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Improving Object Classification Using Zernike Moment, Radial Cheybyshev Moment Based on Square Transform Features: A Comparative Study

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Abstract: In many applications, different kinds of moments have been utilized to classify images and object shapes. Moments are important features used in recognition of different types of images. In this paper, three kinds of moments: Structure Moments, Radial cheybyshev moments, Radial cheybyshev moments computation on square Transform have been evaluated for classifying object images using Back propagation classifier. Experiments are conducted using MIT, PASCAL VOC and ORL database which contains car, bicycle, Trucks and face images. The main objective is to make hybrid descriptor which combines structure moment with Zernike moments and Radial Cheybyshev Moments to capture shape and boundary information. In this paper the effect of Zernike moments, Radial Cheyshev moments on new density function in recognition rate improvement are studied. The test results are carried out and a comparative study with two of the existing techniques are included to show the effectiveness of the proposed technique.

Key words: Radial Cheybyshev moment · Zernike Moment · Radial Cheybyshev moment on Square Transform · Zernike Moments on Square Transform · Unit Circle · Rotation Invariance · Area of the Object · Center of Mass

INTRODUCTION

Image moments constitute an important feature extraction method (FEM) which generates high discriminative features, able to capture the particular characteristics of the described pattern, which distinguish it among similar or totally different objects. Among the several moment families introduced in the past, the orthogonal moments are the most popular moments widely used in many applications, owing to their orthogonality property that comes from the nature of the polynomials used as kernel functions, which they constitute an orthogonal base. As a result, the orthogonal moments have minimum information redundancy meaning that different moment orders describe different parts of the image. The most well known orthogonal moment families on unit disc in the continuous space are: Zernike, Pseudo-Zernike, Orthogonal Fourier-Mellin, chebyshev Fourier. The polynomials orthogonal on a rectangle originate from 1D OG polynomials whose 2D versions were created as products of 1D polynomials in x and y. The main advantage of the moments orthogonal on a rectangle is that they preserve the orthogonality even on the sampled image. The popular orthogonal moments defined on rectangle are Legendre moments and Cheybyshev moments They can be made scale-invariant but creating rotation invariants from them is very complicated. The polynomials orthogonal on a disk are intrinsically 2D functions. They are constructed as products of a radial factor (usually a 1D OG polynomial) and angular factor which is usually a kind of harmonic function. When implementing these moments, an image must be mapped into a disk of orthogonality which creates certain re-sampling problems. On the other hand, moments orthogonal on a disk can easily be used for construction of rotation invariants because they change under rotation in a simple way. The most well known orthogonal moment families are: Zernike, Pseudo-Zernike,

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Legendre, Fourier-Mellin, Tchebichef, Krawtchouk, with the last two ones belonging to the discrete type moments since they are defined directly to the image coordinate space, while the first ones are defined in the continuous space.

A regular moment has the form of projection of (x, y) onto the monomial

$$M_{p,q} = \iint_D i(x,y).x^p y^q dxdy$$

The basis set X^p and Y^q is not orthogonal. The moments contain redundant information. As X^p and Y^q increases rapidly as order increases, high computational precision is needed. Image reconstruction is very difficult.Where $Kernal_{nm}$ (.) corresponds to the moments kernel consisting of specific polynomials of order n and repetition m, which constitute the orthogonal basis and NF is normalization factor. Moments have the ability to carry information of an image with minimum redundancy, while they are capable to enclose distinctive information that uniquely describes the image content. Due to these properties once finite number of moments upto a specific order n_{max} is computed, the original image can be reconstructed by applying a simple formula, inverse to (1),of the following form

$$\ddot{f}(x_i, y_j) = NF \sum \sum Kernel_{nm}(x_i, y_j) M_{mn}$$

Related Work: Geometric moments were used to generate a set of invariants that were then widely used in pattern recognition [1], ship identification [2], aircraft identification [3], scene matching [4], image analysis [5], object representation [6], edge detection [7] and texture analysis [8].Shape is one of the fundamental visual features in the Content-based Image Retrieval (CBIR) paradigm. These can be broadly categorized as region based and contour-based descriptors. Contour-based shape descriptors make use of only the boundary information, ignoring the shape interior content. Examples to contour-based shape descriptors include Fourier descriptors [9,10], Wavelet descriptors [11,12], curvature scale space descriptor [13].

