14thAnnual International Conference on Industrial Engineering and Operations Management
Dubai, United Arab Emirates (UAE), February 12-14, 2024
Publisher: IEOM Society International, USA
Published: February 12, 2024 DOI: 10.46254/AN14.20240413

Differentiation and Visualization of Board Image Changes: A Comprehensive Computational Approach using Python

Basel Sultan, Hamzeh Alshraida and Daryl Santos
Systems Science and Industrial Engineering Department
Watson Institute for Systems Excellence (WISE)
Thomas J. Watson College of Engineering and Applied Science
The State University of New York at Binghamton
Binghamton, NY 13902, USA
bsultan2@binghamton.edu, halshra1@binghamton.edu, santos@binghamton.edu

Fernando Franco
Foxconn Industrial Internet
Mount Pleasant, WI 53177, USA
fernando.franco@fii-usa.com

Abstract

As products progress towards the end user in a standard supply chain, numerous firms are starting to acknowledge the significance of reverse logistics. Reverse logistics takes care of the return products to suppliers or vendors. In the return merchandise authorization (RMA) process, one of the main steps that decides the cost of repairing is to ascertain whether the damage is customer induced damage (CID) or vendor induced damage (VID). In this paper, a comprehensive computational procedure using Python and various libraries, including Pillow (PIL), NumPy, and SciPy was implemented in an electronic manufacturing company to automate and optimize the process of making the CID vs. VID decision.

Keywords
Python, Pillow (PIL), customer induced damage (CID), vendor induced damage (VID), and return merchandise authorization (RMA).

1. Introduction
In a typical supply chain paradigm, materials or services conventionally progress from suppliers to customers in a forward-moving direction. Businesses have historically focused their endeavors on this forward-moving supply chain to reduce cycle times, minimize costs, and improve customer service. Nevertheless, certain business operations necessitate the movement of materials in the opposite direction—specifically, from customers back to suppliers. Instances of this reverse flow include the return of new materials or the returning of used materials for recycling, refurbishing, or salvaging. This counter-directional movement is formally recognized as reverse logistics (Retzlaff-Rober and Frolick 1997).

The contemporary challenges within the supply chain encompass concerns such as reverse logistics, product pricing strategies, and the environmental impact of pollutants. In their pursuit of providing customers with the best value, supply chains consistently strive to optimize costs while ensuring product quality. Consequently, it is imperative for each supply chain to formulate a judicious product pricing policy to remain competitive in the market. To achieve this, companies are increasingly steering towards the automation of processes that can be streamlined, aiming to enhance overall quality, while concurrently reducing response times.

In the Printed Circuit Board Assembly (PCBA) manufacturing process, when products are returned from customers, the board undergoes a sequence of steps. These include making the CID vs. VID (a.k.a., CID/VID) decision, incoming Automated Optical Inspection (AOI), Functional Board Testing (FBT), optional repair station, Packing AOI, and finally, the packing phase (see Figure 1) (Sultan et al. 2023). In the majority of PCBA manufacturing companies, the CID/VID decision step is conducted. This involves a comparison of the initial AOI image of the PCBA before it leaves the facility with the AOI image obtained upon its return from the customer. If a defect is identified in both images, it is categorized as VID; otherwise, it is classified as CID. While the current process does incorporate computer technology and image comparisons, it is sometimes referred to as a "manual" process as it lacks automation.

