AUTOMATED TOOL PATH PLANNING FOR INDUSTRIAL ROBOT IN MATERIAL HANDLING IN WAREHOUSE AUTOMATION

by

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DEDICATION

I would like to dedicate my thesis to my family members and friends for the constant support.

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TABLE OF CONTENTS

LIST OF TABLES

Table **Page**

LIST OF FIGURES

ABSTRACT

The warehouses today continue to rely on human workers because of the failure to implement the autonomous order picking system to meet the demands in terms of speed, safety and accuracy. In this research study, we aim to present an automated system specially designed to properly pick and place different objects in warehouses. The designed robot has the capability to detect an object from a shelf and assess the objects. Once the robot estimates the pose, the robot utilizes the gripper to successfully pick the object and place it at the desired location. The research study further discusses in detail about the commercial products such as ABB robots, Robotiq grippers and Cognex vision system. The main objective of this study is to integrate the commercially available components to ease the object handling in warehouses for the end customers. In this study, we integrated commercially available Robotiq-2 finger gripper, Cognex 2D vision system and ABB IRB 120 robot to pick and place randomly placed objects in the warehouse shelves. The proposed model includes the hardware setup, configuration, calibration steps and software setup of this system. The model results in successful object recognition followed by picking and placing of the randomly placed object in a warehouse shelf. Multiple iterations were carried out where different light exposures were tested.

1. INTRODUCTION

1.1 Background

Warehouse automation has seen a significant development in the last century, from the start of the pallet jack in 1918 to the invasion of Kiva systems in 2003. To remove the unorganized handling of material, an intelligent and accurate palletizing is required. Kiva systems primarily aim at reducing the time taken to complete the process of picking the product, packing all the up to delivery. The system consists of hundreds of networked autonomous vehicles and control software which facilitates storing, moving and sorting inventory to be a dynamic process. These inventory pods are placed in the center of the warehouse and the operators are positioned at the respective inventory stations which are situated around the perimeter. Once an order is received, the Kiva inventory pod brings the appropriate shelf to the nearest operator. Then the operator picks out the suitable item and places it in the carton for packaging. This system has no doubt made the process of picking and restocking quicker but heavily relies on humans to complete the final process (Raffaello, 2008).

Till today speed and reliability are the greatest limiting factors in handling single objects that are presented with appreciable packing density. The commercial cost of robust and supple object picking and restocking in warehouses is high. In 2013, during the Christmas season, Amazon alone sold 426 items per second which were hand-picked and boxed (Kuan-Ting Yu, 2015). In order to minimize this problem, in 2015 Amazon Robotics organized the first Amazon Picking Challenge (APC) for two days in Seattle, WA, USA. The goal of this challenge is to integrate the state-of-the-art in object perception, motion planning, grasp planning and task planning with long lasting goal of warehouse automation. This competition sets a benchmark for artificial intelligence and robot learning. The challenge goal was to design an autonomous robot for self-picking and restocking, which is currently done by human workers (Nikolaus Corell, 2016). The 2015 APC modelled a basic version of general picking and restocking problem. It has a work space of 2x2 meters in front of shelving unit occupied with objects. The given time was 20 minutes to autonomously pick as many items as possible from the list of anticipated objects. The items are ranged in size, shape and material, and their arrangement was sufficiently limited for the first challenge. In response to this initiative, engineers believe industrial robots to be the most promising addition to increase productivity. However, these machines are unable to function in a dynamic environment. To overcome this, the researchers have attempted to equip these machines with artificial intelligence which helps them to work in a dynamic environment. The engineering challenge of this dissertation is to automate self-picking and restocking objects in warehouse automation.

