GanoDIP : GAN Anomaly Detection through Intermediate Patches

A PCBA Manufacturing Case

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Introduction

Quality Control

Data Driven Activities

- Data Collection
- Detect abnormalities

High Product Quality

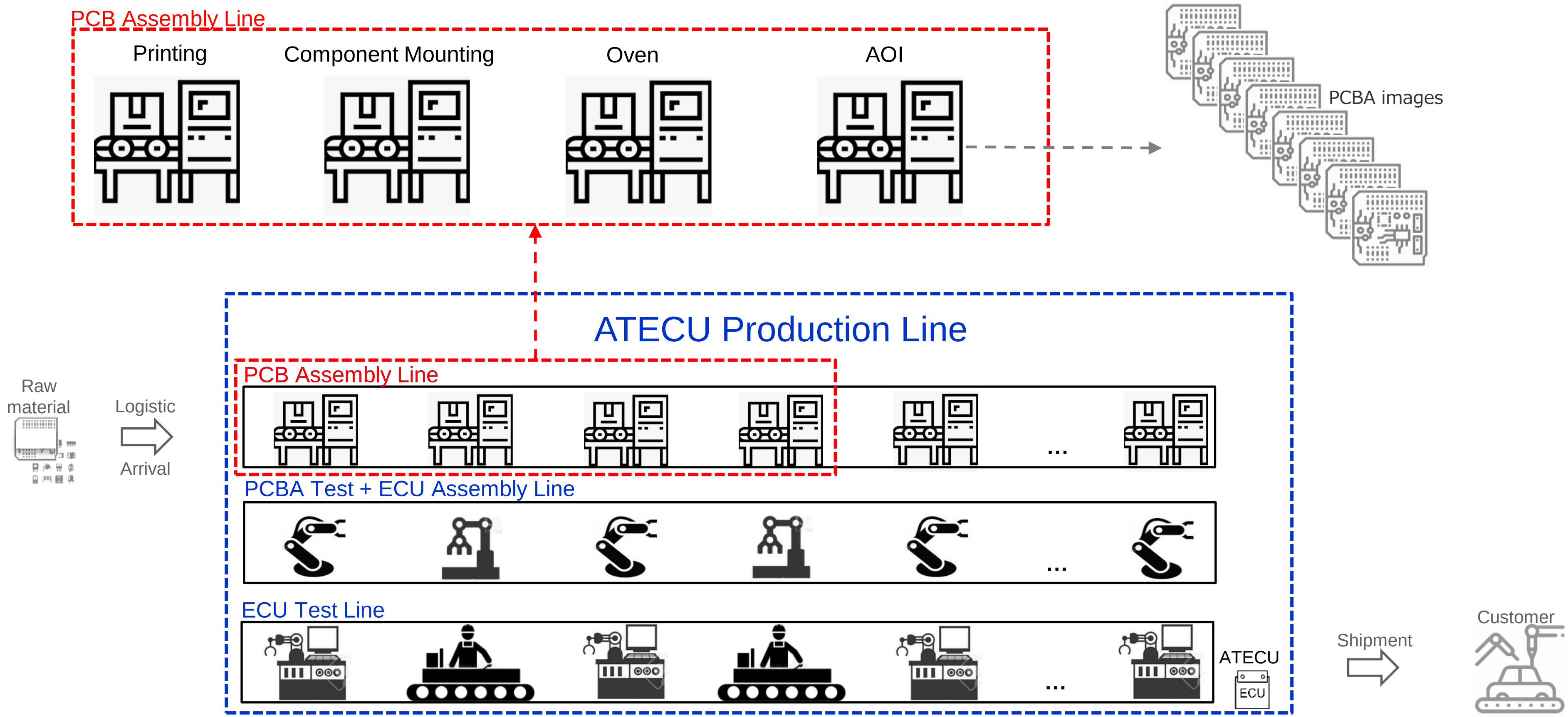
- Enable Continuous flow
- Reduce Scrap and Rework

if necessary

Industrial Context

Automatic Optical Inspection is the 1st visual tester of the line

- Ideal candidate to apply EDER
- Many data available that reflect the intermediate quality



