Image-Based Analysis of PCB Panels

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Abstract. The PCB manufacturing is becoming more and more important as the consumer electronics products, such as mobile phones, tablet PCs, automatic washing machines and so on, are indispensable for our everyday life. To increase the throughput of the PCB manufacturing, single PCBs are usually designed to be connected with each other via connection tabs to form clusters. Such clusters are named “panels”. For automatic depaneling of PCB panels there are numerous machines from different manufacturers available in the market. But the configuration of the depaneling machines is complex and time-consuming. In this paper, a vision-based automated approach is proposed to simplify and accelerate this preparation process. The necessary information for the configuration can be obtained by analyzing the images of panels taken under backlighting conditions. After the segmentation of the images, all tabs are localized. The geometry information in the local regions of the tabs is used for the generation of appropriate milling curves which drive milling cutters to depanel the PCB clusters later. Thus, PCB manufacturers can benefit from reduced idle running of machines and labor costs.

Keywords
PCB panel, vision, image processing, segmentation, morphological operation, model fitting.

1. Introduction

The PCB (printed circuit board) manufacturing is becoming more and more important as the consumer electronics products, such as mobile phones, tablet PCs, automatic washing machines and so on, are indispensable for our everyday life. To increase the throughput of the PCB manufacturing, single PCBs are usually designed to be connected with each other via connections tabs to form clusters. Such clusters are named “panel”. A part of a demo panel is illustrated in Fig. 1. All to be removed connection tabs are marked with red ellipses. The single PCBs in a panel can be machined together using modern production technologies and depaneled into separated parts after any production process. There are numerous depaneling machines from different manufacturers available in the market. According to given milling curves, they are able to depanel the PCB clusters with equipped milling cutters automatically. But the configuration of the machines for automatic depaneling, including finding connection tabs and determining milling curves which are mostly manually carried out, is complex and time-consuming, especially when the manufacturers for the depaneling does not have access to the design files (computer-aided design files, etc.) of the panels. As a result, small batch productions could become inefficient due to too much idle running of machines and unprofitable by reason of additional labor costs.

Since last decades, a variety of papers for image-based analysis of PCBs have been presented. In [1] and [2] approaches for the preprocessing of PCB images are reported. By applying these techniques, relevant components of PCBs are localized in the images and can be used for further analysis. For AOI (automatic optical inspection) a series of algorithms are proposed in [3], [4], [5] and [6]. Based on images, the quality of produced circuits with respect to completeness and correctness can be automatically inspected. M. Mogant et al. gave also a survey of existent AOI systems in [7]. Most of these research works are focused on the defect detection in the PCB manufacturing. To the best of author’s knowledge, there are very few publications in the area of automatic depaneling. Therefore, it is a fairly new field of research.

In this paper, the image-based analysis of PCB panels is presented. Images of panels are segmented into foreground (panels) and background using both gray and color value information. With aid of morphological operations, global structural and geometric information of panels can be obtained. Tabs are then localized in images by considering their characteristic features. To improve the quality of
the analysis, the segmentation is refined in local regions of found tabs. Appropriate milling curves used to drive milling cutters later are generated by employing the most fitting line or circle models of the tab (slot) edges.

The remainder of this paper is organized as follows: the segmentation of panel images and the detection of to be removed tabs are presented in section 2 as global operations. In section 3, the refinement of the segmentation and the milling curve generation are locally carried out. A conclusion of the image-based analysis is drawn in section 4.

2. Global Analysis

Single PCBs are connected with each other only via tabs in panels. Therefore, it is critical to detect all to be removed tabs. To achieve this, a set of global analysis operations are employed.

2.1. Segmentation

Images of panels can be divided into two segments: foreground and background. Panels, including non-conductive substrates or laminates, conductive tracks or etched copper sheets and electronic components, are the foreground. As it is illustrated in Fig. 1, besides tabs, there are also pre-milled areas in the panel between to be separated PCBs. They are the “slots” and important for the localization of tabs later. Slots build with other opened areas in PCBs and boundary areas out of panels together the background in images. To determine slots in images, a segmentation of panel images is then to be performed.

