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MULTIMODAL FINGER DORSAL KNUCKLE MAJOR AND MINOR PRINT RECOGNITION SYSTEM BASED ON PCANET DEEP LEARNING

Nour Elhouda Chalabi[1], Abdelouahab Attia[2] and Abderraouf Bouziane[3]
[1,3]Department of Computer Science, Mohamed El Bachir El Ibrahimi University of Bordj Bou Arreridj, Algeria
[2]LMSE Laboratory, Mohamed El Bachir El Ibrahimi University, Algeria

Abstract

Hand-based recognition systems with different traits are widely used techniques and are trustworthy ones. We can find it in different real life fields such as banks and industries due to its stability, reliability, acceptability, and the wide range features. In this paper, we present a finger dorsal knuckle print multimodal recognition system, where we use PCAnet (principal component analysis network) deep learning to extract the features from both Major and Minor finger dorsal knuckles to allow a deeper insight into the exploited trait. Then SVM is used for the matching stage of the two modalities, followed by a score level fusion method to combine the scores using different rules. In order to establish the effectiveness of the proposed system, several experiments in the course of this work have been done on the finger knuckle images of the publicly available database PolyUKV1. The results show that the proposed method has better results in comparison with a unimodal system.

Keywords:

Finger Knuckle Print, Major, Minor, PCAnet, Score Level Fusion, SVM

1. INTRODUCTION

Fingerprint, palm print, hand geometry, hand shape and hand veins recognition models are known as hand-based authentication systems. The hand-based systems have been under the spotlight for quite a long time. The reliable features that provide stability, acceptability, simplicity and ruggedness are the reason for the success of the systems. Nowadays, many companies, industries, and authorizations, rely on hand-based technologies for different needs, especially for security purposes.

Knuckle fingerprint is referred to as FKP [1]. It is one of the hand-based traits where the images contain information about the individual's finger knuckle lines and textures, which can turn to be a unique anatomical trait and can be used to identify a person. These traits have been introduced and studied in order to overcome some of the limitations and drawbacks set by other hand-based technologies [2] along with the discrepancies of the low cost and small size imaging devices used to record the structure [3] [4]. The FKP is divided into two types: the major finger knuckle and the minor finger knuckle [5].

2. LITERATURE OVERVIEW

Until now, a promising and considerable amount off work based on FKP [22] has been established regardless of the system unimodal or multimodal with other modalities, but Woodard and Flynn [6] were the ones who firstly introduced FKP in 2005. They examine the features of a finger surface, exploit local curvature patterns on the 3D finger, and quantify them into various shape indexes. For matching, they use sensor which is expensive, heavy and huge, and hence could not be used as a commercialized biometric system [7].

In [8], the author uses a digital camera for image acquisition. Subsequently, hand localization and finger localization are done followed by finger Major knuckle localization. Finally, features extraction is carried out.

In [9], the author proposes digital image processing based on a ridge feature-oriented algorithm. Firstly, it starts with extracting the ridge features from FKP images and then evaluates their similarity by Hidden Markov Model (HMM) or Support Vector Machine (SVM).

In [10], the author has presents a system for recognition in FKP using Directional Filter Bank (DFB). For feature extraction, LDA is employed for dimensionality reduction purposes and finally Euclidean distance is used for matching and classification.

In [11], the author proposes an FKP identification system by extracting the illumination and reflectance images using Adaptive Single Scale Retinex (ASSR) algorithm. He then combines the Histograms of Oriented Gradients (HOG) based on the illumination and reflectance FKP images that were extracted earlier. Since the proposed work is multimodal, a fusion technique is employed, lastly after features selection the classification is done using cosine similarity distance measure.

In [12], the author proposes an FKP recognition system, by extracting three local features, which are the local orientation, the local phase, and the phase congruency. Systematically using the phase congruency, finally, a score level fusion is made.

In [13], the author proposes an FKP recognition system using ASOC (Steerable Orientation Coding) to extract feature map and Multilevel Histogram Thresholding method for the quantization. The similarity measurement are done by angular matching function.