ATECU: Automatic Transmission Electronic Control Unit = finished product
PCBA: Printed Circuit Board Assembly = intermediate product
AOI: Automatic Optical Inspection = PCBA judgement process

Problem Definition

False Positive Rate implies manual inspection

- Waste of time
- Risk of misjudgment

Zero Defect Target
=
Low Type II error rate
(FNR - missed detections)

Severe Test Limits
=
High Type I error rate
(FPR - false alarms)

Baseline = ~8s./PCBA inspection time

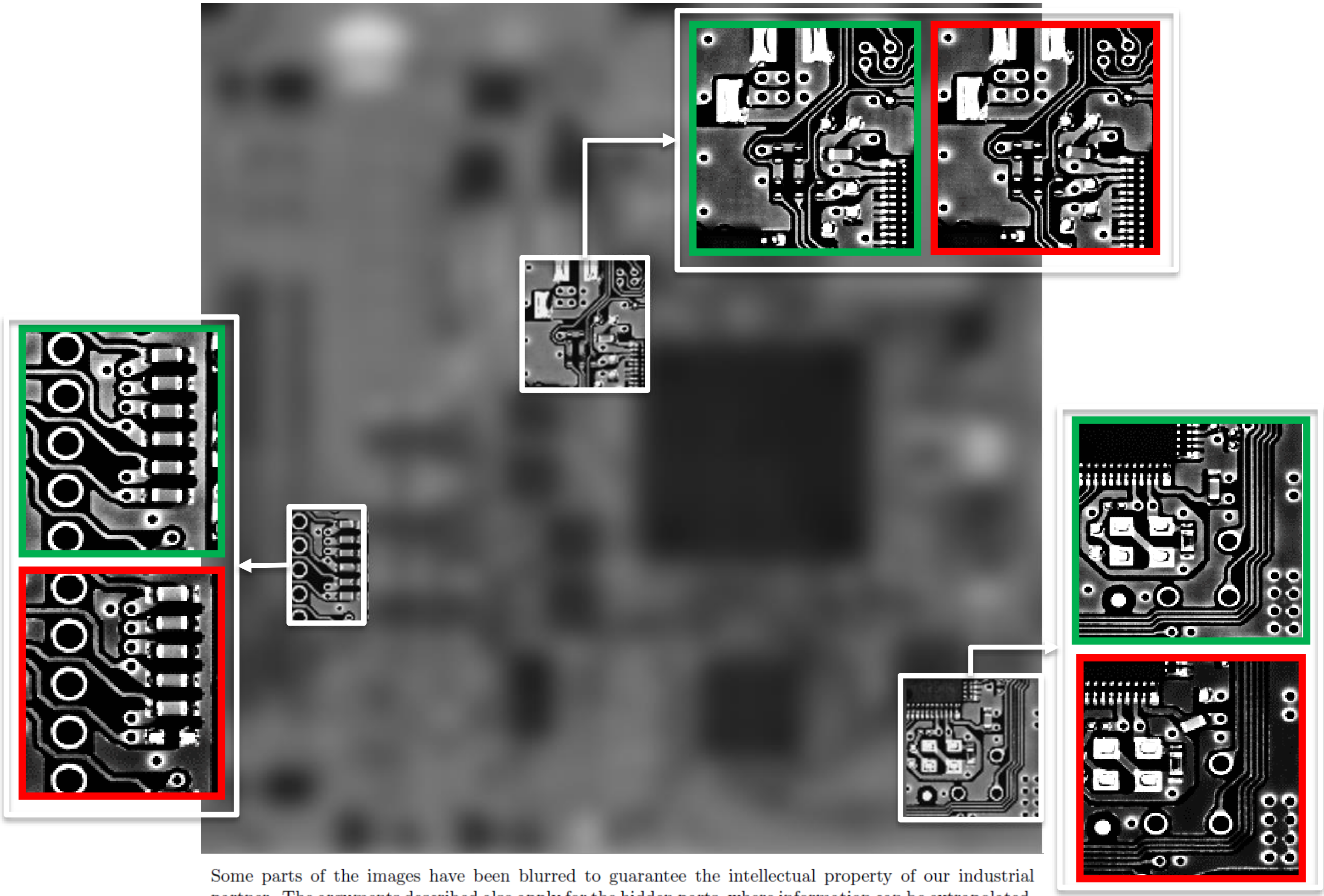
Target = Reduce the FPR while maintaining the FNR at 0%

