FEATURE EXTRACTION METHODS FOR IC CHIP MARKING INSPECTION – A COMPARISON

R.Nagarajan Sazali Yaacob Paulraj Pandian M.Karthigayan
Mohamed Rizon

School of Mechatronics,
Northern Malaysia University College of Engineering, 01000 Kangar,
Malaysia

ABSTRACT

In this paper, an Industrial machine vision system incorporating Optical Character Recognition (OCR) is employed to inspect the marking on the Integrated Circuit (IC) Chips. This inspection is carried out while the ICs are coming out from the manufacturing line. A TSSOP-DGG type of IC package from Texas Instrument is used in the investigation. The IC chips are laser printed. This inspection system ensures that the laser printed marking on IC chips is proper. The inspection has to identify the print errors such as illegible character, missing characters and up side down printing. The vision inspection of the printed markings on the IC chip is carried out in three phases namely image preprocessing, feature extraction and classification. MATLAB platform and its toolboxes are used for designing the inspection processing technique. Projection profile and Moments are employed for feature extraction. A neural network is used as a classifier to detect the defectively marked IC chips coming from the manufacturing line. Four different neural network input structures are considered for optimizing the training speed in projection profile extraction method and two different moments is used for moments feature extraction method. The performance of projection profile is compared with that of few feature extraction methodologies. In neural network, feature extracted from moments and projection profile are used for inspection. Both feature extraction methods are compared in terms of marking inspection time

طرق استخراج الميزات الخاصة بتأشير الدوائر المتكاملة – دراسة مقارنة

أر. نكاراجان و سازلي يعقوب و باولراج بانديان
و كي كارثجيان و محمد رايزون

مدرسة الميكاترونك – كلية الهندسة – جامعة شمال ماليزيا

الخلاصة

يتناول البحث منظومة ضوئية لتمييز الحروف لفحص عمليات التأشير على الدوائر المتكاملة حيث تتم عملية الفحص عند خروج الدائرة المتكاملة من خط الانتاج .

خلال هذه الدراسة استخدمت دوائر متكاملة مصنعة من قبل شركة تكساس انسترومنت مطبوع عليها بواسطة الليزر . حيث يتم من خلال الكشف التأكد من جودة عملية الطبع . استخدم برنامج **MATLAB** لغرض عملية الفحص .

I. INTRODUCTION

Since 1950, Optical Character Recognition (OCR) has been very active in the application of automatic pattern recognition; now it is used to recognize the printed characters at high speed [1, 2]. AI techniques are widely used in recognition of both hard written and printed character [1-4]. The OCR is applied for business card recognition [5] where the manual input is optional; however, by scanning, the OCR is able to create an easier database. The document reading and analysis have reached an important place in certain markets. The application of OCR in the postal automation has followed into the banks and industrial inspection processes [6, 7].

IC chips play a vital role in electronic industries. Mass production of IC chips have brought down the price of the electronic products. Texas Instrument is one of the well-established IC chips manufacturing companies in the world market. In the Texas group, Texas Instrument, Malaysia, is one of the leading producers of IC chips in region of the world. The IC chips undergo many inspections and verifications to ensure a guaranteed quality. Quality control

of IC is performed by inspecting the placement of die, inspecting lead dimension, inspecting packaging and inspecting marking of symbols (IC number, year of manufacture and batch code etc). In this paper OCR is employed to check the markings of the IC chips especially, marking on the *Thin Shrink Small Outline Packages (TSSOP-DGG)* using neural network and fuzzy logic. Figure 1 illustrates various marking errors that can occur during production where as Figure 2 shows the error free marking.

II. INDUSTRIAL SETUP

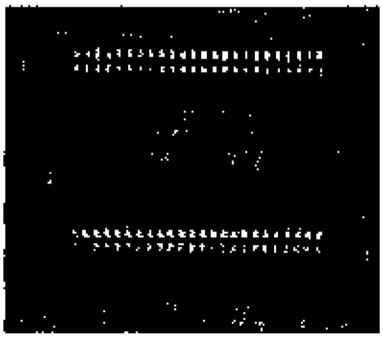
In Texas Instrument inspection set up, a digital video camera is used to capture the marking of IC chips coming out of manufacturing line one by one. These images are zoomed about 20 to 30 times in size. Figure 3 shows the dimensions of IC chip. The zooming index depends on the size of the IC chip. The earlier industrial version of inspection system checks about 7300 to 7500 IC chips per hour. IC chips undergo on fly inspection as shown in Figure 4 where OCR checks any defects in the markings on the ICs.

