Ordinal Palmprint Represention for Personal Identification

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Abstract

Palmprint-based personal identification, as a new member in the biometrics family, has become an active research topic in recent years. Although great progress has been made, how to represent palmprint for effective classification is still an open problem. In this paper, we present a novel palmprint representation —— ordinal measure, which unifies several major existing palmprint algorithms into a general framework. In this framework, a novel palmprint representation method, namely orthogonal line ordinal features, is proposed. The basic idea of this method is to qualitatively compare two elongated, line-like image regions, which are orthogonal in orientation and generate one bit feature code. A palmprint pattern is represented by thousands of ordinal feature codes. In contrast to the state-of-the-art algorithm reported in the literature, our method achieves higher accuracy, with the equal error rate reduced by 42% for a difficult set, while the complexity of feature extraction is halved.

1. Introduction

Biometrics makes use of the physiological or behavioral characteristics of people such as fingerprint, iris, face, palmprint, gait, and voice, for personal identification [1], which provides advantages over non-biometric methods such as password, PIN, and ID cards. It is an essential technology for many mission-critical applications, such as homeland security, e-commerce, banking, etc.

Palmprint is the unique inner surface pattern of human hand, including a number of discriminating features, such as principal lines, wrinkles, ridges, minutiae points, singular points, texture, etc. Compared with other biometric traits, the advantages of palmprint are the availability of large palm area for feature extraction, the simplicity of data collection and high user acceptability.

Although the study of palmprint recognition has a shorter history than fingerprint and face recognition, more attention has been directed towards this promising field in recent years [2-11]. Various palmprint representations have been proposed for recognition, such as Line features [2], Feature points [3], Fourier spectrum [4], Eigenpalms features [5], Sobel's and morphological features [6], Texture energy [7], Wavelet signatures [8], Gabor phase [9], Fusion code [10], Competitive code [11], etc. However, there does not exist a common palmprint representation, which is important to standardization. For example, finger minutiae have been regarded as the standard format of fingerprint, which may facilitate exchange of biometric data in nonproprietary format among multiple vendors or applications [12]. And how to model palmprint pattern effectively and efficiently is still not well addressed although it is the most important issue in palmprint recognition.

In this study, we attempt to explore a convincing solution, that of using ordinal measures, as an answer to the representation problem. The representation of ordinal measures unifies several state-of-the-art palmprint recognition algorithms of David Zhang et al. [9-11]. The internal representations of those algorithms can be seen as special cases of ordinal measures. This forms a framework which may help to understand the discriminant power of palmprint pattern, guide further research and enlighten new ideas.

The rest of this paper is organized as follows. Section 2 presents a general framework of palmprint recognition based on ordinal features and interprets several state-of-the-art palmprint encoding methods within the ordinal framework. In Section 3, a novel palmprint representation method is proposed in the framework. Experimental results are reported in Section 4. Section 5 concludes this paper.

2. Ordinal Representation for Palmprint Recognition

2.1. Ordinal Measures

Ordinal measures come from a simple and

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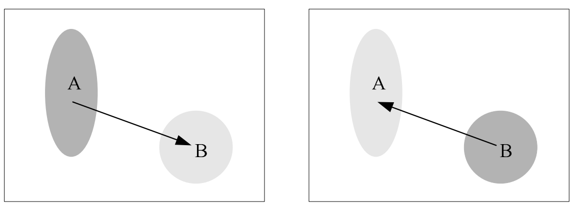
straightforward concept that we often use. For example, we could easily rank or order the heights or weights of two persons, but it is hard to answer their precise differences. For computer vision, the absolute intensity information associated with an object can vary because it can change under various illumination settings. However, ordinal relationships among neighborhood image pixels or regions present some stability with such changes and reflect the intrinsic natures of the object.