Anomaly Detection State-of-the-art in the machine learning field

High Resolution and Small Details: the PCBA Dataset

Deal with Normal variability and Small Defects

A lot of information in the overall image
Dense-in-components areas yield abrupt changes in pixel intensity



Some parts of the images have been blurred to guarantee the intellectual property of our industrial partner. The arguments described also apply for the hidden parts, where information can be extrapolated.

State-of-the-Art Anomaly Detection Techniques

Unsupervised Methods

Difficult to collect enough abnormal images (imbalanced dataset)
Difficult to ensure that all anomalies could be covered in the dataset

OC SVM - Kernel PCA models

Poor discriminative performance with high-dimensional images

Autoencoders models

Good reconstruction for normal, but also for abnormal (complex dataset)

Adversarial learning-based models

Train a generator to capture the normal distribution, and a discriminator to distinguish original and generated images

GanoDIP Training Step

Generator-Discriminator
Encoder

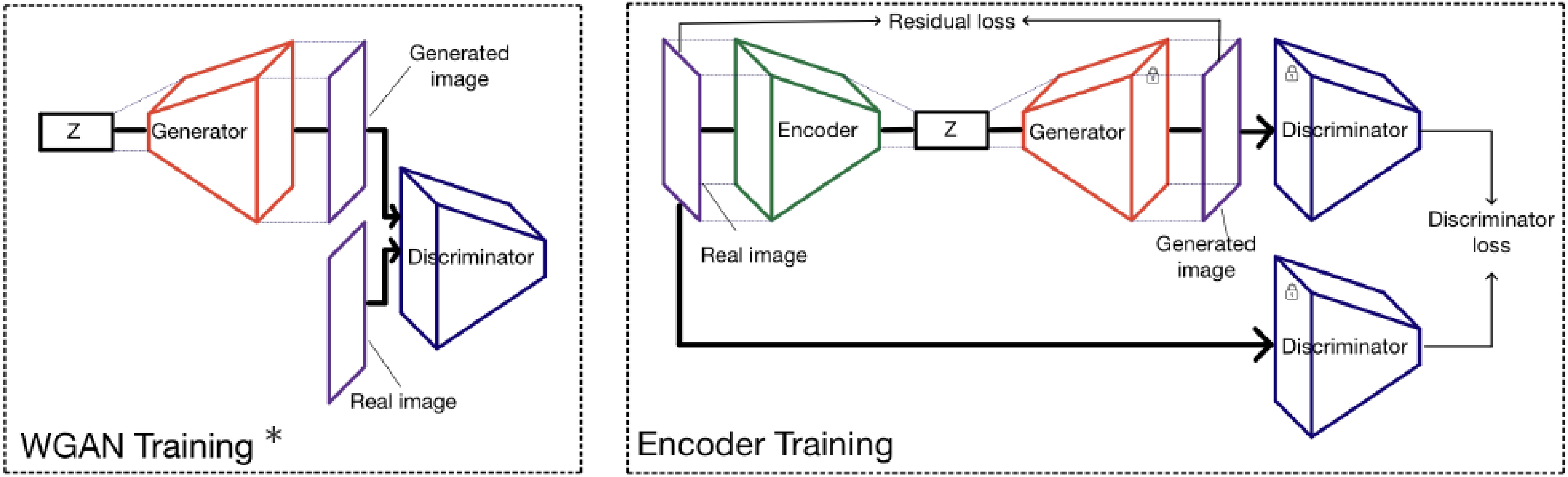
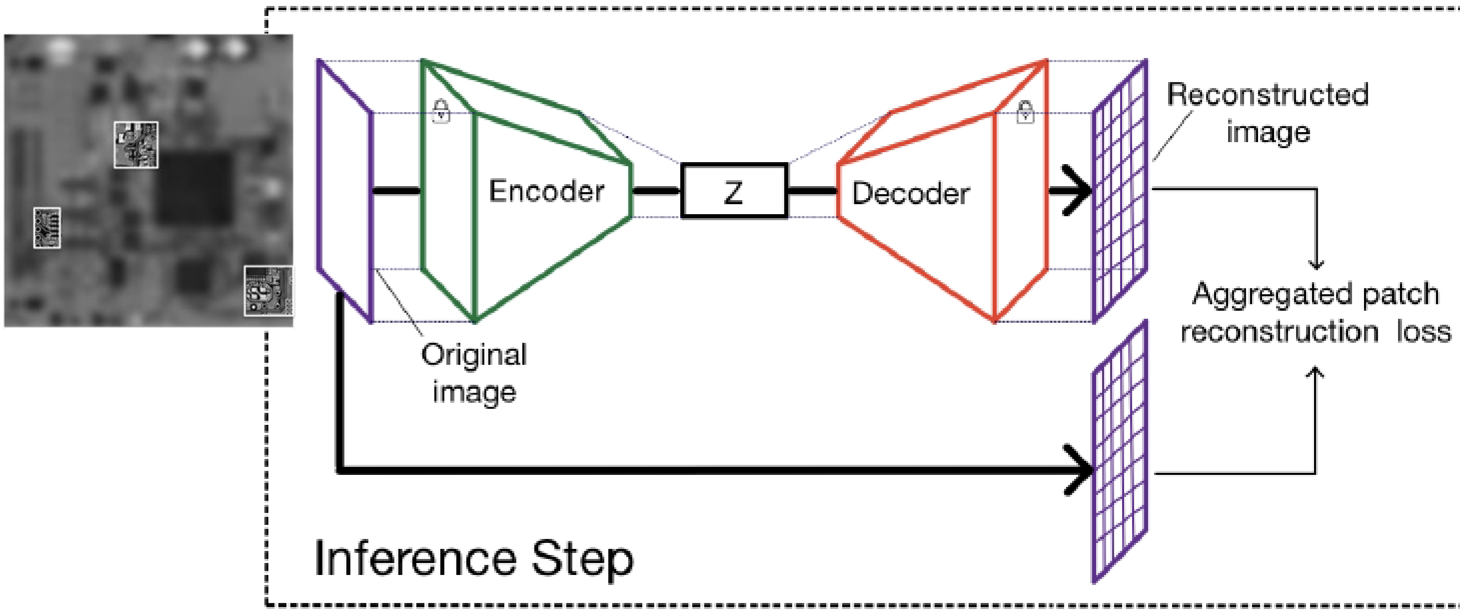


Figure inspired from Schlegl et al. (2019) presenting the training strategy of f-AnoGAN, which is used as the first step of the proposed method GanoDIP.

* WGAN is a GAN that minimizes the Wasserstein distance improving the learning stability

GanoDIP Inference Step

Intermediate Patches
Anomaly Score



$$\text{Anomaly Score} = \frac{1}{m}\sum_{k=1}^{m}\{\text{MSE}_k \mid \text{MSE}_k \in m \text{ highest MSE}_i\},$$

where m corresponds to the $\alpha\%$ of the patches with the highest anomaly score, and i is the patch index.

