Towards Regional Fusion for High-Resolution Palmprint Recognition

Ruifang Wang, Daniel Ramos, Julian Fierrez and Ram P. Krish
ATVS - Biometric Recognition Group, Escuela Politecnica Superior (EPS)
Universidad Autonoma de Madrid (UAM)
Francisco Tomas y Valiente 11, 28049 Madrid, Spain
Email: {ruifang.wang, daniel.ramos, julian.fierrez, ram.krish}@uam.es

***Abstract*—The existing high resolution palmprint matching algorithms essentially follow the minutiae-based fingerprint matching strategy and focus on full-to-full/partial-to-full palmprint comparison. These algorithms would face problems when they are applied to forensic palmprint recognition where latent marks have much smaller area than full palmprints. Therefore, towards forensic scenarios, we propose a novel matching strategy based on regional fusion for high resolution palmprint recognition using regions segmented by major creases features. The matching strategy includes two stages: 1) region-to-region palmprint comparison; 2) regional fusion at score level. We first studied regional discriminability of a high resolution palmprint under the concept of three regions, i.e., interdigital, hypothenar and thenar, which is the most significant difference between palmprits and fingerprints. Then we implemented regional fusion based on logistic regression at score level using region-to-region comparison scores obtained by a commercial SDK, MegaMatcher 4.0. Significant improvement of recognition accuracy is achieved by regional fusion on a public high resolution palmprint database THUPALMLAB. The EER of logistic regression based regional fusion is 0.25%, while the EER of full-to-full palmprint comparison is 1%.**

***Keywords*-High resolution palmprints; regional fusion.**

I. Introduction

Due to the availability of live-scan palmprint technology and significant attention in forensic and civil applications, high resolution palmprint recognition has aroused research highlights recently, which deals with palmprints captured at 500 ppi at least. Though a high resolution palmprint image, as shown in Figure 1, is deemed to have rich types of features such as minutiae, principal lines, and pores, available high resolution palmprint matching algorithms [1]–[3] essentially follow the minutiae-based fingerprint matching strategy and focus on full-to-full/partial-to-full palmprint comparison. These algorithms would face problems when they are applied to forensic palmprint recognition where latent marks have much smaller area than full palmprints, which was also argued in a recent work on forensic palmprint recognition [4]. Motivated by the potential performance improvement of high resolution palmprint recognition, especially applied to forensic palmprint recognition, we are trying to develop a finer palmprint matching strategy by observing and utilizing unique properties of palmprint images compared to fingerprints.

As indicated in [5], the three palm regions divided by three major creases, i.e., interdigital, hypothenar and thenar, have different performance according to matching accuracy,

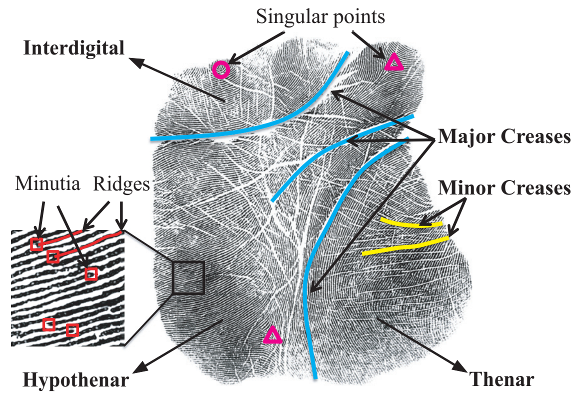


Fig. 1. A sample full palmprint with high resolution and its feature types.

which meant that the thenar region had much lower accuracy than interdigital and hypothenar regions. This property can be considered as a unique aspect of palmprints while it does not exist in fingerprints and motivates regional fusion for high resolution palmprint recognition. And it also makes the regions segmented by using the three major creases more meaningful than the equal segmented regions in [2] when applied to regional fusion. Inspired by the application of logistic regression for score fusion in speaker recognition [6], we consider that regional fusion using logistic regression should be able to outperform the three region-to-region comparisons separately and even achieve better performance than full-to-full comparison. Furthermore, regional fusion would be a significant step towards practical forensic evaluation of evidence in palmprints. This is due to the fact that forensic palmprint source searching, i.e., latent-to-full palmprint comparison, essentially rely on region-to-region comparison since the latent marks are usually partial palmprint images with a much smaller area than full palmprints in a background database for source searching.

