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Fusion of Finger Knuckle Scores to Hand Geometry and Palm Print Scores using Multi-Spectral Hand Image Acquisition

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Abstract: Biometric System has been dynamically materializing in various industries for the past few years and it is ongoing to roll to grant higher security features for access control system. Several types of unimodal biometric systems have been expanded. Though, these systems are only able to offer low to middle range of security aspect. Therefore, for higher security aspect, the fusion of two or more unimodal biometrics (multiple modalities) is needed. This study proposes a multimodal Biometric System for person recognition using Multi-Spectral Hand Image Acquisition and Fusion of Finger knuckle scores to Hand Geometry and PalmPrint scores. PalmPrint, Hand Geometry and Finger-Knuckle-Print (FKP) textures are concurrently obtained using Multi-Spectral Hand Image Acquisition from the user's facade standardized textured 3D hand for recognizing the similarity between the hand postures. The features of FKP are mined using the scale invariant feature transform (SIQT) and the speeded up robust features (SSF). The three modalities are combined and the fusion is applied at the matching-score level by using weighted sum rule method. The experimental results illustrated that the proposed system improves the metrics of similarity scores in terms of rate and time of similarity verification, minimize size of hand data features and reduction of templates in multimodality matching.

Key words: Finger knuckle, Hand Geometry, PalmPrint, fusion, sum

INTRODUCTION

The rapid growth in several applications for some different fields such as public security, access control and surveillance, needs reliable and regular personal recognition for efficient security control. At present, a number of biometric based tools have been built and hand-based person recognition is one of these tools. Hand-based person recognition provides a consistent, low-priced and user-friendly feasible solution for a series of access control applications. In reality, contrary to other modalities similar to face and iris, the human hand holds an extensive variety of modalities which are Hand Geometry, Fingerprint, PalmPrint and Finger-Knuckle-Print (FKP). These modalities will be definitely used by biometric systems because of some benefits that the biometry of human hand provides.

Initially, data acquisition is relatively simple and inexpensive via commercial low-resolution cameras. Next, hand-based access systems are very appropriate for indoor and outdoor usage and will research well in great weather and illumination situation. Third, hand features of adults are more constant over time and they are not vulnerable to major variations. At last, human hand-based biometric information is very consistent and it can be effectively used for identifying people along with several populations.

PalmPrint and Hand Geometry recognition is one sort of biometric technology and a comparatively new biometric feature. A simple PalmPrint and Hand Geometry Biometric System have a sensor module for acquiring the PalmPrint and Hand Geometry, a feature extraction module for representation and a matching module for decision making.

A FKP-based biometric identification is more fresh biometric technology and it has fascinated an increasing amount of consideration. The image-pattern structure of a finger-knuckle comprises information that is capable of recognizing the identity of an individual. The FKP biometric identifies a person based on the knuckle lines and the textures in the outer finger facade. These line structures and finger textures are constant and remain unchanged all through the life of an individual. A significant issue in FKP recognition is to mine FKP features that can distinguish an individual from the other. There are several approaches for FKP recognition using line-based and texture-based techniques in various literatures.

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This study describes the biometric recognition system based on a fusion of PalmPrint, Hand Geometry and FKP using Multi-Spectral Hand Image Acquisition. The PalmPrint, Hand Geometry and FKP images are used as inputs of the matcher modules. The outputs of the matcher modules are merged using the concept of data fusion at matching score level with Weighted Sum Rule Method.

Literature review: Researchers have proposed several promising methods for PalmPrint, Hand Geometry and FKP biometrics. 3D digitizer is utilized in (Kumar and Manimala, 2011) to obtain intensity and range images of the user's hand presented to the system in an arbitrary pose. In 3D PalmPrint recognition (Kanhangad and Zhang, 2011), once calculating and enhancing the mean-curvature image of the 3D PalmPrint data both line and orientation features are extracted from it.

Multimodal (2D as well as 3D) PalmPrint and Hand Geometry features are concurrently extracted from the user's pose normalized textured 3D hand are employed for matching. Finger-Knuckle-Print (FKP) recognition algorithm using Band-Limited Phase Only Correlation (BLPOC)-based local block matching is presented in (Loris and Alessandra, 2009).

Finger back surface imaging is presented by Kumar and Ravikanth (2009) using peg-free imaging. The finger back surface images from each of the users are normalized to reduce the scale, translation and rotational variations in the knuckle images. Method for constructing human finger from its fractional part is introduced by Meraoumia *et al*. (2010). Taalamana System and golden ratio are used to forecast the feature value. The method of extracting user quality is based on the confidence of producing reliable matching scores (Kumar and Zhang, 2010) from the user templates.

