Information Moment for Chinese Character Recognition

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Abstract – **Moment invariants firstly introduced by M. K Hu in 1962, has some shortcomings. After counting a large number of statistical distribution information of Chinese characters, the authors put forward the concept of information moments and demonstrate its invariance to translation, rotation and scaling. Also they perform the experiment in which information moments compared with moment invariants for the effects of similar Chinese characters and font recognition. At last they show the recognition rate of 88% by information moments, with 70% by moment invariants.**

Key words – *information moment*; *Chinese character recognition*; *moment invariants*

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1 Introduction

Chinese character which is an indispensable part of Chinese culture has several thousand years of history; also it is one of the largest numbers of characters. Currently, the use of the Chinese characters printed materials greatly increases and therefore how to put them into computer fast and efficiently has been a key issue. Moment invariants have become a classical tool for object recognition during the last 30 years and Hu[1] derived his seven famous invariants.

Moment invariants have many advantages, for example, its invariance to Translation, Rotation and Scaling (TRS) is quite useful in pattern recognition and image processing. But Hu′s moments are using less robust to noise and a improved tool is needed.

Based Hu′s theory, various methods to the theoretical derivation of moment-based rotation invariants was published. For example, Li[2] used the Fourier-Mellin transform to derive invariants up to the order 9, Wong et al[3]. used complex monomials up to the fifth order, and Jin and Tianxu[4] published another algorithm used to derive higher-order moment invariants. Teague[5] and Wallin et al[6]. proposed using Zernike moments. Mostafa and Psaltis[7] introduced the idea of using complex moments for deriving invariants[8].

In this paper, we present a new algorithm for Chinese characters recognition named information moment. In Section 2, the distribution information of Chinese characters are discussed and their regularity is established. In Section 3, the Laplacian of Gaussian (LOG) is introduced for the basis of information moments. We define the information moments and investigate their properties in section 4. The recognition power of information moment is presented through experiments in section 5.

2 The distribution information of Chinese characters

Character images used in this experiment are binary, and pixel distribution of each character is uneven and various.

A great amount of characters will show regularity. Here, look the centers of Chinese character as the origin, look different length outward as the radius, Statistics the amount of information on each circle. For a large number of Chinese characters, statistics the information on the distribution, then get the average, and then can come to the overall distribution of Chinese characters. It can be Mathematical expressed as

$$g(r) = \sum_{\theta} f(r, \theta)/N, \tag{1}$$

$$H(r) = - g(r)\log g(r). \tag{2}$$

The figure of function is shown in Fig. 1.

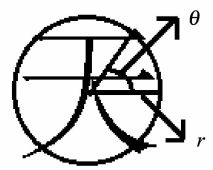

Fig. 1 Figure of function

Fig. 2 shows three Chinese characters.

Fig. 2 Three Chinese characters

The three characters′ distributions are shown in Fig. 3.

In order to count the regularity of distribution infor-

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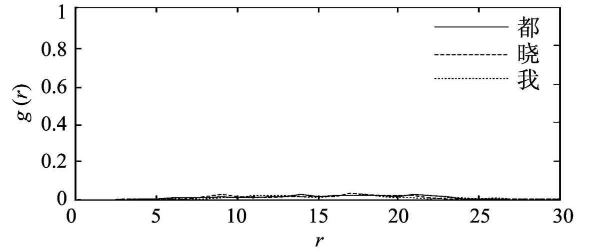


Fig. 3 Information distributions of three characters

mation of 3500 Chinese characters, we use this method: first calculating the $g(r)$ of each character, and then summing up the total g(r), at last reaching the conclusion of $H(r)$.

The results are shown in Fig. 4 and Fig. 5.