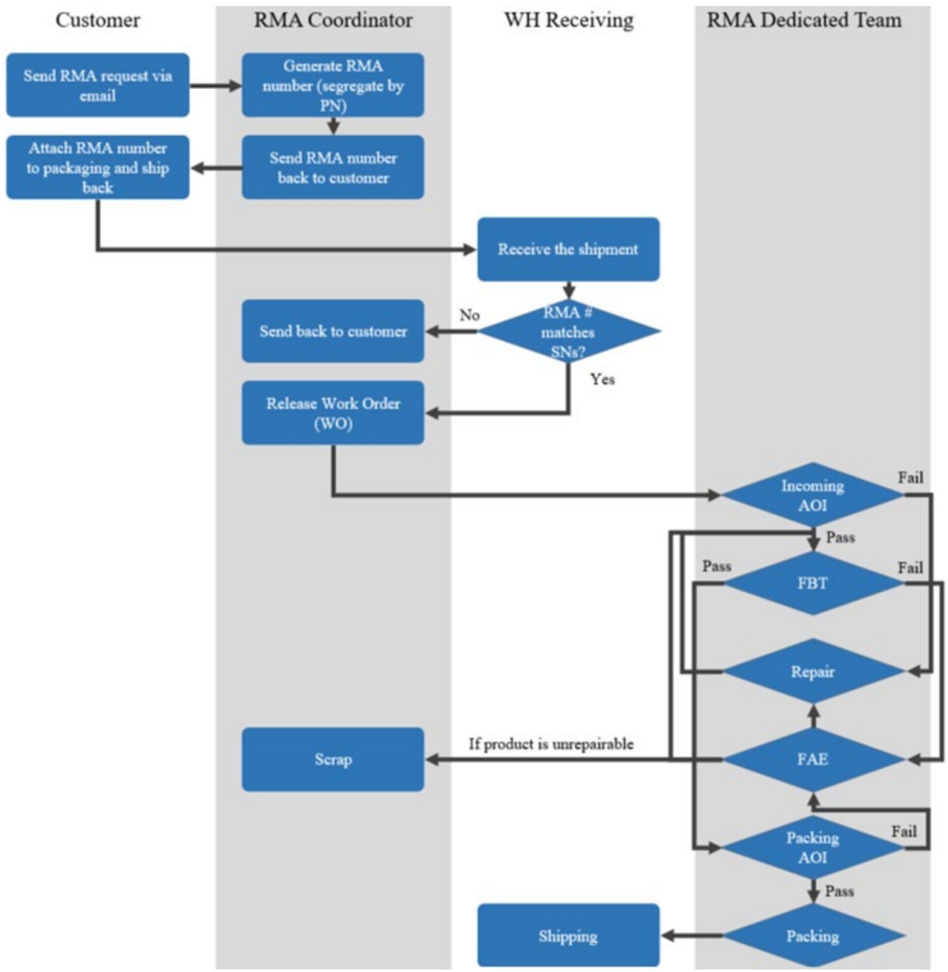

Figure 1. RMA Process for Electronic Manufacturing Company in USA

1.1 Objectives

The primary objectives of this study encompass the following key goals:

- Optimizing the RMA process within an electronic manufacturing company, specifically by streamlining and optimizing the time required for the CID/VID decision step.
- Enhancing the quality of the CID/VID decision step in the RMA process through the implementation of automation, leveraging the Python programming language and its library modules to achieve increased accuracy and efficiency.
- Elevating customer satisfaction levels by expediting the CID/VID feedback process, ensuring a quicker and more precise response to customers' concerns.

2. Literature Review

Reverse logistics is another issue in designing a supply chain which refers to the act of managing and directing activities related to equipment, products, components, materials, or systems that return back from the customer due to a defect detection from the customer end. A supply chain tries to maximize the overall profit of the chain. This happens through increasing the supply chain revenue or decreasing its costs (Shabbir et al. 2021).

Xiao et al. (2015) studied the use of strain measurement technologies, such as PCBA strain gauge selection technology, in evaluating the dependability of PCBAs. Techniques for strain gage testing during PCBA assembly as well as techniques for analyzing strain data. As a result, technical staff involved in electronic processes can identify and manage hazardous PCBA manufacturing processes in addition to swiftly and accurately establishing relevant evaluation schemes.

A high-pixel density camera has been used in a tracking system created by Luo et al. (2014) to capture the motions of several juvenile adult worms executing salt chemotaxis on 25 cm by 25 cm agar plates. Particle-tracking software was used to analyze the data and shape analysis algorithms that are contained in two exclusive Python packages.