The software used in this inspection set up does not apply AI techniques. Instead, simple binary logic is employed in marking inspection. It has been found in Texas Instrument (M), the success rate of the inspection system is still to be improved. This paper investigates the application of AI techniques such as neural network in marking inspection of IC chips with an ultimate objective of modifying the existing software.

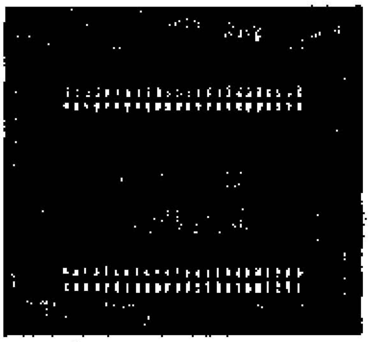
III. MARKING INSPECTION PROCESS

In Texas Instrument (M), the IC chips are lined up in a running conveyor for marking inspection. The marking on the IC chips are captured as a movie clip by a Charged Couple Device (CCD) non-standard camera. Images of the IC chips are extracted from the Moving Picture Expert Group (MPEG) format. The software then identifies whether the IC marking is of good equality. IC with non acceptable quality of marking is rejected without identifying the type of errors in marking. In this paper more systematic procedure is proposed for inspecting and also for classifying IC chip marking.

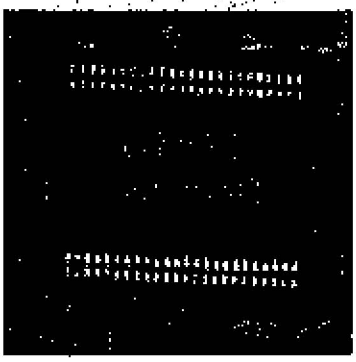
In this paper, the extracted images, thus captured, are made to undergo certain image processing techniques [6] namely preprocessing [1,7], feature extraction [8,9] and classification using AI techniques [10-13] These processing sequence are shown in Figure 5.



(a)Illegible



(b) Upside Down Print



(c) Missing Character

Figure 1. IC Marking in Illegible Character Group

Figure 2. An Error Free Marking

Figuer 3. Dimension of IC chips

Figure 4. IC chips in the conveyor

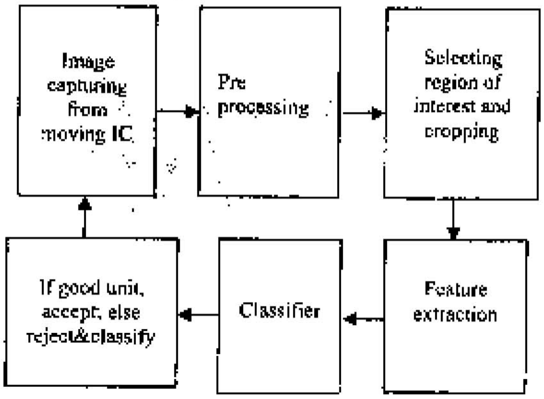


Figure 5. Image Processing Sequence

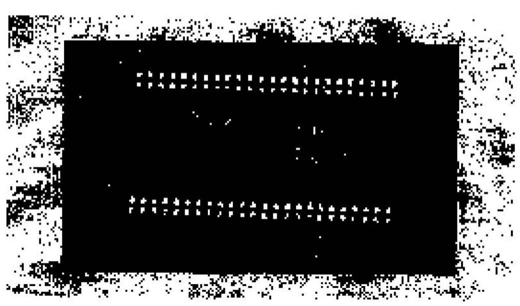


Figure 6. Grayscale Image

Preprocessing

The inspection begins with the extraction of single image from the moving picture. The extracted color image is converted into a 256 gray scale image as shown in Figure 6. Then, the gray scale image is the binarized with a suitable threshold value as shown in Figure 7. The binarization converts the image pixels into '0' (black) and '1' (white). The threshold value differentiates the foreground and background of the given image. Threshold value is selected after performing a set of experiments using MATLAB. Region of Interest (ROI) specified by the production inspector is shown in Figure 8. If the ROI is not specified, a search forthe ROI from the extracted full image can be performed but it is time consuming. From the specified ROI area the sum of the white pixels of each row and those of each column are determined. Cropping marking from ROI is done by summing row and column of the ROI

