An Automatic Bump Detecting System for LCD COG Module Using Fuzzy Reasoning

Xinjun Sheng, Lei Jia, Zhenhua Xiong and Han Ding

Abstract

The Chip-on-Glass (COG) package, which assembles the driver IC onto a glass substrate with Anisotropic Conductive Film (ACF), is mainly used in the Liquid Crystal Display (LCD) module. With the higher demand of display capacity, the stability of COG interconnection under fine pitch package becomes more important and difficult. Interconnection test and bump microscopic inspection are commonly used to confirm the viability of the interconnections, and are accomplished manually by engineers, which are repetitious and can merely give out the conductive particle numbers in rough. According to the existent ACF-COG interconnection resistance models, the conductivity of bump and pad can be quantitatively analyzed with the conductive particle contact area. In order to implement an automatic system for the bump microscopic inspection to count the particle number and achieve the distribution of contact areas, it is necessity to realize the bump detecting and extracting automatically. In this paper, an automatic bump detecting system using fuzzy reasoning is proposed, and can perform the bump image extraction with a high accuracy. With this system, the particle contact areas and conductive particle number can be analyzed automatically.

Keywords: ACF-COG modules, Bump detecting, Fuzzy reasoning, Hough transform, Microscopic inspection.

1. Introduction

The liquid crystal displays (LCDs), currently occupying the mainstream position among the display industry, are widely used in a variety of areas, such as the communications, consumer and computer electronics. The chip-on-glass (COG) interconnection, with which the driver IC is bonded onto a glass substrate with anisotropic conductive film (ACF), is the common-used package process of the medium or small size panels in industry. The ACF is a film consisted of the adhesive epoxy matrix with conductive particles dispersed in it, and is largely used in the LCD industry due to the ability to precise control of the volume of material, density of the conductive particles. The conductive particles commonly are metal-coated polymer spheres with 3-5 µm in diameter and the adhesives are thermosetting resins. The electric conductivity interconnection is achieved through the conductive particles trapped by the chip bump and the corresponding substrate pad, while the adhesive matrix provides stable adhesion and the electric insulation after curing.

The ACF, same as the anisotropic conductive adhesive (ACA) and the anisotropic conductive paste (ACP), offers several advantages for the LCD packaging in [1], [2]: a) fine pitch capability; b) low temperature processing capability (T_c=190-200°C, commonly); c) the capability of self-adjustment with the surface tolerance.

With the higher demand on the display capacity in panel industry, the fine pitch capability of ACF-COG is under continuous exploiting. The stability of COG interconnection becomes more important in the finer pitch package. In the industry, the engineers usually verify the process parameters and determine the module material through the following process: a) designing the dummy chips; b) running the manufacturing process with presumptive parameter sets; c) testing the interconnection resistance and inspecting the module; d) making the reliability tests on the module; e) optimizing the process parameters and the materials. The optimized process and material features should be achieved by trial-and-error procedure, and the process is repetitive and relies on the engineering experience.

In order to converge the optimizing process promptly, a series of interconnection models have been designed to predict the contact resistance between the electrodes for the ACA/ACF assemblies [3]-[7]. These models give out the composition of interconnection resistance, the governing equations and assumptions in varied extents. It is found that large discrepancies exist among these models and between contact resistance values experimentally...
measured and what these models predict [7]. However, there is a common perspective among these models that the particle track resistance is determined by the contact area, and can be computed roughly with the area vector, and the interconnection resistance can be achieved based on each electric track resistances with parallel circuit resistance equation. In order to explore the relations among the contact area and the process parameters (bonding pressure, temperature, driver IC bump layout, material specifications, etc.), and the relation between the contact area and resistance, a bump inspection system has been proposed and designed. Among the system, the bump detecting is the necessity to the automatic inspection system, and should detect the bump region and provide localization for the following bump region analyzing algorithm.

The automatic detection system for the bumps in ACF-COG assemblies has not been fully exploited in industry. The similar function is accomplished by manual, and the analysis between the conductive area and interconnection reliability only remains at a qualitative level since the lack of quantitative data from the inspection system.

2. Detection approach

In this section, the detection approach to localize the bump region is presented.

