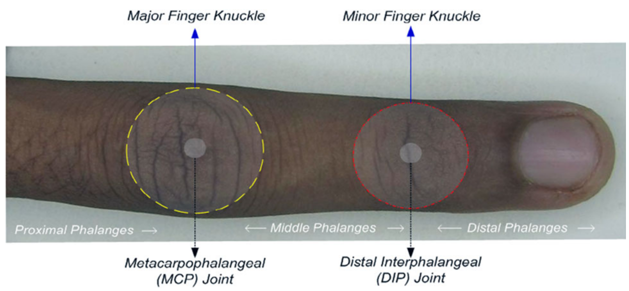

Fig. 2 Finger dorsal image which identifying the *major* and *minor* knuckle pattern regions with respect to the MCP/DIP joints [14]

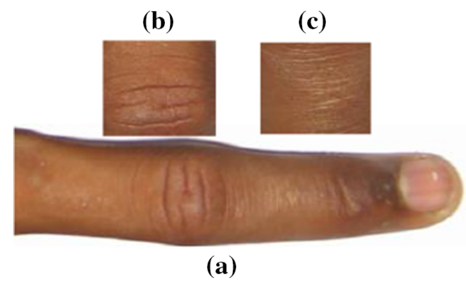

Fig. 3 Sample of finger knuckle with their regions

and distal phalange. Finger knuckle has high textured area, and it is independent to any behavioral aspect. Also, it is user-centric, contactless and simply accessible and available.

2.1.2 Region of interest (ROI) extraction

Better individual identification system based on (major, minor, dorsal) finger knuckle patterns will involve precise extraction of region of interest images (ROI). The database that has been used in this work contains a ROI trait of major and minor regions. These ROI templates have been extracted as follows [11]:

Step 1: Each of the acquired finger dorsal images is subjected to binarization. In this process, the Otsu's thresholding method has been used.

Step 2: The resulting images are denoised by automatically removing the isolated regions/pixels (<100 pixels) so that the longest object representing finger is only retained.

Step 3: The binarized finger shape has been used to estimate the location of fingertip from the convex hull of the images.

Step 4: The location of fingertip is employed to remove the background image over the fingertip.

Step 5: The orientation of fingers has been estimated from the binarized image by using the methods of moment, similar to method used in [29].

Step 6: Coarse segmentation that segments a small portion of acquired finger images can include minor finger knuckle region while excluding major knuckle region and major part of fingernail.

Such segmentation strategy requires some crude assumptions for the maximum ratio of nail length to the finger length and assumption that the major finger knuckle region is located somewhere in the middle of the acquired finger dorsal image. The resulting coarsely segmented image is further subjected to nail check and removal steps, which consist of segmenting the image and locating the bonding box region for smaller parts and removing them. The width of the resulting image is computed and used to estimate the scale factor for the scale normalization. The edge detection of resulting image is used to locate the center of minor finger knuckle image. This is achieved by estimating the location of the centroid for the resulting edge detected image and segmenting a fixed size region (160×180 pixels) that represents minor finger knuckle region for the finger dorsal image (Fig. 3).

2.2 Binarized statistical image features extraction

Binarized statistical image features (BSIF) is a local image descriptor. BSIF is based on binarizing the outputs of the linear convolution filters [30]. Based on unsupervised model, BSIF trained an ensemble of convolution filters from original images using ICA (independent component analysis). These learned filters are used to represent each pixel of the major, minor and finger dorsal images as a binary string by calculating its responses to learned convolution filters. Every binary string for each pixel is considered as a local descriptor of the image intensity pattern in the neighborhood of that pixel. The histogram of the pixels binary string values allows one to characterize the texture properties within the image sub-regions.

