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# Finger-Knuckle-Print identification System Using Hidden Markov Model and Discret Cosine Transform

*Abdallah Meraoumia[1], Salim Chitroub[2], Ahmed Bouridane[3]*

[1]Univ Ouargla, Fac. des nouvelles technologies de l'information et de la communication,
Lab. Génie Electrique, Ouargla 30 000, Algeria

[2] Laboratory of Intelligent and communication Systems Engineering (LISIC), Electronics and Computer Science Faculty, USTHB. P.O. box 32, El Alia, Bab Ezzouar, 16111, Algiers, ALGERIA

[3]Department of Computer Science and Digital Technologies, Northumbria University Newcastle,
Pandon Building, Newcastle upon Tyne NE2 1XE, UK.

[1]Ameraoumia@gmail.com, [2]S_chitroub@hotmail.com, [3]Bouridane@qub.ac.uk

***Abstract*—Automatic personal identification from their physical and behavioral traits, called biometrics technologies, is now needed in many fields such as: surveillance systems, security systems, physical buildings and many more applications. In this paper, we propose an efficient online personal identification system based on Finger-Knuckle-Print (FKP) using the Hidden Markov Model (HMM) and two-dimensional Block based Discrete Cosine Transform (2D-BDCT). In this study, a segmented FKP is firstly divided into non-overlapping and equal-sized blocks, and then, applies the 2D-BDCT over each block. By using zigzag scan order (starting at the top-left) each transform block is reordered to produce the feature vector. Subsequently, we use the HMM for modeling the feature vector of each FKP. Finally, Log-likelihood scores are used for FKP matching. Our experimental results show the effectiveness and reliability of the proposed approach, which brings both high identification and accuracy rate.**

***Keywords— Biometrics; identification; Finger-Knuckle-Print; 2D-BDCT, HMM.***

## I. Introduction

Traditionally, identification strategies are based on something we know, e.g., a password or a personal identification number (PIN), or something we own, e.g., a card, or a key. Unfortunately, passwords can be guessed by an intruder; cards can be stolen or lost. Biometrics, which deals with identification of individuals based on their physical or behavioral features, has been emerging as an effective identification technology to achieve accurate and reliable identification results. The biometrics has significant advantages over traditional identification techniques due to biometric characteristics of an individual are not transferable and unique for every person and are not stolen or broken [1].

Currently, a number of biometrics-based technologies have been developed and hand-based person identification is one of these technologies. This technology provides a reliable, low cost and user-friendly viable solution for a range of access control applications. In contrast to other modalities, like face and iris, hand biometry offers some advantages [2]. First, data acquisition is economical via commercial low-resolution cameras, and its processing is relatively simple. Second, hand based access systems are very suitable for several usages. Finally, hand features are more stable over time and are not susceptible to major changes. Some features related to a human hand are relatively invariant and distinctive to an individual. Among these features, Finger-Knuckle-Print (FKP) is one biometric that has been systematically used to make identification for last years. FKP identification is a biometric technology which recognizes a person based on his/her finger knuckle pattern. The rich texture information of FKP offers one of the powerful means in personal identification [3].

An important issue in FKP identification is to extract FKP features that can discriminate an individual from the other. Based on texture analysis, our biometric identification system used the 2D-BDCT for features extracted from FKP images. In this method, a FKP is firstly divided into non-overlapping and equalized blocks, and then, applies the 2D discrete cosine transform over each block. By using zigzag scan order each transform block is reordered to produce the feature vector, then concatenated all vectors for produce an observation vector. Subsequently, we use the HMM for modeling the observation vector of each FKP. Finally, Log-likelihood scores are used for FKP matching. In this work, a series of experiments were carried out using a FKP database. To evaluate the efficiency of this technique, the experiments were designed as follow: the performances under different finger types were compared to each other, in order to determine the best finger type at which the FKP identification system performs. However, because our database contains FKPs from four types of fingers, an ideal FKP identification system should be based on the fusion of these fingers at different fusion levels.

The rest of the paper is organized as follows. The proposed scheme of the unimodal biometric system is presented in section 2. Feature extraction and modeling process are discussed in section 3. This section including also an overview of 2DBDCT and the HMM-modeling. The experimental results, prior to

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fusion and after fusion, are given and commented in section 5. Finally, the conclusions and further works are presented in sections 6.

