FICS PCB X-ray: A dataset for automated printed circuit board inter-layers inspection

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Abstract—Advancements in computer vision and machine learning breakthroughs over the years have paved the way for automated X-ray inspection (AXI) of printed circuit boards (PCBs). However, there is no standard dataset to verify the capabilities and limitations of such advancements in practice due to the lack of publicly available datasets for PCB X-ray inspection. Furthermore, there is a lack of diverse PCB X-ray datasets that encompass images from X-ray Computed Tomography (CT). To address the lack of data, we developed the first comprehensive publicly available dataset, "FICS PCB X-ray," to aid in the development of robust PCB-AXI methodologies. The dataset consists of diverse images from the tomographic image domain, along with challenging cases of unaligned, raw X-ray data of PCBs. Further, the dataset contains projection data and the reconstructed volume which is converted into a Tiff stack. Annotated X-ray layer images are also available for image processing and machine learning tasks. This paper summarizes the existing databases and their limitations, and proposes a new dataset, “FICS PCB X-ray”.

Index Terms—AXI dataset, PCB dataset, image processing, computer vision, machine learning, automated X-ray inspection.

1 Introduction

Over the past decade, the shift of the electronic supply chain from vertical to horizontal has enabled adversaries to perform various attacks on the security, reliability, and quality features of the hardware [1]–[4]. PCBs are used in a wide variety of applications such as aerospace, automotive, military, medical, and telecommunication. Adversarial attacks on PCBs used in various applications can have motives such as information leakage, system corruption with hardware Trojans, or denial of service. Such attacks can compromise the national security of a country. Hence, PCB assurance is of utmost importance.

Assurance consists of measuring the security, reliability, and quality metrics of the PCBs. There exists many PCB testing techniques such as in-circuit testing, functional testing, and bare board testing. However, such techniques cannot identify defects or malicious modifications outside of their range of testing. For complete PCB assurance, it is necessary to evaluate the PCBs both optically and internally. In the past few years, much work has been done in the automated visual inspection (AVI) domain [4]–[9]. However, along with the advantages of identifying and detecting defects on the PCB layers, optical inspection has limitations (for e.g., Trojans hidden in the internal layers of the PCB would not be detected by optical imaging). Over the years, the available surface mount technologies (SMTs) have made it possible to manufacture densely populated PCBs with smaller and smaller components and multiple layers. Due to the advent of SMTs, new chip packages are used (for e.g. BGA and QFN), making it impossible to see the solder connections optically. Moreover, AXI is used by manufacturers for "in-line" verification of solder and components, whereas X-ray computed tomography and laminography are primarily used "off-line" for reverse engineering and failure analysis [10]. Hence, there is a need for automated X-ray inspection methods to evaluate the PCBs internal layers.

To address this need, we propose “FICS PCB X-ray," a comprehensive dataset for automated X-ray inspection of PCBs. The proposed dataset will be expanded along with our previous work in the optical domain [11], as part of an ongoing initiative toward multi-modal PCB assurance. "FICS PCB X-ray" aims to encourage collaboration between the hardware and computer vision/machine learning communities. The contributions of this dataset are as follows :

1) An open-source diverse X-ray dataset “FICS PCB X-ray" of printed circuit boards (PCBs) for inter-layer inspection.
2) “FICS PCB X-ray" is a collection of projection X-ray data of PCBs along with the reconstructed volume converted into a Tiff stack (16-bit Tiff files).
3) The Tiff stack is preprocessed and annotated as shown in Figure 1. These files can be used for performing reconstruction into a 3D volume, or performing 2D analysis and for netlist extraction.

The rest of the paper is organized as follows: Section 2 reviews the existing databases in the optical, medical, and X-ray domain and lists the challenges for PCB X-ray data collection. Section 3 emphasizes X-ray data collection re-

Dataset will be available in September 2022 for download at https://www.trust-hub.org/data quirements and describes X-ray computed tomography and reconstruction in detail. Section 4 describes the proposed “FICS PCB X-ray" data collection process, while Section 5 highlights the newly enabled research directions. Section 6 summarizes the challenges and future work and 7 concludes the paper.

2 Literature Review

Over the past few years, extensive research has been done in the field of optical PCB inspection since optical images are quick and easy to obtain. Hence, automated optical inspection is a popular approach for PCB assurance [4]–[9]. Although it is easy to obtain optical data using a microscope or DSLR camera, optical data is limited to a PCB’s surface-level information. On the other hand, X-ray data may be difficult and time-consuming to collect [12], but it captures a PCB’s inter-layer information. Such inter-layer information is essential for detecting defects or malicious modifications within a PCB’s layers and for overall PCB assurance (security, reliability, and quality).

