Analysis of Multibiometric Palmprint Recognition System for Authentication

Akila P, Gayathri R, Meenatchi R, Ramya M (ECE)
Guided by Dharini D (Professor)
K. Ramakrishnan College of Engineering

***Abstract*—Multi biometrics can provide higher identification accuracy than single biometrics, so it is more suitable for some real-world personal identification applications that need high-standard security. Among various biometrics technologies, palm print identification has received much attention because of its good performance. Combining the left and right palm print images to perform multi biometrics is easy to implement and can obtain better results. However, previous studies did not explore this issue in depth. In this paper, we proposed a novel framework to perform multi biometrics by comprehensively combining the left and right palm print images. This framework integrated three kinds of scores generated from the left and right palm print images to perform matching score-level fusion. The first two kinds of scores were, respectively, generated from the left and right palm print images and can be obtained by any palm print identification method, whereas the third kind of score was obtained using a specialized algorithm proposed in this paper. As the proposed algorithm carefully takes the nature of the left and right palm print images into account, it can properly exploit the similarity of the left and right palm prints of the same subject. Moreover, the proposed weighted fusion scheme allowed perfect identification performance to be obtained in comparison with previous palm print identification methods.**

Keywords—Palm print recognition, biometric and multi biometric

INTRODUCTION

Palm print recognition inherently implements many of the same matching characteristics that have allowed fingerprint recognition to be one of the most well-known and best publicized biometrics. Both palm and finger biometrics are represented by the information presented in a friction ridge impression. This information combines ridge flow, ridge characteristics,and ridge structure of the raised portion of the epidermis. The data represented by these friction ridge impressions allows a determination that corresponding areas of friction ridge impressions either originated from the same source or could not have been made by the same source.

Because fingerprints and palms have both uniqueness and permanence, they have been used for over a century as a trusted form of identification. However, palm recognition has been slower in becoming automated due to some restraints in computing capabilities and live-scan technologies.Palm recognition technology exploits some of these palm features. Friction ridges do not always flow continuously throughout a pattern and often result in specific characteristics such as ending ridges or dividing ridges and dots. A palm recognition system is designed to interpret the flow of the overall ridges to assign a classification and then extract the minutiae detail a subset of the total amount of information available, yet enough information to effectively search a large repository of palm prints. Minutiae are limited to the location, direction, and orientation of the ridge endings and bifurcations (splits) along a ridge path.The images in Figure present a pictorial representation of the regions of the palm, two types of minutiae, and examples of other detailed characteristics used during the automatic classification and minutiae extraction processes.

Palmprint identification is an important personal identification technology and it has attracted much attention. The palmprint contains not only principle curves and wrinkles but also rich texture and miniscule points, so the palmprint identification is able to achieve a high accuracy because of available rich information in palmprint.Various palmprint identification methods,such as coding based methods and principle curve methods have been proposed in past decades. In addition to these methods,subspace based methods can also perform well for palmprint identification. For example, Eigen palm and Fisher palm are two well- known subspace based palmprint identification methods.

PREVIOUS WORK

In recent years, 2D appearance based methods such as 2D Principal Component Analysis (2DPCA), 2D Linear Discriminant Analysis (2DLDA), and 2D Locality Preserving Projection (2DLPP) have also been used for palmprint recognition.Further, the Representation Based Classification (RBC) method also shows good performance in palmprint identification. Additionally, the Scale Invariant Feature Transform (SIFT) which transforms image data into scale-invariant coordinates, are successfully introduced for the contactless palmprint identification.Extensive experiments show that the proposed framework can integrate most conventional palmprint identification methods for performing identification and can achieve higher accuracy than conventional methods. This work has the following notable contributions.

First, it for the first time shows that the left and right palmprint of the same subject are somewhat correlated, and it demonstrates the feasibility of exploiting the crossing matching score of the left and right palmprint for improving the accuracy of identity identification. Second, it proposes an elaborated framework to integrate the left palmprint,right palmprint, and crossing matching of the left and right palmprint for identity identification. Third, it conducts extensive experiments on both touch-based and contactless palmprint databases to verify the proposed framework.In biometrics there are two types of identity matching: identification and verification.

