Localizing Components on Printed Circuit Boards Using 2D Information

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Abstract—Information retrieval based re-configurable recycling is crucial for solving the environmental and social problems raised by the dramatically increasing amount of waste printed circuit boards. However, the indispensable localization of mounted components for the desired information retrieval is an unsolved problem for state-of-the-art techniques so far. In this paper, for the first time, a feasible solution addressing this problem by using general 2D information is proposed. In the form of a sophisticated modular analysis pipeline, complementary information sources are combined appropriately for capturing the sought objects. With a novel background removal algorithm and an additional candidate validation step, the proposed approach significantly outperforms state-of-the-art localization approaches in case of PCB images. Moreover, with respect to the intended trade-off between complexity and performance, it is quite straightforward to re-construct the deployed workflow accordingly by considering the knowledge obtained in a comprehensive evaluation of diverse combination possibilities.

I. INTRODUCTION

In spite of the clear benefits of rapid innovation and development in electronics, we are also facing a series of environmental and social problems raised by the dramatic increase in amount of waste electrical and electronic equipment (WEEE). Inappropriate recycling and disposal of WEEE lead not only to a significant waste of resources, but also to serious damage to health and environmental pollution. Especially in many developing countries the recycling of WEEE still mainly relies on manual processing, where an adequate worker protection and an environment-friendly disposal management are often missing. To tackle these problems, automated systems for economic recycling and ecological disposal are highly desirable.

As the central functional units of most electronic products, printed circuit boards (PCBs) are of special interest for recycling. However, due to their high variability and the usually lacking knowledge about the assembled components, an automated comprehensive recycling is still an open question in state-of-the-art technology. In practice, most of the deployed autonomous recycling systems are aiming at certain metallic materials, which are dominant and commonly available in PCBs, while the remaining scraps are often landfilled or incinerated. These serious deficiencies have been confirmed by the survey research in [1] and the observations made in [2]. According to the research results presented in [2]–[4], a variety of further valuable materials and many hazardous substances are also contained in PCBs. Regarding the huge amount of the annually discarded electronic products, there is an increasing need for more advanced PCB recycling systems.

To address this challenge in current PCB recycling, an information retrieval based re-configurable processing pipeline was first proposed by Li et al. in [5], which is illustrated in Fig. 1. Depending on the input PCBs and the retrieved information, the entire processing pipeline is configured for the optimal recycling with respect to the integrated processing units and the user-defined benefit/cost factors. Obviously, the retrieved information has the most impact on the recycling performance. For achieving the desired information retrieval, several subsequent research activities were conducted for realizing the underlying subsystems: from image pre-processing to surface reconstruction and from identifying devices to recognizing mounted components for the desired information retrieval in [5]–[10], the focus of this paper is on components of diverse colors, shapes and sizes using general 2D information, where no specific imaging condition is required.

Following the idea of Li et al., we propose a sophisticated approach for localizing components on PCBs by employing general 2D information obtained using an industrial camera. As a complementary analysis to the established information retrieval in [5]–[10], the focus of this paper is on components from middle to large size. In Fig. 2, some components of interest are exemplarily marked with red rectangles in a demo PCB image for a visual impression. To the best of our knowledge, we propose for the first time a feasible solution for localizing PCB components of diverse colors, shapes and sizes using general 2D information, where no specific imaging condition is required.

For the reader’s convenience, the remainder of this paper is organized as follows: after a review of state-of-the-art object localization techniques, an overview of the proposed approach for localizing PCB components is presented in Sec. II, while the implementation details are provided in Sec. III. To assess the performance of the proposed approach, a comprehensive
evaluation is conducted on a well-defined dataset using appropriate measures in Sec. IV. In the last section, some general conclusions are presented.