Automated X-ray inspection is vital for complete PCB assurance and reverse engineering. In the past, there have been several AXI methodologies proposed such as [1], [13]–[15]. Many such proposed methodologies are trained and tested on private, unpublished datasets that are unavailable to the public. This makes it difficult to use and evaluate existing AXI methods and understand their assumptions, benefits, and limitations. Hence, the lack of available data delays progress in hardware assurance and reverse engineering.

Though there are many X-ray datasets in the medical domain (e.g. X-ray CT dataset for Covid-19 detection [16]) and some PCB datasets in the optical domain (e.g. AVI dataset for PCB component detection [11]), there are very few PCB datasets in the X-ray domain [17]. Of the few PCB datasets in the X-ray domain, none of them include tomographic data of entire PCBs. For example, [17] includes X-ray data of PCB solder joints as regions of interest, rather than the entire board.

X-ray data collection is challenging, time-consuming, and memory intensive. Plus, the X-ray parameters need to be carefully tuned to accurately represent each PCB since boards can have various number of layers, population densities, and materials which absorb X-rays differently. Hence, the entire process is expensive. To the best of our knowledge, “FICS PCB X-ray" is the first publicly available X-ray tomographic dataset of entire PCBs. "FICS PCB X-ray" will enhance the research in the academic and industrial domain.

3 X-ray Data Collection and Reconstruction

PCB manufacturing has been developed over the years as a subtractive process, while recent advances have led to 3D printed electronics using additive manufacturing [19]. When manufacturing a PCB, both subtractive and additive processes require design verification to ensure reliability and functionality of the device.

Additive manufacturing enables geometrically complex designs with novel footprints, which introduces new challenges during verification. Optical methods have been primarily used for verification of PCB manufacturing. On the other hand, volumetric tools are increasingly being used to verify surface mounted components, solder and internal connections, or for design verification. Non-destructive inspection, such as X-ray CT, is required to examine the intricate internal circuitry.

Recently, CT has been demonstrated for effective geometric analysis and defects detection. Furthermore, it is been used for successful quantitative comparison as well as structural quantification. Porosity analysis for 3D printed steel parts is also demonstrated with CT [20]. However, developing automated methods for PCB inspection will require large amounts of collected and curated X-ray data. In the following section, we highlight the various X-ray CT specifications which are optimal for the evaluation of PCB designs and components.

3.1 Tomographic Collection

Tomography is accomplished through the collection of multiple 2D images from 360 degrees and then through a reconstruction process creating a 3D volume, slices or sections that can be created from the volume. For the case of X-ray tomography, the reconstruction is based upon 2D projections which represent the density of the sample.

In order to maintain uniformity across the PCB X-ray dataset, the settings and parameters for each PCB design are selected based upon the PCB’s overall size, thickness, and components density. During X-ray setup for tomographic collection, 2D X-ray images are collected to determine the appropriate X-ray acceleration voltage (X-ray penetration) in KeV and the current (X-ray contrast) in micro amps. A typical PCB X-ray tomographic setup is displayed in Figure 2.

Larger PCB designs require a larger distance between the source, sample, and detector in order to maintain the PCB within the Field of View (FoV). This larger distance results in less magnification, and a lower spatial resolution. These large PCBs can be imaged in sections, and the reconstructed data can be stitched together to enable high spatial resolution imaging. It is critical to maintain a spatial resolution smaller than the distance between the PCB layers ($\tilde{5}0$ microns). This is necessary, otherwise the voxel size will contain data from more than one layer causing aliasing of the data, thereby increasing the difficulty for segmentation. Certain X-ray collection settings can have a large effect upon time required for a scan. For example, doubling either the exposure time or the number of projections can double the collection time. However, doubling both quantities can quadruple the collection time. Smaller PCB designs (i.e. less than 3-5 inches in dimension) commonly require 1-2 hour of scan time, while large PCBs (i.e. 5-12 inches) can require 3-5 hours of collection time.

3.2 Reconstruction

X-ray data is often limited by the data collection parameters, frequently due to an incomplete quantity of projections.

