ANALYSIS OF SCANNING ACOUSTIC MICROSCOPY IMAGES OF IC CHIPS

J. A. Khan, M. Mina, L. Udpa, S. S. Udpa
Department of Electrical Engineering
and Computer Engineering
Iowa State University
Ames, IA 50011

INTRODUCTION

The detection, isolation, and characterization of flaws in components represent a critical need in manufacturing and quality control. Nondestructive testing (NDT) provides an effective way of inspecting materials for ensuring the quality and integrity of products and systems. Consequently, nondestructive inspection finds extensive application in several industries such as steel, nuclear and electronic industries for the evaluation of complex test objects with minimal interruption of routine operations[1].

With the increasing volume of manufactured integrated circuit (IC) chips and the demand for reliable and inexpensive components, an important concern for the electronics industry is the detection of flaws which occur during various stages of the manufacturing process. Figure 1 shows a typical IC chip package. Typical defects include: i) poor (uneven) die attachment which can result in delaminations and cracks. ii) poor package attachment and package cracks ii) accidental short or open circuits, occurring during the metallization and wire bonding stages. The detection of these conditions is a matter of significant interest to the semiconductor industry.

Ultrasonic analysis of IC chip packages have been primarily used for the location of bond wires and inspection of die attach material distribution [2]. Scanning Acoustic Microscopes (SAM) can be used for evaluating the integrity of components and IC chips. The volume of IC chips to be inspected is typically very large and there is a need to automate the analysis of the C-scan images generated by the SAM system. This paper

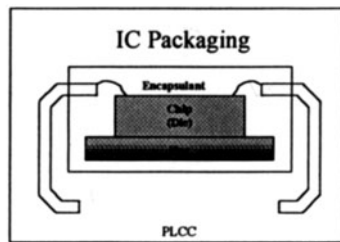


Figure 1. Typical IC packaging

describes an algorithm for detecting flaws which occur during the metallization stage of IC chip manufacturing, using C-scan images acquired from a SAM system. The next section gives a brief description of the SAM system used in acquiring C-scan images. The algorithm for automatic analysis of the acquired SAM images is discussed in the following section. Finally, results of implementation of the algorithm to experimental IC chip images are presented and discussed in subsequent sections.

SCANNING ACOUSTIC MICROSCOPY

Figure 2 shows a schematic of a typical scanning acoustic microscopy system. The object under test is insonified using an acoustic transducer which is excited by pulses from an excitation source. The energy which is reflected back by the specimen is picked up by a receiving transducer. The received signal is then processed and analyzed for defect characterization. The excitation transducer is usually mounted on a computer controlled scanner which moves it in a raster fashion. In the reflection mode SAM system, the same transducer is used as an exciter as well as the receiver. As the transducer is moved over the specimen, the receiver acquires the signal, and determines the peak signal value at each point in the scan. A gray-level mapping is done to convert the peak value into a pixel gray level to produce an image. This is called the C-scan and is represented as a square image of pixel values with gray level values in the range [0-255].

ANALYSIS OF SAM IMAGES

The overall objective is to develop image processing algorithms to automate analysis of IC chip images using pattern recognition and classification techniques. This study will consider two different approaches, image subtraction, and texture based segmentation. The former is based on matching the test image with a reference image which is defect free, and identify the flaws by comparing the two images. The latter utilizes pattern recognition and classification techniques to directly identify the flaws.

Figure 3 depicts C-scan images of typical IC metallization patterns, where pads of various shapes are deposited on a substrate (usually ceramic or lead). The pads, substrate and any defects which may occur during metallization, are also seen.

Image Subtraction

This approach simply consists of comparing the test image with a reference image. However, the test image may be rotated, translated, and scaled (RTS) with respect to the reference image. This is due to differences in the acquisition conditions, introduced by positioning of the sensors, differences in the transducers, and relative positioning of the sample during scanning. Consequently, a strategy for image registration is first required to determine the RTS parameters for transforming the test image appropriately before the two images can be subtracted. A digital image warping procedure was used for estimating the registration parameters. The warping equation is given by:

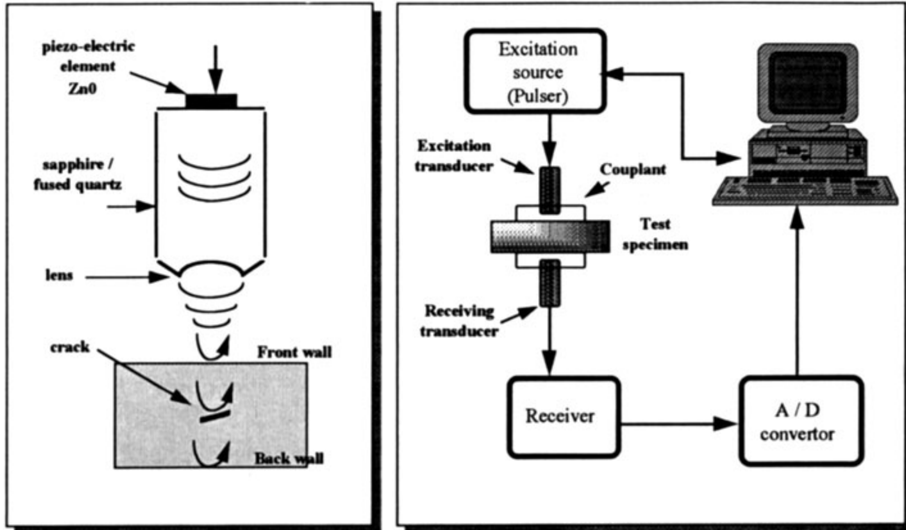


Figure 2. Scanning Acoustic Microscopy (SAM) system

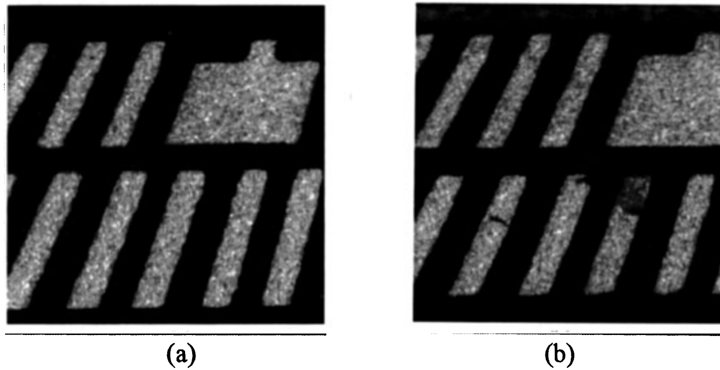


Figure 3. Typical IC chip images (a) defect free metallization, (b) metallization with defects.

$$
\begin{aligned}
x' &= c_1 x + c_2 y + c_3 xy + c_4 \\
y' &= c_5 x + c_6 y + c_7 xy + c_8
\end{aligned}
\tag{1}
$$

where (x,y) and (x',y') are the pixel coordinates of the original and transformed images respectively. Coefficients c_1 to c_8 can be calculated using a set of predetermined points called "tie-points" as shown in figure 4. However, the accuracy of registration depends on the selection of tie points in the test and reference images.

Texture Based Segmentation

The second approach is based on the observation that the pads, substrate and defect regions in the image possess different textures. Due to the unique texture of the defect regions, segmentation of the image based on texture is used to determine the location of the defects. The overall approach is shown in figure 5.

Feature Extraction

Features used in this work are based on the co-occurrence matrix and histogram of the image. The co-occurrence matrix based features, introduced by Haralick [4] have been used in many applications. These matrices identify the spatial relationships of pairs of gray levels of pixels in an image. The elements of the matrices represent the number of occurrences of pairs of gray levels of pixels, that are separated by certain distance and lie along a certain direction, in a digital image and are formally defined as follows:

Let $I: Lx \times Ly \rightarrow G$ be a digital image, with horizontal and vertical spatial domains $Lx = \{1, 2, \ldots, nx\}$ and $Ly = \{1, 2, \ldots, ny\}$ respectively, and gray levels $G = \{0, 1, \ldots, NG-1\}$. The four dimensional histogram $S = f(i, j, d, \theta)$, where i, j are gray levels of pixels at a distance d apart, θ is the angle of the line joining the centers of these pixels. We assume a symmetric relationship: $f(\theta) = f(\theta + \pi)$, that is $f(i, j, d, \theta) = f(j, i, d, \theta)$. Figure 6 illustrates the set of neighboring resolution pixels separated by a distance 1.