1.2 Industrial Robots

A robot is an automated machine which is responds to a set of commands. An industrial robot is a product of controlled multipurpose programmable manipulators with three or more axes (Frank, 2010). The main purpose for the invention of the industrial robots was to minimize the cost of production. This revolutionized the manufacturing industry as these robots increased productivity and quality when compared to human workers. George Devol owns the first patent on a programmed article transfer for industrial robot, which dates back to 1954. He teamed up with Joseph Engelberger and founded the first robot company named Unimation. Soon after, in 1961, the General

Motors plant was the first to install an industrial robot for getting parts from a die-casting machine. Through the following years, Unimates were sold for workpiece handling and spot-welding of car bodies. The robots proved to be reliable and ensured uniform quality which led to an increase in production. Soon many other companies began developing and manufacturing industrial robots, this sowed the seed to an industry thriving on innovation. It was quite a few years before companies started making profits (Martin, 2008).

ASEA (presently ABB) came up with the first microcomputer-controlled industrial robot in the year 1973, which featured continuous path motion for arc-welding or machining application. The life span of this robot has been proven to last over 20 years. In 1978, Hiroshi Makino from Japan, invented the selective compliance assembly robot arm (SCARA). This design was efficient for fast and compliant arm motions which was a perfect fit for small part assembly (Martin, 2008).

In 70's and 80's industrial robot development technology rapidly increased but was underdeveloped in terms of the technology at the time. Between 2005 and 2008, installations of industrial robots grew rapidly, the average sales were about 115,000 units. These sales took a hit in 2009 due to global economic and financial crisis. Between 2011 and 2016, the demand rose to about 212,000 units per year, which was an 84% increase compared to the annual average supply between 2005 and 2008. There was a significant increase in sales by 16% in 2016, which indicates a tremendous rise in the demand for industrial robots all over the world. Through 2020, an increase of 15% on average per year has been predicted by the International Federation of Robotics (IFR) (IFR, 2017).

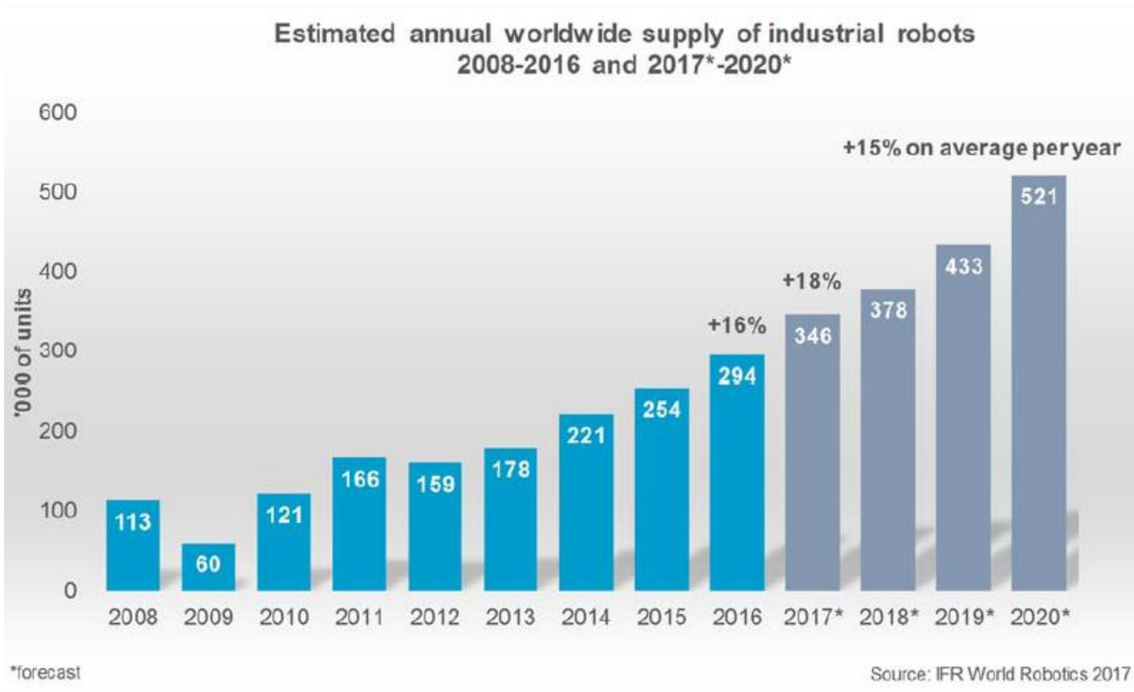

Figure1: Estimated Annual Worldwide Supply of Industrial Robots (ifr.org) (IFR, 2017)

1.2.1 Types of Industrial Robots

An industrial robot serves as a robot arm to facilitate manufacturing applications in a factory setting. Classification of industrial robots is based on type of movement (Degree of Freedom). These are shown in the following figure 2.

