Optical Sensor Evaluation for Vision Based Recognition of Electronics Waste

Florian Kleber, Christopher Pramerdorfer, Elisabeth Wetzinger, and Martin Kampel

***Abstract*—For the online and offline classification of printed circuit boards and SMD components mounted on the board a sensor evaluation of optical sensors with different characteristics is presented. In overall a high resolution multispectral camera, a DSLR, an IP camera, and the RGB sensor of the Asus Xtion Pro Live have been evaluated for 2D images. For the 3D acquisition the Asus Xtion Pro Live is compared to the Bluetechnix M100 time of flight sensor. The sensor analysis shows the affected recognition performance of printed circuit boards and SMD components. Based on the sensor comparison, a pilot plant for the recycling of electronics waste is presented.**

***Index Terms*—Electronic waste, recycling, sensor evaluation.**

I. Introduction

Automated recycling systems for electronics waste to reclaim rare-earth elements are not yet in place. Thus, a vision based recognition of electronics waste is proposed by means of a pilot plant in an industrial setting. This paper summarize a sensor study, which is the basis for the vision based recognition.

Example systems for optical classification tasks on conveyor belts using color can be found in Kutila *et al.* [1] and Picón *et al.* [2], [3], whereas Kutila et al. utilize a combination of RGB camera arrays and inductive sensor and Picón *et al.* use hyperspectral cameras. Torres *et al.* [4] introduce a disassembly system used for nondestructive recovery of PC components using a circular rotatable worktable, a movable stereoscopic vision system mounted above the worktable and a robot arm with an attached camera used to recover the components.

A technique for detection and classification of objects (in this case recyclable packaging such as TetraPaks) on a moving conveyor belt using a combination of a two-dimensional source of structured light (a laser beam) and a CCD camera is presented by Mattone *et al.* [5], [6]. A rule-based module is utilized to obtain a geometrical description of the objects on the conveyor belt and as a classifier a neural network approach is used.

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Guerra and Villalobos [7] describe four different inspection approaches for a three-dimensional automated inspection system for SMDs (Surface Mounted Devices) on PCBs (Printed Circuit Boards) detecting the presence or absence of components using a sheet of light technique and range images. In their survey article, Moganti *et al.* [8] provide an overview on automatic PCB inspection algorithms, a.o. also on visual/optical inspection. They also focus on important aspects such as the lighting conditions recommended for image processing systems in this context.

Further approaches in automated inspections of PCBs are Crispin and Rankov [9] using a genetic algorithm template-matching approach or a subpattern level inspection system in [10] used to examine the PCB before insertion of components and soldering to locate defects after etching with a segmentation process described in Moganti and Ercal [11]. Another template-based approach utilizing an elimination-subtraction method classifying the defect located on an empty PCB into one of seven types is proposed in Wu *et al.* [12].

In order to solve relevant object recognition tasks comprising the scenarios of PCB recognition and SMD component detection, a sensor study to show the different characteristics of optical sensors is needed. This paper shows an evaluation of optical sensors regarding different uses cases (PCB recognition and SMD component detection). Additionally, an acquisition system (pilot plant) with a conveyor belt is proposed, which allows to capture PCB images in a stable environment.

The paper is organized as follows: Section II summarizes the setup for the pilot plant and the corresponding vision based analysis. The evaluation of the sensors, 2D as well as 3D, is presented in Section III. Finally, conclusions are drawn in Section IV.

II. Pilot Plant Setup

The pilot plant describes an acquisition system that allows to capture PCB images with a stable illumination and different sensors. The system integrates several optical sensors, flexible illumination, a conveyor belt, and is integrated within a dark room to avoid the influence of ambient light conditions. The included sensors are: Asus Xtion Pro Live and Bluetechnix time of flight (TOF) depth sensors; Asus Xtion Pro Live, Axis P1346, and Nikon D4 RGB cameras; and a Hamamatsu C9300-124 MultiSpectral (MS) camera. The illumination system consists of Bicolor LEDs for the RGB cameras and 2 Heureka!light (Equipoise Imaging) LED panels [13] with 11 different wavelengths for the MS camera. The schematic setup of the pilot plant is shown in Fig. 1.

