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A Dataset for Computer-Vision-Based PCB Analysis

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Abstract

We present a public dataset with the aim to facilitate research on computer-vision-based Printed Circuit Board (PCB) analysis, with a focus on recycling-related applications. The dataset contains 748 images of PCBs from a recycling facility, captured under representative conditions using a professional DSLR camera. For all these images we provide accurate segmentation information for the depicted PCBs as well as bounding box information for all Integrated Circuit (IC) chips (9313 samples). Furthermore, we provide textual information of the labels for a subset of 1740 IC samples. By including these different aspects of information, our dataset is useful for designing and testing a variety of methods for PCB analysis, from PCB classification over IC chip localization to the detection of specific chips. We discuss the benefits of PCB analysis for recycling, present dataset statistics, and use the dataset to evaluate two example methods, one for detecting specific PCBs, and one for recognizing mainboards.

1 Introduction

Printed Circuit Boards (PCBs) are mandatory for the production of electronics; most electronic devices contain one or several PCBs [1]. Consequently, there is a significant amount of waste PCBs from discarded electronics, demanding for effective recycling for two reasons. First, PCBs contain toxic materials that can cause environmental damage if not treated properly [1]. Second, PCBs contain a significant fraction of metals (about 30% on average [2]) that can be reclaimed, which is both economic and ecological. The required separation of metals is performed mechanically or chemically [2] in a destructive process.

Existing recycling lines do not utilize information on the input PCBs; the input stream is shredded to small particles from which metals can be extracted [2]. However, such information is valuable as it allows for more selective and thus effective means of recycling. For instance, knowledge of the origin of each PCB in the waste stream (e.g. from computers or flat panel displays) enables automatic sorting and optimized recycling lines for specific kinds of PCBs. Knowledge of mounted components can also be utilized for improved recycling. For example, certain Integrated Circuit (IC) chips contain valuable chemical elements such as gallium [3]. Selective recycling of ICs increases the concentration of such elements in the processed waste, facilitating their reclamation and creating new recycling opportunities (gallium, for instance, is currently not recycled [3]). Furthermore, knowledge of the presence of valuable components such as certain IC chips allows for reuse; such components can be removed (manually or automatically), tested, and reused before the PCB is destroyed in the recycling process.

To this end, the goal is to obtain information on each PCB that enters the recycling chain in a way that is both economic and efficient, which excludes manual labor. A promising alternative is to employ computer vision; optical sensors allow for around-the-clock and real-time analysis without having to interfere with the input stream, the required hardware is readily available, and the power consumption is low compared to other parts in a typical recycling appliance.

Different methods for optical PCB analysis have been proposed. Herchenbach et al. [4] use a combination of a RGB camera and a depth sensor to detect through-hole components on PCBs via depth- and color-based segmentation. Li et al. [5] present methods for detecting surface mounted devices. Small devices like resistors are located based on assembly information present on the board itself. IC chips are detected by means of color-based segmentation, utilizing the fact that such chips have a homogeneous color and a rectangular shape. Li et al. [6] perform text recognition on both boards and mounted components. They evaluate different optical character recognition engines in terms of robustness to text size and orientation and propose preprocessing steps to improve the text recognition performance. The authors of [7] present a method for recognizing specific PCBs in waste streams via local feature matching and geometric verification.

Apart from [7] all these works make us of own, private datasets, and lack detailed information on the characteristics of these datasets (e.g. PCB selection, image acquisition setup). The extent of these datasets appears to be small; in [4] the dataset comprises 21 PCB images while in [5] IC segmentation performance is assessed using images with 128 ICs in total. The dataset used in [6] consists of 860 PCB segments with text, but there is neither information on the number of PCBs these segments were extracted from, nor on the text selection process. Furthermore, it seems that all datasets used in these works were obtained from clean PCBs. However, in practice waste PCBs are typically dusty and often have scratches and some damaged components. The dataset used in [7] is publicly available and more extensive (480 images of 80 different PCBs), but consists of low-quality images that are inadequate for analysis at the component level.

