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PERFORMANCE ANALYSIS OF WAVELET & BLUR INVARIANTS FOR CLASSIFICATION OF AFFINE AND BLURRY IMAGES

[1]AJAY KUMAR SINGH, [2]V P SHUKLA, [3]S R BIRADAR, [1]SHAMIK TIWARI

[1]Asstt Prof., Dept of Computer Sc. & Engg, FET, MITS Laxmangarh, India

[2] Professor, Dept of Mathematics, FET, MITS Laxmangarh, India

[3] Professor, Dept of Computer Sc. & Engg, SDM, Dharwad, India

E-mail: [1]ajay.kr.singh07@gmail.com , [2]vpshukla.et@mitsuniversity.ac.in , [1]shamiktiwar@gmail.com

ABSTRACT

Image degradation occurs while acquisition because of so many reasons for example low illumination, noise, occlusion etc. Geometric distortion and radiometric degradations are also one of the widespread difficulties in computer vision. This paper presents a system to classify multi class images deformed due to geometrical transform, blur contamination or the combination of both. Different blur and affined invariant moment descriptors in spatial domain are used to tackle this problem, which are invariant to centrally symmetric blurs. In this paper, performance of the proposed system is analyzed in contrast to wavelet feature based system. The performance of the system is demonstrated through various experiments. Experimental results exhibits that method is effective and computationally inexpensive and can be applied to images having several geometrical and blur degradation in the same image.

Keywords: *Blur invariant moment; Neural Network; Gaussian Blur; Affine Transform; Multiclass Classification*

1. INTRODUCTION

Pattern recognition is one of the important and active research topics in the field of image analysis. It is important due to extensive presence in large number of computer vision applications. Despite the ability to recognition of pattern by human being, still it is crucial to automate the pattern recognition methods which can be applied to images geometrically distorted or radiometric degraded or in presence of both. A lot of research efforts have been made to develop such robust methods of pattern recognition which are affectless to different kinds of geometric and radiometric transformations. Geometric as well as gray level degradations are introduced during image acquisition process by such factors as imaging geometry, illumination changes, wrong focus, lens aberration, random sensor errors, object occlusion etc.

A large number of methods have been proposed Wood, J [1] to deal with image affected by geometrical transformations like translation, scaling and rotation. Affine moment invariants features are proposed by Reiss [2] and Flusser and Suk [3, 4] independently which are very useful in recognition of object images which are deformed geometrically. Concept of affine normalization was given by Rothe et al [5]. They have used two different affine decompositions XSR and XYS. XSR consists of two skews, anisotropic scaling and rotation and XYS consists of two skews and anisotropic scaling. Zernike moments were introduced by Shutler & Nixon [6] to describe not only shape of an object but also its movement in an image. Khalid M. [7] presented a method for approximate and fast computation of geometric moments, where the numerical error is absolutely removed. Complex moments could be computed exactly as a combination of exact geometric moments. As a result, affine moment invariants are computed accurately.

Flusser and Suk [8] proposed a system of blur invariants which was based on geometrical moments of the image. These moment invariants as well as their corresponding invariants in frequency domain are well accepted image descriptors and have been used in several applications, such as in image matching and registration in remote sensing [8] and [9], in medical imaging by Y. Bentoutou et

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al. [10] and Y. Bentoutou and N. Taleb [11], in face recognition on out-of-focus photographs J. Flusser et al [12], in normalizing blurred images into canonical forms by Y. Zhang et al [13] and Y. Zhang [14], in blurred digit and in image forgeries detection B. Mahdian and S. Saic [15].

Suk and Flusser [16] derived combined blur and affine moment invariants and shown a demonstration in digit recognition. Classification accuracy is compared by two features Affine Moment Invariant (AMI) and Combined Affine and Blur Invariant (CBAI). Authors have implemented the classification of out of focus blur and affined degraded images using minimum distance classifier. Minimum distance classifier show poor classification accuracy in comparison of back propagation neural network while classification of large class of real world object class. The current work presents a further application of CBAI moments in classification of large class of object class.

In this paper a neural based classification system is proposed for classifications of multiclass classification of geometrically degraded as well as blurred object images. This work compares the performance of the combined blur and affine invariant moment features with wavelet feature. The organization of this paper is as follows: In section 2 image degradation models blurring as well as affine transformation are reviewed. In section III we establish the relationship between moment invariants, affine moment invariants and combined blur and affine moment invariants. Section IV presents the working methodology of classification system. The experimental results for evaluating the performance of the proposed system are given in section V. The performance of the features combined blur and affine invariant moments is compared with the wavelet based features for affine transformed, blurred and combined affine and blurred images. At the last some concluding remarks are presented.