The preprocessed image is cropped based on the presence of white pixel in the ROI area. The ROI white pixel is summed in row and column wise. The row sum is taken into consideration to split the two rows as shown in Figure 9 Then the column sum of each row creates the required ROI of each character

Figure 7. Binarized image

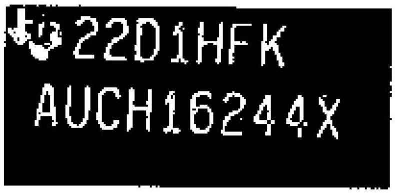


Figure 8. ROI Area of binarized image

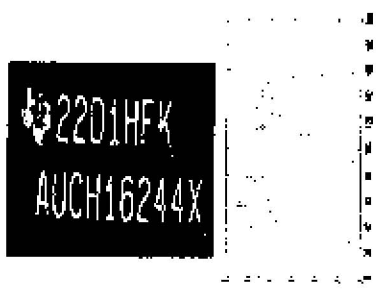


Figure 9. Row sum for Separating Two Rows

Feature Extraction Methods

In this paper four different feature extraction methods are discussed for IC marking inspection and their performances are compared. The methods are Projection Profile, Moments, Zoning and contour profile

Projection Profile:

The row-sum (P_h) and column-sum (P_v) features of each character are displayed as projection profiles. Horizontal projection (row sum) and vertical projection (column sum) as shown in Figure 10, are extracted for the each character image. Let S (n, m) be a binary image of n rows and m columns. Then,

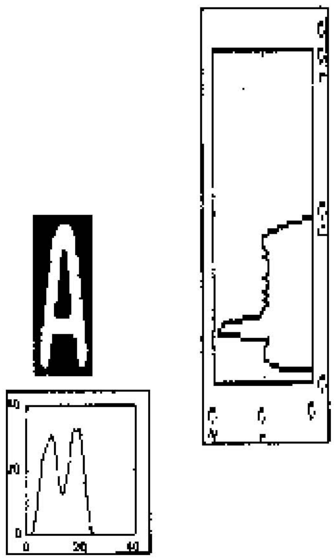


Figure 10. Projection Profile for Acceptable IC image "A"

Vertical Profile: Sum of white pixels of each column perpendicular to the x-axis; this is represented by the vector P_v of size n as defined by [8]:

$$P_v[i] = \sum_{j=1}^{n} S[i,j], \qquad i = 1,2,3,\ldots,m \qquad (1)$$

Horizontal Profile: Sum of white pixels of each row perpendicular to the y-axis; this is represented by the vector P_h of size m

$$P_h[j] = \sum_{i=1}^{m} S[i,j], \qquad j = 1,2,3,\ldots,n \qquad (2)$$

Profile projection of an acceptable image character "A" and that of an illegible character "A" are shown in Figure 10 and Figure 11 respectively to differentiate the acceptable and illegible characters

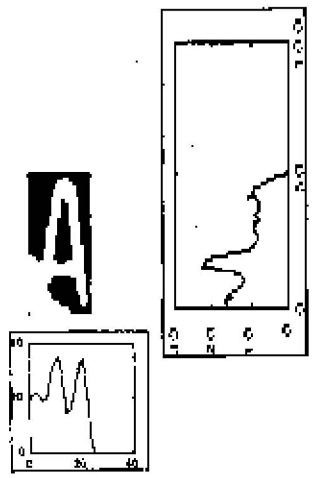


Figure 11. Projection Profile for Illegible Image "A"

Moments

Moments have been used in recognizing the printed and hand written characters and are also widely used in pattern recognition. There are different types of moments used for recognition of characters; here Central moments of binary image for each column of the image orders are obtained. The image orders can be 2 or 3. In the order 1, moments values are zero. On the other hand, orders more than 3 produces smaller and smaller moments values that cannot be generally used for feature extraction.

Let f(x,y) be an image. Then, the 2D continuous function of the moment of order (p+q), M_{pq}, is defined as [6].

$$M_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x^p y^q f(x,y)dxdy \qquad (3)$$

The central moment , μ_{pq}, of f(x,y) is defined as is [6].

$$\mu_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}(x-\bar{x})^p(y-\bar{y})^q f(x,y)dxdy \qquad (4)$$

where $\bar{x} = \frac{M_{10}}{M_{00}}$ and $\bar{y} = \frac{M_{01}}{M_{00}}$.