Due to the motivations described above, in this work, we propose a novel matching strategy based on regional fusion using the three regions segmented by major creases features. The matching strategy includes two stages: 1) region-to-region palmprint comparison; and 2) regional fusion based on logistic regression at score level. Firstly, we segment each palmprint from a public high resolution palmprint database,

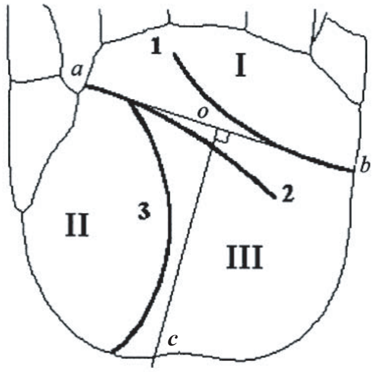


Fig. 2. Palmprint regions (I - interdigital region, II - thenar region and III - hypothenar region) and datum points (a, b-endpoint, o-their midpoint) [8]. c is the intersection point of the bottom boundary of a palm and the perpendicular bisector of the line segment a-b. The lines indicating the region segmentation applied are highlighted.

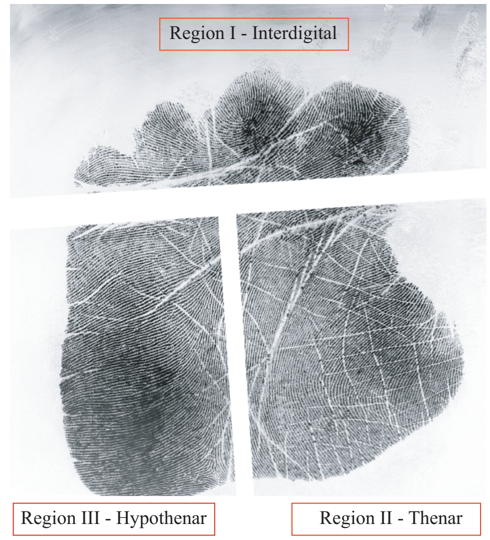


Fig. 3. Segmented regions for a sample palmprint.

THUPALMLAB [7], into three regions manually based on datum points which have been defined in [8] due to the remarkable advantage of invariable location. Then, based on the study of regional discriminability, we perform regional fusion at score level using region-to-region comparison scores obtained by a commercial SDK, MegaMatcher 4.0 [9]. Regional fusion is implemented by the FoCal Toolkit [10] which implements logistic regression based score fusion. Experimental results on the database THUPALMLAB containing 1280 full palmprints from 160 palms show that regional fusion improves the recognition accuracy. The EER of logistic regression based regional fusion is 0.25%, while the EER of full-to-full palmprint comparison is 1%.

The rest of the paper is organized as follows. Section 2 shows an experimental study and analysis of regional discriminability. Section 3 describes regional fusion based on logistic regression for high resolution palmprint recognition and reports experimental results. Conclusions are given in Section 4.

II. Regional discriminability

As observed from Figure 1, the three regions have different feature properties: 1) the interdigital region contains significant singular points and heart line which could improve its discriminability, 2) the thenar region contains many more minor creases and wrinkles which deteriorate its discriminability, 3) the hypothenar region contains more regular ridges which improve its discriminability. To check these observations, we implemented region segmentation based on datum points marked manually, and obtained region-to-region matching results on the database THUPALMLAB [7] using a commercial SDK, MegaMatcher 4.0 [9]. The THUPALMLAB database contains 1280 full palmprints from 160 palms, i.e., 80 subjects with left and right palms, and 8 impressions captured from each palm with a resolution of 500 ppi. In the following sections, we use a testing subset from THUPALMLAB for experimental analysis, including palmprints from the last 50 subjects, i.e., $50 \times 2 \times 8 = 800$ palmprint images.

