International Journal of Scientific & Engineering Research, Volume 5, Issue 5, May-2014
ISSN 2229-5518

A New Approach for Shape Recognition of Color Image Using PCA

C.Senthilkumar, Dr.S.Pannirselvam

Abstract - In 2D shape, some simple approaches are used to recognize shape by using translation, rotation and scaling factors. These factors are used only for binary and gray scale images but it is difficult to use for a color image. Hence, it needs to extent another way of finding solutions for shape recognition. In two dimensional color shape without regard to their translation, rotation, scaling factors has been suggested. The input colour image is separated into various components such as red, green, blue etc. The covariance matrix is constructed directly from the original image matrix and its eigen vector are derived for the image features extraction. The first principal component may be calculated by their boundary points. The boundary points are divided into groups by projecting them onto principal component and each shape is partitioned into several blocks. These blocks are used to calculate the remaining features. Finally, the proposal efficiency matching algorithm compares two sets of features of all the three or more components of the two shapes to verify the similar or not.

Index Terms - Principal Component Analysis (PCA), Pattern Recognition (PR), eigen value, eigen vector, co-variance matrix.

1. Introduction

Computer imaging is a fascinating and exciting area to be involved in today. One of the most interesting aspects of computer imaging information is the ability to send and receive complex data that transcend ordinary written text. Visual information, transmitted in the form of digital images is becoming a major roll of communication in the modern era.

Automatic Recognition has a number of industrial application such as description, classification and grouping of patterns are important problems in a variety of engineering and scientific disciplines such as biology, psychology, medicine, marketing, computer vision, artificial intelligence and remote sensing for example cursive wood, a human face, specific signal, numerical/character recognition [20]. Recently a lot of attention has been given to the problem of shape recognition of color images. Shape recognition is very elementary for humans in the real world, but it is difficult for the computers. This is especially due to translation, rotation or scaling of the images.

In this paper, Sections I are discussed the introduction of image processing and recognition. The related works are presented in Section II and Section III explains the concept of Principal Component Analysis, Section IV focuses on shape feature extraction and shape matching algorithm proposed.

• ***Prof.C.Senthilkumar*** *was born on January 10th 1963. He is working as Associate Professor, Department of Computer Science in Erode Arts & Science College (Autonomous), Erode, Tamilnadu, India. He has obtained his Masters degree in Computer Science and M.Phil degree in Computer Science from Alagappa University, Karaikudi. He is research supervisor for M.Phil programmes. His interest area includes Image Processing, Data Mining and Neural Networks. He has presented 3 papers in National conferences. PH: 9486273812.E-mail: csincseasc@gmail.com*

• ***Dr. S. Pannirselvam*** *was born on June 23rd 1961. He is working as Associate Professor and Head, Department of Computer Science in Erode Arts & Science College (Autonomous), Erode, Tamilnadu, India. He is research supervisor for M.Phil and Ph.D programmes. His area of interests includes, Image Processing, Artificial Intelligence, Data Mining. He has presented more than 15 papers in National and International level conferences. He has published more than 21 papers in International journals.PH: 9443305432.E-mail: pannirselvam08@gmail.com*

Section V discusses the experimental results and analysis of shape recognition. The conclusions are presented in Section VI.

2. Related Work

Over the past few decades, applications of PCA are to be recognizing the binary component, face recognition, finger recognition, construction for linear mathematical representation and to find the pattern of image. Many approaches to recognize object are PCA [14], ICA [15], LDA [16, 18] and KPCA [18] the familiar techniques in digital image processing. Now PCA become a popular choice to recognize color image [11].

A method [1] presented to perform fast recognition of two-dimensional (2D) binary shape. This method depends on a new polygon approximation technique, which extracts suitable feature vectors with specified dimension.

Shape matching [2] is designed for segment matching problem and to reduce the computation time. The obtained results shows at low levels to speed up and improve the accuracy of results at higher levels.

A method [3] developed to cater objects that is reported based on the use of autoregressive model parameters. It represents the shapes of boundaries detected in digitized binary images of the objects. The object identification technique is insensitive to object size and orientation.

An efficient method [4] to recognize two-dimensional shapes without need of their translation, rotation and scaling factors has been suggested. In this method describes the uses the entire boundary points to calculate the first principal component. The training data set is less for PCA outperform LDA and also that PCA is less sensitive to different training data sets [12].

