2-D Wavelet Transform In Ball Grid Array (BGA) Substrate Conduct Paths Inspection

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ABSTRACT

This study presents a novel approach by using two-dimension Wavelet Transform (2-D WT) to localize the open and short boundary defect candidates on Ball Grid Array (BGA) substrate conduct paths. Once the potential defects are addressed, traditional inspection algorithms can be implemented for further analysis on these defect candidates. Therefore, the defect-detecting scope and inspection effort will be significantly reduced. The binary BGA substrate image is processed that shows only the boundaries of BGA substrate conduct paths, which is further decomposed directly by 2-D WT. Since the most of wavelet energy is clustered in the edges of image objects, the wavelet transform modulus sum (WTMS) of each edge pixel on BGA substrate conduct path boundaries is initially collected. By comparing the WTMS of an edge pixel with its WTMS on adjacent decomposition level, an edge pixel is determined to be a strongly irregular edge point (e.g. potential open or short defects) or not. Real BGA substrates with synthetic boundary defects are used as test samples to evaluate the performance of the proposed approach. Experimental results show that the proposed method is able to capture all the open and short defects on BGA substrate conduct paths without any missing error by appropriate across-level ratio and specified decomposition level.

Keywords: 2-D WT, BGA substrate, WTMS

1. INTRODUCTION

In recent years, one advanced type of bare Printed Circuit Board (PCB) called the Ball Grid Array (BGA) substrate (see figure 1), has been extensively used in smaller size and sophisticated electrical products. Because linewidths and line spacings on BGA substrates are much finer than conventional PCBs, defects on BGA substrate become difficult to detect and could seriously disable conductivity.

In general, traditional bare PCB inspection algorithms by machine vision can be classified into three categories [1]: referential approaches, non-referential approaches, and hybrid approaches. Referential approaches detect large size defects by comparing the test board image with stored defect-free board image in steps of pixel-to-pixel or template-to-template. Referential approaches suffer from time-consuming for matching operations, sensitive to noise and angular error, and requires large amounts of data storage for image templates [2-4, 5-7]. Non-referential approaches perform well to verify small or medium size defects by specification knowledge but only for certain types of defects (such as line widths, spacing violations, etc.). A serious defect such as a circuit short could be falsely accepted as a portion of conduct paths [4, 8-10]. Non-referential approaches are also error prone when encounter rotational variations during inspection [4, 8-10]. Hybrid methods combine referential approaches and non-referential approaches to acquire all the benefits of both approaches for detecting various defect types in different sizes. Hybrid methods generally achieve better identification results among the existing inspection systems. However, hybrid methods also inherently suffer from greater computation efforts, rotational error, and noise effects [5-7, 11].

In the past decade, wavelet theory has inspired the development of a powerful methodology for processing signals, images, and other types of scientific and technical applications. One-dimension Wavelet transform (1-D WT) became popular especially in localized frequency analysis because they are able to decompose a 1-D input signal \( f(t) \) respectively into smooth and detailed parts by low-pass and high-pass filters on multi-resolution levels. The detailed parts represent the higher frequency oscillations of \( f(t) \) [12-14]. Therefore, the local deviations over a short interval of time for detailed components of \( f(t) \) at fine scales indicate the abnormalities. 1-D WT has been

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Figure 1. Real BGA substrate conduct paths (The conduct paths are located on the top side of BGA substrate): (a) Original image with a 25mm x 18mm field of view and 640 x 480 pixels resolution; (b) Binary image of the BGA substrate shown in (a)[18-19]

Fig. 2. The COI of point $x_0$ [23-24]

Successfully implemented in feature extraction and classification tasks [12, 15-17].

Two-dimension wavelet transform (2-D WT) deals with the input functions such as images, matrices, and 2-D data and holds for the properties of 1-D wavelet transform as well. Since relatively few coefficients are needed to represent the image [14], 2-D WT has been widely used in image coding and compression, noise removal, and analysis for contour and corners of an object. One efficient method to denoise image is wavelet transform modulus sum (WTMS) approach [21-24]. The WTMS of a pixel $x_i$ is computed by the sum of the wavelet coefficients at detail scale in a specified domain centering on $x_i$ and along its gradient vector direction. Since most of wavelet energy is concentrated on the edges of objects within an image, the WTMS of pixel $x_i$ is determined to identify whether $x_i$ is an edge pixel. Furthermore, there also exists an inherent relationship between the WTMS of a pixel $x_i$ and its WTMS at adjacent decomposition level. That is, pixel $x_i$ belongs to image objects if $x_i$ satisfy the inherent relationship of WTMS. On the contrary, pixel $x_i$ may be a noisy pixel and ignored if $x_i$ violates the inherent relationship of WTMS.