The bump inspection system is constituted by an acquisition system and a processing system to perform the diagnosis on the acquire images (see Figure 3). The bump detection is the main step of the image processing. In order to evaluate the capabilities of bump image processing, the images were captured manually by Olympus BX 51 optical microscope. The input images have a resolution of 640×480 pixels, and each pixel is 10/3 μm in spatial coordination. With a mechanical positioning tool moving the camera or the inspected COG module to reach a fixed position to acquire the image, the bump inspection system can acquire the region of interest (ROI). For this reason, it is possible to develop an automatic bump inspection system for the LCD COG module.

In this paper, the bump detecting is handled as an edge detection and localization problem, and the proposed approach contains the four subsequent steps: the image acquisition, the preprocessing, automatic angle adjustment, and the bump region detection. The bump detection approach and each of its steps are shown in Figure 2.

The first step is the image acquisition. The image acquired by camera from the bottom view of COG module contains the amplified bumps in the ROI, and the number of bumps is commonly more than one. Before the geometry extraction for the bumps, the pre-process of image automatic rotation is performed to make the following image energy analysis easier.

The third step is the bump boundary detection. In this step, the boundary subset is detected by the correlation between the features extracted from the image and the bump geometric feature. The former features are the horizontal and vertical energy of the image. With the boundary detection, the inspection system extracts the bump regions for the following bump analyzing. Each of the steps is described in detail in the following sections.
3. Image preprocessing

Each image acquired by the camera commonly contains more than one bump, and these bumps are in parallel and designed in rectangle figuration. As it is show in Figure 3, the image boundaries are difficult to be detected directly because of: 1) the gap filled by the conductive particles or even by bubbles in sometime; 2) low contrast because of poor illumination; 3) the existent non-straightness of bump manufacturing. Considering the above difficulties, the bump detection uses the region gray energy gradient method to come across the vague edge feature. In this case, it is easier for the following process to ensure the bump in orthogonal position.

A. Image edge detection

The edge detection process has the capability of simplifying the image analysis by drastically reducing the amount of data to be processed, while at the same time preserving useful structural information about object boundaries. We use Canny edge detector [9] to locate the position of pixels where significant edges exist. Figure 4 shows the edge images of sample bumps, which prove that the particle aggregations and bubbles will blur the boundaries. Moreover, the bubbles and particle excessive aggregation commonly represent the assembly defect, and require to be explored in detail. Therefore, these images will be inspected with the bump areas and the surrounding areas in the following process.

We proposed an automatic alignment algorithm based on the Hough transform for the bump images. Several features such as the orientations and lengths of the detected line segments are used to determine the bump orientation and achieve the inclining angle.

B. Hough transform and automatic rotation

Hough transform can detect straight lines in a binary image by mapping the feature points in x-y space to the
parameter space [10]-[13]. With Hough transform, all the lines in the image passing through the point \((x_0, y_0)\) can be expressed in the parameter space \((\rho, \theta)\) as follows:

\[ \rho = x_0 \cos \theta + y_0 \sin \theta \]  

where \(\rho\) is the perpendicular distance from the origin to the line passing through \((x_0, y_0)\) and \(\theta\) is the angle between the norm of the line and the x axis as shown in Figure 5.a. If there several points in the image aligned along the line, the length of segments formed by the points will be added to \(H(\rho, \theta)\). In practical applications, the accumulation values, an array \(H(\rho_k, \theta_1)\), on the intersect point can be used to detect straight line segments along the line.

Let us consider a bump region with boundary lines BL, BB, BR, and BT, with BL and BR being parallel sides with distance of bump width, as well as BT and BB with distance of bump height, as shown in Figure 5.a. The image of these bump region boundaries in the Hough Space is shown in Figure 5.b. As expected, there are \(4n\) peaks in the ideal case, in which \(n\) represents the number of bumps in the image. \(H_{ht}, H_{ht}, H_{hn},\) and \(H_{rn}\) are correspondingly the representatives of the left and right sides of \(1^{\text{st}}, \ldots, \text{nth bump}, \) whilst \(H_t\) and \(H_b\) are the top and bottom sides of bump. The number of line segments aligned in the bump side will be accumulated in the \(H(\rho_k, \theta_1)\), for example, the segments number of \(BL_{ht}\) is equal to the \(H(\rho_1^1, \theta_1)\). With the Hough transform, the segment sets of bump sides can be expressed as:

- **Left sides of ith bump** \(\in \{BL_{ht}^i | H(\rho_2^{2i-1}, \theta_1)\}\)
- **Right sides of ith bump** \(\in \{BR_{ht}^i | H(\rho_1^{2i-1}, \theta_1)\}\)
- **Top side of bumps** \(\in \{BT_{ht}^i | H(\rho_2^{2i+1}, \theta_2)\}\)
- **bottom side of bumps** \(\in \{BB_{ht}^i | H(\rho_2^{2i}, \theta_2)\}\)

\[
\begin{align*}
\rho_2^{2i} - \rho_2^{2i-1} &= w \cdot l_{bh} \\
\rho_1^{2i} - \rho_1^{2i-1} &= w \cdot l_{bw} \\
\rho_1^{2i+2} - \rho_2^{2i} &= w \cdot l_{bp} \\
\end{align*}
\]

with \(i \in \{1, \ldots, n\}\)  

in which, \(w\) is the width of an image pixel divided by the bump side length, whilst \(l_{bh}, l_{bw}\) and \(l_{bp}\) are the length of bump height, bump width, and bump pitch, respectively.

It can be easily observed that the left and right sides commonly longer than the top and bottom sides, which are the general features for the driver IC bumps of ACF-COG modules since the driver ICs are designed to stripe to be accommodated to the LCD glass edge margin. Therefore, the peak of Hough matrix for the image occurs at the \(\theta_1\) position, the left and right sides. Considering this features, the sets of bump sides can be achieved while the peaks satisfy specific geometric features:

1. There are \(2n + 2\) sets with peaks, among which \(2n\) sets appear at \(\theta = \theta_1\); the other \(2\) sets at \(\theta = \theta_2\).
2. There are two pairs with H peaks are perpendicular, which represents the \(\Delta \theta = 90^\circ\) in the \(\theta\) axis. Considering the bump manufacturing linearity tolerance, fix the \(\theta_1\) value with while the absolute ceil integral value of \(\theta_1\) minus \(\theta_2\) equal to \(90^\circ\): \(\text{ceil}(\theta_1 - \theta_2) = 90^\circ\).
3. The distances on \(\rho\) axis between peaks obey the Equation 2.

However, these relations may not be completely true since that there are lots of noise coming from the particles and bubbles. The relations 1 and 2 are relatively robust because the bump sides have more segments (see Figure 6).
Let $I$ be a $m \times n$ matrix associated with the grayed image from the acquisition. The horizontal and vertical vector of $I$, $H_i$ and $V_j$, are defined as follows:

$$H_i = \sum_{j=1}^{n} r_{ij}$$

(4)

$$V_j = \sum_{i=1}^{m} c_{ij}$$

(5)

where $r_{ij}$ is the $i$th row of $I$, and $c_{ij}$ is the $j$th column of $I$ respectively. The vectors $H_i$ and $V_j$ have dimensions $1 \times n$ and $1 \times m$.

Let $\nabla H_i$ and $\nabla V_j$ be the gradient values of the horizontal and vertical energy of the rotated grey image. $\nabla H_i$ and $\nabla V_j$ are $1 \times (n-1)$, $1 \times (m-1)$ vectors respectively, and defined as follows:

$$\nabla H_i = \sum_{j=1}^{n-1} (r_{i(j+1)} - r_{ij})$$

(6)

$$\nabla V_j = \sum_{i=1}^{m-1} (c_{(i-1)j} - c_{ij})$$

(7)

\[\nabla H_i = \begin{cases} \nabla H_i, & \nabla H_i \geq h_{thd} \\ 0, & \nabla H_i < h_{thd} \end{cases} \]

\[i = 1, \ldots, n - 1\]

\[h_{thd} = \text{sort}(\nabla H_i)_{(n \times \text{sel}(w \times lbp))} \]

(8)

\[\nabla V_j = \begin{cases} \nabla V_j, & \nabla V_j \geq v_{thd} \\ 0, & \nabla V_j < v_{thd} \end{cases} \]

\[j = 1, \ldots, m - 1\]

\[v_{thd} = \text{sort}(\nabla V_j)_{(n \times \text{sel}(w \times lbh))} \]

