The Comparison of Object Recognition and Identification by Using Image Processing Base on the Neural Network, the Hough transform and the Harris Corner Detection

Jaruwan Toontham, Chaiyapon Thongchaisuratkrul

***Abstract*— This paper presents an object recognition and identification system using the back propagation neural networks. The performance of Hough Transform and the Harris Corner detection are compared with the following procedures and methods; the webcam is used to capture the object and create an input image, change the color image from RGB to gray scale, resize, learn and recognize the objects by neural network, and separate the objects by the robot arm. Three different types of objects in this study are triangle, rectangle and rigid circle. The object recognition and identification from the neural network, the Hough transform, and the Harris corner detection are compared. The results showed that the neural network gives more accuracy than the Hough transform and the Harris corner detection.**

***Index Terms*— Hough Transform, Harris Corner Detection, Back Propagation Neural Network**

I. Introduction

The Object recognizing is one of the most challenging problems in computer vision [1]. The combination of computer vision and machine learning techniques has recently been considerable progress in developing real world object recognition system base on the use of invariant local feature [2]—[4]. In this research, the neural network is applied for an object recognition and identification. The Hough transform and the Harris corner detection are studied for comparing with neural network. There are many research studies employed the neural network for different reasons. Back propagation algorithm was used for recognize and identify the construction of Batu Aceh [5]. Fourier Descriptor Pattern was used to classify the objects resulting as the vectors. The back propagation algorithm used these vectors to recognize and identify the objects was introduced by Qureshi and Jalil [6]. The fingerprint authentication system can indicate the characteristics of all ages was used the back propagation presented by Sohel and Amiruzzaman [7]. Multi-layer neural networks including forward and back propagation for real time object recognition is illustrated for teaching [8]. The Hopfield Neural Network is used to recognize the parts of the computer motherboard. The result of this technique was simulated in Matlab and discussed in [9].

Manuscript received June 3, 2011, revised September 15, 2011.
Jaruwan toontham is with King Mongkut's University of Technology North Bangkok, Bangkok,Thailand.(e-mail: nudiddl@hotmail.com)
Chaiyapon Thongchaisuratkul is with the King Mongkut's University of Technology North Bangkok, Thailand. (e-mail: srp@kmutnb.ac.th)

In our work, a robot arm was designed to use a neural network method to recognize, identify, and separate the objects. The triangle, rectangular, and rigid circle objects are used to verify the system.

II. Image Preprocessing and Enhance

The images of the object from webcam that used in our experiment have different quality such as brightness, contrast, or noise. The fuzzy image processing (FIP) is used to adjust brightness of the image. The process includes image fuzzification, membership modification, and image defuzzification which can be showed in Figure 1 [9].

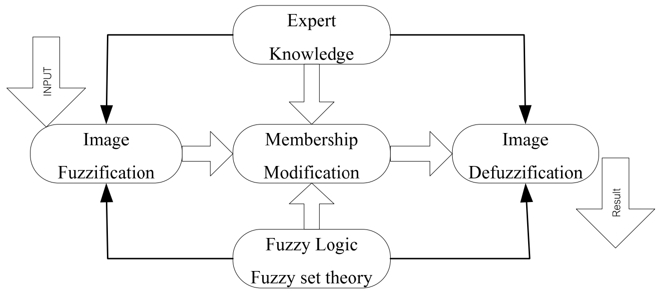


Fig. 1 Fuzzy Image Processing

To adjust the brightness of the image, the INT operator with the following methods is used. The original image matrix X of N x M is the array of fuzzy singleton of each member represented by the degree of brightness levels p, $p = 0,1,2,3 \ldots P-1$ with p values between 0 and 255 can be written as follows,

$$X = \begin{pmatrix} \mu_{11}/x_{11} & \mu_{12}/x_{12} & \ldots & \mu_{1M}/x_{1M} \\ \mu_{21}/x_{21} & \mu_{22}/x_{22} & \ldots & \mu_{2M}/x_{2M} \\ \vdots & & & \\ \mu_{N1}/x_{N1} & \mu_{N2}/x_{N2} & \ldots & \mu_{NM}/x_{NM} \end{pmatrix}$$

where $0 \le \mu_{mn} \le 1, m = 1,2 \ldots M, n = 1,2 \ldots N$. The equation (1) is used to calculate.

$$\begin{aligned} T_1(\mu_{mn}) &= T_1'(\mu_{mn}) = 2\mu_{mn}^{\ 2}, & 0 \le \mu_{mn} \le 0.5 \\ &= T_1''(\mu_{mn}) = 1 - 2(1-\mu_{mn})^2, & 0.5 \le \mu_{mn} \le 1 \end{aligned} \quad (1)$$

Each pixel of image brightness is adjusted as follows, if the values are greater than 0.5 increases the brightness of the pixels, if the values are less than 0.5 decreases the brightness of the pixels. The procedure of the fuzzy image enhancement is showed in Figure 2.