In [14], the author takes advantage of two hand modalities FKP and palm print by presenting a multimodal system. The proposed work firstly fixes the ROI size for both modalities palm and FKP followed by an enhancement in images by a modified CLAHE algorithm. Next, Line Ordinal Pattern (LOP) based transformation scheme is employed to reduce the pose illumination effects. After that, the original feature space is mapped into high dimensional sub feature set. In this phase, the K2DPCA is carried out on each set in order to extract high order statics. For matching, the authors use Random Forest method. In addition, the fusion of the two modalities is done by weighted sum score level rule.

In [15], the authors have proposed a multimodal recognition system by combining palm print and FKP. The authors use 1D Log-Gabor response for feature extraction from both traits. Therefore, each image for FKP and palm print is represented in real and imaginary templates. The comparison is done using Hamming distance. In biometrics there are various works and studies that show the effectiveness and robustness of deep learning methods such as face detection, speech recognition and detection, finger knuckle recognition, [16] etc. Thus, the main idea of deep learning is to discover multiple levels of representation of the discriminant characteristics of biometric modality effectively and efficiently.

In this paper, we propose a multimodal system based on PCAnet deep learning where we use the finger's dorsal major and minor knuckles as modalities and score level fusion rule in an aim for more accuracy in classification. Therefore, we enhance the system's performance by using the finger dorsal major and minor knuckle and a PCAnet deep learning method [17] to extract the features from the ROI of the major and minor knuckle images. The process details are explained in the Proposed Methodology section of this paper. Then the SVM multiclass is employed in the matching stage. After that, a scores level fusion of finger dorsal major and minor knuckles is done. Then, a final decision is made by an evaluation of performance.

The rest of this paper is organized as follows: section 3, the proposed method. Section 4 shows the experimental results. In the last section a conclusion proposed.

3. PROPOSED METHOD

As indicated previously, the focus of this work is to introduce a multimodal system (see Fig.1) for finger dorsal major and minor knuckle print recognition using PCAnet deep learning with the fusion of both traits using a score level fusion rule at the matching stage. The proposed system includes:

Step 1: Extraction of region of interest (ROI) for both major and minor finger knuckle,

Step 2: Feature extraction using PCAnet,

Step 3: Matching phase for both traits,

Step 4: Fusion phase using the score level fusion rules by combing the matching scores obtained from the previous phase to finally end up with one score.

Step 5: Lastly a decision takes place depending on the score (rejected or accepted) this enhanced structure takes advantage of each modality also it can be used to overcome some of the limitations of different traits.

3.1 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 joins the proximal phalange and middle phalange, while the minor knuckle is the area which is between middle phalange 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.

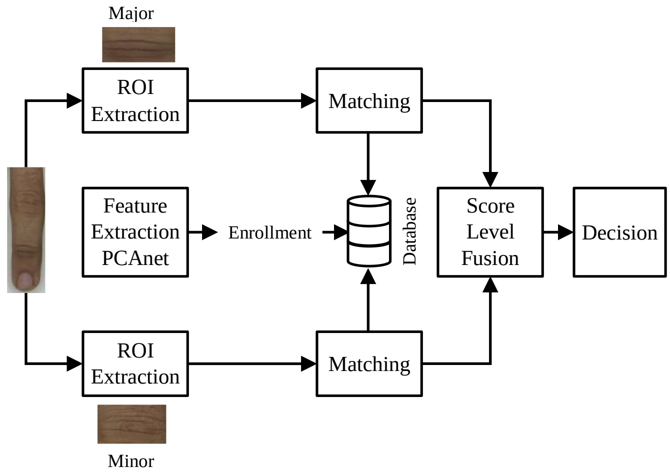


Fig.1. Proposed Method

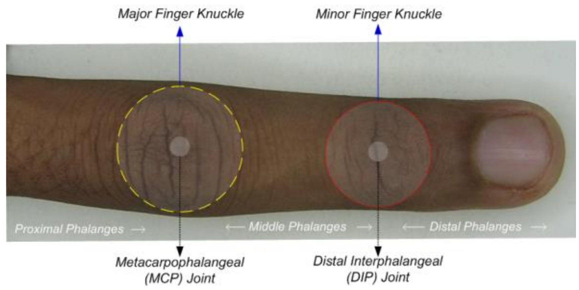


Fig.2. Finger Dorsal Image which identifying the major and minor knuckle pattern regions with respect to the MCP/DIP joints [5]