If f(x,y) is a digital image then equation (2) becomes

$$\mu_{pq} = \sum_x \sum_y (x-\bar{x})^p(y-\bar{y})^q f(x,y) \qquad (5)$$

where p and q are nonnegative integer values.

The moment values are considered for extracting the feature. This method takes the central moments value of each column of the binary image. D_i, i =1,..,k is the central moment value of each column from 0 to k of the marking. D_i can be computed using Equation (5). In this work k is taken as 25.

Zoning

Zoning feature extraction method has been performed. The term "zone" implies a segmentation of more complex spatial realities. It has a high degree of similarity with the term "region". Zoned region of the image will be same through out image processing. Zoning is widely used in commercial OCR system. The recognizer uses information about the word shape. As this information is strongly related to word zoning [14]. It was designed to recognize the machine printed characters. A two level zoning is shown in Figure. 12. Here, the image is separated into two portions as top and bottom zones. The presence of white pixels in each zone is summed up. Zoning is applied to marking but this has a limitation. The sum of each zone, some

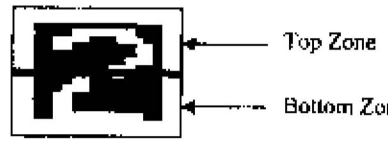


Figure 12. Two Level Zoning for Character "2"

times, will be the same value even though it is illegible. But by taking both zone sum values, the marking can be classified. These sums of each zone can be taken as features of top and bottom zones.

Contour Profile

A point operation can add lines to an image. One can also accomplish thresholding with a point operation that divides an image into disjoint regions on the basis of gray level. This is useful for defining boundaries. This is called contour profile. Contour profile is one of the fundamental techniques used for object identification in the field of pattern recognition [15]. The contour projection for character '2' is presented in Figure 13. The outer vertical and horizontal profiles of black pixels in white background are computed. These profiles are unique for any alphanumeric characters and have been used as features [9].

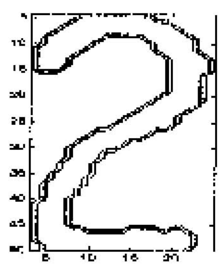


Figure 13. Contour Image for "2"

IV. FEATURE EXTRACTION PROCESSING TIME

In addition to projection profile, other feature extraction methods such as moments, contour profile and zoning [9] are considered for determining the processing time. Processing time is important in real-time industrial inspection of marking of IC. Among these four features extraction methods, the processing by projection profile requires less time compared to other three methods. The moments processing is higher but nearer to profile projection processing time, so we have considered moments also as feature. Table 1 illustrates the effectiveness of projection profile and moments as the methodology feature extraction.

V. MARKING INSPECTION USING NEURAL NETWORK

Recently, there has been a high level of interest in applying artificial neural network for solving many problems [10-13]. The application of neural network gives easier solution to complex problems such as character recognition. Here, neural network is employed to classify the character by the extracted features (row and column profiles and moments of different order). A feed forward neural network is proposed to identify acceptable or to classify the various types of errors in marking as shown in Figure 14 and Figure 15 respectively. The moments value for two different orders such order 2 and order 3 and projection profile data (extracted features) are considered for training. The extracted features are taken as input to the network model.

The network consists of 4-output neurons and 1- hidden layer of 20 neurons. The output of the neural network cannot be binary since the weight updating algorithm and activations are analog. However, each output can be made to converge either towards zero or towards one. An additional analog-digital 'modifier' is included at the output in orders to get binary output data. The binary output neuron gives the classification as shown in Figure 14 and Figure 15. In order to determine the output input size of the neural network in term of minimizing the time; the network is trained with different input sizes such as 28 neurons (14 rows + 14 columns), 38 neurons (25 rows + 13 columns), 75 neurons (50 rows + 25 columns) and 94 neurons (63 rows + 31 columns) and It has been trained for moments order 2 and 3. Zooming control of camera can offer these character size in terms of pixels

The networks with each of the above mentioned data are trained using a backpropagation training algorithm. The learning parameters for projection profile