Feature level fusion of Finger Knuckle Prints (FKPs) is implemented by Hanmandlu and Grover (2012). Feature selection is done by the t-norms using Reinforced Hybrid evolutionary technique. Apart from that Loris and Alessandra (2009) and Meraoumia *et al*. (2010) also investigated knuckle features by fusing the knuckle print pattern from the middle and ring fingers. Fine experiment result had indicated that knuckle print is a reliable biometric modality.

Multi-Representation Biometric System is presented by Aoyama *et al*. (2011) for person recognition using palm images and by combining two different representations of the PalmPrint. Nandakumar *et al*. (2008) proposed a framework for the optimal mixture of match scores that is based on the likelihood ratio test. The distributions of valid and impostor match scores are formed as finite Gaussian Mixture Model.

Motivated by the matching approaches of human PalmPrint experts (Dai *et al*., 2012) developed a PalmPrint recognition scheme. It quantitatively studied statistics of main features in PalmPrint and a segment-based matching and fusion algorithm is proposed to handle the skin distortion and the unstable discrimination power of dissimilar PalmPrint regions.

There are restrictions to a single biometric observation for example variation in an individual biometric feature because of the condition of a sensor, the health condition of a human, illumination variation and so on. To conquer such confines, Kang and Park (2010) propose a Multimodal Biometric Method integrating finger vein recognition and finger geometry recognition at the score level.

MATERIALS AND METHODS

Fusion of finger knuckle scores to Hand Geometry and PalmPrint scores using Multi-Spectral Hand Image Acquisition: This study describes the Biometric Identification System based on a score level fusion of PalmPrint, Hand Geometry and FKP using Multi-Spectral Hand Image Acquisition. Researchers utilized the knuckle print from four fingers, specifically the pointed, middle, index and little fingers. The knuckle prints of interest said to the horizontal-like lines distributed on the palm region of the knuckles. Because of regular bending exercise of the knuckles, these flexion lines are extremely clear as compared to the surrounding skin region on the fingers (Fig. 1).

The knuckle prints typically appear on three locations in which I indicate as upmost, middle and base prints (Fig. 1a). Among the three places, middle prints contribute the main features for identification as it constitutes more affluent line texture. As for PalmPrint (Fig. 1b), only the centre area of the palm area is employed as Region of Interest (ROI) and it contains significant line

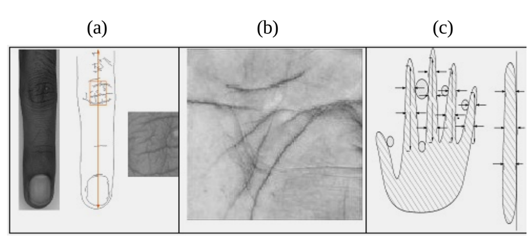

Fig. 1: a) Finger knuckle print; b) PalmPrint and c) Hand Geometry

patterns and dominant wrinkles. Every human hand is unique. Finger length, width, thickness, curvatures and relative location of these features distinguish every human being from every other person (Fig. 1c).

Figure 2 shows the block diagram of the proposed multimodal biometric recognition system. It based on the fusion of finger knuckle scores to Hand Geometry and PalmPrint scores at the matching-score level. Multimodal biometric recognition scheme involves for PalmPrint, Hand Geometry and FKP modalities, image feature extraction module and matching module. The course of recording a user's hand template is known as enrollment. The matching between the verified ROI and registered one in database for PalmPrint, Hand Geometry and FKP are performed. Matching scores from both unimodal biometric recognition systems are integrated into a unique matching score using fusion at the matching-score level using weighted sum rule method. Based on this unique matching score, a final result is made (the user is identified or rejected). This enhanced structure takes benefit of the ability of each unimodal biometric and will be used to conquer some of their limitations.

Feature extraction of PalmPrint and Hand Geometry: TCIB approach is employed for feature extraction of PalmPrint and Hand Geometry. It initially localizes the hand posture in the acquired hand images. These acquired images are stored, since the intensity and range images of the hand are obtained simultaneously. These binary images are upgraded by morphological operators which remove inaccessible noisy regions. Finally, the chief linked constituent in the resulting binary image is measured to be the set of pixels in proportion to the hand. Center of the palm is then located at a rigid distance along a line that is perpendicular to the line joining the two finger valley points. Figure 3 demonstrates the feature extraction of PalmPrint and Hand Geometry using TCIB approach. From the training sample sets, choose the image for feature extraction process. Calculate the RGB color value, texture value and combine value for the given training samples. The similar process is being handled over the specified input image. Once identifying the color texture values for the given image, the features are extracted with the chosen training image set.

