Neural Network Based Classification Using Blur Degradation and Affine Deformation Invariant Features

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Abstract

Identification of affine deformed and simultaneously blur degraded images is an important task in pattern analysis. Use of global moment features has been one of the most popular techniques for pattern recognition and classification. In this paper, we introduce an approach to derive blur and affine combined moment invariants(BACIs). A neural network(NN) model is then employed to classify objects using these BACIs.

Introduction

The objective of a typical computer vision system is to analyze images of a given scene and recognize the content of the scene. Most of these systems share a general structure which is composed of four building blocks: image acquisition, preprocessing, feature extraction, and classification. The main focus of this paper is on the feature extraction and classification problems.

Images to be processed are usually unsatisfactory with geometric distortion and/or blur degradation. About geometric deformations, we mainly discuss the 2-D general affine transformation, which transforms the original image $f(x, y)$ to a new image $f'(x', y')$ and has the following form:

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = A \begin{pmatrix} x \\ y \end{pmatrix} + B \qquad (1)$$

where $A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}$ is a homogeneous affine

transformation matrix, $B = \begin{pmatrix} b_1 \\ b_2 \end{pmatrix}$ is the translation

transformation, and $a_{11}a_{22} - a_{21}a_{12} \neq 0$.

In real applications, since imaging systems and imaging conditions are usually imperfect, the observed image generally represents a blurred version of the original scene. For example, satellite images obtained

from Advanced Very High Resolution Radiometer suffer from blur due to a multiparametric composite point spread function of the device. If $f(x, y)$ is the ideal image, $g(x, y)$ is the observed image. The blur model of the image is given as

$$g(x, y) = f(x, y) * h(x, y), \qquad (2)$$

where $h(x, y)$ is the point spread function(PSF) and "*" is the convolution operation.

An efficient method to extract features which are invariant to both blur degradation and affine deformation is very useful in many application areas such as remote sensing, astronomy and medicine etc. Moments and functions of moments have been utilized as pattern features in a number of applications, see for example (Chung and Wong 1997; Teh and Chin 1988) etc.

Generally speaking there are two approaches to get moment invariants with respect to geometric transformation. One is to find invariant functions of the moments of the image directly (Flusser and Suk 1993; Reiss 1993; Taubin and Cooper 1989) using algebraic, tensor, and matrix techniques respectively. The other approach is to normalize the image by finding a linear coordinate transformation that results in a standard form of the image. If an object is in its standard form, then any feature that can be calculated is invariant. Based on the method proposed in (Flusser and Suk 1998), we are able to extract the blur invariant features directly from the blurred image without the PSF identification and image restoration.

But so far there is no method available to derive affine and blur combined invariants systematically even though this concept was mentioned in (Flusser and Suk 1998). Note that any simple combination of the existing schemes on blur and affine invariant feature extraction without any modification cannot obtain the required features. In this paper we will introduce an image normalization method that can give moment invariants which are invariant with respect to both blur

degradation and affine deformation. Firstly, we normalize an image to a standard form. The key point of this step is that the degree of blur should not have any influence on such a standard form. To ensure this, we impose normalization constraints by using blur invariant moments in contrast with existing methods. To guarantee the existence of a solution, we then extend the normalization transformation from real domain to complex domain. The resulting moments of this step are still affine invariants. Then we construct blur invariants based on the obtained standard form and this gives blur and affine combined invariants.

Neural networks can perform different tasks, one of which is in the context of a supervised classifier (Tang, Sriniivasan, and Ong 1996; Khotaanzad and Lu 1990). As classifiers, neural networks have the advantage of allowing more complex decision boundaries in feature space, and this results in lower error rates. In this paper a neural network approach is used to do classification using BACIs.

The organization of this paper is as follows. In section 2, the feature extraction procedure is described. Section 3 briefly introduces the structure of the neural network classifier and then gives the experimental results. The conclusions are given in section 4.

Extraction of BACIs

In this section, we mainly discuss the procedure of obtaining the blur and affine combined moment invariants(BACIs). Firstly we introduce the basic knowledge about moments. Then the normalization procedure to get a standard form of an image is given. Lastly we construct blur invariants based on the obtained standard form and this gives BACIs.