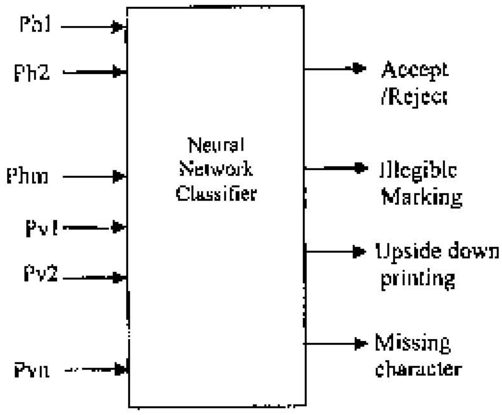


Figure 14. Neural Network Model for Projection Profile

and moments are chosen as given in Table 2 and Table 3 respectively: The cumulative errors versus epoch characteristics of the training for projection profile are shown in Figure 16 - Figure 19 and for moments (order2 and order 3) are shown in Figure 20 and, Figure 21.

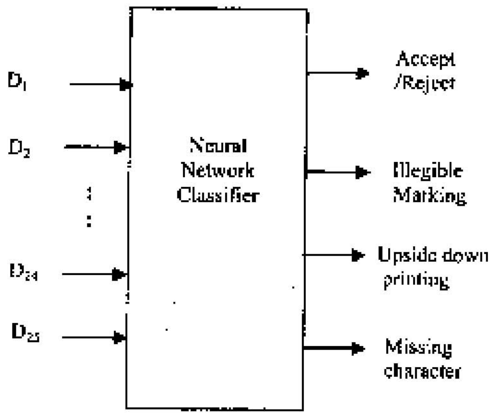


Figure. 15 Neural network model for moments

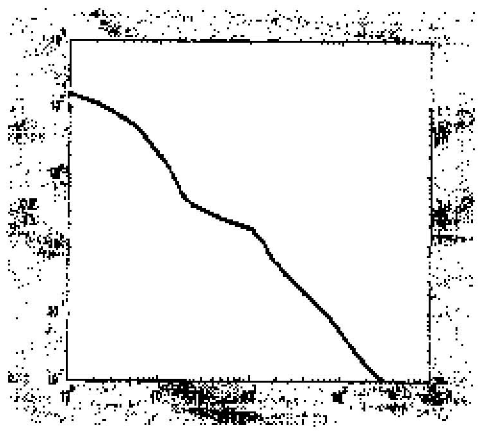


Figure.16 Cumulative Error (C.E) versus Epoch Plot for 28 input for Neural Network Classifier

Table 1 Processing Time for Each Methodology

Methodology Feature Extraction	Processing Activities	Processing Time
Projection profile	Reading image, gray scale, binary image, cropping the image, taking projection profile to the cropped, Taking row sum and column sum and writing it to a file.	0.1900 - 0.2100 sec
Moments	Reading image, gray scale, binary image, cropping the image, taking moments to the cropped and writing it to a file.	0.2610 - 0.2710 sec
Zoning	Reading image, gray scale, binary image, cropping the image, separating the cropped marking into 2 zones, Taking sum of two zones separately and writing it to a file.	0.3310 - 0.3600 sec
Contour Profile	Reading image, gray scale, binary image, cropping the image, taking contour to the cropped, take row sum and column sum and writing it to a file.	1.0620 - 1.2020 sec

The networks with each of the above listed input sizes are trained using a backpropagation training algorithm. The learning parameters are chosen as in Table 1 and Table 2: These figures indicate a reasonable convergence characteristic. The time and epoch details are given in Table.1 and Table 2.

The Training is carried out for 12 times in each case by reshuffling input data with the same network model. Table 2 and table

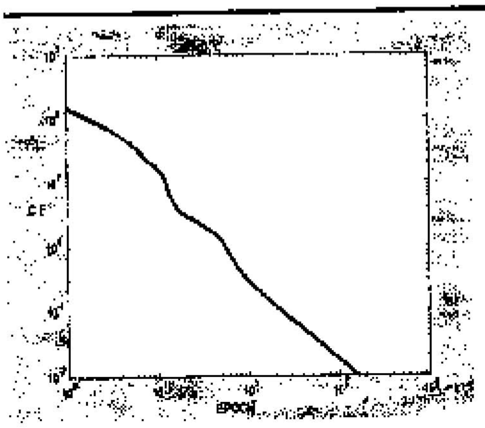


Figure.17 Cumulative Error (C.E) versus Epoch Plot for 38 input for Neural Network Classifier

Figure 19. Cumulative Error (C.E) versus Epoch Plot for 94 input for Neural Network Classifier

