On Image Recognition using Hopfield Net and Ellipse Fitting

Rakibul Pervej†, Nayeema Akter†, Ahsan Raja Chowdhuryζ, Md. Al-Amin Bhuiyan‡

†Dept. of Computer Science & Engineering, Northern University Bangladesh (NUB), Dhaka, Bangladesh.
ζDept. of Computer Science & Engineering, University of Dhaka, Dhaka, Bangladesh.
‡Dept. of Computer Science & Engineering, Jahangirnagar University, Savar, Dhaka, Bangladesh.

Summary
This paper presents an image recognition scheme using Hopfield net and ellipse fitting procedure. The method is based on geometrical and visual analysis of the image features. The system is commenced with capturing image using a digital camera. On image enhancement, processing and analysis, images of elliptical shape are being approximated as 'ellipse' using principal component analysis. Hebbian learning has been employed for ellipse fitting and recognition has been established by means of Hopfield Neural Network. Experimental results demonstrate that our method is capable of recognizing elliptical image patterns efficiently.

Keywords: *Ellipse Fitting, Hopfield Net, Hebbian Learning (HL), Thersholding, Principle Component Analysis (PCA).*

1. Introduction

Detection and recognition of geometric primitives in images are the fundamental tasks of computer vision. Hough transform (HT) provides a popular method for extracting geometric shapes. Primitives on the HT are represented by parametric curves with a number of free parameters. The principal concept of the HT is to define a mapping between an image space and a parameter space. Each edge point in an image is transformed by the mapping to determine cells in the parameter space whose associated parameters are such that the defined primitive passes through the data point. The chosen cells are accumulated and after all the points in an image have been considered, local maxima in the accumulator correspond to the parameters of the specified shape.

A fair amount of research work has been accomplished in literature on ellipse fitting. The existing ellipse fitting techniques can be categorized in to two types: (i) Least square fitting and (ii) Clustering. Least squares fitting technique [1] focuses on finding a set of parameters that minimize some distance measure between the data points and the ellipse. The implicit second order polynomial given in equation (1) is used to fit the data points to a conic and the constraint b^2-4ac<0 is used to represent the conic as an ellipse.

$$F(p,X)=p.X=0,\ b^2-4ac<0. \qquad (1)$$

Manuscript received May 5, 2008
Manuscript revised May 20, 2008

These methods are computationally better but are very sensitive to outlines. Clustering methods focus on mapping sets of points to the parameter space, which are appropriately quantized depending on the application. Hough transform methods are the example of this type of technique. These techniques [2,3] have some advantages, like high robustness to occlusion and no requirement for pre-segmentation. But they suffer from great shortcomings of high computational complexity and non-uniqueness of solutions, which can render them unsuitable for real applications [4,5]. This paper investigates the application of principal component analysis to represent the image of an ellipsoidal object such as a fruit, as an ellipse. This allows for the reduction and simplification of data, making it easier for the higher stages of processing. This algorithm needs only a few simple operations to calculate the ellipse parameters. Further more, the set of data points can be drastically reduced appropriately in an extremely simple manner without diminishing the accuracy. This estimated set of data points are applied to the HL which is an artificial neural network approach of performing principal component analysis (PCA) on that set of data and is used in association with this algorithm to estimate the ellipse parameters in 2D. Later, Hopfield network is employed for the recognition of individual image patterns.

2. Image Processing

Before performing PCA, a set of data points is extracted from the image. Images to be recognized are obviously color images. These are first converted into gray scale image. The gray scale images sometimes may be of poor contrast because of the limitations of the lighting conditions or suffer from various sources of noise. Therefore, image enhancement is essential to improve the image quality to a better and more understandable level for feature extraction or image interpretation. In this research, we used histogram equalization and low pass filtering for image enhancement. Next, global thresholding is used to segment the object from the background to extract the set of points.

