INTELLIGENT VISUAL INSPECTION OF BOTTLING PRODUCTION LINE THROUGH NEURAL NETWORK

(Date received: 19.2.2008)

Riza Sulaiman[1] and Anton S. Prabuwono[2]
Department of Industrial Computing
Faculty of Information Science and Technology,
Universiti Kebangsaan Malaysia,
43600 UKM Bangi, Selangor.
E-mail: rs@ftsm.ukm.my[1]

ABSTRACT

This paper presents research done on developing an intelligent visual inspection system for automatic inspection of bottling production line. The objective of this research is to enhance on modeling, integrating, and implementation of intelligent visual inspection system in the process of quality control in industrial manufacturing. The system will inspect each individual product in real-time process. Levenberg-Marquardt backpropagation neural network has been applied for this system to differentiate between acceptable and unacceptable product, for example, the misplacement of a bottle cap. A simulation of the operation was attempted in the Robotics System Laboratory of Industrial Computing Department, Universiti Kebangsaan Malaysia. The experiments were done by using developed software (Real-TIVI) and hardware, i.e. conveyor belt, adjustable halogen lamp, personal computer, web camera (webcam) to capture the image, and plastic bottle as an object of visual inspection. From this experiment, the maximum regular speed of a rotating object was 106 rpm. The result shows the system is accurate to determine between acceptable (normal) and non-acceptable (no cap or misplace of cap) during the maximum speed when the distance between webcam and the object was at 15 cm.

Keywords: *Bottling Production Line, Neural Network, Quality Control, Visual Inspection*

1.0 INTRODUCTION

In industrial manufacturing, product inspection is an important step in the production process. Since product reliability is of utmost importance in most mass production facilities, 100 percent product inspection of all parts, sub-assemblies, and finished product is often being attempted. The most difficult task for inspection is inspecting by visual appearance. Visual inspection seeks to identify both functional and cosmetic defects. The visual inspection in most manufacturing process depends mainly on human operators whose performance is generally inadequate and variable. Advances in technology have resulted in better, cheaper image analysis equipment, which enable the use of affordable automated visual inspection system [1]. The major advantages of automatic operation are speed and diagnostic capabilities.

There has been extensive research in the area of visual inspection system. These activities include, among others, delicate electronics component manufacturing, quality textile production, metal product finishing, glass manufacturing, machine parts, printing products and granite quality inspection, integrated circuits (IC) manufacturing and many others [2-9]. Visual inspection technology improves productivity and quality management and provides a competitive advantage to industries that employ this technology.

The requirements for the design and development of a successful visual inspection system vary depending on the application domain and are related to the tasks to be accomplished, environment, speed, *etc*. For example, in visual inspection applications, the system must be able to differentiate between acceptable and unacceptable variations or defects in products, while in other applications, the system must enable users to solve guidance and alignment tasks or, verify measurement and assembly tasks.

1.1 PROBLEM STATEMENT

There exists no industrial vision system capable of handling all tasks in every application field. Only once the requirements of a particular application domain are specified, then appropriate decisions for the design and development of the application can be taken [10]. The first problem to solve in automated visual inspection task is to understand what kind of information the visual inspection system is to retrieve and how this translates into measurements or features at the images. The artificial intelligence techniques have been applied for visual inspection to differentiate between acceptable and unacceptable (reject) products. This paper presents a neural network application to recognise between accepted and rejected products in the real-time visual inspection system, especially in bottling production line.

2. RELATED WORK

2.1 IMAGE PROCESSING TOOLS

Image processing is usually performed within rectangles, circles or along lines and arcs. Image processing operators include filtering (*e.g.* smoothing, sharpening), edge detection, threshold, morphological operations, *etc*. Such operations can be used to improve image quality (*e.g.* reduce noise, improve contrast) and to enhance or separate certain image features (*e.g.* regions, edges) from the background. Image processing operations transform an input image to another image having the desired characteristics.