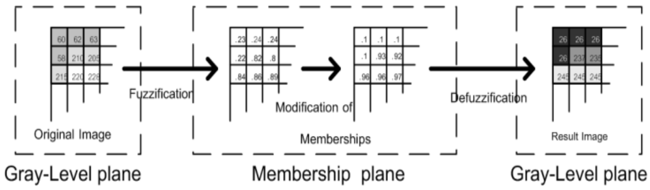


Fig. 2 Fuzzy Image Enhancements

III. EASE OF USE PIXEL AVERAGE MEAN

The pixel average mean is used for resize before the learning process.

A. Change the image color

The image colors are changed to gray scale.

B. Resize the image

The image are resize to 14×32 pixel.

C. Calculate pixel average mean

The y axis of the image is calculated for pixel average mean. The result has 32 columns per image. The example pixel of the gray scale showed in Figure 3.

120	35	80	120	62	120	•••	120	68	120	80	35	136
65	35	80	120	62	20		20	68	120	80	40	80
120	35	80	120	62	120		121	68	120	80	40	136
120	35	80	120	62	120		120	68	120	80	40	120
203	35	80	120	62	255		253	68	120	80	40	200
120	35	80	120	62	120		120	62	100	80	40	120
100	35	80	69	62	20		33	62	100	80	40	100
255	35	80	120	62	200		202	62	120	80	40	230
120	35	80	14	62	2		8	62	80	80	40	120
255	255	255	120	62	120		134	62	120	255	40	255
120	35	80	120	62	1		5	62	120	255	40	120
120	35	80	120	62	120		120	64	120	80	40	120
120	35	80	120	62	120		120	68	120	80	40	120
120	35	80	120	62	120	•••	120	68	120	80	40	120

Fig. 3 The example pixel of gray scale

IV. THE NEURAL NETWORK

Artificial Neural Networks are created in the computer as the simulation. The results are illustrated that how the computer works as the human brain for pattern recognition, listening, or reading the human language. This can be implemented as a "robot" [10], [11].

The structure of neural network consists of input units, hidden units, and output units. The paths are connected between each unit have weights which can be changed during learning phase. Neural network learning is based on back propagation algorithm. The neural network learning techniques are considered as a human learning which can be identified as supervised and unsupervised learning. Supervised learning means learned by taught [12] such as the students are learning by the teachers. Unsupervised learning means learned without taught such as the student can be identified the plant and animal species by shape or by behavior without teaching [13].

In this research, two neural network methods—Learning Vector Quantization Neural Network (LVQ)[14] and Back Propagation Neural Network (BPN) are implemented. The method that gives more accuracy is selected.

A. Learning Vector Quantization Neural Network

The structure of Learning Vector Quantization neural network shown in Figure 4 consists of 32 inputs, 10 competitive layers and 3 outputs.

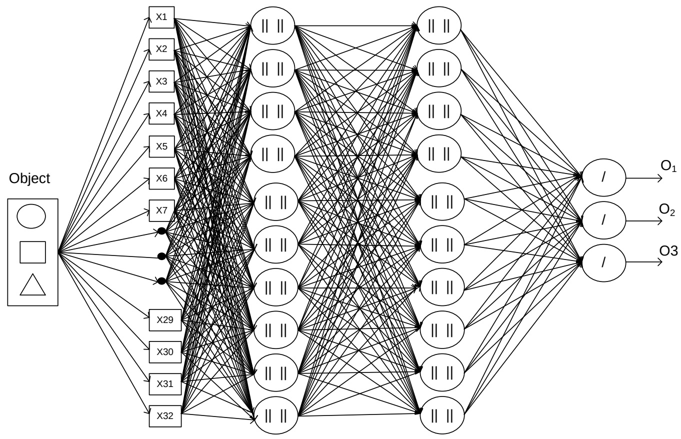


Fig. 4 The structure of Learning Vector Quantization Neural Network

LVQ has 3 layers including input layer, Kohonen classification (competitive) layer, and output layer.