Instead of using 1-D tangents of BGA substrate conduct path boundaries as the input of 1-D WT [20], this paper directly uses the 2-D BGA substrate image as an input function of 2-D WT. Because the geometrical shapes between the boundary defects (e.g. open and short) and normal circular pad holes on BGA substrate image are similar, open and short defects can not be distinguished from the normal conduct paths solely by 2-D WT. Although some non-defective pixels are mis-classified by the proposed approach, but all open and short defects are precisely located and the number of potential defective pixels is much less than the numerous pixels on an image. Therefore, the inspection effort for the open and short defects on BGA substrate is significantly reduced because only these defective pixel candidates are required further validation by referential, non-referential, or hybrid approaches. Thus, the 2D wavelet-based proposed approach presented in this study can be considered as an effective pre-processing technique in BGA substrate conduct paths inspection.

In this paper, the binary BGA substrate image is initially processed to show only the boundaries of BGA substrate conduct paths, which is further directly decomposed by 2-D WT. The BGA substrate image is decomposed into four subimages including smooth, horizontal, vertical, and diagonal parts at each decomposition level. Because the WTMS approach is originally designed to denoise image so it will be modified for detecting the abnormalities on BGA substrate conduct path boundaries. Then, the 2-D wavelet coefficients on horizontal and vertical subimages at specified decomposition levels are applied to locate the abnormal edge pixels (e.g. open and short defect candidates) based on the modified WTMS approach in this study.

This paper is organized as follows: In section 2, the WTMS approach is briefly discussed. The proposed potential defects detecting algorithm based on 2D WT and modified WTMS are described in section 3. Experimental verification of the proposed method is shown in section 4. Finally, the conclusion is given in section 5.
2. WAVELET TRANSFORM MODULUS SUM (WTMS)

After a 1-D signal is decomposed by 1-D WT, a specified interval of neighboring points centering on point \( x_0 \) are sequentially clustered at each detail decomposition level. The support of 1-D WT across different detail decomposition levels is called the cone of influence (COI), see figure 2). The WTMS inside the COI of \( x_0 \) at each detail decomposition level. Denoted by \( N_j(x_0) \), the points inside the COI of \( x_0 \) at the \( j \)th detail decomposition level (e.g. \( D_3 \) scale) is defined as follows [23-24]:

\[
N_j(x_0) = [p_i | p_i = x_0 \mp \eta_j \pm 1 \ldots x_0 \pm \eta_j - 1, x_0 \pm \eta_j] 
\]

where \( \eta = K \cdot s \)

\( K \) : Half of the mother wavelet support length.

\( s : 2^j \) ( \( j = 1, 2, \ldots, J \))

The wavelet transform modulus sum (WTMS) for points in COI of \( x \) at \( D_3 \) scale is denoted by \( N_j f(x) \), which is defined as follows [23-24]:

\[
N_j f(x_0) = \sum_{p_i \in N_j(x_0)} |d_j(p_i)| \tag{2.2.1}
\]

Where \( d_j(p_i) \) represents the 1-D wavelet coefficient of signal point \( p_i \) at \( D_3 \) scale.

If point \( x_0 \) is a regular point of input signal, the following relationship between \( N_j f(x_0) \) and \( N_{j+1} f(x_0) \) holds [23-24]:

\[
\frac{N_{j+1} f(x_0)}{N_j f(x_0)} = 2^\alpha + 1 \quad \text{for} \ 1 \leq j < J \quad \text{and} \ \alpha \geq 0 \tag{2.2.2}
\]

The \( \alpha \) value is called Lipschitz exponent. This implies that \( N_j f(x_0) \) will increase at least double as the scale increases. On the other hand, if point \( x_0 \) is an irregular point (noise) of input signal, the following relationship for \( N_j f(x_0) \) and \( N_{j+1} f(x_0) \) holds [23-24]:

\[
\frac{N_{j+1} f(x_0)}{N_j f(x_0)} = 2^\alpha + 1 \quad \text{for} \ 1 \leq j < J \quad \text{and} \ \alpha < 0 \tag{2.2.3}
\]

Therefore, the signal points with the Lipschitz exponent greater than 0 will be collected to reconstructed the 1-D signal. With this practice, the original noise can be removed.

