Chinese Chess Character Recognition with Radial Harmonic Fourier Moments

Wang Kejia
School of Electronic Engineering
Beijing University of Posts and Telecommunications
Beijing, China
Inner Mongolia Electronic Information Vocational Technical College
Huhhot, China
wang.ke-jia@hotmail.com

Zhang Honggang
School of Information and Communication Engineering
Beijing University of Posts and Telecommunications
Beijing, China
zhhg@bupt.edu.cn

Ping Ziliang
School of Electronic Engineering
Beijing University of Posts and Telecommunications
Beijing, China
Inner Mongolia Normal University
Huhhot, China
pzl@imnu.edu.cn

Haiying
Physics and Electronic Information College
Inner Mongolia Normal University
Huhhot, China
nmghy@hotmail.com

***Abstract*—Radial harmonic Fourier moments (RHFMs) are invariant to translation, rotation, scaling and intensity, which own excellent image description ability, noise-resistant power, and less computational complexity. In this paper, RHFMs have been applied to the rotated Chinese Chess character recognition, which is the key step in chess recognition for vision system of Chinese Chess playing robot. In order to evaluate the efficiency of this method, experiments on both toy images and real chess images were carried out respectively. The experimental results indicate that the proposed method achieves an average recognition rate of 99.49% in artificial datasets and 99.57% in real-world datasets. The results demonstrate that the RHFMs have excellent performance in rotated Chinese Chess character recognition.**

Keywords-rotated Chinese character recognition; Chinese Chess; Radial harmonic Fourier moments (RHFMs); moment invariants

I. INTRODUCTION

For the past decade, great efforts have been made to develop an efficient Chinese character recognition method [1, 2]. Many algorithms based on local or global features have been proposed. These methods are widely applied to on-line and off-line character recognition, printed and handwritten character recognition. Researchers have made great progress in this field, and some methods have been successfully used in commercial products. However, there are still some challenges in various special applications. For instance, rotated Chinese character recognition is not very well developed. In some special occasions, rotated Chinese character recognition is significant, for example, in vision system of Chinese Chess playing robot. Chinese Chess is an extremely popular two-player board game in China and some other Asian countries. The chess pieces are flat circular disks, painted red and black separately identifying which player the piece belongs and marked with 11 different Chinese characters identifying the piece. Chess recognition is a part of vision system for Chinese Chess playing robot. Owing to the arbitrary orientation of chess pieces are placed, rotated Chinese character recognition is a crucial step in chess recognition.

There are some previously proposed approaches for rotated Chinese character recognition such as ring projection, radicals matching, stroke-based features, moment Fourier descriptor, Fourier-wavelet descriptor, Gabor filtering, Zernike moments, etc[3-13]. These methods are designed for general rotated Chinese character recognition, so that most of which require extensive preprocessing, and have higher computational complexity. Furthermore some of these rotation invariant features are unstable for arbitrary rotation of character. To the best of our knowledge, few literatures discussed the rotated Chinese chess character recognition. The Radial harmonic Fourier moments (RHFMs) are translation, rotation, scaling, and intensity invariants, which own excellent image description ability, noise-resistant power, and simple computation[14]. Take the characteristics of Chinese chess into consideration, in this paper, RHFMs have been applied to the rotated Chinese Chess character recognition.

The rest of this paper is organized as follows: Some related works about invariant moments are introduced in section 2. In section 3, the definition and normalization method for multi-distortion invariance of the RHFMs is discussed and the feature extraction and recognition method is given. We investigate and compare the performance of RHFMs with Zernike moments (ZMs) and Jacobi–Fourier moments (JFMs) in terms of experiments on both artificial and real-world datasets. Experimental results are given in section 4. Section 5 concludes this paper.

II. RELATED WORKS

The moment invariants are highly concentrated multi-distorted invariants image features. They have been extensively employed as the invariant global features of an image in pattern recognition, image classification, target identification, and scene analysis. Hu firstly introduced moment invariants in 1962, based on methods of algebraic

1520-5363/11 $26.00 © 2011 IEEE
DOI 10.1109/ICDAR.2011.275

invariants[15]. Using nonlinear combinations of geometric moments, he derived a set of invariant moments which has the desirable properties of being invariant under image translation, scaling, and rotation. However, the geometric moments are not orthogonal, thus the invariant moments suffer from information redundancy, and reconstruction of the image from these moments is deemed to be quite difficult.