For angles quantized to 45 degree intervals, the unnormalized frequencies are defined as:

$$
\begin{aligned}
s(i,j,d,0^{o}) = \#\{((k,l),(m,n)) \in (Ly \times Lx) \times (Ly \times Lx) | \\
k - m = 0, |l-n| = d, I(k,l) = i, I(m,n) = j\}
\end{aligned}
\tag{2}
$$

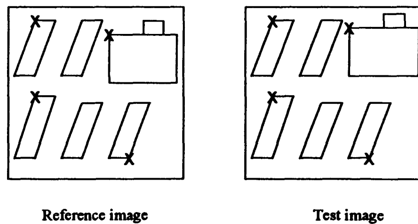


Figure 4. Tie point selection for the reference and the test image

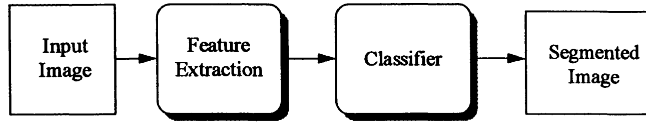


Figure 5. Overall approach for texture segmentation method

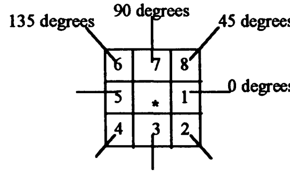


Figure 6. Neighborhood of pixel *. Neighbor pixels in four directions indicated by line segments

$$\begin{aligned} s(i,j,d,45^o) = \# \{((k,l),(m,n)) \in (Ly \times Lx) \times (Ly \times Lx) | \\ (k-m=d, l-n=-d) or (k-m=-d, l-n=d) \\ I(k,l)=i, I(m,n)=j\} \end{aligned} \quad (3)$$

where $s(i,j,d,\theta)$ denotes the elements of the corresponding co-occurrence matrices, and # denotes the number of elements in the set. Similar equations also hold for directions of 90 degrees and 135 degrees. Appropriate frequency normalization is done by dividing each element of the matrix by a normalizing factor:

$$R = 1 / (M-d)(N-d) \quad (4)$$

Haralick [4] defines several texture measures or features based on these co-occurrence matrices. The features considered in our application are:

Energy:

$$E(s(\theta,d)) = -\Sigma[s(i,j,\theta,d)]^2 \quad (5)$$

Homogeneity:

$$L(s(\theta,d)) = \Sigma\Sigma \frac{1}{1+(i-j)^2} s(i,j,\theta,d) \quad (6)$$

Inertia:

$$I(s(\theta,d)) = \Sigma\Sigma(i-j)^2 s(i,j,\theta,d) \quad (7)$$

The sensitivity of the three features to the textures under consideration were evaluated using sample images. This resulted in the selection of homogeneity in two directions, 0 and 90 degrees.

Features based on the first order histogram of a neighborhood of each pixel was also considered. These features measure the statistical properties of the gray-levels in the image. The features derived from the histogram for this application are:

Mean:

$$mean = \sum_{i=0}^{N_G-1} i \times hist[i] \tag{8}$$

Energy:

$$energy = \sum_{i=0}^{N_G-1} hist[i] * hist[i] \tag{9}$$

Correlation:

$$corr = \sqrt{\sum_{i=0}^{N_G-1} i * i * hist[i]} \tag{10}$$

Here $hist[i]$ is the histogram of the image window.

The three features given by equations (8) to (10), along with homogeneity elements described by equation (6) in two directions, form the feature vector which is used in the classification of the textures in the SAM images generated from IC chip inspection.

Classification

The feature vector is applied to a multilayer perceptron neural network classifier. The multilayer perceptron belongs to a class of feed forward artificial neural network (ANN) [5]. The network is trained using the well established back-propagation training algorithm, where known patterns are presented during training to estimate the network weights.

A three layer network with an input, output and one hidden layer, was used for classification. For training the ANN, a set of feature vectors calculated using a reference image of the defect free sample were used as input. Such an image contains only two classes of texture regions: the "object" (corresponding to the pads deposited on the chip) and the "background" (corresponding to the substrate on which the pads are deposited). In the classification stage, the feature vectors calculated at each pixel position is presented to the trained multilayer perceptron and the output classification is mapped to a gray level image, which then forms the segmented image. The logic at the two output nodes used to label the input pixel is as described below:

$$[1\ ,\ 0] \Leftrightarrow \text{"}object\text{"}$$

$$[0\ ,\ 1] \Leftrightarrow \text{"}backround\text{"}$$

$$[any\ other\ combination] \Leftrightarrow \text{"}defect\text{"}$$

RESULTS

Figure 7 depicts the original image showing incomplete metallization and the image obtained after registration and subtraction. The reference image is shown in figure 3a. In general, the accuracy of the method depends on the tie-points selected by the user. Consequently, registration and subtraction method is not very suitable for automation. However, the method is fast and simple, given a set of reasonable tie-points.