The advent of digital computers, storage devices, image sensors, and digital cameras has facilitated the capture, storage, and processing of images in digital formats. Digital image processing, a field that leverages digital computers, storage devices, and digital sensors, involves the extraction and manipulation of data from both digital and analog images. This technology finds extensive applications in various domains, including the following (Pajankar 2017):

- Digital Image Processing: Encompassing tasks such as enhancement, denoising, and correction of digital images.
- Medical Image Processing and Diagnostics: Supporting applications in the medical field for image analysis and diagnostic purposes.
- Space Image Processing: Handling and processing photos obtained from ground-based and Hubble telescopes related to astronomical observations.
- Filmmaking and Visual Effects: Contributing to the creation and enhancement of visual effects in filmmaking.
- Biometrics: Involving finger, face, and iris recognition for security and identification purposes.
- Industrial Applications: Applied in industrial settings for tasks such as product inspection and sorting.

This comprehensive utilization of digital image processing systems underscores the versatility and significance of this technology across diverse fields (Pajankar 2017).

Chityala and Pudipeddi (2020) provided an overview of various Python modules essential for image processing, including NumPy, SciPy, Matplotlib, Python Imaging Library (PIL), OpenCV, and Scikit-learn (scikits). NumPy is particularly highlighted for its capability to manipulate arrays and matrices through a collection of high-level mathematical functions. Within NumPy, two primary data structures for storing mathematical matrices are employed, namely, arrays and matrices. Arrays, being more versatile, are the preferred choice in NumPy and across modules utilizing NumPy for computation.

SciPy, another integral module, serves as a comprehensive library comprising programs and mathematical tools tailored for scientific programming in Python. Additionally, Scikit-learn, often referred to as scikits, is instrumental in the development of novel algorithms, which can subsequently be seamlessly integrated into SciPy for broader scientific computation purposes.

3. Methods

Figure 2 illustrates the flow chart depicting this new approach to detecting and visualizing differences between two images of RMA board. A comprehensive computational procedure was employed that utilizes Python and various modules, including Pillow (PIL), NumPy, and SciPy. The process began with the preprocessing of input images labeled as “Before” and “After”. These images were loaded and processed using the Pillow library, undergoing resizing to ensure consistency with the dimensions of the smaller image. Subsequently, grayscale conversion and histogram equalization were applied to enhance contrast, facilitating more effective difference detection.

The crux of this methodology focuses on difference detection. Pixel-wise absolute differences were calculated between equalized images using the "ImageChops.difference" method from Pillow. The resulting difference image was then converted to a binary format, effectively discerning significant differences from background noise. The binary thresholding, a pivotal step, allowed adjustability based on the sensitivity requirements of the analysis.

Following the detection stage, distinct difference regions using the binary difference image, transformed into a NumPy array for analytical purposes are identified. Leveraging "SciPy's ndimage.label" function, unique regions within the image where differences occurred were identified and labeled. For each region, precise coordinates for centroids were calculated.