3.2 EXTRACTION OF REGION OF INTEREST (ROI)

Perfect individual identification system based on (Major, Minor, Dorsal) finger knuckle patterns involves precise extraction of the region of interest (ROI). In this work, the database that has been used provides an ROI sample. According to [20] these ROI templates have been extracted as follows:

Step 1: Binarization of every dorsal finger image using Otsu's thresholding method.

Step 2: The resulting images are de-noised 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 finger-tip from the convex hull of the images.

Step 4: The location of finger-tip is employed to remove the background image over the finger-tip.

Step 5: The orientation of fingers has been estimated from the binarized image by using the methods of moment, similar to the method used in [20].

Step 6: Coarse segmentation is employed in order to segment a small portion of acquired finger images that can include minor finger knuckle region while excluding major knuckle region and major part of finger nail.

Such segmentation method requires some assumptions for the maximum ratio of nail length to the finger length for assuming that the major finger knuckle region is located somewhere in the middle of the acquired finger dorsal image.

The resulting coarsely segmented image is subjected to nail check and removal steps that consist of: segmenting the image, locating the bonding box region for smaller parts and removing them. To estimate the scale factor for the scale normalization the width of the resulting image is computed and used. In order to locate the center of minor finger knuckle image, the edge detection of resulting image is used. This is done by first 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. Process of ROI extraction in FKP

3.3 FEATURE EXTRACTION

One of the important phases in any recognition system application is features extraction, since the classification depend on the results provided from this stage. Moreover, the PCAnet deep learning has been used to extract the feature vector of each dorsal finger surface images for both major and minor.

3.4 PCANET DEEP LEARNING

PCAnet represents one of the simple deep learning network baseline presented by [17]. It is a wildly used technique in image classification. While other deep learning network like the convolutional deep network (ConvNet) take an obscure knowledge and huge number of labeled training data, PCAnet trains more easily. PCAnet is founded on three basic processing components: (1) Cascaded Principal Component Analysis (PCA) aims to extract high-level features, (2) followed by binary hashing, and (3) lastly histograms.

3.5 PCANET FILTER BANK

As shown in Fig.3, PCA filter bank has two stages of filter bank convolution. For the first stage, the filter banks are estimated after running PCA algorithm over filters that consist of a set of vectors where each vector stands for a small window of the $k_1 \times k_2$ size around each point (pixel) of each trait of the dorsal finger surface major and minor. After that, we take the mean of the entries for each vector, and we process the subtraction between the latter and the mean of each entry of the vector. Then, PCA is run on those vectors and retain the principal components (W of size $k_1 \times k_2 \times L_{S1}$), where L_{S1} is the primary Eigenvectors. Hence, each principal component W is considered as a filter and can be converted to $k_1 \times k_2$ kernel. In the end, this filter is convolved with the input image as follows:

$$I_l(x,y) = h_l(x,y) * I(x,y) \tag{1}$$

where * refer to discrete convolution and $l \in [1,2,..,l_{s1}] \cdot I$ is the resulting filtered image using h filter. Hence, using the L_{S1} columns of W then taking each input of finger dorsal surface major or minor images I, and next convert it into L_{S1} output images.

The following stage was performed by iterating the algorithm on all the output images resulting from the previous stage. For the processing of every output image, I is taken as the mean and removed from each input of the computed vector. After that, the vectors are concatenated with each other and another PCA filter bank (with L_{S2} filters) is estimated. Every obtained filter at the end is convolved with I to make a new image.

$$I_{l,m}(x,y) = h_m(x,y) * I_l(x,y)$$

where is in $[1,2,\ldots,ls_2]$

Thus, by repeating the convolution process for the both the filters, L_{S1} and L_{S2}, the output images and generated using the output images of the first stage.