According to the orthogonal theory, an image function can be decomposed with orthogonal and completed function systems to form the independent orthogonal image moments, and original image can be reconstructed by the weighted superposition of the moments. Teague has suggested the notion of orthogonal moments and introduced Legendre moments and Zernike moments using the corresponding orthogonal functions as kernels for image description[16]. ZMs of the *n*th order with repetition *m* are defined as

$$A_{nm} = \frac{n+1}{\pi}\int_0^{2\pi}\int_0^1 \left[V_{nm}(r,\theta)\right]^* f(r,\theta)\,r\,dr\,d\theta, \qquad (1)$$

$n = 0,1,2,\cdots, m = -n,-n+2,\cdots,n$,

$V_{nm}(r,\theta)$ are Zernike polynomials

$$V_{nm}(r,\theta) = R_{nm}(r)\exp(jm\theta), \qquad (2)$$

where the radial part is

$$R_{nm}(r) = \sum_{s=0}^{(n-|m|)/2}(-1)^s \frac{(n-s)!}{s!\left((n+|m|)/2-s\right)!\left((n-|m|)/2-s\right)!} r^{n-2s}. \qquad (3)$$

The image reconstruction from orthogonal moments is easy and optimal when using only a finite set of moments. Teh and Chin evaluated various types of image moments, including geometric moments, Legendre moments, Zernike moments, pseudo-Zernike moments, rotational moments, and complex moments, in terms of noise sensitivity, information redundancy, and capability of image description. They found that ZMs have the best overall performance[17].

Henceforward various orthogonal moments have been proposed and their proprieties have been discussed. Sheng et al. proposed the Orthogonal Fourier–Mellin moments (OFMMs), which are constructed by the Gram–Schmidt orthogonalization of a set of monomials of the lowest powers. The OFMMs have better performance than the ZMs, especially for the description of small images[18]. Ping et al. proposed Chebyshev–Fourier moments (CHFMs), which have almost the same performance as OFFMs for shape description[19]. However, CHFMs tend to be infinite at the origin, which create difficulties in describing an image near the center of the image. Ping et al. proposed a generic orthogonal moments: Jacobi–Fourier moments[20]. JFMs are defined as

$$\Phi_{nm} = \int_0^{2\pi}\int_0^1 f(r,\theta)J_n(p,q,r)\exp(-jm\theta)\,r\,dr\,d\theta, \qquad (4)$$

n, m are integers, $J_n(p,q,r)$ are the deformed Jacobi polynomials, which have the relation with Jacobi polynomials $G_n(p,q,r)$ as follows

$$J_n(p,q,r) = \sqrt{\frac{w(p,q,r)}{b_n(p,q)r}}\,G_n(p,q,r), \qquad (5)$$

where

$$w(p,q,r) = (1-r)^{p-q}\,r^{q-1} \quad (p-q>-1, q>0), \qquad (6)$$

$$b_n(p,q) = \frac{n!\left[(q-1)!\right]^2(p-q+n)!}{(q+n-1)!(p+n-1)!(p+2n)}, \qquad (7)$$

$$G_n(p,q,r) = \frac{n!(q-1)!}{(p+n-1)!}\times\sum_{s=0}^{n}(-1)^s\frac{(p+n+s-1)!}{(n-s)!s!(q+s-1)!}r^s, \qquad (8)$$

p and q are real parameters, the value variation of which will form different Jacobi polynomials. The kernel function of JFMs consists of radial Jacobi polynomial and angular Fourier complex exponential factor. Almost all orthogonal moments with the kernel function consisted of radial orthogonal polynomial and angular Fourier exponential factor in polar coordinate system, such as ZMs, OFMMs, CHFMs, are special cases of the JFMs and can be derived from the JFMs in terms of different parameter values. These moments have the property of being rotational invariant. Bhatia and Wolf have shown that a polynomial that is invariant in form for any rotation of axes about the origin must be of the form

$$V(r\cos\theta, r\sin\theta) = R_n(r)\exp(jm\theta), \qquad (9)$$

where $R_n(r)$ is a radial polynomial in r of degree n [21]. Essentially, the kernels of JFMs including its special cases comply with this form.