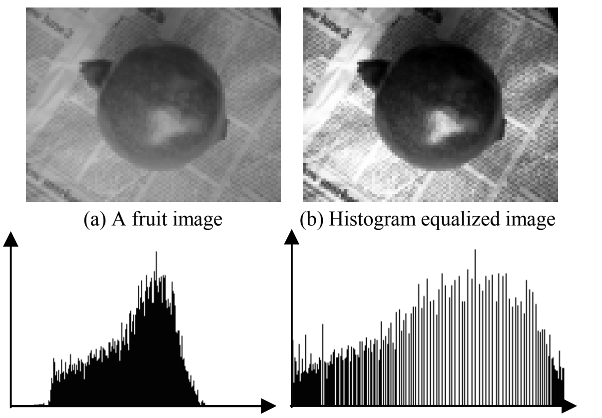
A. Histogram Equalization

The gray level histogram [6] of a typical natural scene that has been linearly quantized is usually highly skewed toward the darken levels; a majority of the pixels pass as a luminance less than the average. In such images, detail in the darken region is often not perceptible. In this case, histogram modification is employed to enhance the image, where the original image is resulted so that the histogram of the enhanced image follows some desired form.

The histogram of an image determines the distribution of gray levels in an image. It is a stable object representation which is unaffected by occlusion, changing in viewing conditions and that the histogram has the advantage of being insensitive to rotation, scaling, small deformations of objects and being immune to noise. It provides a useful indication of different gray levels in an image. Histogram equalization redistributes the gray level: an attempt to flatten the frequency distribution, as shown in **Fig. 1**. More gray levels are allocated where there are most pixels, fewer gray levels where there are fewer pixels. This trends to increase contrast in the most heavily populated region of the histogram. Our goal with histogram equalization is to expand the gray levels of the image to fill the entire 0-255 spectrum. To do this, we need to calculate the cumulative frequencies within the image. The histogram equalization can be expressed as [6]:

$$s_k = T(r_k) = \sum_{j=0}^{k} p_r(r_j)$$

$$= \sum_{j=0}^{k} \frac{n_j}{n} \quad k = 0,1,2,\ldots\ldots L\text{-}1 \tag{2}$$



(a) A fruit image (b) Histogram equalized image

(c) Histogram of image (a) (d) Histogram of equalized image (b).

Fig. 1 Histogram equalization of the fruit image.

(a) Original image (b) DOG filtering (c) Thresholding

Fig. 2 Image filtering and thresholding.

where n = number of pixel, and

n_j = number of pixel with gray level r_j.

B. Filtering

Various sources of noise may exist in the input image. The fine details of the image represent high frequencies, which mix up with those of noise. When low-pass filtering is used, some details in the image may be erased as well. In this experiment, Difference of Gaussian (DOG) filtering is used to suppress the noise, as shown in **Fig. 2**.

C. Binarizarion

The automatic binarization of gray level image that separates object from its background is performed to minimize the correlation function between binary and original gray level image. Image pixels that belong to background are given one value and the pixels that belong to the objects are given another value. An optimum threshold value is the value where the maximum amount of information about the object of interest is revealed and the minimum amount of information is lost [1].

In this research the threshold value has been chosen iteratively. The binarization is accomplished depending on the threshold value chosen form the histogram of the image. In this case, 8-Bit gray level images consisting of N pixels containing gray level values 0 to 255 with probabilities $p(0)$ to $p(255)$, shown in the following equations hold:

$$g(0) = \sum_{i=0}^{theta-1} p_i \le G \tag{3}$$

$$g(255) = \sum_{i=theta}^{255} p_i \tag{4}$$

The binarization process is illustrated in **Fig. 2 (c)**.