Image analysis is related to the extraction and measurement of image features and transforms these image features to numbers, vectors, character strings, *etc*. For example, lines, regions, characters, holes, rips, tears can be gauged or counted. The ultimate goal of image analysis is geared towards pattern recognition, *i.e.* the extraction of features that can be used by classifiers to recognise or classify objects [10]. A comparative chart of some of the most popular image processing tools and a proposed technology (Real-TIVI) is given in the Table 1.

Table 1 : Comparison of some of the most image processing tools and Real-TIVI

Software Package	Library	Visual Programming	Command Line	Dedicated Hardware	Source Code
IPL Lib	Yes	Yes	No	Yes	No
Sherlock32/MVTools	Yes	Yes	No	Yes	Yes
Image-Pro plus	Yes	Yes	No	No	No
OPTIMAS	Yes	Yes	No	No	No
WiT	Yes	Yes	Optional	Yes	No
PC Image Flow	Yes	Yes	Datacube	Yes	No
Intel Image Processing Lib.	Yes	No	MMX		No
HALCON	Yes	Yes	No	No	No
VISION97	Yes		Yes (frame grabber)	No	No
AdOculos	Yes	Yes	No		No
MIL	Yes	Yes	Matrox	Yes	No
Rhapsody	Yes	No	No	Yes	No
Real-TIVI	Yes	Yes	No	No	Yes

2.2 NEURAL NETWORK APPROACH

Neural networks are being successfully applied across a wide range of application domains in business, medicine, geology and physics to solve problems of prediction, classification and control. Neural networks are composed of a number of similar elementary processing units (neurons) connected together into a network [11]. Neurons are arranged in layers with the input data initialising the processing at the input layer. The processed data of each layer passes through the network towards the output layer. Neural networks adapt the weights of their neurons during a training period based on examples, often with a known desired solution (supervised training). After sufficient training, the neural network is able to relate the problem data to the appropriate solution spaces, *i.e.* generate input/output relations, thus offering a viable solution to a new problem through examples [12].

Neural networks are capable of handling a variety of image classification tasks in industrial vision environments, ranging from simple gauging to advanced classification problems, such as fault detection, optical character recognition, operation prediction, engine monitoring and control, *etc*. They can be used either as standalone techniques *e.g.* wood [13], seam [3], and surface roughness inspection [14], or in conjunction with other methods (*e.g.* solder joint inspection) [15]. Neural networks have been applied in all classes of quality inspection, namely dimensional quality [16,15,17], surface quality [3,14,18,19], structural quality [20] and operational quality [21]. They are applicable in almost every situation where a relationship between input and output parameters exists, even in cases where this relationship is very complex and cannot be expressed or handled by mathematical or other modeling means. Table 2 summarises features of the most commonly used neural network tools and the proposed system.

Table 2: Summarise the features of the most commonly used neural network tools

Package Name	Types of Neural Network	Industrial Applications	Package or Library	User Interface	Code Generation/ DLL
Brain Maker	Backpropagation		Software package	Graphical	C
Neuro Solution	Recurrent backpropagation, Backpropagation through time	Summaries of applications included	Software package	Graphical	C++/DLL
G2 NeurOnline	Backpropagation, RBF, Rho, Auto associative	Detailed petrochemical application included	Software package	Graphical object oriented	
SPRLIB ANNLIB	Backpropagation, pseudo-Newton, Levenberg-Marquardt, Conjugate gradient descent, BFGS, Kohonen maps		C/C++ Libraries		
ILIB			C/C++ Libraries		
Neural Connection	Multilayer perceptron, RBF, Kohonen, Bayesian		Software package	Graphical	
DataEngine, v.i,ADL	Multilayer perceptron, Kohonen, Feature map, Fuzzy, Kohonen network		Software package	Graphical	C++/DLL
Trajan 3.0	Offers all of the above architectures and training algorithms		Software package	Graphical	DLL
Real-TIVI	Backpropagation, Levenberg-Marquardt	Bottling machine, Modular Automation Production System (MAPS)	Libraries	Graphical	Visual C++

3.0 SYSTEM DESIGN AND MODELING

A software program for work for image processing in defect detection of real-time visual inspection system has been developed. The developed program is called Real-Time Intelligent Visual Inspection (Real-TIVI). The program will start at image acquisition and will go through a series of processes before the results can be output. Figure 1 shows the Real-TIVI software framework, which was developed. The process starts with image acquisition, where image will be captured, followed by preprocessing the captured image captured to reduce noises. Images are then enhanced to ease the analysing process. After the image have been enhanced, the edges of image are then determined. Lastly, according to the parameter of edges, the status of a bottle in the bottling process can be determined by using neural network and action can be taken to follow up this result [23].