A. Region segmentation based on datum points

As shown in Figure 2, due to the stability of the principal lines, the endpoints a and b of the life line and the heart line which intersect both sides of the palm, and their midpoint o are also stable according to their locations in the full palmprint. They were defined as datum points in [8]. Some significant properties of datum points can be used for region segmentation: (1) the locations of the endpoints and their midpoint are rotation invariant in a palmprint; (2) a palm can be divided into three regions: interdigital region (I), thenar region (II) and hypothenar region (III) by the connections between the endpoints and their perpendicular bisector, i.e., line segments a-b and o-c.

Aimed to obtain reliable results regarding regional discriminability, we segment each palmprint into three regions manually. Firstly, we manually choose endpoints a and b according to their definition and obtain their position with X and Y axis values. Then we calculate the position of their midpoint o. Finally we divide each palmprint into those three regions by treating the line segments $a-b$ and $o-c$ as boundary lines. One example of segmented regions for a palmprint is shown in Figure 3. Three subsets are generated from the testing database (800 palmprints) of THUPALMLAB after manual region segmentation and named as Subset I, II and III corresponding to interdigital region (I), thenar region (II) and hypothenar region (III) respectively.

B. Experimental analysis

To standardize the experimental study, we then use the commercial SDK MegaMatcher 4.0 to implement feature extraction and region-to-region matching on the three subsets I, II and III separately. For each subset, there are 2800 genuine comparison attempts and 4950 impostor comparison attempts. The EER results are 1.18%, 6.57% and 0.89% corresponding

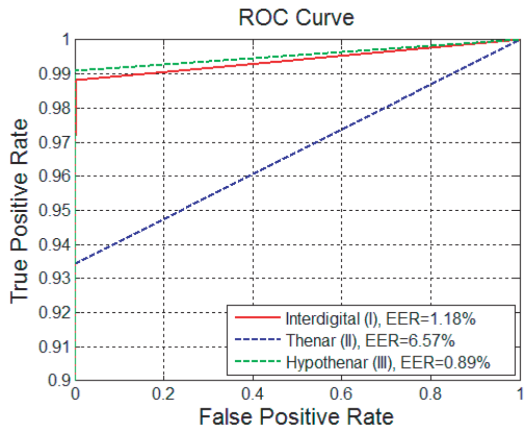


Fig. 4. ROC curves for the three region-to-region comparisons.

to interdigital region , thenar region and hypothenar region respectively. The ROC curve is shown in Figure 4. It indicates that on the THUPALMLB database, the thenar region shows much lower matching accuracy, which is consistent with the observation at the beginning of this section and the result reported in [5]. However, the hypothenar region outperforms interdigital region on the THUPALMLB database.

In addition to regional discriminability, we also calculated correlation coefficients between different region-to-region score sets. The correlation results are shown in Table I. The results indicate that there is high correlation between genuine scores from different regions, while impostor scores from different regions are practically independent, which motivates us to implement regional fusion. Figure 5 shows scatter plots of three region-to-region comparisons to demonstrate the relationship between different regional comparison score sets.

III. Regional fusion

Based on the above experimental study on regional discriminability, we propose and implement a new two-stage matching strategy based on regional fusion for high resolution palmprint recognition, as shown in Figure 6. The first stage is to obtain region-to-region comparison scores as implemented in Section II-B. The second stage is to obtain regional fused scores using logistic regression. The implementation of the second stage is detailed in the following sections.

A. Regional fusion using logistic regression

The fusion considered is a linear combination of the score sets s_1, s_2, s_3 obtained from region-to-region comparison of the three regions, i.e.,

$$s_f = \omega_0 + \sum_{i=1}^{3} \omega_i \cdot s_i, \tag{1}$$

where s_f is the fused output score, and $\omega = [\omega_0, \omega_1, \omega_2, \omega_3]$ is a vector of real-valued weights trained using logistic regression.