Dataset Pre-Processing and Experimental Protocol

360 normal images for train set
50 normal + 18 abnormal images for test set

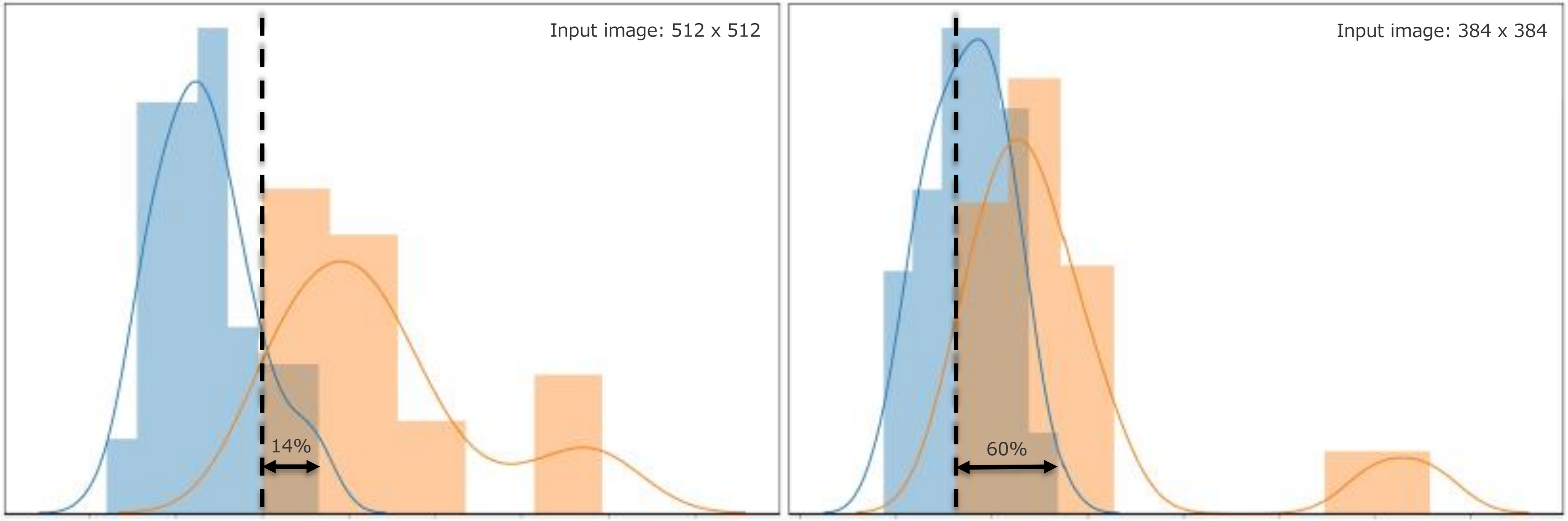
Resizing 4500x4340 => 512x512
Normalization