D. Morphological Operation

Morphology is a nonlinear processing operation that process images based on their shapes. Morphological operations apply a structuring element to an input image, creating an output image of the same size. In a morphological operation, the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors. In this reserch, morphological dilation and erosion operations are employed. The dilation of an image f by a structuring element s is given by

$$f \oplus S = \begin{cases} 1 & if \;\; s \;\; hits \;\; f \\ 0 & otherwise \end{cases} \tag{5}$$

To compute the erosion, we position the structuring element in such a way that its origin is at image pixel coordinates (x,y). The erosion of an image f by a structuring element S is given by

$$f\Theta S = \begin{cases} 1 \ \ if \ \ s \ \ fits \ \ f \\ 0 \ \ otherwise \end{cases} \quad (6)$$

3. Ellipse Fitting

Ellipse fitting technique finds a curve which matches a series of data points and possible other constraints to approximate an ellipse. In this research we investigate the use of PCA with a neural network approach employing Hebbian learning for the approximation of an image of a hypothetically ellipsoidal object as an ellipse.

A. Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is a classical statistical technique which analyses the covariance structure of multivariate data. PCA determines the directions along which the variation of data occur and the corresponding importance of that direction [7]. The first principal component gives the direction where the maximum variance could be observed. The second principal component is the direction of the next maximal variation and is orthogonal to the first and so on. We take the image of an ellipsoidal object, representing it as a set of data points and use a HL based algorithm to approximate it as an ellipse. Furthermore, we define a measure for calculating the error of fit, and outline a simple technique to determine the goodness of fit.

B. HL for Ellipse Fitting

Generalized Hebbian Learning (GHL) is an Artificial Neural Network (ANN) approach of performing PCA on a set of data to estimate the ellipse parameters in n-dimensions. The algorithm for using HL for ellipse fitting is shown in **Fig. 3**.

C. Method of Calculation

Ellipse parameters are being computed on segmentation of the image. The method only requires a simple segmentation of the image and needs only a few simple operations to calculate the ellipse parameters.

After acquiring data, the mean vector **c** = [c_1 c_2] is calculated to get the center of the ellipse. Then the mean is removed to center the data around the origin. Let X consists of n 2-dimensional data points. The covariance matrix **S**, which indicates how strongly correlated the components are and **S** is calculated as follows:

$$\mathbf{S} = \frac{1}{n-1}\overline{X}^T\overline{X}, \text{ where } \overline{X} = X - c \quad (7)$$

The two eigen values λ_i and eigen vectors v_i of S are calculated as follows:

$$\lambda_{1,2} = \frac{1}{2}\left(\sigma_{11} + \sigma_{12} \pm \sqrt{(\sigma_{11} - \sigma_{12})^2 + 4\sigma_{12}^2}\right) \quad (8)$$

$$v_1 = \frac{\sigma_{12}}{\sqrt{(\lambda_1 - \sigma_{11})^2 + \sigma_{12}^2}} \quad (9)$$

$$v_2 = \frac{\lambda_1 - \sigma_{11}}{\sqrt{(\lambda_1 - \sigma_{11})^2 + \sigma_{12}^2}} \quad (10)$$