Zernike moments, which are proven to have very good image feature representation capabilities, are based on the orthogonal Zernike radial polynomials [14] They are effectively used in pattern recognition since their rotational invariants can be easily constructed. The primary advantages Zernike moments have over other types of moments are their orthogonality and robustness [15]. Zernike polynomials are orthogonal only in the continuous domain of the interior of a unit circle. Computing Zernike moments also requires mapping of radial distances to the range [-1, 1] and numerical approximation of the continuous moment integrals [16]. Mukundan *et al*. [17] has suggested the use of discrete orthogonal moments to eliminate the problems associated with the continuous orthogonal moments. They introduced Chebyshev moments based on the discrete orthogonal Chebyshev polynomial. They showed that Chebyshev moments are superior to geometric, Zernike and Legendre moments in terms of image reconstruction capability. However, this first formulation of Chebyshev moments did not have rotational invariance. Recently, Mukundan [18] introduced Radial Chebyshev moments which possess rotational invariance property. In this section we present a brief overview of the radial Chebyshev moments (RCM).

The paper [19] introduces structure moment invariants based on the geometric moment invariants from transforming the density in geometric moments into a square density. To support our proposed approach,an algorithm for object shape analysis is designed and experiments based on square transform are conducted[19].Experiments give an encouraging high recognition rate by using the structure moment invariants.

The objective is to evaluate system performance for various sorts of databases for its robustness and scalability. Several research in the recent past shows that Radial Cheybyshev moment proves better results for Facial expression recognition, Hand Gesture classification. RCM are mostly employed for character recognition because of the improved image reconstruction ability.

So we proposed a new approach that combines the features of structure moment and RCM. The new square density function introduced in the RCM, increasing the possibilities for correct recognition for all images. After a successful recognition, the matched features are inserted into the detected match database model, enhancing the views for a model and further improving recognition robustness. We proposed hybrid descriptor which is suitable for all kinds of objects to capture shape and boundary information and method proves significant improvement for all object categories.

The five object classes that have been selected are car, bicycle, face, truck and Caltech 101 different object category. The training database consisted of 150 images from each category. The testing dataset is constructed from 50 different images containing the car with different angle in each. The test dataset is used to classify using both the method. All images are scaled to size 64x64 pixels gray images for

Fig. 1: Some examples of objects from MIT ,VOC2007,ORL face,Caltech101 Object Database

Background Study

Geometric Moments: The properties of Geometric moments has the form of projection of i(x,y) function on to the monomial $x^p y^q$. Properties of Geometric moment are as follows.For a 2D continuous function i(x,y), the moment of order(p+q) is defined as

$$M_{p,q} = \iint_D i(x,y).x^p y^q \,dxdy \tag{1}$$

$M_{0,0}$ = Area of the object

$(M_{0,1}, M_{1,0})$ = Center of mass for p,q=0,1,2,3.....

A unique theorem[7] states that if i(x,y) is piecewise continous and has non zero values only in finite part of the xy plane,moment of all orders exist and the moment sequence m_{pq} is uniquly determined by i(x,y).Conversely m_{pq} is uniquly determines by i(x,y).the central moments can be expressed by

$$\mu_{pq} = \Sigma\Sigma(x-x)^p (y-y)^q\, i(x,y) \tag{2}$$

Where

$x = m_{10}/m_{00}$ and $y = m_{01}/m_{00}$

Normalized Central Moments: The normalized central moments are defined as

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{w}} \quad w=\frac{p+q}{2}+1 \tag{3}$$

The resulting moment functions which are taken as representative features of the image are invariant with respect to translation, rotation and scale change (Hu1962)

- Centralized moments invariant to translation
- Normalized central moments invariant to translation and scale.
- Hu invariant moments invariant to translation, scale and rotation.

