Microelectronics Reliability 55 (2015) 213–220

Contents lists available at ScienceDirect

Microelectronics Reliability

journal homepage: www.elsevier.com/locate/microrel

Genetic algorithms for defect detection of flip chips

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ARTICLE INFO

Article history:
Received 26 April 2014
Received in revised form 2 August 2014
Accepted 8 September 2014
Available online 26 September 2014

Keywords:
Back propagation network
Defect inspection
Flip chip
Genetic algorithm
Vibration analysis

ABSTRACT

Flip chip packaging technology is widely used in high density assembly and superior performance devices. The solder joints are sandwiched between dies and substrates, leading to the defects optically opaque. Defect inspection of flip chips become more difficult. In this paper, a nondestructive detection method was presented. Ultrasonic excitations were forced on the surface of the flip chips and the raw vibration signals were measured by a laser scanning vibrometer. Eleven time domain features and twenty-four frequency domain features were extracted for analysis. After that, the genetic algorithm was introduced for feature selection and the back propagation network was adopted for classification and recognition. The flip chips were divided into three categories: good flip chips, flip chips with missing solder joints, and flip chips with open solder joints. They are recognized under the features selected by genetic algorithms rapidly and accurately, compared with those under other feature datasets, demonstrating that the approach using genetic algorithms is effective for defect inspection in flip chip packaging.

1. Introduction

Flip chip technology combined with solder joints interconnections has been used widely in IC package, in which the bare die is flipped over and placed down on the substrate. It is an advanced package form pioneered by IBM in early 1960s. With the tendency of flip chips towards ultra-fine pitch and high density together with the new requirements of packaging materials such as lead free and low-K, manufacturing defects and fatigue failures happen more easily in flip chips [1,2], and the inspection becomes more critical and difficult. As flip chips use solder joints underneath the chips for interconnections, this configuration makes the defects hard to access with automated optical inspection equipment [3]. Then, a lot of defect inspection technologies are developed including electrical testing, X-ray inspection, infrared thermography and acoustic microscopy imaging (AMI). Electrical testing inspects the solder joints by measuring changes in electrical resistance [4]. Probes are contacted with the pre-designed test pads and a small electrical current passes through the chips to check each solder joint. This test is time consuming and expensive for complex boards, and any type of mechanical contact may make the defective joints pass this testing [5]. X-ray inspection includes X-ray radiography and tomography. X-ray radiography applies transmission of X-rays through the chips and substrates to perform defect inspection. The internal material has distinctly different X-ray absorbency [6], thus the variances in the shape and thickness of solder joints can be revealed by X-ray images, and a fuzzy rule-based system was proposed to inspect the defective solder joints by use of the X-ray images. This method is difficult to inspect cracks in the direction perpendicular to the image plane. X-ray tomography is capable of accessing defects in the vertical direction. However, this technique is not suitable for in-line inspection applications because of its time-consuming and the harmful radiation. Infrared thermography is also proposed for solder joint inspection. Chai [7] utilized the hot spots of thermography to detect the solder joints of high density when an electrical current passed through the daisy chained chips, which is suitable for voids and partial cracks detection. Lu [8] realized to inspect the missing solder joints by exploring the pulsed phase thermography with large scale solder joints. With the decrease of solder joint size, infrared thermography is limited to the infrared wave length so as to rough flip chip images, and then the realization of accessing the defects is unpractical. AMI is a widely used technique for flip chip inspection and scanning acoustic microscopy has gained wide acceptance in industry. It employs ultrasonic source to scan across the sample surface, and uses the reflected ultrasonic waves to indicate the internal conditions of the component [9]. Semmens utilized high frequency acoustic microscopy to analyze flip chip failures [10]. Zhang [11,12] applied a sparse signal representation method to

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http://dx.doi.org/10.1016/j.microrel.2014.09.006
0026-2714/

improve scanning acoustic microscopy and evaluate microelectronic packages. Cross-correlation method and neural network were combined to detect the missing solder joint defects and Sebastian Brand [13] promoted wavelet and pulse separation analysis for ultrasonic inspection of flip chip solder joints. High frequency scanning acoustic microscopy is very efficient for packaging inspection, but the diffraction and attenuation of the signal is the main handicap. The main constituents of electronic packaging are laminated substrates and the acoustic signal is diffracted by the glass fibers which are embedded within the epoxy matrix. As the laminated substrate is present between the moulding compound and the solder balls matrix, the diffraction is the main cause of the difficulties for defects detection.

