AUTOMATED VISION INSPECTION BASED IC COMPONENT LOCATOR USING DEEP LEARNING

IBRAHIM SOLIMAN MOHAMED

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

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IBRAHIM SOLIMAN MOHAMED

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DEDICATION

For my beloved father and mother.

ABSTRACT

With the coming of the era of industrial revolution 4.0, manufacturers produce high-tech products. As the production process is refined, inspection technologies become more important. Specifically, the inspection of a printed circuit board (PCB), which is an indispensable part of electronic products, is an essential step to improve the quality of the process and yield. Image processing techniques are utilized for inspection, but there are limitations because the backgrounds of images are different, and the kinds of component shape and size parameters are normally various. In order to overcome these limitations, methods based on machine learning and deep learning have been developed recently. In this project, I have developed an IC components locator software to help in inspection process, this software is relying on 2 model of most popular object detection on deep learning field (Yolo V3 and Faster RCNN), I have trained bot models and preformed a comparison between their results in term of mAP, loss, inference time and training time. Yolo V3 and Faster RCNN have been trained on a filtered open source dataset of PCB that contains 163 Images, an annotation and augmentation tool has been developed in purpose of increasing the amount of our dataset. Finally, OPENVINO toolkit has used for optimization process and infer both models on various Intel CPU to run our deep learning network on edge.

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LIST OF SYMBOLS AND ABBREVIATIONS

2D	:	2 Dimensions
ALU	:	Arithmetic Logic Unit
AOI	:	Automated Optical Inspection
API	:	Application Programming Interface
AVI	:	Automated Vision Inspection
BFLOP	:	Billion Floating Point Operations
CNN	:	Convolutional Neural Network
CPU	:	Central Processing Unit
DLDT	:	Deep Learning Deployment Toolkit
DNN	:	Deep Neural Network
DSLR	:	Digital Single-Lens Reflex
FN	:	False Negative
FP	:	False Positive
FPGA	:	Field-Programmable Gate Array
FPN	:	Feature Pyramid Networks
FVI	:	Final Vision Inspection
GPU	:	Graphical Processing Unit
HOG	:	Histogram of Oriented Gradients
IC	:	Integrated Circuit

IoU	:	Intersection of Union
IPU	:	Imaging Processing Unit
IR	:	Intermediate Representation
JPG	:	Joint Photographic Group
mAP	:	Mean Average Precision
PCB	:	Printed Circuit Board
PNG	:	Portable Network Graphics
R-CNN	:	Region Convolutional Neural Network
ROI	:	Region of Interests
RPN	:	Region Proposal Network
SIFT	:	Scale-Invariant Feature Transform
SSD	:	Single Shot Multibox Detector
SVM	:	Support Vector Machine
TP	:	True Positive
UTeM	:	Universiti Teknikal Malaysia Melaka
VPU	:	Vision Processing Unit
YoloV3	:	You Only Look Once Version 3

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CHAPTER 1

INTRODUCTION

1.1 Project Background

The machine-controlled inspection of Printed Circuit Boards (PCBs) serves a purpose that is long-established in technology. the aim is to alleviate human inspectors of the tedious and inefficient task of trying to find those defects in PCBs that could lead on to electrical failure. As an example, circuit breaks have rather obvious implications for electrical failure, and human inspectors typically miss those defects. It is merely arduous to visually examine many thousands of printed wires with parts placement, every couple of thousandths of a feet across, for several hours each day without any mistakes or misses that can cause a lot of problem in production line. Such mistakes, whereas dead perceivable, also are pricey. The time is anticipated once the print circuit boards are going to be thus fine that human inspectors should use microscopes instead of the magnifying glasses currently in use. With the rapid-movement limitations of microscopic viewing, the unskillfulness of human scrutiny is going to be intolerable. Automated, machine based mostly, scrutiny relieves this drawback by providing a machine computer vision solution. Obviously, there square measure employment, and wide-ranging economic implications of such technology that should be thought of alongside the technology itself. So, Inspection automation has become a unique and important tool to boost quality in printed circuit board (PCB) manufacturer factories. Nowadays Manufacturing Industries needs machine-controlled inspection since, within the fabrication processes, there square measure uncertainties, tolerances, defects, relative position and orientation errors, which may be analyzed by vision sensing, Machine algorithms and Deep Neural Networks.

This project proposes an approach for printed circuit board (PCB) component locator using the power of most recent deep learning networks that could achieve an impressive result in purpose of inspection automation, the main function of this project is generating data that includes the location, dimensions and categories of each component, this data can help in generating inspection board recipe. Currently this recipe is created for each new board in production line manually by operator using a custom-made bounding box drawing mechanism and type selection for each component.