(9)

where $\nabla H_i$, $\nabla V_j$ are the $i$th element of $\nabla H_i$, $\nabla V_j$, and $\nabla H_i$, $\nabla V_j$ are the $i$th element of $\nabla H_i$, $\nabla H_i$; $h_{thd}$, $v_{thd}$ are the filter threshold of $\nabla H_i$, $\nabla V_j$, and fixed with the possible side number. In order to include the effective bump sides, the threshold value is magnified by $\text{sel}$ value, which is the selection coefficient.

With the filter energy gradient vectors in horizontal and vertical directions, the sets of bump sides can be achieved as the follows:

$$\begin{align*}
B_{Le} &= \{i \mid \nabla H_i < 0\} \\
B_{Re} &= \{i \mid \nabla H_i > 0\} \\
I_e &= \text{ceil}(n \times |\sin\alpha|), \ n - \text{ceil}(n \times |\sin\alpha|) \\
B_{Te} &= \{j \mid \nabla V_j < 0\} \\
B_{Be} &= \{j \mid \nabla V_j > 0\} \\
j_e &= \text{ceil}(m \times |\sin\alpha|), \ m - \text{ceil}(m \times |\sin\alpha|)
\end{align*}$$

(10)

(11)

where $i$ and $j$ are searched in the above subsets to remove the edge noise brought by the image rotation.

As the above process, the bump side sets of the sample image with energy gradient can be achieved as Figure 7. In Figure 7.a, the blue line is the horizontal energy and, the green line is the energy gradient with the offset of half vertical dimension, and the red line the filtered
energy gradient with amplification to be observed easily. It is evident that the bump side sets are easy to be polluted by the pattern noise, such as the particle aggregation like Figure 7.a. However, the bump side sets from energy gradient method are less sensitive to the bump shadow than those from the Hough Transform. Considering these advantages of the above two method, we fix the final bump sides with the combination of the two series of sets.

![Image](a) The left and right sides of bumps.

(b) The filtered energy gradient of vertical direction.

Figure 7. The bump side sets with energy gradient.

**B. Bump side fixation**

According to the geometric feature of bump design, we fix the bump sides with the above two series of side sets. Considering that there are several large gradient values at the bump sides because of the bump manufacturing error and the bump shadow, the element from the bump side sets using Hough transform is selected as the bump side if the element exists. Otherwise, the bump side is determined by the bump sets from energy gradient computation. Therefore, the fixation rule, using fuzzy reasoning [14]-[17], is designed as Table 1, which gives the logistics to combine the side sets and geometric features. In the experiment evaluation, we found that there was neither the line edge nor the energy gradient. In this case, the energy of supposed bump area was compared with the common bump to search the bump surrounded by the bubbles.

<table>
<thead>
<tr>
<th>Line edge</th>
<th>Energy gradient^a</th>
<th>Bump area Energy</th>
<th>L/U side</th>
<th>R/B side</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>Low</td>
<td>LC</td>
<td>Low</td>
<td>Low</td>
</tr>
<tr>
<td>Low</td>
<td>Low</td>
<td>HC</td>
<td>Medium</td>
<td>Medium</td>
</tr>
<tr>
<td>Low</td>
<td>P-high</td>
<td>HC</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Low</td>
<td>N-high</td>
<td>HC</td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td>High</td>
<td>Low</td>
<td>LC</td>
<td>Low</td>
<td>Low</td>
</tr>
<tr>
<td>High</td>
<td>Low</td>
<td>HC</td>
<td>Medium</td>
<td>Medium</td>
</tr>
<tr>
<td>High</td>
<td>P-high</td>
<td>LC</td>
<td>Medium</td>
<td>Low</td>
</tr>
<tr>
<td>High</td>
<td>N-high</td>
<td>HC</td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td>High</td>
<td>P-high</td>
<td>HC</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>High</td>
<td>N-high</td>
<td>HC</td>
<td>Low</td>
<td>High</td>
</tr>
</tbody>
</table>

^a. P-high and N-high mean that there are positive or negative maxima of energy gradient.