A simple illustration of ordinal measures is shown in Fig. 1 where the symbols "$\prec$" or "$\succ$" denote the inequality between the average intensities of two image regions. The inequality represents an ordinal relationship between two regions and this yields a symbolic representation of the relations. For digital encoding of the ordinal relationship, only a single bit is enough, e.g. "1" denotes "$A \succ B$" and "0" denotes "$A \prec B$", and the equality case (a low possibility event) can be assigned to either.



(a) (b)

Figure 1: Ordinal measure of relationship between two regions. An arrow points from the darker region to the brighter one. (a) Region A is darker than B, i.e. $A \prec B$. (b) Region A is brighter than B, i.e. $A \succ B$.

Sinha [13] was probably the first to introduce ordinal measures to visual object representation. Based on the fact that several ordinal measures on facial images, such as eye-forehead and mouth-cheek are invariant with different persons and imaging conditions, Sinha developed a ratio-template for face detection, which could be automatically learned from examples [13]. Combining qualitative spatial and photometric relationships together, Lipson et al. [15] applied ordinal measures to image database retrieval. Bhat and Nayar employed the rank permutation of pixel intensity values in image windows for stereo correspondence [16]. After introducing ordinal measures into co-occurrence model, Partio et al. obtained better texture retrieval results than traditional gray level co-occurrence matrices [17].

Because of the simplicity of ordinal representation, Thoresz [14] believed that this scheme could be used only for simple detection and categorization and did not expect it to be applied to complex discrimination tasks, especially recognizing an input image into billions of classes such as biometric applications.

However, we demonstrate in this paper that the ordinal measures can play a defining role for the complex palmprint recognition task.

2.2. A Unified Framework for Palmprint Recognition

Here, we propose a general framework of palmprint recognition based on the ordinal representation (Fig. 2).

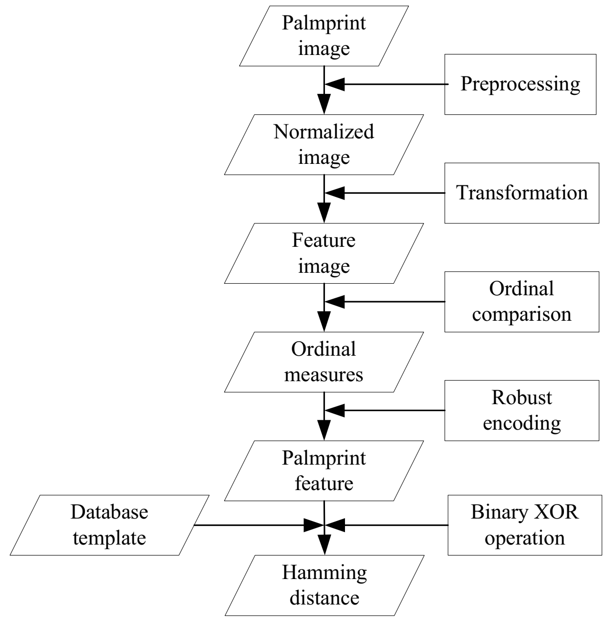


Figure 2: Robust encoding of ordinal features for palmprint recognition.

For an input palmprint image, the central subimage in the aligned coordinate system is cropped from it for feature extraction. To obtain the special measurements for ordinal comparison, the normalized palm image is transformed to feature image. Then the ordinal measures are obtained by qualitatively comparing several quantities in feature image. In practice, the transformation and ordinal comparison can be combined into one step via differential filtering. The result of ordinal comparison may be the sign of an inequality, the rank order of all measurements involved in comparison, maximum or minimum value associated index, and so on. After ordinal comparison, all results are coarsely quantized into binary bits so as to strengthen the robustness of palm feature and facilitate matching step. All binary codes are concatenated to generate a palmprint feature, which is the input of matching engine. Finally, the dissimilarity between the input palmprint's ordinal feature and the template stored in database is measured by their Hamming distance.