Moreover, the COI skill and the adjacent scale relationship are also valid to deal with the 2-D signal (e.g. image) denoising by 2-D WT. However, the wavelets are designed to be the partial derivatives of a smooth function along the \( x \) and \( y \) directions, respectively. That is, \( \psi(x,y) = \partial \varphi^n(x,y) / \partial x \) and \( \psi^2(x,y) = \partial \varphi^n(x,y) / \partial y \). Therefore, the modulus of wavelet transform (WTM) at a particular point \((x_0,y_0)\) is denoted by \( M_j(x_0,y_0) \) and defined as follows [23-24]:

\[
M_j(x_0,y_0) = \sqrt{d^1_j(x_0,y_0)^2 - d^2_j(x_0,y_0)^2} \tag{2.2.4}
\]

\[
A_j(x_0,y_0) = \tan^{-1} \left( \frac{d^2_j(x_0,y_0)}{d^1_j(x_0,y_0)} \right) \tag{2.2.5}
\]

where

\( d^1_j(x_0,y_0) \): 2-D wavelet coefficient for point \((x_0,y_0)\) by wavelet \( \psi(x,y) \) at the \( j \)th scale.

\( d^2_j(x_0,y_0) \): 2-D wavelet coefficient for point \((x_0,y_0)\) by wavelet \( \psi^2(x,y) \) at the \( j \)th scale.

\( A_j(x_0,y_0) \): The gradient vector direction of the wavelet coefficient on point \((x_0,y_0)\) at the \( j \)th detail scale.

Since the direction of gradient vector indicates the local maximum variation, the edges of an image can be detected by following the gradient vector direction. It implies that only the pixels along their gradient vector directions need to be considered. The COI derived along gradient vector direction is called directional cone of influence (DCOI), see figure 3). The WTMS inside the DCOI of a point \((x_0,y_0)\) at the \( j \)th detail decomposition level is denoted by \( N_j f(x_0,y_0) \) and described as follows [23-24]:

\[
N_j f(x_0,y_0) = \sum_{(x,y) \in D_j} M_j(x,y) \tag{2.2.6}
\]

Where

\( D_j = \{(x,y) | (x-x_0)^2 + (y-y_0)^2 \leq K \cdot s^2, (y-y_0)/(x-x_0) = \tan^{-1}(A_j(x_0, y_0))\} \)

\( K \): Half of the mother wavelet support length.

\( s : 2^j \) ( \( j = 1, 2, \ldots, J \))
With the same practice in 1-D case, if point \((x_0, y_0)\) is a regular pixel of an image, the following inter-scale relationships between \(N_j f(x_0, y_0)\) and \(N_{j+1} f(x_0, y_0)\) hold [23-24]:

\[
\frac{N_{j+1} f(x_0, y_0)}{N_j f(x_0, y_0)} = 2^{1+2} \quad \text{for } 1 \leq j < J \text{ and } \alpha \geq 0 \quad (2.2.7)
\]

\[
N_{j+1} f(x_0, y_0) - N_j f(x_0, y_0) > \gamma \quad (2.2.8)
\]

Where \(\gamma\) is a pre-defined threshold.

Due to wavelet decomposition effect, the image noise became blur and the wavelet energy is smaller as the decomposition level increases. Although more pixels inside DCOI are taken into account at detail level \(j+1\), the WTMS of noisy pixels still can not satisfy the inter-scale relationship in equation (2.2.7). The pixels fulfill equations (2.2.7) and (2.2.8) are used to reconstruct the image by inverse wavelet transform [23-24].

### 3. POTENTIAL DEFECTS DETECTING PROCEDURE

#### 3.1 2-D WT Property on BGA Substrate Conduct Paths

As described in section 2.2, WTMS approach is able to remove image noise successfully because the noise decays rapidly as image decomposition proceeds. Edge pixels will also blur at adjacent levels due to the decomposition of wavelet energy. That is, the wavelet coefficient for an edge pixel at the \(j\)th level is greater than that of at the \((j+1)\)th level. Since most of wavelet energy is preserved by edges of image object, an edge pixel still has much larger wavelet coefficient than that of background pixels at same decomposition level.

To implement the WMTS concept in BGA substrate inspection, an image of binary BGA substrate is processed that shows only the substrate inspection, an image of binary BGA substrate level.

An edge pixel still has much larger wavelet coefficient than regular edge pixel at finer detail decomposition level. Therefore, as far BGA substrate conduct path boundaries as concerned, abnormal edge pixels on open and short defects may perform differently from the normal edge pixels in equations (2.2.7) and (2.2.8).