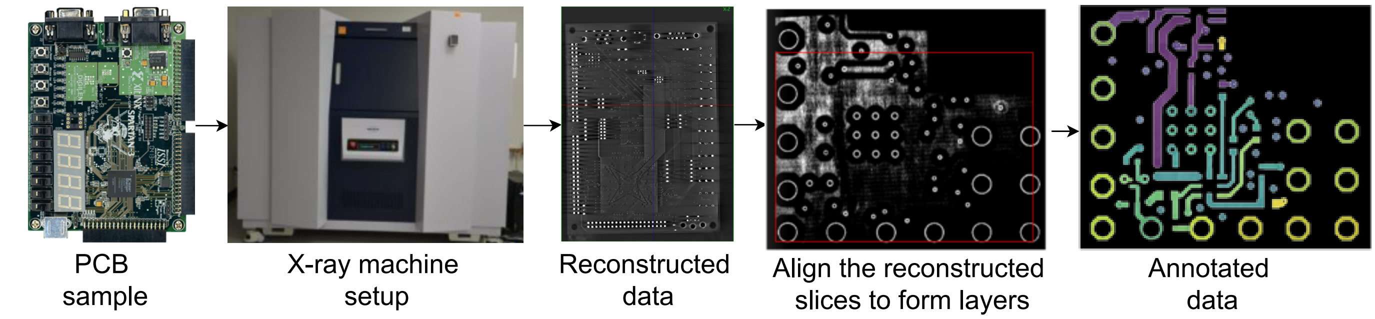


Fig. 1: Collection of dataset overview. Here the PCB sample is setup in an X-ray and the collected data is reconstructed. After reconstruction the slices are stacked together to form a layer and then the layer image is annotated.

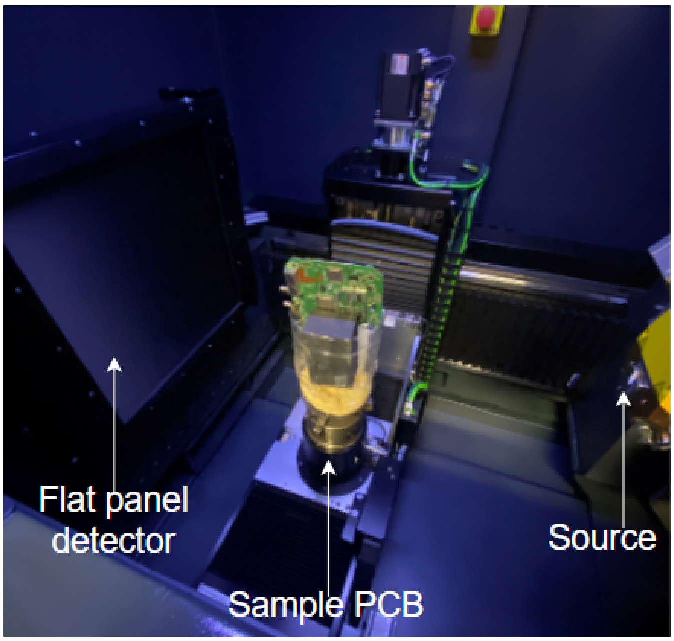


Fig. 2: Setup of a PCB inside the X-ray machine (NANO-CT - GE V|TOME|X M 240) for collecting data with flat panel detector, sample PCB and source in the image view.

Imaging abnormalities such as beam hardening, ring artifact, and layer aliasing occur for various reasons such as when there are less number of projections collected or when they are non-uniform [21]. Traditional reconstruction techniques are not able to effectively reconstruct noisy or dense regions with incomplete data such as artifact-laden data [22]. Advanced reconstruction techniques are being developed using artificial intelligence (AI), but this requires access to a large, curated dataset [23], which is not available for the PCBs.

The reconstruction techniques used are commercial techniques from the GE Phoenix Datos software and the Bruker Skyscan reconstruction software. The limitations due to reconstruction artifacts are mitigated through manual labeling and data curation. Commercial reconstruction is able to provide an accurate volume for subject matter experts (SMEs) to extract the PCB design as ground truths, but commercial segmentation tools are not yet able to perform this task automatically.

There are many different quality metrics for quantifying the difference between reconstruction algorithms (for example, peak signal-to-noise ratio (PSNR), among others). The focus of this dataset is to be able to extract 100% of the PCB netlist through computer vision and machine learning techniques given the limitations of commercial reconstruction.