3.1 CONFIGURATION SUBSYSTEM

The content of a configuration subsystem is video configuration module. Video configuration module used to configure the information *e.g.* to choose proper webcam device, image brightness, image colour, *etc*. This module is also used to configure the information such as image size and image resolution. In this system, image size is fixed *i.e.* 352 x 280 pixels, and the image input format is in grayscale.

3.2 IMAGE PROCESSING SUBSYSTEM

Image processing subsystem consists of some modules as shown in Figure 1, *i.e.*:

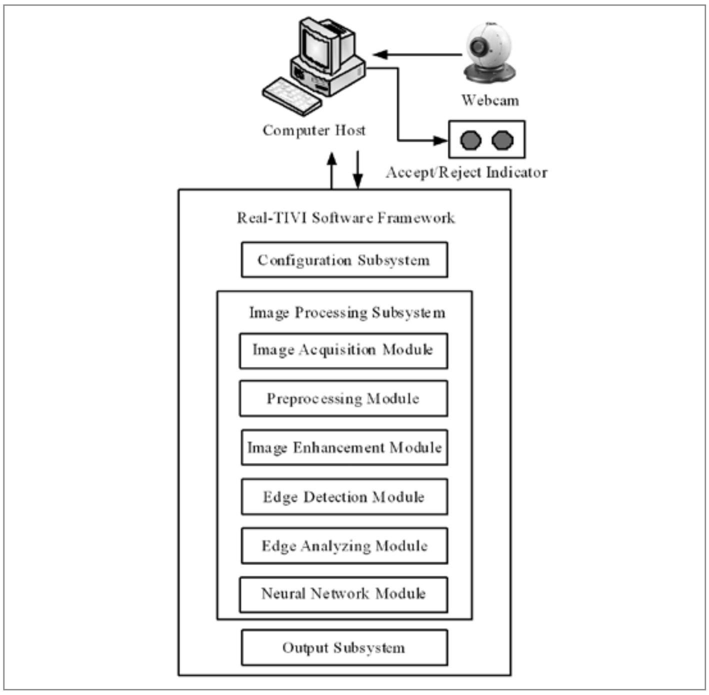

Figure 1 : Real-TIVI software framework

3.3 IMAGE ACQUISITION MODULE

In the development of a vision system, image acquisition is the first and the most important step. Any deficiency of the initial image can cause a major problem while processing and analysing the image. Hardware equipment plays a very important role in acquiring the image with sufficient contrast and sharp focusing. Microsoft Visual C++ has been chosen as the development tools. Using the tools mentioned, there are several ways to acquire a video stream from a webcam. The most common ways are DirectX, QuickCAM or video for windows (VFW). A real-time series of image can be acquired using the tools mentioned. Each individual image was stored and further analysing can be carried on there after.

3.4 PREPROCESSING MODULE

After the image has been captured from the first stage, each image will go through the preprocessing stage to eliminate noise inside the image, to enhance the result of the output. Imaging sensor including camera-like devices, rarely have evenly illuminated image. Even in the absence of vignette (which causes off-axis rays to be lost by collision with the lens mount at large apertures – typically *f*/2 or greater) image brightness falls off rapidly away from the axis of the imaging lens [24].