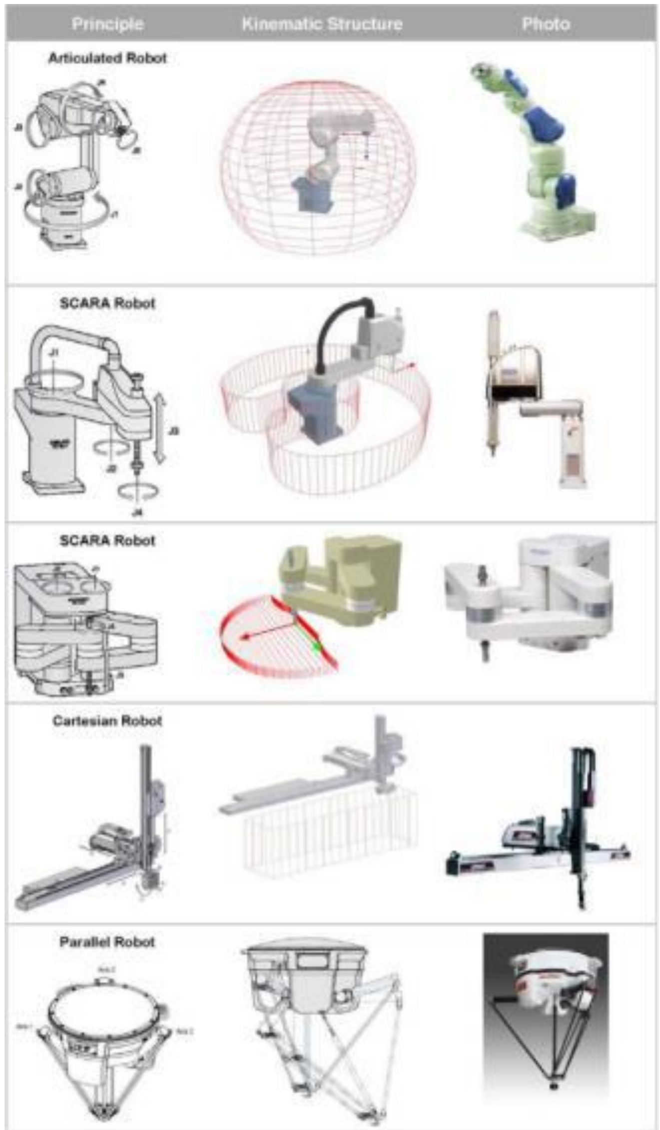

Figure 2: Types of Industrial Robots. (ifr.org)

Cartesian robots are capable of work in 3 translations using linear slides while SCARA robots can rotate around a vertical axis in addition to 3 translations. These robots perform simple tasks such as pick and place or stamping operations. 6-axis robots are articulated robots that consist of 6 DOF which can perform complex tasks like welding, grinding, painting, picking and restocking, heavy material handling and packaging.

To make industrial robots more efficient, it is essential for manufacturers to integrate them with end effectors and suitable vision sensors which results in high efficiency, high accuracy and high quality.

1.2.2 ABB IRB 120 industrial robot:

This industrial robot is the newest generation of 6-axis industrial robot weighs 25 kg, it can handle a 3kg payload with 580mm reach. This robot is designed particularly for flexible robot-based automation in manufacturing industries. IRB 120 is known for its fast pick and place applications which combine with extreme flexibility along with 10-micron repeatability. This robot delivers a significant increase in cycle time of up to 25% due to maximum speeds of axis 4,5 and 6. These robots come with two types of controllers: IRC5 Compact or IRC5 single cabinet controller. In this study, this robot is armed with IRC5 compact controller with teach pendant and robot control software called Robotware as shown in figure 3. This software manages the entire robot system in terms of motion control, integration, development, communication and implementation of application programs. The programs are written in Rapid language to control the robot by using teach pendant. A maximum of 3-kg weighing end effector including payload can be mounted on the robot's mounting flange on axis 6. In this research, we have integrated Robotiq two-finger gripper with this robot which will be discussed in depth in the following section.