III. RHFMs-based Character Recognition

The kernel function of RHFMs also follows the form of (9), which chose orthogonal and completed triangular function as radial function. The RHFMs are translation, rotation, scaling, and intensity invariant. Compared with other moments, RHFMs have a superior performance. Therefore we will apply RHFMs for Chinese Chess character recognition.

A. Definition of RHFMs

The RHFMs kernel function set $P_{nm}(r,\theta)$ defined in a polar coordinate system consists of two separable function sets: the function $T_n(r)$ to be a radial function and the Fourier exponential factor $\exp(jm\theta)$ to be an angular function:

$$P_{nm}(r,\theta) = T_n(r)\exp(jm\theta), \qquad (10)$$

where n, m are integers, and $T_n(r)$ is defined as:

$$T_n(r) = \begin{cases} \frac{1}{\sqrt{r}} & if\ n=0 \\ \sqrt{\frac{2}{r}}\sin\left[(n+1)\pi r\right] & if\ n=odd \\ \sqrt{\frac{2}{r}}\cos(n\pi r) & if\ n=even \end{cases} \qquad (11)$$

The set of $T_n(r)$ is orthogonal in the interval $0 \le r \le 1$, Hence The RHFMs kernel function set $P_{nm}(r,\theta)$ is orthogonal in the interior of the unit circle:

$$\int_0^{2\pi}\int_0^1 P_{nm}(r,\theta)P_{kl}(r,\theta)rdrd\theta = \delta_{nk}\delta_{ml}, \quad (12)$$

where $\delta_{nk}\delta_{ml}$ are Kronecker symbols, and $r=1$ is the maximum size of the objects that can be encountered in a particular application.

In the polar coordinate system, an image function $f(r,\theta)$ can be decomposed with the set of $P_{nm}(r,\theta)$ as:

$$f(r,\theta) = \sum_{n=0}^{\infty}\sum_{m=-\infty}^{+\infty} \phi_{nm} T_n(r)\exp(jm\theta), \quad (13)$$

where ϕ_{nm} are the coefficients of the decomposition and referred to as the RHFMs :

$$\phi_{nm} = \int_0^{2\pi}\int_0^1 f(r,\theta)T_n(r)\exp(-jm\theta)rdrd\theta. \quad (14)$$

B. Normalization and Invariance

The RHFMs are not multi-distorted invariants themselves, but can be normalized to be invariant for the translation, rotation, scaling and intensity variation of an image. First of all, the zero order and first order of the geometric moments, *Gpq*, was calculated to determine the centroid of the image- $x_c = G10/G00$, $y_c = G01/G00$, and then the centroid was taken as the origin of the coordinate system. All the moments calculated in this coordinate system are translation invariant. Secondly, because of the Fourier exponential factor $\exp(-jm\theta)$ in the integral kernel, any rotated angle of the image in the coordinate plane, φ, will cause a phase factor $\exp(jm\varphi)$ for all moments, while the modular of the RHFMs, $|\phi_{nm}|$, reserves invariant. Finally, we discuss the scaling- and intensity- distortion invariance. Suppose the distorted image is $gf(r/k,\theta)$, where g is the intensity variation factor, k is the scale variation factor. The Fourier–Mellin moments of the distorted image are

$$\begin{aligned} M'_{sm} &= \int_0^{2\pi}\int_0^1 gf(r/k,\theta)r^s\exp(-jm\theta)rdrd\theta \\ &= gk^{s+2}\int_0^{2\pi}\int_0^1 f(r,\theta)r^s\exp(-jm\theta)rdrd\theta \\ &= gk^{s+2}M_{sm} \end{aligned} \quad (15)$$