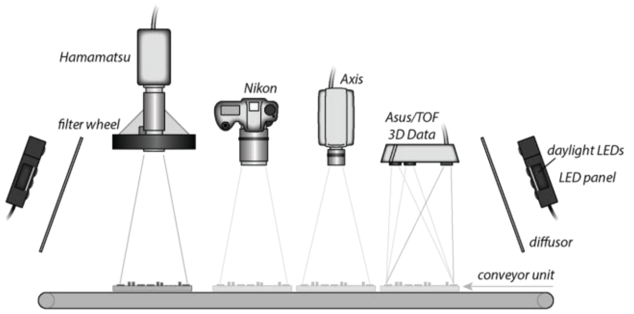

Fig. 1. Schematic setup of the pilot plant.

In order to provide a uniformly distributed illumination, diffusers are placed between the lighting and the object. The use of LEDs with different spectra replace the need for a filter wheel, which eliminate the optical distortions of the filters. Fig. 2(a) shows an image of the final setup, where the different spectra of the illumination system are shown in Fig. 2(b). To avoid specular reflections polarizers are used to provide polarized light. Since metallic parts on the PCBs are possible, polarization filters in front of the camera and a polarized illumination must be used. Fig. 2(c) shows the difference of an image of a PCB which is taken without polarization filters and with the use of polarization filters. It can be seen that specular reflections are suppressed and a uniform illumination is achieved.

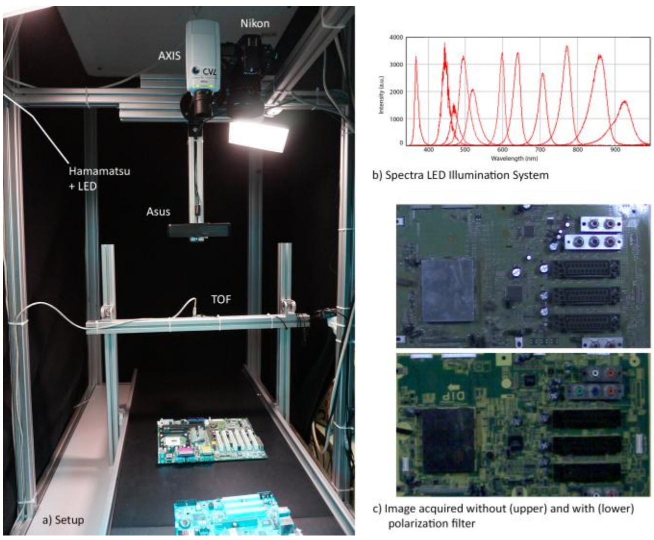

Fig. 2. (a) Pilot plant (b) spectral wavelengths of the illumination system (c) difference of acquisition with and without polarization filters.

III. Sensor Evaluation

The current section describes the characteristics of the different sensors and the influence to the recognition system.

Depth sensors measure distances as opposed to incident light, providing information on the scene geometry. In order to analyze the applicability of the Asus and TOF depth sensors, these sensors are used to record depth maps of 25 PCBs. These PCBs are positioned at a common origin on the unmoving conveyor belt, and 30 frames are recorded over 15 seconds for each PCB and sensor. The distances between the Asus and TOF sensors and the PCBs are about 80 cm and 40 cm, respectively. These distances are optimal in terms of data quality and field of view, as found empirically.

The sensors are analyzed with respect to their ability to distinguish between different PCBs, i.e. PCB recognition. For this purpose, the similarity of PCB k to all other PCBs on a per-pixel basis is analyzed, taking sensor noise into account. Thus, 30 available frames per PCB k are used to train a standard classifier (e.g. Support Vector Machine (SVM) [14]), to classify pixels as belonging or not belonging to PCB k. On this basis, a confusion matrix is built, whose ij-th entry encoded the number of pixels of PCB i that are classified as belonging to PCB j.

Fig. 3 shows the minimum, median, and maximum entries of this matrix for each PCB i, as fractions of the ii-th entry (i.e. larger values denote a higher discriminability). The defined measure provides information regarding the relative performance of the individual sensors -- as shown, the Asus sensor outperforms the TOF sensor. Thus, in the final setup the Asus sensor is used for the acquisition of 3D data.