In this paper, the open-source filters [30] have been used, which were trained using 503*5*3 images. Three major steps construct the BSIF filters: mean subtraction of each patches, dimensionality reduction using PCA (Principle Component Analysis) method and estimation of statistically independent filters (or basis) using ICA. Give a finger knuckle patterns image sample I of size $n \times m$ and a filter F_i of same size, filter response is achieved as follows [30]:

$$r_i = \sum_{n,m} I(n,m) F_i(n,m) \tag{1}$$

where F_i represents the convolution filters $i = \{1, 2, \ldots, m\}$, which characterize statistically independent filters whose outputs can be computed simultaneously and then binarized in order to get the binary string as follows [30]:

$$b_i = \begin{cases} 1 \text{ if } r_i > 0 \\ 0 \text{ otherwise} \end{cases} \tag{2}$$

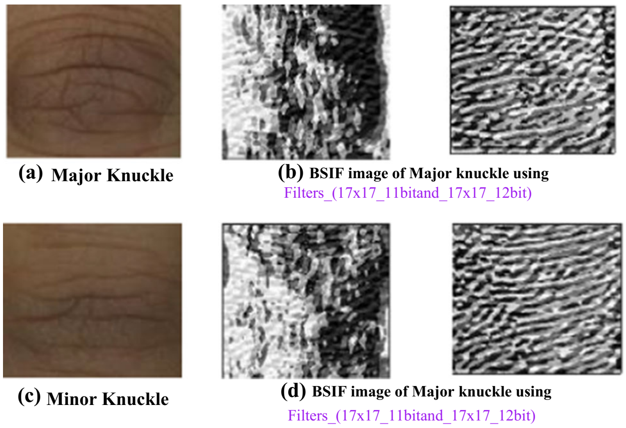

Fig. 4 Samples of the major and minor ROI image with tier outputs BSIF filter of a size 17×17 and of length 11 and 12bits

Finally, the results of BSIF features are achieved as a histogram of pixel's binary codes. These histograms can competently describe the texture components of the Finger dorsal patterns images. There are two essential factors into BSIF descriptor explicitly: the filter size and the length of the filter (i). Single filters with a fixed length may not be capable of generalizing well the finger knuckle patterns with varying intensities, scale and orientations

Figure 4 shows an example of a major and minor knuckle image with the BSIF filters processing. Figure 4a presents the input ROI of major image. Figure 4b illustrates the result of BSIF filter with a size 17×17 and of length 11 bits and 12 bits, while Fig. 4c presents the input ROI of minor image. Figure 4d depicts the results of the individual convolution of the ROI minor image with BSIF filter with a size 17×17 and of length 11 bits and 12 bits.

2.3 Dimensionality reduction

The histograms achieved from the encoded minor, major and finger dorsal pattern images using BSIF descriptor are combined into one large feature vector. Dimensionality reduction is performed on these large vectors with high dimensions before matching stage. The principal component analysis (PCA) is a frequently and straight forward technique for dimensionality reduction, yet in PCA separability between classes is ignored [31]. To avoid PCA's issue and to reach more improved separability of feature subspace, linear discriminative analysis (LDA) [32] may be deployed, which may lead to attractive performances for recognition stage. However, LDA still assumes a common covariance matrix among the classes that violates the normality principle. To suppress these limitations of PCA and LDA and utilizing their strengths, in this paper, PCA + LDA has been adopted, where PCA algorithm is applied to reduce the dimensionality of large features, while LDA algorithm is applied on PCA weights to increase the separability between the classes.

2.4 Matching module and normalization score

In the matching stage of the presented system, the nearest-neighbor classifier that uses the cosine Mahalanobis distance has been employed. The criterion for similarity or dissimilarity is to minimize the distance (score) between the input query trait and the stored template. Suppose that two vectors Vi and Vj refer to the feature vectors of query and template in the database images, respectively. The distance between V_i and Vj is given by the following formula:

$$d_{Ma}\left(V_i, V_j\right) = \left(V_i - V_j\right)^T C^{-1}\left(V_i - V_j\right), \tag{1}$$

where C stands for the covariance matrix. Prior to finding the decision, a method named min-max normalization model has been used to transform the matching score into [0 1]. Given a set of matching scores $\{X_k\}$, where $K = 1, 2, \ldots, n$. The normalization scores are calculated as:

$$X_K^{'} = \frac{X_K - \min}{\max - \min} \tag{4}$$

where $X_K^{'}$ represents the normalized scores. This normalized score is used to make the final decision (accept/reject) individual.