where M_{sm} is the Fourier–Mellin moments of the original image. When all the distorted images in the training set are normalized, the ratio M_{10}/M_{00} is chosen to be a constant and slightly smaller than the minimum M'_{10}/M'_{00} of all the images in the training set to ensure that the normalized images remain inside the unit circle. Then factor k and g are calculated for each image in the training set by using (16) and (17):

$$k = \left(\frac{M'_{10}}{M'_{00}}\right)\Big/\left(\frac{M_{10}}{M_{00}}\right) \quad (16)$$

$$g = \left[\left(\frac{M_{10}}{M_{00}}\right)\Big/\left(\frac{M'_{10}}{M'_{00}}\right)\right]^2 \cdot \frac{M'_{00}}{M_{00}} \quad (17)$$

For each distorted image, let $\rho = r/k$, then

$$\begin{aligned} \phi'_{nm} &= \int_0^{2\pi}\int_0^k g\ f(r/k,\theta)T_n(r/k)\exp(-jm\theta)rdrd\theta \\ &= gk^2\int_0^{2\pi}\int_0^1 f(\rho,\theta)T_n(\rho)\exp(-jm\theta)\rho d\rho d\theta \\ &= gk^2\phi_{nm} \end{aligned} \quad (18)$$

Let

$$\Phi_{nm} = \phi_{nm}/gk^2, \quad (19)$$

Φ_{nm} are then calculated by (14) and (19) for all images of the training set, which is scaling- and intensity-distortion invariant.

C. Feature Extraction and Recognition

RHFMs with *n, m*=0, 1, 2, 3, 4 of input image were calculated, a 25-dimensional multi-distorted invariant feature vector constructed with modular of the RHFMs, $|\Phi_{nm}|$,were obtained to describe it. The average vector of training samples was used as a representative of its class. A simple minimum city block distance classifier was used in recognition. The city block distance was defined as

$$d_i = \sum_{n,m=0}^{4}\left||\Phi_{nm}| - (|\Phi_{nm}|)_i\right|, \quad (20)$$

where $|\Phi_{nm}|$ is the modulus of the RHFMs of the testing image, and $(|\Phi_{nm}|)_i$ is that of the class *i*. A testing image was classified to the class *i* for which the distance d_i was minimum.

IV. EXPERIMENTAL RESULTS

Experiments on both artificial and real-world datasets were carried out to verify the ability of the RHFMs for Chinese chess recognition, and the results were compared with ZMs and JFMs. In our experiments, just translation and rotation invariants were applied, because the experiment samples are binary images and scale-normalized.

A. Experiments on Toy Examples

The goal of toy experiments is to demonstrate the recognition power of RHFMs for rotated Chinese character. A database consisted of binary images of the 11 Chinese characters in 64×64 pixel matrices was constructed. In order to test the rotation invariance, each character was rotated by every 10 deg to generate the 36 rotated samples. Some samples are shown in Fig. 1.

In the experiment, 18 samples of each character were chosen as the training samples to constitute the training set and the remaining samples of all characters were taken to be the testing set. We calculated 25 RHFMs of the training images for each character and derived an average feature vector to represent it, then classified the testing images with a minimum city block distance classifier. ZMs and JFMs with $p=4, q=3$ were also extracted and used in classification for comparison. The recognition performances of the training and testing sets were evaluated, respectively. The results are given in Table 1.

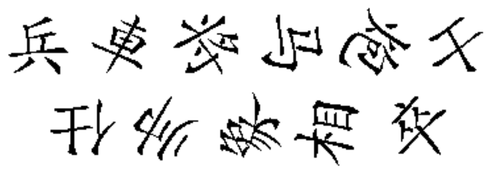

Figure 1. Sample images in artificial database

TABLE I. THE RECOGNITION RATES OF ARTIFICIAL DATASET

Features	Training Set	Testing Set	Average
RHFMs	99.49%	99.49%	99.49%
JFMs	100%	99.75%	99.88%
ZMs	100%	100%	100%

RHFMs can achieve a recognition rate of 99.49% on both training set and testing set. JFMs can achieve a recognition rate of 100% on training set and 99.75% on testing set, which results in an average recognition rate of 99.88%. ZMs can correctly identify all the images in the training set and testing set. These experimental results illustrate that RHFMs, JFMs and ZMs are efficient in rotated Chinese character classification. They have similar high discrimination power in ideal environment. Compared with RHFMs, the average recognition rate of JFMs and ZMs are slight higher.

