COMPUTER VISION SYSTEM FOR INDUSTRIAL SCREWING AUTOMATION

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DEDICATION

This project report is dedicated to my late father, who taught me that the best kind of knowledge to have is that which is learned for its own sake. It is also dedicated to my mother, who taught me that even the largest task can be accomplished if it is done one step at a time.

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ABSTRACT

This project proposes a software that incorporates computer vision algorithms to detect screw types, screw locations, and to locate screw holes on an object to ensure a smooth flow of automated assembly processes. The existing systems are found to be less adaptable for performing automated assembly and do not satisfy real-time constraints. These systems are affected by several factors that exist in the industrial environment such as lighting conditions and calibration issues which affect the effectiveness of the automation. This encouraged to develop an adaptable system, which is adaptable to variation in object locations, lighting conditions and works in real-time constraints. This achieved by developing two subsystems, where firstly, a camera is mounted above a screw tray to detect screws by using You Only Look Once version 3 (YOLO v3) detection algorithm with Darknet. YOLO v3 is trained on a collected dataset and validated using two approaches: train/test split and 3-fold cross validation. Secondly, another camera is mounted above an object to localize screw holes on the object by using a blob detector technique. A graphical user interface is designed to show the results and to make the system more user-friendly and easy to monitor. Experimental results show that the screw detection subsystem is able to detect the screws under different lighting conditions with mAP of 93.8% and localization accuracy with a maximum error of 1.26% in the *x*-axis and 2.84% in the *y*-axis. Also, the blob detector subsystem is able to localize the screw holes with a maximum error of 0.26% in the *x*-axis and 0.58% in the *y*-axis. Besides that, both subsystems are able to work in real-time constraints with a speed of 7-10 FPS. It is envisaged that the computer vision software will make the assembly process more effective and increase productivity, also enhance the flow of the process.

ABSTRAK

Projek ini mencadangkan perisian yang menggabungkan algoritma penglihatan komputer untuk mengesan jenis skru, lokasi skru, dan mencari lubang skru pada objek untuk memastikan aliran lancar proses pemasangan automatik. Sistem yang sedia ada didapati kurang fleksibel, kurang sesuai untuk melaksanakan pemasangan, dan tidak memenuhi kekangan masa yang diperlukan. Sistem ini terdedah kepada kesan pencahayaan dan isu penentukuran yang wujud dalam persekitaran industri yang mempengaruhi keberkesanan automasi. Ini memberi motivasi kepada perkembangan penyelesaian yang fleksibel, yang tidak memerlukan lekapan dan ia dapat disesuaikan dengan pelbagai lokasi objek, keadaan pencahayaan dan kerja dalam kekangan masa nyata. Ini dicapai dengan membangunkan dua subsistem, pertama, kamera dipasang di atas dulang skru untuk mengesan skru dengan menggunakan algoritma pengesanan You Only Look Once version 3 (YOLO v3) dengan Darknet. YOLO v3 dilatih pada dataset yang dikumpul dan disahkan menggunakan dua pendekatan: pengesahan perpecahan sah dan tiga kali ganda pengesahan silang. Kedua, kamera lain dipasang di atas objek untuk setempatkan lubang skru pada objek dengan menggunakan teknik pengesan gumpalan. Antara muka pengguna grafik direka untuk menunjukkan keputusan dan menjadikan sistem lebih mesra pengguna dan mudah dipantau. Keputusan eksperimen menunjukkan bahawa subsistem pengesanan skru dapat mengesan skru di bawah keadaan pencahayaan yang berlainan dengan mAP 93.8% dan ketepatan penyetempatan dengan ralat maksimum 1.26% dalam paksi-x dan 2.84% dalam paksi-y. Juga, subsistem pengesan blob dapat melokalkan lubang skru dengan ralat maksimum 0.26% dalam paksi-x dan 0.58% dalam paksi-y. Selain itu, kedua-dua subsistem dapat bekerja dalam kekangan masa sebenar dengan kelajuan 7-10 FPS. Adalah dijangkakan bahawa perisian penglihatan komputer akan menjadikan proses perhimpunan lebih berkesan dan meningkatkan produktiviti, juga meningkatkan aliran proses.