Moments

We now give the definition of moments. The two dimensional $(p+q)$-th order geometric moment m_{pq} of a gray-level image $f(x,y)$ is defined by

$$m_{pq} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^p y^q f(x,y) dx dy. \tag{3}$$

The $(p+q)$-th order central moment μ_{pq} is defined as

$$\mu_{pq} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - x_c)^p (y - y_c)^q f(x,y) dx dy, \tag{4}$$

where x_c and y_c are given by the relations

$$x_c = \frac{m_{10}}{m_{00}} \quad and \quad y_c = \frac{m_{01}}{m_{00}} \tag{5}$$

and point (x_c, y_c) is called the center of gravity or centroid of the image $f(x,y)$.

New Constraints of Normalization

If an image is deformed by affine transformation and degraded by blur simultaneously, we cannot obtain the same standard position for both the original image and the degraded image using the existing normalization methods, such as those mentioned in (Voss and Suesse 1997).

We now propose a new scheme which uses blur invariant moments as normalization constraints. By this scheme, all the degraded images of the same object with different blur degrees have the same standard position with respect to affine transformation. We use four third order central moments μ_{30}, μ_{12}, μ_{21}, μ_{03}, which are the simplest and lowest order blur invariants, as normalization constraints.

A nonsingular homogeneous affine transformation matrix A can be separated into an x-shearing, a y-shearing, and an anisotrope scaling matrix as follows:

$$\begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix}$$
$$= \begin{pmatrix} \alpha & 0 \\ 0 & \delta \end{pmatrix} \begin{pmatrix} 1 & 0 \\ \gamma & 1 \end{pmatrix} \begin{pmatrix} 1 & \beta \\ 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix}. \tag{6}$$

An appropriate normalization procedure must be designed so that the four third order moments can be used correctly to guarantee that the later normalization constraints will not destroy the previous ones. For x-shearing normalization, we choose one which will not be destroyed by the y-shearing normalization in the steps followed. Among the four third order blur invariants only $\mu_{30}=0$ satisfy this requirements. For y-shearing normalization, we choose $\mu_{03}=0$. For the anisotrope scaling normalization, $\mu_{21}=\mu_{12}=1$ are used. However, there may be no solution in the real domain under these constraints. Thus we extend the normalization transformation, as presented in the remaining part of this section, to the complex domain.

Extraction of Blur and Affine Combined Invariants

In this section, we will derive the blur and affine combined moment invariants step by step. In the following, μ_{pq} denote the central moments of the original image.

X-Shearing Normalization Let μ'_{pq} denote the central moments after x-shearing normalization. Then

$$\mu'_{pq} = \sum_{k=0}^{p} \binom{p}{k} \beta^{p-k} \mu_{k,p+q-k}. \tag{7}$$

We use the constraint that $\mu'_{30} = 0$ to implement the x-shearing normalization, i.e.,

$$\mu'_{30} = P(\beta) = 0, \tag{8}$$

where $P(\beta) = \mu_{30} + 3\beta\mu_{21} + 3\beta^2\mu_{12} + \beta^3\mu_{03}$.

Y-Shearing Normalization Let μ_{pq}'' be the central moments after y-shearing normalization, then

$$\mu_{pq}'' = \sum_{l=0}^{q} \binom{q}{l} \gamma^{q-l} \mu_{p+q-l,l}'. \qquad (9)$$

Similarly, we use $\mu_{03}'' = 0$ to constrain the y-shearing normalization, i.e.,

$$\mu_{03}'' = P(\gamma) = 0, \qquad (10)$$

where $P(\gamma) = 3\gamma^2 \mu_{21}' + 3\gamma \mu_{12}' + \mu_{03}'$.