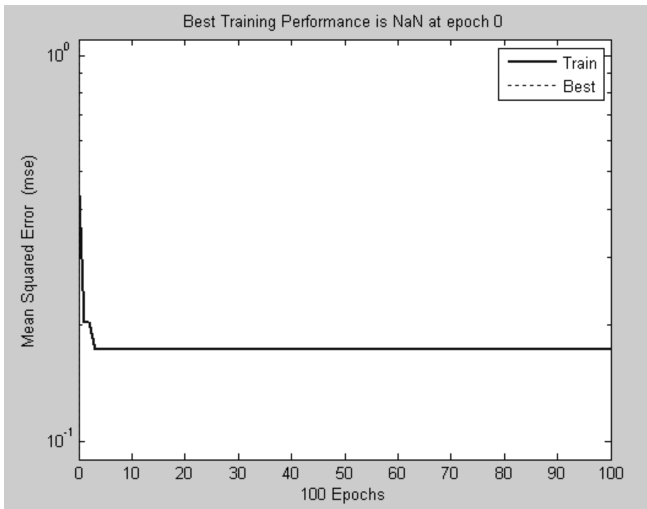


Fig. 5 The mean square error and epoch of LVQ

B. Back Propagation Neural Network

The structure of back propagation neural network showed in Figure 6. Experimentations for finding the best method of performance and gradient showed in Table 1.

TABLE 1 PERFORMANCE AND GRADIENT IN VARIOUS FORMATS.

Format	Performanc	gradient	Train
32-10-10-1	$4.58e^{-5}$	0.02	Trainlm
32-10-20-1	.000785	0.1	
32-30-30-1	$1.77e^{-5}$	0.0186	
32-10-10-1	0.001	0.00523	traingd
32-20-20-1	0.001	0.00583	
32-30-30-1	0.001	0.00655	
32-10-10-1	0.001	0.00125	traingdm
32-20-20-1	0.001	0.00736	
32-30-30-1	0.516	1.33	

The best format is selected by gradient 0.00125, because the value was close to setting target. The threshold value is 0.0001 for 32 input layers, 10 hidden layers and 1 output.

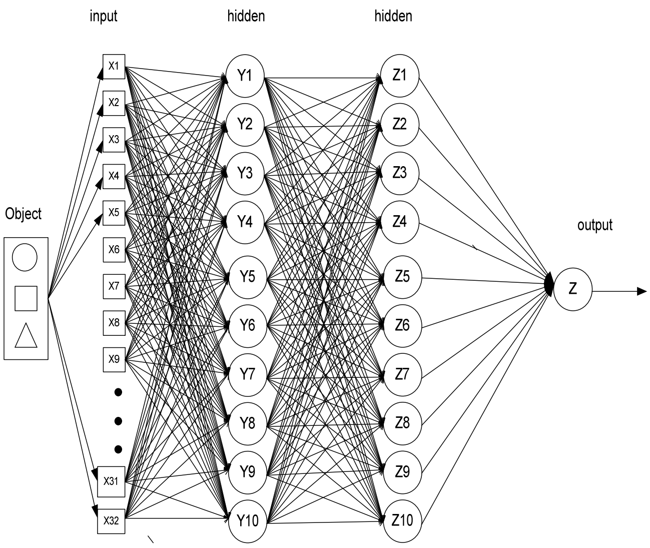
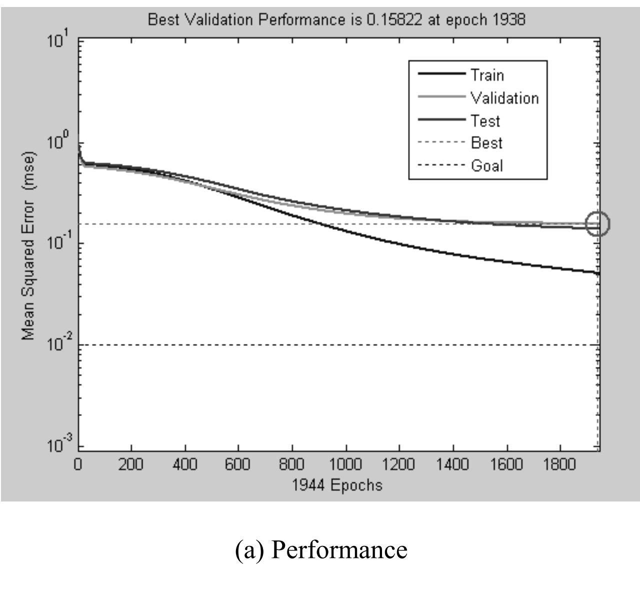
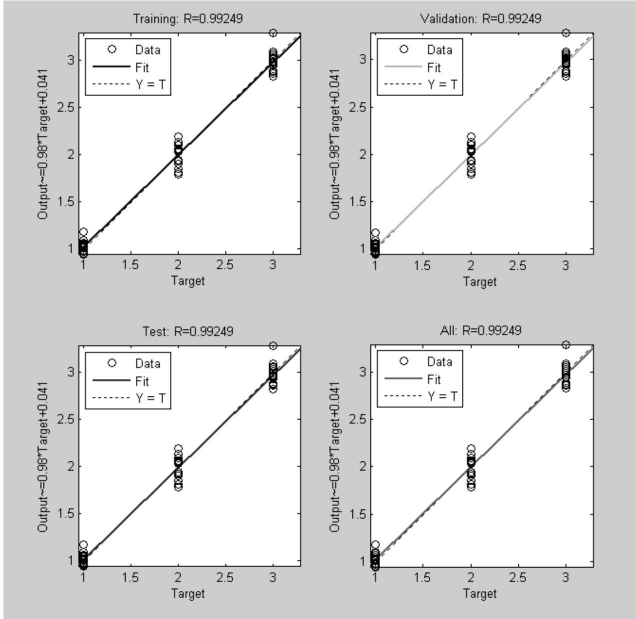