2. IMAGE DEGRADATION

The problem of image detection and classification depends entirely on the quality of image. The quality of the image is degraded by various factors. The block diagram of general degradation model is shown in figure 1.

2.1 Blurring Model

Noise is unwanted information which diminishes image quality. Noise may be described as process(n), which affects the acquired image (I) and is not part of the scene (initial signal (S). Then the degradation process of an image can be

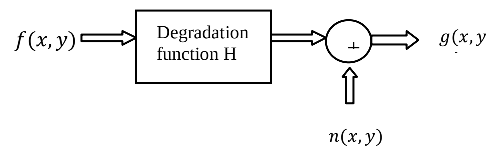

Figure 1: Image Degradation Model

modeled by the following convolution process as described in [17, 18].

$$i(x,y) = s(x,y) \otimes h(x,y) + n(x,y) \quad (1)$$

where $i(x,y)$ is the affected image, $s(x,y)$ is original signal, $h(x,y)$ is the point spread function that caused the degradation and $n(x,y)$ is the additive noise (i.e. signal independent) in spatial domain. Where $\otimes$ represents two dimensional convolution. The process of applying of the blurring function to an image is represented by convolution i.e. some area of the source image convolves into one pixel of the blurred image. Convolution operations defined in spatial domain is counterpart of the multiplication in frequency domain, so image degradation model is

$$I(u,v) = S(u,v)H(u,v) + N(u,v) \quad (2)$$

Motion blur occurs in an image because of relative motion between image capturing device and the scene. Let the image to be acquired has a relative motion to the capturing device by a regular velocity ($v_{relative}$) and makes an angle α radians with the horizontal axis for the duration of the exposure interval $[0, t_{exposure}]$, the distortion is one dimensional. Expressing motion length as $= v_{relative} \times t_{exposure}$, , the point spread function (PSF) in spatial domain can be modeled by Renting Liu [19] and Papageorgiou C. P. & T. Poggio[20].

$$h(x,y) = \begin{cases} \frac{1}{L} \; if \; \sqrt{x^2+y^2} \; \leq \frac{L}{2} \; and \; \frac{x}{y} = -\tan\alpha \\ 0 \qquad otherwise \end{cases} \quad (3)$$

The defocus blur also known as out of focus blur appears due to a system of circular aperture. It can be modeled as a uniform disk as by Arivazhagan S et al [21] and Arivazhagan S et al [22]

$$h(x,y) = \begin{cases} \frac{1}{\pi R^2} & if \; \sqrt{x^2+y^2} \; \leq R \\ 0 & otherwise \end{cases} \quad (4)$$

Where R is the radius of the disk.

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Sometimes image contains co-existence of both blurs. In that case the blur model becomes:

$$h(x,y) = a(x,y) \otimes b(x,y) \quad (5)$$

Where $a(x,y)$, $b(x,y)$ are point spread functions for motions and defocus blur respectively and $\otimes$ is convolution operator. The degradation process model equation (1) and equation (2) can be expressed as equations (6) and (7) respectively:

$$i(x,y) = s(x,y) \otimes a(x,y) \otimes b(x,y) + n(x,y) \quad (6)$$

$$I(u,v) = S(u,v)A(u,v)B(u,v) + N(u,v) \quad (7)$$

2.2 Affine Transforms

Transformations which preserves the collinearity after transformation are affine i.e. all points lying on a line initially still lie on a line after transformation and ratios of distances (e.g., the midpoint of a line segment remains the midpoint after transformation) presented by Eric Weisstein et al.[22]. An affine transformation is a combination of rotations, translations, scaling, and shears, is represented by following equations

$$u = a_2 x + a_1 y + a_0 \quad (8)$$

$$v = b_2 x + b_1 y + b_0 \quad (9)$$

Where translation is affected by a_0 , b_0 , while a_2 and b_1 affects the scaling and combination of these two causes rotations and shears.

Complex affine transforms can be constructed by a sequence of basic affine transforms. Transform combinations are defined in terms of matrix operations. The affine transformations are expressed in terms of matrix as follows

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} a & b & c \\ d & e & f \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \quad (10)$$

an equivalent expression using matrix notation is

$$q = Tp \quad (11)$$

Where q, T and p are defined above.