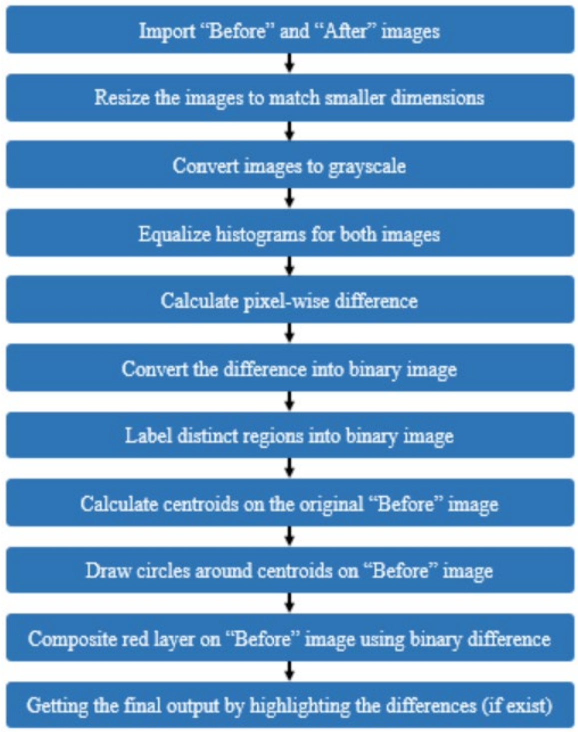

Figure 2. Methodology Flowchart

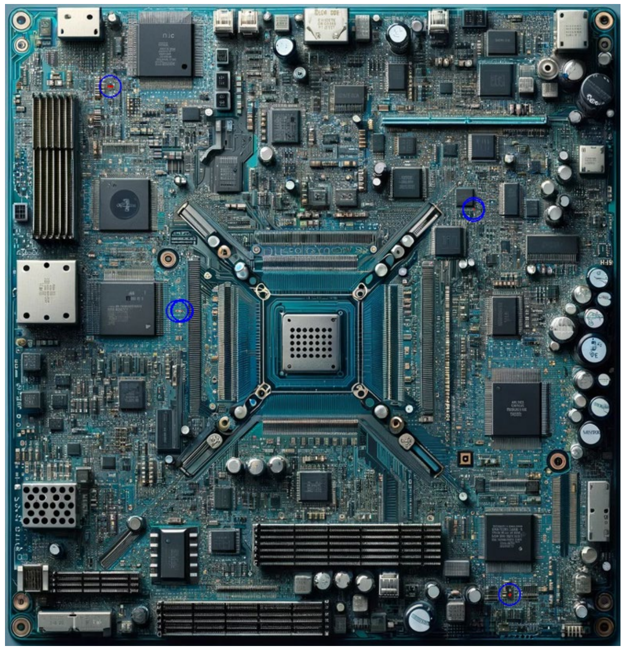

Figure 3. Visual Representation for Differences

The final stage involved visualizing these differences. A composite image was created by applying a red-colored layer to the original “Before” image, utilizing the binary difference image as a mask. This technique effectively highlighted difference areas. Additionally, to emphasize each identified region, blue circles were drawn around centroids on the composite image using the "ImageDraw" module from the Pillow library. Both circle radius and color were adjustable to meet specific visualization requirements, as depicted in Figure 3. This visualization technique proves particularly effective for scenarios requiring precise localization and clear visual representation of changes between “Before” and “After” states, such as in image-based change detection, quality control, or comparative image analysis.

4. Results and Discussion

Prior to the implementation of the study's methodology within the company, the CID/VID decision process was not automatically conducted by the RMA quality engineer. This procedure involved exporting images of the PCBAs before they left the facility and after their return from the customer. Subsequently, the RMA quality engineer utilized the Cadence Allegro Viewer program—a software tool developed by Cadence Design Systems, specializing in electronic design automation (EDA) software. The Allegro Viewer is specifically tailored for visualizing and reviewing electronic designs crafted with Cadence Allegro PCBA tools.

In this manual process, the RMA quality engineer employed the Allegro Viewer to compare both sets of images, seeking to identify defects upon their experience. If a defect was discerned in both the pre-shipment and post-customer images, it was categorized as VID. Conversely, if the defect was only present in the image obtained after the product's return, it was labeled as CID. In cases where no defects were identified in either image, the outcome was recorded as No Defect Detected (NDD). This manual CID/VID decision process served as the basis for the subsequent implementation of this study's automated methodology, aimed at optimizing and enhancing the efficiency of this critical quality assessment.

4.1 Numerical Results

The duration of the manual CID/VID decision-making for a specific PCBA was meticulously monitored and recorded in Table 1. The average time invested in completing the CID/VID step was observed to be 6.2 minutes per individual PCBA. This translates to a significant allocation, consuming approximately 25.7% of the RMA quality engineer’s time within a standard working day, assuming a workload of 20 PCBAs processed per day.

After the successful implementation of the proposed automated image analysis process, which involves importing both “Before” and “After” images and executing the programmed code, notable efficiency improvements were observed. Importing both images was accomplished within approximately 10 seconds. Subsequently, running both images through the programmed codes was observed to take between 15-40 seconds, depending on the size of the imported images. As a result, the total time required for CID/VID decision-making was significantly reduced to a range of 25-55 seconds.