Feature extraction of FKP: The feature extraction process of FKP is shown in Fig. 4. SIQT and SSF are used to haul out the limited features of FKP. Both SIQT and SSF have been designed for mining tremendously characteristic invariant features from images. An auxiliary, mined aspect vectors are recognized to be discrete, hard to balance, robust to alternation and moderately invariant to clarification. Therefore, features can be coordinated correctly with elevated probability beside features from a huge database of FKPs. SIQT and SSF key-points mined from the FKP images.

Fusion of finger knuckle scores to Hand Geometry and PalmPrint scores: In this study, several decision-level fusion rules are used to combine the FKP scores to the palm print score and Hand Geometry scores. In particular, researchers have tested the proposed system with AND and OR-voting rules, sum rule as well as weighted sum rule. The AND and OR-voting rules are the simplest

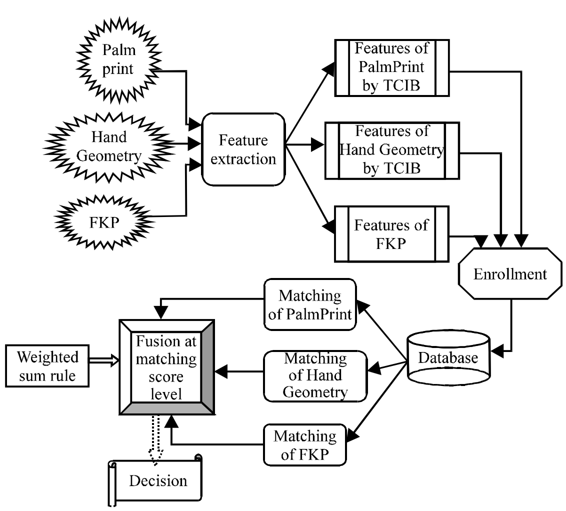

Fig. 2: The block diagram of the proposed PalmPrint, Hand Geometry and FKP-Based Biometric Recognition System

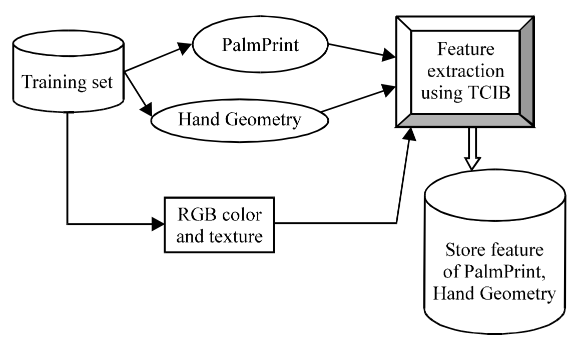

Fig. 3: Feature extraction of PalmPrint and Hand Geometry

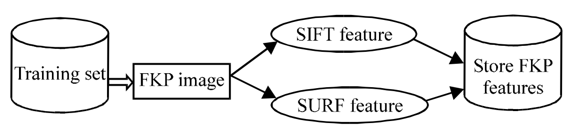

Fig. 4: Feature extraction of FKP

fusion methods. The AND-voting rule fusion decision is done only when all the classifiers have the same opinion. For OR-voting rule fusion, a decision is achieved when one of the classifiers makes a decision. In contrast, sum rule takes the average of the scores from the three modalities (FKP, PalmPrint and Hand Geometry). The summation of three single-modal classifier matching score is calculated as:

$$S = P_{ms} + H_{ms} + F_{ms} \qquad (1)$$

Where:

P_{ms} = The matching score of PalmPrint
H_{ms} = Hand Geometry
F_{ms} = Finger knuckle print

output the class with the least value of S. The main benefit of this rule is its simplicity and the truth that it does not require any training.

The final type of fusion method adopted in this research is the weighted sum rule. There exist different classifiers with different performances; therefore weights will be used to merge the individual classifiers. Because three models of biometrics are used in the system, the weighted sum S_w will be formed as:

$$S_w = (1\text{-}w)\,(P_{ms} + H_{ms} + F_{ms}) \qquad (2)$$

where, w is the weight which falls within value from 0-1.

Experiment evaluation of fusion of finger knuckle scores to hand geometry and palm print scores: In order to establish the usefulness of the proposed Multimodality System (FKP, PalmPrint and Hand Geometry), researchers performed verification experiments on the obtained database. In the proposed system, images are obtained using Multi-Spectral Hand Image Acquisition. The proposed scheme, fusion of finger knuckle scores to Hand Geometry and PalmPrint scores is implemented by using the Java platform. The experiments were conducted on an Intel P-IV machine with 2 GB memory and 3 GHz dual processor CPU.