3. MOMENT INVARIANTS

The 2-D moment of order $(p+q)$ of a digital image $f(x,y)$ of size $M \times N$ is defined as [17] are

$$m_{pq} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} x^p y^q f(x,y) \quad (12)$$

where $p = 0,1,2 \ldots \ldots$ and $q = 0,1,2 \ldots \ldots$ are integers. The corresponding central moment of order $(p+q)$ is defined as

$$C_{pq} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (x-\bar{x})^p (y-\bar{y})^q f(x,y) \quad (13)$$

for $p = 0,1,2 \ldots \ldots$ and $q = 0,1,2 \ldots \ldots$, where
$\bar{x} = \frac{m_{10}}{m_{00}}$ and $\bar{y} = \frac{m_{01}}{m_{00}}$

The normalized central moments c_{pq} are defined as

$$c_{pq} = \frac{C_{pq}}{C_{00}^{\gamma}} \quad (14)$$

where $\gamma = \frac{p+q}{2} + 1$ for $p+q = 2,3, \ldots$

3.1 Affine Moment Invariants

A set of seven affine invariant moments were derived by [2]-[4] from second and third moments

$$\mu_1 = c_{20} + c_{02} \quad (15)$$
$$\mu_2 = (c_{20} - c_{02})^2 + 4c_{11}^2 \quad (16)$$
$$\mu_3 = (c_{30} - 3c_{12})^2 + (3c_{21} - c_{03})^2 \quad (17)$$
$$\mu_4 = (c_{30} + c_{12})^2 + (c_{21} + c_{03})^2 \quad (18)$$
$$\mu_5 = (c_{30} - 3c_{12})(c_{30} + c_{12})[(c_{30} + c_{12})^2 - 3(c_{21} + c_{03})^2] + (3c_{21} + c_{03})(c_{21} + c_{03})[(c_{30} + c_{12})^2 - (c_{21} + c_{03})^2] \quad (19)$$

$$\mu_6 = (c_{20} - c_{02})[(c_{30} + c_{12})^2 - (c_{21} + c_{03})^2] + 4c_{11}(c_{30} + c_{12})(c_{21} + c_{03}) \quad (20)$$
$$\mu_7 = (3c_{21} - c_{03})(c_{30} + c_{12})[(c_{30} + c_{12})^2 - 3(c_{21} + c_{03})^2] + (3c_{12} - c_{30})(c_{21} + c_{03})[3(c_{30} + c_{12})^2 - (c_{21} + c_{03})^2] \quad (21)$$

3.2 Blur Invariants

As stated by the Flusser and Suk [4] the blur inavriants based on geometric moments can be represented as

If $(p+q)$ is even then $C(p,q) = 0$
If $(p+q)$ is odd then

$$C(p,q) = c_{pq} - \frac{1}{c_{00}} \sum_{n=0}^{p} \sum_{m=0}^{q} \binom{p}{n} \binom{q}{m} C(p-n, q-m).c_{nm} \quad (22)$$

Here $C(p,q)$ is invariant to convolution with any centrosymmetric function $h(x,y)$.

3.3 Combined Blur and Affine Invariants

Combined blur affine invariants are moment invariants whose values do not change if image is convolved with blur function and transformed by affine transform.

As stated by T. Suk [16] odd order moments can be used as blur and affine invariant moments. We used following four moments as features for

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classification of blurred and affined transformed images.

- Third order only

$$I_1 = (c_{30}^2 c_{03}^2 - 6c_{30}c_{21}c_{12}c_{03} + 4c_{30}c_{12}^3 + 4c_{21}^3 c_{03} - 3c_{21}^2 c_{12}^2)/c_{00}^{10} \quad (23)$$

- Fifth order only

$$I_2 = (c_{50}^2 c_{05}^2 - 10c_{50}c_{41}c_{14}c_{05} + 4c_{50}c_{32}c_{23}c_{05} + 16c_{50}c_{32}c_{14}^2 - 12c_{50}c_{23}^2 c_{14} + 16c_{41}^2 c_{23}c_{05} + 9c_{41}^2 c_{14}^2 - 12c_{41}c_{32}^2 c_{05} - 76c_{41}c_{32}c_{23}c_{14} + 48c_{41} c_{23}^3 + 48c_{32}^3 c_{14} - 32c_{32}^2 c_{23}^2)/c_{00}^{14} \quad (24)$$