Based on normalized central moments, Hu[20] introduced seven nonlinear functions which are invariant with respect to object's translation, scale and rotation. The basis set (x^p, y^q) is not orthogonal. The moments contain redundant information. As (x^p, y^q) increases rapidly as order increases, high computational precision is needed. Image reconstruction is very difficult.

Zernike Moments: Teague [21] first introduced the use of Zernike moments to overcome the shortcomings of information redundancy present in the popular geometric moments. Zernike moments are a class of orthogonal moments and have been shown effective in terms of image representation. Zernike moments are rotation invariant and can be easily constructed to an arbitrary order. Although higher order moments carry more fine details of an image, they are also more susceptible to noise. Therefore we have experimented with different orders of Zernike moments to determine the optimal order for our problem. Zernike moments require lower computational precision to represent images to the same accuracy as regular moments.

The Zernike polynomials are a set of complex, orthogonal polynomials defined over the interior of a unit circle $x^2 + y^2 = 1$ [14,15]

$$V_{nm}(x,y) = V_{nm}(\rho,\theta) = R_{nm}(\rho)e^{jm\theta} \tag{13}$$

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

where n is a non-negative integer, $0<=|m|<=n$, $j=\sqrt{-1}$, $\rho=\sqrt{(x^2+y^2)}$, $\theta = tan^{-1}\left(\frac{y}{x}\right)$

Projecting the image function onto the basis set, the Zernike moment of order n with repetition m is:

$$A_{nm} = \frac{n+1}{\pi}\sum_x \sum_y f(x,y)V_{nm}(x,y), x^2+y^2 \le 1 \tag{14}$$

It has been shown in [8] that the Zernike moments on a rotated image differ from those of the original un rotated image in phase shifts, but not in magnitudes. Therefore $|A_{nm}|$ can be used as a rotation invariant feature of the image function. Since $A_{n,-m} = A_{nm}$ $|A_{n,-m}|$=$|A_{nm}|$ and therefore, we will use $|A_{nm}|$ for features. Since $|A_{00}|, |A_{11}|$ are the same for all of the normalized symbols, they will not be used in the feature set. Therefore the extracted features of the order n start from the second order moments up to the nth order moments Structure Moment In information optics, which provide the analytical method to the structure complexity of the 2-D objects in paper[11]. The degree of abundant structure of the 2-D object is consistent with the integral as follows

$$\overline{S_F} = \iint I_0^2(x, y)dxdy \tag{15}$$

For this reason, in order to achieve the goal of recognition, we mapped the object function f(x) to another transformation space, then we got a new moment and we called it structure moment invariant:

$$\mu_i = \langle F(f), {}_i \rangle = \int_\Omega F(f(x)) * \Psi_i(x)dx \tag{16}$$

According to [22], if f (x, y) is a limitary two-dimensional function, F(f£©=f²and the basis function is a non-ortho-normal basis, then moment of order (p + q) can be defined as

$$M_{pq} = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} x^p y^q f^2(x,y))\, dxdy \quad (p,q=0,1,2,\dots) \tag{17}$$

Zernike Moment Computation on Square Transform: To compute the Zernike moment of a digital image using structure moment, we just need to change f(x,y) in the following equation

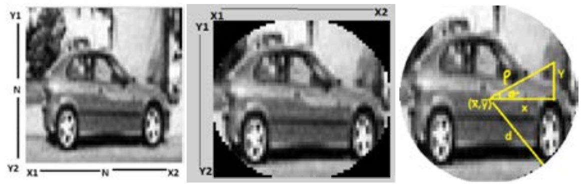
$$A_{nm} = \frac{n+1}{\pi}\sum_x\sum_y f(x,y)V_{nm}(x,y), x^2+y^2 \le 1$$

F(f)=f²

According to (22), if f (x, y) is a limitary two-dimensional function, F(f)=f²and the basis function is a set of complex, orthogonal polynomials, then moment of order (n +m) can be defined as follows

$$A_{nm} = \frac{n+1}{\pi}\sum_x\sum_y f^2(x,y)V_{nm}(x,y), \quad x^2+y^2 \le 1$$

In our implementation of Zernike moments, we use grayscale images with spatial resolution of 64×64. All of these grayscale images are normalized into a unit circle with fixed radius of 32 pixels. Overview of proposed method is described in Figure 2.