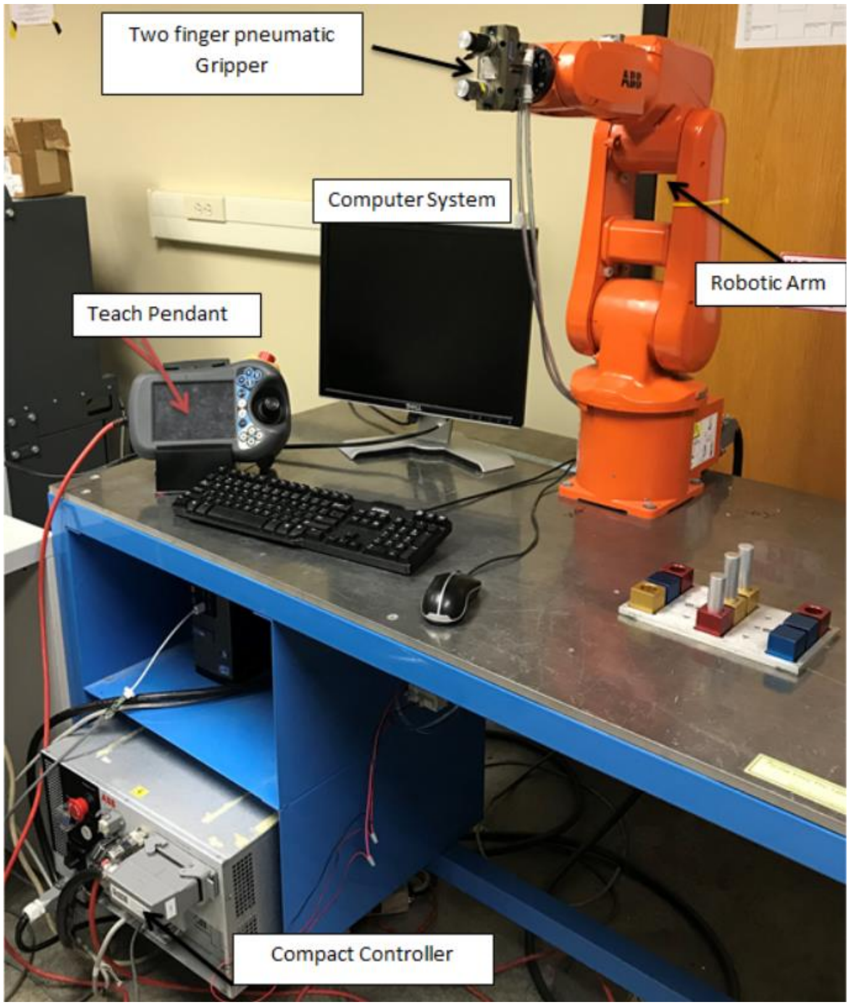

Figure 3: ABB IRB 120 Robot with compact controller

1.3 End Effectors

Humans are constantly working towards acquiring specific skills in order to make work easier and more efficient. With the increased use of industrial robots, jobs usually done by human hands have been replaced by machines. This led to the increased need for prehension tools, also known as “grippers”.

What sets apart industrial robots apart from conventional dynamic machines is 1st the degrees of freedom and programmability. 2nd is the ability to attach any possible end effecter on the end of the kinematic chain. This variability opens up unlimited possibilities for tasks solutions. Grippers enable the industrial robots to ensure temporary contact with the object to be grasped. They carry and mate the object with the desired place by ensuring the position and orientation. Grasping is achieved by the force generated between the fingers. The term "gripper" is also used in situations where nothing is particularly grasped, for example, vacuum suction grippers, magnetic grippers, universal grippers and so on. End effectors also include multi finger grippers, machine tooling, tool changers, collision sensors, rotary joints, press tooling, compliance devices, paint guns, deburring tools, welding torches, pneumatic devices, and silicon wafer handlers, angular and parallel impactive grippers, ingressive grippers, and the list goes on.