- Third and fifth

$$I_3 = (c_{30}^2 c_{12}c_{05} - c_{30}^2 c_{03}c_{14} - c_{30}c_{21}^2 c_{05} - 2c_{30}c_{21}c_{12}c_{14} + 4c_{30}c_{21}c_{03}c_{23} + 2c_{30}c_{12}^2 c_{23} - 4c_{30}c_{12}c_{03}c_{32} + c_{30}c_{03}^2 c_{41} + 3c_{21}^3 c_{14} - 6c_{21}^2 c_{12}c_{23} - c_{21}^2 c_{03}c_{32} + 6c_{21}c_{12}^2 c_{32} + 2c_{21}c_{12}c_{03}c_{41} - c_{21}c_{03}^2 c_{50} - 3c_{12}^3 c_{41} + c_{12}^2 c_{03}c_{50})/c_{00}^{11} \quad (25)$$

$$I_4 = (2c_{30}c_{12}c_{41}c_{05} - 8c_{30}c_{12}c_{32}c_{14} + 6c_{03}c_{12}c_{23}^2 - c_{30}c_{03}c_{50}c_{05} + 3c_{30}c_{03}c_{41}c_{14} - 2c_{30}c_{03}c_{32}c_{23} - 2c_{21}^2 c_{41}c_{05} + 8c_{21}^2 c_{32}c_{14} - 6c_{21}^2 c_{23}^2 + c_{21}c_{12}c_{50} c_{05} - 3c_{21}c_{12}c_{41}c_{14} + 2c_{21}c_{12}c_{32}c_{23} + 2c_{21}c_{03}c_{50} c_{14} - 8c_{21}c_{03}c_{41}c_{23} + 6c_{21}c_{03}c_{32}^2 - 2c_{12}^2 c_{50}c_{14} + 8c_{12}^2 c_{41}c_{23} - 6c_{12}^2 c_{32}^2)/c_{00}^{12} \quad (26)$$

$$I_5 = (c_{30}c_{41}c_{23}c_{05} - c_{30}c_{41}c_{14}^2 - c_{30}c_{32}^2 c_{05} + 2c_{30}c_{32} c_{23}c_{14} - c_{30}c_{23}^3 - c_{21}c_{50}c_{23}c_{05} + c_{21}c_{50}c_{14}^2 + c_{21} c_{41}c_{32}c_{05} - c_{21}c_{41}c_{23}c_{14} - c_{21}c_{32}^2 c_{14} + c_{21}c_{32}c_{23}^2 + c_{12}c_{50}c_{32}c_{05} - c_{12}c_{50}c_{23}c_{14} - c_{12}c_{41}^2 c_{05} + c_{12}c_{41}c_{32}c_{14} + c_{12}c_{41}c_{23}^2 + c_{03}c_{41}^2 c_{14} - 2c_{03}c_{41}c_{32} c_{23} + c_{03}c_{32}^3)/c_{00}^{13} \quad (27)$$

- Seventh order only

$$I_6 = (c_{70}^2 c_{07}^2 - 14c_{70}c_{61}c_{16}c_{07} + 18c_{70}c_{52}c_{25}c_{07} + 24c_{70}c_{52}c_{16}^2 - 10c_{70}c_{43}c_{34}c_{07} - 60c_{70}c_{43}c_{25}c_{16} + 40c_{70}c_{34}^2 c_{16} + 24c_{61}^2 c_{25}c_{07} + 25c_{61}^2 c_{16}^2 - 60c_{61} c_{52}c_{34}c_{07} - 234c_{61}c_{52}c_{25}c_{16} + 40c_{61}c_{43}^2 c_{07} + 50c_{61}c_{43}c_{34}c_{16} + 360c_{61}c_{43}c_{25}^2 - 240c_{61} c_{34}^2 c_{25} + 360c_{52}^2 c_{34}c_{16} + 81c_{52}^2 c_{25}^2 - 240c_{52}c_{43}^2 c_{16} - 990c_{52}c_{43}c_{34}c_{25} + 600c_{52}c_{34}^3 + 600c_{43}^2 c_{34}^2)/c_{00}^{18} \quad (28)$$

4. METHODOLOGY

The key building blocks of the classification system employed in this paper are discussed in section 2 & 3. In this section how these blocks are implemented, is presented. The major steps involved in pattern recognition system are preprocessing of training and testing images, feature extraction and classification as performed by J.Flusser and T.Suk [8], J. Flusser, T. Suk, and S. Saic [12], Renting Liu et al.[19] and Papageorgiou C. P. and T. Poggio [20]. Our model of classification of multi class images is presented in fig 3. The procedure involves first two steps as preprocessing of images i.e. degradation of images. As discussed in section 2, the images are deformed by affine transformation and blur. Which is followed by extraction of moments based features discussed in section 3 and given as input to neural classifier for supervised learning and to predict the class.