II. PROPOSED APPROACH

A. Related Work

Object localization is fundamental for computer vision and image understanding applications. In most cases, not only the sought objects, but also their position information needs to be extracted. There are in general two categories of approaches for achieving this purpose: exhaustive search-based, e.g. [13]–[15], and pixel grouping-based, e.g. [16], [17]. The most common form of an exhaustive search is the sliding window-based analysis. By scanning whole images using sliding windows of different sizes and aspect ratios, the objects of interest should be captured by some of these windows. Subsequently, all local regions cropped by the sliding windows are fed to pre-trained classifiers for selecting those windows optimally separating the sought objects from background. Using sliding windows of well-defined sizes and aspect ratios with respect to the intended application, objects of interest can be detected and localized very precisely. However, the unavoidable huge search space of candidates leads to extremely high computational complexity. In contrast, the pixel grouping-based approaches always rely on some directed candidate generation strategies, which should provide task-relevant candidates at a considerably reduced number. Exploiting diverse information sources (e.g. local continuity/discontinuity in terms of intensity, color and texture, global distribution of extracted local features, a priori knowledge), pixels of images are grouped into regions to form meaningful candidates. Just as for the exhaustive search-based approaches, pre-trained classifiers are employed for selecting the regions that match optimally to the objects of interest. Apparently, such approaches are bearing the risk of missing the sought objects if the candidate generation fails to capture all relevant regions.

B. Deployed Workflow

As illustrated in Fig. 2, the sought PCB components exhibit a very high degree of variability in size and shape. This could lead to an exponentially increased effort for searching through all local regions of possible sizes and aspect ratios in case of exhaustive search. Therefore, it is more practical to realize the desired localization by generating candidates using appropriate pixel grouping strategies. To significantly reduce the risk of missing relevant candidates by only employing single strategies and as inspired by [16], a reasonable solution is to incorporate the diversification strategy for exploiting the potential of complementary information sources, such as various color spaces, scales and pixel grouping strategies. This strategy has shown quite encouraging results in previous work [16], [17] and should be able to provide a more comprehensive set of region candidates in our case, too. Bearing these considerations in mind, we developed our localization approach in the form of sequential modular processing stages. The proposed workflow is visually presented in Fig. 3 and briefly introduced in the following.

Beginning with a couple of pre-processing steps for removing image noise and uneven illumination, the PCB images are subsequently represented over a set of scales in the scale space. Then, a variety of features, typically intensity, color, edge and texture, are extracted in images of different scales. Based on the extracted features and by employing diverse strategies for pixel grouping, region merging and background removal, numerous region proposals for sought PCB components are generated. Finally, a component/background classifier is trained on a pre-defined dataset in terms of distinctive features and deployed for categorizing the obtained region proposals in test images into components or background regions.

III. IMPLEMENTATION

In this section each stage of our proposed localization approach is described in detail. To keep the deployed workflow more general, all considered processing steps for achieving the identified objectives are presented. Further information on the optimal combination of certain features and strategies, as well as on the parameter selection, is provided in Sec. IV.

A. Pre-processing

The localization process begins with standard pre-processing operations for improving the image quality by removing noise and uneven illumination. Two of the most frequently used de-noising filters are Gaussian and median. Gaussian filtering suppresses high frequency noise, while information with lower local variation is kept as relevant image content. The median filter leads to a similar noise suppression, where pepper-and-salt noise is better removed and edges are preserved. For the purpose of illumination normalization, the comprehensive color normalization in [18] is of special interest since no parameter tuning is required. For illustration, two pre-processed images after respective median filtering and comprehensive color normalization are presented in Fig. 3(b).
B. Scale-space Representation

A scale-space representation is commonly combined with other image analysis methods if features and objects are presented on a wide range of spatial scales. To this end, selecting appropriate scales or employing an automatic scale selection mechanism are often considered and proved to be essential for extracting relevant information [19]. However, since PCB components can be found at all possible scales and it is difficult to define a general fitness function guiding the automatic scale selection, we prefer to generate a scale space covering all possible components and utilize the power of machine learning in the final stage to omit non-relevant detections. In consideration of preserving significant edges and computational efficiency, the non-linear scale space (NSS) implementation [20] based on the fast explicit diffusion schemes introduced in [21] is adopted in our workflow for generating multi-scale images. Two PCB images of different scales are illustrated in Fig. 3(c) for demonstrating the post-NSS results.

C. Feature Extraction

In contrast to publications on feature detection/matching, the term “feature” has a more general meaning here. It refers to the information employed for grouping pixels and distinguishing objects of interest from background. Thus, intensity, color, edge and texture are extracted in this stage and used as inputs for generating region proposals with the diversification strategy. For compactness, all extracted features are listed below, along with respective references for more details:

- intensity: gray value of pixels;
- color: pixel value represented in different color spaces, e.g. RGB, HSV, $L^*a^*b^*$ and $L^*u^*v^*$;
- edge: edge response obtained using the learning-based structured random forests introduced in [22];
- texture: local texture features captured using cut-off windows according to [23], [24] and no filter bank required.