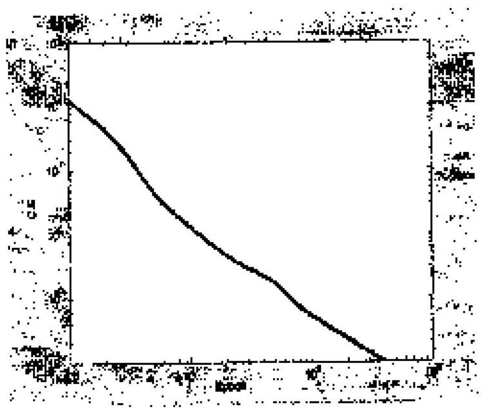


Figure 18. Cumulative Error (C.E) versus Epoch Plot for 75 input for Neural Network Classifier

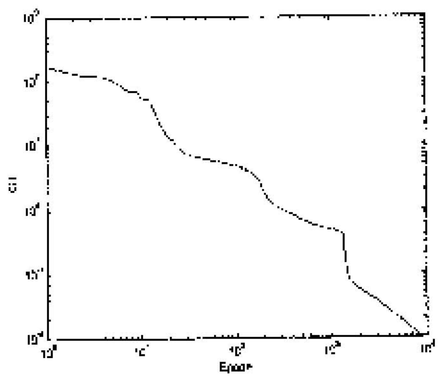


Fig. 20 Cumulative error versus epoch plot for moments second order

3 indicate the maximum and minimum epoch and duration of convergence in seconds within 12 trials. 'Ave' is the mean value among all 12 trials.

The cumulative errors are made to converge to the training and testing tolerance levels. Among the four different input training, the optimum input size for a fast processing is determined as (50+25) as shown in Figure 22.

VI. CONCLUSION

AI techniques such as neural network are applied to marking inspection of IC chips. The preprocessing and two feature extraction methods have been suggested for this inspection. A feed forward neural network has been developed for training and testing the samples of marking. have been involved in this training. Trainings are carried out for moments order 2, moments order 3 and projection profile using backpropagation algorithm. Comparing moments order 2 and order 3, order 3 is faster for training. Among these training, projection profile is found to be faster in training. The projection profile method of marking classification can be used for real time application such as marking inspection whe n the IC chips are coming out of manu facturing line in semiconductor industries Processing time for different feature extraction has been carried out. Among feature extraction projection profile and moments are found to be faster than other two. Two different feature extraction (moments and projection profile) method

Table 2 Data Trained for Different Input Sizes of Neural Network

BackPropagation Algorithm No. of training of each input size: 12 times
Output neurons: 4 Hidden neurons: 20 Learning rate: 0.25
Activation function: $(1/(1+e^{-x}))$ Momentum factor: 0.87 No. of samples tested : 664 Training tolerance: 0.01 No. of trained samples: 400
Testing tolerance: 0.1

S.No	Input Size	Training Epoch	No. of Epoch			Time(Sec)			Misclassification
			Min	Max	Ave	Min	Max	Ave	
1	28	4500	4400	3165	3860.5	186	132	162.2	0
2	38	2200	2201	1633	1961	116	87	103.6	0
3	**75**	**2000**	**1012**	**724**	**896.6**	**86**	**62**	**73.8**	**0**
4	94	2000	1087	654	821.3	112	67	84.7	0

Table 3. Data Trained for Two Different Moments order for Neural Network

BackPropagation Algorithm Training done: 12 times Testing tolerance: 0.05
Output neurons: 4 Hidden neurons: 20 Learning rate: 0.2
Activation function: $(1/(1+e^{-x}))$ Momentum factor: 0.87 No. of samples: 664
Training tolerance: 0.01 No. of trained samples: 400

S.No	Order	Training Epoch	No. of Epoch			Time(Sec)			Misclassification
			Min	Max	Ave	Min	Max	Ave	
1	2	16000	8414	16567	9254	316	624	401	0

