15th European Signal Processing Conference (EUSIPCO 2007), Poznan, Poland, September 3-7, 2007, copyright by EURASIP

ORDINAL REPRESENTATIONS FOR BIOMETRICS RECOGNITION

Tieniu Tan and Zhenan Sun

Center for Biometrics and Security Research & National Laboratory of Pattern Recognition
Institute of Automation, Chinese Academy of Sciences, P.O. Box 2728, Beijing, 100080, P.R. China
email: {tnt, znsun}@nlpr.ia.ac.cn

ABSTRACT

Biometrics provides a reliable method for automatic personal identification and has wide and important applications. The success of a biometric recognition system depends critically on its feature representation model for biometric patterns. The most challenging issue in biometric feature representation is to achieve sensitivity to inter-class differences and at the same time robustness against intra-class variations. Many biometric representation schemes have been reported but the above issue remains to be resolved. In this paper, we introduce ordinal measures for iris, face and palmprint image representation in an attempt to resolve this issue. With this so-called ordinal representation model in place, many best-performing biometric recognition methods may be interpreted as special cases of this model. In this sense, the proposed ordinal representation model forms a general framework for biometric pattern representation. Extensive experimental results on public biometric databases demonstrate the effectiveness and generality of this representation.

1. INTRODUCTION

Biometric authentication makes use of the physiological or behavioral characteristics of subjects such as fingerprint, iris, face, palmprint, gait, and voice, for personal identification [1]. Since biometrics associates the identity of a person with his unique body measurement, it is much more reliable than non-biometric methods such as password, PIN, and ID cards. With fast development of biometric sensors and algorithms, biometrics has become an essential technology for many mission-critical applications, such as homeland security, e-commerce, banking, etc.

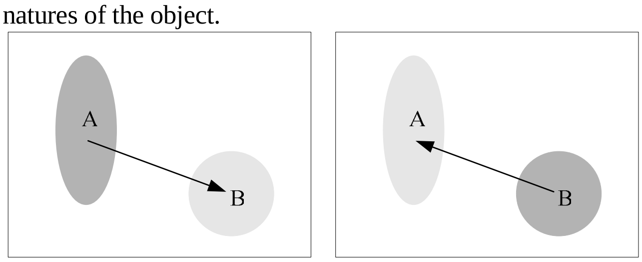
In a computer-based biometric system, the main challenge is how to make a machine "remember" each person via his biometric representation. A common practice is to encode the input biometric signal into compact features so as to maximize intra-class similarity and inter-class dissimilarity. Therefore the performance of a biometric system relies greatly on its feature representation scheme. Although great progress has been made in biometrics research, how to represent biometric patterns effectively is still an open problem. For example, a common representation of iris, palmprint and face images has not been proposed, which is very desirable to standardize biometric feature encoding and storage format [2]. So we have to use image rather than feature template to facilitate global interoperability in applications such as e-passport. In this paper, we propose a general biometric representation based on ordinal measures, to demonstrate that state-of-the-art iris, palmprint and face feature models could be unified in a framework. Such a framework could explain why some biometrics algorithms perform best. More importantly, this work suggests possible ways to develop new and better ordinal features.

The rest of this paper is organized as follows. Section 2 gives a brief introduction to ordinal measures. In Section 3, a general framework for iris recognition is presented based on ordinal measures. Section 4 discusses how to explore effective ordinal features for palmprint recognition. We conclude this paper in Section 5.

2. A BRIEF INTRODUCTION TO ORDINAL MEASURES

Stevens suggested four levels of measurements from coarse to fine: nominal, ordinal, interval and ratio measures [3]. Ordinal measures come from a simple and 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. This kind of qualitative measurement, which is related to the relative ordering of several quantities, is defined as ordinal measures (or OM for short).

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 neighboring image pixels or regions present some stability with such changes and reflect the intrinsic natures of the object.



(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. $A \succ B$.

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 “$A \prec B$” and “0” denotes “$A \succ B$”, and the equality case (a low possibility event) can be assigned to either.