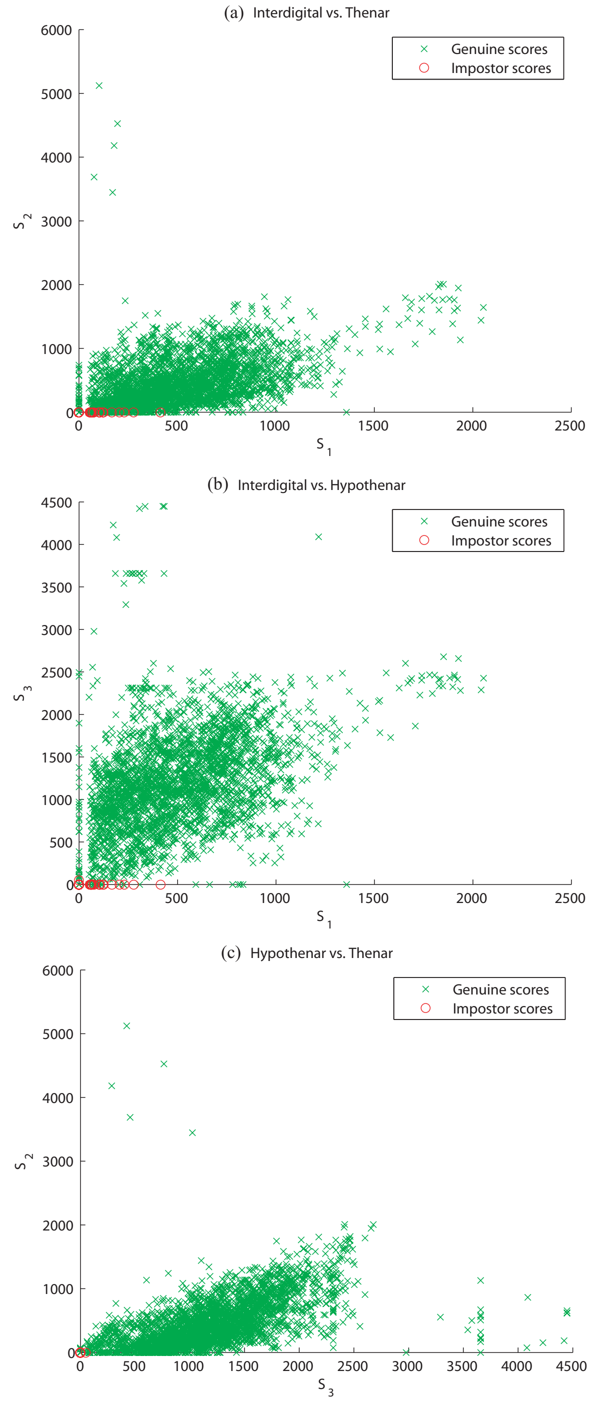


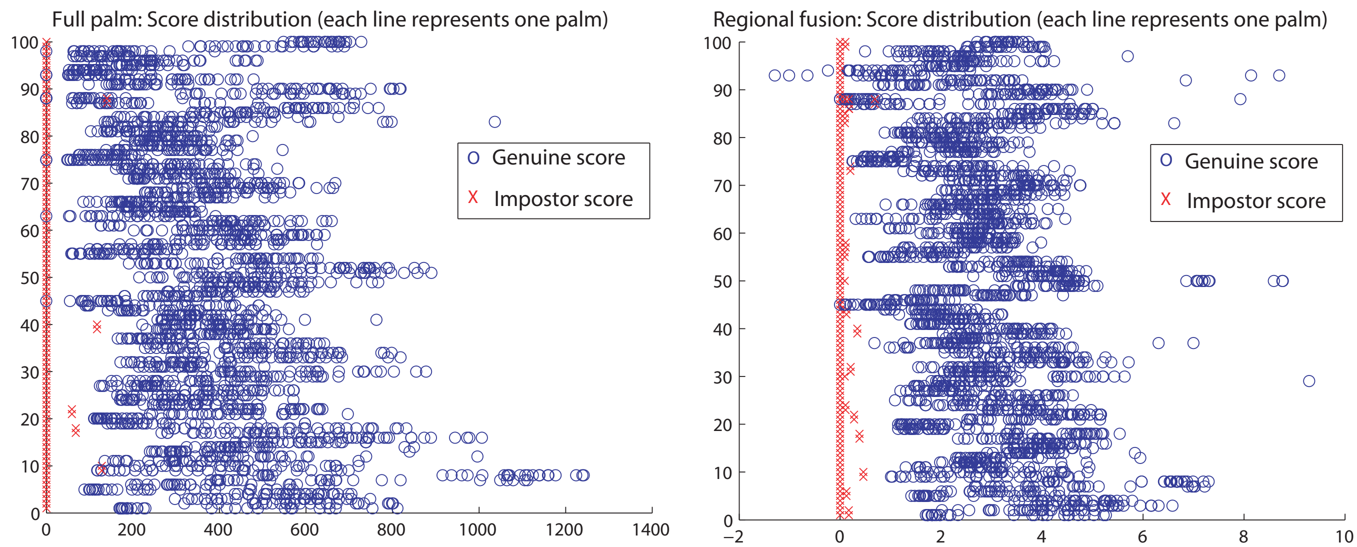
Fig. 5. Scattered score distribution of three region-to-region score sets. (a) Interdigital (S_1) vs. thenar (S_2), (b) interdigital (S_1) vs. hypothenar (S_3), (c) hypothenar (S_3) vs. thenar (S_2).