## II. SYSTEM OVERVIEW

The proposed system consists of preprocessing, feature extraction, matching and decision stages. To enroll into the system database and modeling, the user has to provide a set of training FKP images. Typically, an observation vector is extracted from each finger which describes certain characteristics of the FKP images using Discrete Cosine Transform technique and modeling using Hidden Markov Model. Finally, the models parameters are stored as references models. For identification, the same observation vectors are extracted from the test FKP images and the log-likelihood is computed using all of models references in the database. Our database contains FKPs from four types of fingers, for this raison, each FKP modalities are used as inputs of the matcher modules (subsystem). For the multimodal system, each sub-system compute its own matching score and these individual scores are finally combined into a total score (using fusion at the matching score level), which is used by the decision module. We have also tried the various image fusion rulers and various feature extraction fusion rulers to choose the best one for FKPs classification.

## III. FEATURE EXTRACTION AND MODELING

### *A. 2D Block based discrete cosine transform*

Discrete Cosine Transform (DCT) is a powerful transform to extract proper features for FKP identification. The DCT is the most widely used transform in image processing algorithms, such as image/video compression and pattern recognition. Its popularity is due mainly to the fact that it achieves a good data compaction, that is, it concentrates the information content in a relatively few transform coefficients [5]. In the 2D-BDCT formulation, the input image is first divided into, $\eta 1\times \eta 2$ blocks, and the 2D-DCT of each block is determined. The 2D-DCT can be obtained by performing a 1D-DCT on the columns and a 1D-DCT on the rows. Given an image, where, represent their size, the DCT coefficients of the spatial block are then determined by the following formula:

$$Fij = C(v)C(u)\sum_{m=0}^{M-1}\sum_{n=0}^{M-1} f_{ij}(n,m)\psi(n,m,u,v) \qquad (1)$$

$$\psi(n,m,u,v) = cos\left[\frac{(2n+1)u\pi}{2M}\right] cos\left[\frac{(2m+1)v\pi}{2M}\right] \qquad (2)$$

$u, v = 0, 1, \cdots, M-1$, $i = 1, \cdots, \eta 1$, $j = 1, \cdots, \eta 2$ with $\eta 1 = H/M$, $\eta 2 = W/M$ and $F\,i\,j\,(u, v)$ are the DCT coefficients of the $B\,i\,j$ block, $f\,i\,j\,(n, m)$ is the luminance value of the pixel $(n, m)$ of the $B\,i\,j$ block, $H \times W$ are the dimensions of the image, and

$$C(u) = \begin{cases} \frac{1}{\sqrt{2}} & if \quad u = 0 \\ 1 & if \quad u \neq 0 \end{cases} \qquad (3)$$

After transformation process, if M = 8, there will be 64 DCT coefficients contained within each transformed block, where the coefficient at the top-left is called DC $\langle F\,i\,j\,(0, 0)\rangle$ coefficient and the rest is called AC coefficients.

### *B. Observation vector*

The block-based approach partitions the input image, with size H×W, when H = 220 and W = 110, into small non-overlapped blocks; each of them is then mapped into a block of coefficients via the 2D-DCT. Most popular block size is commonly set to M×N with M=8. The number of blocks extracted from each FKP image equals to:

$$\eta = \lfloor \eta_1 \rfloor * \lfloor \eta_2 \rfloor = \left\lfloor \frac{220}{8} \right\rfloor * \left\lfloor \frac{110}{8} \right\rfloor = 351 \text{ blocks} \qquad (4)$$

Then, we form a feature vector from the 2D-DCT coefficients of each image block. The 2D-DCT concentrates the information content in a relatively few transform coefficients top-left zone of block, for this, the coefficients, where the information is concentrated, tend to be grouped together at the start of the reordered array, Thus, a suitable scan order is a zigzag starting from the DC (top-left) coefficient. Starting with the DC coefficient, each coefficient is copied into a one-dimensional array. So, each block can be represented by a vector of coefficients:

$$\mathrm{O_{ij}} = \left[\mathrm{F_{ij}}(0,0) \;\; \mathrm{F_{ij}}(0,1) \;\; \mathrm{F_{ij}}(1,0) \ldots\ldots \mathrm{F_{ij}}(\mathrm{U,V})\right]^{\mathrm{T}} \qquad (5)$$

*U, V* are chosen as well as the identification rate was maximum. Thus, $U, V \in [0 .. 7]$ and the size of $O_{ij}$ is $\tau$ with $\tau \in [1 .. 64]$. Finally, the results $o_{ij}$ of a blocks image are combined in the single template as follows:

$$\mathrm{V_{Obs}} = \left[\mathrm{O_{11}} \quad \mathrm{O_{12}} \quad \mathrm{O_{13}} \ldots\ldots \mathrm{O_{\eta 1 \eta 2}}\right] \qquad (6)$$

where the size of resulting observation vector is $[\tau, \eta]$.