4 Our Dataset

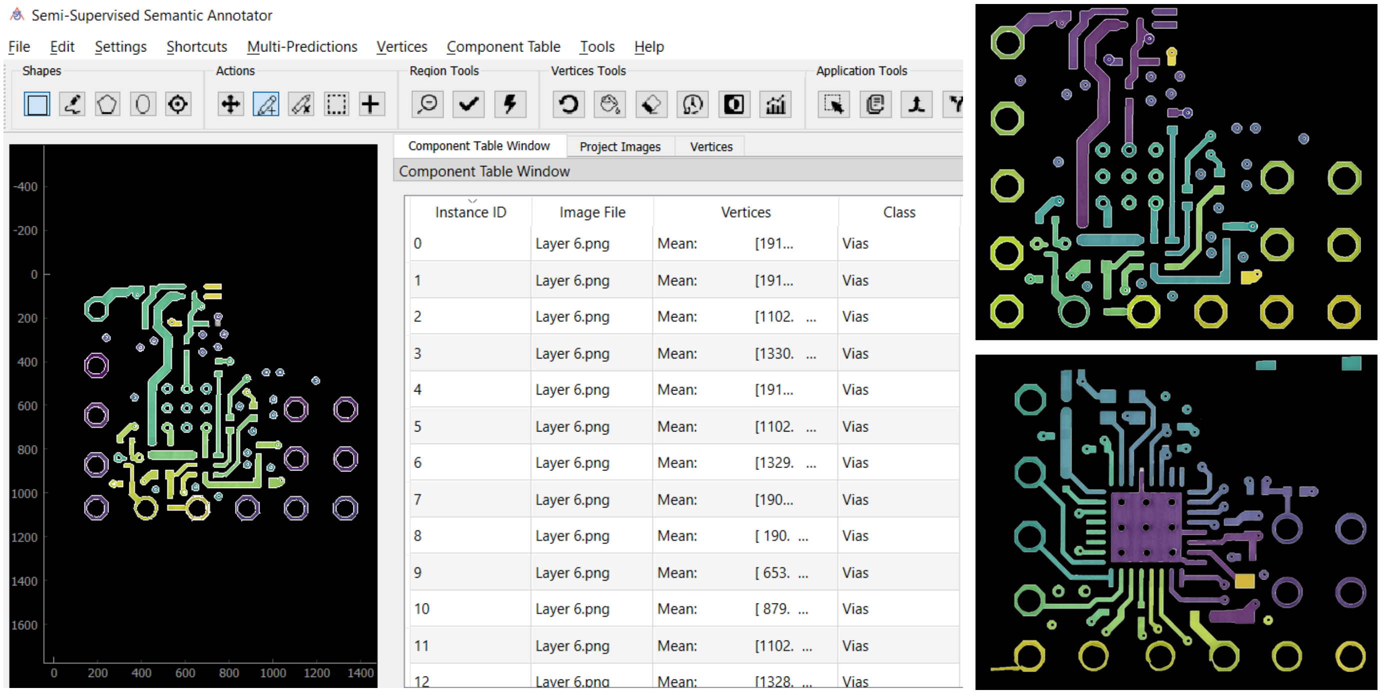
4.1 Workflow of collecting data

Within the X-ray research community there is a split between the "creators" that provide iterative improvement of the X-ray process through hardware and software upgrades, and that of the "users" who utilize X-ray tools for their specific application such as agriculture, medicine, and electronics, etc. The X-ray tool users often utilize commercial based X-ray tools which have the limitation of proprietary software and the lack of ability to perform analysis upon X-ray data in its raw format. For this reason, there is often a lack of transparent PCB X-ray data for researchers to quantifiably compare analysis results upon. It is therefore a critical first step of widespread collection and curation of experimental data before the research from the lab can be integrated into a robust industrial application for automated inspection.

Currently, the lack of PCB X-ray data has limited the ability to develop these robust applications for automated inspection. In this dataset we have acquired X-ray images from various types of PCB designs within a framework that accounts for developing machine learning techniques. Each PCB sample must pass the data collection validation where the data is checked for noise, artifacts, and that the minimum feature size of the PCB design is greater than the spatial resolution of the voxel size.

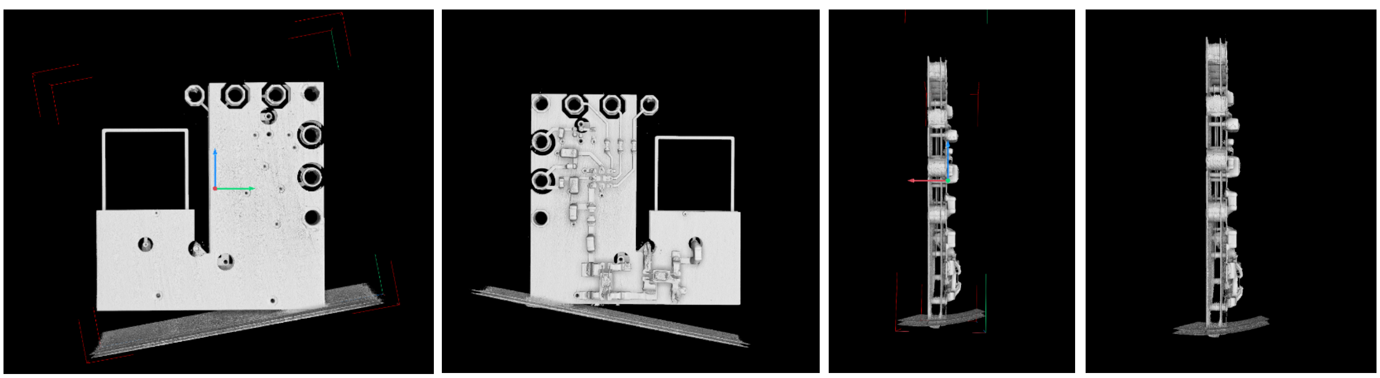
Although there are only 5 PCB samples within the dataset, each sample contains 3D volumetric data that can be extracted into 2D slices for analysis. It has been shown that the training of 2D networks that analyze each 3D slice one by one is currently the most used technique for 3D inspection [24].