The experiments are carried over with sets of test images. In order to evaluate the performance of the proposed Multimodality system for FKP, PalmPrint and Hand Geometry, the features are applied to those test sets of images with SIQT and SSF Methods. Based on scale invariant feature transform (SIQT) and the speeded up robust features (SSF), the texture values are produced and features are efficiently mined in a secure way. Then, it would match the template values and efficiently recognize the given image similarity. Obtained scores of FKP, PalmPrint and Hand Geometry then applied to fusion process for matching scores. The proposed system, fusion of finger knuckle scores to Hand Geometry and PalmPrint scores is efficiently designed for identifying the similarity of image and improved the multimodal biometric security using Multi-Spectral Hand Image Acquisition. The experiments conducted here aim to test the proposed fusion method selected for evaluation. The match scores for finger knuckle print, Hand Geometry and PalmPrint were each generated and then the fusion method were implemented through the methods described in study. The performance of proposed fusion method at score level matching is then presented for comparison. The performance of the proposed multimodality biometric system using metrics of similarity scores is measured in terms of:

- Rate and time of similarity verification
- Minimize size of hand data features
- Reduction of templates in multimodality matching

RESULTS AND DISCUSSION

To exhibit fusion of information from various biometric modalities, researchers preferred to fuse the match scores from finger knuckle scores to the scores generated by the Hand Geometry and PalmPrint. Score level fusion of finger knuckle print, Hand Geometry and PalmPrint was achieved by employing a Weighted Sum-Rule Method. Both fingerprint and PalmPrint match scores were normalized to the scale of [0, 1] by utilizing min-max normalization technique (Kumar and Ravikanth, 2009). The resulting ROC curves corresponding to the individual finger knuckle print, Hand Geometry and PalmPrint biometrics as well as the fused result are shown in Fig. 5-7. Fusing the information from a finger knuckle print, Hand Geometry and PalmPrint resulted in match performance that clearly exceeds that of either of the individual biometric traits Table 1.

Figure 5 shows the performance result of similarity verification from the given set of images and the fusion results are compared with each single trait (finger knuckle print, Hand Geometry and PalmPrint). In order to expose effectiveness of the fusion result (FKP+PalmPrint+Hand Geometry), researchers have conducted the experiment in terms of similarity verification time for various number of images. For using 25 images, the score level fusion system can consumes less similarity verification time (nearly 5 sec) compared with each unimodal similarity verification (Hand Geometry consumes 27 sec, PalmPrint consumes 23 sec and FKP consumes 29 sec) (Table 2).

From Fig. 6, it can safely be see the benefits of using the fusion of FKP and geometry and PalmPrint. The figure

Table 1: Rate and time of similarity verification

Number of images	Time of similarity verification (sec) Hand Geometry	PalmPrint	FKP	FKP + PalmPrint + Hand Geometry
5	10.06	3.56	16.79	1.04
10	12.63	7.78	17.05	2.12
15	19.79	11.12	21.18	2.43
20	18.13	15.08	25.56	2.81
25	27.87	23.96	29.07	5.26

Table 2: Size of hand data features

Number of users	Size of hand data features Proposed Multimodality System	Existing TCIB
2	1	3
4	2	5
6	2	8
8	3	6
10	4	9

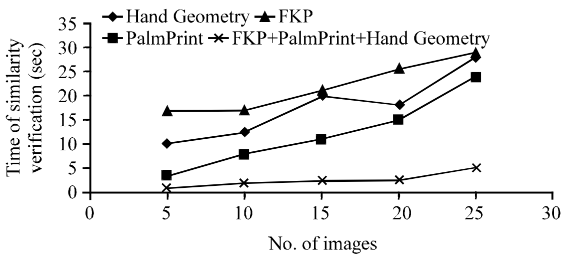

Fig. 5: Rate and time of similarity verification

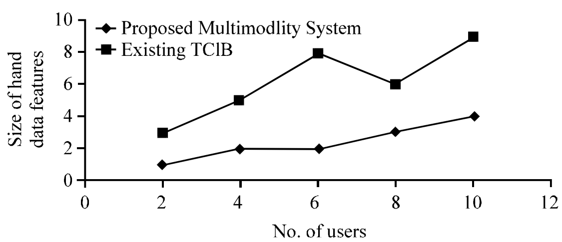

Fig. 6: Size of hand data features

demonstrates the size of hand data features using proposed multimodality system and existing TCIB System. Proposed multimodality system using score level fusion is having the small size of hand data features compared with TCIB System using feature level fusion (Table 3). Proposed multimodality system using score level fusion achieves better result (maximum usage of 4 features) than TCIB System using feature level fusion (maximum usage of 9 features of hand).