(a) (b) (c)

a) Original Image

b) Compute the Unit Disk

c) Computational range

Fig. 2: The computation process of the unit disk mapping for Zernike Moments Computation

The following steps are necessary to extract features of any image using Zernike moments.

- First of all convert color image to gray-scale image
- Perform Translation and Scale Normalization
- Convert Cartesian to Polar coordinate transformation.
- Extract the Zernike Moment, Radial Cheybyshev Moment Features
- Extract the Zernike Moment, Radial Cheybyshev Moment based on square Transform
- Compare New density function of Zernike with radial Cheybyshev Moment

The translation normalization is achieved by moving the image center to the image centroid. The scale normalization is achieved by set the image's 0th order regular moment m00 to a predetermined value β.

Translation Normalization: A translation of □ in the x dimension and □in the y dimension of an image, f (x, y), results in a new image, f□ (x, y), defined by

f □(x, y) □f (x˜ □, y˜ □)

The transformed moment values $\{m'_{pq}\}$ are expressed in terms of the original moment values $\{m_{pq}\}$ of f (x, y) as

$$m'_{pq} = \sum_{r=0}^{p}\sum_{s=0}^{q}\binom{p}{r}\binom{q}{s}(\alpha)^{p-r}(\beta)^{q-s}m_{rs}$$

f(x,y) =$f(x+\bar{x}, y+\bar{y})$

where $\bar{x} = \frac{m_{10}}{m_{00}}, \bar{y} = \frac{m_{01}}{m_{0c}}$

Scale Normalization: A scale change of □in the x dimension and □in the y dimension of an image, f (x, y), results in a new image, f □(x, y), defined by

f □(x, y) □ f (x˜ □, y˜ □)

The transformed moment values $\{m'_{pq}\}$ are expressed in terms of the original moment values $\{m_{pq}\}$ of f (x, y) as

$$m'_{pq} = \alpha^{1+p}\beta^{1+q}m_{pq} \qquad \alpha \neq \beta$$
$$m'_{pq} = \alpha^{2+p+q}m_{pq} \qquad \alpha = \beta$$

Unit Circle Mapping: The center of the image and disk must be same. Where x1,x2 are X-axis dimensions and y1, y2 are Y axis dimensions of the pixel rectangle. $\overline{x}, \overline{y}$ is the center of the unit disk, ρ is polar value and θ is polar angle [22]. Now the image is mapped into polar co-ordinates and onto unit circle as: Compute the distance d as in equation (11)

$$d = \sqrt{(x2 - \bar{x})^{2\frac{1}{2}} + (y2 - \bar{y})^{2\frac{1}{2}}} \tag{11}$$

Compute the distance vector ρ and angle θ as in equation (5) for any (x,y) pixel in f(x,y) in polar coordinates as

$$\rho = \sqrt{\frac{(x - \bar{x})^2 + (y - \bar{y})^2}{d}}, \theta = tan^{-1}\frac{x - (x)}{(y - \bar{y})} \tag{12}$$

This step maps pixel coordinate (x1,x2) to (-1,+1) and (y1,y2) to (-1,+1) in polar. In this way almost all the pixels in image bound box as given in Fig. 3 are inside unit circle except some foreground pixels.

Radial Cheybyshev Moments: The computation of orthogonal moments of images pose two major problems indicated by Mukundan & Ramakrishna [16, 23]. The image coordinate space must be normalized to the range (typically, -1 to +1) where the orthogonal polynomial definitions are valid. The continuous integrals in the computation of ZM must be approximated by discrete summations without losing the essential properties associated with orthogonality. Chebyshev moments completely eliminate the two problems referred above and preserve all the theoretical properties, since their implementation does not involve any kind of approximation.

