

A real time marking inspection scheme for semiconductor industries

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Abstract In this paper, a real time industrial machine vision system incorporating optical character recognition (OCR) is employed to inspect markings on 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 Instruments is used in the investigation. The IC chip markings are laser printed. This inspection system tests whether the laser printed marking on IC chips is proper. The inspection has to identify print errors such as illegible characters, missing characters and upside 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. The MATLAB platform and its toolboxes are used for designing the inspection processing technique. Speed of the marking inspection is mostly dependent on the effectiveness of the feature extraction technique. The performances of four feature extraction techniques are compared in terms of their respective speed. The feature extracted data are used in a neural network for classifying the marking errors. A suggestion to optimize the number of input neurons of the neural network for a fast classification is also presented.

Keywords IC chip marking inspection · Machine vision · Projection profile · Neural network

1 Introduction

Since 1950, the optical character recognition (OCR) has been very active in the application of automatic pattern recognition; now it is used to recognize printed characters at high speed [1, 2]. Artificial Intelligence techniques are widely used in recognition of both handwritten and printed characters [1–4]. The OCR is applied for business card recognition [5] where the manual input is optional. By scanning, the OCR is able to create a database more easily. Document reading and analysis have reached an important place in certain markets. The OCR previously used in postal automation is now being applied in banks and industrial inspection processes [6, 7].

IC chips play a vital role in electronic industries. Agile manufacturing of IC chips have brought down the price of electronic products. 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 the printed markings. In this paper, a methodology of inspection and verification of marking quality of IC chips as they are coming through the production conveyor system is proposed. The proposed real time inspection uses an OCR assisted with neural network. Four different input structures are considered for neural network in optimizing the inspection speed. Markings on thin shrink small outline packages (TSSOP-DGG) manufactured by Texas Instruments (Malaysia) are used as examples. Figure 1 illustrates various marking errors that can occur during production, whereas Fig. 2 shows the error-free marking.

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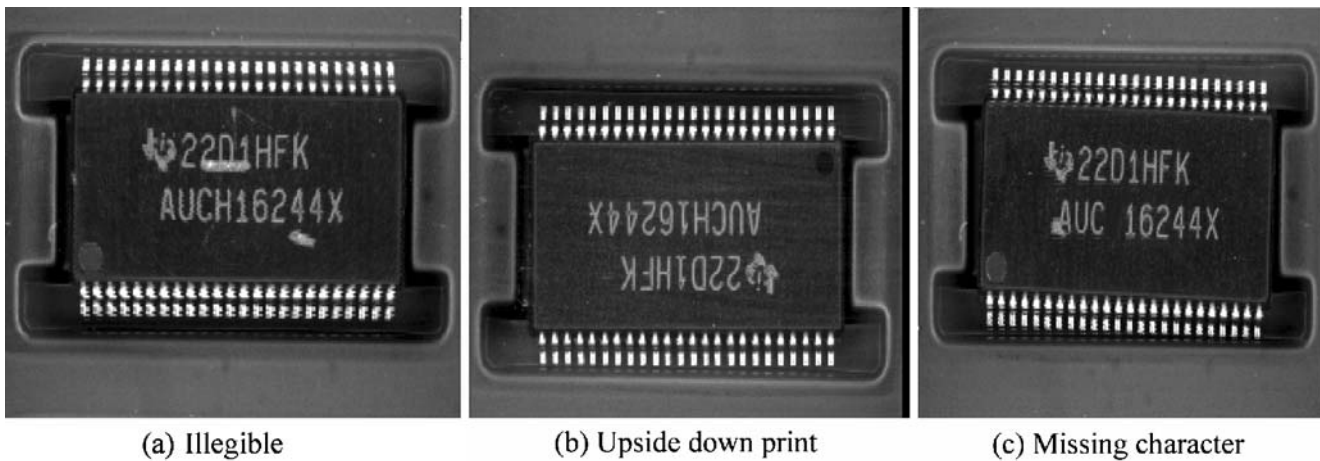


Fig. 1 IC marking errors. **a** Illegible. **b** Upside down print. **c** Missing character

2 Industrial setup

In an IC marking inspection set-up as shown in Fig. 3, a digital video camera is used to capture the markings on IC chips coming out of a manufacturing line one by one. These images are zoomed about 20 to 30 times. Figure 4 shows the dimensions of the IC chip and its marking. The zooming index depends on the size of the IC markings. A typical industrial version of an inspection system has to check about 7,300–7,500 IC chips per hour. IC chips have to undergo inspection as they are coming in the conveyor as shown in Fig. 5. The conveyor holds the chips in place and does not allow any positional changes. The distance between the camera and the chip is fixed. For this reason the problems of rotation and scaling of images do not occur.