$\alpha = 0{,}15\%$
Patch Size = 4x4

GPU nVidia Geforce RTX 2080 TI
Python 3.7, CUDA10.1, Tensorflow 2.3

Training Time ~ 27 hours
Inference Time ~ 5 seconds / image

Evaluation: Quantitative Assessment



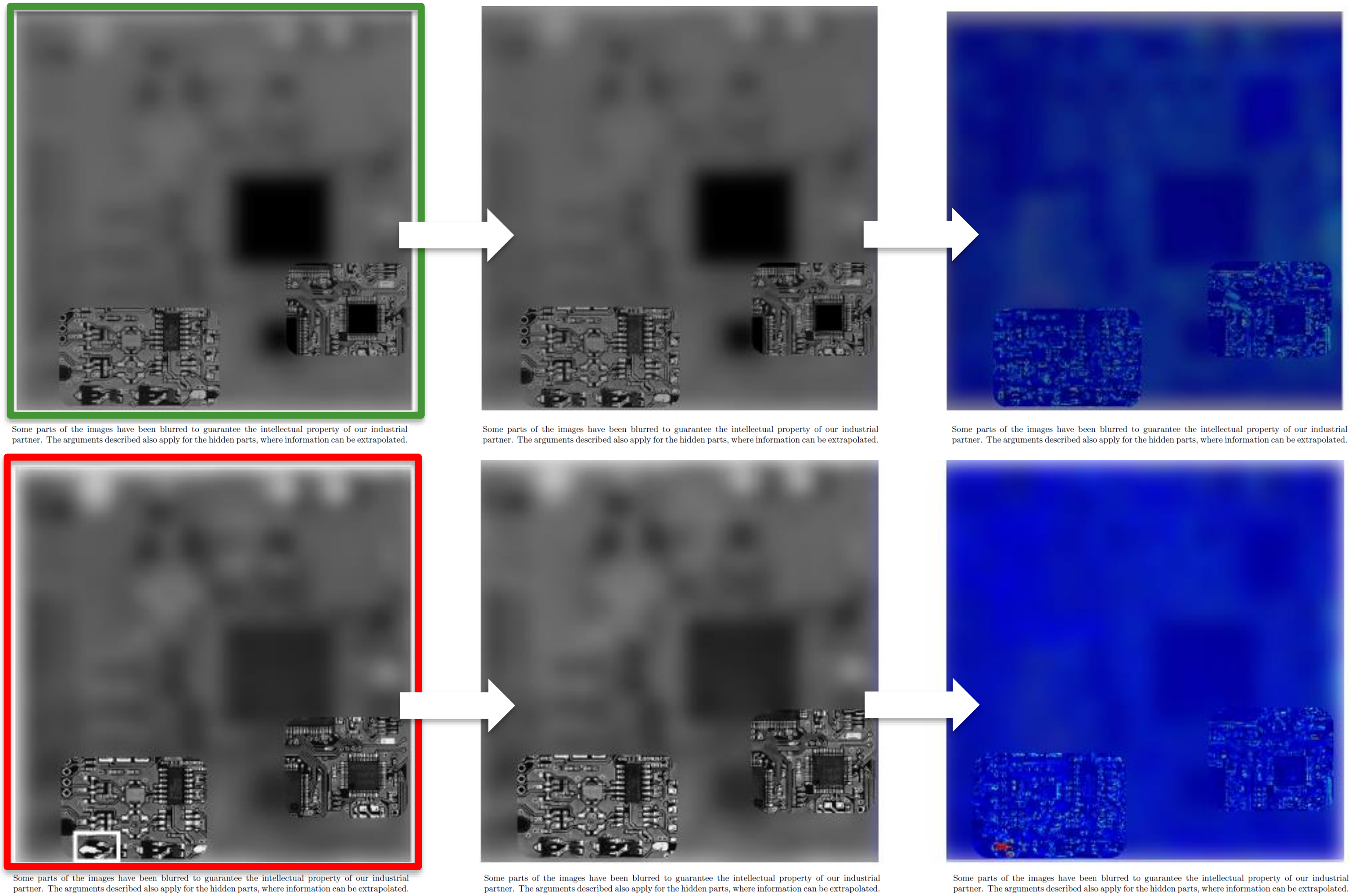
Anomaly scores for normal (blue) and abnormal (orange) images of the test dataset. The x-axis is the anomaly score of the test images and the y-axis corresponds to the score frequency.

If constraint is 0% FNR => threshold placed at the best anomaly score for abnormal distribution.

FPR = 14%
Industrial partner inspection time decreased from 8 to 2,2 seconds

Evaluation: Qualititive Assessment (1/2)