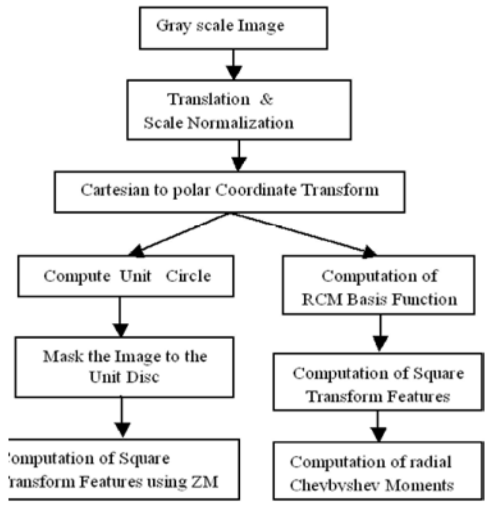


Fig. 3: Block Diagram of Feature Extraction

The scaled orthogonal Chebyshev polynomials for an image of size N x N are defined according to the following recursive relation:

$t_o(x)=1$
$t_1(x)=(2x-N+1)/N$

$$t_p(x) = \frac{(2p-1)t1(x)tp-1(x)-(p-1)\left\{1-\frac{(p-1)^2}{N^2}\right\}tp-2(x)}{}, p>1$$

and the squared-norm ρ (p, N) is given by

$$\rho(p,N) = \frac{N\left(1-\frac{1}{N^2}\right)\left(1-\frac{2^2}{N^2}\right)\cdots\left(1-\frac{p^2}{N^2}\right)}{2p+1}$$

p=0,1,…,N-1

The radial Chebyshev moment of order p and repetition q is defined as:

$$S_{pq} = \frac{1}{2\pi\rho(p,M)}\sum_{r=0}^{m-1}\sum_{\theta=0}^{2\pi} t_p(r)e^{-jq\theta}f(r,\theta)$$

where m denotes (N/2)+1. In the above equation, both r and θ take integer values. The mapping between (r,) and image coordinates (x, y) is given by:

$$x = \frac{rN}{2(m-1)}\cos(\theta) + \frac{N}{2}$$
$$y = \frac{rN}{2(m-1)}\sin(\theta) + \frac{N}{2}$$

Radial Cheybyshev Moment Computation on Square Transform: To compute the Cheybyshev moment of a digital image using structure moment, we just need to change f(x, y) in the equation.

The radial Chebyshev moment of order p and repetition q is defined as:

$$S_{pq} = \frac{1}{2\pi\rho(p,M)} \sum_{r=0}^{m-1} \sum_{\theta=0}^{2\pi} t_p(r) e^{-jq\theta} f(r,\theta)$$

$F(f) = f^2$

According to (14), if f (x, y) is a limitary two-dimensional function, $F(f)=f^2$ and the basis function is a set of complex, orthogonal polynomials, then moment of order (n +m) can be defined as follows

$$S_{pq} = \frac{1}{2\pi\rho(p,M)} \sum_{r=0}^{m-1} \sum_{\theta=0}^{2\pi} t_p(r) e^{-jq\theta} f^2(r,\theta) \quad (21)$$

MATERIALS AND METHODS

In the implementation of Zernike moments, we use gray scale images with spatial resolution of 64×64. All of these images are normalized into a unit circle with fixed radius of 32 pixels. The utilization of moments up to a higher order generally leads to a better image representation power. For selecting the appropriate number of features, we perform experiments at various maximum orders of moments p_{max}=6 for ZMs. Standard gray level images are displayed in Fig. 1 are used where the full set of Zernike and Structure moments are computed by using traditional methods. The results of feature extraction include the calculation of ZM and structure moment of the loaded images of 16x16 spatial resolutions. The image is subdivided into four sub blocks each of which is mapped into 8x8 sub pixels. For p_{max}=10, we obtain 72 features per block. Feature descriptor contains 288 features for all the four sub blocks. Several image examples based on Zernike of different orders are given and analyzed. The similar experiments are performed for Zernike moment based on square density.