where $v_1 = [v_1 v_2]^T$ and $v_2 = [v_2 \ -v_1]^T$

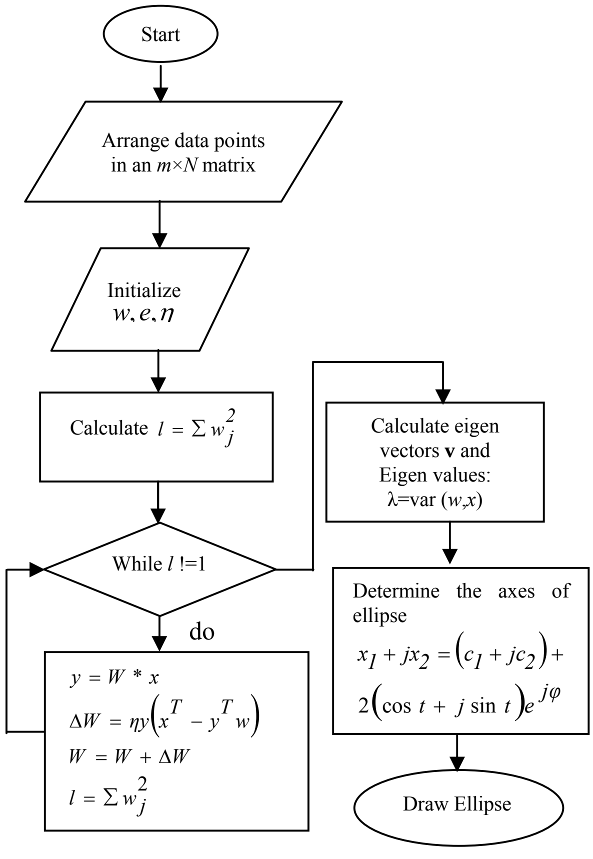


Fig. 3 Ellipse fitting algorithm using HL.

The mean of data, c_1, c_2, the eigenvalues λ_1, λ_2, and the direction of the first eigenvalue, uniquely define the ellipse [7]. Eqn (11) shows this and **Fig. 4** shows an ellipse, fitted to the image of a mango.

$$x_1 + jx_2 = (\cos t + j\sin t)e^{j\phi} + (c_1 + jc_2) \quad (11)$$

(a) A fruit image (b) Ellipse fitting

Fig. 4 Ellipse fitting.

The betterness of the ellipse fit can then be calculated to test the feasibility of the approximation. For this reason we propose a simple method to suit the target application. We define a threshold T, and take any fit that has an error measure below it as acceptable. The threshold is determined experimentally to suit the application.

4. Image Recognition

Image recognition system performs the operation by means of given rules or pattern matching for achieving image recognition. Acquisition of a great deal of knowledge and the effective usage are important. Therefore, developing sophisticated learning system for obtaining adequate knowledge is required. For this an artificial neural network model "Hopfield Network" is employed.

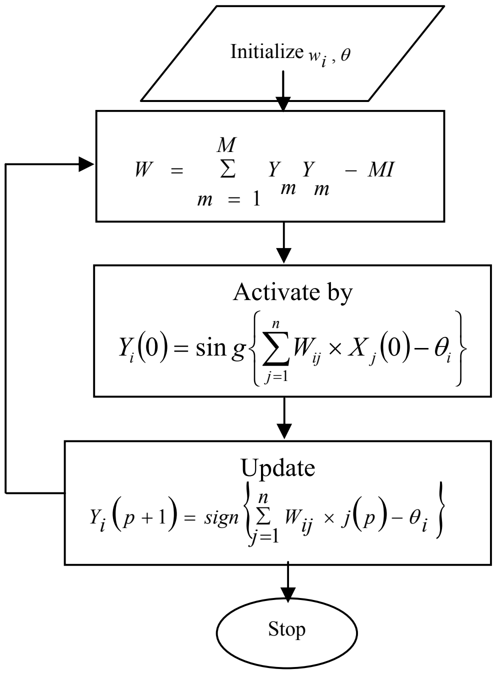


Fig. 5 Algorithm for Hopfield network.

A. Hopfield Networks

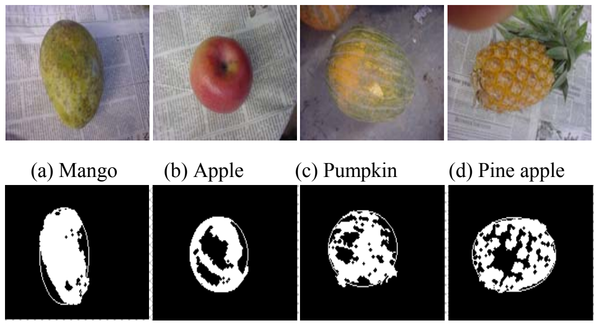
Hopfield networks are recurrent neural networks with feedback loops from their outputs to the inputs. After applying a new input, the network output is calculated and fed back to adjust the input. Then the output is calculated again, and the process is repeated until the output becomes constant. In the Hopfield network, synaptic weights between neurons are usually represented in matrix form as:

$$W = \sum_{m=1}^{M} Y_m Y_m^T - MI \tag{12}$$

where M is the number of states to be memorized by the network. Y_m is the n-dimensional binary vector, and I is the $m \times m$ matrix. The retrieval process of Hopfield network is illustrated in **Fig. 5**.