Fig. 6 The structure of BPN 32-10-10-1



(a) Performance



(b) Regression

Fig.7 The performance and regression of BPN

The accurate percentage comparison between LVQ and BPN found that the BPN gets accurate percentage 97.54 more than the LVQ which gets accurate percentage 74.5455. Therefore, in this study the supervisor BPN is selected to learn and recognize objects.

V. CONVENTIONAL HOUGH TRANSFORM (CHT)

The conventional Hough transform is used to recognize the shape by detecting linear curve and circle in the picture [15 ,16,17,18]. For detection the linear line, the equation (2) is given.

$$\rho = x\cos\theta + y\sin\theta \qquad (2)$$

If the x, y coordinate of the pixel on the image plane x, y, ρ is perpendicular, the distance is the origin to straight lines in plane image x, y, the θ is the angle from x-axis perpendicular to y-axis.

Two-dimensional accumulator cell A(i, j) was created which the components of ρ_i, θ_j for every pixel with coordinates x, y images of any pixels on the same line in the same accumulator cell. When the ρ and the θ have the same amount, and the accumulation in the accumulator cell is greater than the specified threshold, the values are converted back to the coordinates x, y. This recognizes that the line is rated at point on the plane x, y. In the same way, the CHT can find a curve and a circle as given in equation (3).

$$r^2 = (x - C_x)^2 + (y - C_y)^2 \qquad (3)$$

When the point (C_x, C_y) is the center of the circle along the x and y axis, r is the radius of the circle or arc. In the case of a circle, accumulator cell is A(i, j) 3-dimensional, the parameters contain C_x, C_y and r. These parameters are used to calculate the coordinates x, y on the same circle or arc. The method is used the same as a straight line calculation.

VI. Harris Corner Detection

The Harris Method is used for object corner detection. This method does not change the value of scale, noise, rotation, variance of light by calculating the local auto correlation function [2], [19]—[21]. This function considers a signal measures from the local changes of the signal with patches shifted by a small amount in different directions as given in equation (4).

$$c(x,y) = \sum \left[I(x_i, y_i) - I(x_i + \Delta x, y_i + \Delta y) \right]^2 \qquad (4)$$

When $w(x, y)$ is a window function, $I(x + u, y + v)$ is a shifted intensity, and $I(x + y)$ is an intensity. The small shifted windows are approximated by equation (5).

$$E(u,v) \cong M \begin{bmatrix} u \\ v \end{bmatrix} \qquad (5)$$

M is a 2x2 matrix which can be calculated by the image derivatives as shown in equation (6).

$$M = \sum_{x,y} w(x,y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \qquad (6)$$

If window was shifted, the intensity value and the eigenvalue of M (λ_1, λ_2) are changed. There are three cases to be considered:

1) If both λ_1, λ_2 are small, so that the local auto-correlation function is flat, the windowed image region is an approximately constant intensity.