Identification is a one-to-many comparison of an individual‟ s biometric sample against a template database of previously gathered samples.Verification refers to a one- to-one comparison between a previously acquired template of an individual and a sample which we want to authenticate. An application providing verification support would also require some other means for theuser to claim his identity (e.g. information contained in a smart card, keyboard for user input), while for identification purpose this is not needed.Palmprint recognition uses the persons palm as a bio-metric for identifying or verifying person‟ s identity. Palmprint patterns are a very reliable biometric and require minimum cooperation from the user for extraction.

Palmprint is distinctive, easily captured by low resolution devices as well as contains additional features such as principal lines,wrinkles and ridges. Therefore it is suitable for everyone and it does not require any personal information of the user. Palm normally contains three flexion creases (principal lines), secondary creases (wrinkles) and ridges. The three major flexions are genetically dependent; most of other creases are not. Even identical twins have different palmprints.These non-genetically deterministic and complex patterns are very useful in personal identification. Palm is the inner surface of the hand between the wrist and fingers.Palm area contains large number of features such as principle lines, wrinkles, minutiae, datum point features and texture images. Most of the system uses the low resolution image.

EXISTING SYSTEM

Palmprint identification is an important personal identification technology and it has attracted much attention. The palmprint contains not only principle curves and wrinkles but also rich texture and miniscule points, so the palmprint identification is able to achieve a high accuracy because of available rich information in palmprint .Various palmprint identification methods, such as coding based methods and principle curve methods have been proposed in past decades. In recent years, 2D appearance based methods such as 2D Principal Component Analysis (2DPCA),2D Linear Discriminant Analysis (2DLDA) , and 2D Locality Preserving Projection (2DLPP) have also been used for palmprint recognition.

EXISTING METHODS

A.Line Based Method

Lines are the basic feature of palmprint and line based methodes play an important role in palmprint verification and identification. Line based methods use lines or edge detectors to extract the palmprint lines and then use them to perform palmprint verification and identification. In general, most palms have three principal lines: the heartline, headline, and lifeline, which are the longest and widest lines in the palmprint image and have stable line shapes and positions**.**Thus, the principal line based method is able to provide stable performance for palmprint verification. Palmprint principal lines can be extracted by using the Gobor filter, Sobel operation, or morphological operation.

B. Coding based method

Coding based methods are the most influential palm-print identification methods. Representative coding based methods include the competitive code method, ordinal code method, palmcode method and Binary Orientation Co- occurrence Vector (BOCV) method , and so on.

C. Subspace Based Methods

Subspace based methods include the PCA, LDA, and ICA etc. The key idea behind PCA is to find an orthogonal subspace that preserves the maximum variance of the original data. The PCA method tries to find the best set of all samples by using the following objective function:

JPC A=arg maxW|WTStW|

Where St is the total scatter matrix of the training samples, and W is the projection matrix whose columns are orthonormal vectors. PCA chooses the first few principal components and uses them to transform the samples in to a low-dimensional feature space.LDA tries to find an optimal projection matrix W and transforms the original space. to a lower-dimensional feature space. The goal of LDA is to maximize the ratio of the between-class distance against within-class distance which is defined as:

JLDA=arg maxW|WTSbW|/|WTSwW|

Where Sb is the between-class scatter matrix, and Sw is the within-class scatter matrix. In the subspace palmprint identification method, the query palmprint image is usually classified into the class which produces the minimum Euclidean distance with the query sample in the low- dimensional feature space.

D. Representation Based Method

The representation based method uses training samples to represent the test sample, and selects a candidate class with the maximum contribution to the test sample. The Collaborative Representation based Classification (CRC) method, Sparse Representation-Based Classification (SRC) method and Two-Phase Test Sample Sparse Representation (TPTSSR) method are two representative representation based methods. Almost all representation based methods can be easily applied to perform palmprint identification. The CRC method uses all training samples to represent the test sample.

E. SIFT Based Method

SIFT was originally proposed for object classification applications, which are introduced for contactless palmprint identification in recent years. Because the contactless palmprint images have severe variations in poses, scales, rotations and translations, which make conventional palmprint feature extraction methods on contactless imaging schemes questionable and therefore, the identification accuracy of conventional palmprint recognition methods is usually not satisfactory for contactless palmprint identification. The features extracted by SIFT are invariant to image scaling, rotation and partially invariant to the change of projection and illumination.