In the implementation of Radial Cheybyshev, we use gray scale images with spatial resolution of 64×64. The image is subdivided into four sub blocks each of which is mapped into 8x8 sub pixels. For Pmax=10, we obtain 72 features per block. Feature descriptor contains 288 features for all the four sub blocks. Several image examples based on RCM of different orders are given and analyzed. The similar experiments are performed for RCM based on square transform. The absolute values of RCM are given in Table 1 and for RCM using Square transform given in Table 2.

The back propagation algorithm is used to train the multi layer perceptron with different choices for the number of hidden layer nodes and is fixed to be 1 as being a simple network resulting with small error and found to perform well. The number of input layer nodes is equal to the dimension of the feature space obtained from features. The number of output nodes is usually determined by the application, which is 1 (either “Yes/No”) where a threshold value nearer to 1 represents “Yes” and a value nearer to 0 represents “No”. For measuring the retrieval accuracy of the moments, we consider the precision and recall performance measure. The time taken for the computation of ZMs for p_{max}=10, is 0.036s, respectively. The retrieval accuracy and CPU time performance for Structure moment based Zernike is 0.021s respectively.

The similar experiments are performed for RCM based on square transform. The absolute values of RCM are given in Table 2 and for RCM using Square transform given in Table 3. The retrieval accuracy and CPU time performance for Radial Cheybyshev moment based on square transform is 11.7292 sec respectively. The average classification performance is depicted in Table 4 and in Figure 4.

Thus, a comparative study of three most popular moments feature extraction methods (structure, Zernike and Radial cheybyshev) to recognize the images of 2D

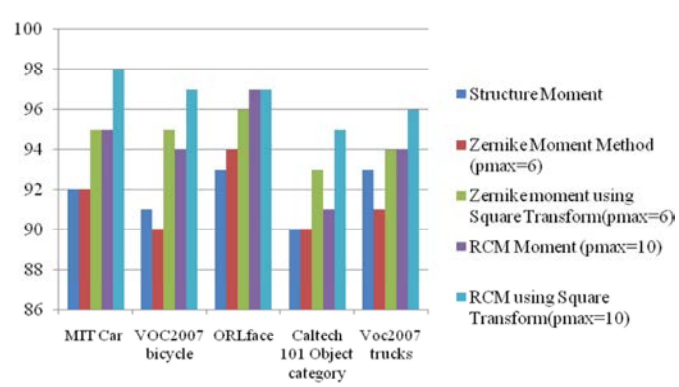


Fig. 4: The correct classification rate for Car, Bicycle, Truck and face database using Moment based approaches

Table 1: Related Work Summary

Orthogonal Moments	Computational load(p^{th} order)	normalization factor	Type	Coordinate system
Zernike Mukundan,1998	(p+1)*(p+2)/2	$\frac{n+1}{\pi}$	Continuous	Unit Disc polar coordinates
Pseudo-Zernike Mukundan,1998	$(P+1)^2$	$\frac{n+1}{\pi}$	Continuous	Unit Disc polar coordinates
Legendre Mukundan,1998	$(P+1)^2$	$\frac{(2n+1)(2m+1)}{4}$	Continuous	[-1,1]
Cheybyshev Mukundan,2001	$(P+1)^2$	F(n,N)*F(m,N) Where F(n,N)=$\frac{N^{-2n}}{(2n!)\binom{N+n}{2n+1}}$	discrete	Image dimensions
Radial Cheybyshev Mukundan	$(P+1)^2$	$\frac{1}{2\pi\rho(p,M)}$	discrete	Image dimensions

Table 2: Absolute values of Radial Cheybyshev moments & Their Mean values

No. of Features	2nd Order (4x1)	3rd order (6x1)	4th order (9x1)	5th order (12x1)	6th order (16x1)
1	0.7568	0.71	0.6746	0.6632	0.6473
2	0.0565	0.053	0.0503	0.0495	0.0483
3	0.6063	0.5689	0.5405	0.5314	0.5186
4	0.0124	0.0117	0.0111	0.0109	0.0106
5		0.0436	0.0414	0.0407	0.0397
6		0.71	0.6746	0.6632	0.6473
7			0.0503	0.0495	0.0483
8			0.5405	0.5314	0.5186
9			0.0111	0.0109	0.0106
10				0.0407	0.0397
11				0.6632	0.6473
12				0.0495	0.0483
13					0.5186
14					0.0106
15					0.0397
16					0.6473
Mean	0.0266	0.1277	0.016489	0.059892	0.050075