Among the bump side fixation, it is important to select a real bump side as a search start point. In the proposed approach, a geometry correlation coefficient \( CP \) is used to find the left valid bump side. Let \( CP \) be the frequency intersect with the supposed bump sides. Let \( sBLS, sBRS \) be the supposed left and right bump side sets. Therefore, \( CP \), \( sBLS \), and \( sBRS \) can be represented as the follows:

\[
sBLS_i = \left[ BL_{eg}^i + w * l_{bp} - tol, BL_{eg}^i + w * l_{bp} + tol \right] \cup \ldots \\
\cup \left[ BL_{eg}^i + w * l_{bp} * (n_{sb} - 1) - tol, BL_{eg}^i + w * l_{bp} * (n_{sb} - 1) + tol \right]
\]

\[
sBRS_i = \left[ BL_{eg}^i + w * (l_{bp} + l_{bw}) - tol, BL_{eg}^i + w * (l_{bp} + l_{bw}) + tol \right] \cup \ldots \\
\cup \left[ BL_{eg}^i + w * (l_{bp} + l_{bw}) + tol \right]
\]

\[
CP_i = size(sBLS_i \cap BL_{eg}) + size(sBRS_i \cap BR_{eg})
\]

where \( n_{sb} \) is the number of supposed bumps, and equals to \( floor \left( \frac{m - w * l_{bp}}{w * l_{bp}} \right) \). and \( tol \) is the coefficient for bump side tolerance. Using \( CP_i = size(sBLS_i \cap BL_{eg}) + size(sBRS_i \cap BR_{eg}) \) (12), we can achieve the start search index from the left bump side set of energy gradient, and the value is \( BL_{eg}^i \), in which \( i \) satisfies that \( CP_i \) has the global maximum.

According to the fixation rules and the search start point determination method, we propose the bump side fixation algorithm:

**Algorithm** Bump side fixation combining with the side sets using HT and energy gradient. (Forward search)

**Require:** \( BL_{eg}, BR_{eg}, BT_{eg}, BM_{eg} \) \{side sets of EG\}

**Require:** \( BL_{ht}, BR_{ht}, BT_{ht}, BM_{ht} \) \{side sets of HT\}
01: \( BL_{ss} \leftarrow BL_{eg} \), \( i \) satisfies that \( CP_i = \max(CP) \)
02: \( BL \leftarrow BL_{ss} \) \{Initialization of the bump left sets\}
03: \( sBR_{Sj} \leftarrow [BL + w \ast l_{bw} - tol, BL + w \ast l_{bw} + tol] \)
04: if \( BR_{ht} \cap sBR_{Sj} \neq \emptyset \) then \( BR = BR_{ht} \cap sBR_{Sj} \)
05: else if \( BR_{eg} \cap sBR_{Sj} \neq \emptyset \) then \( BR = BR_{eg} \cap sBR_{Sj} \)
06: else then \( BR = BL + w \ast l_{bw} \)
07: end if
08: for \( 1 \leq j \leq n_{sb} \) do
09: \( sBLS_j \leftarrow sBR_{Sj} \) using (12)
10: if \( BL_{ht} \cap sBLS_j \neq \emptyset \) then \( BL_t = BL_{ht} \cap sBLS_j \)
12: else if \( BL_{eg} \cap sBLS_j \neq \emptyset \) then \( BL_t = BL_{eg} \cap sBLS_j \)
13: end if
14: \( BR_t \leftarrow 0 \) \{Initialization of temporary right side\}
15: if \( BR_{ht} \cap sBRS_j \neq \emptyset \) then \( BR_t = BR_{ht} \cap sBRS_j \)
16: else if \( BR_{eg} \cap sBRS_j \neq \emptyset \) then \( BR_t = BR_{eg} \cap sBRS_j \)
17: end if
18: if \( BL_t \neq 0 \ AND \ BR_t \neq 0 \) then
19: \( BL = BL \cap BL_t; BR = BR \cap BR_t; \)
20: else if \( BAE < \text{threshold} \) then use the geometry side to substitute the zero side.
21: end if
22: end for

The algorithm is given out with the forward direction on the image horizontal axis, and can not extend to the backward direction with the \( n_{sb} = \text{floor}(BL_{ss}/(w \ast l_{bp})) \) and attention to the side set construction for supposed bumps.