Table 1. Manual CID/VID Decision Station Time

# PCBA	CID/VID Decision Time (min)
1	12
2	12
3	11
4	12
5	13
6	12
7	10
8	6
9	7
10	5
11	4
12	5
13	6
14	7
15	11
16	7
17	12
18	5
19	5
20	7
21	6
22	4
23	8
24	4
25	5
26	7
27	6
28	5
29	5
30	6
Average	6.17

4.2 Graphical Results

Figure 4 presents a crucial case study exemplifying the effectiveness of the proposed automated image analysis process in a real-world scenario. The study began with the capture and storage of an AOI image of a PCBA before its shipment. Upon its return, prompted by customer-reported failures, a second AOI image was acquired to identify any discrepancies. This automated process replaces a previously manual, operator-dependent procedure that was both time-consuming and susceptible to oversights, potentially leading to missed differences and increased rework costs.

The adoption of the automated method signifies a significant leap forward. Rapid detection of differences at a pixel scale is now achieved within seconds. As depicted in Figure 4, the automated analysis precisely delineated the disparities between the pre-shipment (Figure 4, left) and post-return (Figure 4, right) images. Notably, the identified failure was attributed to bent pins in the BGA socket, a problem likely arising from mishandling during shipping or customer mishandling. This conclusion was drawn through a meticulous comparison with the AOI images of the outgoing board, revealing intact pins. This finding underscores the heightened accuracy and efficiency of the automated process in pinpointing specific issues that might have eluded manual inspections.

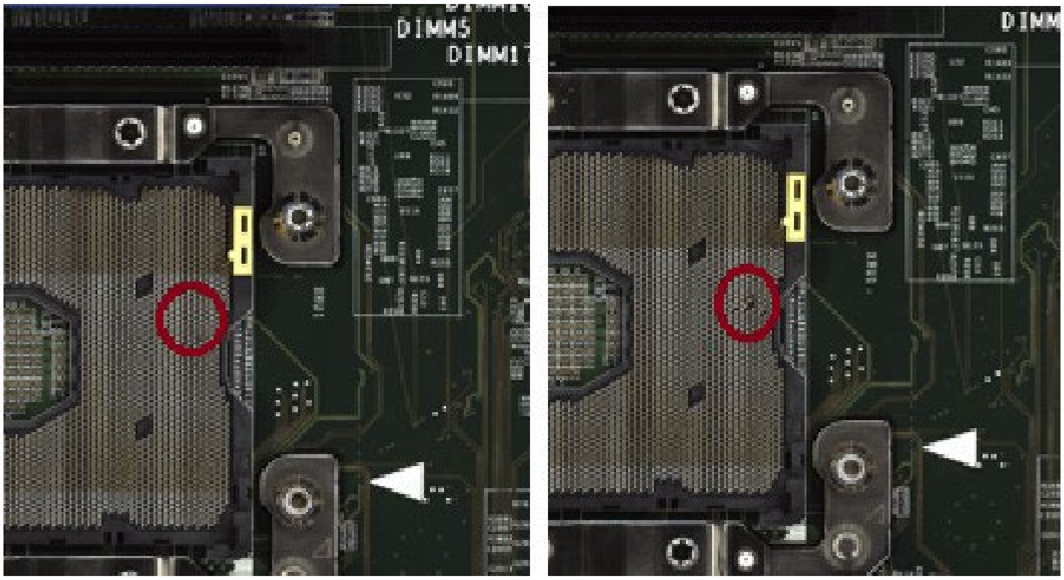

Figure 4. Case Study PCBA: "Before" (left) and "After" (right) AOI Images

5. Conclusions

A computational procedure leveraging Python and modules such as Pillow (PIL), NumPy, and SciPy was implemented within a PCBA manufacturing company to automate the CID/VID decision-making station in the RMA process. The decision-making time was reduced from an average of 6.2 minutes to under one minute for an example PCBA. Furthermore, the automated process demonstrated an enhancement in decision quality by eliminating the human factor from the decision-making process.