B. Experimental analysis

We implement regional fusion using the FoCal Toolkit [10] which implements logistic regression based score fusion. The testing database from THUPALMLAB contains 800 palmprints from 100 palms, the same as in Section II-B. Following a leave-one-out training scheme, i.e., leaving out all

TABLE I
CORRELATION RESULTS OF DIFFERENT REGIONAL SCORES.

Region	Genuine score correlation coefficient			Impostor score correlation coefficient		
	I	II	III	I	II	III
I	1	0.4714	0.4031	1	0	-0.0007
II	0.4714	1	0.5564	0	1	0
III	0.4031	0.5564	1	-0.0007	0	1



(a) (b)

Fig. 8. Score distribution (per palm each line). (a) Full-to-full comparison, (b) regional fusion based on logistic regression.

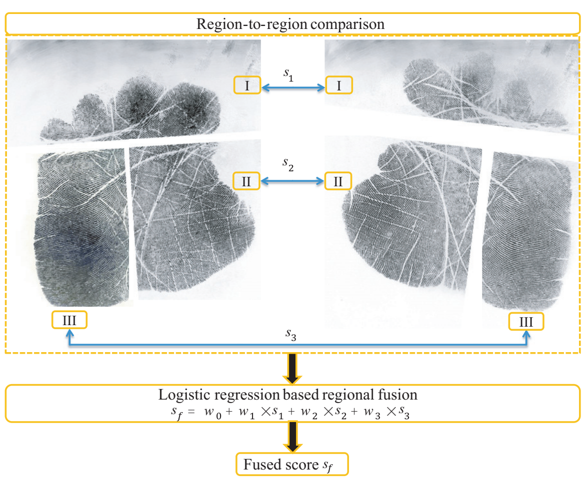


Fig. 6. Proposed matching strategy based on regional fusion.

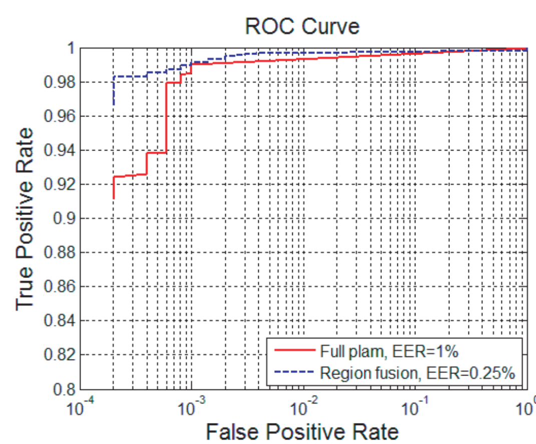


Fig. 7. ROC curves of regional fusion and full-to-full comparison.