The framework has some desirable properties for palmprint recognition:

1) The ordinal measures render the palmprint representation robust againt various intra-class variations, such as illumination settings, dirties

or sweats on palm, signal noises, pose change, misalignment (including translation and orientation registration errors), and nonlinear deformations.

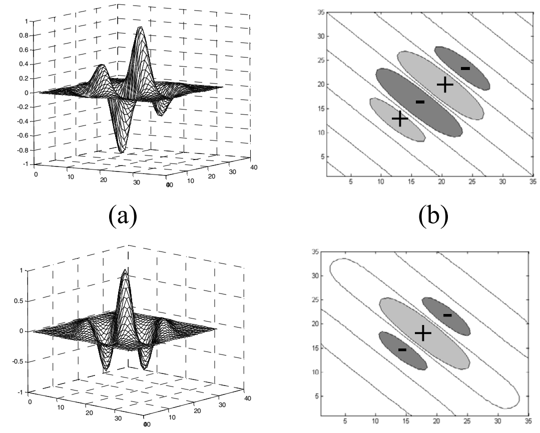
2) Each bit palmprint feature code represents a ordinal relationship among several image regions, which is rich of information. Because the palmprint code has equal probability to be 1 or 0 for an arbitrary pattern, its entropy is maximized. Although the discriminability of a single palm code is limited, a composite palm template formed by thousands of ordinal feature codes has sufficiently high degrees-of-freedom to differentiate all individuals in the world. Thus the randomness of palmprint pattern is well encoded.
3) The palmprint template is compact. Thousands of ordinal comparison results only need memory less than 1K bytes, which provides the possibility to store the palmprint template in IC card, mobile phone or PDA.
4) The dissmilarity between two palmprints can be measured by bitwise XOR operator, which could be computed on-the-fly.

2.3. Gabor Based Representations as Special Cases of Ordinal Representation

Based on the proposed framework, we illustrate that the Gabor based representations proposed by Zhang et al. [9-11], which reported the best recognition performance in literature, are special cases of ordinal measures.

Gabor based encoding filters used in palm code [9] are essentially ordinal operators (see Fig. 3). For odd Gabor filtering of local palmprint region, the image regions covered by two excitatory lobes are compared with the image regions covered by two inhibitory lobes (Fig. 3b). The filtered result is qualitatively encoded as “1” or “0” based on the sign of this inequality. Similarly, even Gabor generated palm code is mainly determined by the ordinal relationship between one excitatory lobe-covered region and two small inhibitory lobes-covered regions (Fig. 3d). Because the sum of original even Gabor filter’s coefficients is not equal to 0, the average coefficient value is reduced from the filter to maximize the information content of the corresponding palm code [9].

However, ordinal relationship is not restricted to intensity measurement. As a byproduct of Gabor phase measure (i.e. ordinal intensity measure), the orientation energy or magnitude was also obtained by orthogonal Gabor filtering. Thus it is possible to combine ordinal intensity measures and ordinal energy measures together. In [10], the local energy along four different orientations were compared each other to obtain the maximum. Then the palmprint is represented using the Gabor filtered ordinal intensity measures whose basic lobes are along the maximum energy orientation. Fusion code was demonstrated as a more discriminative representation than single type ordinal measure based representation [10].



(a) (b) (c) (d)

Figure 3: Odd and even Gabor filters used in [9]. (a) Odd Gabor filter (orientation= 45°). (b) Ordinal comparison of image regions using odd Gabor filter, “+” denotes excitatory lobe covered image region and “-” represents inhibitory lobe covered image region. (c) Even Gabor filter (orientation= 45°). (d) Ordinal comparison of image regions using even Gabor filter.