### *C. Hidden Markov model*

A hidden Markov model is a collection of finite states connected by transitions. Each state is characterized by two sets of probabilities [6]: a transition probability and either a discrete output probability distribution or continuous output probability density function which, given the state, defines the condition probability of emitting each output symbol from a finite alphabet or a continuous random vector. An HMM can be written in a compact notation $\lambda = (A,B,\pi)$ to represent the complete parameter set of the model, where , and, represents, respectively, state transition probability distribution, probability distribution of observation symbols and initial state distribution. Finally, forward backward recursive algorithm, Baum-Welch algorithm and Viterbi algorithm are used to solve evaluating, training, and decoding, respectively [7].

## IV. EXPERIMENTAL RESULTS AND DISCUSSION

### *A. Experimental database*

We experimented our method on Hong Kong polytechnic university (PolyU) FKP Database [8]. The database has a total of 7920 images obtained from 165 persons. This database

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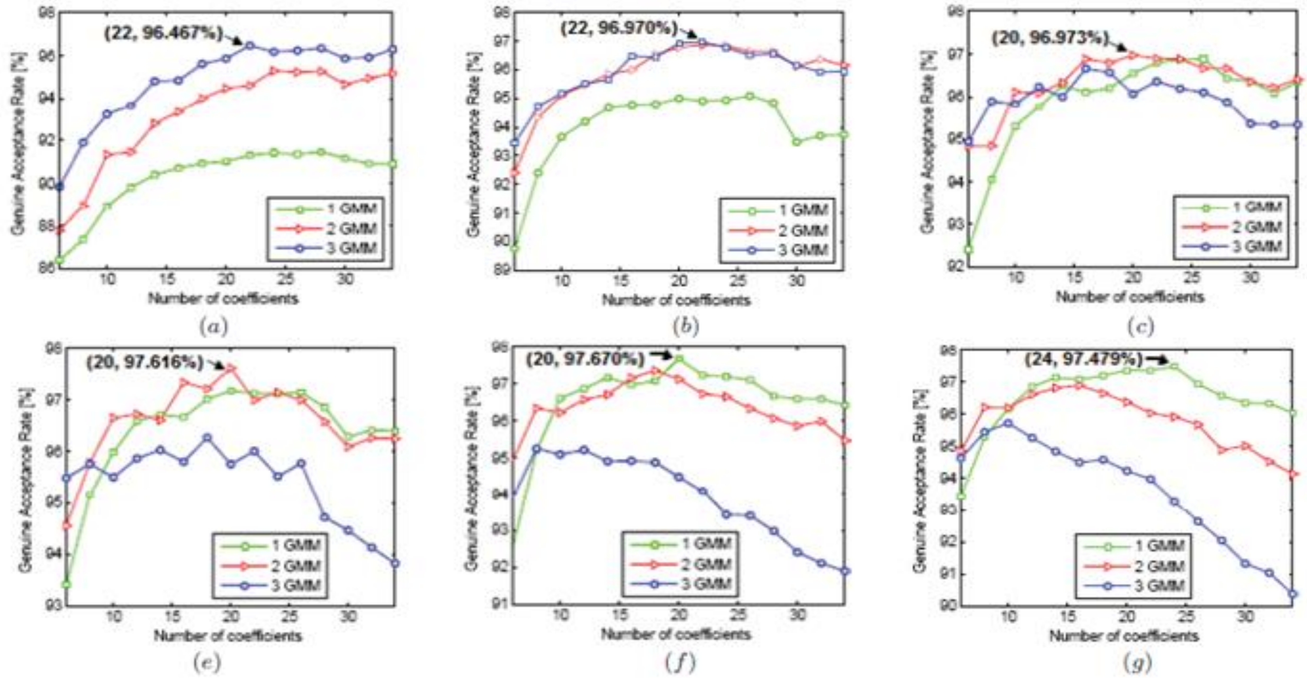


Fig. 1. System performance under different stats number. (a) One state, (b) Two states, (c) Three states, (d) Four states, (e) Five states and (f) Six states.

including 125 males and 40 females. Among them, 143 subjects are 20~30 years old and the others are 30~50 years old. These images are collected in two separate sessions. In each session, the subject was asked to provide 6 images for each of Left Index Fingers (LIF), Left Middle Fingers (LMF), Right Index Fingers (RIF) and Right Middle Fingers (RMF). Therefore, 48 images were collected from each subject.