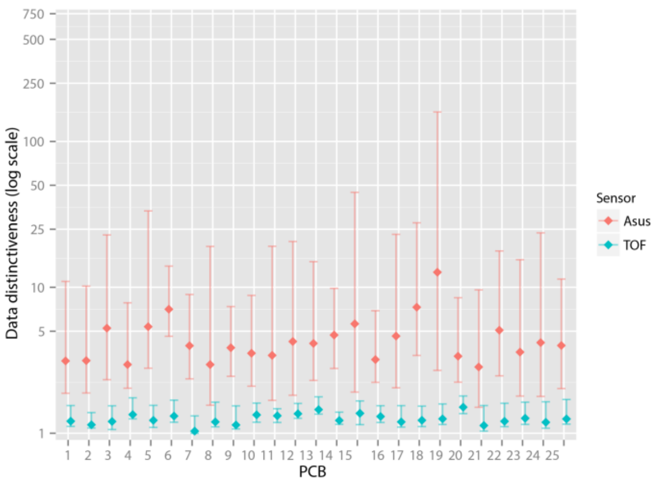

Fig. 3. Data distinctiveness of the Asus and TOF depth sensors.

Holes can occur due to specular surfaces; the number of PCB pixels for which no measurements are available vary between 0% and 30% on the aforementioned dataset. As incomplete data can lower the results on PCB recognition and particularly component detection, the information from multiple frames of the same PCB is combined, as it passes the view of the sensor (see Section Depth Data Improvements).

The three considered RGB cameras differ in terms of resolution and framerate; the Asus and Axis cameras have a medium resolution (1280×1024 px and 1280×960 px, respectively) and framerate (15 and 30 fps, respectively), whereas the Nikon camera has a high resolution of 4928×3280 px but a low framerate (around 5, depending on the settings). Consequently, the Asus and Axis cameras can be used for (online) PCB recognition, while the needed resolution of the Nikon camera is needed for component detection, or Optical Character Recognition (OCR)[1]. The different sensor properties of the cameras are tested with respect to the PCB and component recognition task.

The results as illustrated in Fig. 4 suggest that all RGB cameras achieve higher results for this task than the Asus and TOF depth sensors (due to the lower resolution). The Axis camera performed better than the Asus RGB camera on average. Furthermore, the Axis supports higher framerates and is more configurable (e.g. white balance, exposure).

[1] see https://code.google.com/p/tesseract-ocr/wiki/FAQ.

Thus, the RGB images of the Axis camera are used for the final setup. The Nikon camera performed best due to its high resolution and low noise.

Considering these results, the Axis camera is most suitable for PCB (online) recognition because it produces images that are sufficiently distinctive for this task while being faster to process than the high-resolution Nikon images.

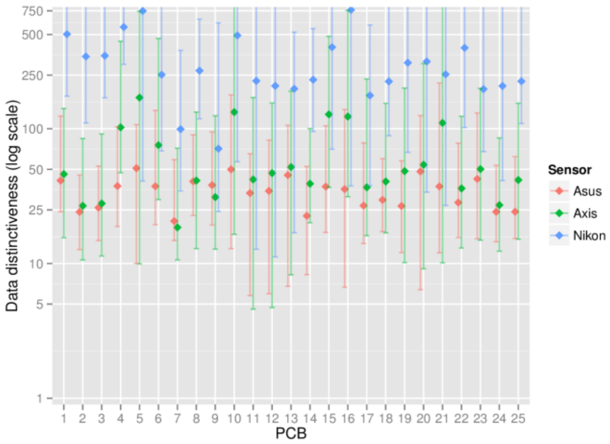

Fig. 4. Data distinctiveness of the RGB sensors.

A MS image can be described as the same image of one scene in different spectral ranges. MS imaging was originally developed for remote sensing applications and has recently found its way to the field of conservation [15]. In addition to its applicability for art conservation [16], the imaging technique has also proven effective for the analysis of historical and degraded documents [17]. The different spectral response of PCB boards is described in Kleber *et al.* [18]. The Hamamatsu MS camera is sensible to a broader range of the electromagnetic spectrum than RGB cameras, providing possible advantages for PCB recognition and component detection. For example, IR radiation penetrates the PCB substrate to some extent, rendering copper traces visible. Furthermore, the contrast of the components labels depends on the wavelength of the illumination and the incident illumination angle (see Fig. 5).