The biological plausibility of visual ordinal measures has been verified by many neuroscience researchers [4][5]. DeAngelis et al. [4] found that many striate cortical neurons’ visual responses saturate rapidly regarding the magnitude of contrast as the input, which tells us the determining factor of visual cognition is not the absolute value of contrast, but the contrast polarity. Rullen et al. [5] suggested that temporal order coding might form a rank-based image representation in the visual cortex.

Many computer vision researchers have enjoyed the effectiveness of ordinal measures. Sinha [6][7] 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 [6][7]. Combining qualitative spatial and photometric relationships together, Lipson et al. [8] applied ordinal measures to image database retrieval. Bhat and Nayar employed the rank permutation of pixel intensity values in image windows for stereo correspondence [9]. After introducing ordinal measures into co-occurrence model, Partio et al. obtained better texture retrieval results [10]. Smeraldi [11] proposed a complete family of multi-scale rank features, namely Ranklets to describe the orientation selective ordinal measures of image regions. Sadr et al. [12] developed a regularization approach for image construction from ordinal measures.

Because of the simplicity of ordinal representation, Thoresz [13] 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 have demonstrated in our previous work [22-25] and outlined in this paper that the ordinal measures can play a defining role for the complex biometric recognition task.

3. ORDINAL REPRESENTATION FOR BIOMETRIC RECOGNITION

The formation of most biometric patterns is based on imaging technology. According to Lambertian model, there are three determining factors on the intensity field of a digital biometric image: geometry of physical surface, reflection ratio of the surface, and illumination. For a small local region of a biometric image, the underlying physical surface is nearly planar and the strength of illumination is also uniformly distributed. So it is reasonable to assume that the intensity field *I(x,y,t)* of one biometric pattern could be expressed as

$$I(x, y, t) = \rho(x, y) k(x, y, t) \tag{1}$$

where $\rho(x, y)$ denotes the reflection ratio of biometric surface, and $k(x, y, t)$ is the illumination strength received by biometric surface along the sensor direction. It is clear that $\rho(x, y)$ is the intrinsic features of biometrics and invariant to imaging conditions, but $k(x, y, t)$ is a variable as a function of illumination, pose, and other uncertain factors although it is approximately equal in the local region, i.e. $k(x, y, t) \approx k(x + \Delta x, y + \Delta y, t)$.

Based on above analysis, we show that the objective of biometric feature representation is to estimate $\rho(x, y)$ given $I(x, y, t)$. However it is a very difficult task to reconstruct the exact value of $\rho(x, y)$ from intensity without other information. So we return to the ordinal features of $\rho(x, y)$ rather than its interval or ratio measurement. Fortunately, the idea of ordinal representation of $\rho(x, y)$ is possible and effective.

Firstly, we could estimate the ordinal relationship between $\rho(x, y)$ and $\rho(x + \Delta x, y + \Delta y)$ by comparing the relative order of $I(x, y, t)$ and $I(x + \Delta x, y + \Delta y, t)$.

$$\begin{aligned}\frac{\rho(x, y)}{\rho(x + \Delta x, y + \Delta y)} &= \frac{I(x, y, t)}{k(x, y, t)} / \frac{I(x + \Delta x, y + \Delta y, t)}{k(x + \Delta x, y + \Delta y, t)} \\ &\approx \frac{I(x, y, t)}{I(x + \Delta x, y + \Delta y, t)}\end{aligned} \tag{2}$$

Since $\dfrac{\rho(x, y)}{\rho(x + \Delta x, y + \Delta y)}$ is the invariant feature of biometrics, for intra-class biometric samples acquired at t_1 and t_2 the corresponding ordinal measures should be indentical.

$$\begin{aligned} & I(x, y, t_1) \gtrless I(x + \Delta x, y + \Delta y, t_1) \\ \Leftrightarrow\ & I(x, y, t_2) \gtrless I(x + \Delta x, y + \Delta y, t_2)\end{aligned} \tag{3}$$

Equation (3) indicates the core idea of ordinal measures based biometric recognition scheme, establishing the identity of input image by checking consistency of its ordinal measures with the template.