#### 3.2 Potential open and Short Defects Detecting Procedure

Unlike the denoising technique discussed in section 2-2, 2-D wavelet energy of detail vertical and horizontal parts are both included in WTMS to capture the open and short defects in varying shapes. That is, the WTM for a pixel \((x_0, y_0)\) on an image at the \(j\)th scale (denoted by \(WTM_j(x_0, y_0)\)) is redefined as follows:

\[
WTM_j(x_0, y_0) = \sqrt{d^h_j(x_0, y_0)^2 + d^v_j(x_0, y_0)^2} \quad (3.2.1)
\]

Similar to DCOI concept, the domain and tracing process for the relevant edge pixels centering on pixel \((x_0, y_0)\) at the \(j\)th scale is redefined in this study. The domain is denoted by \(D_j\) and stated as follows:

\[
D_j = \{(x, y) : \sqrt{(x-x_0)^2 + (y-y_0)^2} \leq \tau x + s \} \quad (3.2.1)
\]

where

- \(\tau\): Half of the mother wavelet support length.
- \(s\): \(2^j\) \((j = 1, 2, ..., J)\)

Domain \(D_j\) is a square which contains \([2 \text{ int.} \sqrt{2} s] + 1\times[2 \text{ int.} \sqrt{2} s] + 1\) pixels. Edge tracing process starts from pixel \((x_0, y_0)\) and searches for the \(j\)th maximal WTM pixel (denoted by \((x^1_1, y^1_1)\)) and \(2^j\) WTM pixel (denoted by \((x^1_1, y^1_1)\)) around the 8-pixels neighborhood of \((x_0^0, y_0^0)\). Recording the locations and WTM of pixels \((x_0^0, y_0^0), (x_1^1, y_1^1), \) and \((x_1^1, y_1^1)\), Setting the pixels \((x_0^0, y_0^0), (x_1^1, y_1^1), \) and \((x_1^1, y_1^1)\) to zero. Then, finding the \(j\)th maximal WTM pixel around the 8-pixels neighborhood of \((x_1^1, y_1^1)\) and \((x_1^1, y_1^1)\) respectively and denoting them as \((x_1^1, y_1^1)\) and \((x_1^1, y_1^1)\). In this manner, searching process proceeds along the \((x_1^1, y_1^1)\) and \((x_1^1, y_1^1)\) (e.g. \(n_1, n_2 \in \text{Integer}\)) directions and stops when their 8-pixels neighborhood windows are both beyond the compass of \(D_j\). The WTMS at pixel \((x_0, y_0)\) (denoted by \(WTMS_j(x_0, y_0)\)) at the \(j\)th level is determined by summing the WTM of recorded pixels in tracing process. That means,
\[ WTMS_j(x_i^0, y_i^0) = \sum_{k=n^2}^{n^1} WTJM_j(x_k^j, y_k^j) \quad (3.2.2) \]

Since open and short defects are strongly abnormal edges and the most of their wavelet energy is preserved in lower decomposition levels. The WTMS for a irregular edge pixel at the \( J^p \) scale may be greater than that of at the \( J+1 \) \( ^p \) scale if \( J \) is set to 1 or 2. Therefore, the WTMS inter-scale relationship stated in equation (2.2.7) for a pixel \((x_i^0, y_i^0)\) is modified as follows:

\[ \frac{WTMS_{j+1}(x_i^0, y_i^0)}{WTMS_j(x_i^0, y_i^0)} = 2^{\alpha + 1} \leq 2 \quad \text{for} \quad j = 1, 2 \quad (3.2.3) \]

The pixels fulfill equation (3.2.3) are suspicious abnormal edge pixels, however, true open and short defects may not completely included in abnormal edge pixel candidates. There may exist a specified domain of \( \alpha \) at appropriate decomposition level to capture true open and short defects with any missing error by equation (3.2.3). The validation task is presented in section 4.

In order to reduce computational complexity from numerous pixels on an image, pixels should be selected by a threshold before WTMS calculation. Since the conduct paths are respectively located on the top, bottom, right, and left sides of BGA substrate, the open and short defects on top and bottom sides are mainly in horizontal shape. The images for open and short defects on right and left sides can be respectively rotated in \(-90^\circ\) and \(90^\circ\) orientations so that they are also mainly in horizontal shape. In this manner, the wavelet energy of open and short defects at detail horizontal (e.g. \( s_1 \cdot d_1 \)) part may act unusually. Assuming the 2D wavelet coefficients on defect-free BGA substrate conductor path boundaries at the \( s_1 \cdot d_1 \) part (e.g. \( d_{1, m, n} \)) are normally distributed. The population mean \( \mu_{ad} \) and standard deviation \( \sigma_{ad} \) are estimated by collecting the 2D wavelet coefficients on defect-free BGA substrate conductor path boundaries at \( s_1 \cdot d_1 \) part. A threshold \( (\mu_{ad} \pm 3\sigma_{ad}) \) is acquired in advance and widely accepted by industry. If the \( d_{1, m, n} \) of a pixel \((x_i, y_i)\) is out of \((\mu_{ad} \pm 3\sigma_{ad})\), then \( x_0 \) is qualified to calculate its WTMS \( j(x_i^0, y_i^0) \) and across-level relationship stated in equations (3.2.2) and (3.2.3).