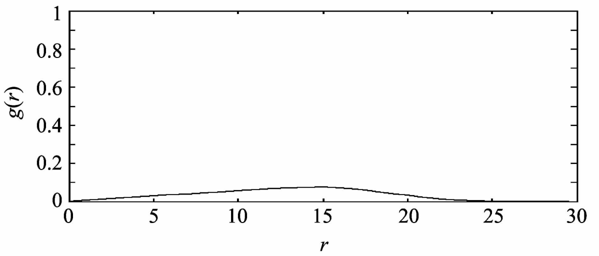


Fig. 4 Distribution of 3500 Chinese characters

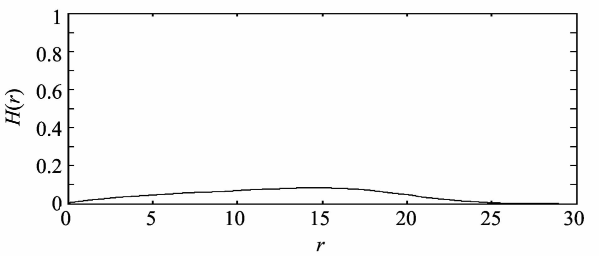


Fig. 5 Entropy of 3500 Chinese characters

From the above picture can see this: both of the $g(r)$ and $H(r)$ curves are similar to the function curve of sin which has more information in the middle of radius. According to this rule, we have tried to find a function curve that can strengthen the rich information region which is the middle of the radius, weaken in the sparse information region. Of course, the function curves can be calculated the image from different angles.

3 Transform core

Laplacian of Gaussian type is mainly used for edge detection. Also known as the Mexican hat function. The functional form example is shown as[9]

$$\nabla^2 h(r) = \frac{1}{\sqrt{2\pi\sigma^4}}\left(\frac{r^2}{\sigma^2} - 2\right)e^{\frac{-r^2}{\sigma^2}}. \tag{3}$$

Translate the function of formula (5) and change the value of δ , we may use it as a core of transformation of information moments. Here we transform the 11 curves for the information moments. The pieces of its curves are shown in Fig. 6, Fig. 7 and Fig. 8.

Calculating the eleven curves with the objective, the

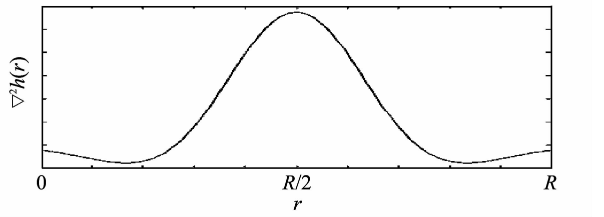


Fig. 6 LOG operator curves 1

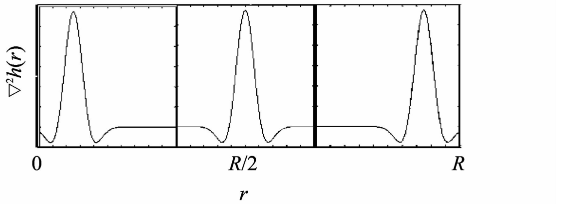


Fig. 7 LOG operator curves 2

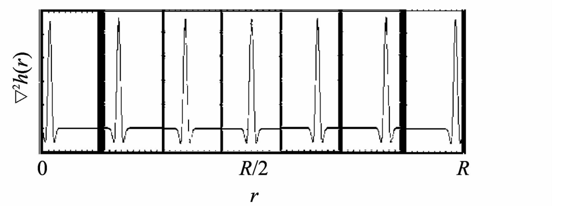


Fig. 8 LOG operator curves 3

amount can be a set of invariants of LOG operator information invariants.

4 Log operator information invariants

4.1 Definition

Information moments can be defined as the following formula based on formula (5):

$$C_{pq} = \sum_0^a \varphi_{p,q}(r)g(r)r, \tag{4}$$

$$\varphi_{pq} = \frac{1}{\sqrt{2\pi\sigma^4}}\left(\frac{(r - qR/2p)^2}{\sigma^2} - 2\right)e^{\frac{-(r-qR/2p)^2}{\sigma^2}}. \tag{5}$$

Here will select one of the 11variables as the information invariants.