Usually, the marking and inspection software used in conventional and existing inspection set-up does not adopt any AI techniques. A simple binary logic is employed in such a case [8]. This paper investigates the application of an AI technique such as neural network in the marking

inspection of IC chips with an ultimate objective of minimizing the inspection time.

3 Marking inspection process

In a manufacturing system, the IC chips are lined up in a running conveyor for marking inspection. Markings 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 quality. An IC with non-acceptable marking quality is usually rejected without identifying the type of error in marking. In this paper, a new proposal is suggested for classifying errors in cases where the marking is not of acceptable quality.

The images, captured through the camera system, are made to undergo certain image processing techniques [6], namely, preprocessing [1, 7], feature extraction [9–13] and classification [14–18]. The processing sequence is as shown in Fig. 6.

3.1 Preprocessing

Inspection begins with the extraction of a single image from the moving picture. The extracted color image is converted into a 256 gray scaled monochrome image, typically as shown in Fig. 2. Then, the gray scale image is binarized using a suitable threshold value. The binarized image is as shown in Fig. 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. A suitable threshold value is selected after performing a set of experiments using MATLAB. The region of interest (ROI) as specified by the factory

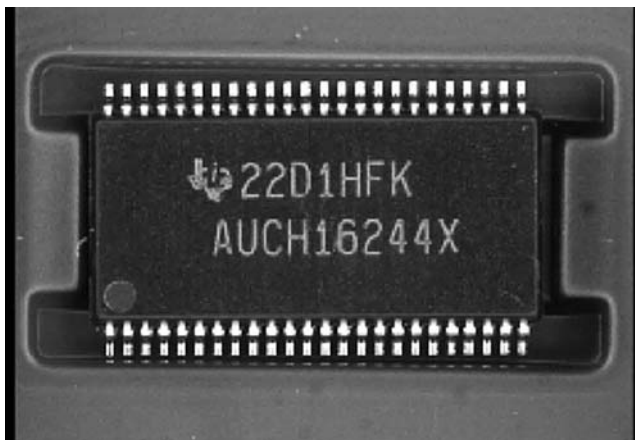
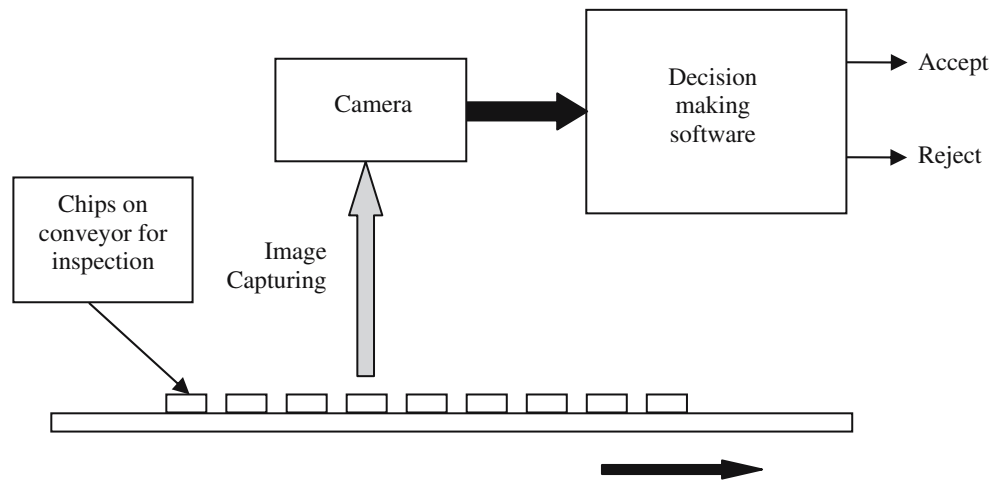


Fig. 2 An error-free marking

Fig. 3 Schematic diagram of marking inspection setup at Texas Instruments



production inspector is given in Fig. 8. If the ROI is not specified, a search for the ROI from the extracted full image can be performed. From the specified ROI, the sum of the white pixels of each row (as shown in Fig. 9) can determine the line of row separation; then cropping each marking in a row through column sum of white pixels determines the line of character separation.