3.6 BINARY HASHING

In this stage the L_{S1}, L_{S2} output images stored previously have been converted into binary format by using a Heaviside step function as follows:

$$I_{l,m}^{B}(i,j) = \begin{cases} 1 & if\ I_{l,m}(i,j) \geq 0 \\ 0 & otherwise \end{cases} \tag{2}$$

where $I_{l,m}^{B}$ represent the binary image. Then around each pixel, we sight the vector of L_{S2} binary bits as a decimal number. Therefore, we convert the L_{S2} outputs into a single integer-valued (image).

$$I_l^D(i,j) = \sum_{m=1}^{L_{s2}} 2^{m-1} I_{l,m}^{B}(i,j) \tag{3}$$

where I_l^D refer to the hashed image. Each value of pixels is an integer value in range $\left[0, 2^{L_{s2}-1}\right]$.

3.7 HISTOGRAM COMPOSITION

In this last stage, all the hashed images I_l^D have been separated into NB blocks and the histogram of each block (B) is computed. Moreover, these blocks can be over-lapping or non-overlapping depending on the application, or disjoint respectively. As a result, the features extracted from I_l^D is obtained by concatenating all the histograms of block B as follows:

$$v_1^{hist} = \left[B_1^{hist}, B_2^{hist}, \ldots, B_{NB}^{hist}\right] \tag{4}$$

After the encoding step, the feature vector of the input image I is then concatenated as:

$$v_1^{hist} = \left[v_1^{hist}, v_2^{hist}, \ldots, v_{L_{s1}}^{hist}\right] \tag{5}$$

3.8 PARAMETERS OF PCAnet

To evaluate the performance of the suggested recognition system based on PCAnet, the latter requires a fixed parameter including: the number of stage, number of filter, filter size, block wise histogram size and overlapping. This parameter is very important to generate the best features that represent an input finger dorsal knuckle for major or minor and to increase the accuracy of the recognition system. So, these parameters are selected as shown in Table.1.

Table.1. PCANet parameters of both modalities Major and minor finger knuckle

Finger dorsal knuckle major	**Finger dorsal knuckle minor**
Number of Stages = 2	Number of Stages = 2
Number of filters = [7 7]	Number of filters = [7 7]
Filter size = [4 4]	Filter size = [4 4]
Block size = [28 28]	Block size = [28 28]
Overlapping = 0.5%	Overlapping = 0.5%

3.9 SVM CLASSIFIER

Support vector machine (SVM) [18], is a supervised learning method that classifies data by drawing a set of support vectors used in pattern recognition. SVM has recently received a lot of intention and has shown a good performance. Simply speaking SVM is binary classifier based on kernel function that project data into another higher-dimensional space.

In this work, multi-class SVM has been applied, this later generates 165 classes individually for the authorized individual using single modality finger dorsal knuckle major or minor. Moreover, for each of all the 165 subjects, there are 6 major feature vectors for classification and 6 minor feature vectors for classification. Every feature vector consists of a unique image of finger dorsal knuckle major and minor of type (LIF, LMF, RIF, and RMF). After that SVM finds the hyperplane that separates the largest possible between two or more sets of the object (points of the same class on the same side), though maximizing the distance from either class to the hyperplane.

3.10 SCORE LEVEL FUSION

Score level fusion is a commonly used method as it is simple to use and permits the achievement of results with high performance [19]. Thereby, the output of the two matching modules finger dorsal knuckle major and minor are fused using fusion rules. The aim is to combine the outputs scores in order to generate a unique score that will be used in the process of decision making. Those rules are usually represented by *mul*, *min*, *max* and *sum*. The results of such rules have been evaluated to compute evaluation metrics described in the next subsection which is used to make the decision of rejecting or accepting the person.

