PALMPRINT IMAGE SYNTHESIS: A PRELIMINARY STUDY

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ABSTRACT

In this paper we present a preliminary study of palmprint image synthesis and propose a framework for synthesizing palmprint texture. We first extract principal lines of real palmprints using edge detection and synthesize wrinkles and ridges of palm using patch-based sampling. Then we incorporate principal lines, wrinkles and ridges to obtain the final synthetic image. After that multiple images are derived from each artificial palm to simulate the intra-class images. Our approach can generate large palmprint databases which preserve inter-class and intra-class variations. Experimental results demonstrate that the synthetic images bear a close resemblance to real palmprints in terms of appearance as well as statistical properties, showing a promising usage in algorithms evaluation and comparison.

***Index Terms*—** Biometrics, image synthesis, palmprint, texture, database

1. INTRODUCTION

Automatic personal identification based on biometrics utilizes the physiological and behavioral characteristic of people such as face, fingerprint, iris, etc. Palmprint recognition is a relatively new biometrics, and has been witnessed a significant development during recent years[1, 2]. However, those algorithms are all evaluated on relatively small databases[3, 4], which means none of them has undergone extensive testing. This scenario raises a practical demand of large palmprint databases as common platform to evaluate and compare various palmprint recognition algorithms. Collecting large biometric databases not only is an expensive task due to time and efforts involved, but also brings in controversy issues in terms of privacy concerns. To overcome this problem, synthesizing artificial palmprint image provides an alternative, without involving any efforts from volunteers.

Synthesis of biometric images has gained steady progress in the past few years. Cappelli et al.[5] proposed a fingerprint synthesis approach, and the synthetic data have been successfully applied to International Fingerprint Verification Competition (FVC) [6]. Efforts have been devoted to face and iris image synthesis as well [7, 8]. In this paper, we address the issue of palmprint image synthesis, with the purpose of providing an artificial palmprint database for academic and/or commercial usage. To the best of our knowledge, this is the first attempt to synthesize palmprint images.

Palmprint is the unique pattern in the inner surface of human hand between the wrist and the fingers, referring to those principal lines, wrinkles and ridges on the palm. It is different from neither regular nor stochastic natural texture in that its principal lines present regular structure whereas its wrinkles and ridges have stochastic display. In this paper, we employ patch-based sampling described in the work of Liang et al.[9] to synthesize textures of wrinkles and ridges. However, the methodology of this method is random spatial sampling, making it unable to preserve structural texture like principal lines, which is visually important. To overcome this drawback, we incorporate principal lines extraction with patch-based sampling to synthesize palmprint, during which images are made dissimilar enough as if they were captured from different palms. Then we introduce deformation to each unique synthetic palmprint to generate multiple intra-class images. This framework ensures that the artificial palmprint databases carry inter/intra-class variations. Our approach is able to generate realistic palmprint images, with the principal lines and other textural details well preserved.

The remainder of this paper is organized as follows: Section 2 presents the patch-based sampling incorporating with principal lines extraction to synthesize palmprint texture. Section 3 describes how to generate multiple intra-class palmprints. section 4 provides experiments and discussions. Section 5 concludes the paper.

2. METHODOLOGY FOR PALMPRINT SYNTHESIS

The framework of the proposed palmprint synthesis approach is illustrated in Fig.1. Before synthesis, a square central subregion of the palm, which is called the normalized palm, is extracted, following the method employed in [1]. The normalized palm is the key region for feature extraction in literatures [1, 2], therefore it is target region that is aimed to synthesize in this paper.

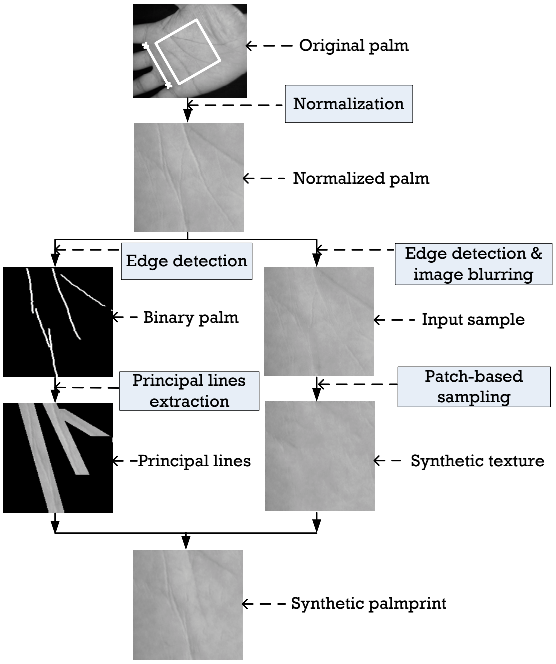


Fig. 1. The framework of palmprint image synthesis.