Cyuen et al. [13] presented the problem of face recognition using independent component analysis (ICA). More specifically they are going to address two issues on face representation using ICA and the independent components (ICs) are independent but not orthogonal, images outside a

ISSN 2229-5518

training set cannot be projected into these basis functions directly with a least-squares solution method using Householder Transformation to find a new representation.

PCA [14] removes the some less important component and also reduces the size of the images. ICA [15] is similar to PCA except that the distributions of the components are designed to be non Gaussian. LDA [16] the execution of the LDA encounters the complex computation in difficulty for original color images. KPCA [18] is to apply non-linear mapping from the input image to the feature space.

3. Principal Component Analysis

Principal Component Analysis (PCA) [5,6] was first described by Karl Pearson in 1901. The basic concept of PCA is to reduce dimensionality of a data set, which consists of a large number of interrelated variables, while preserving the variations present in the data set as much as possible. This is accomplished by transforming the original set of variables into a new set of variables, called Principal Components (PCs), which are uncorrelated. Then, these PCs are ordered so that the first few PCs, retain most of the variations.

The color images are usually represented with size n×m pixel by a vector in an n×m dimensional space. In practice, however these n×m dimensional spaces are too large to allow robust and difficult to make fast object recognition. A common way to solve this problem is to use dimensionality reduction techniques that become one of the most popular techniques for this purpose in Principal Component Analysis (PCA) [12].

Let x denote an n-dimensional unitary column vector. Our idea is to project image A, an m x n random matrix, onto x by the following linear transformation [13],[21].

$$Z = AX \tag{1}$$

Thus, after transmission it is obtained an m-dimensional projected vector y, which is called the projected feature vector of image A [19].

Let us consider data of m variables for n individuals, as indicated in table-1, to explain the PCA technique. In general, the PC is given by

$$Z_i = a_{j1}x_1 + a_{j2}x_2 + \ldots\ldots + a_{jm}x_m \tag{2}$$

subject to the condition

$$a_{j1}^2 + a_{j2}^2 + \ldots\ldots + a_{jm}^2 = 1 \tag{3}$$

and also that Z_j is uncorrelated with Z_i, i<j.

The main purpose of the above process is to take m variables X_1, X_2 ,...,X_m and find combinations of these variables to produce a new set of variables Z_1, Z_2 ,...,Z_m. These new variables are ordered in such a way that Z_1 displays the first largest amount of variation, Z_2 shows the second largest variation, and so on.

PCA just involves finding the Eigen values of the covariance matrix. Assuming that the eigen values are ordered such that $\lambda_1 > \lambda_2 > \ldots\ldots > \lambda_i = 0$, then X_i corresponds to the i^{th} PC.

Algorithm: Principal Component Analysis

Step 1: *Read input image in color.*

Step 2: *Collect interrelated data and store in matrix format.*

Table 1

Pixels	Dimensions
1.	$X_{11}, X_{12}, X_{13} \ldots\ldots\ldots X_{1m}$
2.	$X_{21}, X_{22}, X_{23} \ldots\ldots\ldots X_{2m}$
.	. .
.	. .
.	. .
n	$X_{n1}, X_{n2}, X_{n3} \ldots\ldots\ldots X_{nm}$

Step 3: *From the input matrix construct transformation vector using formula*

$$\mathbf{Z = aj1\ x1 + aj2\ x2 = \ldots\ldots ja_m\ x_m} \tag{4}$$

Step 4: *Apply PCA technique to the given original matrix.*

Step 5: *Construct transformation vector and it is represented as*

$$\mathbf{p = H\ (b-m)} \tag{5}$$

Step 6: *Find the mean vector of image using the formula*

$$M = \frac{1}{n}\sum_{i=1}^{n} b[i] \tag{6}$$

Step 7: *Find Covariance matrix using the formula*

$$C = \frac{1}{n}\sum_{i=1}^{n} b[i - M]\,(bi - M)^T \tag{7}$$

Step 8: *Find out Eigen value for C matrix*

Step 9: *Getting old data back*

$$\mathbf{[B] = [[H]*[P]] + [M]} \tag{8}$$

Let us consider data of 'm' variables for 'n' individuals to explain the PCA techniques. In general the PC is given by

$$Z_j = a_{j1}x_1 + a_{j2}x_2 + \ldots + a_{jm}x_m \tag{9}$$

Subject to the condition $a_{j1}^2 + a_{j2}^2 + \ldots\ldots a_{jm}^2 = 1$ and also that Zi is uncorrected with Zj, i < j

Let us consider an example with only two variables X1 and X2 in Fig.1.