Figures 8 and 9 show the results of texture based segmentation. Pixels with gray level 0 (black) represent the defects. It can be seen that the algorithm works reasonably well for both input images. This method is computationally intensive but can be fully automated.

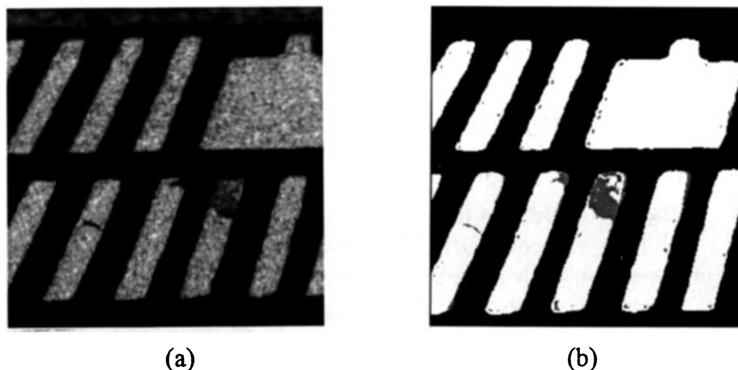
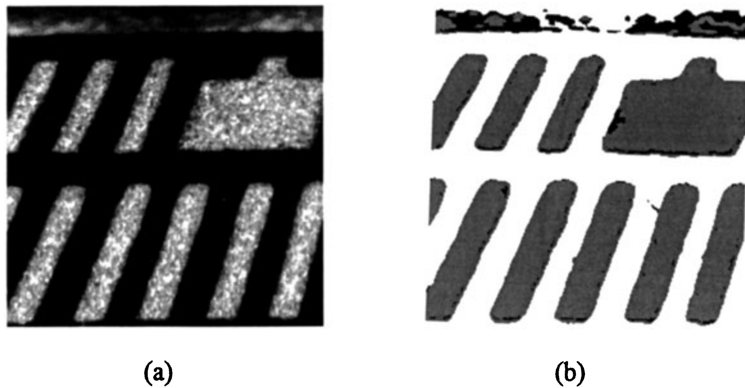


Figure 7. (a) Input SAM image with incomplete metallization (b) Registered and subtracted image

Figure 8. (a) Input SAM image with incomplete metallization (b) Segmented image



(a) (b)

Figure 9. (a) Input SAM image with excessive metallization (b) Segmented image

CONCLUSIONS

Two approaches for analysis of SAM IC chip images using pattern recognition and classification techniques are described. The approaches utilize either image registration parameters or texture features to characterize the image. While image registration is fast and accurate, it requires accurate tie point selection, which needs to be done manually for best result: Texture based segmentation uses the first order histogram and the second order co-occurrence matrices with a multilayer perceptron neural network classifier. The network is trained to identi two classes of textures that occur in the defect free images. The network is than used to detect the third class of texture belonging to the defect region. The network is able to identify the pixel in the test image which belongs to the defect region even though it was not trained with the feature vectors from the defect class. Although this method is computationally intensive, it is ful automated.

REFERENCES

1. R. B. Thompson, and D. O. Thompson, Ultrasonics in Nondestructive Evaluation Proceeding of the IEEE, Vol-73, pp. 1716-1755, 1985.
2. E. M Tatistcheff, Evaluation of Plastic Packages for Integrated Circuits using Scanning Laser Acoustic Microscopy (SLAM), DEC internal document, 1989.
3. S. M. Wu, and Y. C. Chen, Statistical Feature Matrix for Texture Analysis, CVGIP, Vol-54, pp. 407-419, 1992.
4. R. M. Haralick, K. Shanmugam, and I. Dinstein, Textural Features for Image Classification, IEEE Trans. on Systems, Man, and Cybernetics, Vol. SMC-3, 1973.
5. R. P. Lippmann, An Introduction to computing with Neural Nets, IEEE ASSP Magazine, pp. 4-22, 1987.