3.2 Feature extraction

Quality of marking is tested by extracting certain features of the marked characters. In character recognition, four feature extraction methods are being used in the literature [9–13]. These methods are explained in this section with the context of IC chip marking. The methods are projection profile, moment, zoning and contour profile.

3.3 Projection profile

This feature extraction method involves the row sum and column sum of white pixels [9]. The pattern of row-sum (P_h) and the pattern of column-sum (P_v) of white pixels define the feature of each character. This is known as

projection profile. These patterns are extracted for each character image. Let $S(n, m)$ represent a binary image of n rows and m columns. Then, the vertical profile is defined as the sum of white pixels of each column perpendicular to the x -axis; thus, it is represented by the vector P_v of size m as defined by

$$P_{v[j]} = \sum_{i=1}^n s[i, j] \quad j = 1, 2, 3, \dots, m \quad (1)$$

The horizontal profile is the sum of white pixels of each row perpendicular to the y -axis; thus, it is represented by the vector P_h of size n , where

$$P_{h[i]} = \sum_{j=1}^m s[i, j] \quad i = 1, 2, 3, \dots, n \quad (2)$$

Then, the projection profile is defined as $P = \{P_v, P_h\}$. Projection profile of an error free image character “A” and that of an illegible character “A” are shown in Figs. 10 and 11,

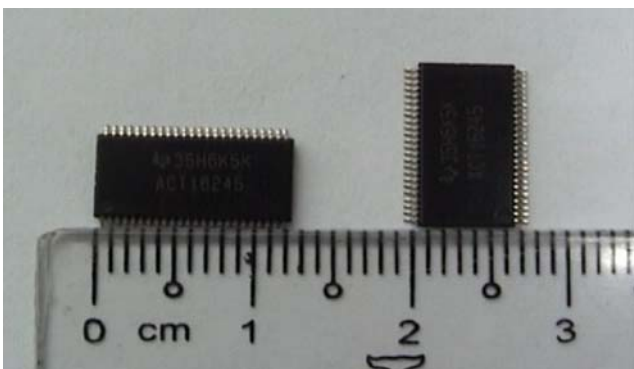


Fig. 4 Dimensions of IC chips

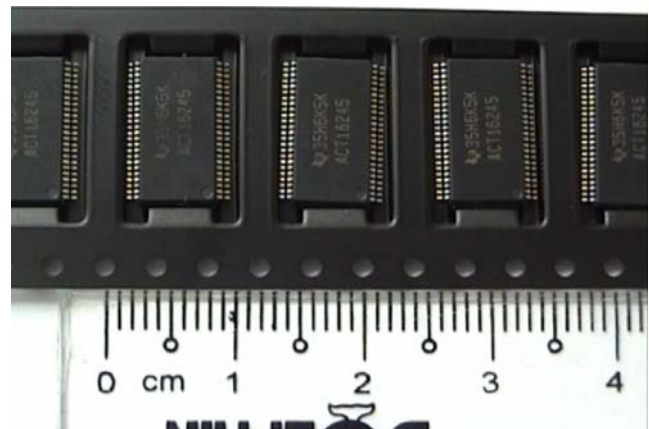


Fig. 5 IC chips in the conveyor

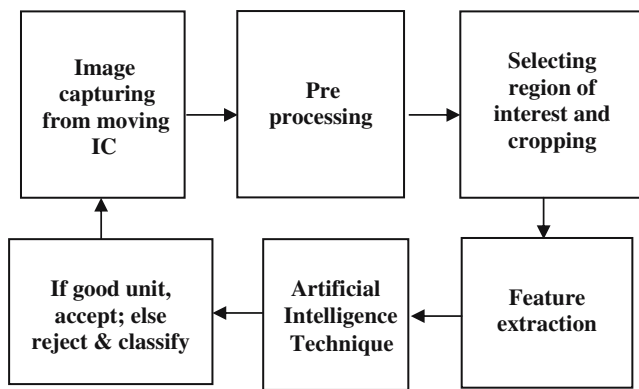


Fig. 6 Image processing sequence

respectively, to differentiate the acceptable and non acceptable features.

