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Nondestructive diagnosis of flip chips based on vibration analysis using PCA-RBF

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ABSTRACT

Flip chip technology combined with solder bump interconnection has been widely applied in IC package. The solder bumps are sandwiched between dies and substrates, leading to conventional techniques being difficult to diagnose the flip chips. Meanwhile, these conventional diagnosis methods are usually performed by human visual judgment. The human eye-fatigue can easily cause fault detection. Thus, it is difficult and crucial to detect the defects of flip chips automatically. In this paper, a nondestructive diagnosis system based on vibration analysis is proposed. The flip chip is excited by air-coupled ultrasounds and raw vibration signals are measured by a laser scanning vibrometer. Forty-two features are extracted for analysis, including ten time domain features, sixteen frequency domain features and sixteen wavelet packet energy features. Principal component analysis is used for feature reduction. Radial basis function neural network is adopted for classification and recognition. Flip chips in three states (good flip chips, flip chips with missing solder bumps and flip chips with open solder bumps) are utilized to validate the proposed method. The results demonstrate that this method is effective for defect inspection in flip chip package.

1. Introduction

Semiconductor manufacturing is an increasingly prosperous industry, where device testing is one of the most important parts. Flip chip technology pioneered by IBM in early 1960s has been applied widely in IC package, in which the bare die is flipped over and placed down on the substrate. With the tendency of flip chips towards ultra-fine pitch and high density together with the new packaging materials such as lead free and low-K, both manufacturing defects and fatigue failures occur more easily in flip chip packages [1], and nondestructive diagnosis of flip chips becomes more crucial. Solder bumps underneath the chips for interconnections are considered as the significant constraint for defect inspection with automated optical detection instruments [2]. Plenty of flip chip diagnosis technologies have been proposed including electrical testing, X-ray inspection, infrared thermography and acoustic microscopy imaging (AMI).

Electrical testing equipment measures the changes of flip chips in electrical resistance for defect inspection [3]. Flip chips are fixed on the pre-designed test pads and probes are contacted with the pre-designed test pads in order to switch on a small electrical current for checking the solder bumps. This test is time consuming and expensive. The pre-designed boards are complex and each kind of flip chip needs one board. Furthermore, any type of mechanical contact can cause the defective bumps pass this testing [4].

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X-ray inspection includes X-ray radiography and tomography. X-ray radiography evaluates flip chips by transmitting X-rays through the chips and substrates. The variances in the shape and thickness of solder bumps can be obtained by X-ray images due to different X-ray absorbency of the internal material [5]. A fuzzy rule-based system was proposed to inspect the defective solder bumps by use of the X-ray images [6]. 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 online inspection applications because of time-consuming and harmful radiation. Infrared thermography is proposed for solder bump inspection by measuring the variance of the flip-chip surface temperatures. Chai [7] utilized the hot spots of thermography to detect the solder bumps 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 inspection of the missing solder bumps by exploring the pulsed phase thermography. With the decreased dimension of solder bumps, infrared thermography is limited to the infrared wave length and the realization of accessing the defects is unpractical. AMI is widely used for flip chip diagnosis, and scanning acoustic microscopy has gained wide acceptance in semiconductor industry. Semmens employed high frequency ultrasound to scan across the samples, and analyzed the reflected ultrasonic waves to indicate the internal conditions of the component [9]. Zhang [10,11] applied a sparse signal representation method to improve scanning acoustic microscopy and evaluate microelectronic packages. Cross-correlation method and neural network were combined to detect the missing solder bump defects [12], and wavelet and pulse separation analysis were used for ultrasonic inspection of flip chip solder bumps [13]. High frequency scanning acoustic microscopy is very efficient for packaging inspection, but the diffraction and attenuation of the signal between the solder bumps and the laminated substrates is the main handicap. Besides, the vibration analysis, a method widely applied in machinery fault diagnosis [14], was also introduced for diagnosis of flip chips. Ume [15,16] developed a laser ultrasound inspection system, which took advantage of laser ultrasound excitation and interferometer techniques to measure the transient out-of-plane displacement response of package electronic devices. The error ratio, correlation coefficient, finite element analysis and modal analysis methods were introduced for realizing recognition of different defects in flip chip solder bumps.

In this paper we developed a vibration analysis system for flip chip diagnosis, combining an ultrasonic generator and a laser scanning vibrometer. Ultrasounds are generated by the ultrasound transducer and focused on the flip chip surface to induce vibrations. The laser scanning vibrometer measured the out-of-plane displacement of the chip. Three kinds of flip chips with good, missing and open solder bumps were detected. Forty-two features including ten time domain features, sixteen frequency domain features and sixteen wavelet packet energy features were extracted based on the vibration signals. The principle component analysis (PCA) was introduced to reduce the dimension of features and the radial basis function network (RBF) was adopted for classification and recognition.

The rest of the paper is organized as follows. Section 2 describes the basic theory of PCA-RBF briefly. The experiment of flip chip diagnosis based on vibration analysis using PCA-RBF is presented in Section 3. In Section 4, results and discussion of feature extraction, feature reduction and flip chip diagnosis are studied. The conclusion in Section 5 closes the paper.

2. Principle of PCA-RBF

PCA is a mathematical method that utilizes an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of uncorrelated variables [17]. It is a way to identify patterns in data, and expressing the data in such a way as to highlight their similarities and differences. It can be used to reduce the data dimensionality and also to eliminate some irregularities from the data. The feature reduction process is as follows.

Given a set of m dimension feature vectors x_i ($i=1, 2,\ldots, n$), normally $m < n$, the mean vector μ is computed by $\mu = \frac{1}{n}\sum_{i=1}^{n} x_i$ and the covariance matrix C of feature vectors is calculated by

$$C = \frac{1}{n}\sum_{i=1}^{n}(x_i-\mu)(x_i-\mu)^T \tag{1}$$

The eigenvalues and the eigenvectors are computed by matrix manipulation of the covariance matrix C, and we obtain $Cy_j = \lambda_j y_j$, where λ_j ($j=1,2,\ldots, m$) are the eigenvalues sorted in descending order and y_j ($j=1,2,\ldots, m$) are the corresponding eigenvectors. The matrixes of eigenvectors and eigenvalues can be constructed as $Y = [y_1, y_2, \ldots ,y_m]$ and $A = diag[\lambda_1, \lambda_2, \ldots ,\lambda_m](\lambda_1 > \lambda_2 > \ldots > \lambda_m)$. In order to reduce the feature dimensions, k ($k\leq m$) eigenvectors corresponding to the k largest eigenvalues are selected. A threshold θ is introduced to decide the number k by computing the proportion of the k largest eigenvalues in all eigenvalues.

$$\frac{\sum_{j=1}^{k}\lambda_j}{\sum_{j=1}^{m}\lambda_j} \geq \theta \tag{2}$$

Given the parameter θ, the number k can be determined. Then the principal components (PCs) with low dimensions are decided as $P = [y_1, y_2, \ldots ,y_k]^T x_i$. Three properties of PCs have been reported in [18]. Firstly, they are uncorrelated; secondly, they have sequentially maximum variances and finally the mean-squared approximation error by the several PCs corresponding to the largest eigenvalues is minimal.

Artificial neural network (ANN) is an adaptive system which can capture and represent complex input/output relationships [19]. As a typical ANN, the RBF neural network is a feedforward network with its architecture as shown in Fig. 1. It includes three layers, i.e., an input layer, a hidden layer and an output layer. The neuron number of the input layer is determined according to the number of the features. The information of the input neurons will transfer to the neurons of the hidden layer [20]. The hidden neurons have