B. Experiments on Real Chess Images

In order to assess the effectiveness of the RHFMs in real scene, experiments on real-world datasets have also been performed. For this purpose, a chess image database of real photographs and real rotations was constituted. We acquired the images by CCD camera. Each chess piece was captured 32 times with different rotation angles which were randomly chosen within [0º, 360 º]. Therefore, we get 32 samples for each chess piece and 352 samples for the all. The chess pieces were segmented from original images and normalized to 64×64 pixel, as shown in Fig. 2. Then the color images were converted into binary images with adaptive threshold offered by OpenCV. The binary images are shown in Fig.3.

The experiment further was performed on the binary images. Half of the database was used for training and the other half for testing. We also compare the RHFMs with ZMs and JFMs $(p=4, q=3)$ in recognition with a minimum city block distance classifier. The results are tabulated in Table 2.

RHFMs reach 99.14% recognition rate on training set and 100% on testing set. An average recognition rate is 99.57%. JFMs achieve a recognition rate of 98.58% on training set, 96.87% on testing set, and 97.73% on average. A recognition rate of 93.75% on training set, 86.93% on testing set, 90.34% on average can be achieved with ZMs. The results clearly indicated that the RHFMs have excellent performance in real Chinese Chess character recognition, which is superior to the ZMs and JFMs. Since digital images are scanned and stored with a limited resolution in the computer, the rotation of chess will cause image distortion. Furthermore due to the original image and the process of

Figure 2. Sample color images in real-world database

Figure 3. Sample binary images in real-world database

TABLE II. THE RECOGNITION RATES OF REAL-WORLD DATASET

Features	Training Set	Testing Set	Average
RHFMs	99.14%	100%	99.57%
JFMs	98.58%	96.87%	97.73%
ZMs	93.75%	86.93%	90.34%

binarization, noise was also introduced in the binary images. The experimental results reveal that ZMs and JFMs are more sensitive than RHFMs to distortion and noise. The recognition rates of ZMs and JFMs have been a decline in the presence of distortion and noise, whereas the performance of the RHFMs is not affected. The reliability and robustness of the proposed recognition method remains very stable and high.

V. CONCLUSION

In this paper, we proposed a rotated Chinese Chess character recognition method based on RHFMs which are translation, rotation, scaling, and intensity invariant. We evaluated the proposed method on both artificial and real-world datasets respectively and got satisfactory results compared with ZMs and JFMs. The experimental results demonstrate that the RHFMs outperform the others in terms of overall performance for image recognition and robustness to distortion and noise. The results confirmed the effectiveness and the feasibility of the RHFMs in rotated Chinese Chess character recognition. These clearly show the potential of the proposed method for practical application in Chinese Chess playing robot vision system for chess recognition. Since the discrimination power provided by each dimension of the feature vector is not equivalent, the selection of feature and the selection of dimension of the feature space will be further studied. The classifier selection is also the topic for our future research.

ACKNOWLEDGMENT

This paper was partially sponsored by the grants from the Fundamental Research Funds for the Central Universities, 111 Project of China (B08004), Scientific

Research Foundation for the Returned Overseas Chinese Scholars, State Education Ministry, and NSFC (Natural Science Foundation of China) under Grant No. 61065004.

REFERENCES

[1] Tian-Fu Gao and Cheng-Lin Liu, "LDA-based compound distance for handwritten Chinese character recognition," in 9th International Conference on Document Analysis and Recognition, ICDAR 2007, September 23, 2007 - September 26, 2007, Curitiba, Brazil, 2007, pp. 904-908.

[2] Yan Jiang, Xiaoqing Ding, and Zheng Ren, "A suffix tree based handwritten Chinese address recognition system," in 9th International Conference on Document Analysis and Recognition, ICDAR 2007, September 23, 2007 - September 26, 2007, Curitiba, Brazil, 2007, pp. 292-296.