3.5 IMAGE ENHANCEMENT MODULE

After the noises have been removed at the preprocessing stage, the image is then processed to maximise the contrast to give optimum output for processing the edges [25]. In our case, since the colours of our target unit are in bright colour, whereas the background in dark colour, therefore to maximise the contrast of the image, a simple algorithm as below are being perform:

IF (P_{old} >threshold_value) THEN
$P_{new} = P_{old}$ + enhance_brightness
ELSE
$P_{new} = P_{old}$ - enhance_darkness
IF ($P_{new} > 255$) THEN $P_{new} = 255$
IF ($P_{new} < 0$) THEN $P_{new} = 0$

The first part of the algorithm is used to maximise the contrast of two regions and the edge in the image. If the pixel value in a pixel is more than a threshold value, certain value of brightness (enhance_brightness) is added to the pixel. Whereas, when it is less than the threshold value, certain value of darkness value (enhance_darkness) is subtract from the pixel. Since the value of a pixel range from 0 – 255, therefore, the second part of the algorithm is used to ensure the pixel value after calculation are within the range.

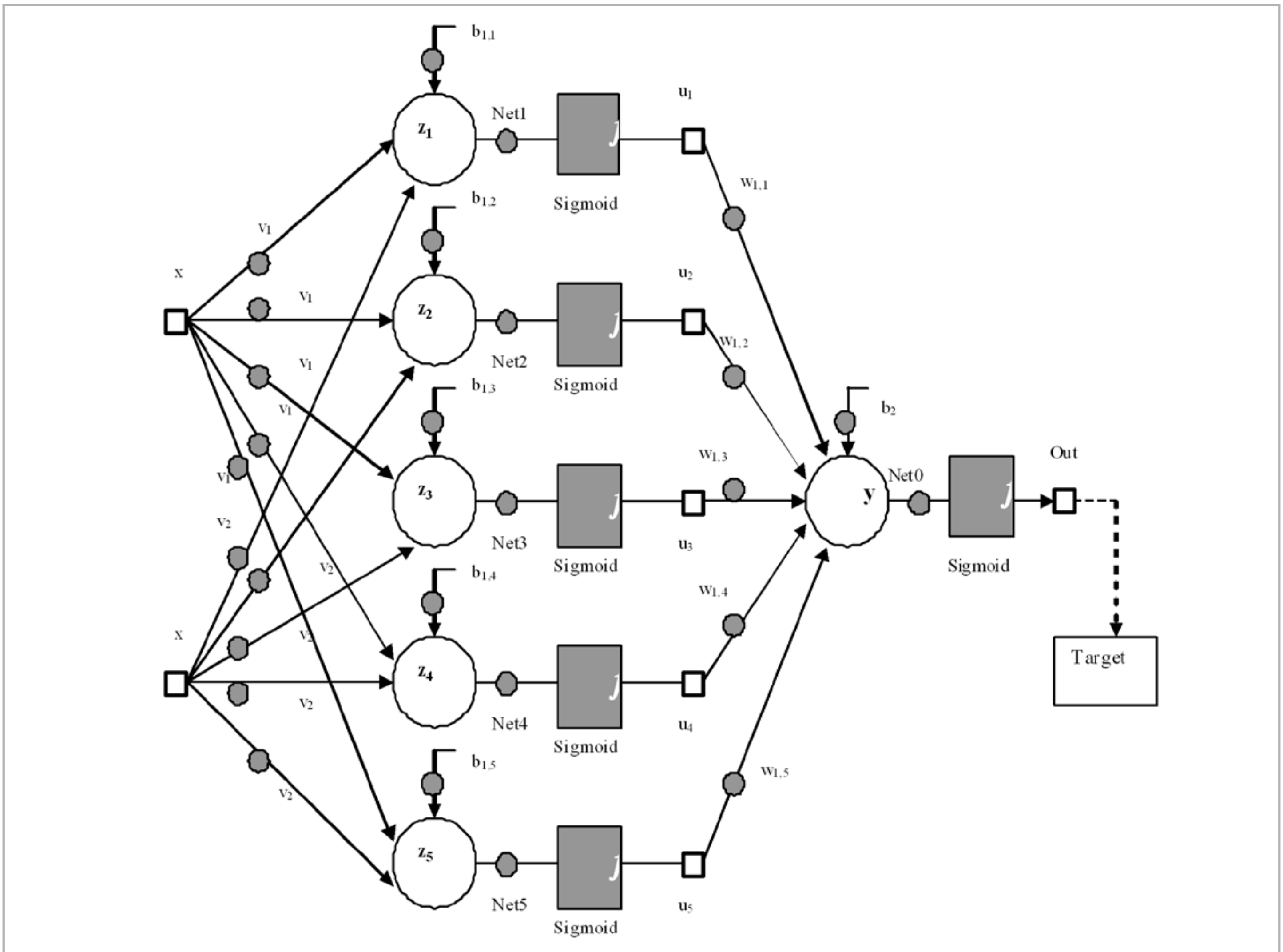

Figure 2 : Architecture of back-propagation neural network

3.6 EDGE DETECTION MODULE

Edge detection is the most important and basic part of image processing. The major edge detection methods are review from the signal processing and artificial intelligence point of view. Human vision system and computer vision shows that an object can be expressed by it edges, and many kinds of identification algorithm can be generalised easily from the edge expression. Edge can be define as the line of intersection between two surfaces, or in the software point of view, the notation of edge implies to the variation of brightness in a region of pixels. In this software, the edge detection methods using Vertical Sobel Operator with special modification for best suiting the application [26].

3.7 EDGE ANALYSING MODULE

After the edges have been detected from the edge detection stage, the parameter return from the edge detection result is being used for analysing and determining size of the object. The function is to define and measure height and width of the object under inspection.

3.8 NEURAL NETWORK MODULE