D. Candidate Generation

In this stage numerous region proposals are generated to capture components presented in PCB images. Moreover, since there are many non-object proposals induced by cluttered background, a cancellation of such false candidates is also conducted in consideration of background properties, which should significantly reduce the number of candidates to be validated in the final stage of the deployed workflow in Fig. 3.

1) Pixel Grouping: as stated in Sec. II, it is important to exploit the potential of diverse pixel-grouping strategies for reducing the risk of missing relevant candidates. To this end, several state-of-the-art region proposal generation algorithms are combined for improved performance.

Segmentation is one of the most studied pixel-grouping techniques, where local smoothness/similarity is considered for partitioning images into meaningful subregions. Due to the computational efficiency and the well approximated optimal partition, graph-based methods have gained increasing attention over the last decade. The graph cuts-based (GC) [25], [26] and the efficient graph-based (FH) [27] variants have found wide applications in computer vision and are also employed in our proposed localization workflow. Another valuable class of segmentation methods is the local distribution-based variants, among which the mean shift segmentation (MS) [28] provides superior results in most cases. In contrast to the graph-based methods, an initial segmentation is omitted for the mean shift segmentation and no parameter tuning is required if the spatial and the range bandwidth are determined. Due to its reliable performance, this algorithm is considered for generating additional proposals.

Segmentation methods may run into over- and under-segmentation problems. One of the feasible solutions to address such problems is to partition images into over-segmented regions, which are merged later to form more appropriate
region candidates. The data compression-based algorithms CTM [23] and TBES [24] were proposed to merge regions according to their texture features. Adjacent regions are merged if the coding length of all feature vectors is reduced compared to the previous case of single regions. By this means, the optimal combination of regions is achieved if the global minimum description length is obtained. A more generic merging approach is the selective search [16]. By considering a bundle of complementary color spaces and similarity measures, initial over-segments are hierarchically grouped to form region candidates at different scales. For an adequate diversification of complementary information sources, all objects of interest can be captured. These two different classes of merging algorithms are employed in our work to increase the probability of correctly localizing PCB components.

2) Background Removal: For mechanical support, flame retardancy and electronic isolation, PCBs are manufactured on the basis of substrates. As illustrated in Fig. 2, the applied substrate is visible in background regions and covered by components mounted on the surface of the PCB. As a result, false region candidates induced by cluttered background can be removed if substrate regions are identified in PCB images. Apparently, all regions filled with the same substrate show similar color values. Thus, it is feasible to achieve the desired separation of background from components by merely exploiting color information. For this purpose, a background estimation algorithm is developed and clusters PCB images into foreground and background regions.

To cluster image pixels with respect to their color values, a 3D histogram is first constructed in the corresponding color space for each image. By applying the mean shift-based mode seeking in this 3D histogram, the color space is clustered into several disjoint regions. To avoid possible fragmentation of clusters due to the quantization of color values, a 3D connected-components analysis is conducted as the post-clustering processing to join neighboring clusters. For suppressing tiny clusters and to reduce the number of regions in the clustered image, a further merging operation is employed to link small clusters with their nearest neighbors, or in other words the most similar color clusters. Finally, regarding the clustered color space, the PCB image is divided into subregions using the pixel color values. By visual inspection, we have noticed that substrate regions are distinctive from PCB components with respect to the following aspects:

- dominance in images;
- irregularity of contours;
- extent;
- orientation of gradients.

To solve the background separation problem in a more flexible manner and to easily adapt the approach to new PCB images, a weak classifier is trained to recognize the substrate regions (instead of using any thresholds-based decision rules). Aiming at a good compromise between low rejection rate of true components and high rejection rate of false background candidates, the classifier should determine background regions with a high confidence and an adequate sensitivity.