Because of the inadequacy of the above methods, a fast, accurate, noncontact and nondestructive system for flip chip solder joint inspection is urgent. Then the vibration analysis inspection method was proposed. Ume [14–16] developed a laser ultrasonic and interferometer inspection system, which used laser ultrasound and interferometer techniques to measure the transient out-of-plane displacement response of package electronic devices under pulsed laser excitation. The error ratio, wavelet, correlation coefficient, spectral analysis, finite element analysis and modal analysis methods were introduced for realizing good recognition of different defects in flip chip solder joints.

In this paper we developed a vibration analysis system for flip chip solder joint inspection, combining the ultrasonic transducer and a laser scanning vibrometer. Ultrasonic waves were generated by the ultrasonic transducer and then focused on the flip chip surface to induce vibrations. The laser scanning vibrometer measured the out-of-plane displacement of the chip surface. Three kinds of flip chips with good, missing and open solder joints were detected. Eleven time domain features and twenty-four frequency domain features were extracted based on the vibration signals. The genetic algorithm (GA) was introduced to select the most significant features and the back propagation network (BP) was adopted for classification and recognition.

2. Theoretical background

2.1. Vibration signals acquisition

The flip chips produce forced vibration under the excitation of the ultrasonic source. The vibration equation of the chip can be expressed as

$$([K] - \omega^2[M])\{C\} = 0 \tag{1}$$

where $[K]$ is the stiffness matrix of the chip system, $[M]$ is the mass matrix, and $\{C\}$ is the column vector containing the Rayleigh-Ritz Polynomial coefficients [15,17]. When defects such as missing and open solder joints appear in the flip chips, the mass and stiffness of the chip will be changed, causing the changes of the vibration responses. Hence, it is practicable to inspect the defects of flip chip solder joints through the vibration signals [14–17].

2.2. Principle of BP network

Artificial neural network (ANN) is an adaptive system that is able to capture and represent complex input/output relationships [18]. It has predictive capability and can learn patterns from real data that are noisy, imprecise and incomplete. Theoretically, BP network as one of the typical ANNs can approximate any nonlinear functions and we decide to adopt a three-layered BP network to classify and recognize the defects of flip chips. Fig. 1 shows the architecture of the BP network. The BP network consists of three layers, i.e., input layer, hidden layer, and output layer. The neuron number of the input layer is selected according to the number of the features used for classification. Investigations are carried out to obtain the optimized number of hidden neurons. The output layer describes the classification and recognition results, and the reciprocal effect between the input and output neurons is indicated by the hidden layer. The training process of BP network is described as follows.

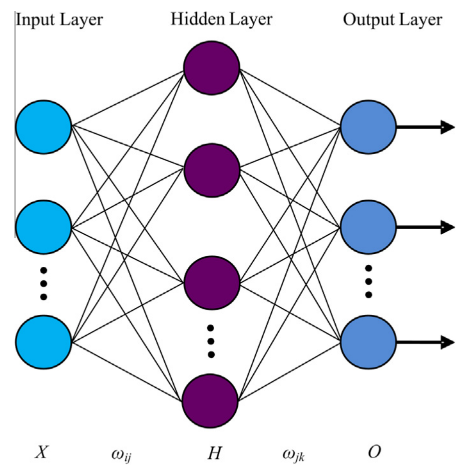

Fig. 1. Architecture of the BP network.

(1) Choosing the input X_i of the input layer neuron i, the weight ω_{ij} from the input layer neuron i to the hidden layer neuron j, and the threshold a_j of the hidden layer neuron j, the output H_j of the hidden layer neuron j is calculated by

$$H_j = f\left(\sum_{i=1}^{n}\omega_{ij}X_i - a_j\right) \tag{2}$$

(2) According to the output H_j, the weight ω_{jk} from the hidden layer neuron j, and the threshold b_k of the output layer k, the output value O_k of the output layer k can be obtained, which represents the defects in different kinds

$$O_k = \sum_{j=1}^{l}H_j\omega_{jk} - b_k \tag{3}$$

(3) The predictive error e_k is calculated by subtracting value O_k from Y_k

$$e_k = Y_k - O_k \tag{4}$$

(4) In order to predict reliably, the BP neural network has to be trained properly. The weight values and the threshold values are updated using the BP algorithm. The updating rules are as follows

$$\omega_{ij} = \omega_{ij} + \eta H_j(1 - H_j)X_i\sum_{k=1}^{m}\omega_{jk}e_k \tag{5}$$

$$\omega_{jk} = \omega_{jk} + \eta H_j e_k \tag{6}$$

$$a_j = a_j + \eta H_j(1 - H_j)\sum_{k=1}^{m}\omega_{jk}e_k \tag{7}$$

$$b_k = b_k + e_k \tag{8}$$

where n is the neuron number of the input layer X, l is the neuron number of the hidden layer H, m is the neuron number of output layer O, η is the learning parameter, Y_k is the expected value.