Levenberg-Marquardt back-propagation neural network has been chosen as support tool to determine between acceptable and unacceptable plastic bottle. The system is trained to get the best performance between target and output. After training, mathematical equation from back-propagation neural network model integrates the equation into Microsoft Visual C++ platform. This will recognise inspected bottle status in a real-time process. The analysis results are divided into options 'accept' or 'reject' product. Figure 2 shows the architecture of back-propagation neural network as a model in the system.

The steps and mathematical formulae below were used to get a model of back-propagation neural network in Matlab.

Each input unit (x_i, $i = 1,2,3,\ldots n$) receives a signal xi and send the signals to all of units in the next layer (hidden layer). Each unit of hidden layer (z_in_j, $j = 1,2,3,\ldots p$) will be added the weighted input signals:

$$z\_in_j = b_{1j} + \sum_{i=1}^{n} x_i . v_{ij} \tag{1}$$

The activation function to get an output signal of first layer is:

$$z_j = f\,(z\_in_j) \tag{2}$$

Thereafter, send the signals to all of units in the next (second) layer or output layer. This step will be done to the number of hidden layer. Each output unit (Y_k, $k = 1,2,3,\ldots m$) will add weighted output signal:

$$y\_in_k = b_{2k} + \sum z_i . w_{jk} \tag{3}$$

The activation function to get an output signal of second layer is:

$$y_k = f\,(y\_in_k) \tag{4}$$

3.9 OUTPUT SUBSYSTEM

After the object parameters recognized in previous stage, output subsystem provide an interface for the Real-TIVI software to interact. In output subsystem, output unit is a file consists of important information obtained from previous stage.

4.0 EXPERIMENTAL DESIGN

The experimental design and hardware for implementation of the Real-TIVI system is described in this section. Figure 3 shows hardware configuration for examination of the system. The system was developed and examined using some hardware below:

- Personal computer (PC) Intel Pentium III 996 MHz, with 128MB random access memory (RAM).
- Minicon Autoveyor as a conveyor belt, which can move 106 rpm.
- FlyCAM-USB 300 webcam, type of complementary metal oxide semiconductor (CMOS) with 352 × 288 pixels resolution.
- Adjustable halogen lamp as a lighting source with illumination 0 – 4270 lux.