4.1 Data Set

To have a performance analysis the data base is taken from Columbia Object Image Library (COIL-100) S. Nene [24]. Columbia Object Image Library (COIL-100) is a database of color images of 100 objects. The objects were placed on a motorized turntable against a black background. Around 1250 images of fourteen categories are used for training and testing the performance of proposed neural network based classification system. Sample images of fourteen categories are shown in fig 2

Figure 2: Sample Image Of 14 Categories From COIL-100 Database

4.2 Preprocessing of Images

Since the goal of this work is to compute the performance of combined affine blur invariants. Database [24] discussed in above paragraph contains the distortion free images. So these images are degraded using image degradation model discussed in section 2 i.e. affined transformed and blurred. So before feature extraction some preprocessing is required to degrade the images as follows

1. The size of the images is minimized to 128x128 in order to ease the computation.
2. The colored minimized RGB (red-green-blue) images are converted to gray level images.
3. Now the gray images are degraded through affine transformation.
4. Affined transformed images are introduced with Gaussian blur with different sizes mask.

All these steps are applied to all the fourteen class images to produce a large database of size 1250 images. After these preprocessing steps changes in original images takes place are shown in fig 4.

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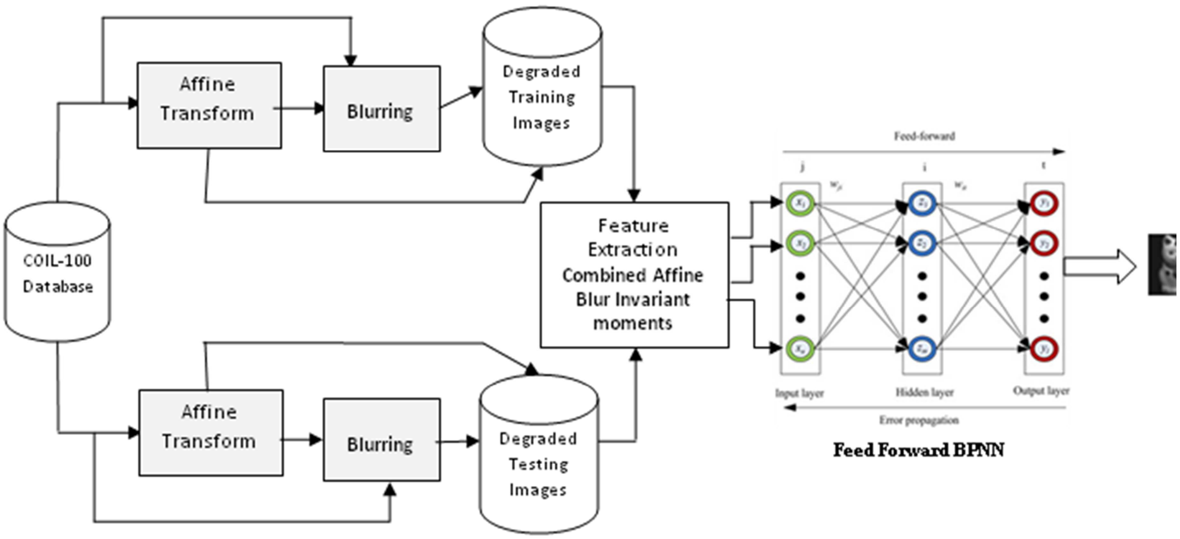

Figure 3:Methodology of the System

4.3 Feature Vector Extraction

This paper presents the notion of representation of images using a set of moment invariant function. Combined Affine Blur Invariant moments discussed in section 3 are extracted from images degraded through various geometrical transformations or by blurring or combination of two.

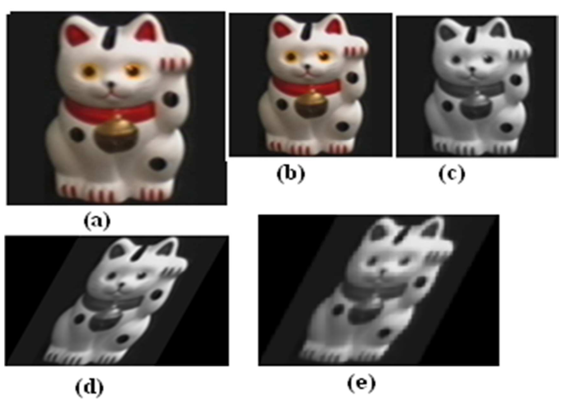

Figure 4: Image processing steps applied on one sample image (a) Original RGB image of size 256X256 (b) RGB image resized to 128X128. (c) Gray image (d) Affine transform applied on image (e) Blur introduction in image (d) with 9X9 mask and sigma=0.7

Six features are extracted from each of the training and testing images and kept in a vector. Totally 1232 images of fourteen class and feature vectors representing these images with six combined affine blur invariant moments form a matrix. In this research we evaluate the proposed system in multi class object classification tasks, comparing it to wavelet based feature extraction methods with affine transform effect, blur effect and combined effect of affine and blur, which is accomplished by feature extraction of affined transformed images in the first case, then feature extraction of only blurred images and at last feature extraction of images with combined deformation.