3 Database and metrics

Here, we present the database that is used in experimental evaluation of the introduced person identification and authentication system based on finger dorsal patterns as well as the measures of performance evaluation.

3.1 Database

The proposed scheme has been tested on the publicly available finger knuckle images database (version 1.0) that is provided by Hong Kong Polytechnic University [28]. This database has 2515 finger dorsal images from the middle finger collected from 503 subjects. In this dataset, about 88% of the subjects are younger than 30 years old. The format of these images is bitmap (*.bmp). Also, authors have provided with this database the ROI traits of the minor and major knuckles for each finger dorsal image. Each finger type has 5 images. There are total 7545 images.

3.2 Performance evaluation measures

Generally, any biometric recognition systems can be evaluated in two modes (verification/identification). In the identification mode, the results have been illustrated by the recognition rate known as Rank-1 that is calculated by the following formula:

$$\text{Rank - 1} = \frac{N_i}{N} \cdot 100(\%) \tag{5}$$

where N_i stands for the quantity of images effectively assigned to the right identity, whereas N denotes the overall number of images attempts to be identified. Moreover, in the closed-set identification task, we need to present the cumulative match curves (CMC). The CMC explain the accuracy performance of a biometric system and show how frequently the individual's template appears in the ranks based on the match rates [10]. For this reason, we present the CMC curve in the experimental results.

In the verification mode, the error equal rate (EER) has be presented, i.e., when the FAR (false accept rate) equals the FRR (false reject rate). Besides this, the receiver operating characteristics (ROC) curves have been used. A ROC curve gives more details of how the FAR values are changed compared to the values of the genuine acceptance rate (GAR) values. Other measures are also widely used in the mode of verification such as the VR@1%FAR (i.e., verification rate at operating point of 1% FAR). This operating point is commonly adopted in the biometric research community particularly when the number of comparisons for "inter-class" tests (or "imposter tests") is more than 1000. The verification rate is important for investigating the behavior of systems with low FAR employing a big database as well as for simulating large-scale application in order to enhance system's security with its performance.

Table 2 Performance: EER, Rank-1 and VR@1%FAR for minor finger knuckle by deferent BSIF sizes

Minor finger knuckle	Identification	Authentication	
	Rank-1	EER (%)	VR@1%FAR (%)
17 × 17 and 12 bit	**94.04**	**1.19**	**98.61**
15 × 15 and 12 bit	91.75	1.71	97.51
13 × 13 and 12 bit	90.46%	1.80	97.91
11 × 11 and 12 bit	86.78%	2.59	95.83
9 × 9 and 12 bit	78.73%	3.87	92.84
7 × 7 and 12 bit	61.23%	6.56	86.08
5 × 5 and 12 bit	42.25%	10.22	66.50

Table 3 Performance: EER, Rank-1 and VR@1%FAR for dorsal finger knuckle by deferent BSIF sizes

Dorsal finger knuckle	Identification	Authentication	
	Rank-1 (%)	EER (%)	VR@1%FAR (%)
17 × 17 and 12 bit	**98.31**	**0.30**	**99.90**
15 × 15 and 12 bit	97.61	0.39	99.70
13 × 13 and 12 bit	96.82	0.40	99.60
11 × 11 and 12 bit	95.73	0.79	99.30
9 × 9 and 12 bit	92.74%	1.02	98.91
7 × 7 and 12bit	85.98	2.09	97.22
5 × 5 and 12 bit	68.99%	4.29	89.36

Table 4 Performance: EER, Rank-1 and VR@1%FAR for major finger knuckle by deferent BSIF sizes