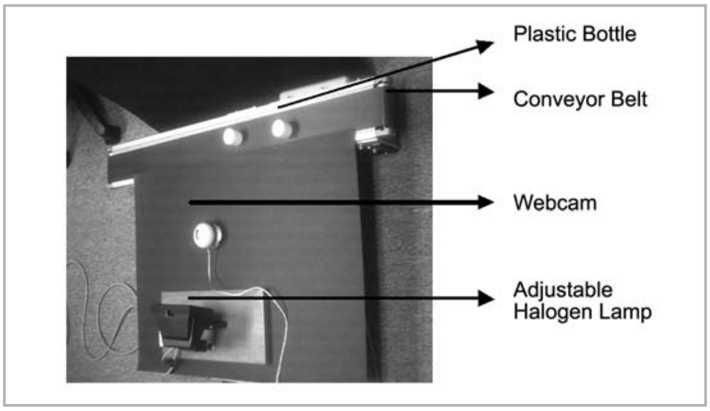

Figure 3: Hardware configuration

5.0 RESULTS

5.1 PRECISION OF THE IMAGE CONFIGURATION

Precision of the image configuration have been studied within the range of image capturing speed of 1 frame per second (*fps*), 5 *fps*, 10 *fps*, 15 *fps*, 20 *fps*, 25 *fps*, and 30 *fps*. 100 random samples were taken from each experiment. Figure 4 shows a graph of the percentage of image configuration precision with image capturing speeds 1 – 30 *fps*. The results are not satisfactory in the minimum speed of capturing an image (1 *fps*), and also occurred in the maximum speed (30 *fps*). Optimum value achieved in the speed of the image capturing 20 *fps*.

5.2 INFLUENCE OF THE VARIOUS MOVING SPEED

An experiment on various speed of moving object implemented to study the object dimension precision. The result shows a blur effect on an object with speed more than 106 rpm. It occur only 8.136 % compare with the static object. Figure 5 shows experiment result of the influence of various moving speed to object dimension measurement.

In various moving speed, the interval range between two objects differ too. This research results shows for speed that of 106 rpm and 103 rpm, the interval range are 17 cm and 16 cm, respectively. While for speed 86, 64 and 25 rotations per minute (rpm), interval range is 15 cm. Thus, for speed below 86 rpm, interval range is constant (15 cm).