4.3 Neural Network Based Classification

A successful pattern recognition methodology presented by [25]-[29] depends greatly on the particular choice of the classifier. An artificial neural network is system which can be seen as an information-processing paradigm. Artificial Neural Network (ANN) has been designed as generalizations of mathematical models identical to human cognition system. They are composed of interconnected processing units called neurons that work as a collective unit. It can be used to establish complex relationships among inputs and outputs by identifying patterns in data. The feed forward neural network refers to the neural network which contains a set of source nodes which forms the input layer, one or more than one hidden layers, and single output layer. In case of feed forward neural network input signals propagate in one direction only; from input to output. There is no feedback path i.e. the output of one layer does not influence same layer. One of the best known and widely acceptable learning algorithms in training of multilayer feed forward neural networks is Back-Propagation. The back propagation is a type of supervised learning

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algorithm, which means that it receives sample of the inputs and associated outputs to train the network, and then the error (difference between real and expected results) is calculated. The idea of the back propagation algorithm is to minimize this error, until the neural network learns the training data. This can be implemented by:

$$\Delta w_{ji}(n+1) = \rho\left(\gamma_{kj}\emptyset_{pj}\right) + \delta\Delta w_{ji}(n) \qquad (29)$$

Where ρ is the learning rate, δ is momentum, γ_{kj} is the error and n is the number of iteration.

5. RESULTS AND DISCUSSION

The performance of the proposed multiclass classification system is evaluated using COIL-100 database created in [24]. We have taken fourteen classes of images. Then two different types of degradation (affine transform and blur) are fabricated with different parameters. This process generates above 1700 images. The performance of the combined affine blur invariant moment feature is compared with the wavelet features. In this section the performance of proposed system is evaluated on three different problems. So, three different experiments are set up for investigation. In the first experiment performance of the proposed system is compared with wavelet feature of the images deformed due to affine transformation. Second experiment analyzes the performance of the system of multiclass images deformed due to blur. Combined effect of affine transform and blur in images is compared in last experiment. The experimental result of each of the experiment is discussed in successive headings.

5.1 Affine Transform Effect

In the first experiment, the effect of geometrical transform in multiclass image classification is observed under two different methods. To evaluate the performance of the proposed method on the images distorted by affine transform, a synthetic database is developed from original images. One by one image are taken from each class then affine transform i.e. a sequence of geometrical transformations scaling, rotation, shearing etc are applied with different parameters to generate degraded images. This way a fabricated affine transformed database is prepared. Features combined affine blur invariant moments discussed in section 3 are extracted from the training images. A multi layer feed forward neural network with back propagation learning algorithm and different parameters such as number of epochs, no of hidden layers is established. Then it is trained with training feature matrix. Five images of each class are taken for training the classifier while 25 images are used for testing the performance. Performance of this experiment is compared with the wavelet feature based classification [27] as shown in table 1.

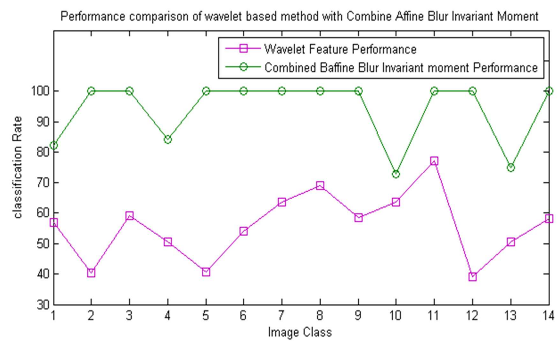

Figure 5: Performance Of Proposed Method For First Experiment

Fig 5 shows the classification rate of each of the class in proposed system; where for the class 4 and 10 system gives 84.38 per and 72.80 per respectively which is slightly lesser than the overall accuracy of the system, for the remaining classes the classification rate is about 100 per. The overall accuracy for this problem is calculated as shown in table 4 is 85.7 per, while the wavelet based system perform poorly as classification rate presented in table 1 and overall accuracy is 45.7 per.

5.2 Blur Effect

In this experiment blurred images are taken for training and testing the performance of the system proposed. Gaussian blur with different filter size and standard deviation is introduced in fourteen class of COIL-100 [24] database. Generation of blurring image involves the selection of image from each category, setting up the value of standard deviation sigma as 0.25 with different filter size 3X3, 4X4, 5X5, 6X6, 7X7, 8X8, 9x9 and 10x10 images are degraded, which produce 8 distorted images. This process is repeated for different value of σ = 0.5, 0.75, 0.8 and 0.9 which generates 32 degraded images of each class in turn produce 448 for fourteen classes. Combined affine blur invariant moment features are extracted from 112 images for training the classifier and remaining are used for testing the classification accuracy. The result of the proposed system is compared with wavelet feature based system [27] and presented table 2 and performance graph fig 6.