Major finger knuckle	Identification	Authentication	
	Rank-1 (%)	EER (%)	VR@1%FAR (%)
17 x 17 and 12 bit	**95.43**	**1.59**	**98.21**
15 x 15 and 12 bit	94.43	1.50	98.01
13 x 13 and 12 bit	93.54	1.88	97.61
11 x 11 and 12 bit	91.95	2.09	97.71
9 x 9 and 12 bit	88.17	2.68	96.42
7 x 7 and 12 bit	76.94	4.17	91.35
5 x 5 and 12 bit	54.47	8.35	77.04

4 Experiment results

In this section, we report three different experiments: Experiment I—unimodal system using one modality under consideration via the BSIF filters, Experiment II—multimodal finger knuckle identification system that utilizes jointly three modalities major, minor and dorsal finger knuckle print, Experiment III—comparison with existing dorsal fingers patterns recognition systems.

4.1 Experiment I—Unimodal System

The aim of this experiment is to test all BSIF filters. For comprehensive study, every BSIF filter with different parameter combination is applied on each individual modality (major, minor and dorsal finger knuckle print). This will help selecting the best BSIF parameters and respective filters. However, the filter parameters (filter size (k) and filter length (n)) have a great influence on performance of single system. Thus, several sub-experiments were performed in both identification and verification modes using dorsal finger knuckle patterns and their modalities major and minor as a single traits. Results are described in Tables 2, 3 and 4. In each Table, it is easy to see that the performance increases with the increase in the length (n) of the BSIF descriptor.

From these Tables of the single system using BSIF on the minor, major and dorsal finger modalities, the better achieved

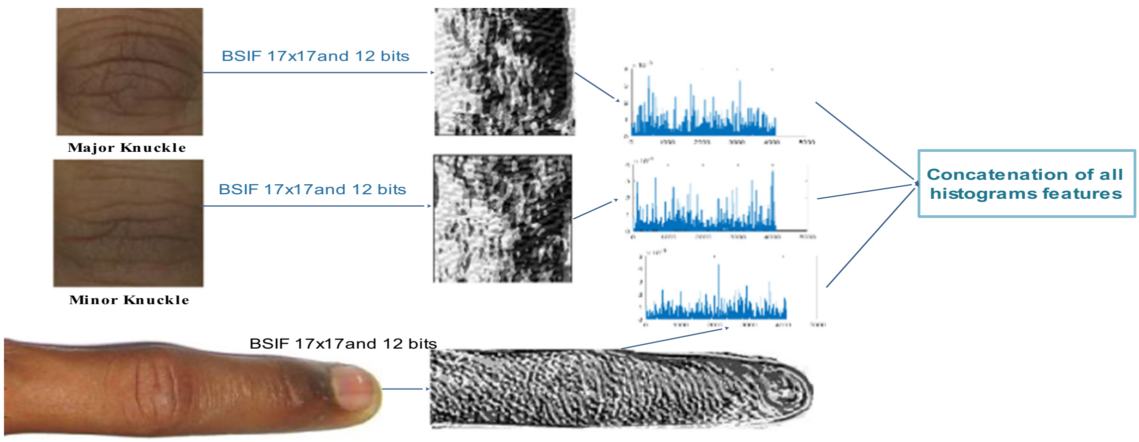

Fig. 5 Feature-level fusion-extracting BSIF histograms for each modalities and combination all of them

Table 5 Performance-EER, Rank-1 andVR@1%FAR for fusion major, minor finger knuckles and finger dorsal patterns by deferent BSIF sizes

Fusion major, minor finger knuckles and finger dorsal patterns	Identification	Authentication	
	Rank-1 (%)	EER (%)	VR@1%FAR (%)
(17×17, 17×17 and 17×17)12 bit	99.60	0.00	100.00
(15×15, 15×15 and 15×15) 12 bit	99.40	0.02	100.00
(13×13, 13×13 and 13×13) 12 bit	99.40	0.00	100.00
(11×11, 11×11 and 11×11) 12 bit	98.61	0.01	100.00
(9×9, 9×9 and 9×9) 12 bit	96.62	0.20	100.00
(7×7, 7×7 and 7×7) and 12 bit	90.66	1.15	98.81