In this paper we present a dataset that aims to overcome these limitations. The dataset contains images of 165 different PCBs that were extracted from a waste stream in a recycling facility, and the PCBs were not altered before image capture. As such, the dataset is genuine in terms of both the distribution of depicted PCBs and their condition. In practice, PCBs typically enter the recycling chain on a conveyor belt and are thus oriented arbitrarily. To reflect this circumstance, our dataset contains multiple images of each

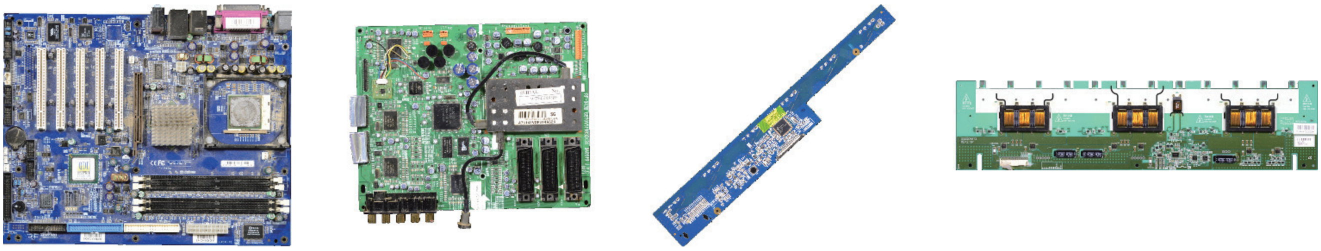

Figure 1. Segmented example images from the dataset.

PCB in different orientations. This enables the design and testing of methods that are robust in this regard.

In total there are 748 images in the dataset. For each image we provide accurate segmentation information for the depicted PCB as well as bounding boxes for all IC chips. For a subset of these chips we also provide textual information as stated on the chips. By providing such different aspects of PCB information, our dataset is useful for the design and evaluation of a variety of recycling-related methods, as demonstrated in Section 4. The dataset is freely available online[1].

The rest of this paper is organized as follows. Section 2 details the image acquisition setup and labeling process. A statistical analysis of the dataset is given in Section 3. Section 4 presents two exemplary applications that use different aspects of information provided by the dataset. Conclusions are drawn in Section 5.

2 Image Acquisition

In order to ensure representative data, we built an image acquisition system that resembles conditions under which vision-based methods for PCB recycling are expected to operate in practice (Figure 2).

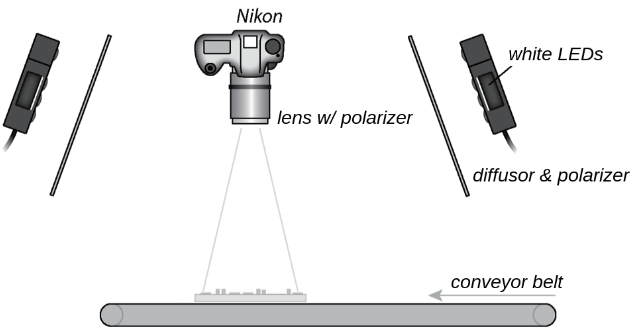

Figure 2. Image acquisition setup.

The acquisition system includes a black conveyor belt for carrying the waste stream. A professional DSLR camera, a Nikon D4 with a 60mm f/2.8 lens, is mounted above this conveyor belt at a distance of 107cm. The camera position and lens ensure that larger PCBs such as mainboards are fully visible in a single image in any orientation. The Nikon D4 has a continuous shooting speed of up to 10 frames per second and can be controlled from a PC, rendering it suitable for real-time vision applications. The resolution of all images is 4928×3280 pixels, which amounts to a spatial resolution of about 222ppi (87.4 pixels per cm).

[1] `http://www.caa.tuwien.ac.at/cvl/research/cvl-databases/pcb-dslr-dataset/`

The images are thus suitable for applications that demand high resolution and quality, such as component detection and text recognition.

In order to ensure a constant illumination, the acquisition system is surrounded by opaque curtains that block outside light. Inside the system polarized light is used for illuminating the waste stream. In conjunction with a polarization filter in front of the camera lens, this effectively suppresses specular reflections.

Our dataset comprises images of 165 different PCBs that were sampled randomly from a waste stream in a recycling facility (Figure 1 shows examples). The PCBs originate from PCs, laptops, flat panel displays, and other electronic devices. In practice, neither the orientation nor the exact location of waste PCBs on the conveyor belt is known a priori. For this reason the dataset includes multiple (three to five) images for each PCB, with varying PCB orientations and positions.

In addition to these raw images our dataset provides different aspects of PCB information. Each image is associated with PCB segmentation information in the form of a binary image. This segmentation was carried out accurately using GrabCut [8]. By providing this data our dataset can be used to gain information on the geometry of PCBs and for evaluating methods for automatic PCB segmentation. Furthermore, we provide bounding box information for each IC chip in each PCB image, for a total number of 9313 samples. For a subset of 1740 samples we also provide textual information as stated on the chips. This information can be used to train and test methods for detecting such chips. Figure 3 illustrates an image from the dataset.