To the best of our knowledge, in the field of palmprint recognition, competitive code proposed by Kong et al. [11] performs the best in terms of accuracy. There, each palmprint image region has a dominant line segment and its orientation is regarded as the palmprint feature. Because the even Gabor filter is well suited to model the line segment, it was used to filter the local image region along six different orientations, obtaining the corresponding contrast magnitudes. Based on the winner-take-all competitive rule, the index (ranging from 0 to 5) of the minimum contrast magnitude was represented by three bits, namely competitive code [11]. The success of this method also depends on ordinal measures because the process of competition for winner is based on ordinal comparison essentially and all we can learn from the three bit competitive codes are five ordinal contrast relationships.

Thanks to the ordinal measures, these algorithms [9-11] all perform well in large scale testing, in terms of both accuracy and efficiency. Therefore, we conclude that the ordinal measures are perhaps the most suitable representation for palmprint-based identification system.

3. Orthogonal Line Ordinal Features

The ultimate purpose of the proposed framework is to guide the development of new algorithms. Following the framework, a possible improvement could be made by choosing well-designed ordinal measures as the palmprint representation, into which the characteristics of palmprint pattern should be incorporated. We propose a novel palmprint representation, namely, *Orthogonal Line Ordinal Features (OLOF)*, as illustrated in Fig. 4, where normalized subimage is referenced by finger gaps using an algorithm similar to Zhang et al.'s [9]. OLOF is so called because the two regions involved in ordinal comparison are elongated or line-like, and the two are geometrically orthogonal.

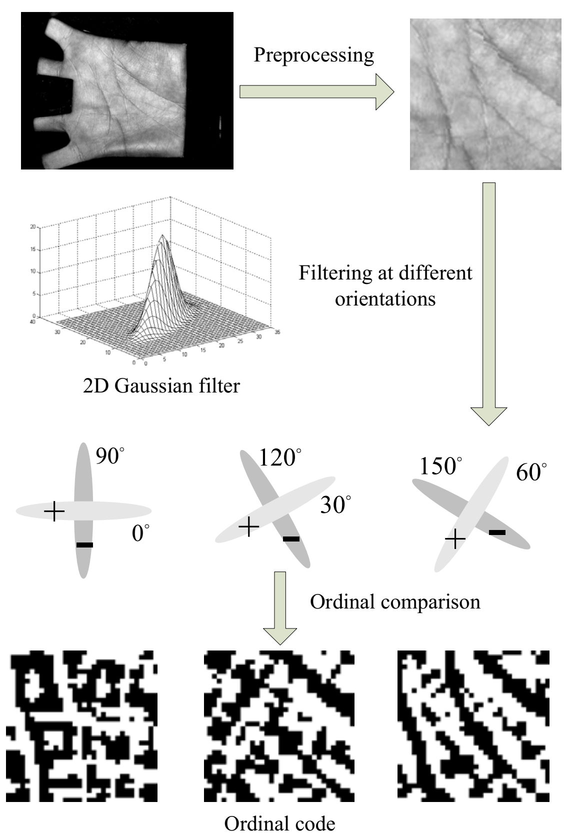


Figure 4: Orthogonal line ordinal features for palmprint recognition.

The ideas are motivated by the most stable and robust ordinal measures available in palmprint pattern, i.e. randomly distributed negative line segments versus their orthogonal regions. In low resolution palmprint images, the line patterns are mainly constituted by principal lines and wrinkles, whose intensity is much lower than their orthogonal regions. Of course detection of all line segments in palmprint is impossible in realtime applications. Nevertheless if we apply thousands of ordinal operators onto a palmprint image, most of them correspond to robust ordinal measures. This assumption is verified in the following experiments.

Here we use 2D Gaussian filter to obtain the weighted average intensity of a line-like region. Its expression is as follows:

$$f(x,y,\theta)=\exp[-(\frac{x\cos\theta+y\sin\theta}{\delta_x})^2-(\frac{-x\sin\theta+y\cos\theta}{\delta_y})^2] \quad (1)$$

where θ denotes the orientation of 2D Gaussian filter, δ_x denotes the filter's horizontal scale and δ_y denotes the filter's vertical scale. We control the scale ratio δ_x/δ_y higher than 3 to make its shape like a line (see Fig. 4).