Anisotrope Scaling Normalization Let μ_{pq}''' be the central moments after anisotrope scaling normalization, then,

$$\mu_{pq}''' = \alpha^{p+1} \delta^{q+1} \mu_{pq}''. \qquad (11)$$

We now use $\mu_{12}'''=\mu_{21}'''=1$ to process the scaling normalization. Then from equation (11), we get

$$\alpha = \sqrt[5]{\frac{\mu_{12}''^2}{\mu_{21}''^3}}, \quad \delta = \sqrt[5]{\frac{\mu_{21}''^2}{\mu_{12}''^3}}. \qquad (12)$$

Finally, it is summarized that the resulting image satisfies the normalization constraints

$$\mu_{30}''' = 0, \quad \mu_{12}''' = 1, \quad \mu_{21}''' = 1, \quad \mu_{03}''' = 0. \qquad (13)$$

Parameter Selection Criteria Note that $P(\beta)$ will have three solutions and $P(\gamma)$ will have two solutions. Thus we will have six groups of β and γ. This means that we will have six standard positions for a given object. Clearly some of them are unnecessary and need to be deleted so that only one standard position is left. This can be done by appropriately selecting parameters β and γ. We now give the following two lemmas on how to select parameters β and γ. The proofs can be found in (Zhang 1999).

Lemma 1 *If $P(\beta)$ has three real roots, namely $\beta_i, i = 1, 2, 3$, then for each β_i, $P(\gamma)$ will result in two real roots.*

Lemma 2 *If $P(\beta)$ has a pair of conjugate complex roots, $P(\gamma)$ has a pair of conjugate complex roots. In this case, only the real root of $P(\beta)$ can satisfy the normalization constraints (13).*

When $P(\beta)$ has three real roots. we will have six real groups of solutions from equation (8) and (10). By considering μ_{pq}''' in (11), a suitable group of β and γ can be obtained as follows:

$$\{\beta, \gamma\} = arg \min_{\{\beta, \gamma\}} \mu_{pq}'''(\beta, \gamma). \qquad (14)$$

That is, the group of (β, γ) that results in the minimum value of a given μ_{pq}''' is chosen.

When $P(\beta)$ has a pair of conjugate complex roots parameter β is chosen to be the real root of $P(\beta)$. γ is chosen as the root of $P(\gamma)$ that gives the same sign of the real part and imaginary part of a given μ_{pq}'''.

Blur and Affine Combined Invariants Based on the affine invariant moments obtained by normalization, blur and affine combined moment invariants can be constructed. If the PSF is central symmetry, only the odd order blur invariants exist. The third, fifth and seventh order blur and affine combined invariants can be derived as follows. In the following equations μ_{pq}^{AI}, which are affine invariant, denote the moments obtained at the standard position.
The third order BACIs are

$$BACI_{01} = \mu_{03}^{AI} = 0, \quad BACI_{02} = \mu_{12}^{AI} = 1,$$
$$BACI_{03} = \mu_{21}^{AI} = 1, \quad BACI_{04} = \mu_{30}^{AI} = 0.$$

The fifth order BACIs are

$$BACI_1 = \mu_{50}^{AI},$$
$$BACI_2 = \mu_{41}^{AI} - \frac{6}{\mu_{00}^{AI}} \mu_{20}^{AI},$$
$$BACI_3 = \mu_{32}^{AI} - \frac{3}{\mu_{00}^{AI}} (\mu_{20}^{AI} + 2\mu_{11}^{AI}),$$
$$BACI_4 = \mu_{23}^{AI} - \frac{3}{\mu_{00}^{AI}} (3\mu_{02}^{AI} + 2\mu_{11}^{AI}),$$
$$BACI_5 = \mu_{14}^{AI} - \frac{6}{\mu_{00}^{AI}} (\mu_{02}^{AI}),$$
$$BACI_6 = \mu_{05}^{AI}.$$