They are:

$$C_{11} = \sum_0^a \frac{1}{\sqrt{2\pi(R/6)^4}}\left(\frac{(r - R/2)^2}{(R/6)^2} - 2\right)e^{\frac{-(r-R/2)^2}{(R/6)^2}} g(r)r, \tag{6}$$

$$C_{21} = \sum_0^a \frac{1}{\sqrt{2\pi(R/12)^4}}\left(\frac{(r - R/4)^2}{(R/12)^2} - 2\right)e^{\frac{-(r-R/4)^2}{(R/12)^2}} g(r)r, \tag{7}$$

$$C_{22} = \sum_0^a \frac{1}{\sqrt{2\pi(R/12)^4}}\left(\frac{(r - 2R/4)^2}{(R/12)^2} - 2\right)e^{\frac{-(r-2R/4)^2}{(R/12)^2}} g(r)r, \tag{8}$$

$$C_{23} = \sum_0^a \frac{1}{\sqrt{2\pi(R/12)^4}}\left(\frac{(r - 3R/4)^2}{(R/12)^2} - 2\right)e^{\frac{-(r-3R/4)^2}{(R/12)^2}} g(r)r, \tag{9}$$

$$C_{31} = \sum_0^a \frac{1}{\sqrt{2\pi(R/24)^4}}\left(\frac{(r - R/8)^2}{(R/24)^2} - 2\right)e^{\frac{-(r-R/8)^2}{(R/24)^2}} g(r)r, \tag{10}$$

$$C_{32} = \sum_0^a \frac{1}{\sqrt{2\pi(R/24)^4}}\left(\frac{(r - 2R/8)^2}{(R/24)^2} - 2\right)e^{\frac{-(r-2R/8)^2}{(R/24)^2}} g(r)r, \tag{11}$$

$$C_{33}=\sum_{0}^{a}\frac{1}{\sqrt{2\pi(R/24)^4}}\left(\frac{(r-3R/8)^2}{(R/24)^2}-2\right)e^{\frac{-(r-3R/8)^2}{(R/24)^2}}g(r)r,\ (12)$$

$$C_{34}=\sum_{0}^{a}\frac{1}{\sqrt{2\pi(R/24)^4}}\left(\frac{(r-4R/8)^2}{(R/24)^2}-2\right)e^{\frac{-(r-4R/8)^2}{(R/24)^2}}g(r)r,\ (13)$$

$$C_{35}=\sum_{0}^{a}\frac{1}{\sqrt{2\pi(R/24)^4}}\left(\frac{(r-5R/8)^2}{(R/24)^2}-2\right)e^{\frac{-(r-5R/8)^2}{(R/24)^2}}g(r)r,\ (14)$$

$$C_{36}=\sum_{0}^{a}\frac{1}{\sqrt{2\pi(R/24)^4}}\left(\frac{(r-6R/8)^2}{(R/24)^2}-2\right)e^{\frac{-(r-6R/8)^2}{(R/24)^2}}g(r)r,\ (15)$$

$$C_{37}=\sum_{0}^{a}\frac{1}{\sqrt{2\pi(R/24)^4}}\left(\frac{(r-7R/8)^2}{(R/24)^2}-2\right)e^{\frac{-(r-7R/8)^2}{(R/24)^2}}g(r)r.\ (16)$$

4.2 Properties

1) Translation invariance

When the image changes into polar coordinates, centroid is to be the origin of new coordinates, so obviously, the information moments have translation invariance. Of course, we can easily verify the information moments of translation invariance by conducting experiments.

2) Rotation invariance

Because we count the sum of the angles in changing image into polar coordinate, the information moments have rotation invariance. The same can also be verified by experiments.

3) Scaling invariance

For scaling invariance, the information moments do not have good prosperity as translation and rotation invariance. This is due to many factors, currently cannot be able to solve it. Yet in the real applications, it is not necessarily need information invariants have scale invariance. We can let the test image has the same size with the Training set by normalizing the image in preprocessing[10]. This is a common approach now.

5 Experiments and analysis

5.1 Properties verification

Through experiments, we can clearly see that moment invariants have good recognition properties of translation, rotation and scale invariance. The data from the three kinds of changes are similar to each other. Information moments also have very good features in translation and rotation changes, except for scale changes.

Here, we take ‘变’ for example. Some images about ‘变’ are shown in Fig.9, Tab.1 and Tab.2.