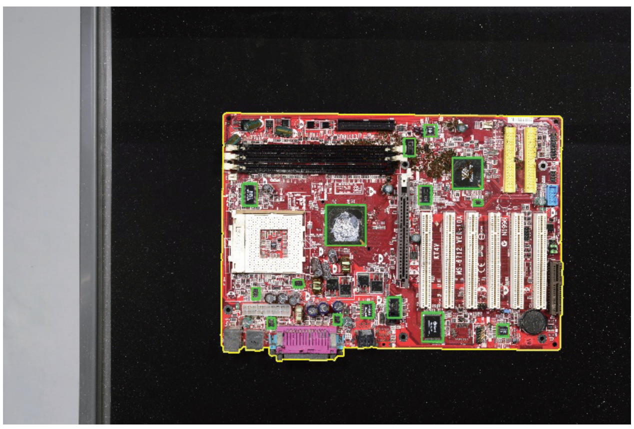

Figure 3. An image from the dataset (the conveyor belt is clearly visible). PCB segmentation information and IC locations are highlighted.

In order to facilitate the use of our dataset, we provide APIs for easy data access in three common programming languages, Matlab, Python, and C++. The following code sample shows how to access the image and IC chip information of a certain PCB with Python. A complete API description is available online.

```
db = PCBDataset('path/to/dataset')
pcb10 = db.pcb(10)  # load specific PCB
image = pcb10.image()  # PCB image
ics = pcb10.ics()  # list of IC locations
```

3 Dataset Statistics

This section presents statistics on our dataset. All statistics were obtained using a single image per PCB, resulting in 165 images in total. The total number of unique labeled IC chips in the dataset is 2048.

The depicted PCBs vary significantly in size; the minimum, median, and maximum PCB sizes are 37.3cm^2, 350.2cm^2, and 835.7cm^2, respectively. PCB sizes were extrapolated from the segmentation information and are therefore approximative.

Figure 4 shows the distribution of the number of IC chips per PCB. It is visible that the majority of PCBs contain less than 20 of these chips. More precisely, of the 165 different PCBs in the dataset, 11 contain no such chips, 42 PCBs (25.5%) contain at most 3 chips, 84 PCBs (50.9%) contain at most 9 chips, and 137 PCBs (83.0%) contain at most 19 chips. The largest number of IC chips on a single PCB is 135.

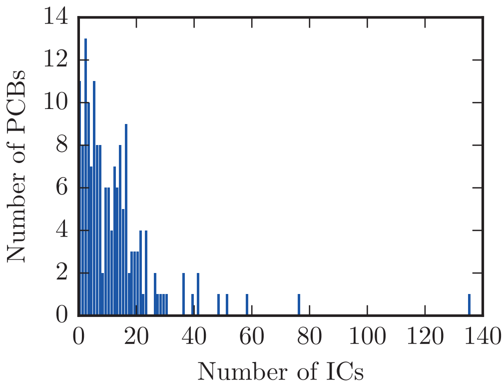

Figure 4. Histogram of the number of IC chips per PCB. Most PCBs contain less than 20 IC chips.

There is a large variance in the size (area) and aspect ratio (ratio between larger and smaller side length) of IC chips. This is illustated in Figure 5, which shows the joint distribution of these properties among the 2048 IC chips. It is visible that the size distribution is skewed towards the left, i.e. there are more small ICs than large ones. 25% of the IC chips are less than 0.51cm^2 in size, 50% are smaller than 0.87cm^2, and 75% are smaller than 2.29cm^2. The smallest chip is only 15mm^2 in size. 5% of IC chips (mostly CPUs and other mainboard chips) are larger than 7.9cm^2.

4 Evaluation of PCB Recognition Methods

This section demonstrates the use of our dataset for designing and evaluating methods for vision-based

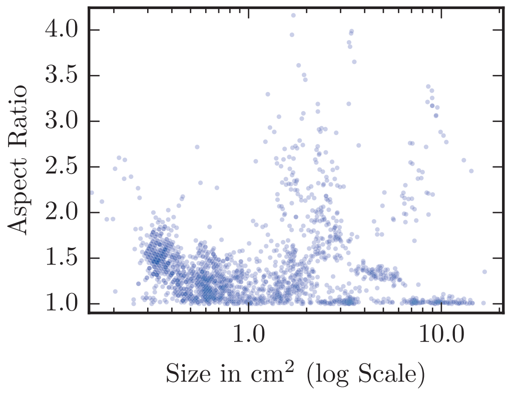

Figure 5. Joint distribution of size and aspect ratio among the IC chips in the dataset.

PCB analysis. Due to space constraints we focus on two basic examples, recognition of specific PCBs and distinction between mainboards and other PCBs.