### *B. Selecting 2D-BDCT coefficients and HMM parameters*

A series of experiments were carried out using the FKP database to selection the best number of 2D-BDCT coefficients and the HMM parameters (number of states and number of Gaussian Mixture Model (GMM)), This is carried out by comparing all states and *k-GMM*, with= 1 to 6 and = 1 to 3, for several 2D-BDCT coefficients and finding the number of states and GMM that gives the best identification rate. The problem we address is as follows: we want chosen the number of 2D-BDCT coefficients, the *states* and their *k-GMM* such that the Genuine Acceptance Rate (GAR) is maximized. Thus, the 2D-BDCT coefficients reflect the compact energy of different frequencies. Most of the higher frequency coefficients are small and they become negligible, as result, the features derived from the 2D-BDCT computation is limited to an array of summed spectral energies within a block in frequency domain [9]. In Fig. 1, we plot the system performance as a function of the number of 2D-BDCT coefficients selection in each block for various numbers of GMM and various numbers of states in the HMM. The reason Fig. 1 was generated was to show how the number of 2D-BDCT coefficients, numbers of states in the HMM and GMM used might have an effect on the performance of our system. We observe that the identification accuracy becomes very high at certain coefficients, where it actually exceeds 96 % and slight decrease in identification accuracy as we go to higher numbers of coefficients. Also, note that only 20 coefficients with $M$ = 5 states and $k$ = 1 GMM are enough to achieve good accuracy (see Fig. 1.*(f)*).

### *C. Unimodal identification test results*

The goal of this experiment was to evaluate the system performance when we using information from each modality (each finger). For this, we found the performance under different modalities (LIF, LMF, RIF, and RMF). By adjusting the matching threshold, a ROC curve, which is a plot of FRR against FAR for all possible thresholds, can be created. For this, the numbers of training and test samples are 495 and 1485. We matched all the 1485 FKP images (test) with each other to obtain 245025 distances. Thus, we have a total of 1485 genuine matching and the remaining, 243540, impostor matching. Fig. 2.*(a)* compares the performance of the system for varying fingers. The experimental results indicate that the LIFs perform better than the LMFs, RIFs and RMFs in terms of Equal Error Rate (EER) (2.282 %). Therefore, the system can achieve higher accuracy at the LIFs compared with the other fingers of a person. The results expressed as a False Acceptance Rate (FAR) and False Rejection Rate (FRR) depending on the threshold and the distance distributions of genuine and imposter matching's obtained by the proposed scheme, if the LIF is used, are plotted in Fig. 2.*(b)* and Fig. 2.*(c)*, respectively. Finally, the system was tested with different thresholds and the results are shown in Table. 1.

### *D. Multimodal identification test results*

The goal of this experiment was to investigate the systems performance when we fuse information from some fingers of a person. In fact, at such a case the system works as a kind of

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TABLE I. OPEN SET IDENTIFICATION TEST RESULTS IN THE CASE OF SINGLE BIOMETRIC

| DATABASE | LEFT INDEX FINGER | | | LEFT MIDDLE FINGER | | | RIGHT INDEX FINGER | | | RIGHT MIDDLE FINGER | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $T_o$ | FAR | FRR | $T_o$ | FAR | FRR | $T_o$ | FAR | FRR | $T_o$ | FAR | FRR |
| 165 Persons | 0.9500 | 7.125 | 0.889 | 0.9500 | 6.712 | 1.481 | 0.9300 | 6.549 | 1.704 | 0.9100 | 7.719 | 0.963 |
| | **0.9699** | **2.282** | **2.282** | 0.9669 | 2.754 | 2.754 | 0.9502 | 2.998 | 2.998 | 0.9449 | 2.297 | 2.296 |
| | 0.9900 | 0.352 | 9.333 | 0.9900 | 0.355 | 9.185 | 0.9800 | 0.573 | 8.444 | 0.9800 | 0.350 | 6.593 |