2) If one eigenvalue is high and the other low, so the local auto-correlation function is ridge shaped, then only local shifts in one direction (along the ridge) cause little change in $C(x,y)$ and significant change in the orthogonal direction, this indicates an edge.

3) If both eigenvalues are high, so the local auto-correlation function is sharply peaked, then shifts in any direction will result in a significant increase, this indicates a corner.

VII. Conveyer System and Arm

The conveyor system simulation was designed using a servo motor driving the conveyor belt 10 cm width, 62 cm long, as shown in Figure 8. The robot arm is a revolute robot type (RRR) and controlled by the microcontroller as shown in Figure 9.

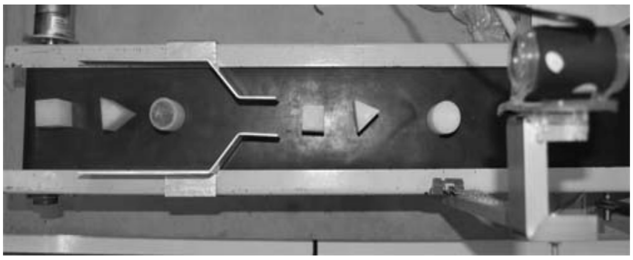


Fig.8 Conveyor model

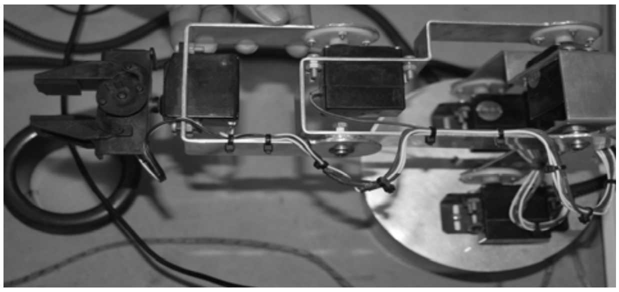


Fig. 9 The revolute robot arm

VIII. Experiments and Result

The aim of this study was to compare the efficiency of inspection triangle, squares, and circle objects by using neural network, the Hough transform, and the Harris Corner Detection. The software was developed by using the Opencv library and Microsoft Visual C++. The results are collected by testing three different objects. The revolute robot arm was used to catch the object for separating. There are two experiments were implemented.

A. Each object type is implemented for robot to detect and separate 100 times. The result is showed in Table 2.

B. Three object types are mixed for robot to detect and separate. This experiment consists of 100 pieces of each object type. The result is shown in Table 3.

TABLE II Percentage of detect and separate the same objects

Object	Hough Transform	Corner Detection	BPN
rigid circle	98	99	99
Rectangular	97	95	99
Triangular	96	95	99

TABLE III Percentage of detect and separate the three objects

Object	Hough Transform	Corner Detection	BPN
rigid circle	98	99	99
Rectangular	96	95	99
Triangular	96	94	99

The performance of both Harris corner detectors and Hough transform were reduced while the objects have more corner points. The percentages of detect and separate the same objects and the three objects are similar results. The experimental results of black propagation neural network get more accurate than the Hough transform and the Harris corner detection.

IX. Conclusions and Discussion

The black propagation neural network can be used for the object identification and shape recognition. The algorithm can be implemented with the robot arm to separate the objects. The experimental results get more accurate than the Hough transform and the Harris corner detection. The error is occurred form the light affect and the angle of the camera. However, the error for black propagation neural network can be occurred since the training data was difference. The maximum error was 1% for the black propagation neural network.

References

[1] G. Dorko, and C. Schmid , "Selection of Scale-Invariant Parts for Object Class Recognition," *9th IEEE International Conference on Computer Vision (ICCV 2003)* .,Vol. 1, 2003, pp. 634-639.

[2] D. G. Lowe, "Object Recognition from Local Scale-Invariant Features," *Proceeding of 7th IEEE International Conference on Computer Vision*.,Vol. 2, Sep 1999, pp. 1150-1157.

[3] D. G. Lowe, "Local Feature View Clustering for 3D Object Recognition," *Proceeding of 2001 IEEE International Conference on Computer Vision and Pattern Recognition*. Vol. 1, Dec 2001, pp. I-682-I-688.

[4] C. Schmid, and R. Mohr, "Local Grayvalue Invariants for mage Retrieval," *IEEE J. Pattern Analysis and Machine Intelligence*., Vol. 19, May 1997, pp. 530-535.