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ANN	-	Artificial neural network
GUI	-	Graphical user interface
YOLO	-	You only look at once
2D	-	Two dimensions
3D	-	Three dimensions
LIRA	-	Limited receptive area
AI	-	Artificial intelligence
CAD	-	Computer-aided design
THT	-	Tracking hough transform
MSER	-	Maximally stable extremal regions
ROI	-	Region of interest
SV	-	Selective search
SVM	-	Support vector machine
RPN	-	Region proposal network
GPU	-	Graphics processing unit
CPU	-	Central processing unit
FPS	-	Frame per second
CNN	-	Convolution neural network
AP	-	Average precision
mAP	-	Mean average precision
IoU	-	Intersection over union

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CHAPTER 1

INTRODUCTION

1.1 Background Study

A screw is a mechanical part that uses to join two components together. This process of joining two components by inserting the screw into a pre-threaded hole is called ‘screwing’. Screws are used in assembling products as they make the disassembly and maintenance of these products easier [1].

Nowadays, most of the screw assembly processes are implemented manually [2] or by repetitive automation with complicated fixtures [3]. The manual screwing process achieves adaptability in which the screws and the objects to be assembled do not need to be in a structured environment. Furthermore, it consumes much time and needs a large workforce to achieve it that may slow down the process.

Alternatively, some industries use repetitive automated assembly systems. These systems are faster and more reliable which makes them more productive with less workforce. However, these systems require the screws and the objects to be localized precisely before implementing the screwing process, so feeders to feed the screws to screwing tools are used for this purpose. These feeders occupy a large space in the working environment and they need to be changed if the object is changed which makes the automated systems time-consuming to redesign the assembly line and more expensive.

This encourages a need for a more adaptable and flexible automated assembly system. Such a system requires high accuracy in identifying and localizing the screws and the screw holes on the object. Also, the system should be designed by considering its performance in terms of speed, cost, and adaptivity to variation in lighting conditions.

1.2 Problem Statement

Currently, most of the screwing assembly operations are performed either manually or by repetitive automated systems. The manual screwing process consumes a lot of time and not reliable. Whereas, the repetitive automated system is not flexible, not adaptable to change in the working environment and it has a lack of intelligence as it requires additional components such as feeders.

The screwing assembly process has limitations that make it difficult to be automated. The difficulties are due to the requirements of adaptability, flexibility, and intelligence to implement the screwing operation (a human worker has the intelligence to do the screwing assembly process). This encourages the necessity for an automated system that has enough intelligence and adaptability to achieve the screwing assembly process.

Depending on this information, the need for improving a more intelligent screwing automation system is a necessity to enhance system performance. The system must satisfy real-time constraints and can locate the screws and holes precisely in a random workspace. Also, the system should be able to compensate for the lighting condition effect in detection objects or holes.

1.3 Objectives

The objectives of the research are:

(a) To design a software environment for a computer vision application using the YOLO detection algorithm for detection screws in different lighting conditions and in real-time constraints.

(b) To design a software environment for detection holes, and their locations in the object using blob detector in real-time constraints and various lighting conditions.

(c) To design a graphical user interface (GUI) to make the system more user-friendly.

1.4 Scope of the Project

(a) The fasteners (screws) type are: Frearson head screw (+), Slotted head screw (-), and Internal hexagonal (Allen) head screw.

(b) Each type of screw will be in a tray, and each tray will have 4 screws.

(c) The precision in determining the hole position is 1mm [4].

(d) The PC will be used to run the system.

(e) A webcam camera C922 Logitech is used for screw detection, and C310 Logitech is used for hole detection.

(f) The Python language will be used as a software program language.

1.5 Organization of this Report

The rest of this thesis is organized as follows, Chapter 2 reviews related previous assembly processes in general and screwing assembly process particularly. In addition to that, object detection systems and computer vision detection algorithms are reviewed. Chapter 3 discuss the design of the screwing automation system and methodology used to detect the screws and holes. While chapter 4 highlights the results found for the screw detection with the YOLO v3 algorithm and hole detection with a blob detector. Chapter 5 discuss the results found and presents a conclusion for our results obtained.

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