The seventh order BACIs are

$$BACI_7 = \mu_{70}^{AI} - \frac{21}{\mu_{00}^{AI}} (\mu_{50}^{AI} \mu_{20}^{AI}),$$

$$BACI_8 = \mu_{61}^{AI} - \frac{3}{\mu_{00}^{AI}} (2\mu_{50}^{AI} \mu_{11}^{AI} + 5\mu_{41}^{AI} \mu_{20}^{AI} + 5\mu_{40}^{AI})$$
$$+ \frac{90}{\mu_{00}^{AI\,2}} (\mu_{20}^{AI\,2}),$$

$$BACI_9 = \mu_{52}^{AI} - \frac{1}{\mu_{00}^{AI}} (\mu_{50}^{AI} \mu_{02}^{AI} + 10\mu_{32}^{AI} \mu_{20}^{AI} + 20\mu_{31}^{AI}$$
$$+ 10\mu_{41}^{AI} \mu_{11}^{AI} + 5\mu_{40}^{AI}) + \frac{30}{\mu_{00}^{AI\,2}} (\mu_{20}^{AI\,2} + 4\mu_{20}^{AI} \mu_{11}^{AI}),$$

$$BACI_{10} = \mu_{43}^{AI} - \frac{3}{\mu_{00}^{AI}} (6\mu_{22}^{AI} + 4\mu_{31}^{AI} + \mu_{41}^{AI} \mu_{02}^{AI} + 4\mu_{32}^{AI} \mu_{11}^{AI}$$
$$+ 2\mu_{23}^{AI} \mu_{20}^{AI}) + \frac{36}{\mu_{00}^{AI\,2}} (2\mu_{11}^{AI\,2} + 2\mu_{20}^{AI} \mu_{11}^{AI\,2} + \mu_{02}^{AI} \mu_{20}^{AI}),$$

$$BACI_{11} = \mu_{34}^{AI} - \frac{3}{\mu_{00}^{AI}} (6\mu_{22}^{AI} + 4\mu_{13}^{AI} + \mu_{14}^{AI} \mu_{20}^{AI} + 4\mu_{23}^{AI} \mu_{11}^{AI}$$
$$+ 2\mu_{32}^{AI} \mu_{02}^{AI}) + \frac{36}{\mu_{00}^{AI\,2}} (2\mu_{11}^{AI\,2} + 2\mu_{02}^{AI} \mu_{11}^{AI\,2} + \mu_{20}^{AI} \mu_{02}^{AI}),$$

$$BACI_{12} = \mu_{25}^{AI} - \frac{1}{\mu_{00}^{AI}}(\mu_{05}^{AI}\mu_{20}^{AI} + 10\mu_{23}^{AI}\mu_{02}^{AI} + 20\mu_{13}^{AI}$$
$$+ 10\mu_{14}^{AI}\mu_{11}^{AI} + 5\mu_{04}^{AI}) + \frac{30}{\mu_{00}^{AI\,2}}(\mu_{20}^{AI\,2} + 4\mu_{02}^{AI}\mu_{11}^{AI}),$$

$$BACI_{13} = \mu_{16}^{AI} - \frac{3}{\mu_{00}^{AI}}(2\mu_{05}^{AI}\mu_{11}^{AI} + 5\mu_{14}^{AI}\mu_{02}^{AI} + 5\mu_{04}^{AI})$$
$$+ \frac{90}{\mu_{00}^{AI\,2}}(\mu_{02}^{AI\,2}),$$

$$BACI_{14} = \mu_{07}^{AI} - \frac{21}{\mu_{00}^{AI}}(\mu_{05}^{AI}\mu_{02}^{AI}).$$

Note that $BACI_{01}$ to $BACI_{04}$ are normalization constraints which are the same for all normalized images. Thus we use the fourteen features $BACI_1$ to $BACI_{14}$ during classification process.