The orthogonal line ordinal filter, comparing two orthogonal line-like palmprint image regions, is specially designed as follows:

$$OF(\theta)=f(x,y,\theta)-f(x,y,\theta+\frac{\pi}{2}) \quad (2)$$

For each local region in normalized palmprint image, three ordinal filters, $OF(0)$, $OF(\pi/6)$, and $OF(\pi/3)$, are performed on it to obtain three bit ordinal codes based on the sign of filtering results. Finally, three ordinal templates named as ordinal code are obtained as the feature of the input palmprint image (Fig. 4). The matching metric is also based on Hamming distance.

4. Experiments

The proposed palmprint recognition method using orthogonal line ordinal features is compared with the state-of-the-art recognition methods [9-11]. Two public databases, PolyU Palmprint Database [18] and UST Hand Image Database [19] are used for the evaluation of the recognition performance. The databases are among the largest in size in the public domain.

4.1. Results on PolyU Palmprint Database

There are totally 600 palmprint images of 100 different palms (hence 100 classes) in the database. Six samples from each of these palms were collected in two sessions, where 3 samples were captured in the first session and the other 3 in the second session. The average interval between the first and the second collection was two months.

After preprocessing, input palmprint image is normalized to 128 $\times$128 subimage. Then four types of palm features, our ordinal code, palm code [9], fusion code [10], and competitive code [11] are obtained. After all possible intra-class and inter-class comparisons are implemented in PolyU Palmprint Database, the verification performance of the four methods are illustrated in Fig. 5. There are totally 1,500 intra-class comparisons and 178,200 inter-class comparisons. Because ordinal code and competitive code can separate intra-class and inter-class Hamming distances perfectly based on some threshold, their false error rates are not shown in ROC curves (Fig. 5).

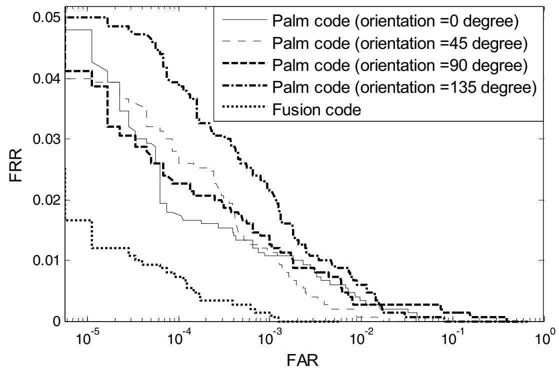


Figure 5: Verification performance comparison on PolyU Palmprint Database.

Computer resource costs and accuracy measures of these four methods are compared in Table 1. Feature extraction speed testing is performed using Matlab 7.0 on a Pentium IV 2.4GHz processor with 256 MB RAM. Equal error rate (EER, a point in ROC when false accept rate is equal to false reject rate) and the discriminating index d' (d-prime) [20] are used to measure the accuracy of an algorithm.

Table 1. Comparison of four ordinal palmprint representations on PolyU database.

Algorithm	Feature size	Feature extraction time	EER	d'
Palm code $\theta = 45^\circ$ [9]	256 Bytes	63 ms	0.34%	4.98
Fusion code [10]	256 Bytes	293 ms	0.11%	5.31
Competitive code [11]	384 Bytes	233 ms	0	5.44
Ordinal code	384 Bytes	120 ms	0	6.49

From the experimental results, we can see the discriminating index of ordinal code is larger than competitive code's. Another advantage of ordinal code is that its feature extraction time is only half of competitive code's. The reason is that competitive code needs twice ordinal filtering to generate one binary feature code while ordinal code only needs once.