The to be machined panels are produced by different manufacturers and have diverse colors and forms. To enable a robust segmentation despite the diversity of the panels, the backlighting technique is employed. Using a diffuser before the light source, the background is imaged by the camera as bright white areas with homogeneous brightness. The substrates or laminates of panels which are chromatic and the bright white areas with homogeneous brightness. The substrates or laminates of panels which are chromatic and the areas covered by conductive material and electronic components, are the foreground. As shown in Fig. 1, the foreground in the panel image can be further divided into two parts: semi-transparent (substrate) and non-transparent (conductive material and electronic components). For convenience, \( K, M \) and \( D \) denote the background, the semi-transparent areas and the non-transparent areas in \( I \) with

\[
I = K \cup M \cup D
\]  

(3)

where \( K \cap M = \emptyset, K \cap D = \emptyset \) and \( M \cap D = \emptyset \). While \( D \) is with gray values close to 0, \( K \) has the greatest gray values in the grayscale image \( I_G \) of \( I \) and they are concentrated to 255. \( M \) has gray values distributed between 0 and 255. Then it is possible to use a simple thresholding algorithm to separate \( D \) and \( K \) into two different segments. By applying the OTSU method introduced in [8] to \( I_G \), two segments \( S_{G,L} \) and \( S_{G,H} \) are available and there is

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(4)

where \( S_{G,L} = D \cup M_{G,L}, S_{G,H} = K \cup M_{G,H}, M = M_{G,L} \cup M_{G,H} \) and \( M_{G,L} \cap M_{G,H} = \emptyset \). The grayscale image of the demo panel is illustrated in Fig. 2(a). In Fig. 2(b) the histogram of corresponding gray values is presented. A red solid line is plotted to indicate the found threshold. Similarly, the variation image \( I_V \) of \( I \) can also be segmented into two parts because \( M \) has great variations and the other areas in \( I \) are with the \( r, g, b \) values varying only slightly from the average values. By applying the OTSU method again, two segments \( S_{V,L} \) and \( S_{V,H} \) are available after the thresholding and there is

\[
I = S_{V,L} \cup S_{V,H}
\]  

(5)
where $S_{V,L} = K \cup D_{V,L}$, $S_{V,H} = M \cup D_{V,H}$, $D = D_{V,L} \cup D_{V,H}$ and $D_{V,L} \cap D_{V,H} = \emptyset$. The variation image of the demo panel is illustrated in Fig. 2(c). In Fig. 2(d) the histogram of corresponding variation values is presented. There is also a red solid line plotted to indicate the found threshold.

Taking into account the segments $S_{G,H}$ and $S_{V,L}$ after thresholding $I_G$ and $I_V$, the background in $I$ can be obtained using

$$K = S_{G,H} \cap S_{V,L}.$$  \hspace{1cm} (6)

In Fig. 2(e) the found background mask of the demo panel is represented by white areas. For a better illustration in Fig. 2(f), contours of the background areas are plotted in red. It is obvious that the background is determined correctly at large scale in the panel image.

### 2.2. Tab Localization

Not all background areas are slots and relevant for the localization of connection tabs. Therefore, non-slot objects have to be removed after the segmentation of panel images. The boundary areas out of panels are considered here also as "slots", for they could be blended with some slots together. The non-slot objects are some holes and square or quasi-square blanks in panels designed for the assembly. They will be canceled based on their characteristic features.

To obtain the structural and geometric information of background areas, the mask of in last subsection determined background is skeletonized through a thinning operation. In contrast to slots, holes are thinned to be single points or sets of few points. They can be detected without great effort by regarding the ratios between their original sizes and the sizes of their skeletons. Besides the thinning operation, another powerful geometry analysis method is the image moment invariants as described in [9]. Square and quasi-square objects have centroids at the centers of their convex hulls which are completely filled. Furthermore, the pairwise eigenvectors of their covariance matrices have almost the same lengths. Such special features are used for the cancellation of these objects in the generated background masks.

Since non-slot objects are canceled and slots structural information is obtained and presented by their skeletons, connection tabs can then be localized. Looking back into Fig. 1, it is easy to see that each tab can be determined by two slots in direct neighborhood. In the images with skeletonized slots, tabs are localized correspondingly by the end point pairs of immediate slot neighbors. It is to be kept in mind that many tiny branches of slots are additionally created due to the sensitivity of the thinning operation to small disturbances, for example, inadequately smoothed slot edges. To achieve the desired localization result, a pruning operation removing the unexpected tiny branches is carried out. In Fig. 3(a) $br_1$, $br_2$ and $br_3$ are the additionally created branches. After pruning, only relevant structures are maintained in Fig. 3(b). With respect to the pairwise to the connection tabs arranged end points, ROIs (regions of interest) are built for each tab as bounding boxes and will be used for the local analysis later. A median filter is employed to cancel the ROIs with irregular sizes in which there are no actual tabs available. For the demo panel, all found tabs with their ROIs are indicated by red rectangles in Fig. 4.

3. Local Analysis

Tabs can be considered as breaks between the slots in direct neighborhood. After depaneling, the two slots of each slot pair should be combined to form a new slot with continuous profile. Thus, the geometric information in local regions of tabs is relevant for the milling. It is then reasonable to perform a local analysis instead of global operations for the milling curve generation. The total processing time could also be reduced as the panel images need only to be partly processed at this step.