The implementation encountered challenges attributed to variations in the lighting conditions of the AOI images. It became evident that a more stringent control over AOI lighting was imperative to mitigate the potential introduction of discrepancies between the old and new images. Such discrepancies, if not adequately addressed, had the potential to be erroneously identified as defects in this program. Therefore, the need for enhanced control over AOI lighting emerged as a critical aspect to ensure the accuracy and reliability of the automated image analysis process.

References

Chityala, R. and Pudipeddi, S., *Image Processing and Acquisition Using Python*, 2nd Edition, CRC Press, 2020.

Luo, L., Wen Q., Ren J., Hendricks M., Gershow M., Qin Y., Greenwood J., Soucy E., Klein M., Smith-Parker H., Calvo A., Colon-Ramos D., Samuel D. and Zhang Y., Dynamic Encoding of Perception, Memory, and Movement in a C. elegans Chemotaxis Circuit, *Neuron,* vol., 82, pp. 1115-1128, 2014.

Pajankar, A., Introduction to Python and Digital Image Processing, *Practical Python Data Visualization,* pp. 25-39, 2017.

Retzlaff-Rober, D. and Frolick, M. N. Reducing Cycle Time in Reverse Logistics, *Cycle Time Research,* January, vol., 3, pp. 69-78, 1997.

Shabbir, M. S., Siddiqi A. F., Yapanto L., Tonkov E., Poltarykhin A. L., Pilyugina A. V., Petrov A. M., Foroughi A. and Valiullina D. A., Closed-Loop Supply Chain Design and Pricing in Competitive Conditions by Considering the Variable Value of Return Products Using the Whale Optimization Algorithm, *MDPI*, 2021.

Sultan, B., Santos, D. and Hsieh, M. *A Framework for Reverse Engineering Process for an Electronic Manufacturing Company: A Case Study,* Houston, TX, The 8th North American International Conference on Industrial Engineering and Operations, 2023.

Xiao, H., Luo, D. and Wang, Q., *Study on Application of Strain Measuring Technology in PCBA Reliability Evaluation,* Guangzhou, China, International Conference on Electronic Packaging Technology, 2015.

Biographies

Basel Sultan is an Industrial and Systems Engineering MS degree student at The State University of New York at Binghamton. He is a graduate research project assistant conducting his work as an RMA Coordinator at Foxconn Industrial Internet Company. Basel earned his BS degree in Industrial Engineering from Sultan Qaboos University (2022), including a semester taken from Marmara University through an exchange program (Spring 2019). Basel has an accumulated three years of a proven track record of experience in different companies and organizations. Basel's research interests include supply chains, optimization, and design of experiments, project management, and not-for-profit operations. Basel is a member of the Palestinian Engineers Association.

Daryl Santos is a State University of New York (SUNY) Distinguished Service Professor at Binghamton University. He has received the SUNY Chancellor's Award for Teaching and the SUNY Chancellor's Award for Scholarship and Creative Activities. Daryl holds a BS degree in Operations Research and Industrial Engineering from Cornell University (1987), an MS degree in Industrial Engineering from the University of Houston (1990), and a PhD degree in Industrial Engineering from the University of Houston (1993). He also holds a Lean Six Sigma Black Belt from Dartmouth College's Thayer School of Engineering. Daryl is the founding managing editor of the Industrial and Systems Engineering Review (ISER) Journal.

Hamzeh Alshraida is an industrial engineer holding a bachelor's degree of Science and Technology from Jordan University and a master's degree from Binghamton University, NY. He is currently pursuing his Ph.D. at Binghamton University, as a Watson Institute for Systems Excellence (WISE) graduate research project engineer, conducting his research at Foxconn Industrial Internet, San Jose, California. Hamzeh is interested in the context of electronics manufacturing and process optimization.

Fernando Franco is the RMA Manager for Foxconn Industrial Internet in Mount Pleasant, Wisconsin. Fernando is a native of Milwaukee, Wisconsin. Fernando studied Electrical Engineering at Milwaukee Area Technical College and University of Wisconsin Milwaukee, before advancing his career through various technical and leadership roles with two industry leaders GE Healthcare and Foxconn.