TABLE II. OPEN SET IDENTIFICATION TEST RESULTS IN THE CASE OF FUSION AT IMAGE LEVEL

| COMBINATION | DWT | | PCA | | LAPLACIAN | | GRADIANT | | CONTRAST | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $T_o$ | EER | $T_o$ | EER | $T_o$ | EER | $T_o$ | EER | $T_o$ | EER |
| LIF-LMF | 0.9797 | 3.015 | 0.9774 | 3.646 | 0.9775 | 2.856 | 0.9802 | 2.558 | 0.9780 | 2.587 |
| LIF-RIF | 0.9738 | 3.165 | 0.9671 | 4.770 | 0.9727 | 2.786 | 0.9752 | 2.505 | 0.9728 | 2.517 |
| LMF-RMF | 0.9709 | 2.788 | 0.9655 | 4.088 | 0.9688 | 2.421 | 0.9708 | 2.440 | **0.9690** | **2.146** |
| RIF-RMF | 0.9588 | 2.905 | 0.9540 | 3.034 | 0.9586 | 2.522 | 0.9605 | 2.294 | 0.9582 | 2.458 |
| All Fingers | 0.9800 | 3.086 | 0.9658 | 3.254 | 0.9760 | 3.182 | 0.9790 | 2.646 | 0.9760 | 2.992 |

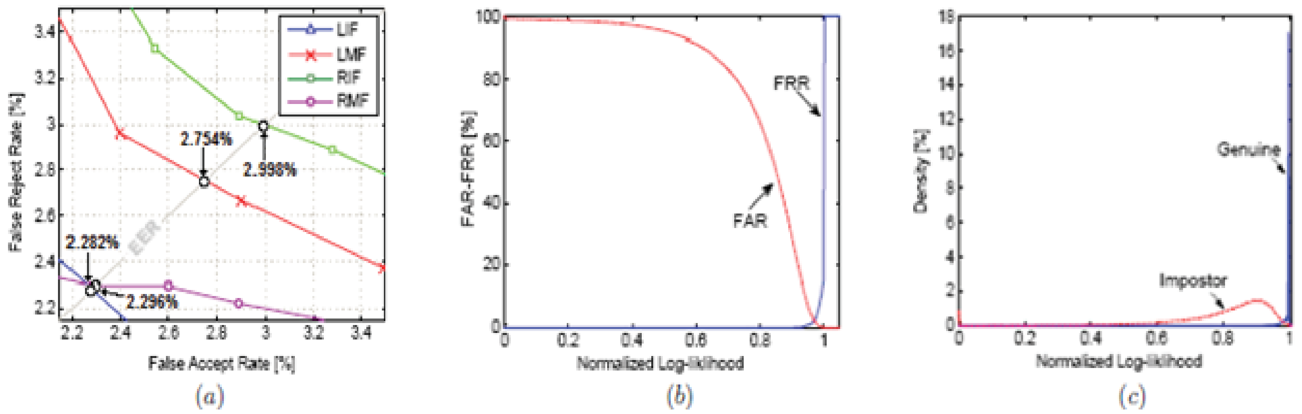


Fig. 2. Unimodal system performance. (a) The ROC curves for all finger types, (b) The dependency of the FAR and the FRR on the value of the threshold (LIF modality) and (c) The genuine and impostor distribution (LIF modality).

multimodal system with a single biometric trait but multiple units. Therefore, information presented by different biometrics (finger types) is fused to make the system efficient.

*1) Fusion at image level:* Image fusion is the process by which two or more images are combined into a single image. For that, a series of experiments were carried out using the FKP database to selection the best combination and fusion technique (DWT, PCA, LAPLACIAN, GRADIANT and CONTRAST) [10, 11] that maximize the GAR. However, in order to see the performance of the identification system, we usually give, in Table 2, the results for all the fusion techniques and the possible combinations. Thus, the result suggests that the fusion of LMF and RMF with CONTRAST technique has performed better than other (EER = 2.146 % and= 0.9690).

*1) Fusion at feature level:* We also investigated the integration of multiple biometric modalities at the representation level. The data obtained from each biometric modality (LIF, LMF, RIF and RMF) is used to compute a feature vector. The idea of fusion at the feature extraction level is to concatenate the feature vectors of different biometrics (different fingers). The new observation vector has a higher dimensionality and represents a person's identity in a different feature space. Several fusion techniques has been proposed by various researchers. To find the better of the all fusion techniques, with the lowest EER, table showing the results were generated (see Table 3). This Table shows that the LMF and RMF combination with HORIZONTAL technique offers better results (EER = 1.126 % and = 0.9618).