Classification Using NN

Based on the BACIs obtained in the last section, image classification can be performed using neural network classifiers. A block diagram of our blur and affine invariant classification system is presented in Figure 1.
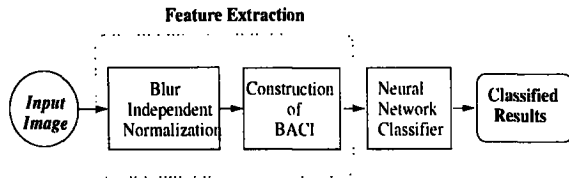

Figure 1: The system architecture

Figure 2: The structure of MLP

Figure 3: Set of fish images used as reference
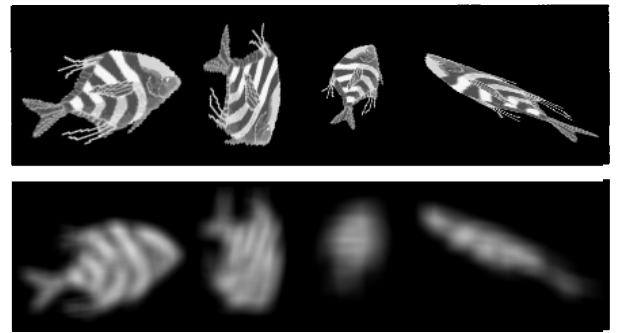
Figure 4: Sample images of fish 3 from the database.

Feedforward neural networks have been frequently used for pattern recognition and classification. Multilayer perceptrons (MLPs) networks trained with the back propagation algorithm are typical representative of this class of networks. MLPs consist of multiple layers of neurons: an "input layer", one or more "hidden layers", and an "output layer". The structure of the MLP with one hidden layer is shown in Figure 2. The network attempts to implement a mapping between an input feature set and a desired output pattern.

In our experiment, an MLP with one hidden layer is used. The number of neurons in the input layer is the same as the number of features. In our case, the fourteen blur and affine combined moment invariants are used as inputs to the neural network. The number of hidden neurons is determined heuristically based on the trade-off between complexity and classification ability of the net. The number of neurons in the output layer is equal to the number of classes which is ten in our studies. The activation function for the neurons of the hidden layer and the output layer used is the sigmoid function.
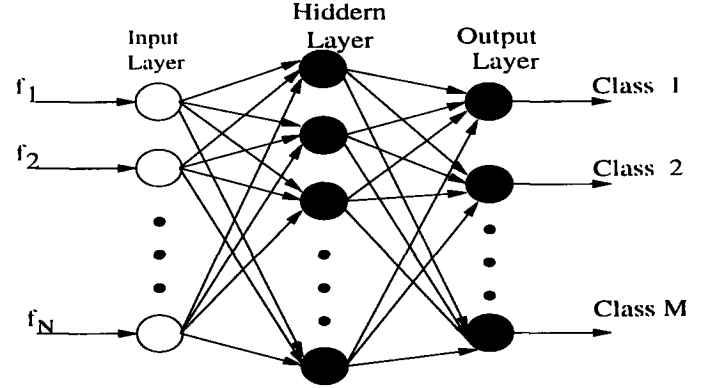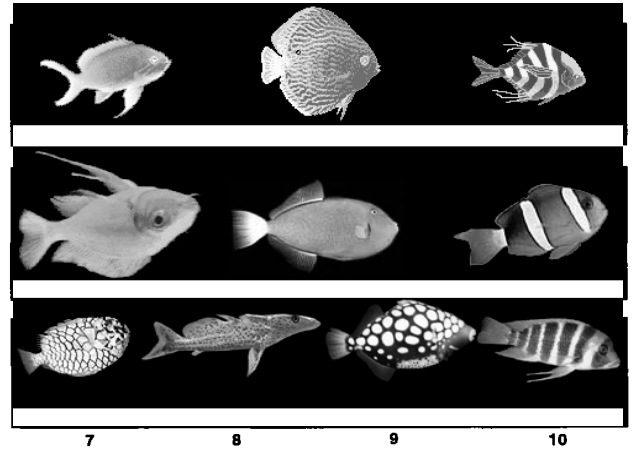
Our test objects consists of gray-level images of fish that are presented directly to the system. The reference objects are shown in Figure 3. One hundred different affine deformed, blur degraded, and affine and blur combined images are generated for each reference object. Examples of these images for fish 3 are shown

in Figure 4. The first row is fish 3 deformed by different affine transformations. The second row is the corresponding blur and affine combined versions.