3.4 Zoning

The term “zone” implies a segmentation of more complex spatial realities. It has a high degree of similarity with the term “region”. The zoned region of an image will be maintained throughout image processing. Zoning is widely used in commercial OCR systems. The recognizer uses information about the word shape. As this information is strongly related to word zoning [10], it was designed to recognize the machine printed characters. It is found that feature extraction through zoning with more than two zones increases the computation time. Hence, we follow a two-level zoning for extracting features of a printed character. This two-level zoning is as shown in Fig. 12. Here, the image is separated into two portions such as top and bottom zones. The total number of white pixels in each zone is determined. The feature Z of a character is thus defined as $Z=\{t,b\}$ where t and b are total white pixels of top and bottom zones, respectively. Zoning can be applied to marking inspection but this has a limitation. Occasionally the sum of white pixels in a zone can be the same value as the error free character even though the character is

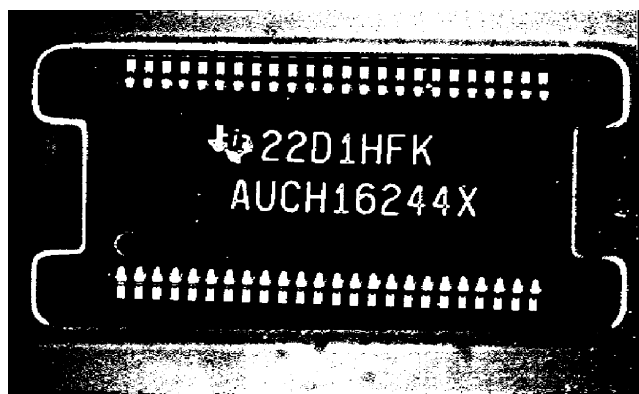
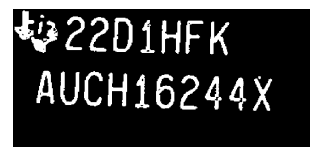


Fig. 7 Binarized image

Fig. 8 ROI of binarized image



illegible. However, by considering both zone sum values collectively, the marking can be classified.

3.5 Moments

Moments have been used in recognizing printed and handwritten characters and are also widely used in pattern recognition [11]. There are different types of moments used for recognition of characters including zernike moments, central moments and moments invariants. Several desirable properties that can be derived from moments are also applicable to shape analysis. Central moments processing time is faster than zernike moments and moments invariant [13]. Central moments of the binary image for each column of the image orders can be obtained. The image orders can be 2 or 3. In the order 1, moment values are zero. On the other hand, orders more than 3 produce smaller and smaller moment values that cannot be generally useful 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]:

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

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

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

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

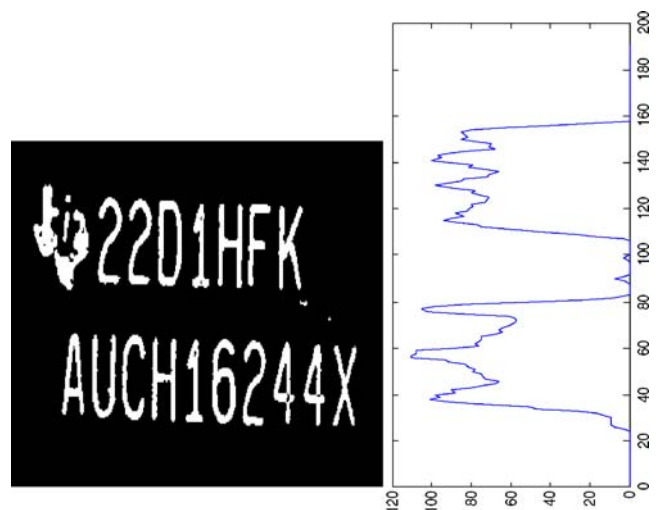
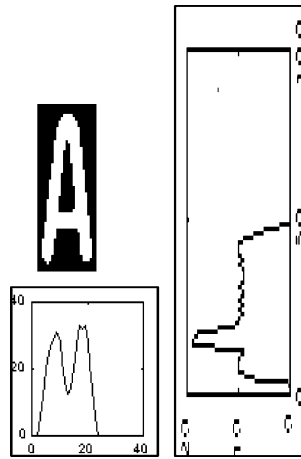