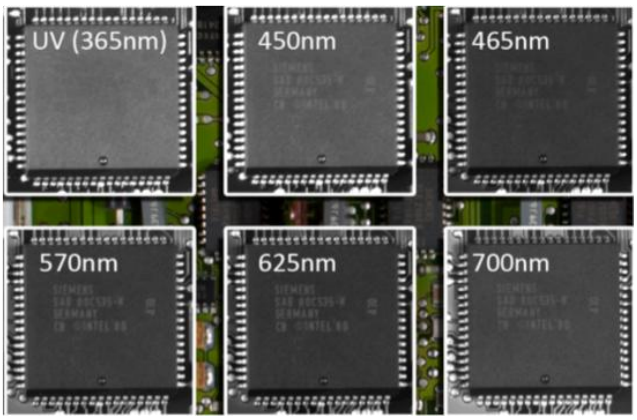

Fig. 5. Images of the same IC illuminated with different wavelengths and different incident illumination angle.

In order to determine the illumination wavelength that is best suited for PCB recognition, the tests explained above are repeated for all wavelengths supported by the Heureka LEDs. Fig. 6 shows the results for a selected number of wavelengths. IR3 (870nm wavelength) achieved the highest scores for detecting copper traces. However, the results suggest that MS images are less suitable for PCB recognition than RGB images (the Nikon camera with a similar resolution performed significantly better). This is caused by the narrow-wavelength illumination.

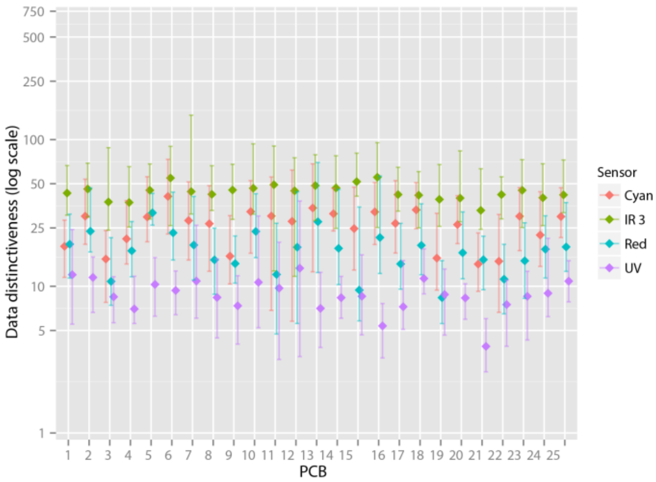

Fig. 6. Data distinctiveness of MS images with different illumination wavelengths.

A. PCB Recognition Performance

In order to verify the suitability of the Axis sensor for PCB recognition, a sparse-descriptor-based object recognition is tested. The recognition method follows the standard pipeline, namely (i) keypoint detection, (ii) descriptor computation, (iii) descriptor matching, and (iv) geometric verification. The system employs SURF keypoints and descriptors to achieve rotation invariance and, to some extent (sufficient for our task), robustness with respect to perspective distortion.

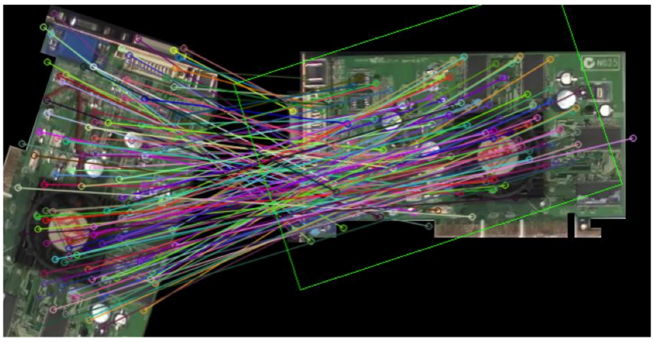

Fig. 7. PCB matching.

For evaluation purposes, a descriptor database is created, comprising the 25 test PCBs recorded using the Axis camera. Then, each of the test PCBs is matched against the database after applying a rotation of 36*k, k in {0,...,9} degrees to the query image to verify rotation invariance and the ID of the best match (in terms of number of matching descriptors and descriptor distances) is compared to the correct ID. No recognition errors are observed (Fig. 7 shows an example result), highlighting the suitability of Axis images for PCB recognition.