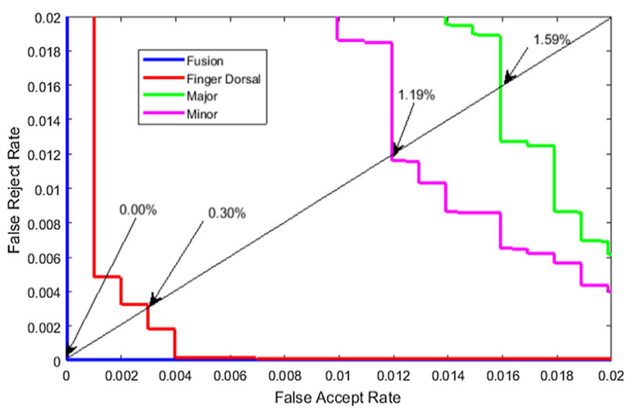

Fig. 6 The EER of major minor knuckle and dorsal finger with their Fusion

result is of the BSIF filter (17×17) with the length of 12 bit son dorsal finger. The system achieved EER $= 0.30\%$, Rank-1 $= 98.31\%$ and *VR@1%FAR= 99.90* in verification and identification modes, respectively.

4.2 Experiment II—multibiometric FKP recognition system

The primary goal of this experiment is to investigate performance of the system under information fusion, since multimodal systems that combine information from different sources are usually capable of improving accuracy compared to that of single biometric systems. Therefore, we considered different scenarios where the information presented by different finger-knuckle-print types (minor, major, and dorsal finger) modalities is incorporated. We studied performance at feature-level fusion. Namely, the information was fused by combining all features in one large vector. The BSIF filters that achieved high ranking performance on single modality have been selected and used in multimodal system. The filters utilized are (17×17), (15×15), (13×13), (11×11), (9×9), (7×7) with the length of 12 bits. As shown in Fig. 5, these chosen filters are applied to each input dorsal finger-knuckle-print modalities. Figure 5 also represents an example of BSIF textural information combination at feature level.

Six distinct experiments were conducted by fusing only features of specific BSIF filters fingers that reported in Table 5. We can see in Table 5 that the multimodal dorsal finger-knuckle-print systems that fuse information improve the accuracy than unimodal systems. For example, using (17×17, 17×17 and 17×17) with 12 bit for person authentication (Table 5) resulted into 0.00% (EER) and 99.60% (Rank-1 accuracy), while (15×15, 15×15 and 15×15) 12 bit and (13×13, 13×13 and 13×13) with 12 bit achieved 99.40% (Rank-1 accuracy).