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Table 1: Performance Comparison Of Proposed System With Wavelet Features On Affined Images

	Wavelet Based					Combined Affine Blur Invariant moment				
Class	False Negative Rate	False Positive Rate	True Positive Rate	True Negative Rate	Classif. Accur.	False Negative Rate	False Positive Rate	True Positive Rate	True Negative Rate	Classif. Accur.
1	36.36	50	63.64	50	56.82	0	35.3	100	64.7	82.35
2	63.64	55.6	36.36	44.4	40.38	0	0	100	100	100.00
3	81.82	0	18.18	100	59.09	0	0	100	100	100.00
4	54.55	44.4	45.45	55.6	50.53	0	31.25	100	68.75	84.38
5	54.55	64.3	45.45	35.7	40.58	0	0	100	100	100.00
6	54.55	37.5	45.45	62.5	53.98	0	0	100	100	100.00
7	72.73	0	27.27	100	63.64	0	0	100	100	100.00
8	18.18	43.8	81.82	56.3	69.06	0	0	100	100	100.00
9	54.55	28.6	45.45	71.4	58.43	0	0	100	100	100.00
10	72.73	0	27.27	100	63.64	54.4	0	45.6	100	72.80
11	45.45	0	54.55	100	77.28	0	0	100	100	100.00
12	36.36	35.7	63.64	14.3	38.97	0	0	100	100	100.00
13	54.55	44.4	45.45	55.6	50.53	49.8	0	50.2	100	75.10
14	63.64	20	36.36	80	58.18	0	0	100	100	100.00

Table 2: Performance Comparison Of Proposed System With Wavelet Features On Blurred Images

	Wavelet Based					Combined Affine Blur Invariant moment				
Class	False Negative Rate	False Positive Rate	True Positive Rate	True Negative Rate	Classif. Accur.	False Negative Rate	False Positive Rate	True Positive Rate	True Negative Rate	Classif Accur.
1	18.2	33.3	81.8	66.7	74.25	0	0	100	100	100
2	0	5.4	100	94.6	97.3	0	0	100	100	100
3	18.2	18.2	81.8	81.8	81.8	0	0	100	100	100
4	18.2	21.7	81.8	78.3	80.05	0	0	100	100	100
5	0	35.3	100	64.7	82.35	0	0	100	100	100
6	31.8	0	68.2	100	84.1	0	0	100	100	100
7	9.1	0	90.9	100	95.45	0	0	100	100	100
8	0	15.4	100	84.6	92.3	0	0	100	100	100
9	40.9	23.5	59.1	76.5	67.8	0	0	100	100	100
10	0	15.4	100	84.6	92.3	0	0	100	100	100
11	45.5	0	54.5	100	77.25	0	0	100	100	100
12	18.2	0	81.8	100	90.9	0	0	100	100	100
13	0	8.3	100	91.7	95.85	0	0	100	100	100
14	18.2	0	81.8	100	90.9	0	0	100	100	100

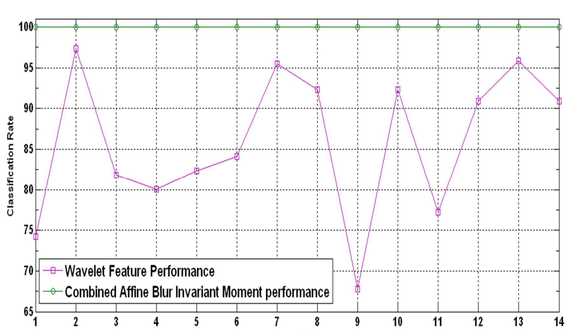

Figure 6: Performance Of Proposed Method For Second Expt

Fig 6 presents the classification rates in presence of the Gaussian blur. Similar to the first experiment, the calculated invariants from blurred images outperformed the wavelet based features. Performance of the wavelet feature based system is considerably dropped in presence of blur. The reason behind is that Gaussian blur reduces the high frequency components of the image, so Gaussian blur basically behaves like a low pass filter.

5.3 Combined Effect

In this experiment, performance is measured on multi class images degraded through affine transform and blur both. Firstly a database of degraded images is prepared by applying a sequence of deformation processes. The quality of images is degraded by geometrical transformation in combination such as scaling, rotation and shearing, which is followed by contamination of Gaussian

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blur in each of the image produced by previously degraded images.