### 4. EXPERIMENTAL RESULTS

The proposed defect detecting approach using modified WTMS approach in section 3.2 is evaluated for locating the open and short defect candidates on BGA substrate conduct paths. An LED ring lighting source and a 25mm lens with 12mm extension ring were used to increase the visibility of the BGA substrate conductor paths. The defect detection program was edited in the C language and executed on the vision package software named “Optimas” using a personal computer with Pentium II CPU.

Three binary BGA substrate image samples were tested to estimate the defect detection capabilities of the proposed algorithms (shown in figure 4). These sample images showed only the boundaries of conduct paths. The test samples were in approximately 8.5mm x 9mm field of view, which contain 330 x 350, 318 x 336, and 333 x 360 pixels in sample1, sample2, and sample3, respectively (see figures 4(a)-4(c)). The resolution of three sample images was about 40 pixels/mm. There were 10 synthetic boundary defects in each test sample, which contains 5 opens and 5 shorts. Accordingly, there were 30 defects in this experiment totally. Defects with both simple and complicated shapes were included to fit the real inspection environment. Detection error is defined as a missing error failing to alarm a true open or short defect.

Since wavelets with smaller support length are more stable in capturing local abnormalities at detail decomposition level [19], the wavelet c6 are used in this section. Therefore, the \( \tau \) value for determining the bounds of \( D_j^1 \) is 3 and 6 for \( j = 1 \) and \( j = 2 \), respectively. The identification results of proposed approach were shown in Table 1.

In Table 1, if \( \alpha \) is set to be less than \(-1\), the total number of missing error is respectively 8 and 2 for \( j = 1 \) and \( j = 2 \). Although there are 3130 pixels on sample 1 out of \((\mu_{ad} \pm 3\sigma_{ad})\), only 106 and 145 pixels of them are satisfied by equation (3.2.3) at \( j = 1 \) and \( j = 2 \), respectively. As shown in Table 1, the performance of the 2\( ^{nd} \) decomposition level (e.g. \( j = 2 \)) is better than the 1\( ^{st} \) decomposition level (e.g. \( j = 1 \)) in detecting the true open and short defects either \( \alpha < -1 \) or \( \alpha < -0.5 \). This implies that the 2\( ^{nd} \) decomposition level preserves much more wavelet energy than the 3\( ^{rd} \) decomposition level does. Thus, the cross-level relationship stated in equation (3.2.3) at the 2\( ^{nd} \) decomposition level is more effective in distinguishing the defects from normal conduct paths. In addition, true open and short defects in test samples can be captured completely without missing error if \( \alpha \) is less than 0 at either \( j \) equals to 1 or 2.

Although hundreds of defect candidates are detected when \( \alpha < 0 \), it is still much smaller with respect to the numerous pixels on an sample (i.e. A sample image contains more than 100,000 pixels). Traditional inspection algorithms can focus on the suspicious open and short detects for further analysis to save inspection effort.

### 5. CONCLUSION

This paper points out a 2-D wavelet-based scheme in detecting the potential open and short defects on BGA substrate conduct paths. The proposed approach can be considered as an effective
pre-process technique to save the inspection effort of following conventional PCB inspection approaches. The binary image of BGA substrate conduct paths are initially transformed into an image that shows its 2-D boundaries, which is further analyzed by 2-D WT to evaluate the wavelet energy preservation at edges across decomposition levels. Strongly irregular edges like open and short defects preserve much more wavelet energy than normal edges do at finer scale (e.g. the 1st and 2nd decomposition levels). Therefore, the inter-scale relationship ratio (α) of WTMS can be used as an indicator to detect suspicious abnormal edges. The proposed approach has been validated to capture open and short defects without any missing error by c6 wavelet if α <0 and j is set to 1 or 2 under approximately 40 pixels/mm image resolution. Moreover, the proposed method is template-free and easy to build the required threshold (e.g. µsd1±3σsd1) for dealing with varied BGA substrate conduct path layouts. Therefore, it is especially suitable for small batch production.

**REFERENCE**

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