The following are the types of robotic grippers:

1. Impactive Gripper: These grippers have direct impact on the object by using jaws or claws to grasp the object. In this study, we have used the Robotiq 2-finger adaptive gripper which is discussed later.
2. Ingressive Gripper: The term ingressive refers to a gripping method where the gripper will penetrate the surface of the object to a certain depth. These methods are used mainly in soft materials like fabric, textile and fibrous components.
3. Astrictive Gripper: Here picking is done by the forces in the form of vacuum suction, magnetic or electrostatic charge displacement.
4. Contigutive Gripper: Contigutive refers to touch. In order to grasp an object, the gripper surface must have a direct contact with the object for adhesion to take place (such as glue, surface tension or freezing)

1.3.1 Robotiq 2-Finger Adaptive Gripper

This is an impactive gripper manufactured by Robotiq. The company has two types of Robotiq 2-finger adaptive grippers, namely the 2-finger 85 adaptive gripper and the 2-finger 140 adaptive gripper. The first type has the finger opening dimensions of 85mm and the second type has the finger opening dimensions of 140mm. In these two grippers, the gripper chassis remains the same, while the finger kits are selected depending on the required finger opening. The gripper is selected based on the size and shape of the object. In this research, the Robotiq 2-finger 85 adaptive gripper was used. The gripper and its parts are shown in figure 4. The gripper's unique quality to quickly pick, place and handle a variety of objects make it an effective end-of-arm tool. This gripper consists of a single actuator for the opening and closing movement of the fingers. These fingers can adjust to the shape of the object with either a parallel or encompassing grip. In addition to this, hollow objects are picked by entering the hollow opening and applying pressure on the outer ends of the fingers. These are shown in figure 5.