### 3.1. Segmentation Refinement

Using gray and color value information and the OTSU thresholding method, background in panel images was segmented correctly at large scale in Section 2. But in single ROIs of tabs the segmentation of background might be unsatisfying for the milling curve generation due to the globally determined thresholds. A refinement of the background segmentation is then necessary.
3.2. Milling Curve Generation

Slots are pre-milled areas in panels. To obtain continuous profiles of PCBs after depaneling, all milling curves should be generated based on the slot edges in local regions of tabs. However, the edges could be in complex forms and, as a result, can not be directly used as references.

During depaneling, all possible milling curves are lines and arcs which can also be approximated by small line segments. Regarding this, the slot edges are fragmented into line segments using the generalized line model

$$ax + by + c = 0 \quad (8)$$

where $a$, $b$, and $c$ are constants, $x$ and $y$ are pixel coordinates of edge points. In contrast to using line models with slopes and intercepts, singularities caused by special line orientations are avoided using this model. To fragment the edges correctly and efficiently, three criteria are employed for the evaluation of the model fitting. They are the maximum error $Err_{max}$ of single points off the estimated line model, the RMSE (root mean square error) $Err_{RMSE}$ of all points off the estimated line model and the ratio $\eta$ of the number of related points to the length of the current line segment. To accelerate the decomposition of slot edges, the binary search algorithm is applied. For a better understanding of this, the chain code of the points on an edge is illustrated in Fig. 5. $p_s$ is the given starting position in the chain code, $p_e$ is the end position, $p_m$ is the middle position of the entire chain, $p_{m1}$ is the middle position between $p_s$ and $p_m$, $p_{m2}$ is the middle position between $p_m$ and $p_e$. In the first step, the points between $p_s$ and $p_m$ are used for the line fitting. After evaluating the estimated line model with respect to all related points, it can be determined, whether the estimated line model is valid. If a valid line model is presented, the points between $p_s$ and $p_{m2}$ are used for the line fitting again. If the boundaries defined for $Err_{max}$, $Err_{RMSE}$ and $\eta$ are exceeded, no valid line model is available and only the points between $p_s$ and $p_{m1}$ are used for the line fitting again. This process is to be repeated until a valid line model is found and no further point can be appended to it. In order to prevent too many and too small line segments, an iterative fusion of immediate segment neighbors is carried out. The line segments with about the same slopes and intercepts are combined with each other. Accordingly, the restrictions of $Err_{max}$, $Err_{RMSE}$ and $\eta$ are slightly relaxed to achieve appropriate decomposition result.

Usually more line segments than needed will be fragmented. To select the relevant segments for the milling curve generation, following conditions must be considered:

- a reference segment can not be too short;
- the corresponding line model must come into contact with the other slot;
- there must be another line segment parallel to the current segment with a non-negligible displacement.

For linear milling, the final milling curves are estimated using (8) and the found reference line segments. A demo tab in local region is presented in Fig. 6(a). Obviously, it should be linearly milled. In Fig. 6(b) all originally found line segments are plotted in random colors. After the iterative fusion and the cancellation of irrelevant edge fragments, only four line segments are left in Fig. 6(c) and they are the valid references. The generated milling curves are plotted in solid blue lines in Fig. 6(d). To adapt the generation process also
to arched milling curves, the found reference line segments are evaluated using both (8) and the generalized circle model
\[(x + a')^2 + (y + b')^2 + c' = 0\] (9)

where \(a', b'\) and \(c'\) are constants. The better fitting model, line or circle, is to be employed for the milling curve generation. Another demo tab is illustrated in Fig. 7(a). Valid reference segments are presented in Fig. 7(b). Red curves in Fig. 7(c) and Fig. 7(d) are generated lines respectively arcs for depaneling. In consideration of the reference segments plotted in thick blue curves in Fig. 7(c) and Fig. 7(d), arched milling curves are preferred.

Some further demo tabs are illustrated in Fig. 8. All of them will be appropriately milled using the generated milling curves.

4. Conclusion

In this paper, the image-based analysis of PCB panels is proposed for automatic depaneling. Instead of the conventional machine configuration approach for automatic PCB depaneling which is time-consuming and can only be carried out by skilled workers, the image-based approach enables an automated configuration process: after the to be removed connection tabs are globally localized, appropriate milling curves are generated using local geometric information for obtaining continuous profiles of single PCBs after depaneling. All of these analysis operations can be rapidly conducted using common industrial PCs. Thus, PCB manufacturers can benefit from reduced idle running of machines and labor costs.

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References


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