Table 3: Performance Comparison Of Proposed System With Wavelet Features On Affined Blurred Images

	Wavelet Based					Combined Affine Blur Invariant moment				
Class	**False Negative Rate**	**False Positive Rate**	**True Positive Rate**	**True Negative Rate**	**Classif Accur.**	**False Negative Rate**	**False Positive Rate**	**True Positive Rate**	**True Negative Rate**	**Classif. Accur.**
1	72.7	67.1	27.3	32.9	30.1	0	0	100	100	100
2	59.1	33.4	40.9	66.6	53.75	0	0	100	100	100
3	70.5	13.3	29.5	86.7	58.1	0	0	100	100	100
4	81.8	84.5	18.2	15.5	16.85	0	0	100	100	100
5	81.8	33.3	18.2	66.7	42.45	0	0	100	100	100
6	68.2	46.2	31.8	53.8	42.8	0	0	100	100	100
7	77.3	34.3	22.7	65.7	44.2	0	0	100	100	100
8	77.3	54.5	22.7	45.5	34.1	0	0	100	100	100
9	40.9	66	59.1	34	46.55	0	0	100	100	100
10	77.3	16.7	22.7	83.3	53	0	0	100	100	100
11	77.3	71.4	22.7	28.6	25.65	0	0	100	100	100
12	81.8	0.0	18.2	100	59.1	0	0	100	100	100
13	54.5	47.4	45.5	52.6	49.05	0	0	100	100	100
14	72.7	82.1	45.5	17.9	31.7	0	0	100	100	100

In this process, 11 images are produced in the first step of degradation with different parameters of scaling, rotation and shearing. A Gaussian blur for the standard deviation σ= 0.25, 0.5, 0.75, 0.8 and 0.9 with different mask sizes is fabricated to produce 88 images of each class and 1232 images of fourteen classes. Then their affine blur invariants are calculated of 210 images from 14 classes i.e. 15 from each class for training of neural network and remaining are used for evaluating the performance of the classifier. In order to make a comparison the wavelet features proposed by [27] are also used in this experiment.

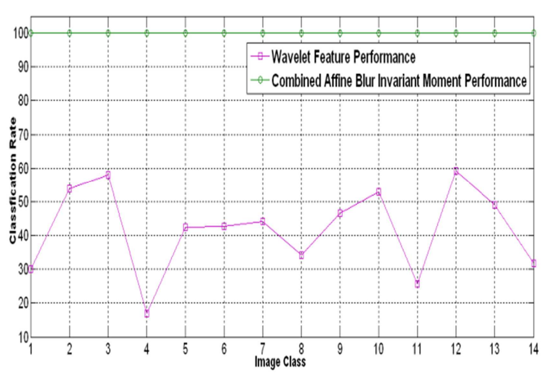

Figure 7: Performance Of Proposed Method For Third Experiment

In the third experiment also similar to second experiment combined affine blur invariant moment computed from the degraded images exceeds the wavelet based features in [27] 100 per overall accuracy is achieved for proposed system, while for wavelet performs most terrible as presented in performance graph fig 7.

Table 4: Over All Accuracy In Percentage

	Wavelet based System	**Proposed system**
Affine degraded Image	45.5	85.7
Blur affected Images	84.4	100
Combined affine and Blurred affected Image	30.4	100

The overall accuracy of the system presented in table 4, shows that proposed feature based model is robust in compare to wavelet feature based system. The overall accuracy of affined degraded and combined degradation of affine and blur images is significantly improved.

6. CONCLUSION AND FUTURE WORK

In this research work a combined affine blur Invariant moments descriptors are calculated for images degraded through various degrading mechanism. The experiment results demonstrated the discrimination power of the invariant moments for multi class degraded images. In geometrically distorted image pixel intensity values located at position (x_1,y_1) in to (x_2,y_2) by scaling, rotation and shearing. In order to estimate the performance three experiments are carried out. In the first experiment, fourteen classes of images from COIL-100 database have been employed and synthetically degraded by affine transform. Powerful invariant based features

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successfully classified the different class's positive and negative samples.
The robustness of the proposed system invariant to blur has been analyzed in second experiment. Wavelet feature based system is also compared with proposed moment based system and performed better, wavelet shown the poorer classification results. In the third experiment, the original images are deteriorated by sequence of affine transform and Gaussian blur degradation. Despite the occurrence of several degradation the system produce the successful classification accuracy. Finally the chances are always there for improvements. Further, invariant moments in frequency domain may be used for feature description of degraded images recognition.

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