Therefore, the SIFT based method is insensitive to the scaling, rotation, projective and illumination factors, and thus is advisable for the contactless palmprint identification.The SIFT based method firstly searches over all scales and image locations by using a difference-of- Gaussian function to identify potential interest points. Then an elaborated model is used to determine finer location and scale at each candidate location and keypoints are selected based on the stability.Then one or more orientations are assigned to each keypoint location based on local image gradient directions. Finally, the local image gradients are evaluated at the selected scale in the region around each keypoint.In the identification stage, the Euclidean distance can be employed to determine the identity of the query image.A smaller Euclidean distance means a higher similarity between the query image and the training image.

Disadvantages of existing system

1. No single biometric technique can meet all requirements in circumstances.
2. The limitation of the existing system is unimodal biometric technique and have less perfomance.
3. Processing time is high.

PROPOSED SYSTEM

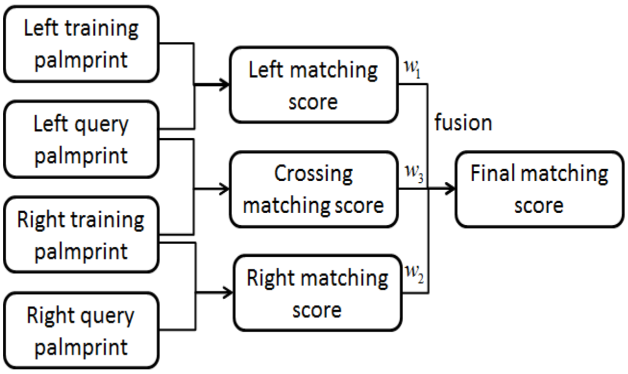
In this paper, we propose a novel framework of combining the left with right palmprint at the matching score level. The procedure of the proposed framework. In the framework, three types of matching scores,which are respectively obtained by the left palmprint matching, right palmprint matching and crossing matching between the left query and right training palmprint, are fused to make the final decision.The framework not only combines the left and right palmprint images for identification, but also properly exploits the similarity between the left and right palmprint of the same subject.Extensive experiments show that the proposed framework can integrate most conventional palmprint identification methods for per-forming identification and can achieve higher accuracy than conventional methods.

This work has the following notable contributions.:

1. First, it for the first time shows that the left and right palmprint of the same subject are somewhat correlated, and it demonstrates the feasibility of exploiting the crossing matching score of the left and right palmprint for improving the accuracy of identity identification.
2. Second, it proposes an elaborated framework to integrate the left palmprint, right palmprint, and crossing matching of the left and right palmprint for identity identification.
3. Third, it conducts extensive experiments on both touch- based and contactless palmprint databases to verify the proposed framework.

This subsection describes the main steps of the propose framework.

The framework first works for the left palmprint images and uses a palmprint identification method to calculate the scores of the test sample with respect to each class. Then it applies the palmprint identification method to the right palmprint images to calculate the score of the test sample with respect to each class.



After the crossing matching score of the left palmprint image for testing with respect to the reverse right palmprint images of each class is obtained, the proposed framework performs matching score level fusion to integrate these three scores to obtain the identification result.

Fig. 3 (a)-(d) depict the principal lines images of the left palmprint shown in Fig. 2 (a)-(d). Fig. 3 (e)-(h) are the reverse right palmprint principal lines images corresponding to Fig. 2 (i)-(l). Fig. 3 (i)-(l) show the principle lines matching images of Fig. 3 (a)-(d) and Fig. 3 (e)-(h), respectively. Fig. 3 (m)-(p) are matching images between the left and reverse right palmprint principal lines images from different subjects. The four matching images of Fig. 3 (m)-(p) Fig. 2. Palmprint images of four subjects. (a)-(d) are four left palmprint images; (e)-(h) are four right palmprint corresponding to (a)-(d); (i)-(l) are the reverse right palmprint images of (e)-(h).