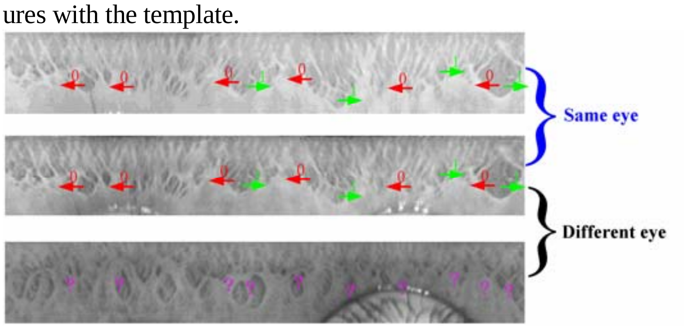


Figure 2 – Stable ordinal measures in intra-class iris images

Although the discriminating power of one bit ordinal code is limited, a biometric template combining by thousands of ordinal relations is powerful enough for personal identification. For example, we could find sufficient stable ordinal relations in iris images (Fig. 2). For inter-class biometric patterns, the possibility of matching two ordinal relations in corresponding region is only 50%, but for intra-class samples, most of ordinal measures should be matched except some weak relations affected by noise. So ordinal representation is sensitive to inter-class variations and robust to intra-class variations, which is desirable property for biometric recognition.

Of course, ordinal measures are not limited in one pixel's intensity. The values used for ordinal comparison may be the results of image transformation or the weighted intensity of a group of pixels. For example, we could derive a series of ordinal measures from Equation (2).

$$\begin{aligned} & f(I(x,y,t)) < f(I(x+\Delta x, y+\Delta y, t)) \\ & \Rightarrow f(\rho(x,y)) < f(\rho(x+\Delta x, y+\Delta y)) \end{aligned} \tag{4}$$

$$\begin{aligned} & w_1 I(L_1) + w_2 I(L_2) < w_3 I(L_3) + w_4 I(L_4) \\ & \Rightarrow w_1 \rho(L_1) + w_2 \rho(L_2) < w_3 \rho(L_3) + w_4 \rho(L_4) \end{aligned} \tag{5}$$

where *f(x)* is a monotonic increasing function, w_i (i=1,2,3,4) is positive coefficient and (L_i) (i=1,2,3,4) is spatial location in a region.

In order to extract different kinds of ordinal features, we propose Multi-lobe Ordinal Filter (MLOF) with parameters, such as distance, scale, orientation, number, location (Fig. 3). Each local biometric region is encoded to 1 or 0 based on sign of its filtering results with MLOF (Fig.4). Feature matching of different binary ordinal templates can be based on Hamming distance.

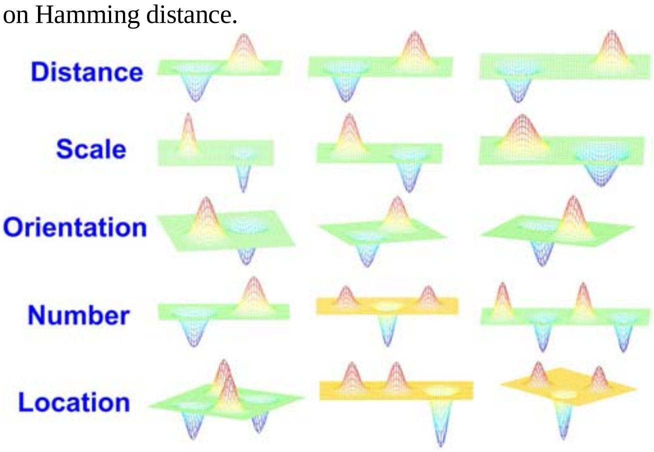


Figure 3 – Examples of Multi-lobe Ordinal Filter

It is interesting to find that some state-of-the-art iris [14], palmprint [15] and face [16] recognition algorithms may be seen as special cases of ordinal measures. For example, Gabor based encoding filters used in iris code [14] and palm code [15] are essentially ordinal operators (see Fig. 5). For odd Gabor filtering of local image patch, the image regions covered by two excitatory lobes are compared with the image regions covered by two inhibitory lobes (Fig. 5b). The filtered result is qualitatively encoded as “1” or “0” based on the sign of this inequality. Similarly, even Gabor generated iris code is mainly determined by the ordinal relationship between one excitatory lobe-covered region and two small inhibitory lobes-covered regions (Fig. 5d). Because the sum of original even Gabor filter's coefficients is not equal to 0,