There are total 1000 images in the database for the 10 reference objects. The available samples are divided into two sets for training and testing. We use 40 training images and 60 testing images per reference object. For each image, the fourteen BACIs, $BACI_1$ to $BACI_{14}$, are calculated and fed to the neural network to perform the classification process. The values of BACIs of fish 3 and the four images in the second row of Figure 4 are listed in Table 1.

Fish 3	original image	BDADI 1
$BACI_1$	0 + 0.5222i	0 + 0.5217i
$BACI_2$	-0.4332 + 0.1610i	-0.4333 + 0.1577i
$BACI_3$	-0.5104 + 0.2611i	-0.5111 + 0.2608i
$BACI_4$	-0.2999 + 0.1816i	-0.3008 + 0.1787i
$BACI_5$	-0.4051 + 0.2019i	-0.4056 + 0.1996i
$BACI_6$	-0.5104 + 0.2216i	-0.5111 + 0.2199i
$BACI_7$	-0.1262 + 0.4173i	-0.1310 + 0.4168i
$BACI_8$	0 - 1.5507i	0 - 1.5450i
$BACI_9$	0.8441 - 0.7754i	0.8442 - 0.7725i
$BACI_{10}$	0.2321 + 0.2211i	0.2282 + 0.2286i
$BACI_{11}$	0.4077 + 0.0320i	0.4045 + 0.0356i
$BACI_{12}$	0.8441 - 0.4720i	0.8442 - 0.4674i
$BACI_{13}$	0.5652 - 0.1491i	0.5629 - 0.1442i
$BACI_{14}$	0.7047 - 0.3203i	0.7036 - 0.3149i
BDADI 2	**BDADI 3**	**BDADI 4**
0 + 0.5273i	0 + 0.4953i	0 + 0.5542i
-0.4348 + 0.1590i	-0.4195 + 0.1599i	-0.4439 + 0.1896i
-0.5121 + 0.2636i	-0.5077 + 0.2477i	-0.5041 + 0.2771i
-0.3024 + 0.1809i	-0.2851 + 0.1708i	-0.3093 + 0.2134i
-0.4072 + 0.2024i	-0.3964 + 0.1850i	-0.4067 + 0.2348i
-0.5121 + 0.2278i	-0.5077 + 0.2059i	-0.5041 + 0.2489i
-0.1274 + 0.4137i	-0.1247 + 0.3922i	0.0871 + 0.4513i
0 - 1.5650i	0 - 1.4336i	0 - 1.715i
0.8502 - 0.7825i	0.8182 - 0.7168i	0.8550 - 0.8573i
-0.2307 + 0.2207i	0.2126 + 0.1963i	0.2816 - 0.2302i
0.4078 + 0.0334i	0.3695 + 0.0234i	0.4644 + 0.0092i
0.8502 - 0.4735i	0.8182 - 0.4289i	0.8550 - 0.5516i
0.5617 - 0.1472i	0.5220 - 0.1327i	0.6157 - 0.2050i
0.7087 - 0.3191i	0.6702 - 0.2850i	0.7353 - 0.3987i

Table 1: The values of BACIs of fish 3 and its blur degraded and affine deformed images(BDADI) as shown in the second row of Figure 4

The main problem in using an MLP is how to choose optimal parameters for the network. There is currently no standard technique for automatically setting the parameters of an MLP. Table 2 shows the best results obtained after numerous experiments. The percentage of correct classifications in the test set is about 99% and clearly this is very high. Most of the errors are due to the quantization caused by affine transformation. Future work could be done in the feature extraction stage to improve the performance of the system.

No. Of Hiddern Neurons	Learning Rate	Momentum Rate	Error Level	Iteration	Initial Weights Range
60	0.05	0.1	0.001	1,000	[-0.5,0.5]

Table 2: Neural Network Parameters

Conclusion

The main objective of this paper is to develop a neural network based blur degradation and affine deformation combined invariant classification system. In the feature extraction stage, we propose a normalization method to determine blur and affine combined invariants. By applying the proposed method, a set of blur and affine combined invariants can be obtained. Then the classification is done using a multilayer perceptron network (MLP) with back-propagation learning. The system has been tested and has shown a high classification accuracy.

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