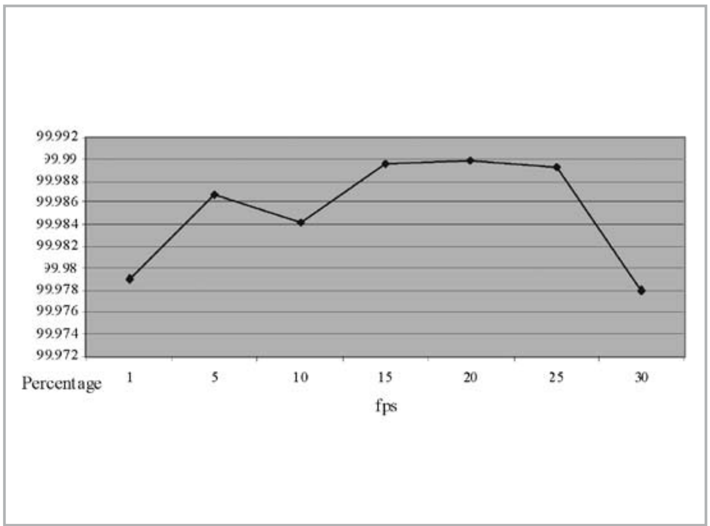

Figure 4 : Graph of the percentage of the image configuration

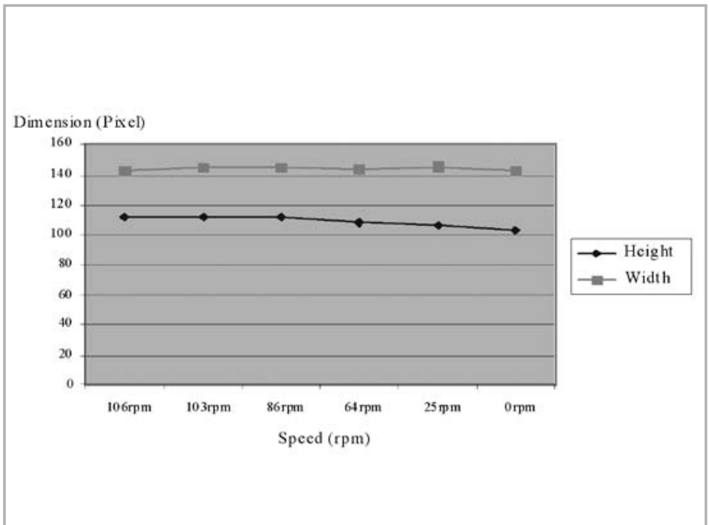

Figure 5 : Graph of the various moving speed to object dimension

5.3 DETECTION ACCURACY

The system examined by using a simulation of bottling machine. The results show that the system inspected bottle moving successfully. Overall, the accuracy of the system to determine between acceptable (normal) and unacceptable (no cap or misplace) is 95 %.

6.0 CONCLUSION

The experiments have been done to examine the Real-TIVI software in a simulation of bottling production line. The experiment result shows the detection accuracy of the system to determine acceptable and unacceptable product is 95 %. The maximum speed in the experiment is 106 rpm and interval range between two objects is 17 cm. It means the system accurately to detect the moving object at maximum speed of 106 rpm, with the distance between webcam and object is 15 cm. ■

NOTATION INDEXES AND SUBSCRIPTS

b_1	hidden layer bias
b_2	layer bias
f	focus
P_{old}	number of old pixel
P_{new}	number of new pixel
u	layer input signal
v_{ij}	input weighted
w	layer input weighted
x_i	input signal
y	layer neuron
y_in_k	number of input signal weighted (layer)
y_k	layer activation function
z	hidden layer neuron
z_in_j	number of input signal weighted
z_j	hidden layer activation function

REFERENCES

[1] Han, C., Mazouz, K. and Saravanan, N. "A printed circuit board inspection system using artificial neural network". In Proceedings of *Twenty-fifth Southeastern Symposium on System Theory*, IEEE, pp. 238–242. (1993)

[2] Sanz, J.L.C. and Petkovic, D. "Machine vision algorithm for automated inspection of thin-film disk heads". *IEEE Transaction on PAMI*, 10, pp. 830–848, (1988).

[3] Bahlmann, C., Heidemann, G. and Ritter, H. "Artificial neural networks for automated quality control of textile seams". *Pattern Recognition* , 32, pp. 1049–1060, (1999).

[4] Tucker, J.W. "Inside beverage can inspection: an application from start to finish". In Proceedings of the Vision'89 Conference, 1989.

[5] Novini, A.R. "Fundamentals of machine vision inspection in metal container glass manufacturing". In Proceedings of the *Vision'90 Conference*, 1990.

[6] Ker, J. and Kengskool, K. "An efficient method for inspecting machine parts by a fixtureless machine vision". In Proceedings of the *Vision'90 Conference*, 1990.

[7] Torres, T., Sebastian, J.M., Aracil, R., Jimenez, L.M. and Reinoso, O. "Automated real-time visual inspection system for high-resolution superimposed printings". *Image and Vision Computing*, 16, pp. 947-958, (1998).

[8] Shafarenko, L., Petrou, M. and Kittler, J. "Automatic watershed segmentation of randomly textured colour images". *IEEE Transactions on Image Processing*, 6, pp. 1530–1543, (1997).

[9] Li, H. and Lin, J.C. "Using fuzzy logic to detect dimple defects of polisted wafer surfaces". *IEEE Transactions on Industry Application*, 30, pp. 1530–1543, (1994).

[10] Malamas, E.N., Petrakis, E.G.M., Zervakis, M., Petit, L. and Legat, J.D. "A survey on industrial vision systems, applications and tools". *Image and Vision Computing*, 21, pp. 171–188, (2003).

[11] Haykin, S. *Neural Networks*, (Prentice-Hall, Englewood Cliffs, NJ), (1999).