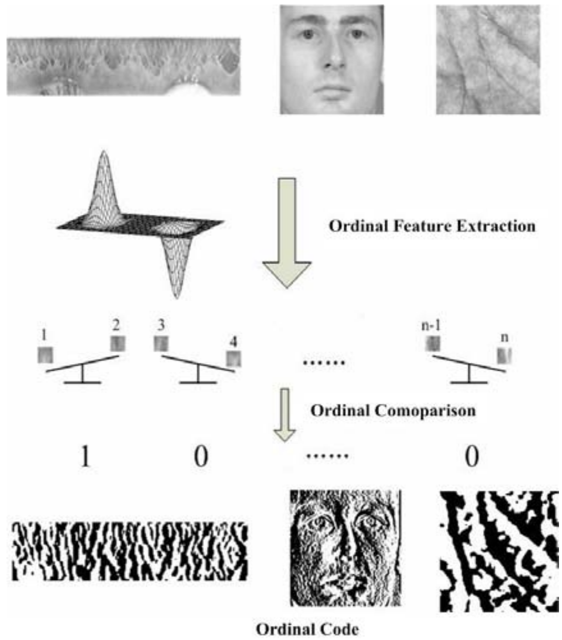
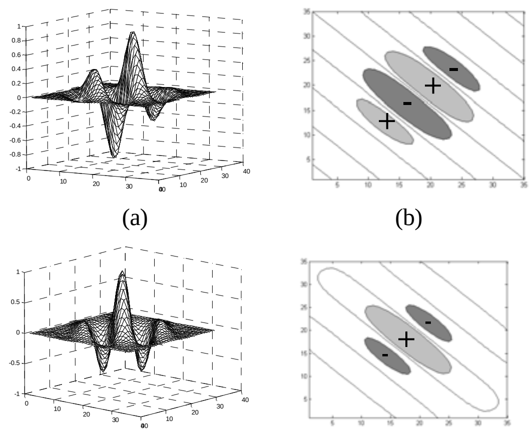


Figure 4 – Biometric Feature Extraction with Multi-lobe Ordinal Filter



(a) (b)

(c) (d)

Figure 5 – Odd and even Gabor filters used in [14][15]. (a) Odd Gabor filter. (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. (d) Ordinal comparison of image regions using even Gabor filter.

the average coefficient value is reduced from the filter to maximize the information content of the corresponding feature code [14][15]. Local binary pattern (LBP) becomes a popular image analysis tool now and has achieved state-of-the-art face recognition performance [16]. In fact, a LBP code just models the ordinal measures between one pixel (region) with its surrounding pixels (regions). In conclusion, ordinal measures form a general framework for biometric representation which may help to understand the discriminating power of biometric patterns, standardize biometric template exchange format, and guide further research. The ultimate purpose of the proposed framework is to guide the development of new algorithms, so we explore novel and better ordinal filters for iris [22][23] and palmprint [24] recognition respectively in the following two sections. How to learn ordinal features for face recognition is discussed in [25]. Further details may be found in [22-25].

4. ORDINAL REPRESENTATION FOR IRIS RECOGNITION

State-of-the-art iris recognition algorithms are based on Gabor [14] and wavelet [17] filters, which could encode ordinal measures between connected image regions. But these methods [14][17] have ignored the rich ordinal information between non-neighboring regions. Within the ordinal framework, we break the limitation of state-of-the-art iris method in local ordinal features and propose non-local ordinal measures for iris image representation. Such a transition is natural from the first line of Fig.3. We argue that non-local ordinal measures are more discriminant and robust than local ordinal measures. Because the adjacent iris image regions are highly correlated with each other, the probability that two more distant regions will differ is much greater than that of two adjacent regions. The larger the contrast magnitude, the more robust the contrast polarity. So long-distance ordinal comparisons are more tolerant to common image degradations than purely local ones.