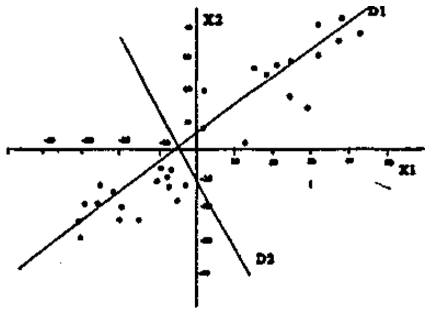


Fig.1 Two Principal components in 2D plane

The Covariance matrix for this sample data is

$$C = \begin{bmatrix} 604.4 & -561.6 \\ -561.6 & 592.5 \end{bmatrix}$$

The corresponding eigen values and eigen vectors are shown in table-2.

Table 2
Eigen Values and Eigen Vectors of sample data

Component	Eigen Value	Eigen Vector	
		x1	x2
1	1160.139	0.710	-0.703
2	36.78	-0.703	0.710

Thus the first principal component accounts for (1160.139/(1160.139 +36.78))* 100= 97% which is called the contribution ratio r. The second PC accounts for only 3% of the spread. Therefore those points projected perpendicularly onto the direction Dl can still maintain the approximate distances between the original points. So the second projected components are discarded.

4. Feature Extraction

4.1 Shape Feature Extraction

The given image is converted into a binary image by simple thresholding and the boundary points are extracted. After the boundary extraction, it was found out the first PC and its eigen vector. Let the boundary points be denoted by $P_i=(x_i,y_i)$, $1 \le i \le m$, where P_1 is the boundary point corresponding to the first projected point onto the first P_1, and P_M is the boundary point corresponding to the last projected point onto the first PC (Fig.2). Then the projected points are divided from boundary points into n blocks according, to the order of the projected points onto the first principal component. The choice of 'n' depends on the trade off between the discrimination power and space / time requirements. The contribution ratio r will be our first feature.

The remaining four shape features are then found. The contribution ratio r_1 of the first principal component of the first block's point is calculated. Similarly remaining factors are calculated the contribution ratio r_1 of each of the i^{th} blocks. The list $(r_1,r_2,\ldots r_n)$ is the second feature of the shape.

The centroid is defined as $C=(C_x, C_y)$ (10)

$$\text{Where} \quad c_x = \frac{1}{k}\sum_{i=1}^{k} X_i \; ; \quad c_y = \frac{1}{k}\sum_{i=1}^{k} Y_i \qquad (11)$$

It is found the n centuriods for the n blocks, $C_i=(X_i,Y_i)$, i=1,2,...,n. The third feature is the list of all average distances *from* the boundary points of each block to its corresponding centroid $(d_1\ d_2\ ,\ldots,d_n)$. The set of all maximum distances and minimum distances from boundary points of each block to *as* corresponding centriod as the fourth feature $(l_1,l_2\ ,\ldots l_n)$ and the fifth feature $(s_1\ s_2\ ,\ldots s_n)$ respectively. The above procedure is repeated for all the three RGB components of the color image and the corresponding features are extracted.

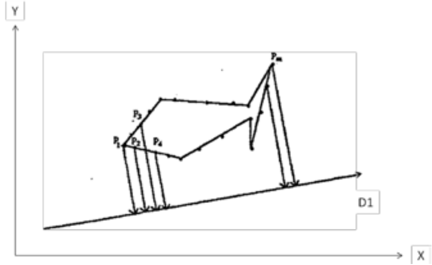


Fig.2 Projected direction

4.2 Shape Matching

Let the features of the reference shape and the input color shape are shown in table 3 and table 4.