5. Experimental Results

The effectiveness and robustness of this approach is justified using different fruit images with various lighting conditions. Experiments are carried out on a Pentium IV 1.2 GHz PC with 256 MB RAM. The algorithm has been implemented using Visual C++. A few of the fruit images and the detected ellipse fitting binary images obtained after running the program is shown **Fig. 6**. **Table 1** summarizes the ellipse fitting results applied to images of different fruits.



(a) Mango (b) Apple (c) Pumpkin (d) Pine apple

(a) Ellipse fitted Mango (b) Apple (c) Pumpkin (d) Pine apple

Fig. 6 Ellipse fitting on different fruit images.

Table 1 Ellipse fitting algorithm applied to fruit images.

Name of the Fruit	Ellipse Parameters					Gravity center of the Fruit		Area (Pixel)
	x	y	a	b	Θ	x_g	y_g	
Apple	73	61	32	33	0.699	73.11	60.83	2129
Mango	65	63	27	43	0.778	64.83	61.37	3156
Pineapple	72	61	46	32	0.675	74.12	61.27	3051
Pumpkin	69	57	38	36	0.708	69.36	59.63	2694

The accuracy of the ellipse fitting algorithm has been calculated by computing the area covered by the ellipse and the area covered by the fruit image after final detection. The fruit area has been calculated as follows. Considering the gray level at each point (x, y) of the given area E of a fruit as the "mass" of (x, y), we can define the center of gravity, as well as the moment of inertia about specified points or lines. The pq-th moment of area E about the origin (0,0) is given by [8]:

$$m_{pq} = \sum_{(x,y) \in E}\sum x^p y^q \tag{13}$$

where (x, y) are the coordinates of the pixel included in area E. The 0-th moment m_{00} represents the area E and the center of gravity of E is the point $(\bar{x}, \bar{y})$ whose coordinates are given by [9]:

$$\left.\begin{array}{l} \bar{x} = \dfrac{m_{10}}{m_{00}} = \dfrac{\sum\sum_{(x,y)\in E} xy^0}{\sum\sum_{(x,y)\in E} x^0y^0}; \bar{y} = \dfrac{m_{01}}{m_{00}} = \dfrac{\sum\sum_{(x,y)\in E} x^0y}{\sum\sum_{(x,y)\in E} x^0y^0} \end{array}\right\} \quad (14)$$

In order to justify the algorithm for oblique ellipse, a set of images of a jackfruit was taken at different orientations. **Table 2** summarizes the ellipse fitting results applied to images of different jackfruits at different inclinations (θ) and **Fig. 7** shows a few of the image samples with the visual outputs.

Table 2 Ellipse fitting algorithm applied to images of different jackfruits.

Name of the Fruit	Ellipse Parameters					Fruit Gravity Center		Area (Pixel)
	x	y	a	B	Θ	x_g	y_g	
Jackfruit1	77	55	49	35	0.59	78.35	55.29	5512
Jackfruit2	79	51	48	35	0.55	79.7	50.04	5420
Jackfruit3	76	48	54	38	0.55	76.77	49.41	6302
Jackfruit4	58	52	40	36	0.72	59.10	52.60	3990

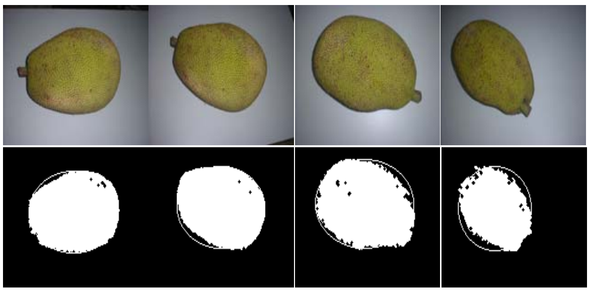


Fig. 7 Ellipse fitting on different jackfruit images.