During my project, a comparison between YoloV3[8] and Faster R-CNN [9] object detection networks will be made as a component locator by training both networks on provided electronics board datasets [10].

1.2 Problem Statement

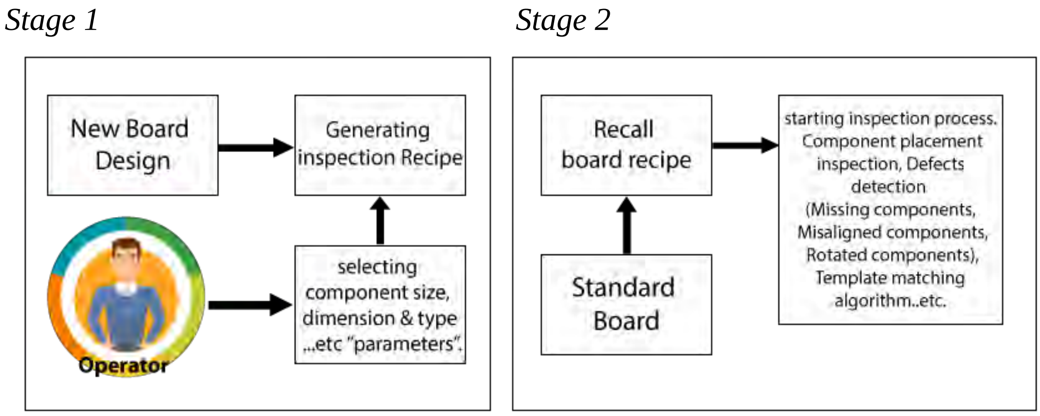

Figure 1.1: Part of PCB Inspection Process

As shown in figure 1, stage 1 shown the procedures that operators follow for a new board in their production line. The operator needs to draw a bounding box around each component and select component's family, type and other parameters that can help in specifying suitable inspection algorithm. This operation is time costly and need much efforts and concentration of the operator. So, my project will be focusing in generating new board recipe or even help in automating part of this inspection stage by allocating, localizing each component and classify some this component, on the other hand the second stage is nearly automated by a lot of popular algorithms in imaging processing fields, and it is nearly stable and required less operator efforts and time.

1.3 Objectives of the Research

i. To develop annotation and augmentation software for dataset preparation.
ii. To train, test and compare IC component locator based on object detection network (YoloV3 vs Faster R-CNN)
iii. To deploy our IC component locator on Intel CPU computer using OPENVINO software development kit.

1.4 Scope of Work

In purpose of automated inspection, a problem statement has been issued about operator manually select and draw bounding box around ROI for each component once there is a new board design and choose the suitable inspection algorithm, so by developing an automated component locator using DNN and CNN, we will be able to save the operator time and effort by automatically identify the ROI for each component, that will help operator in choosing the suitable inspection algorithm in faster way. My network will be developed on Tensorflow or caffe2 framework using python programming language in purpose of reaching ±10 px localization of component body size. Finally, we will optimize our network and deploy it on intel CPU computer using OPENVINO software development kit.

1.5 Report Structure

This thesis is organized and arranged into 5 major chapters. In chapter 1, the overview of PCB inspection is discussed in the project background. In addition, the problem statement, objective and scope of work will be outlined clearly in this section. In chapter 2, the past studies related to PCB automated inspection will be included in this chapter. In chapter 3, all relevant experiments and techniques used in this project will be mentioned in detail. As well as a flowchart of system will be discussed. In chapter 4, the performance of our system will be recorded and interpreted in term of accuracy, computation time and reliability. In last chapter, a conclusion will be drawn from this project. In addition, the recommendation for the future plan which related to the project will be made in this section.

CHAPTER 2

BACKGROUND STUDY

2.1 INSPECTION CATEGORIES

In PCB manufacturing industries, Optical inspection has been grownup quickly in past few decades. It is currently serving a very important role in fabrication and mass production process. Most PCB manufacturing players are currently relying on AOI machines to detect and report different kind of defects on boards when photo-printing or etching. Notwithstanding, AVI (Automated Vision Inspection) that generally additionally referred to as FVI (final vision inspection) is growing in an exceedingly comparatively quick pace, however not nevertheless wide used in the market. AOI and AVI machines are different categories of inspection machines with different function, however their operating concept still similar. several technologies of AVI are designed from AOI. The PCB makers are currently using AOI and AVI