the genuine and impostor scores corresponding to one palm in each iteration, we use both genuine and impostor scores left for training, generated by comparison among impressions of one palm and between the same palm and other palms. To verify the improvement of regional fusion compared to full-to-full comparison, we also obtain full-to-full comparison scores using MegaMatcher 4.0 on the same testing database. As shown in Figure 7, the ROC curve is improved by regional fusion based on logistic regression. The EER of regional fusion using logistic regression is 0.25%, compared to 1% of full-to-full comparison and 1.18%, 6.57%, 0.89% corresponding to the three individual region-to-region comparisons as reported in Section II-B. This indicates that regional fusion outperforms region-to-region comparison as well as full-to-full comparison. Moreover, we find that scores from regional fusion are better aligned than those from full-to-full comparison as shown in Figure 8, in which each line represents one palm and contains

28 genuine scores and 99 impostor scores.

IV. Conclusions

In this work, we proposed a new two-stage matching strategy as shown in Figure 6 for high resolution palmprint recognition, aimed to improve the performance by regional fusion using the three regions segmented by major creases features. We first implemented manual region segmentation based on datum points due to the remarkable advantage of their invariable locations and studied regional discriminability. Then using logistic regression model, we performed regional fusion at score level using region-to-region comparison scores obtained by a commercial SDK MegaMatcher 4.0 [9]. Experimental results on the database THUPALMLAB show that regional fusion improves the recognition accuracy. The EER of logistic regression based regional fusion is 0.25%, while the EER of full-to-full palmprint comparison is 1%.

Regional fusion employs regional discriminability, which could be further applied to forensic applications, mainly latent-to-full palmprint comparison. Towards that direction, our future work will be: 1) developing automatic and database-adaptable region segmentation techniques under the concept of three regions; 2) applying region fusion based on automatic region segmentation to forensic palmprint comparison.

Acknowledgment

R. Wang and R. Krish are supported by Marie Curie Fellowships under project BBfor2 (FP7-ITN-238803). This work has also been partially supported by Spanish Guardia Civil, “Cátedra UAM-Telefónica”, and projects Bio-Shield (TEC2012-34881) and Contexts (S2009/TIC-1485).

References

[1] J. Dai and J. Zhou, “Multifeature-based high-resolution palmprint recognition,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 5, pp. 945–957, 2011.

[2] J. Dai, J. Feng, and J. Zhou, “Robust and efficient ridge-based palmprint matching,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 34, no. 8, pp. 1618–1632, 2012.

[3] R. Cappelli, M. Ferrara, and D. Maio, “A fast and accurate palmprint recognition system based on minutiae,” *IEEE Trans. Syst., Man, Cybern. B*, vol. 42, no. 3, pp. 956–962, 2012.

[4] E. Liu, A. K. Jain, and J. Tian, “A coarse to fine minutiae-based latent palmprint matching,” IEEE Trans. Pattern Anal. Mach. Intell., 2013, to be published.

[5] A. Jain and J. Feng, “Latent palmprint matching,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 31, no. 6, pp. 1032–1047, 2009.

[6] N. Brummer, L. Burget, J. Cernocky, O. Glembek, F. Grezl, M. Karafiat, D. A. van Leeuwen, P. Matejka, P. Schwarz, and A. Strasheim, “Fusion of heterogeneous speaker recognition systems in the stbu submission for the nist speaker recognition evaluation 2006,” *IEEE Trans. Audio, Speech, Lang. Process.*, vol. 15, no. 7, pp. 2072–2084, 2007.

[7] (2011) Thupalmlab palmprint database. [Online]. Available: http://ivg.au.tsinghua.edu.cn/index.php?n=Data.Tsinghua500ppi

[8] D. Zhang and W. Shu, “Two novel characteristics in palmprint verification: Datum point invariance and line feature matching,” *Pattern Recognition*, vol. 32, no. 4, pp. 691–702, 1999.

[9] Neurotechnology. (2011) Megamatcher 4.0 sdk. [Online]. Available: http://www.neurotechnology.com

[10] N. Brummer. (2007) Focal toolkit. [Online]. Available: https://sites.google.com/site/nikobrummer/focal