*2) Fusion at matching score level:* In our system the individual matching scores are combined to generate a single scalar score, which is then used to make the final decision. During the system design we experimented five different fusion schemes [12]: Sum-score (SUM), Sum-weighting-score (WHT), Min-score (MIN), Max-score (MAX) and Mul-score (MUL). Table 4 provides the performance of the identification system. From Table 4, it is clear that our identification system achieves a best performance when using all finger with Sum rule fusion (EER = 0.269 % and = 0.9676).

In Fig. 4.*(a)*, we compare the performance of unimodal and multimodal system. The results show the benefits of using the multimodal system with matching score level fusion. Finally, the results expressed as a FAR and FRR depending on the threshold and the distance distributions of genuine and imposter matching's obtained by the proposed scheme, if the all fingers

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are fused in the case of matching score level by SUM rule, are plotted in Fig. 4.*(b)* and Fig. 4.*(c)*, respectively.

## V. CONCLUSION AND FURTHER WORK

This paper proposes an efficiency scheme for FKP identification using the HMM and 2D-BDCT. Firstly the ROI is divided into non-overlapping and equal-sized blocks, and then, applies the DCT over each block to produce the feature vector. Subsequently, we use the HMM for modeling the feature vector of each FKP. Finally, Log-likelihood scores are used for the matching process. The proposed scheme is validated for their efficacy on PolyU FKP database of 165 users. Our experimental results experimental results indicate that the proposed system has a good capability to identify a person's identity. Our future work will focus on the performance evaluation using other fusion level (*decision*), and combining both FKP and palmprint to get security system with high accuracy.

TABLE III. OPEN SET IDENTIFICATION TEST RESULTS IN THE CASE OF FUSION AT FEATURE LEVEL

| COMBINATION | HORIZONTAL | | ROW | | COLUMN | | VERTICAL | | MEAN | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $T_o$ | EER | $T_o$ | EER | $T_o$ | EER | $T_o$ | EER | $T_o$ | EER |
| LIF-LMF | 0.9720 | 4.682 | 0.9806 | 1.367 | 0.9786 | 1.316 | 0.9607 | 1.646 | 0.9804 | 2.472 |
| LIF-RIF | 0.9798 | 1.230 | 0.9562 | 1.305 | 0.9741 | 1.564 | 0.9561 | 1.305 | 0.9722 | 3.142 |
| LMF-RMF | **0.9618** | **1.126** | 0.9619 | 1.226 | 0.9717 | 1.679 | 0.9619 | 1.224 | 0.9771 | 3.090 |
| RIF-RMF | 0.9495 | 4.748 | 0.9959 | 2.772 | 0.9471 | 2.991 | 0.9959 | 2.772 | 0.9702 | 3.117 |
| All Fingers | 0.9698 | 7.175 | 0.9880 | 1.308 | 0.9727 | 1.695 | 0.9880 | 1.307 | 0.9771 | 2.953 |

TABLE IV. OPEN SET IDENTIFICATION TEST RESULTS IN THE CASE OF FUSION AT MATCHING SCORE LEVEL

| COMBINATION | SUM | | WHT | | MIN | | MAX | | MUL | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $T_o$ | EER | $T_o$ | EER | $T_o$ | EER | $T_o$ | EER | $T_o$ | EER |
| LIF-LMF | 0.9736 | 0.822 | 0.9736 | 0.826 | 0.9857 | 1.097 | 0.9631 | 1.269 | 0.9489 | 0.806 |
| LIF-RIF | 0.9649 | 0.984 | 0.9667 | 0.889 | 0.9807 | 1.369 | 0.9530 | 1.407 | 0.9317 | 1.004 |
| LMF-RMF | 0.9542 | 1.116 | 0.9667 | 0.889 | 0.9795 | 1.183 | 0.9424 | 1.492 | 0.9163 | 1.100 |
| RIF-RMF | 0.9543 | 0.815 | 0.9519 | 0.889 | 0.9758 | 0.983 | 0.9404 | 1.259 | 0.9143 | 0.872 |
| All Fingers | **0.9676** | **0.269** | 0.9682 | 0.278 | 0.9990 | 0.450 | 0.9330 | 1.255 | 0.8829 | 0.296 |