ISSN: 2278-0181
NCICCT - 2016 Conference Proceedings

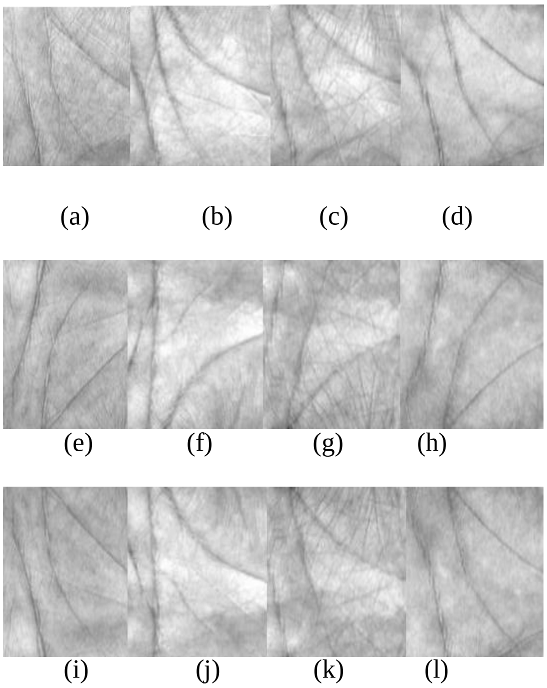


Fig. 2. Palmprint images of four subjects. (a)-(d) are four left palmprint images;(e)-(h) are four right palmprint corresponding to (a)-(d); (i)-(l) are the reverse right palmprint images of (e)-(h).

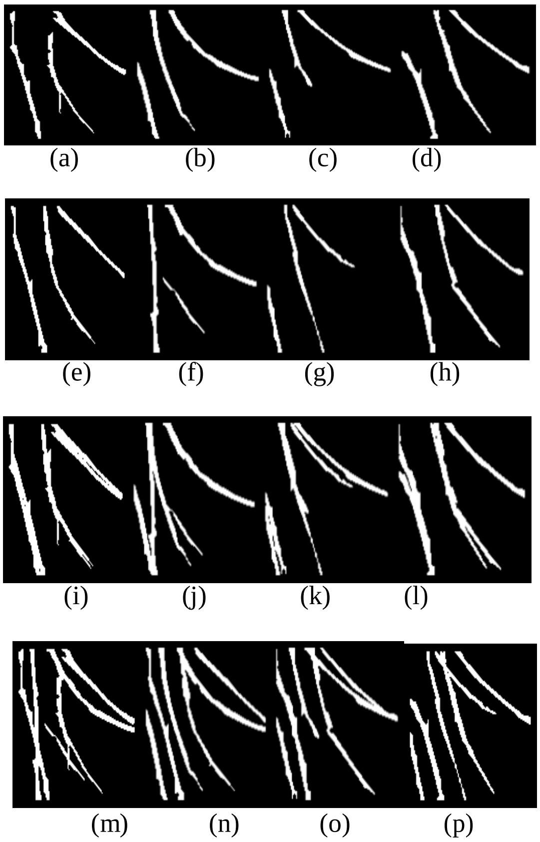


Fig. 3. Principal lines images. (a)-(d) are four left palmprint principal lines images, (e)-(h) are four reverse right palmprint principal lines image, (i)-(l) are principal lines matching images of the same people, and (m)-(p) are principal lines matching images from different people.

The four matching images of Fig. 3 (m)-(p) are: (a) and (f) principal lines matching image, (b) and (e) principal lines matching image, (c) and (h) principal lines matching image, and (d) and (g) principal lines matching image, respectively.

Matching Score Level Fusion

In the proposed framework, the final decision making is based on three kinds of information: the left palmprint, the right palmprint and the correlation between the left and right palmprint. As we know, fusion in multimodal biometric sys-tems can be performed at four levels. s. In the image (sensor) level fusion, different sensors are usually required to capture the image of the same biometric. Fusion at decision level is too rigid since only abstract identity labels decided by different matchers are available, which contain very limited information about the data to be fused. Fusion at feature level involves the use of the feature set by concatenating several feature vectors to form a large 1D vector. The integration of features at the earlier stage can convey much richer information than other fusion strategies. So feature level fusion is supposed to provide a better identification accuracy than fusion at other levels. However, fusion at the feature level is quite difficult to implement because of the incompatibility between multiple kinds of data. Moreover, concatenating different feature vectors also lead to a high computational cost. The advantages of the scorelevel fusion and the weight-sum scorelevel fusion strategy is effective for component classifier combination to improve the performance of biometric identification. The strength of individual matchers can be highlighted by assigning a weight to each matching score. Consequently, the weight-sum matching score level fusion is preferable due to the ease in combining three kinds of matching scores of the proposed method. the basic fusion procedure of the proposed method at the matching score level.

The final matching score is generated from three kinds of matching scores. The first and second matching scores are obtained from the left and right palmprint, respectively. The third kind of score is calculated based on the crossing matching between the left and right palmprint. wi(i = 1, 2, 3), which denotes the weight assigned to the ith matcher, can be adjusted and viewed as the importance of the corresponding matchers.