[5] A. Mohamed, F. Huda Bt Mat, S. Mutalib, S. Abdul Rahman, and N. Habibah Arshad, "Batu Aceh Typology Identification Using Back Propagation Algorithm," *WSEAS Transactions on Information Science & Applications*., Vol. 5, Jan 2008, pp. 14-21.

[6] I.M.Qureshi,and A.Jalil, "Object Recognition Using ANN with Backpopagation Algolithm," *Pakistan Journal of Applied Science*., 2002, pp. 281-287.

[7] F. A. Sohel, and M. Amiruzzaman, "Fingerprint Authentication System Using Back-Propagation," unpublished.

[8] F. Khan, and A. Cervantes, "Real Time Object Recognition for Teaching Neural Networks," *29th ASEE/IEEE Frontiers in Education*, Vol.1, Nov 1999, pp. 11B3/1-11B3/7.

[9] A. Mhmed Ali, S. D.Gore, and M. Al-Sarierah, "The Use of Neural Network to Recognize the Parts of the Computer Motherboard," Journal of Computer Sciences., 2005, pp. 476-480.

[10] D. Janglová, "Neural Networks in Mobile Robot Motion," Inernational Journal of Advanced Robotic Systems, Vol. 1, 2004, pp. 15-22.

[11] S. Jabin, Robot Learning. Janeza Trdine 9, Croatia,CA: Sciyo, 2010, pp. 43-61.

[12] R. Caruana, and A. Niculescu-Mizil, "An Empirical Comparison of Supervised Learning Algorithms," Proceedings *of 23rd International Conference on Machine Learning*. 2006.

[13] H. Tong, T. Liu, and Z. Li, "Unsupervised Learning Neural Network with Convex Constraint: Structure and Algorithm," unpublished.

[14] B. Smitt. (2011). LVQ Nets 4 Image Segmentation [Online]. Available: http://www.engr.mun.ca

[15] J. Toontham, and C. Thongchaisuratkrul, "An Object Recognition and Identification Systems Using The Hough Transform Method," *Proceeding of* ICIIE *2011 Information and Industrial Electronics*., Vol. 1, Jan 2011, pp. V1-5-V1-8.

[16] M. Rizon, H. Yazid, P. saad, A. Y. Md Shakaff , A. Rahman Sadd, M. Sugisaka, S. Yaacob, M. Rozailan Mamat and M.Karthigayan, "Object Detection using Circular Hough Transform," *American J. Applied Sciences*., 2005, pp. 1606-1609.

[17] S. Maji, and J. Malik, "Object Detection using a Max-Margin Hough Transform," unpublished.

[18] M. Smereka, and I. Duleba, "Circular Object Detection Using a Modified Hough Transform," *Int. J. Appl. Math. Comput. Sci*., Vol. 18, 2008, pp. 85–91.

[19] K. toontham, J. Toontham, and C. Thongchaisuratkrul, "An Object Recognition and Identification Systems Using The Harris corner detection Method," *Proceeding of ICMLC 2011 Machine Learning and Computing*., Vol. 1, Feb 2011, pp. V1-409 – V1-410.

[20] L. Teixeira, W. Celes, and M. Gattass, "Accelerated Corner-Detector Algorithms," unpublished.

[21] [21] X. Chen He, and N. H. C. Yung. (2008, May). Corner detector based on global and local curvature properties. *S P I E International Society for Optical Engineering*. [Online]. pp. 057008-1 -057008-12. available: http://hdl.handle.net/10722/57246

Jaruwan Toontham received her B.S.I.Ed. from Rajamungala University of Technology, Thailand, in 1994. She received her MS.Ed from the King Mongkut's University of Technology North Bangkok (KMUTNB), Thailand, in 1999. Now, she is a Ph.D student in King Mongkut's University of Technology North Bangkok (KMUTNB), Thailand.

Chaiyapon Thongchaisuratkrul, Ph.D. He received his B.S.I.Ed. and M.Eng from the King Mongkut's University of Technology North Bangkok (KMUTNB), Thailand, in 1989 and 1992 respectively. He received his Ph.D. from the Vanderbilt University, USA in 2001. He joined KMUTNB as a lecture of Teacher Training in Electrical Engineering Department in 1989. Now he is an assistant professor in the department. He served as the vice president for network and conference of the Thai Robotics Society in 2008. His research interests include intelligent control systems, robotics, energy conservation, and energy resources.