4. EXPERIMENTAL RESULTS

In this section we display the experimental results obtained from the proposed method. Firstly, we introduce the database used in the experiment, then we comment on the results obtained from three experiments: finger dorsal major knuckle and minor knuckle, also the results of the score level fusion of the two modalities, and lastly a comparative study with existing systems.

4.1 DATABASES

The proposed method has been tested on the publicly available finger knuckle images database (Version 1.0) provided by Hong Kong Polytechnic University [20] [21]. This database has 2515 finger dorsal images from the middle finger collected from 503 subjects, in this dataset the age of about 88% of the subjects are below 30. The format of these images are bitmap (*.bmp). This database is provided with the minor and major sample of each finger dorsal image. Each finger type has 5 images in each, where the total number of images is 5030.

4.2 RESULTS FOR UNIMODEL MAJOR AND MINOR

After experimenting each trait individually, we obtained the results shown in Table.2, where we can see that the major modality has a slightly higher rank-one results: 88.27%, while minor obtained: 83.70 identification mode, for the verification mode the major modality gave: 5.95 %, for EER, and 91.85% for verification rate at 1% which is compared to the minor modality is better, where this latter has 6.57% for EER and 88.87%. Additionally, the obtained results can also be verified in Fig.4 that display the (a) ROC, (b) CMC and (c) EER. From the plotted curves, we can see that the major modality has slightly better results. Thus, the major modality has outperformed the minor modality.

Table.2. Performance for different traits

Modalities	**Identification**	**Verification**	
	Rank-one	**EER**	**VR@1%FAR**
Major	88.27%	5.95%	91.85%
Minor	83.70%	6.57%	88.87%

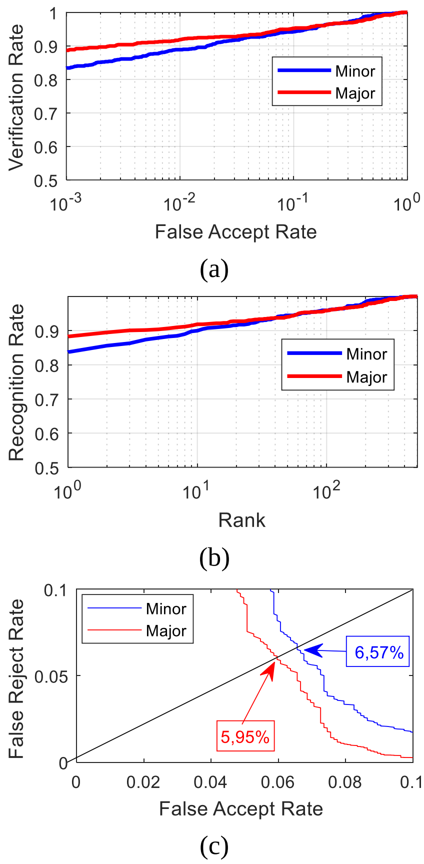
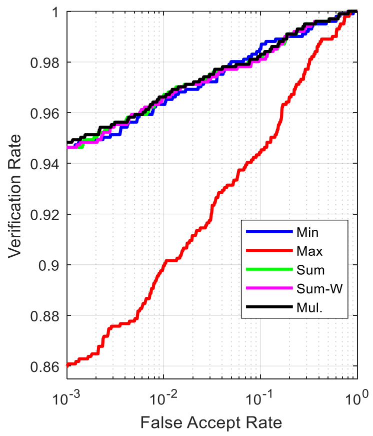


Fig.4. Major and Minor modalities results: (a) ROC (b) CMC (c) EER curves

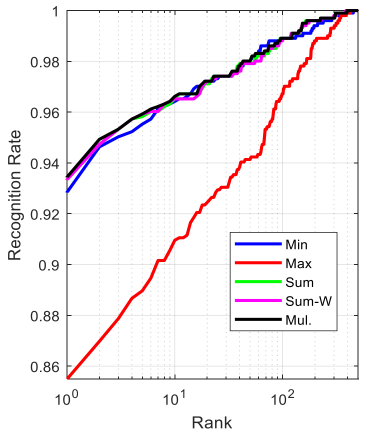
4.3 RESULTS FOR MULTIMODAL OF MAJOR AND MINOR SCORE LEVEL FUSION