E. Validation

Amongst other methods for image classification, the bag-of-visual-words (BoVW) model has shown its success in recent research [29]. Instead of using well-designed features, the occurrence of visual words in local image regions is employed for classification purposes. All visual words are encoded in a vocabulary, which is constructed as the collection of all cluster centers of locally extracted distinctive features (typically SIFT [30] and SURF [31]) on a pre-defined dataset. If the occurrence of visual words is considered in each subregion of a partitioned image separately, the spatial information of all representative features is also integrated for improved classification performance. In our localization approach, the BoVW model is employed for categorizing all region proposals obtained after the candidate generation stage, where objects and non-object candidates should be confirmed and rejected, respectively.

At training time, numerous region proposals are generated for a couple of images with known ground-truth data, e.g. bounding boxes of PCB components. By sampling local features in pre-defined subregions of each image, a huge set of feature descriptors are collected. These descriptors are clustered into $N$ subsets to construct the desired vocabulary of the size $N$. According to the ground-truth data, all region proposals are identified as positive or negative samples. Using the label information of these samples, as well as the established BoVW model, the training of a classifier for validating region proposals at evaluation time is straightforward.

IV. Evaluation

To derive a feasible solution for the component localization problem, a sophisticated approach is developed and diverse methods for achieving complementary analysis results are combined. However, the effectiveness of the diversification strategy and the optimal combination of single methods with respect to the trade-off between complexity and performance still remain unknown. Thus, a comprehensive evaluation of the proposed localization approach is indispensable.

A. Dataset and Measures

Before conducting any evaluation, a well-defined dataset is established for later analysis. The reason for acquiring a dataset is two-fold: some steps of the deployed workflow rely on data-driven learning processes and the localization performance can only be evaluated against the ground-truth data of test images. In our dataset, 31 images of different PCBs are selected and all 1124 components are manually labelled in the form of region masks, so that diverse localization quality measures can be applied without additional processing.

For quantitative evaluation, all localization results are scored in the form of recall and precision. Since pixel-grouping methods are employed in the candidate generation stage, a matched, false or missing detection in this stage is assessed with respect to the region of grouped pixels. On the other hand, region proposals are defined as cropped image tiles in the stage of validating candidates, so the corresponding localization results are assessed with respect to the bounding
boxes. A valid detection is obtained if the intersection-over-union (IoU) score is greater than 0.5.

B. Results

To investigate the performance of single pixel-grouping methods without diversification and the effectiveness of the proposed background removal, we repeated the candidate generation stage several times and activated only one of the three methods: GC, FH and MS for each round, where the background removal is enabled and omitted alternately. For a fair comparison, an adequate parameter tuning is conducted for each considered method. A summary of the obtained localization results is presented in Tab. I, where “−” and “+” denote the activation and omission of the background removal, respectively. Apparently, the overall performance is significantly improved if background regions are cancelled.

All region-merging algorithms have been investigated in a similar manner. However, we have noticed that the CTM and TBES algorithms take extremely long time for conducting the merging process (20 hours on a 2448 × 2050 image, Intel Quad CPU 2.4GHz with 6G RAM), whereas the score of recall falls below 0.2. This led to an immediate dismissal of these algorithms. In contrast, selective search is able to capture the most PCB components in a reasonable time. For a comprehensive comparison, the performance of selective search is evaluated against some state-of-the-art exhaustive search-based object localization approaches in terms of the proposed bounding boxes. As illustrated in Tab.II, an extremely high score of recall is achieved using selective search, while a very low score of precision and a huge number of candidates are also presented. Similar results are also observed for the exhaustive search-based approaches edge boxes [32] and BING [33]. This reveals a general challenge to the state-of-the-art localization approaches in case of PCB images. Regarding the unavoidable high computational complexity caused by all region-merging solutions, this step is completely dismissed in the final deployed workflow.

The first part of the diversification strategy is to combine results obtained over different scales and parameter settings.

Again, we repeated the candidate generation stage by applying single methods on multi-scale images with multiple parameter settings. The summarized performance of diverse combinations is presented in Tab. III. The remaining part of the diversification strategy is to exploit the potential of complementary methods. In Tab. IV, an overview of the combined methods with their performance is also presented.