Differing from the conventional matching score level fusion, the proposed method introduces the crossing matching score to the fusion strategy. When w3 = 0, the proposed method is equivalent to the conventional score level fusion. Therefore, the performance of the proposed method will at least be as good as or even better than conventional methods by suitably tuning the weight coefficients.

IV. EXPERIMENTAL RESULTS

More than 7,000 different images from both the contactbased and the contactless palmprint databases are employed to evaluate the effectiveness of the proposed method. Typical state-of-the-art palmprint identification methods, such as the RLOC method, the competitive code method, the ordinal code method, the BOCV method, and the SMCC method are adopted to evaluate the performance of the proposed framework.Moreover, several recent developed contactless based methodes, such as the SIFT method and the OLOF+SIFT method are also used to test the proposed framework. For the sake of completeness, we compare the performance of our method with that of the conventional fusion based methods.

A.Palmprint Databases

The PolyU palmprint database (version 2) contains 7,752 palmprint images captured from a total of 386 palms of 193 individuals. The samples of each individual were collected in two sessions, where the average interval between the first and second sessions was around two months. In each session, each individual was asked to provide about 10 images of each palm. We notice that some individual provide few images. For example, only one image of the 150th individual was captured in the second session. To facilitate the evaluation of the performance of our framework, we set up a subset from the whole database by choosing 3,740 images of 187 individual, where each individual provide 10 right palmprint images and 10 left palmprint images, to carry out the following experimentsshows some palmprint samples on the PolyU database. The public IITD palmprint database is a contactless palmprint database. Images in IITD database were captured in the indoor environment, which acquired contactless hand images with severe variations in pose, projection, rotation and translation. The main problem of contactless databases lies in the significant intra-class variations resulting from the absence of any contact or guiding surface to restrict such variations [20]. The IITD database consists of 3,290 hand images from 235 subjects. Seven hand images were captured from each of the left and right hand for each individual in every session. In addition to the original hand images, the Region Of Interest (ROI) of palmprint images are also available in the database. Fig. 6 shows some typical hand images and the corresponding ROI palmprint images in the IITD palmprint database. Compared to the palmprint images in the PolyU database, the images in the IITD database are more close to the real-applications.

B. Matching Results Between the Left and Right Palmprint

To obtain the correlation between the left and right palmprint in both the PolyU and the IITD databases, each left palmprint is matched with every right palmprint of each subject and the principal line matching score is calculated for the left palmprint and this subject. A match is counted as a genuine matching if the left palmprint is from the class; if otherwise, the match is counted as an imposter matching.

The PolyU palmprint subsethas 1,870 left palmprint images and 1,870 right palmprints from 187 individuals. Therefore there are 1,870 (1870*1) genuine matches and
347,820 (1870*186) impostor matches in total. In the IITD palmprint database, there are 1,645 left palmprint images and 1,645 right palmprints from 235 different subjects. So in the IITD database the total number of genuine matching and imposter matching are 1,645 (1645*1) and 384,930 (1645*234), respectively.

The False Accept Rate (FAR), False Reject Rate (FRR) and Equal Error Rate (EER) (the point where FAR is equal to FRR) [1] are adopted to evaluate the similarity between the left and right palmprints. The Receiver Operating Characteristic (ROC) curve, which is a graph of FRR against FAR for all possible thresholds, is introduced to describe the performance of the proposed method. The ROC curves of both the PolyU and IITD databases are plotted.

The EERs of two databases are 24.22% and 35.82%, respectively. One can observe that the EER obtained using the IITD database is much larger than that obtained using the PolyU database. The main reason is that palmprint images in IITD database have serious variations in rotation and translation. The experimental results still illustrate that the left palmprint and right palmprint of the same people generally have higher similarity than those from different subjects.

C. Experimental Results on PolyU Palmprint Database

In identification experiments, different kinds of palmprint recogniton methods are applied in the framework, including the line based method [10], coding based methods, subspace based methods, and representation based methods. In the experiments, match_threshold is empirically set to 0.2. The conventional fusion scheme only fuses the left palmprint and right palmprint features, but does not integrate the crossing similarity between the left and right palmprint.

It is impossible to exhaustively verify all possible weight coefficients to find the optimal coefficients. Due to the limit of space, only a set of representative weight
coefficients that minimize the final identification error rate of our framework.Empirically,the score that has the lower identification error rate usually has a larger weight
coefficient. In addition, the optimal weight coefficients vary
with the methods,since each method adopted in the proposed framework utilizes different palmprint feature extraction algorithm.