The development of a curated PCB dataset can be utilized for many applications from optimizing the X-ray data collection process to require reduced number of projections,



(a) (b)

Fig. 3: Annotating the internal layers of PCBs; (a) Our annotation software s3a (developed in-house [18]); (b) examples of annotated internal layers images.



(a) (b) (c) (d)

Fig. 4: Reconstructed volume of one PCB; (a) back with crosshair; (b) front; (c) side one; (d) side two.

to improving the reconstruction process through removal of artifacts and noise by combining machine learning with iterative reconstruction techniques, or developing image processing and deep learning based techniques for semantic segmentation of PCB design features.

4.2 Uncertainty in the X-ray Data

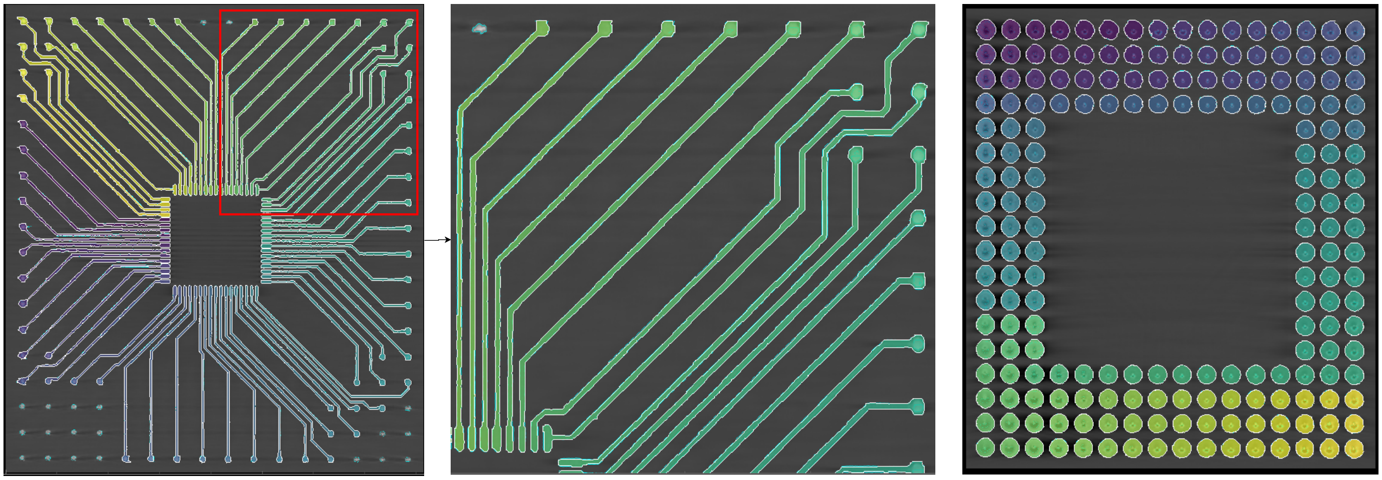
The primary environmental limitations are due to temperature, humidity, and vibrations during the X-ray data collection, which are mitigated through the use of vibrational dampening stage and a climate controlled environment.

The dominant factors for uncertainty in an X-ray scan of a PCB, is the sample composition itself. PCB designs range in complexity from the amount of copper layers, minimum feature size such as vias and micro vias, and the number and placement density of surface mount devices can cause severe noise and artifacts for reconstruction.