Figure 7 shows the matching performance of single biometric trait (finger knuckle print, Hand Geometry and PalmPrint) and multimodal biometric trait (FKP+PalmPrint+Hand Geometry). The performance of the score level fusion system is significantly improved by using the fusion with Weighted Sum Rule Method. (FKP+PalmPrint+Hand Geometry) achieves matching performance from 89-96%.

Table 3: Matching at score level fusion (%)

Number of images	Matching at score level fusion (%) Hand Geometry	PalmPrint	FKP	FKP + PalmPrint + Hand Geometry
5	78.67	76.79	65.59	89.94
10	79.45	77.08	72.67	94.37
15	73.32	83.34	73.94	92.35
20	82.24	84.65	76.89	96.89
25	83.33	85.54	73.01	93.98

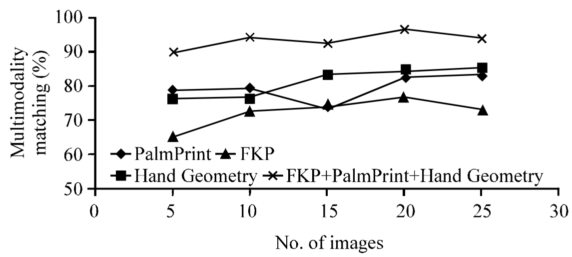

Fig. 7: Matching at score level fusion (%)

The resulting ROC curves along the lines of the single biometric traits such as finger knuckle print, Hand Geometry and PalmPrint biometrics as well as the fused result are shown in Fig. 5-7. Fusing the result from a finger knuckle print, Hand Geometry and PalmPrint resulted in match performance that clearly exceeds that of either of the individual biometric traits.

CONCLUSION

In this study, researchers have designed a biometric identification system based on the fusion of finger knuckle scores to Hand Geometry and PalmPrint scores. Multi-Spectral Hand Image Acquisition has been made to collect the images. Analysis of these data shows that multiple biometric features will be extracted from the multispectral images of the hand including FKP, Hand Geometry and PalmPrint. Fusion process has been performed using weighted sum rule method fusion at the matching-score level enhances the performance of the proposed system. The experimental results demonstrated that information fusion at the matching score level enhances the results of the identification. The obtained results illustrated that the proposed system has the capacities to be used in the environments that require a high security. The designed system attains an excellent recognition rate about 89-96% and provides more security than Unimodal Biometric-Based System.

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REFERENCES

Aoyama, S., K. Ito and T. Aoki, 2011. Finger-knuckle-print recognition using BLPOC-based local block matching. Proceedings of the 1st Asian Conference on Pattern Recognition, November 28-28, 2011, Beijing, pp: 525-529.

Dai, J., J. Feng and J. Zhou, 2012. Robust and efficient ridge-based palmprint matching. Trans. Patt. Anal. Mach. Intelli., 34: 1618-1632.

Hanmandlu, M. and J. Grover, 2012. Feature selection for finger knuckle print-based multimodal biometric system. Int. J. Comput. Applic., 38: 27-33.

Kang, B.J. and K.R. Park, 2010. Multimodal biometric method based on vein and geometry of a single finger. Comput. Vision, 4: 209-217.

Kanhangad, V., A. and D. Zhang, 2011. Contactless and pose invariant biometric identification using hand surface. IEEE Trans. Image Process., 20: 1415-1424.

Kumar, A. and C. Ravikanth, 2009. Personal authentication using finger knuckle surface. Trans. Inform. For. Secur., 4: 98-110.

Kumar, A. and D. Zhang, 2010. Improving biometric authentication performance from the user quality. Trans. Instrum. Measure., 59: 730-735.

Kumar, C.N.R. and S. Manimala, 2011. A novel method of constructing human middle finger from its fractional part. Int. J. Comput. Appl., 15: 47-52.

Loris, N. and L. Alessandra, 2009. A multi-matcher system based on knuckle-based features. Neural Comput. Applic., 18: 87-91.

Meraoumia, A., S. Chitroub and A. Bouridane, 2010. Efficient Person Identification by Fusion of Multiple Palmprint Representations. In: Image and Signal Processing, Elmoataz, A., O. Lezoray, F. Nouboud, D. Mammass and J. Meunier (Eds.). Springer-Verlag, Berlin, Heidelberg, pp: 182-191.

Nandakumar, K., Y. Chen, S.C. Dass and and A.K. Jain, 2008. Likelihood ratio-based biometric score fusion. IEEE Trans. Pattern Anal. Machine Intell., 30: 342-347.