In order to justify the accuracy of the system, 30 different fruit images were taken and their areas were calculated on ellipse fitting experiments. **Fig. 8** illustrates the results for the area of the original image in pixels and the approximated area graphically. Later images were checked at the noisy environments, as shown in **Fig. 9**. For this, Gaussian white noise of mean 0 and variance 0.01, respectively were added to the image in **Fig. 9(a)** and "Salt and pepper" noise with noise density 0.05 to the image in **Fig. 9(b)**. Experimental results demonstrate that our method is capable of finding elliptical shapes of objects in these noisy environments with significant margin.

The neural network method discussed in this paper to calculate the ellipse parameters is compared with that used in [5, 7]. PCA is solely used in [5, 7] for ellipse fitting, but GHL is employed with PCA in the proposed technique and hence possesses the following advantages over [5, 7]:

(i) Simple extensibility to higher dimensions. That is, PCA with GHL can be used to fit ellipse in higher dimension.

(ii) It gives the user control over the error of fit. By changing the length convergence error, the processing and accuracy could be balanced to suit the requirements of the application.

Average processing complexity of the proposed method is better that the existing method, which is shown **Fig. 10.**

Fig. 8 Area of fruit images.

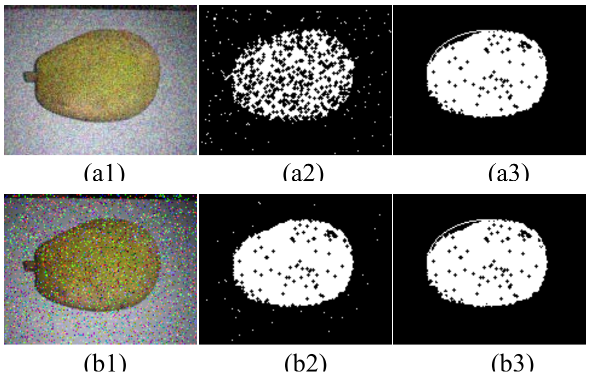


Fig. 9 Jackfruit images at noisy environment: (a1) Image with Gaussian noise, (a2) Color segmented image, (a3) Ellipse fitting, (b1) Image with Salt & Pepper noise, (b2) Color segmented image, (b3) Ellipse fitting.

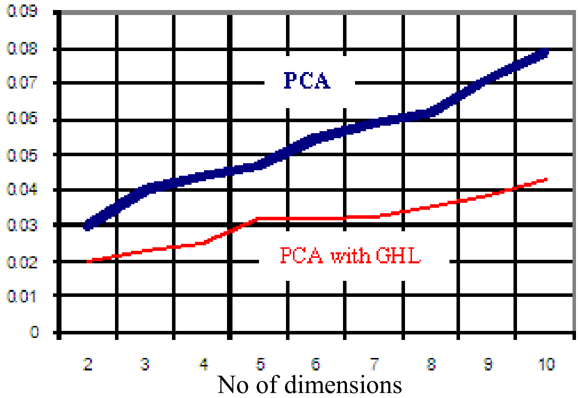


Fig. 10 PCA (existing) vs. PCA with GHL (proposed).

6.Conclusions

This research explores PCA and Hebbian learning rule to fit an ellipse to a set of two dimensional data points and Hopfield net for the recognition of objects. Experimental results demonstrate the advantages conferred by the ellipse-specificity in terms of orientation. The stability properties widen the scope of application of the algorithm from ellipse fitting to cases where the data are not strictly elliptical but need to be minimally represented by an elliptical "blob". In our view, the method presented here offers the best trade-off between speed and accuracy for ellipse fitting, and its uniqueness property makes it also extremely robust to noise and usable in many applications. In cases where more accurate results are required, this algorithm provides an excellent initial estimate.

The use of principal component analysis in the representation of an image of a fruit as an ellipse is concluded, therefore, to be an efficient and suitable method to be used in fruit sorting applications in real-time and could be easily adapted for other similar applications.