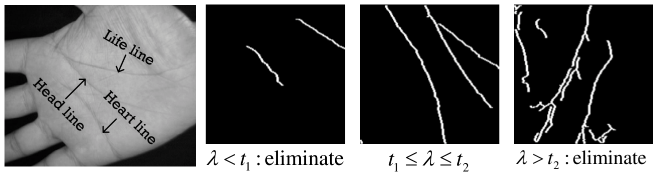


Fig. 2. Principal lines and the extracting strategy.

2.1. Principal Lines Extraction

Principal lines are crucial features of palmprint, defining by their position, thickness and length exhibited. Most palmprints have three principal lines: heart line, head line and life line, as Fig.2 shows. They are the thickest and longest lines on the palm, and often have regular structure.

Principal lines extraction is detailedly described in the work of Wu et al.[10]. To avoid such a complicated procedure [10], we employ Canny operator to detect principal lines. Not every principal line can be detected due to image quality and noises. Since our main purpose is synthesis, it is sufficient if the majority images can be extracted correctly. Our approach for obtaining principal lines is as follows:

1. For each normalized palmprint I_{palm}, Canny operator with appropriate choices of parameters is used to obtain an edge image I_{edge}.
2. Detect the number of non-zero-value pixels (denoted as λ) of the edge image I_{edge}.
3. If $t_1 \le \lambda \le t_2$, then I_{palm} and I_{edge} are combined to extract principal lines; if $\lambda < t_1$ or $\lambda > t_2$, I_{palm} is eliminated, as shown in Fig.2.
4. I_{palm} and I_{edge} are combined together to obtain principal lines.

Thresholds t_1 and t_2 are trained by 100 positive/negative samples each.

2.2. Patch-based Sampling for Palmprint Synthesis

To obtain an input sample I_{in} for synthesis, we blur the edge of the normalized palm to eliminate the effect of principal lines which is undesirable in synthesizing wrinkles and ridges (see Fig.1). Patch-based sampling uses patch (denoted as P) with size $w_B \times w_B$ as basic element in synthesizing. The output texture is composed by a set of patch, $\{P_0, P_1, ..., P_n\}$, with each patch chosen from I_{in}. The basic idea of patch-based sampling is illustrated in Fig.3. Assuming the grey area of the synthetic image I_{syn} has been generated, for the next target patch P_k to be synthesized, its boundary zone B_{syn} is already known. Then exhaustive search is performed on I_{in} for zone B_{in} with the same shape and size as B_{syn}. If the distance of the two zones $\boldsymbol{d}(B_{syn}, B_{in}) \le \delta$, then B_{in} is treated as a match zone of B_{syn}, and the patch with boundary B_{in} could serve as a candidate patch of P_k.

To preserve the stochastic properties of palmprint, a patch set Φ_P is formed, which meets the constraint:

$$\Phi_P = \{P_j \to B_{in^j} | \boldsymbol{d}(B_{syn^k}, B_{in^j}) \le \delta\}, \qquad (1)$$

$$(k = 1, 2, ..., \alpha; j = 1, 2, ..., \beta.)$$

where δ is the distance tolerance, and B_{in^j} is boundary of the j^{th} patch chosen from I_{in}. The target patch P_k is selected randomly from Φ_P. Given a tolerance δ, if $\Phi_P = \varnothing$, then the patch with smallest boundary distance is selected to form the patch set:

$$\Phi_P = \arg min\{P_j \to B_{in^j} | \boldsymbol{d}(B_{syn^k}, B_{in^j})\}. \qquad (2)$$

$$(k = 1, 2, ..., \alpha; j = 1, 2, ..., \beta.)$$

Our approach for palmprint synthesis is as follows:

1. Initiate the image by filling adequate values to the first w_E rows and columns as the known boundary.
2. For $k \le N$, find all the patches which satisfy Eq.1 to form the candidate patch set Φ_P; if $\Phi_P = \varnothing$, then obtain Φ_P using Eq.2.
3. Randomly chose a patch from Φ_P and paste it on the target area of I_{syn}. Update the k^{th} boundary zone using: $B_{syn^k} = (B_{syn^k} + B_{in^j})/2$. set $k = k + 1$.
4. Repeat step 2-3 until $k > N$.