Table 3
Reference color shape features

Feature	Red Image	Green Image	Blue image
Feature1	r^r	r^s	r^b
Feature2	$r_1^r, r_2^r \ldots r_n^r$	$r_1^s, r_2^s \ldots r_n^s$	$r_1^b, r_2^b \ldots r_n^b$
Feature3	$d_1^r, d_2^r \ldots d_n^r$	$d_1^s, d_2^s \ldots d_n^s$	$d_1^b, d_2^b \ldots d_n^b$
Feature4	$l_1^r, l_2^r \ldots l_n^r$	$l_1^s, l_2^s \ldots l_n^s$	$l_1^b, l_2^b \ldots l_n^b$
Feature5	$s_1^r, s_2^r \ldots s_n^r$	$s_1^s, s_2^s \ldots s_n^s$	$s_1^b, s_2^b \ldots s_n^b$

Table 4
Input color shape features

Feature	Red Image	Green Image	Blue image
Feature1	r^{r^1}	r^{s^1}	r^{b^1}
Feature2	$r_1^{r^1}, r_2^{r^1} \ldots r_n^{r^1}$	$r_1^{s^1}, r_2^{s^1} \ldots r_n^{s^1}$	$r_1^{b^1}, r_2^{b^1} \ldots r_n^{b^1}$
Feature3	$d_1^{r^1}, d_2^{r^1} \ldots d_n^{r^1}$	$d_1^{s^1}, d_2^{s^1} \ldots d_n^{s^1}$	$d_1^{b^1}, d_2^{b^1} \ldots d_n^{b^1}$
Feature4	$l_1^{r^1}, l_2^{r^1} \ldots l_n^{r^1}$	$l_1^{s^1}, l_2^{s^1} \ldots l_n^{s^1}$	$l_1^{b^1}, l_2^{b^1} \ldots l_n^{b^1}$
Feature5	$s_1^{r^1}, s_2^{r^1} \ldots s_n^{r^1}$	$s_1^{s^1}, s_2^{s^1} \ldots s_n^{s^1}$	$s_1^{b^1}, s_2^{b^1} \ldots s_n^{b^1}$

4.3 Algorithm

// Proposed Shape Matching //

Let PE : Predetermined tolerance of the i^{th} feature.
Scale : Scaling ratio of the input shape compared to the reference shape.
FIRST: A flag that indicates whether a second matching is needed when the first match fails. Its initial value is FALSE.

Step 1: *if* $|\, r - r' \,| < PE$ *then go to step 2 else go to step 7*
Step 2: *if* $|\, r_1 - r'_1 \,| + |\, r_2 - r'_2 \,| + \ldots + |\, r_n - r'_n \,| < PE$, *then*
go to Step 3 else go to Step 7.
Step 3 : *scale* $= (d'_1/d_1 + d'_2/d_2 + \ldots + d'_n/d_n)/n$
If $|\, d_1{}^{*}scale - d'_1 \,| + |\, d_2{}^{*}scale - d'_2 \,| + \ldots + |\, d_n{}^{*}scale - d'_n \,| < PE_3$, *then go to Step4 else goto Step 7*
Step 4: *if* $|{}_1{}^{*}scale - 1_1 \,| + \ldots + |\, 1_2{}^{*}scale - 1_2 \,| + \ldots + |\, 1_n{}^{*}scale - 1_n \,| < PE$ *, then go to Step5 else go to step7*
Step5 : *if* $|s_1{}^{*}scale - s'_1| + |\, s_1{}^{*}scale - s'_2 \,| + \ldots + |s_n + scale\ - s_n| < PE_5$ *then go step5 else go to step 7.*
Step 6: *Print "Two components are similar" and return.*

Step 7: *if (FIRST=FALSE) then /*reverse the features of the blocks of the input shape */*

$(r'_1, r'_2, \ldots r'_n) \leftarrow (r'_n, r'_{n-1}, \ldots r'_1)$

$(d'_1, d'_2, \ldots d'_n) \leftarrow (d'_n, d'_{n-1}, \ldots d'_1)$

$(1'_1, 1'_2, \ldots 1'_n) \leftarrow (1'_n, 1'_{n-1}, \ldots 1'_1)$

$(s'_1, s'_2, \ldots s'_n) \leftarrow (s'_n, s'_{n-1}, \ldots s_1)$

FIRST=TRUE

Go to Step 1

else print "The components are different"

The proposed new algorithm is applied for all the three components and if all the three components match then only the entire given color image is recognised else the two color shapes are different. The above said algorithm is repeated for all images in standard image database.