REFERENCES

[1] P.L. Rosin, "A Note on the Least Squares Fitting of Ellipses," Pattern Recognition Letters, vol. 10, no. 14, pp. 799-808, 1993.

[2] Z. Zhang, "Parameter estimation techniques: A tutorial with application to conic fitting," Image and Vision computing Journal, vol. 15, no.1, pp.59–76, 1997.

[3] A. W. Fitzgibbon, M. Pilu, and R. B. Fisher, "Direct least squares fitting," Tern Analysis and Machine Intel-ligancy, vol. 21, no.5, pp. 476–480, 1999.

[4] R. Hal´ýr and J. Flusser, "Numerically stable direct least squares fitting of ellipse", In Proceedings of the 6th Conference in Central Europe on Computer Graphics and Visualization, pp. 253–257, 1998.

[5] H. Hotelling, "Analysis of a complex of statistical variables into principal components," Journal of Education Psychology, vol. 24, no. 1, pp. 34-43, 1993.

[6] R. Gonzalez and R. Woods Digital Image Processing, Addison-Wesley Publishing Company, 1992.

[7] S. N. R. Wijewickrema and A. P. Paplinski, "Principal component analysis for the approximation of an image as an ellipse," Technical Report 2004/160, Computer Science and Software Engineering, Monash University, Australia, 2004.

[8] Md. Al-Amin Bhuiyan, Vuthichai Ampornaramveth, Shin-yo Muto, and Haruki Ueno, "Face Detection and Facial Feature Localization for Human-machine Interface," NII Journal, vol. 5, No. 1, pp. 25-38, 2003.

[9] M.A. Bhuiyan, V. Ampornaramveth, S. Muto, and H. Ueno, "On Tracking of Eye for Human-robot Interface", International Journal of Robotics and Automation, vol. 19, No. 1, pp. 42-54, 2004.

Rakibul Pervej completed his B.Sc (Engg.) from Dept. of CSE, Northern University Bangladesh in 2006. He successfully completed his undergraduate project on Image Processing under the supervision of Dr. Md. Al-Amin Bhuiyan. He is now working as a Software Engineer in a renowned software company in Dhaka, Bangladesh. His research interests include Image Processing, Pattern Recognition, Software Engineering and so on.

Nayeema Akter completed her B.Sc (Engg.) from Dept. of Computer Science and Engineering, Northern University Bangladesh in 2006. She successfully completed her undergraduate project on Image Processing under the supervision of Dr. Md. Al-Amin Bhuiyan. Her research interests include Image Processing, Pattern Recognition, Artificial Intelligence, Computer Graphics and so on.

Ahsan Raja Chowdhury received his B.Sc (Hons) and MS degrees in Computer Science and Engineering from the University of Dhaka, Bangladesh, in 2004 and 2006, respectively. He worked with the Dept. of CSE, Northern University Bangladesh from 2004 to 2007 as a faculty member. Now he is the faculty member of the Dept. of CSE, University of Dhaka, Bangladesh. His research interests include Logic Synthesis and Design, Reversible Logic, Image Processing, Artificial Intelligence, Bio-informatics, Wireless Networking (MANET, Wi-Fi).

Md. Al-Amin Bhuiyan received his B.Sc (Hons) and M.Sc. in Applied Physics and Electronics from University of Dhaka, Dhaka, Bangladesh in 1987 and 1988, respectively. He got the Dr. Eng. degree in Electrical Engineering from Osaka City University, Japan, in 2001. He has completed his Postdoctoral in the Intelligent Systems from National Informatics Institute, Japan. He is now an Associate Professor in the Dept. of CSE, Jahangirnagar University, Savar, Dhaka, Bangladesh. His main research interests include Image Face Recognition, Cognitive Science, Image Processing, Computer Graphics, Pattern Recognition, Neural Networks, Human-machine Interface, Artificial Intelligence, Robotics and so on.