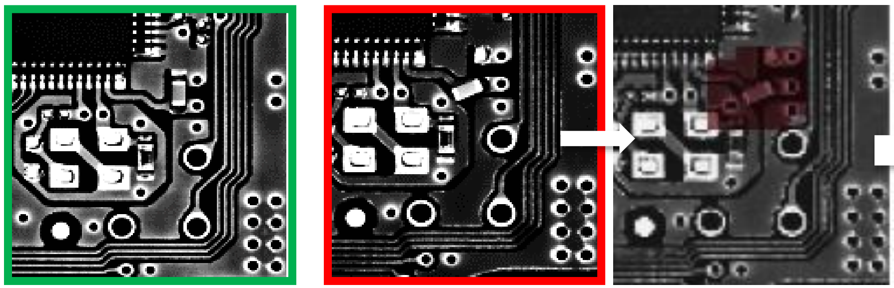
Global image differences

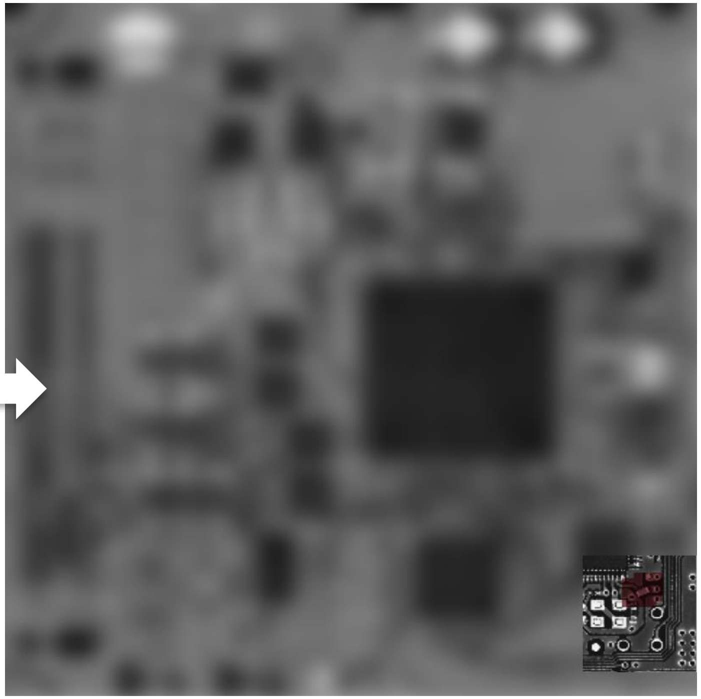


Global image complexity -> limited discriminative performance

Evaluation: Qualititive Assessment (2/2)

Overlay highest anomaly score patches





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Visual Turing Test

Assess the reconstructed images quality
Performed with 5 domain experts
58,2% images correctly labeled – close to the 50% expected

Defects identified + Confidence on future yet unseen defects

Conclusion

TO SUM UP

Distinguish normal and abnormal images
Find defects of different nature
Support actual visual inspection process

RESULTS

0% FNR
14% FPR
72% Inspection time saved

FUTURE WORK

Increase the input image size
Optimize the latent space encoding
Transpose the method on other use cases

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GanoDIP - GAN Anomaly Detection through Intermediate Patches: a PCBA Manufacturing Case

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Abstract

Industry 4.0 and recent deep learning progress make it possible to solve problems that traditional methods could not. This is the case for anomaly detection that received a particular attention from the machine learning community, and resulted in a use of generative adversarial networks (GANs). In this work, we propose to use intermediate patches for the inference step, after a WGAN training procedure suitable for highly imbalanced datasets, to make the anomaly detection possible on full size Printed Circuit Board Assembly (PCBA) images. We therefore show that our technique can be used to support or replace actual industrial image processing algorithms, as well as to avoid a waste of time for industries.

Keywords: Industry 4.0, AOI, PCBA, Anomaly Detection, Imbalanced Dataset, WGAN, Image Processing, Real-World Dataset, Unsupervised Learning

1. Introduction

In the last few decades, the industrial sector evolved with technologies, entering different successive revolutions. From the steam-powered equipment, to the introduction of electricity and IT equipment, the sector takes nowadays advantage of cyber-physical systems. Companies are now facing the 4th industrial revolution, also called Industry 4.0. This new paradigm involves a variety of key enablers, composed of the internet of things (IOT), analytics, data science, machine learning and decision systems. The main objective of these technologies is to optimize the factories productivity. In this context, deep learning, applied to automatic image inspection, offers a high potential to enforce quality control requirements. This can be done because factories own countless images that may be exploited, specifically to detect and localize anomalies in products.

This work proposes to solve a real-world, industrial, anomaly detection problem. Real-world images are considered, taken from the production lines of an Automatic Transmission Electronic Control Unit (ATECU) manufacturer. The product line is composed of successive processes, devoted to manufacture electronic Printed Circuit Board Assembly (PCBA), in order to equip car speed boxes. The first process is the one of interest in our work. It takes images of 100% of the products being manufactured through an Automatic Optical Inspection (AOI), applied on the 2 faces of the PCBA. To detect PCBAs with anomalies in the product line, traditional anomaly detection algorithms (comparison between an image under test and a golden sample image) are currently used in factories, through this process.

Thank you for your kind attention

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