For each PCB scan, the detector is calibrated to determine the real intensity value of the X-ray source during relative scan parameters (KeV and current values), while reducing the geometrical uncertainty in the source to detector distance for reconstruction.The offset and gain calibrations are used to calculate the detector readings when the X-ray source is switched off (Dark-field) and when the X-rays are turned on (Bright-field) [25]. The calibrated average reading from the detector was used to normalize the collected projection as a baseline. In addition to the importance of setting the X-ray scan parameters appropriately to prevent detector saturation and or potential damage to the sample with high energy in relation to spot size.

4.3 Results

The process of X-ray data collection, reconstruction, aligning, and annotation is briefly shown in Figure 1. Whereas



(a) (b) (c)

Fig. 5: Annotations of the internal layers of a additively manufactured PCB (a) traces annotated; (b) ROI of a particular portion of the annotated traces; (c) annotations of the vias.

Figure 2 shows the PCB X-ray data collection setup and Figure 3 highlights our in-house developed annotation software named "s3a" [18] which is used for annotating the X-ray data. Figure 4 depicts the reconstructed volume of one sample PCB from front, back, side one and side two and Figure 5a and Figure 5b depicts the annotated traces on a sample PCB and Figure 5c depicts annotated vias on another sample PCB. The annotations for the layer's images for each of the PCBs are available in the ".CSV" file format. These annotations can be used for training machine learning and/or deep learning based algorithms for traces, vias and pads detection and/or classification. The available Tiff stack images in the dataset can also be used for semantic deep learning training tasks or for algorithms such as active contours and adaptive region based segmentation. Table 1 summarizes the FICS PCB X-ray database which consists of 5 PCB samples, each with different dimensions. The table summarizes the number of layers in each PCB along with their resolution, the approximate number of components, number of Tiff stack images, size of the collected data, number of annotated vias, traces and pads respectively. The features annotated are vias, connections, and pads, with each one consisting of a single connected component. The labeled data for each feature is contained within a .CSV file with its vertices and number count. When there is overlap between features the label will be a connection which can contain vias and/or pads within them. Vias and pads are individually labeled and do not contain other features within them. This enables the use of subtraction between the overlap of connections and vias or pads to determine feature connectivity in the Z direction of the PCB design. The labeling of vias can be either a ring shaped polygon or filled sphere based upon the spatial resolution of the collected data or the manufacturing of the PCB and segmentation of the copper circuitry. For example in Figure 1 the spatial resolution is high enough to enable segmentation of vias as ring shaped polygons, while in Figure 5c, the manufacturing of the PCB combined with the spatial resolution results in sphere shaped segmentation of the vias. Our dataset is the first step in bridging the gap between hardware and computer vision/machine learning communities. With a curated X-ray CT dataset for PCB designs, the ground truth data will enable improvements for PCB specific X-ray reconstruction, segmentation, and automated netlist conversion.

5 Newly Enabled Research

The proposed dataset will enable multiple research directions in the field of hardware security and machine learning.

5.1 AXI PCB Assurance

The proposed X-ray dataset can be used to facilitate research in the field of automated PCB X-ray inspection by enabling other researchers to evaluate and compare existing AXI algorithms. By evaluating and comparing AXI algorihtms, researchers are able to gain a better understanding of the algorithms' assumptions, benefits, and limitations. Such an understanding is necessary for researchers to develop their own, improved AXI algorithms. As AXI algorithms are improved over time, the PCB assurance field will become more robust to inter-layer trojans and defects.

5.2 Multimodal PCB Assurance

In addition, the proposed X-ray dataset can be used in tandem with existing optical datasets (e.g. FPIC [6]) for more complete and practical PCB assurance. Though valuable inter-layer information is revealed in the X-ray spectrum, it can take a long time to collect X-ray data. On the other hand, optical data is much faster to collect, but the optical spectrum only reveals surface-level information. The trade-offs of AXI and AOI can be optimized by combining X-ray and optical data to achieve multimodal PCB assurance. For example, optical data could be collected first and then used to help locate regions of interest, while X-ray can be used after to gather more information from the identified areas of interest.

TABLE 1: Details of the FICS PCB X-ray database

Database	PCBs	Dimensions [in.]	Resolution [μM]	Size [GB]	# of Layers	Approx # of SMDs	# of Images (Tiff Stack)	# of Annotated Vias/Traces/Pads
FICS PCB X-ray	PCB 1	0.87 X 0.87	13.59	29.1	6	22	1430	164/55/29
	PCB 2	0.55 X 0.55	9.87	12.5	4	30	486	37/14/17
	PCB 3	0.60 X 0.60	11.30	8.5	4	22	1920	623/81/0
	PCB 4	1.21 X 1.37	23.04	25.7	5	4	564	325/196/0
	PCB 5	1.22 X 2.55	32.76	32.4	4	55	1101	206/43/100

5.3 Reverse Engineering

X-ray data is able to capture inter-layer information such as traces, vias, pads, and hidden components. This information is valuable for inferring the PCB's circuitry and extracting the netlist. The netlist can then be used for reverse engineering of foreign and competitor technologies or legacy devices. PCB reverse engineering helps researchers and practitioners maintain and repair legacy systems and identify defects and Trojans.