Fig. 9 Row sum for separating a row

Fig. 10 Projection profile for an acceptable image “A”



If $f(x,y)$ is a digital image then Eq. 4 becomes

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

where p and q are nonnegative integer values. The moment values can be considered as extracted features.

3.6 Contour profile

Contour profile is one of the fundamental techniques used for object identification in the field of pattern recognition [12]. Figure 13 represents a cropped binary image of character 2. Its contour projection is presented in Fig. 14. The outer vertical and horizontal profiles of black pixels in white background are computed. These profiles are unique for any alphanumeric character [13]. Contour profile can be used here as the feature of the character in IC chip marking.

4 Feature extraction processing time

All four feature extraction methods are to be compared for their individual feature extraction time [18]. The feature

Fig. 11 Projection profile for an illegible image “A”

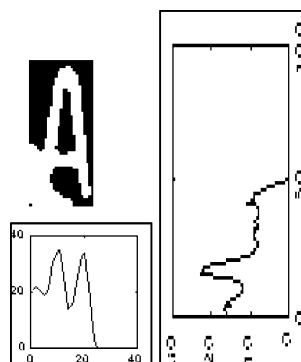
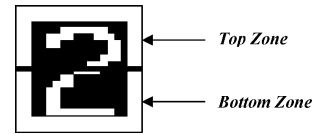


Fig. 12 Zoning for character “2”



extraction time is important in real-time industrial inspection of IC marking. The feature extraction time includes the duration of other processing elements such as reading the image, preprocessing, cropping characters, feature extraction and writing the features in a suitable file. Such a complete procedure is needed for further processing towards character inspection and classification. Feature extraction time can vary from one character to another. Several experiments were conducted for extracting features of all the characters marked on the TSSOP-DGG type IC and the durations of each feature extraction process are computed. Table 1 illustrates the effectiveness of each feature extraction process in terms of processing time. The processing time is based on a PC with Pentium IV Intel chip of 2.4 GHz. From Table 1, it can be easily concluded that the feature extraction time for the projection profile is minimum.

5 Marking inspection using neural network

Application of neural networks gives an easier solution to complex problems such as those involved with character recognition [14–18]. Here, the neural network is employed to classify the marking by the extracted features obtained from the projection profile [18]. A feed forward neural network is proposed to identify the marking as acceptable or to classify the types of errors in marking. The scheme of a neural network is as shown in Fig. 15. The projection profile data of row sums and column sums of the binary image, as computed from Eqs. 1 and 2, are used as input to the networks. There are $(m+n)$ input neurons. The network

Fig. 13 Cropped binary image for “2”

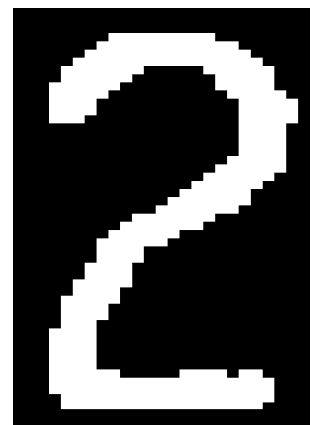
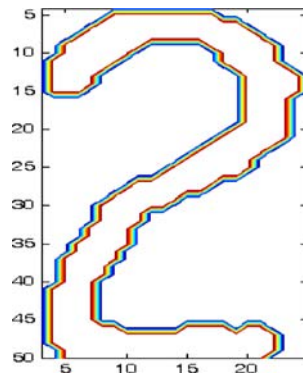


Fig. 14 Contour image for “2”



proposed consists of four output neurons and one hidden layer of 20 neurons.