From the above observations, the optimal candidate generation with less computational complexity is achieved if the FH method is applied on multi-scale images. To cancel false candidates while keeping most localized true objects, combinations of the SIFT and SURF features with the random forest and SVM classifiers are evaluated for achieving the optimal classification performance. For our dataset, the SIFT features and the random forest classifier provide significantly more satisfactory results than the other two options. The final localization is obtained with a recall score of 0.808 and a precision score of 0.510. An overview of the incremental improvement of the overall localization performance can be obtained in Fig. 4. By combining an appropriate pixel-grouping method with extra background removal, the diversification strategy and validation, a feasible solution for localizing PCB components using 2D information is presented.

V. Conclusion

Localizing and retrieving information about the mounted components is the most important step towards re-configurable PCB recycling. However, localizing the sought components using 2D information has been an open question so far and a general challenge for state-of-the-art techniques. In this paper, a feasible solution to address this problem is proposed for the first time. To this end, we developed a sophisticated modular analysis pipeline incorporating a diversification strat-

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**TABLE I**

Summarized performance of single pixel-grouping methods without(−) and with(+) the proposed background removal.

<table>
<thead>
<tr>
<th>combination</th>
<th>recall</th>
<th>precision</th>
<th>candidates</th>
</tr>
</thead>
<tbody>
<tr>
<td>GC−</td>
<td>0.441</td>
<td>0.076</td>
<td>38153</td>
</tr>
<tr>
<td>GC+</td>
<td>0.620</td>
<td>0.178</td>
<td>9600</td>
</tr>
<tr>
<td>FH−</td>
<td>0.454</td>
<td>0.069</td>
<td>3074</td>
</tr>
<tr>
<td>FH+</td>
<td>0.709</td>
<td>0.163</td>
<td>649</td>
</tr>
<tr>
<td>MS−</td>
<td>0.401</td>
<td>0.022</td>
<td>159</td>
</tr>
<tr>
<td>MS+</td>
<td>0.411</td>
<td>0.049</td>
<td>3342</td>
</tr>
</tbody>
</table>

**TABLE II**

State-of-the-art localization approaches.

<table>
<thead>
<tr>
<th>approach</th>
<th>selective search</th>
<th>edge boxes</th>
<th>BING</th>
</tr>
</thead>
<tbody>
<tr>
<td>recall</td>
<td>0.997</td>
<td>0.873</td>
<td>0.247</td>
</tr>
<tr>
<td>precision</td>
<td>0.067</td>
<td>0.032</td>
<td>0.005</td>
</tr>
<tr>
<td>candidates</td>
<td>38153</td>
<td>9600</td>
<td>3074</td>
</tr>
</tbody>
</table>

**TABLE III**

Combining multiple scales and parameter settings.

<table>
<thead>
<tr>
<th>combination</th>
<th>recall</th>
<th>candidates</th>
</tr>
</thead>
<tbody>
<tr>
<td>GC single</td>
<td>0.711</td>
<td>159</td>
</tr>
<tr>
<td>GC multiple</td>
<td>0.673</td>
<td>156</td>
</tr>
<tr>
<td>FH single</td>
<td>0.871</td>
<td>649</td>
</tr>
<tr>
<td>FH multiple</td>
<td>0.887</td>
<td>660</td>
</tr>
<tr>
<td>MS single</td>
<td>0.623</td>
<td>3839</td>
</tr>
<tr>
<td>MS multiple</td>
<td>0.649</td>
<td>3342</td>
</tr>
</tbody>
</table>

**TABLE IV**

Combining diverse methods.

<table>
<thead>
<tr>
<th>combination</th>
<th>recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>GC, MS</td>
<td>0.770</td>
</tr>
<tr>
<td>GC, FH</td>
<td>0.848</td>
</tr>
<tr>
<td>FH, MS</td>
<td>0.842</td>
</tr>
<tr>
<td>GC, FH, MS</td>
<td>0.850</td>
</tr>
</tbody>
</table>
egy. By using a novel background removal algorithm and by appropriately combining complementary information sources, e.g. diverse color spaces, scales, etc., significantly improved localization performance is obtained in comparison to state-of-the-art approaches. Employing an additional validation step based on a data-driven learning process, further improvement of the obtained localization results is also observed. It is worth to mention that we conducted a comprehensive evaluation for diverse combinations. According to the intended trade-off between complexity and performance, it is straightforward to adapt the analysis pipeline if necessary, by activating and dismissing certain analysis methods. For instance, GC is preferred for less candidates and therefore low complexity, while selective search should be considered if a high recall score is required.

REFERENCES