6 Open challenges and future work

The open challenges that should be considered while working with PCB X-ray data are listed below.

1) Advancement in the newly-enabled research as mentioned above can impose new challenges. For example, for multimodal PCB assurance it will be a challenging task to maintain the tradeoffs between AXI and AOI data and algorithms.
2) Data management for a large volumetric database such as PCB X-ray data can be difficult to scale and maintain. It is important to determine the optimal training dataset of PCB designs which will result in a representative assessment of PCB designs currently and in the future. Due to the ongoing technological advancements in the hardware community for PCB designs, packaging, PCB materials, and the supply chain, it will be an open challenge to maintain an up-to-date dataset.
3) Due to the current need to tune the X-ray parameters for each PCB design, there is a need for an automated system for optimizing these settings. This will require domain knowledge from the PCB design, accurate X-ray simulation tools, and algorithms to iteratively improve the quality of PCB scans given a design's parameters.
4) Computed laminography has an advantage compared with tomographic collection where the sample is not a cylindrical sample, but instead has a complex geometry. This complex geometry such as a flat plane similar to a PCB, can cause CT techniques to have large amounts of missing information due to the absorption of X-rays. The inflection point for PCB designs is when the minimum axis size in X or Y is greater than 8-10 inches, above this size, the X-ray penetration for typical 100-200 KeV X-ray sources is not enough to pass through the entire sample. Laminography sacrifices layer depth discernibly for increased spatial resolution with smaller source, sample, detector distances. PCB X-ray collection is achievable with CT for small samples that fit within the FOV, or through stitching multiple scans for large samples. However, laminographic collection is applicable to small, medium, and large sized PCB designs [21].

7 Conclusion

In this paper, we proposed "FICS PCB X-ray," a computed tomographic dataset. To the best of our knowledge, "FICS PCB X-ray" is the first X-ray dataset of entire printed circuit boards. The dataset provides Tiff stack images and annotated layer images for computer vision and machine learning based tasks.

Future work will involve expanding the tomographic dataset along with including a laminographic dataset. The goal is to keep the dataset up-to-date with the evolving PCB technology. The current version of the dataset can be used as a benchmark to test and perform analysis on various AXI algorithms for PCB assurance. "FICS PCB X-ray" is an immense resource for researchers and practitioners in the PCB assurance domain in industry and academia.

References

[1] N. Asadizanjani, M. Tehranipoor, and D. Forte, “Pcb reverse engineering using nondestructive x-ray tomography and advanced image processing,” *IEEE Transactions on Components, Packaging and Manufacturing Technology*, vol. 7, no. 2, pp. 292–299, 2017.

[2] U. J. Botero, R. Wilson, H. Lu, *et al.*, “Hardware trust and assurance through reverse engineering: A survey and outlook from image analysis and machine learning perspectives,” *arXiv preprint arXiv:2002.04210*, 2020.

[3] D. Mehta, H. Lu, O. P. Paradis, *et al.*, “The big hack explained: Detection and prevention of pcb supply chain implants,” *ACM Journal on Emerging Technologies in Computing Systems (JETC)*, vol. 16, no. 4, pp. 1–25, 2020.

[4] M. Azhagan, D. Mehta, H. Lu, *et al.*, “A review on automatic bill of material generation and visual inspection on pcbs,” in *ISTFA 2019: Conference Proceedings from the 45th International Symposium for Testing and Failure Analysis*, 2019, pp. 256–265.

[5] J. True, N. Jessurun, D. Mehta, and N. Asadi, “Quaintpeax quantifying algorithmically intrinsic properties of electronic assemblies via x-ray ct,” *Microscopy and Microanalysis*, vol. 27, no. S1, pp. 1222–1225, 2021.

[6] N. Jessurun, O. P. Dizon-Paradis, J. Harrison, *et al.*, “Fpic: A novel semantic dataset for optical pcb assurance,” *arXiv preprint arXiv:2202.08414*, 2022.

[7] N. Jessurun, O. Paradis, A. Roberts, and N. Asadizanjani, “Component detection and evaluation framework (cdef): A semantic annotation tool,” *Microscopy and Microanalysis*, vol. 26, no. S2, pp. 1470–1474, 2020.