After the procedure of principal lines extraction and patch-based sampling, the results of these two operations are incorporated together to generate an output synthetic palmprint. The joint region of the output image is smoothed by paving patches on its surface, following the strategy of patch-based sampling.

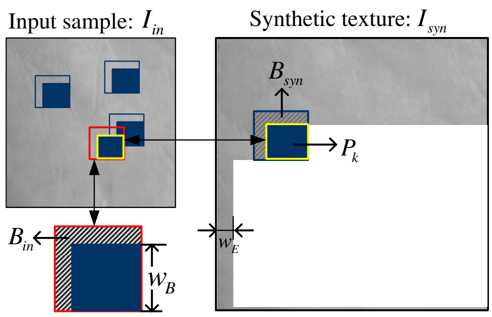


Fig. 3. Illustration of patch-based sampling[9].

3. MULTIPLE INTRA-CLASS IMAGES SYNTHESIS

Multiple images of one palmprint carry intra-class variations attributed to the following factors: hand bending and stretching, illumination change, sensing noise, etc.

Palmprint deformation due to hand bending and stretching mainly appears around the root regions of fingers. Textures near heart line suffer most of the distortion. Motivated by the work of Cappelli et al.[11], we used deformed meshes to model skin deformation. Fig.4 shows the meshes and intra-class variations of real vs. synthetic images. A deformed palmprint is generated by the following steps:

1. Obtain the heart line position of each synthetic image.
2. For pixels around heart line, shift their position based on a set of deformed mesh, shown in Fig.4: mesh (a) corresponds to bending; mesh (b) indicates stretching; mesh (c) illustrates random perturbation.
3. The resultant image of step 2 is smoothed using bilinear interpolation.

The other two effects, illumination change and sensing noise, are relatively easy to achieve. We shift grey scale values to achieve the illumination effect. White Gaussian noise is added to simulate sensing noise effect.

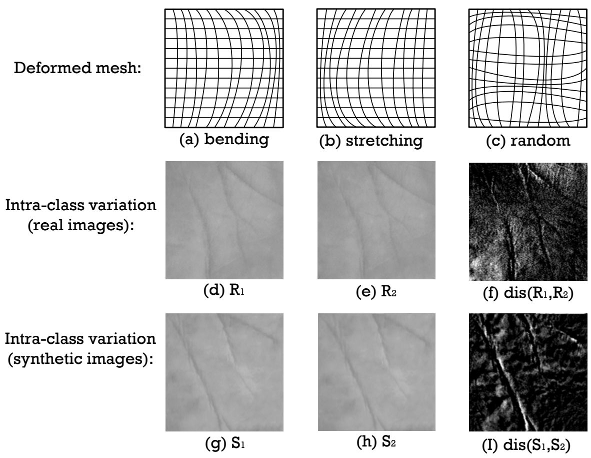


Fig. 4. Intra-class variations. $dis(R_1, R_2)$ denotes the distances of images R_1 and R_2. $dis(S_1, S_2)$ denotes the distances of images S_1 and S_2.

4. EXPERIMENTS AND DISCUSSIONS

In our experiments, three indicators are adopted to analyze the synthetic palmprints to justify their validity in real application.

(I) Appearance: Fig.5 display a set of real and synthetic palmprints. We can see that synthetic palmprints bear close resemblance to real palmprints by well preserving their textural details.

(II) Database Capacity: Since our approach employs real principal lines to synthetic palmprints, one set of three principal lines should be avoided using in multiple classes. However, by shifting positions of principal lines, each of their combination is unique, therefore they can be used to synthesize different classes. Given N real images of different palms, the combination of the three principal lines is N^3 (assuming all the principal lines can be extracted). Therefore, with a rough estimation, N^3 classes of palmprint image can be synthesized from N different real images.

