Welding defect signal extraction technology based on OMP algorithm

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Abstract. Flip-chip technology has been rapidly developed and widely used in the field of microelectronic packaging, and defect detection has also received increasing attention. In the experiment, ultrasonic testing was used to detect defects on flip chip. Aiming at the problem that the interference noise of the ultrasonic detection defect signal seriously affects the location of the defects and the signal extraction, we use the algorithm based on orthogonal matching pursuit (OMP) to extract the defect signal and adopt the Gabor atom library which is optimally matched with the ultrasonic signal to achieve matching the ultrasonic echo signals adaptively and greatly reducing the complexity of the sparse decomposition algorithm. The simulated and actual ultrasonic defect signals were tested separately and compared with the matching pursuit algorithm. The result shows that OMP can extract defect signals more effectively in the noise background.

1. Introduction
As a fast-developing and widely used microelectronic packaging technology, flip-chip soldering technology has many advantages such as high alignment precision, short interconnect line, high input and output density, etc. It is an important means to reduce package size and increase package density[1-2]. When ultrasonic testing is used to detect welding defects, the system is usually accompanied by interference noise, which will pollute the signal ultrasound. Even the signal will be annihilated which will bring difficulties to the subsequent processing of the signal and defect identification under severe cases. Therefore, the issues of signal extraction and noise suppression are important.

In 1993, Mallat and Zhang proposed an idea of sparse decomposition based on overcomplete dictionary[3], by which the signal is represented as a linear combination of several atoms in an overcomplete dictionary to make the signal characteristics more precise and achieve the purpose of signal extraction. This idea has been greatly developed in various fields of signal processing, such as signal processing[4-6], compression[7] and feature extraction[8]. Among many sparse decomposition algorithms, the MP algorithm is almost the fastest, but because of the larger size of atomic library, the computational cost in searching for atoms is too large.

In this paper, OMP algorithm which is matching pursuit introducing orthogonalization is used to extract the welding defect signal. It can accelerate the convergence speed, improve the performance of the algorithm, and effectively extract the defect signal.
2. Matching pursuit algorithm

The idea of the matching pursuit algorithm is that it thinks the input signal has a certain correlation with the atom in the dictionary library. This correlation is represented by the inner product of the signal and the atom in the library, that is, the larger the inner product, the greater the correlation of this atom and the atom in the library, thus the atom can be used to approximate this signal.

The iterative calculation is used to find the atom (also called the best atom) that best matches the original signal from the overcomplete dictionary, and the signal is sparsely decomposed. The basic process is:

1) Calculate the inner product of the signal $y$ and each column (atoms) in the dictionary matrix, and select the one with the largest absolute value, it is the best atom. To meet the condition

$$
| <y, x_{r0} > | = \max_{1 \leq i \leq k} | <y, x_i > |
$$

$r_0$ represents the column index of a dictionary matrix.

2) Signal $y$ is decomposed into the vertical projection component and the residual value of the most matching atom $x_{r_0}$:

$$
y = <y, x_{r_0} > x_{r_0} + R_1 f.
$$

3) For residual value $R_1 f$, the same decomposition is done in step 1), then step $K$ can be obtained:

$$
R_{k} f = < R_{k} f, x_{r_{k+1}} > x_{r_{k+1}} + R_{k+1} f.
$$

$x_{r_{k+1}}$ satisfies:

$$
| < R_{k} f, x_{r_{k+1}} > | = \max_{1 \leq i \leq k} | < R_{k} f, x_i > |.
$$

4) After the $K$-step decomposition, the signal $y$ is decomposed into:

$$
y = \sum_{n=0}^{k} < R_n f, x_{r_n} > R_n f + R_{k+1} f.
$$

among them $R_0 f = y$.

3. Denoising of welding defect signals based on OMP algorithm

3.1. Principle of OMP algorithm

The OMP algorithm\cite{9} is optimized on the basis of the MP algorithm. The atom selection method is unchanged, and orthogonalization processing is added to the selected atoms in the decomposition process. For the atom $x_i$ selected in formula (4), using the Gram-Schmidt orthogonalization method:

$$
U_{k+1} = x_{r_{k+1}} - \sum_{n=0}^{k} < x_{r_{k+1}}, U_n > U_n.
$$

This makes the OMP algorithm converge faster than the MP algorithm with the same accuracy requirements.

3.2. Principle of OMP algorithm

A noisy signal is a signal synthesized by a noiseless (original) signal and noise, noiseless signal is considered to be sparse, that is, it can be represented by a finite number of atoms. The noise is random and non-sparse, that is, it cannot be represented by a finite number of atoms. So the sparse components of the signal can be extracted by noisy signal, and used to reconstruct the signal. In this process, the noise is processed as the residual between the noisy signal and the reconstructed signal. The residuals are discarded during the process to achieve the denoising effect.

In order to get an accurate representation of the signal, it is important to design an appropriate dictionary. The literature\cite{10} shows a good characterization of the ultrasonic detection signal by the Gabor dictionary. According to the original signal characteristics, a compatible Gabor dictionary library is built, and the signal is sparsely decomposed according to the OMP algorithm step. Finally, the noise is removed to achieve the purpose of defect extraction.

4. Experimental results and analysis

In order to compare the signal extraction effect of the OMP algorithm, it is compared with the MP algorithm. Figure 1(a) shows the simulated defect signal, figure 1(b) shows the noise-added signal after...
adding Gaussian white noise, figure 1(c) shows the denoised approximation signal of the five atomic reconstructions searched by the OMP algorithm, and figure 1(d) shows the denoised approximation signal of the five atomic reconstructions searched by the MP algorithm. It can be seen from the figure that the OMP algorithm can accurately extract the defect signal and is closer to the original signal. Though the MP algorithm can detect the defect, the approximated effect is not as good as the OMP algorithm.

Figure 1. Signal extraction effect of two detection methods

In order to observe the difference between the two algorithms more intuitively, the signal-to-noise ratio SNR is used to evaluate the denoised effect. Figure 2 shows the change in signal-to-noise ratio between the two algorithms in each iteration. It can be seen from the figure that the denoising effect of the OMP algorithm is better than the MP algorithm.

Figure 2. Comparison of signal-to-noise ratios of two methods in the iterative process

The data acquisition was performed by an atomic force sound microscope manufactured by Sonoscan, and the waveform was obtained using the A-scan method at a sampling frequency of 230 MHz. Figure 3(a) is a waveform diagram of the acquired defect signal; figure 3(b) is the result of the OMP algorithm denoised process; figure 3(c) shows the result of adding noise to the measured signal; figure 3(d) shows the result of the OMP algorithm after noise is added. It can be seen that the original defect signal can be well matched using the OMP algorithm.
5. Conclusions
In this paper, the OMP algorithm is used to denoise the noisy welding defect signal, and the Gabor dictionary which is best matching the ultrasonic detection signal characteristics is adopted. Compared with the MP algorithm, the result can better match the signal characteristics. Through the simulation of the simulated signal and the measured defect signal, it is proved that the OMP algorithm can extract the defect signal more effectively, and the signal-to-noise after denoising is relatively large.

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