4.2. Results on UST Hand Image Database

UST hand image database contains 5,660 hand images captured from 283 subjects, i.e. 10 samples/class. For each palmprint representation, all possible intra-class comparisons are made to estimate the genuine distribution, totally 25,470 samples. To measure the imposter distribution, one image of each class is randomly selected to construct a testing set. All algorithms are evaluated on the same data set and 159,895 inter-class matching results are used to estimate the imposter distribution. Based on the intra-class and inter-class matching results, the recognition performance of all methods are shown in Fig. 6 and Table 2 for comparison. In this difficult data set, ordinal code's recognition accuracy is significantly higher than competitive code [11].

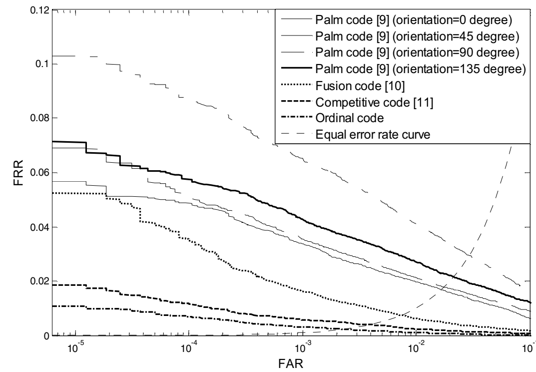


Figure 6: Comparison of four types of palmprint representations on UST hand image database.

Table 2. Comparison of accuracy measures on UST database.

Algorithm	EER	d'
Palm code ($\theta = 0^\circ$) [9]	1.68%	3.44
Palm code ($\theta = 45^\circ$) [9]	1.77%	3.39
Palm code ($\theta = 90^\circ$) [9]	2.95%	2.95
Palm code ($\theta = 135^\circ$) [9]	2.14%	3.25
Fusion code [10]	0.75%	3.40
Competitive code [11]	0.38%	3.51
Ordinal code	0.22%	4.77

4.3. Discussions

From the above analysis and results, we can draw a number of conclusions as follows:

Ordinal measures are robust against illumination, contrast and misalignment variations. The experimental results proved that ordinal measures are the most suitable for palmprint feature representation. On the other hand, the results also proved the statistical richness of ordinal information in palmprint.

The leading palmprint recognition methods, namely palm code [9], fusion code [10], competitive code [11], and ordinal code derived from OLOF, all achieved good recognition performance in different image capture environments. The success of these algorithms depends greatly on the ordinal representation scheme they used.

Although these four types of codes are all based on ordinal measures, their recognition performance could differ to a large extent due to the use of different ordinal operators. In terms of accuracy, ordinal code performs the best, followed by competitive code [11], fusion code [10] and palm code [9].

Another compelling advantage of our ordinal code is that its processing speed is nearly twice fast as that of competitive code [11].

5. Conclusions and Future Work

A general framework for palmprint recognition is proposed based on the ordinal representation. In this framework, palmprint representations used in the state-of-the-art systems are unified and the reasons why the palmprint pattern is so discriminative is explained. We hope this work could contribute to the standization of palmprint recognition. The architecture also provides directions for developing new, improved algorithms. Based on these, a novel palmprint representation, that of *orthogonal line ordinal features,* is proposed. The extensive experiments demonstrate that our method achieves significantly higher accuracy than the state-of-the-art systems with lower computational cost.

Although the orthogonal line ordinal feature is currently the best ordinal measure for palmprint representation, theoretical foundation of this operator has not been well formulated. Exploring the optimal ordinal filter for palmprint recognition theoretically may be without final result, however a new and improved ordinal filter is possible to be found in this process.

In the experiment, we only used the ordinal intensity feature of palmprint images in one scale. Fusion of ordinal features at different scales, with different measurements (such as intensity, energy, contrast and some well-developed texture features) should be beneficial to recognition.

Although this work is presented in the context of palmprint recognition, we think that the proposed framework is general enough and the ideas should be applicable for other recognition tasks, such as face recognition and texture classification.

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