In order to achieve better results and reliability in a person recognition, we proposed a multimodal system that combines two modalities which are the finger dorsal knuckles Major and Minor. However, to demonstrate the efficiency of the proposed system we used several different fusion rules at the score level fusion such as: min, max, sum, weighted sum and product. Table.3 displays the obtained results of the multimodal system, and we can conclude from the results that a multimodal system performs better than a unimodal system.

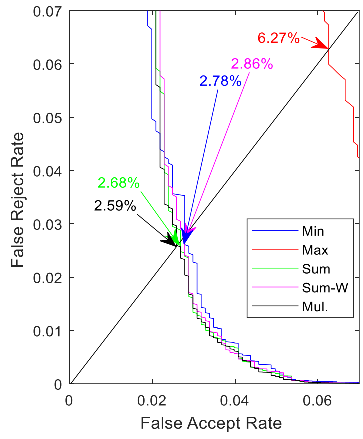
Further reading into the obtained results, we can see that the experiment done using the Product fusion rule has given better results for the Rank-one: 93.44% and EER: 2.59% in comparison with the other rules where the Sum and Weighted has given similar results and slightly less than the Product rule where Rank-one: 93.34% and EER: 2.68%, followed by the Min rule that has given for Rank-one: 92.84% and EER: 2.78. For the verification rate at 1% we observed that the best results obtained is from the Sum and Weighted Sum rules by 96.72% followed by the Product rule: 96.62% then the Min rule: 96.32% and over all the less performing rule is the Max rule. Additionally, the obtained results can also be verified in Fig.5 that display the (a) ROC, (b) CMC and (c) EER curves. For the different rules, we can confirm that the less efficient rule is the maximum fusion rule, while the other rules show closeness overall in the results.



(a)



(b)



(c)

Fig.5. Multimodal results for different rules: (a) ROC (b) CMC (c) EER curves

Table.3. Performance for different rules

Fusion rule	Identification	Verification	
	Rank-one	EER	VR@1%FAR
Min	92.84%	2.78%	96.32%
Max	85.49%	6.27%	89.96%
Sum	93.34%	2.68%	96.72%
Sum-W	93.34%	2.68%	96.72%
Mul	93.44%	2.59%	96.62%

5. COMPARATIVE STUDY

In order to evaluate the effectiveness of the achieved results of the proposed system in this work, we also conducted a comparative study with two semiral works proposed by Kumar et al. [5] [19] the results are shown in Table.4.

Table.4. Performance for different rules

Methods		Minor finger knuckle	Major finger knuckle	Fusion
Kumar et al. [5]	EER (%)	6.32%	3.94%	2.48%
Kumar et al. [19]	EER (%)	1.04%	0.22%	0.16%
Proposed system	EER (%)	6,57%	5,95%	2.59%
	Rank-1 (%)	83,70%	88,27%	93.44%

From Table.3, we can observe that the proposed system performance is not as better as the other work. However, it still gives good results in terms of single modalities, while in terms of fusion, the obtained results are close to the other ones in terms of fusion of modalities at feature-level.

6. CONCLUSION

In this work, we have adopted a multimodal system based score level fusion of Major and Minor finger dorsal knuckle print using PCAnet deep learning and SVM. The proposed method used PCAnet for features extraction from both modalities Major and Minor finger dorsal knuckle and SVM classifier for the matching. The presented work was tested with PolyUKV1 database provided by Hong Kong Polytechnic University. The experiment was divided into two phases the first for single modalities where we tested each modality individually and the second phase where we test the multimodal system based score level fusion. The results show that the efficiency of multimodal system compared to unimodal system, the results also show the difference of results obtained in the case of use of different rules.

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