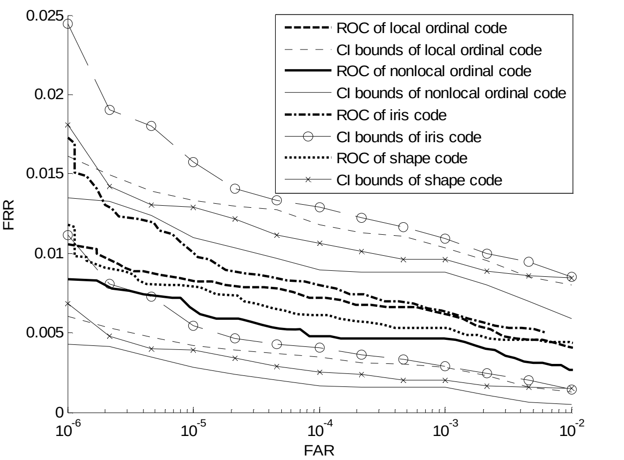


Figure 6 – ROC curves of different ordinal measures based iris recognition algorithms

Experimental results on CASIA Iris Image Database [18] demonstrated our ideas. We extracted 256 bytes iris code [14], shape code [17], local and nonlocal ordinal code (half dipole and half tripole feature code) respectively from the CASIA-IrisV3-Interval dataset, then compared all possible pairwise feature templates to generate ROC curves and confidence interval of FRRs. The results are shown in Fig. 6. From the results we can see that these iris recognition algorithms all perform well and are with overlapped confidence intervals. Their performance is comparable since there are totally 2,048 ordinal measures used in these methods, which are powerful enough to recognize almost all iris images successfully. However there still exist some differences in the reported ROC curves of these four methods, due to the different ordinal filtering strategies employed in feature extraction. Because both iris code and shape code are based on local ordinal measures, their recognition results are similar to local ordinal code. Comparatively, nonlocal ordinal code shows to be advantageous over these state-of-the-art iris recognition methods, although the improvement is moderate.

In terms of computational complexity, ordinal code is also superior to iris code [14] and shape code [17] because ordinal code generation only involves simple low-pass filtering and qualitative comparison. In contrast, iris code and shape code require image filtering with complex Gabor and wavelet kernel respectively. So iris code must pay approximately three times and shape code need twice of ordinal code's computational cost for feature extraction.

5. EFFECTIVE ORDINAL FEATURES FOR PALMPRINT RECOGNITION

Following the same ordinal 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. So we search the ordinal filter space to choose the most suitable ordinal features for palmprint recognition. We have tested the recognition performance of all possible two-lobe ordinal filters on PolyU Palmprint Database V1 (only 600 images) [15]. The top 100 best performing dilobe ordinal filters are shown in Fig. 7.

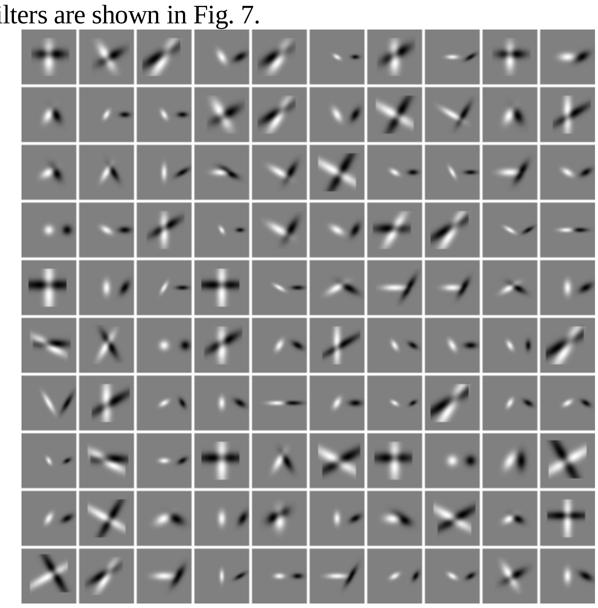


Figure 7 – Best performing di-lobe ordinal filters for palmprint recognition

It is interesting to find that ordinal measures between orthogonal line-like image regions perform very well. The results are reasonable:

- In low-resolution palmprint images, the most discriminative features are the randomly distributed line segments, such as principal lines, wrinkles and ridges. So the shape of elementary filter lobe should be line-like.
- When two line-like image regions' directions are orthogonal, the correlation of the two regions is minimized and ordinal measures are more robust.

Based on above analysis, we propose *Orthogonal Line Ordinal Filters (OLOF)*, as illustrated in Fig. 8, for palmprint recognition.

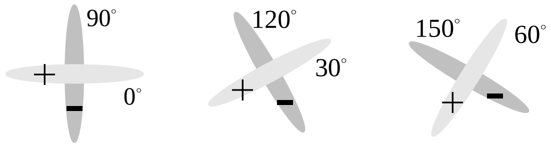


Figure 8 – Orthogonal Line Ordinal Filters

We have compared our method with state-of-the-art palmprint recognition algorithms, i.e. palm code [15], fusion code [19], competitive code [20] on UST hand image database (5,660 images from 283 subjects) [21]. The results are shown in Fig. 9, which demonstrate that our ordinal code based on OLOF performs best.

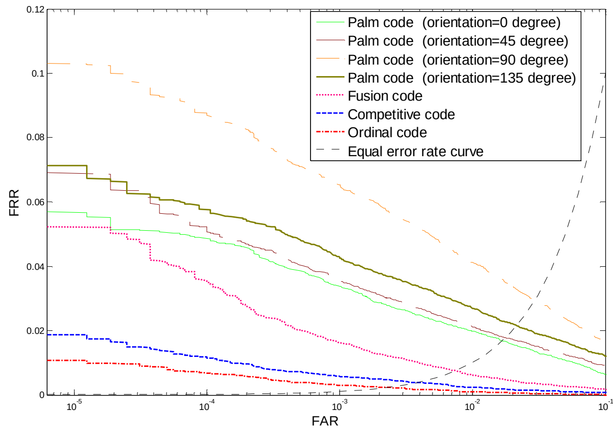


Figure 9 – ROC curves of different ordinal measures based palmprint recognition algorithms

6. CONCLUSIONS

A general framework for biometrics recognition is proposed based on ordinal meausures. In this framework, image feature representation models used in the state-of-the-art iris, palmprint and face recognition systems may be unified. The architecture also provides directions for developing new and improved algorithms. Based on these, non-local and orthogonal line ordinal filters are developed for iris and palmprint recognition respectively. Extensive experiments have demonstrated that our method achieves significantly higher accuracy than the state-of-the-art systems with lower computational cost.

ACKNOWLEDGEMENT

This work is funded by research grants from the National Basic Research Program (Grant No. 2004CB318110), Natural Science Foundation of China (Grant No. 60335010, 60121302, 60275003, 60332010, 69825105, 60605008), and Hi-Tech Research and Development Program of China (Grant No.2006AA01Z193).

REFERENCES

[1] A.K. Jain, R.M. Bolle, and S. Pankanti, Eds., Biometrics: Personal Identification in Networked Society, Norwell, MA: Kluwer, 1999.

[2] ISO/IEC 19794, *Biometric data interchange formats.*

[3] S. Stevens, "On the Theory of Scales of Measurement", Science, Vol.103, No.2684, pp.677-680, June 1946.

[4] G.C. DeAngelis, I. Ohzawa, and R.D. Freeman, "Spatiotemporal Organization of Simple-Cell Receptive Fields in the Cat's Striate Cortex. I. General Characteristics and Postnatal Development", *Journal of Neurophysiology*, vol. 69, no. 4, pp. 1091–1117, 1993.