[3] Kai Wang, Yuan Y. Tang, and Ching Y. Suen, "Multi-layer projections for the classification of similar Chinese characters," in 9th International Conference on Pattern Recognition, Rome, Italy, 1988, pp. 842-844.

[4] Chia-Wei Liao and Jun S. Huang, "A transformation invariant matching algorithm for handwritten chinese character recognition," Pattern Recognition, vol. 23, pp. 1167-1188, 1990.

[5] Shuenn-Shyang Wang, Po-Cheng Chen, and Wen-Gou Lin, "Invariant pattern recognition by moment fourier descriptor," Pattern Recognition, vol. 27, pp. 1735-1742, 1994.

[6] Chiu Hung-Pin, Tseng Din-Chang, and Cheng Jen-Chieh, "Invariant handwritten Chinese character recognition using weighted ring-data matrix," in Document Analysis and Recognition, 1995., Proceedings of the Third International Conference on, 1995, pp. 116-119 vol.1.

[7] V. V. Anh, Q. Tieng, T. D. Bui, and G. Chen, "The Hellinger-Kakutani metric for pattern recognition," in Image Processing, 1997. Proceedings., International Conference on, 1997, pp. 430-433 vol.2.

[8] T. N. Tan, "Rotation invariant texture features and their use in automatic script identification," Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 20, pp. 751-756, 1998.

[9] Guangyi Chen and Tien D. Bui, "Invariant Fourier-wavelet descriptor for pattern recognition," Pattern Recognition, vol. 32, pp. 1083-1088, 1999.

[10] Hung-Pin Chiu and Din-Chang Tseng, "Novel stroke-based feature extraction for handwritten Chinese character recognition," Pattern Recognition, vol. 32, pp. 1947-1959, 1999.

[11] Tai-Ning Yang and Sheng-De Wang, "A rotation invariant printed Chinese character recognition system," Pattern Recognition Letters, vol. 22, pp. 85-95, 2001.

[12] W. M. Pan, C. Y. Suen, and T. D. Bui, "Script identification using steerable gabor filters," in 8th International Conference on Document Analysis and Recognition, August 31, 2005 - September 1, 2005, Seoul, Korea, Republic of, 2005, pp. 883-887.

[13] Hai Lin and Hai-Zhou Li, "Chinese signature verification with moment invariants," in Proceedings of the 1996 IEEE International Conference on Systems, Man and Cybernetics. Part 4 (of 4), October 14, 1996 - October 17, 1996, Beijing, China, 1996, pp. 2963-2968.

[14] Haiping Ren, Ziliang Ping, Wurigen Bo, Wenkai Wu, and Yunlong Sheng, "Multidistortion-invariant image recognition with radial harmonic Fourier moments," J. Opt. Soc. Am. A, vol. 20, pp. 631-637, 2003.

[15] Hu Ming-Kuei, "Visual pattern recognition by moment invariants," Information Theory, IRE Transactions on, vol. 8, pp. 179-187, 1962.

[16] Michael Reed Teague, "Image analysis via the general theory of moments," J. Opt. Soc. Am., vol. 70, pp. 920-930, 1980.

[17] C. H. Teh and R. T. Chin, "On image analysis by the methods of moments," Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 10, pp. 496-513, 1988.

[18] Yunlong Sheng and Lixin Shen, "Orthogonal Fourier-Mellin moments for invariant pattern recognition," J. Opt. Soc. Am. A, vol. 11, pp. 1748-1757, 1994.

[19] ZiLiang Ping, RiGeng Wu, and YunLong Sheng, "Image description with Chebyshev-Fourier moments," J. Opt. Soc. Am. A, vol. 19, pp. 1748-1754, 2002.

[20] Z. L. Ping, H. P. Ren, J. Zou, Y. L. Sheng, and W. Bo, "Generic orthogonal moments: Jacobi-Fourier moments for invariant image description," Pattern Recognition, vol. 40, pp. 1245-1254, Apr 2007.

[21] A.Bhatia and E. Wolf, "On the circular polynomials of Zernike and related orthogonal sets," Proc. Cambridge Philosophical Soc., vol. 50, pp. 40-48, 1954.