5. Experimental evaluation and analysis

The images used in this paper for the experiment-based evaluation of the proposed approach are captured by Olympus BX 51 optical microscope. Four categories of bump figurations are used to evaluate the detecting and extraction algorithm. In order to explore the detecting capability in the high pattern noise images, the modules with bubble defects were selected as the main dataset. The spatial resolution of the images is \( 3.3\mu m \times 3.3\mu m \) and the valid object region is \( 144\mu m \times 192\mu m \).

<table>
<thead>
<tr>
<th>Category</th>
<th>Bump figuration</th>
<th>Image num.</th>
<th>Num. of rows in region</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>100 ( \mu m ) ((H) \times 18 \mu m ) ((W)) with 30 ( \mu m ) in pitch</td>
<td>141</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>80 ( \mu m ) ((H) \times 25 \mu m ) ((W)) with 35 ( \mu m ) in pitch</td>
<td>54</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>80 ( \mu m ) ((H) \times 25 \mu m ) ((W)) with 45 ( \mu m ) in pitch</td>
<td>39</td>
<td>2</td>
</tr>
<tr>
<td>4</td>
<td>80 ( \mu m ) ((H) \times 25 \mu m ) ((W)) with 35 ( \mu m ) in pitch</td>
<td>36</td>
<td>1</td>
</tr>
</tbody>
</table>

As the dataset mainly selected from the images with interconnection defects, there are conductive particle aggregation and the bubbles, in which bubble is especially common. These defects bring the challenge on the bump detection and extraction. In the real bump inspection, the bubble is not very common, thus the actual detection accuracy will be enhanced. Even in this case, the rate of bump extraction exceeds 95%. With the Matlab dynamic link library, the average elapse time of recognition for an image is less than 0.7 second. The runtime performance will be improved when the code is implemented by C++ in future. The detail evaluation performance is list in Table 3.

![Figure 8. The image dataset for evaluation: (a) category 1; (b) category 2; (c) category 3; (d) category 4.](image)

With the analysis on the missing bump recognition, we found that it mainly had been caused by the bump area energy threshold. As the detection results shown in Figure 9, the proposed approach can adjust the misalignment and detect the bumps correctly even in the multi-row bump cases and bubble defect cases. The correlation between the detection and the real bump is good, and more reliable than the manual crop.

6. Conclusions

In this paper, an automatic bump detection approach using fuzzy reasoning is presented. The method uses the Canny edge detector to reduce the operation data and then, utilize the Hough transform and energy gradient to achieve the bump side subsets. The approach combines the two side sets and geometric features using fuzzy reasoning method. The automatic bump detection method has been tested with over 250 images captured by optical microscope, and most of images are full with complex patterns, such as bubbles and even multi-row figurations. The detection results show that the detection method has a good robustness on the bump recognition, and the current bump extraction accuracy exceeds 95%. The proposed approach has been used in the bump
Table 3. Dataset for experimental evaluation.

<table>
<thead>
<tr>
<th>Category</th>
<th>Image num.</th>
<th>Bump num.</th>
<th>Num. of recognized</th>
<th>Num. of error</th>
<th>Elapse time in average</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>141</td>
<td>792</td>
<td>98.9%</td>
<td>9 bumps missed</td>
<td>0.658</td>
</tr>
<tr>
<td>2</td>
<td>54</td>
<td>254</td>
<td>95.3%</td>
<td>12 bumps missed</td>
<td>0.342</td>
</tr>
<tr>
<td>3</td>
<td>39</td>
<td>156</td>
<td>94.9%</td>
<td>8 bumps missed</td>
<td>0.345</td>
</tr>
<tr>
<td>4</td>
<td>36</td>
<td>180</td>
<td>97.8%</td>
<td>4 bumps missed</td>
<td>0.339</td>
</tr>
</tbody>
</table>

Figure 9. The example of detection results on the category sample images.

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References

[7] F. G. Shi, M. Abdullah, S. Chungpaiboonpatana et al., “Electrical conduction of anisotropic conduc-


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