[5] R. Van Rullen and S. J. Thorpe, "Rate Coding versus Temporal Order Coding: What the Retinal Ganglion Cells Tell the Visual Cortex", *Neural Computation*, Vol. 13, No.6, pp. 1255-1283, 2001.

[6] P. Sinha, "Perceiving and Recognizing Three-dimensional Forms", *PhD Dissertation*, Massachusetts Institute of Technology, pp. 141–165, 1995.

[7] P. Sinha, "Qualitative Representations for Recognition", *Lecture Notes in Computer Science*, vol. 2525, pp. 249-262, 2002.

[8] P. Lipson, E. Grimson, and P. Sinha, "Configuration based Scene Classification and Image Indexing", *Proc. of the CVPR*, pp. 1007–1013, June 17-19 1997.

[9] D. Bhat and S. Nayar, "Ordinal Measures for Image Correspondence", *IEEE Transactions on PAMI*, Vol.20, No.4, pp.415–423, April 1998.

[10] M. Partio, B. Cramariuc, and M. Gabbouj, "Texture Similarity Evaluation using Ordinal Co-occurrence", *ICIP*, pp. 1537–1540, Singapore, 2004.

[11] F. Smeraldi, Ranklets: a Complete Family of Multiscale, Orientation Selective Rank Features, *Research Report RR0309-01*, Department of Computer Science, Queen Mary, University of London, UK, September 2003.

[12] J. Sadr, S. Mukherjee, K. Thoresz, and P. Sinha, "The Fidelity of Local Ordinal Encoding", in: T. Dietterich, S. Becker, and Z. Ghahramani (Eds.): *Advances in Neural Information Processing Systems*, MIT Press, Cambridge, MA, 2002.

[13] K.J. Thoresz, "Qualitative Representations for Recognition", *Master Thesis*, Massachusetts Institute of Technology, 2002.

[14] J. Daugman, "High Confidence Visual Recognition of Persons by a Test of Statistical Independence", IEEE Trans. on PAMI, Vol.15, No.11, pp.1148-1161, 1993.

[15] D. Zhang, W. Kong, J. You, and M. Wong, "On-line Palmprint Identification", IEEE Trans. on PAMI, vol. 25, no. 9, pp. 1041-1050, 2003.

[16] T. Ahonen, A. Hadid, M. Pietikainen, "Face Description with Local Binary Patterns: Application to Face Recognition", IEEE Trans. on PAMI, Vol. 28, No. 12, pp. 2037-2041, 2006.

[17] L. Ma, T. Tan, Y. Wang, and D. Zhang, "Efficient Iris Recognition by Characterizing Key Local Variations", IEEE Trans. Image Processing, Vol. 13, No. 6, pp.739–750, 2004.

[18] CASIA Iris Image Database, http://www.cbsr.ia.ac.cn.

[19] W.K. Kong and D. Zhang, "Feature-Level Fusion for Effective Palmprint Authentication", LNCS 3072, pp.761-767, 2004.

[20] W.K. Kong and D. Zhang, "Competitive Coding Scheme for Palmprint Verification", Proc. of the 17th ICPR, vol.1, pp. 520-523, 2004.

[21] UST Hand Image Database, http://visgraph.cs.ust.hk/biometrics/Visgraph_web/index.html.

[22] Z. Sun, T. Tan, Y. Wang, "Robust Encoding of Local Ordinal Measures: A General Framework of Iris Recognition", Lecture Notes in Computer Science, Vol.3087, 2004, pp. 270-282.

[23] Z. Sun, T. Tan, Y. Wang, "Iris Recognition Based on Non-local Comparisons", LNCS, Vol.3338, 2004, pp. 67-77.

[24] Z. Sun, T. Tan, Y. Wang, S. Li, "Ordinal Palmprint Representation for Personal Identification", Proc. of CVPR, Vol.1, 2005, pp.279-284.

[25] S. Liao, Z. Lei, X. Zhu, Z. Sun, S. Li, and T. Tan, "Face Recognition Using Ordinal Features", Lecture Notes in Computer Sciences, Vol. 3832, 2005, pp. 40-46.