B. Component Detection Performance

For component recognition, the same method is used as described in Section *PCB Recognition*, to estimate the applicability of the Axis, Nikon, and MS sensors for SMD component detection (the Asus depth sensor was not tested due to its low resolution). For this purpose, 15 PCB components are selected randomly from the test PCBs (including ICs and capacitors, see Fig. 8), whose corresponding image regions were rotated by 45 degrees and then searched for in the source images.

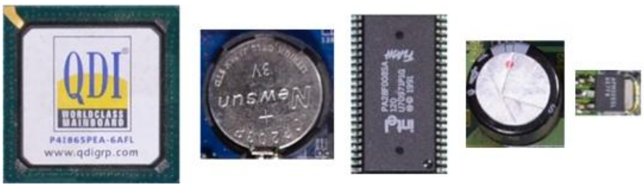

Fig. 8. Selection of test components.

Fig. 9 shows the detection results. Red cells denote that the object is not found, while the color of greenish cells represent the detection certainty; the largest certainty (score 1) observed for each object is assigned a bright green color, while the smallest one (score 0) is assigned a brownish color. It is visible that the resolution of Axis images is too low for component detection. The performance of MS images depends on the illumination wavelength, with Green performing best (14 detection, score sum 9.4). With the Nikon sensor 13 objects are detected, with a score sum of 10.2. Thus, the best results are achieved with the Nikon and the MS camera (Amber, Blue), due to the higher resolution compared to the Axis sensor.

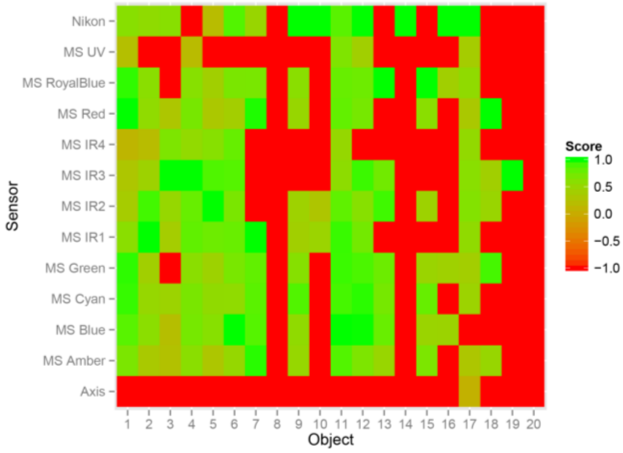

Fig. 9. Object detection results.

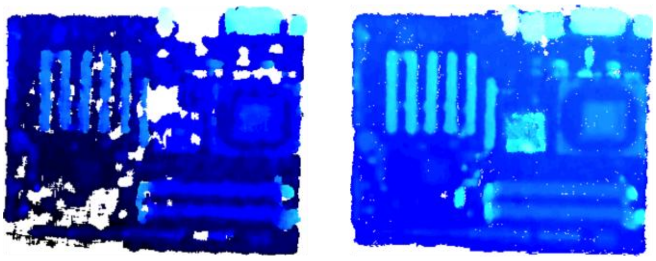

Fig. 10. A single depth map from the Asus sensor (left) and an improved version obtained from five depth maps (right).

C. Depth Data Improvements

Single images of PCBs captured with depth sensors can contain holes in the data due to specular reflections, as described in paragraph *III Sensor evaluation*. A method for combining multiple images of the same PCB to a single improved model is applied to enhance the result. This is accomplished by first converting the individual images (depth maps) to point clouds which are then coarsely aligned using the image timestamps and known conveyor belt speed. Then follows a fine alignment using the Iterative Closest Point (ICP) [19], [20] algorithm. Finally, the aligned point clouds are merged via Poisson surface reconstruction [21], and the result is converted to the final depth map. Fig. 10 illustrates the quality improvements.

IV. Conclusion

A pilot plant setup for vision based analysis of PCB boards for the reclamation of gallium, indium, and rare-earth elements from photovoltaics, solid-state lighting, and electronics waste has been presented. Based on the sensor analysis, the pilot plant uses the Axis sensor for the PCB recognition (high framerate for online analysis). For component detection and analysis, high resolution images have to be used, resulting in the use of the DSLR camera (Nikon sensor in the test setup). The Asus sensor outperformed the TOF sensor for depth image analysis. As future work, the depth data will be combined with the 2D images (Axis sensor) to enhance PCB recognition results. The MS camera will not be used in the final setup, since the advantages of MS images are limited in the proposed application.

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