Table 3: Absolute values of RCM moments on Square Transform function & Their Mean values

No. of Features	2nd Order (4x1)	3rd order (6x1)	4th order (9x1)	5th order (12x1)	6th order (16x1)
1	0.7574	0.7192	0.6864	0.68	0.6786
2	0.0622	0.0589	0.0562	0.0557	0.0556
3	0.6048	0.5743	0.5481	0.543	0.5419
4	0.0209	0.0198	0.0189	0.0188	0.0187
5		0.0137	0.0131	0.013	0.0129
6		0.0048	0.0046	0.0045	0.0045
7			0.1683	0.1667	0.1664
8			0.0086	0.0085	0.0085
9			0.2451	0.2428	0.2423
10				0.0631	0.0629
11				0.04	0.0399
12				0.0534	0.0533
13					0.0307
14					0.0011
15					0.0454
16					0.0286
Mean	0.027875	0.01455	0.03763	0.01491	0.01086

Table 4: Recognition Accuracies of Three methods on Five kinds of Images using Back Propagation Classifier

	Recognition rate (%)					
Data set	Structure Moment p_{max}=5	Zernike Moment Method (p_{max}=6)	Zernike moment using Square Transform (p_{max}=6)	RCM Moment (p_{max}=10)	RCM using Square Transform (p_{max}=10)	Average
MIT Car	92	92	95	95	98	94.4
VOC2007 bicycle	91	90	95	94	97	93.4
ORL face	93	94	96	97	97	95.4
Caltech 101 Object category	90	90	93	91	95	91
VOC2007 Truck	93	91	94	94	96	93.6

Table 5: Classifier Completion time

Method	ZM	ZM on ST	RCM	RCM on ST
Starting Time	19.8433	76.2845	5.9242	50.5376
Completion Time	38.0174	137.9205	17.6534	87.7932
Total Training Time in Sec	18.1741	61.6360	11.7292	37.2556

objects using backprapagation classifier are presented in Table 4. The experimental results showed that the recognition rate of backprapagation classifier based on Radial cheybyshev moments on square transform[24] is higher than the recognition rate of structure and zernike moments. We assess the three moment based methods on two aspects: (i) recognition accuracy, (ii) Classifier completion time.

The power of discrete orthogonal moments lies in their capability to represent image shape features, without the need for using approximation techniques as in the case of Legendre and Zernike moments. From the illustrations, we can see that for the five kinds of images ZM and radial Cheybyshev moments on square transform outperform other methods significantly. Furthermore, the average classification accuracy of the face and car dataset are higher than bicycle, truck and caltech datasets. The retrieval accuracy of RCM on ST for all the image categories was higher than the other moment based approaches. The classifier completion time for all the feature extraction method are recorded in the Table 5. The training time of RCM based on square transform was also less than the Zernike moment based approaches.

CONCLUSION

In this study, the performance of conventional ZMs and structure moment based approaches is compared to that of the proposed ZM on square transform approaches. ZMs on Square Transform combined with BPN Network perform better than that of the approaches analyzed in this study. However, on MIT car, ORL face database the performance ZM on ST combined with BPN is also better. The idea of implementing Radial Cheybyshev moments is that they posses useful rotation invariance property. This paper developed the moment invariants method from a new perspective. The structure moments through transforming the original density functions to the new ones are invariant with respect to translation, scale and orientation and can describe the form of the complicated structure 2-D objects. In order to verify the method, we compared the results of the test of Radial Cheybyshev moments with Radial Cheybyshev features based on square transform, from which we can see that RCM based on structure moments are distinctively better than RCM. In short, a careful selection of highly discriminative features may result in significant improvement in the recognition performance as is evident from the improvement of approximately 2-3% is noticed in this analysis.