The output of the neural network cannot be binary since the weight updating algorithm and activation functions 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 order to get binary output data. The binary output neurons give the required classifications as shown in Fig. 15. Zooming control of the camera can offer any specific character size (nm) in terms of pixels, so that the neural network can have varied ($n+m$) input sizes. In order to determine the optimum input size of the neural network in terms of minimizing the marking inspection 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). Then, the training is repeated to find the optimum input size for the successful output.

The neural network with four different input sizes is trained with different momentum factor values and learning rates. It is found that the network with 75 input size converges faster compared to other input sizes. The values of momentum factors and learning rates were kept in the range of 0.70–0.99 and 0.01–0.3, respectively. Then, the convergence of the output of the neural network with 75 input size is studied with several sets of learning rates and momentum factors. A learning rate of 0.25 and a momentum factor of 0.87 make the network output converge fastest towards the target values.

Table 1 Feature extraction time for each methodology

Feature extraction method	Projection profile	Moments	Zoning	Contour profile
Processing time	0.1900–0.2100 s	0.2610–0.2710 s	0.3310–0.4100 s	1.0620–1.2020 s

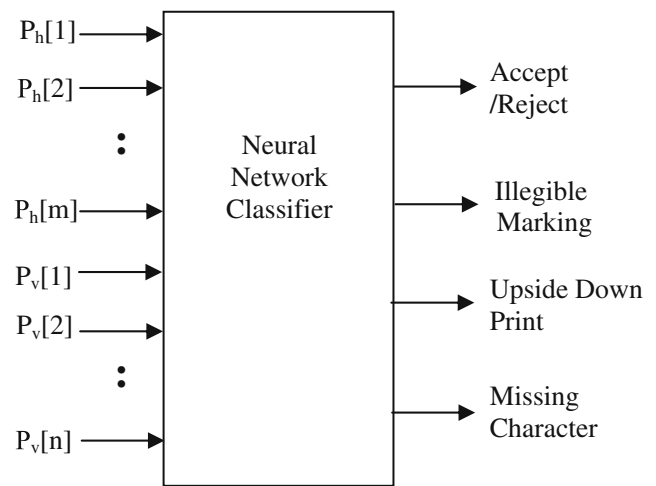


Fig. 15 Neural network for projection profile

The learning rate and momentum factor are fixed at these optimum values during the training with varied input sizes. The network with each of the above listed input sizes is again trained using the backpropagation training algorithm. The training algorithm has offered acceptable convergence characteristics. The training is carried out 12 times in each case by reshuffling input data to the same network model. Table 2 indicates the maximum and minimum epoch and the duration of convergence within 12 trials. In Table 2, ‘Ave’ is the mean value among all 12 trials. The cumulative errors are made to converge to the given set of training and testing tolerance levels. Among the four different input trainings, the optimum input size for a fast processing is determined to be 75 neurons (50 rows+25 columns) for a momentum factor of 0.87 and a learning rate of 0.25.

6 Conclusion

In this paper, a proposal for a real time marking inspection scheme for IC chips coming out from a manufacturing line is presented. Four different feature extraction methods have been studied for the marking inspection. Among them, the projection profile has proved to maintain the smallest processing time and is found to be well suited for real-time marking inspection applications. A feed forward neural network has been trained for marking inspection. The number of inputs to the neural network has been optimized for fast convergence. The neural network can indicate whether the IC marking is acceptable and, if not acceptable, the network can classify the marking errors. The marking inspection software has been developed using MATLAB and its toolboxes, then finally compiled in a C platform.

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 (s)			Misclassification
			Max	Min	Ave	Max	Min	Ave	
1	28	4,500	4,400	3,165	3,860.5	186	132	162.2	0
2	38	2,200	2,201	1,633	1,961	116	87	103.6	0
3	75	2,000	1,012	724	896.6	86	62	73.8	0
4	94	2,000	1,087	654	821.3	112	67	84.7	0

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