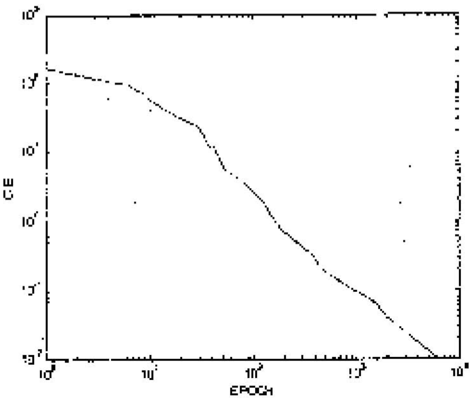


Fig. 21: Cumulative error versus epoch plot for moments third order

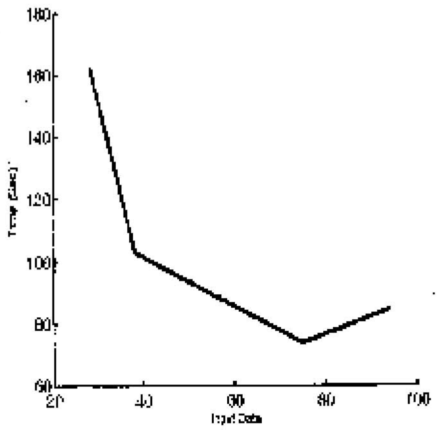


Figure 22. Input Data and Time for Convergence

ACKNOWLEDGEMENT

The authors wish to acknowledge the funding of UMS IRPA grant No: 04-02-10-0024-PR0001 through UTM in carrying out this research.

REFERENCE

1) Mantas. J, " An Overview of Character Recognition Methodologies", *Pattern Recognition*, V01.19, No.6, pp.425-430,1986.
2) Shunji Mori, Ching Y. Suen and Kazuhiko Yamamoto, "Historical Review of OCR Research and Development", *Proceedings of the IEEE*, vol80 (7), July 1992.
3) Adnan Amin, Humoud Al-Sadoun and Stephen Fischer, " Hand-Printed Arabic Character Recognition System Using An Neural Network", *Pattern recognition*, vol.29(4), pp 663-675, 1996.
4) Nagarajan.R, Sazali Yaacob, Paulraj Pandian, Karthigayan.M, Shamsudin Hj Amin and Marzuki Khalid, "A Neural Network Application for Inspecting The Marking of Symbols on Integrated Circuit Chips", *The Seventh Triennial AEESEAP Conference Enhancing Engineering Education and Training*, University of Malaya, Kuala Lumpur, Malaysia, 8 – 9 December,2003.
5) Wumo Pan, Jianming Jin, Guangshun Shi and Q.R. Wang, "A System for Automatic Chinese Business Card Recognition"*Proceedings of the Sixth International Conference on Document Analysis and recognition, IEEE Computer society*, pp.577 – 581, September, 2001.
6) Rafael C. Gonzalez and Richard E. Woods, *Digital Image processing*, Addison-Wesley Longman, Inc, September 1993.
7) Mauritius Seeger and Christopher Dance, "Binarising Camera Images for OCR", *Document Analysis and Recognition, Proceedings. Sixth International Conference*, Pages:54 - 58, September 2001.
8) Abdelwahab Zramdini and Rolf Ingold "Optical Font Recognition From Projection Profiles" *Electronic*

Publishing, Vol.6(3), pp-249-260 September 1993.

9) Oivind Due Trier , Anil K.Jain and Torfinn Taxt, "Feature Extraction Methods for Character Recognition- A Survey", *Pattern Recognition*, Vol.29, No.4, pp.641-662,1996.

10) Sivanandam. S.N and Paulraj.M, "Introduction to Artificial Neural Network", Vikas Publishing House, Chennai, 2003.

11) Laurene Fausett, Fundamentals *of Neural Networks*, Prentice Hall Publishing, 1994.

12) Bernard Widrow and Michael A. Lehr, "30 years of Adaptive Neural Network Preceptron, Madeline and Backpropagation", *Proceedings from IEEE*, vol. 78(9), pp 1415-1442, Sept 1990.

13) Clifford Lau, *Neural Networks-Theoretical Foundation and analysis*, IEEE press, New York, 1992.

14) Powalka. R.K, Sherkat. N and Whitrow. R. J. 1995. Zoning Invariant Wholistic Recognizer for Hybrid Recognition of Handwriting. Proceedings of Third International Conference on Document Analysis and Recognition. Vol.1.

15) Adrian Ciobanu, Hamid Shahbazkia and Hans Du Buf 2000. "Contour Profiling by Dynamic Ellipse Fitting", *Proceedings of 15th International Conference on Pattern Recognition*. vol. 3, pp. 750-753, 2000.