REFERENCES

1. Alt, F.L., 1962. Digital pattern recognition by moments, J. ACM, 9(2): 240-258.
2. Smith, F.W. and M.H. Wright, 1971. Automatic ship photo interpretation by the method of moments, IEEE Trans. Comput, 20(9): 1089-1095.
3. Dudani, S.A., 1977. Aircraft identification by moment invariants, IEEE Trans. Comput., 26(1): 39-45.
4. Wong, R.Y. and E.L. Hall, 1978. Scene matching withinvariant moments, Comput. Vision, Graphics, Image Process. 8(1): 16-24.
5. Teh, C.H. and R.T. Chin, 1988. On image analysis bythe method of moments, IEEE Trans. PatternAnal. Mach. Intell., 10: 485-513.
6. Papademetriou, R.C., 1992. Reconstructing with moments, in Proceedings, 11th International Conference, Pattern Recognition, pp: 476-480.
7. Luo, L.M., X.H. Xie and X.D. Bao, 1994.A modified moment-based edge operator for rectangular pixel image, IEEE Trans. Circuits Systems Video Technol., 4: 552-554.

8. Tuceryan, M., 1994. Moment-based texture segmentation, Pattern Recognition Lett., 15: 115- 123.
9. Granlund, G.H., 1972. Fourier Preprocessing for Hand Print Character Recognition, IEEE Trans. on Computers, 21(2): 195-201.
10. Kauppinen, H., T. Seppanen and M. Pietikainen, 1995.An Experimental Comparison of Auto-regressive and Fourier-Based Descriptors in 2D Shape Classification, IEEE Trans. on Pattern Analysis and Machine Intelligence, 17(2): 201-207.
11. Müller, K. and J.R. Ohm, 1999. Contour Description Using Wavelets, Proceedings of WIAMIS, 99: 77-80
12. Chuang, C.H. and C.C.J. Kuo, 1996. Wavelet Descriptor of Planar Curves: Theory and Applications, IEEE Trans. On Image Processing, 5(1): 56-70
13. Mokhtarian, F., S. Abbasi and J. Kittler, 1996. Robust and Efficient Shape Indexing through Curvature Scale Space, Proc. of the British Machine Vision Conference, pp: 53-62.
14. Khotanzad, A. and Y.H. Hong, Rotation Invariant Image Recognition using Features Selected via a Systematic Method, Pattern Recognition, 23(10): 1089-1101.
15. Khotanzad, A. and Y.H. Hong, 1990. Invariant Image Recognition by Zernike Moments. IEEE, Trans. on pattern analysis and machine intelligence, 12: 5.
16. Mukundan, R. and K. R. Ramakrishnan, 1998. Moment Functions in Image Analysis - Theory and Applications, World Scientific.
17. Mukundan R., S.H. Ong and P.A. Lee, 2001. Image Analysis by Tchebichef Moments, IEEE Transactions on Image Processing, 10(9): 1357-1364.
18. Mukundan, R., 2004. A New Class of Rotational Invariants Using Discrete Orthogonal Moments, Proceedings of the 6th IASTED Conference on Signal and Image Processing, pp: 80-84.
19. Zongmin Li, A., B. Kunpeng Hou, C. Yujie Liu, D. Luhong Diao and E. Hua Li, 2006. The shape recognition based on structure moment invariants, International Journal of Information Technology, 12: 2.
20. Hu, M.K., 1962.Visual Pattern Recognition by Moment Invariants, IRE Transactions on Information Theory, 8: 179-187.
21. Teague, M.R., Image Analysis via the General Theory of Moments, Journal of the Optical Society of America, 70(8): 920-930.
22. Cheng, L., 1990. optics : theory and development, Science Press, Beijing, China.
23. Mukundan, R. and K.R. Ramakrishnan, 1995. Fast Computation of Legendre and Zernike Moments, Pattern Recognition, 28(9): 1433-1422.
24. Athilakshmi, R. and Dr. Amitabh wahi, 2014. An Efficient Method for Shape based Object Classification using Radial Cheybyshev moment on Square transform, Australian Journal of Basic and Applied Sciences, 8(13): 51-60.