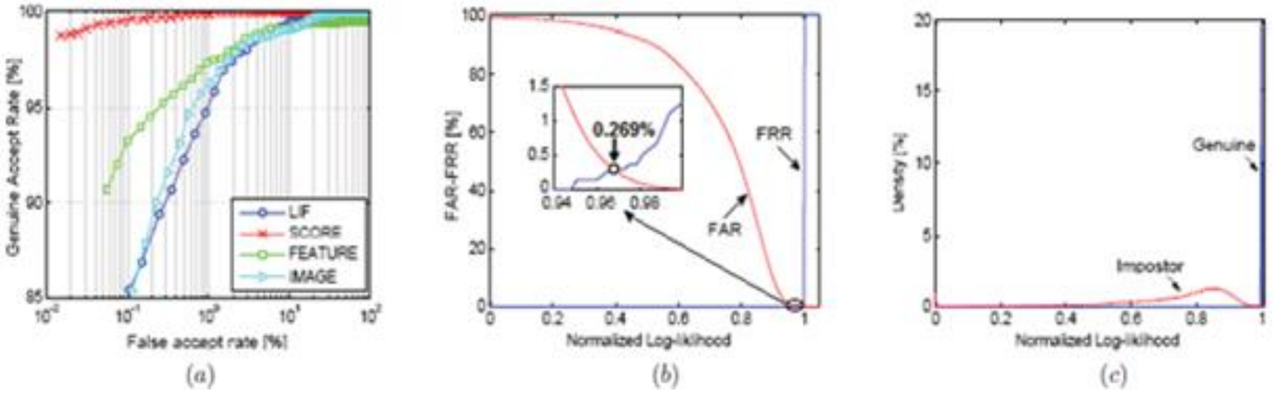


Fig. 3. Multimodal system performance in the case of fusion at matching score level (all fingers) with SUM rule. (a) The comparison between the unimodal and multimodal systems, (b) The dependency of the FAR and the FRR on the value of the threshold and (c) The genuine and impostor distribution.

## REFERENCES

[1] Arun A. Ross, K. Nandakumar and A. K. Jain, "Handbook of Multibiometrics", in Springer Science+Business Media, LLC, New York, 2006.

[2] Ajay Kumar and David Zhang, "Improving Biometric Authentication Performance From the User Quality", in *IEEE transactions on instrumentation and measurement*, vol. 59, no. 3, march 2010.

[3] R. Zhao, K. Li, M. Liu, X. Sun, "A Novel Approach of Personal Identification Based on Single Knuckleprint Image", in *AsiaPacific Conference on Information Processing, APCIP*, 2009.

[4] L. Zhang, L. Zhang, D. Zhang, "Finger-knuckle-print: a new biometric identifier", in: *Proceedings of the ICIP09,* 2009.

[5] Ahmed N, Natarajan T, and Rao K, "Discrete cosine transform", in *IEEE Trans, on Computers*, 23(1):9093.

[6] H. Uguz, A. Arslan, "A biomedical system based on hidden Markov model for diagnosis of the heart valve diseases", in *Pattern Recognition Letters* 28, 2007, pp: 395-404.

[7] Fabien Cardinaux, Conrad Sanderson, Samy Bengio, "Face Verification Using Adapted Generative Models", in *6th IEEE Int. Conf. Automatic Face and Gesture Recognition*, Seoul, 2004, pp. 825-830.

doi:10.15849/icit.2015.0049 

[8] PolyU Finger-Knuckle-Print Database. http://www4.comp.polyu.edu.hk/~biometrics/ FKP.htm.
[9] Ziad M. Hafed and Martin D. Levine, "Face Recognition Using the Discrete Cosine Transform", in *International Journal of Computer Vision* 43(3) , 2001, pp: 167-188.
[10] Akansu, A. N. and Haddad, R. A, "Multiresolution signal decomposition", *Academic Press*, New York, 1992.
[11] Mallat, S. G, "A theory for multiresolution signal decomposition", in IEEE Trans. Pattern Analysis and Machine Intelligence, Vol. 11, No. 7, 1989, pp. 674-693.
[12] A. Meraoumia, S. Chitroub and A.Bouridane, "Palmprint and Finger-Knuckle-Print for efficient person recognition based on LogGabor filter response", in *International Journal Analog Integrated Circuits and Signal Processing*, Vol 69 (1), pp: 17-27, 2011.