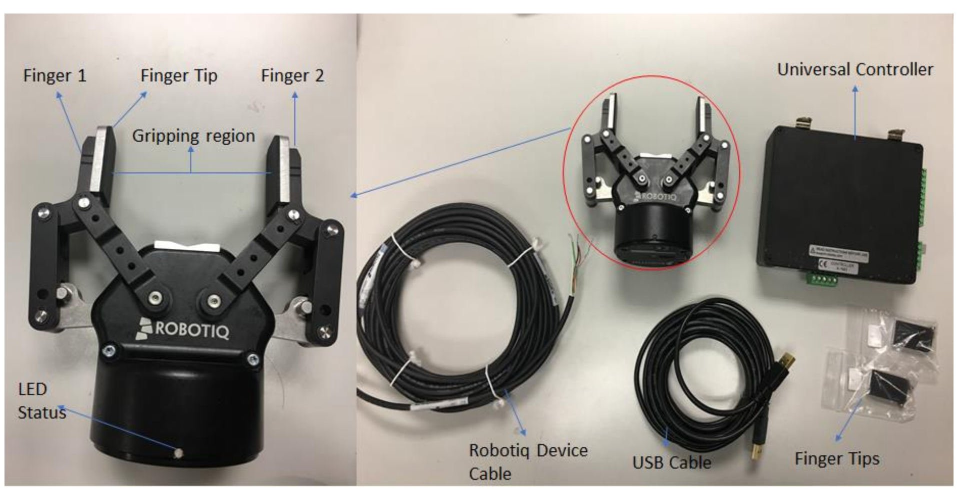

Figure 4: Robotiq two finger gripper and its components

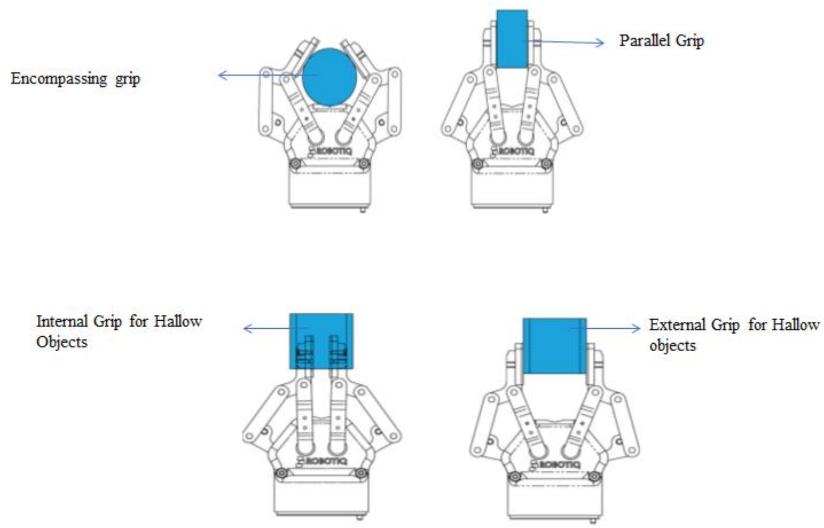

Figure 5: Encompassing, Parallel, Internal and External grips (Cognex, 2018)

The gripper has an equilibrium line which helps the gripper discriminate between a parallel and encompassing grip. When an object is above the equilibrium line, it is picked up by the fingertips using parallel grip in a parallel motion. On the other hand, when an object is below the equilibrium line and close enough to the inside of the palm of the gripper, it is picked using the encompassing grip by closing the fingers around the object. This is shown in figure 5. The integration and configuration of this gripper with ABB IRB 120 robot is explained in detail in Chapter 4.

1.4 Vision System

When industrial robots carry out the process of picking and placing, it is essential that they are able to recognize and manipulate in an unorganized environment. A robotic arm has the inability to see the changes in its workspace (Xinjian, 2014). One of the important concerns with in industrial robot applications is to measure the positioning, orientation and dimensions of the three-dimensional (3D) object. The usual method of finding a 3D object involves the robot programmer manually jogging the robot arm with the end effector by using the robot's teach pendant, record the position by visually validating the accuracy of the jogged position and applying it to pick the actual object. This process is very time consuming as the programmer must visually confirm the accuracy of each jogged position. However, the robot still lacks the ability to detect variations of the object and make the necessary changes. This has proved that the industrial robot applications are in a need for its own visual and sensing systems in order to cater to the high demands for automation of robotic applications (Cheng, 2017).

Various technologies have developed different kinds of vision systems, among them machine vision system can get accurate object dimensions for industrial robots. It does so by using vision cameras, image processing, calibration and data communication (Nguyen, 2000) (Kress, 2004).

Machine vision systems have three broad categories namely: one-dimensional (1D), two-dimensional (2D) and three-dimensional (3D).

1D Vision Systems

1D vision systems are different from other dimensional views in analyzing a digital signal one line at a time rather than analyzing a whole picture. It assesses one line at a time and assesses the variance between the recent one to the previous ten lines. In material manufacturing industry this technique is used in detecting the defects in a continuous process.

2D Vision System

In 2D vision systems uses a single 2D image camera, the image obtained from the camera is processed in two dimensions in a plane. The obtained coordinates are in X and Y translations with rotation around Z.

3D Vision System

3D vision systems typically use either multiple cameras or various laser sensors to identify the size, shape and depth of the object (Hazrat, 2018).

1.4.1 Cognex Vision System

Dr. Robert J. Shillman founded the Cognex Corporation in the year 1981. The first vision system developed was called Dataman, produced in 1982. Dataman has the ability to read, verify and ensure the quality of alphabets, digits and symbols that are marked on objects and its parts. It's the world's first industrial optical character recognition (OCR) system. The vision system they develop today have come a long way since the Dataman. They focus more on functionality and hands-on experience which helps them solve most challenging vision applications in the industry.