5. Experimental Results

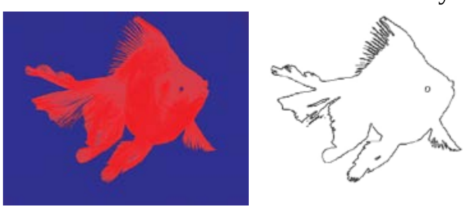
The efficient proposed algorithm is applied on a fish and other color images and successful matching is obtained with the scaled, rotated and translated version of the original image. As long as the images are scaled or translated or both, the above said algorithm are able to find almost 93% of matching. Even when the images are rotated and are able to find successful recognition except a few mismatches. The algorithm is designed to apply the PCA method to the image for the reconstruction and recognition tasks. The following figures and tables show the results which are obtained by the PCA method.

Fig.3 Standard Images used for Experiment

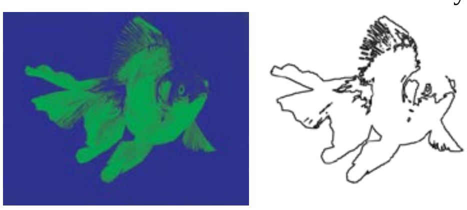
a .Original Image

b. Color Component **c. Boundary Extraction**

Red Red Boundary



Green Green Boundary



Blue Blue Boundary

Fig.4 Separation of Color Component and Boundary Extracted images

Table 5

Overall features comparison of three components

Component	Color (r')	Block Color (r')	Average Distance (d')	Maximum Distance (I')	Minimum Distance (S')
Red	60.2957	99.8850	112.4943	140.6019	0.3842
Green	63.8565	99.6617	65.4861	113.8089	0.6557
Blue	62.5862	99.8464	56.9514	134.5513	0.1790

Table 6

Overall features comparison of three Images

Image	Mean vector(Z)	Eigen Value (E)	Eigen Vector(V)	Total NO. of Points	Color Ratio (r)	
					Ratio 1	Ratio 2
Red	1.0e+003* 2.0915 0.0472 0.0472 3.1710	1.0e+00* 2.0895 3.1731	0.9990 0.0436 -0.0436 0.9990	1096	39.7043	60.2957
Green	1.0e+003* 1.3601 0.1797 0.1797 2.3124	1.0e+00* 1.3274 2.3451	0.9838 0.1794 -0.1794 0.9838	1238	36.1435	63.8565
Blue	1.0e+003* 1.7338 0.0875 0.1797 2.8827	1.0e+00* 1.7272 2.8893	0.9971 0.0755 -0.0755 0.9971	1230	37.4138	62.5862

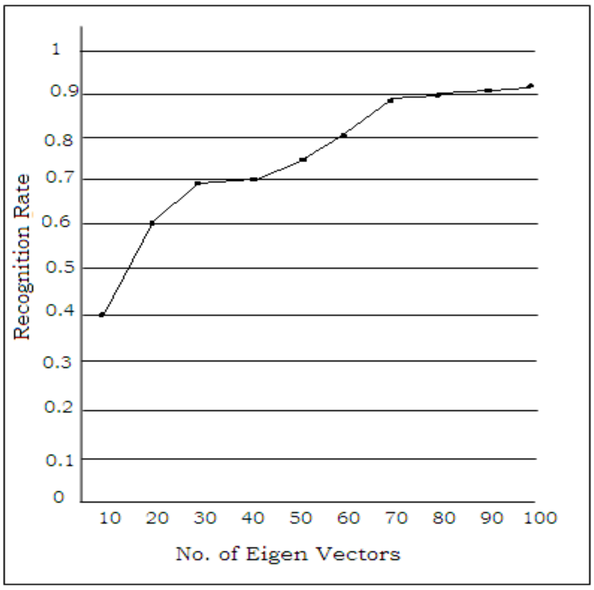


Fig.4 Comparison of Recognition ratio and vectors

From the above fig.4 shows that pictorial representation that is observed from the PCA method completely outperforms and gives good recognition for the color image.