[8] N. T. Jessurun, O. P. Paradis, M. Tehranipoor, and N. Asadizanjani, “Shade: Automated refinement of pcb component estimates using detected shadows,” in *2020 IEEE Physical Assurance and Inspection of Electronics (PAINE)*, IEEE, 2020, pp. 1–6.

[9] S. Ghosh, M. A. M. Sathiaseelan, and N. Asadizanjani, “Deep learning-based approaches for text recognition in pcb optical inspection: A survey,” in *2021 IEEE Physical Assurance and Inspection of Electronics (PAINE)*, IEEE, pp. 1–8.

[10] P. Jula, C. Spanos, and R. Leachman, “Comparing the economic impact of alternative metrology methods in semiconductor manufacturing,” *IEEE Transactions on Semiconductor Manufacturing*, vol. 15, no. 4, pp. 454–463, 2002.

[11] H. Lu, D. Mehta, O. Paradis, N. Asadizanjani, M. Tehranipoor, and D. L. Woodard, “Fics-pcb: A multimodal image dataset for automated printed circuit board visual inspection,” *Cryptology ePrint Archive*, 2020.

[12] S. L. Fisher, D. J. Holmes, J. S. Jorgensen, *et al.*, “Laminography in the lab: Imaging planar objects using a conventional x-ray CT scanner,” *Measurement Science and Technology*, vol. 30, no. 3, p. 035 401, Feb. 2019.

[13] N. Asadizanjani, S. Shahbazmohamadi, M. Tehranipoor, and D. Forte, “Non-destructive pcb reverse engineering using x-ray micro computed tomography,” in *ISTFA 2015*, ASM International, 2015, pp. 164–172.

[14] U. J. Botero, D. Koblah, D. E. Capecci, *et al.*, “Automated via detection for pcb reverse engineering,” in *ISTFA 2020*, ASM International, 2020, pp. 157–171.

[15] U. J. Botero, N. Asadizanjani, D. L. Woodard, and D. Forte, “A framework for automated alignment and layer identification of x-ray tomography imaged pcbs,” in *Proceedings of the Annual GOMACTech Conference*, 2020.

[16] D. Dansana, R. Kumar, A. Bhattacharjee, *et al.*, “Early diagnosis of covid-19-affected patients based on x-ray and computed tomography images using deep learning algorithm,” *Soft Computing*, Aug. 2020.

[17] Q. Zhang, M. Zhang, C. Gamanayake, *et al.*, “Deep learning based defect detection for solder joints on industrial x-ray circuit board images,” in *2020 IEEE 18th International Conference on Industrial Informatics (INDIN)*, vol. 1, 2020, pp. 74–79.

[18] N. Jessurun, O. Paradis, A. Roberts, and N. Asadizanjani, “Component detection and evaluation framework (cdef): A semantic annotation tool,” *Microscopy and Microanalysis*, vol. 26, no. S2, pp. 1470–1474, 2020.

[19] Y. Dong, C. Bao, and W. S. Kim, “Sustainable additive manufacturing of printed circuit boards,” *Joule*, vol. 2, no. 4, pp. 579–582, 2018.

[20] M. R. Khosravani and T. Reinicke, “On the use of x-ray computed tomography in assessment of 3d-printed components,” *Journal of Nondestructive Evaluation*, vol. 39, no. 4, p. 75, Sep. 2020.

[21] P. J. Withers, C. Bouman, S. Carmignato, *et al.*, “X-ray computed tomography,” *Nature Reviews Methods Primers*, vol. 1, no. 1, p. 18, Feb. 2021.

[22] J. Dong, J. Fu, and Z. He, “A deep learning reconstruction framework for x-ray computed tomography with incomplete data,” *PLOS ONE*, vol. 14, no. 11, pp. 1–17, Nov. 2019.

[23] J. Park, D. Hwang, K. Y. Kim, S. K. Kang, Y. K. Kim, and J. S. Lee, “Computed tomography super-resolution using deep convolutional neural network,” *Physics in Medicine &amp Biology*, vol. 63, no. 14, p. 145 011, Jul. 2018.

[24] D. M. Pelt, K. J. Batenburg, and J. A. Sethian, “Improving tomographic reconstruction from limited data using mixed-scale dense convolutional neural networks,” *Journal of Imaging*, vol. 4, no. 11, p. 128, 2018.

[25] R. A. Ketcham and W. D. Carlson, “Acquisition, optimization and interpretation of x-ray computed tomographic imagery: Applications to the geosciences,” *Computers Geosciences*, vol. 27, no. 4, pp. 381–400, 2001, 3D reconstruction, modelling visualization of geological materials.