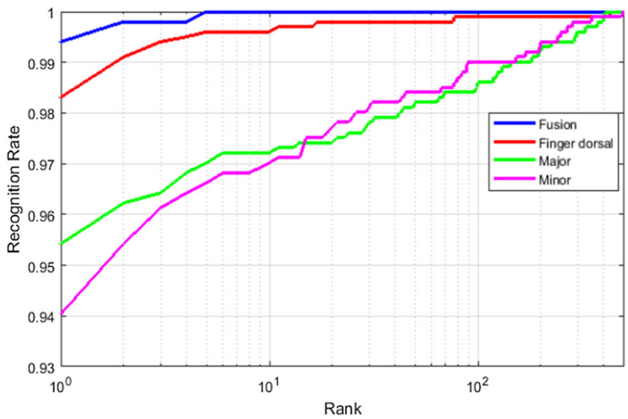

Fig. 7 The CMC curves of major minor knuckle and dorsal finger with their fusion

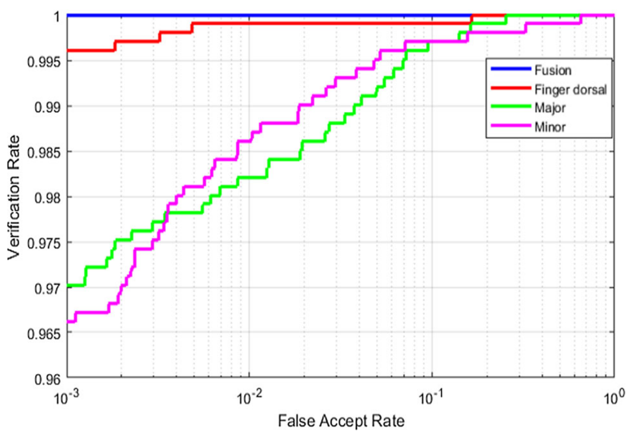

Fig. 8 The ROC curves of major minor knuckle and dorsal finger with their fusion

The comparison results between single modalities and multimodalities are also illustrated in term of EER, CMC and ROC curves, which can be seen in Figs. 6, 7 and 8, respectively. These plots report comparison study between modalities using BSIF filter (17 × 17) with length 12 bit and PCA + LDA method. The results clearly demonstrate that the fusion (multimodal system) outperforms the corresponding unimodal systems. It is easy to see in Fig. 6 that the verification of the system can achieve almost 0.00% error equal rate (EER) under fusion that is better than unimodal system, e.g., EER = 1.19% for minor modality.

The ROC illustrated in Fig. 7 describes the performance of the system. The described verification system can recognize all modalities with high accuracy as the GAR is above 94% (without information fusion) and above 97% (with information fusion). The CMC curve is shown in Fig. 8. The cumulative matching performance, Rank-1 recognition rate, achieves 99.60%. Thus, it can be stated that in this study, the proposed system based on feature-level fusion of minor, major and dorsal knuckle patterns achieves better performance than the use of single modality.

4.3 Comparison with existing dorsal fingers patterns recognition system

For the comparison and for further evaluation of the effectiveness of the proposed system in this study, we also conducted a comparative study with previous works including [14, 21, 24, 26–28]; the results are reported in Table 6. These comparisons are made in both unimodal system and multimodal system and with both modes, i.e., under verification mode with the EER and under identification mode with the Rank-1 performances. From this Table, we can observe that the proposed system outperforms the ones developed in [21, 27, 28] in terms of unimodal under verification rate using minor or major finger. Also, we can see that the proposed system outperforms the ones designed in [14, 21, 28] in terms of fusion of modalities at feature level with 99.60% Rank-1 and 0% of EER for both mode verification rate and identification rate.

Table 6 Comparative of the proposed multimodal system with the existing approaches for minor and major knuckle prints

References		Minor finger	Major finger	Dorsal finger	Fusion
Kumar et al. [28]	EER (%)	6.32%	3.94%	–	2.48%
	Rank-1 (%)	–	–	–	–
Kumar et al. [14]	EER (%)	1.04%	0.22%	–	0.16%
Chalabi et al. [21]	Rank-1 (%)	83.70%	88.27%	–	93.44%
	EER (%)	6.57%	5.95%	–	2.95%
Lalithamani et al. [24]	Rank-1 (%)	–	97.50%	–	–
Joshi et al. [26]	EER (%)	–	0.78	–	–
	Rank-1 (%)	–	99.28	–	–
Thapar et al. [27]	EER (%)	3.36%	3.97%	–	–
Proposed system	EER (%)	1.19%	1.59%	0.30%	**0.00%**
	Rank-1 (%)	94.04%	95.43%	98.31%	**99.60%**

5 Conclusion

In this work, we have considered a feature-level fusion of dorsal finger knuckle print with their regions major and minor knuckle for personal recognition systems. The proposed system uses BSIF for feature extraction process and the nearest-neighbor classifier that employed the cosine Mahalanobis distance for the matching process. Overall, our main findings are as follows. First, we have investigated only single modality (unimodal system). Then, we have selected BSIF filters that achieve high accuracy to be used in further experiments of information fusion. Multimodal system that combines information from all modalities at feature level was investigated.

Experimental results on publicly available dataset showed that fusion at the feature level enhances the performance of the both identification and verification biometric modes. All in all, the achieved results demonstrate that the presented system has a higher recognition rate than prior methods. In the future, we aim to investigate all major and minor regions of all back of the hand via different deep learning topologies.

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