6. Conclusion

In this paper a new technique for image feature extraction and recognition for two dimensional shape Principal Component Analysis has represented, developed and compared fish image for recognition tasks. It is presented in a simple but an efficient method for color shape recognition independent of scaling, translation, and rotation.

Since new algorithm is applied component wise automatically, the probability of mismatch due to this is 1/3. It is found experimentally that the discrimination of shapes by contribution ratio is highly difficult as it will be almost same for most of the images. So, only taking the remaining features into consideration for each of these components contributes to a factor of 1/3. Similarly, tested on two data bases of image covering large variations in pose and illumination proposed algorithms have achieved the promising results as 93% of correct identification. Future work will also concentrate on automatic neural network. Each of these features have for n components. Instead of determining the predetermined tolerances, this work may be extended by using suitable neural network for recognizing the shape by training the net properly.

References

[1] D. A. Mitizas and B. G. Merizois, *Shape Recognition with a Neural Classifier based on a Fast Polygonal Approximation Technique*, Pattern Recognition, Vol.27, No.5, pp.627-636.

[2] B. Bhanu and O.D. Faugeras, *Shape matching of two dimensional object*, IEEE Trans, PAMI-6, pp.137-155.

[3] S.R. Dubious and F.H. Glang, *An Auto regressive model approach to two-dimensional shape classification*, IEEE, PIMI-8, pp.67-75.

[4] Chien-Chen Change, Yaw-Wen Chen, *A Two Dimensional Shape Recognition Scheme based on Principal Component Analysis*, International Journal of pattern recognition and Artificial Intelligence, Vol.8, No.4, pp.859-870.

[5] T. Pal Vadis, *Structural Pattern Recognition.*

[6] D. Ballard and C.Brow, *Computer Vision*, Prentice-Hall, Englewood Cliffs, NJ (1982).

[7] R.Chin and C.Dyer, *Model-Based recognition in robot vision*, Comput, Surv. 18, 67-108 (1986).

[8] Adrian Lowe, *"Introductory Computer Vision and Image processing"*, McGraw-Hill, 1991.

[9] Gonzaliz. R.C. & Woods, E., *"Digital Image Processing, Prentice Hall"*, 1005.

[10] Rhys Lewis, *"Practical Digital Image Processing"*, Ellis Horwood Ltd., 1990.

[11] P.Viola and M.Jones Rapid,Object detection using a boosted cascade of simple features in CVPR, pp.511-518, 2001.

[12] IEEE Transactions on pattern Analysis and Machine Intelligence,vol.23, No.2, Feb 2001, *"PCA Versus LDA"*.

[13] P.Cyuen and J.H. Lai, *"Face representation using independent component analysis"*, Pattern Recognition, Vol.35, No.6, pp.1247-1257, 2002.

[14] M.Turk and A.Pentland, "Eigenfaces for face recognition", Journal cognitive neuroscience, vol.3., no.1,1991.

[15] M.S.Bartlett, H.M.Ladies and T.J.Sejnowski, "Independent Component representation for face recognition" in proceedings of SPIE,Vol.3299, pp.528-539,1998.

[16] P.N.Belhumeur, J.P.Hespandha and D.J.Kriegman, "Eigen faces versus fisher faces: recognition using class specific linear projection", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.19, pp.711-720, 1997.

[17] D.L.Swets and J.J.Weng,"Using Discrimanany eigen features for image retrieval, IEEE Transactional on Pattern Analysis and Machine intelligence, Vol.18, pp.831-836, 1996.

[18] B.Scholkopf,A..Smola,K.Mullar,"NonLinear component analysis as Kernel eigen value problem", Neural computation,Vol.10,no.5, pp.1099-1319,1998.

[19] IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.26, No.1, January 2004, *"Two Dimensional PCA: A New Approach to appearance base face representation and recognition"*.

[20] IEEE Transactional on Pattern Analysis and Machine intelligence, Vol.22, No.1, January 2000. *"Statistical Pattern Recognition"*.

[21] M.H.Yang, "Kernel Eigen faces Vs Kernel Fisherfaces: "Face Recognition using Kernel Method", Proc fifth IEEE Int'e Conf. Automatic Face and Gesture Recognition, pp.215-220, 2002.

[22] H.Hotelling, "Analysis of Complex Statistical variables into Principal Components", Jour. of Educational Psychology.