4.1 Specific PCB recognition

In this section we employ our dataset to evaluate a method for detecting specific PCBs in waste streams that is presented in [7]. This method allows for monitoring the waste stream for certain PCBs that should be treated separately from the rest.

The method represents each PCB as a collection of local features (ORB features [9]) and their spatial relations. Such representations are well-suited for PCB recognition because they are rotation-invariant and robust to small perspective distortions as well as dust and partial PCB damage [7]. The method expects a database that contains such a representation for every PCB that should be recognized, and each PCB in the waste stream P_i is segmented and compared to all database entries $\{D_j\}_{j=1}^{J}$ via local feature matching. This follows geometric verification, utilizing the fact that PCBs are approximately planar; the homography H between P_i and D_j is estimated, and all matches that do not agree with H are discarded. The number of remaining matches between P_i and D_j is regarded as a confidence score, and P_i is assigned to the class with the highest confidence. This is unless this confidence is below a threshold or if $\det(H)$ differs significantly from 1; on the condition that all PCBs are depicted at similar positions, two images of the same PCB are, in approximation, related by an in-plane rotation, implying $\det(H) \approx 1$. In both cases P_i is rejected (classified as not present in the database).

We utilize our dataset to evaluate the performance of this method (the tests in [7] were carried out using a smaller dataset). We randomly select 50 images of different PCBs for the database and use the remaining 698 images for testing. As analysis at the component level is not required in this context, we subsample all images by a factor of 4 for efficiency.

The method classifies 173 of 177 images whose depicted PCBs are present in the database correctly, which corresponds to a false classification rate of 2.3%. The four errors occur because the PCB are erroneously classified as not existing in the database (i.e. the false rejection rate is also 2.3%). Of the 521 samples whose

PCBs are not represented in the database, 6 samples are incorrectly classified as such (false acceptance rate 1.2%). The combined correct classification rate is 98.6%, underlining the effectiveness of the method.

4.2 PCB classification

This section demonstrates the value of information on the geometry of waste PCBs. We show that this information can be used to distinguish between two classes of PCBs, namely (i) mainboards from PCs and notebooks, and (ii) other PCBs. The motivation for this distinction is that mainboards contain certain components (e.g. a large number of IC chips, batteries) that might render separate treatment beneficial.

We perform this classification using two geometrical features, (i) PCB size in cm^2, and (ii) aspect ratio (ratio between the larger and smaller side length of the minimum oriented bounding box). Figure 6 shows the joint distribution of these features among the 748 PCB images in the dataset. It is evident that mainboards are comparatively large and that their aspect ratio is small and varies only little.

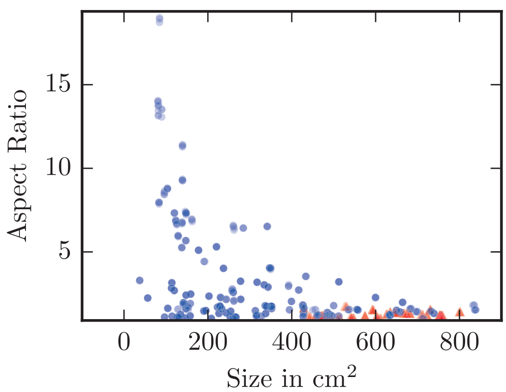

Figure 6. Joint distribution of size and aspect ratio among the PCBs in the dataset. Triangles denote mainboards, dots denote other PCBs.

One approach to classification is to use prior information on common mainboard form factors. This approach is, however, too restrictive as mainboards from laptops have custom form factors. To this end, we instead follow a more generic approach and learn the size and aspect ratio of mainboards and other PCBs from the presented dataset. We manually divide the images in the dataset into two subsets based on whether they depict mainboards and use this data to train a random forest [10] with 50 trees and a maximum tree depth of 3 to avoid overfitting. This results in a correct classification rate of 83% using stratified ten-fold cross-validation. The result demonstrates the value of geometrical information, especially since this information can be combined with appearance information to further improve the classification performance.

5 Conclusions

We have described a new, publicly available dataset that facilitates research on methods for vision-based PCB analysis for recycling purposes. To this end, the dataset was compiled with a focus on comprehensiveness and representativeness, and includes different aspects of information (PCB segmentation, IC chip locations, and IC chip labels). To facilitate the use of the dataset, we provide APIs for Matlab, Python, and C++. We have demonstrated the value of this dataset by using it for designing and testing two exemplary applications that enable selective PCB recycling.

For future work, we plan to extend this dataset by including images from more PCBs. Furthermore, we plan on adding bounding box information for components other than IC chips. We are currently using the dataset for developing a method for IC chip detection.

Acknowledgments

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