(a) (b) (c)

Fig.9 (a) original; (b) scaling; (c) rotation

Tab.1 Date about “变” using moment invariants

	original	scaling	rotation
Φ_1	0.6302	0.6308	0.6308
Φ_2	0.0124	0.0124	0.0124
Φ_3	0.0050	0.0050	0.0050
Φ_4	0.0056	0.0056	0.0056
Φ_5	1.12599e-05	1.13599e-05	1.12599e-05
Φ_6	5.50582e-04	5.50582e-04	5.50582e-04
Φ_7	2.6584e-05	2.6594e-05	2.6584e-05

Tab.2 Date about “变” using information invariants

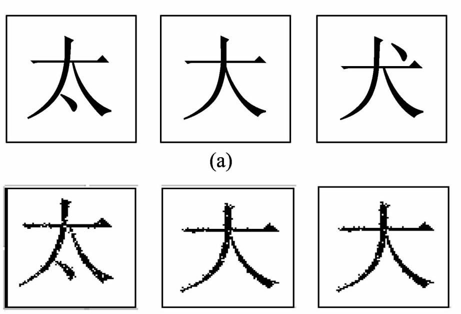
	original	scaling	rotation
C_{11}	0.2449	0.1253	0.2449
C_{21}	0.1828	0.0942	0.1828
C_{22}	0.5218	0.2767	0.5218
C_{23}	0.2864	0.1573	0.2864
C_{31}	0.0879	0.0355	0.0879
C_{32}	0.4497	0.2290	0.4497
C_{33}	0.4848	0.2209	0.4848
C_{34}	1.0653	0.6076	1.0653
C_{35}	0.6453	0.3199	0.6453
C_{36}	0.6094	0.3102	0.6094
C_{37}	0.1035	0.0817	0.1035

5.2 Recognition of similar Chinese characters

Similar Chinese characters recognition is divided into two groups. In both groups, added salt & pepper noises[10] (intensity is 0.1) on the image pixels which are close to the black pixels. In this experiment, used the nearest neighbor classifier[11] and added noises for 20 times for training set then calculated the average data. For test setting, only adding noises for one time. Count the results for 100 times.

First similar character group: 太、大、犬.

Images are shown in Fig.10.



(a)

(b)

Fig.10 First group of similar characters: (a) original images; (b) images after adding noise

Recognition results are shown in Tab.3 and Tab.4.

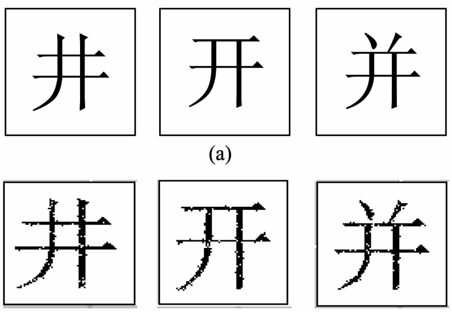
Tab.3 Recognition results of the first group by moment invariants

Recognition rate(%)	太	大	犬
太	85	0	13
大	0	100	0
犬	15	0	87

Tab.4 Recognition results of the first group by information moments

Recognition rate(%)	太	大	犬
太	100	4	0
大	0	0	0
犬	0	96	100

Second similar character group: 井、开、并. Images are shown in Fig.11.



(a)

(b)

Fig.11 Second group of similar characters: (a) original images; (b) Images after adding noise

Recognition results are shown in Tab.5 and Tab.6.

Tab.5 Recognition results of the second group by moment invariants

Recognition rate(%)	井	开	并
井	60	0	40
开	0	100	0
并	40	0	60

Tab.6 Recognition results of the second group by information invariants

Recognition rate(%)	井	开	并
井	75	0	2
开	7	100	0
并	18	0	98

5.3 Recognition of 3500 Chinese characters

In the recognition process of 3500 Chinese characters in the first level font, two methods have add the same random noises[9] (the noise parameter is 0.01) which is the same with the above except for the parameter. Also we use the nearest neighbor classifier[10]. The recognition rate of moment invariants is about 70%, while the recognition rate of LOG operator information moments is about 88%.

6 Conclusion

In this paper, the properties of moment invariance are discussed and based on Hu's theory we have found a new algorithm which are more accurate and more suitable for Chinese characters recognition. Through experiments, the information moments we give present more accurate and suitable features than moment invariants do.

Admittedly, the information moments suffer from some drawbacks like its limitation on scaling invariance. Therefore, in the future research we will concerned on improving the information moments.

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