[12] Bose, N.K. and Liang, P. *Neural Network Fundamentals with Graphs, Algorithms, and Applications*, (McGraw-Hill, New York) (1996).

[13] Drake, P.R. and Packianather, M.S. "A decision tree of neural networks for classifying images of wood veneer". *International Journal of Advanced Manufacturing Technology*, 14, pp. 280–285, (1998,).

[14] Tsai, D.M., Chen, J.J. and Chen, J.F. "A vision system for surface roughness assessment using neural networks". *International Journal of Advanced Manufacturing Technology*, 14, pp. 412–422, (1998).

[15] Kim, T.H., Cho, T.H., Moon, Y.S. and Park, S.H. "Visual inspection system for the classification of solder joints". *Pattern Recognition*, 32, pp. 565–575, (1999).

[16] Hou, T.H. and Pern, M.D. "A computer vision-based shape-classification system using image projection and neural network". *International Journal of Advanced Manufacturing Technology*, 15, pp. 843–850, (1999).

[17] Janannathan, S. "Automatic inspection of wave soldered joints using neural networks". *Journal of Manufacturing Systems*, 16, pp. 389–398, (1997).

[18] Packianather, P.R. and Park, P.R. "Neural networks for classifying images of wood veneer, part II". *International Journal of Advanced Manufacturing Technology*, 16, pp. 424–433, (2000).

[19] Khandogin, I., Kummert, A. and Maiwald, D. "DSP algorithms for the automatic inspection of fixing devices of railroad lines". *International Conference on Signal Processing Applications and Technology (ICSPAT'98)*, 1998.

[20] Moreira, M., Fiesler, E. and Pante, G. "Image classification for the quality control of watches". *Journal of Intelligent and Fuzzy Systems*, 7, pp. 151–158, (1999).

[21] Royce, W.W. "Managing the development of large software systems". In Proceedings of *IEEE WESCON*, pp. 1–9, (1970).

[22] Wayne, L.N. "The automated inspection of moving webs using machine vision". *Application of Machine Vision*, IEE Colloquium, pp. 3/1–3/8.

[23] Meng, C.K., Away, Y., Elias, N.F. and Prabuwono, A.S. "The real-time visual inspection system for bottling machine". Proceedings of *Second National Conference on Computer Graphics and Multimedia*, UTM-ACM SIGGRAPH, pp. 414–417, (2004).

[24] Que, D.S., Lu, L., Wang, H. and Song, X.D. "A fast edge detection method based on the correlation of moving images and its application". In Proceeding of *First Conference on Machine Learning and Cybernetics*, 4, pp. 2197–2200, (2002).

[25] Meng, C.K. "The design and implementation of a real-time vision system for object parameter extraction". M.Sc. Thesis, Department of Industrial Computing, National University of Malaysia, 2005.

[26] Kusumadewi, S. *Develop Artificial Neural Network using Matlab and Excel Link* (in Indonesia Language), (Graha Ilmu, Yogyakarta), (2004).

PROFILES

RIZA SULAIMAN

Riza Sulaiman is an Associate Professor in the Department of Industrial Computing, Faculty of Information Science and Technology, National University of Malaysia (Universiti Kebangsaan Malaysia, UKM). He holds a PhD in Mechanical Engineering, a MSc in Advanced Manufacturing Technology from the University of Portsmouth and B.Eng. (Hons) in Mechanical Engineering from the University of Sunderland, United Kingdom. His research area is in CADCAM, Graphics, Visualisation and Simulation. He is a member of the Institution of Mechanical Engineers (IMechE), United Kingdom and the Board of Engineers Malaysia (BEM). He can be contacted through email rs@ftsm.ukm.my

ANTON SATRIA PRABUWONO

Anton Satria Prabuwono is a PhD candidate in the Department of Industrial Computing, Faculty of Information Science and Technology, National University of Malaysia (Universiti Kebangsaan Malaysia, UKM). His area of studies include Image Processing, Pattern Recognition, Signal Processing, Visual C++ Programming, Software Engineering, Computer Vision, Machine Vision, Automated Visual Inspection, Neural Networks and Industrial Automation