The experimental results of the PolyU database show that the identification error rate of the proposed method is about 0.06% to 0.2% lower than that of conventional fusion methods. The comparison between the best identification results of the proposed method and conventional fusion scheme are depicted.

D. Experimental Results on IITD Palmprint Database

Experiments are also conducted on the IITD contactless palmprint database. For the space limited, not all methods employed in the PolyU database but several promising contactless palmprint identification methods, including coding based methods, the SIFT based method, the OLOF+SIFT method and the SMCC method, are adopted to carry out the experiments. In addition, LDA and CRC based methods are also tested by the database. Large scale translation will cause serious false position problem in the IITD database. To reduce the effect of the image translation between the test image and the training image, the test image will be vertically and horizontally translated with one to three pixels, and the best matching result obtained from the translated matching is recorded as the final matching result.

The palmprint identifi- cation accuracy of the proposed framework is higher than that of the direct fusion of the left and right palmprint for both the PolyU database and the IITD contactless database.The crossing matching score can also be calculated based on the similarity between the right query and left training palmprint. We also conduct experiments to fuse both crossing matching scores to perform palmprint identification. However, as the use of the two crossing matching scores does not lead to more accuracy improvement, we exploit only one of them in the proposed method.

E. Computational Complexity

In the proposed method, since the processing of the reverse right training palmprint can be performed before palmprint identification, the main computational cost of the proposed method largely relies on the individual palmprint identification method. Compared to the conventional fusion strategy that only fuses two individual matchers, the proposed method consists of three individual matches. As a result, the proposed method needs to perform one more identification than the conventional strategy. Thus, the identification time of the proposed method may be about 1.5 times of that of conventional fusion strategy.

V. CONCLUSIONS

This study shows that the left and right palmprint images of the same subject are somewhat similar. The use of this kind of similarity for the performance improvement of palmprint identification has been explored in this paper. The proposed method carefully takes the nature of the left and right palmprint images into account, and designs an algorithm to evaluate the similarity between them. Moreover, by employing this similarity, the proposed weighted fusion scheme uses a method to integrate the three kinds of scores generated from the left and right palmprint images. Extensive experiments demonstrate that the proposed framework obtains very high accuracy and the use of the similarity score between the left and right palmprint leads to important improvement in the accuracy. This work also seems to be helpful in motivating people to explore potential relation between the traits of other bimodal biometrics issues.

REFERENCES

[1] S. Ribaric and I. Fratric, “A biometric identification system based on Eigenpalm and Eigenfinger features,” IEEE Trans., vol. 27, no. 27, Nov 2005

[2] A. K. Jain, A. Ross, “An introduction to biometric recognition,” IEEE Trans., vol. 14, no.1, Jan 2004.

[3] David Zhang, Fellow, “An Online System of Multispectral Palmprint Verification” IEEE Trans .,vol. 59, Feb 2010

[4] A. W. K. Kong, D. Zhang, and M. S. Kamel, “A Survey of palmprint recognition,”Pattern Recognit., vol. 42, no. 7, Jul. 2009

[5] Dhaneshwar PrasadDewangan1,and Abhishek Pandey2 ,“A Survey on Security in Palmprint Recognition: A Biometric Trait Volume 1, Issue 8, October 2012

[6] A. Kong, D. Zhang, and M. Kamel, “Palmprint identification using feature-level fusion,” Pattern Recognit., vol. 39, no. 3, Mar. 2006.

[7] A. Kumar and D. Zhang, “Personal authentication using multiple palm-print representation,” Pattern Recognit., vol. 38, no. 10, ,2005.

[8] D. Zhang, Z. Guo, G. Lu, D. Zhang, and W. Zuo, “An online system of multispectral palmprint verification,” IEEE Trans. Instrum. Meas., vol. 59, no. 2, Feb. 2010.

[9] Z. Guo, G. Wu, Q. Chen, and W. Liu, “Palmprint recognition by a two-phase test sample sparse representation,” in Proc. Int. Conf. Hand-Based Biometrics (ICHB), Nov. 2011.

[10] D. Zhang, Z. Guo, G. Liu, L. Zhang, Y. Liu, and W. Zuo, “Online joint palmprint and palmvein verification,” Expert Syst. Appl., vol. 38, no. 3, Mar. 2011.