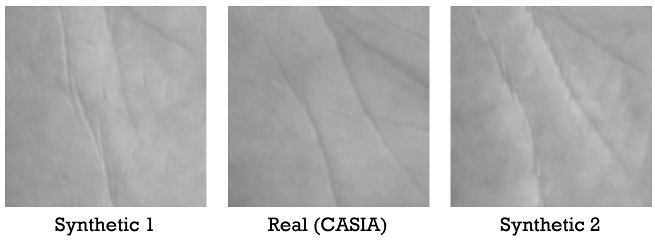
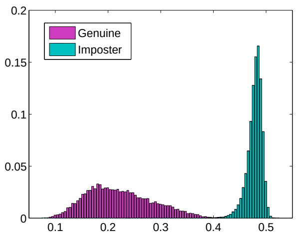


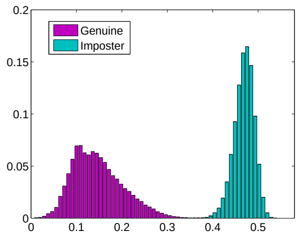
Fig. 5. Samples of real vs. synthetic images.

(III) Statistical Property: To evaluate the statistical property of synthetic palmprints, we obtain the matching score distribution and recognition performance of synthetic vs. real databases for comparison. CASIA[4] palmprint database contains 4,512 palmprints from 564 palms, with 8 images for each palm. Using input samples from CASIA, we first synthesize 300 artificial palmprints, each represents an individual class. By adjusting the deformed parameters when generating intra-class images, we can obtain datasets with different statistical properties. We derive two datasets from the 300 artificial palmprints, denoted as $SynI$ and $SynII$. Each dataset contains 300 classes with 20 images per class, including totally 6,000 images. We make $SynI$ carry heavier deformation and $SynII$ has less deformation. Ordinal code [2] is employed for palmprint recognition to test the real and synthetic databases. All possible intra-class comparisons are made. For CASIA database, one image selected randomly from each class is used for inter-class matching, so there are 15,792 intra-class and 158,766 inter-class comparisons. For synthetic database, two images from each class are used for inter-class matching, so there are 57,000 intra-class and 179,400 inter-class comparisons. The genuine and imposter distribution are plotted in Fig.6(a)(b). The ROC(Receiver Operating Characteristic) curves based criterion, a plot of FAR(False Accept Rate) against FRR(False Reject Rate) is shown in Fig.6(c). Table1 gives Equal Error Rate(EER) [12] and discriminate index (DI) [12] of real vs. synthetic databases.

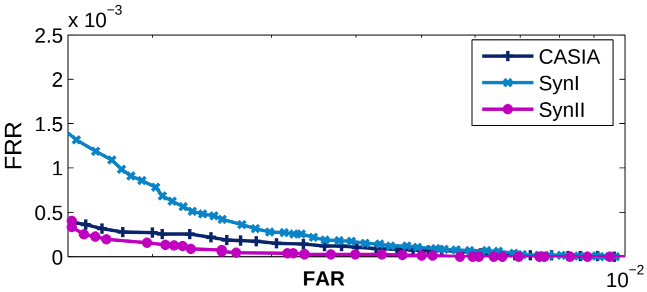
Discussion: Preliminary studies show that: (1) The proposed palmprint synthesis approach is able to generate highly realistic palmprint images as well as synthesize large palmprint databases. (2) The synthetic images carry major statistical characteristic of real palmprints in genuine/imposter distributions. (3) In synthesizing intra-class images, the degree of palmprint distortion is controllable, which means that the global genuine matching score is predictable. $SynI$ gain a higher EER than $SynII$ because we allow heavier distortions happen to $SynI$. This property of synthetic database makes it specially suitable for algorithms evaluation. By setting different levels of difficulties to datasets, the robustness and accuracy of algorithms can be tested.



(a) CASIA[4] database.



(b) $SynII$ database.



(c) ROC curves of CASIA[4], $SynI$ and $SynII$.

Fig. 6. Experimental results.

Performance	EER	DI
CASIA	0.089%	5.6513
$SynI$	0.146%	5.3032
$SynII$	0.086%	6.1227

Table 1. EER and Discriminating Index(DI).

5. CONCLUSION

In this paper, we have proposed a framework for palmprint image synthesis. Principal lines extraction and patch-based sampling are incorporated to generate palmprint textures. Then multiple intra-class images are derived from each unique palmprint. Effective experiments are performed to validate the synthetic palmprints, which demonstrates that the artificial databases have promising future in real applications.

We believe palmprint synthesis is well worth studied, although it has not been addressed before. We will continue to improve the synthesis algorithm in the future, since the current method still uses principal lines of real palmprints. Hopefully we can provide large synthetic palmprint databases for both academic and industrial usage.

6. ACKNOWLEDGEMENT

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