Cognex vision system product line has vision sensors, 2D vision systems and 3D laser profiles which are used for different tasks in the industry. Cognex In-Sight 2D vision systems are outstanding when it comes to tasks like inspecting, identifying and guiding parts. These industrial-grade vision systems are capable of combining cutting-edge vision tools with high-speed image capture and processing. In 2D vision systems there are various s models namely In-Sight 8000 series, In-Sight 7000 series and In-Sight 5705 series. In this study, we have used In-Sight 7000 series vision system as it promises easy integration, high speed and accurate inspections. The compact product design of this vision system is apt to fit into cramped production lines. This vision system comes with prominent vision tools which include PatMax RedLine, SurfaceFX, OCRMax and color ID tools. This series is compatible with different lenses and lights enabling flexibility to customize according to the customer needs. The components of the vision system include lens, lighting and In-Sight Explorer software which are explained in the following section Cognex, 2018).

1.4.1.1 Lens

There are two available lenses for the Cognex 7000 vision system namely, M12 and C-Mount lens. The M12 lens has the features of autofocus and auto lighting while the C-Mount lens gives flexibility to the user to select the exact focal length which depends on the field of view and working distance for vision application. When using a C-Mount lens, a lens cover is used to protect the lens.

1.4.1.2 Focal Length

It is the distance between the center of the lens to the image sensor which is expressed in mm.

1.4.1.3 Field of View (FOV)

This is the maximum total search area where a sensor can inspect.

1.4.1.4 Working Distance

It is the distance between the front of the lens and the object.

1.4.1.5 Lighting

Lighting is an essential component for machine vision in terms of creating a contrast between light to dark transition. Depending on the applications, different lights are selected namely, diffuse light, dome light, ring lights, backlight, line light and so on.

1.4.1.6 Software (In-Sight Explorer)

All Cognex 2D vision systems are compatible with the In-Sight Explorer software which is easy to maneuver and integrate. This software has easy builder view and a spreadsheet view. The easy builder view caters to both novice and experienced operators by providing a step-by-step process to easily configure the vision applications on the vision sensors and vision systems. The spreadsheet view gives a more administrative control over the vision tools. This access gives the operator flexibility to make changes in the programming to solve any problems in the challenging vision applications. The software also establishes the communication between the vision system, industrial robots and computers through standard industrial protocols like Ethernet/IP, PROFINET, Modbus/TCP, Socket messaging and serial communications (Cognex, 2018). The terminologies used in this software are explained below.

1.4.1.7 Vision Program

“Job” is the vision program from Cognex In-Sight camera which comes in the form of a spreadsheet with 400 lines from 0 to 399 and columns from A to Z. This program can be created and edited on a compatible computer by using In-Sight software.

1.4.1.8 Score

The accuracy of the object recognition is expressed in terms of a “score,” which is in the form of percentage between 0 to 100percent.

1.4.1.9 Transformation

The combination of translation and rotation of a 3D object is described as a transformation, which is used to express the geometrical relation between two 3D planes. This transformation is expressed in the form of homogeneous matrix or in a vector form.

1.4.1.10 Camera Calibration

The image captured by the camera in the vision system breaks down the image into smaller squares called pixels. Camera calibration is a process of converting the pixel data into real world data in terms of mm, cm and inch.

1.5 Communication

It is very essential to have a strong connection to the factory network between the robots, grippers, vision systems and computers to make decisions and share data to carry out the suitable task. Industries use various communication types which include DeviceNet, Ethernet/IP, TCP/IP, BUS, Serial port communication and so on.

1.5.1 DeviceNet

DeviceNet was first developed by Allen Bradley based on the controller area network (CAN) developed by Bosch. This network was designed to establish a connection between lower level sensors and actuators with high level controllers. In order to increase the amount of information being communicated per message, the CAN message frame with multi-byte format is used. The Open DeviceNet Vendor Association (ODVA) issues the specifications and deal with the technical assistance for industries wanting to implement DeviceNet. DeviceNet supports data rates of 125, 250 and 500 Kbaud, which are selected according to the data travel distance (Reynders, 2004).

1.5.2 Ethernet/IP

It uses Ethernet frame to establish a communication between various autonomous devices like robots, PCLs, vision systems, grippers and CNC machines. It is managed by ODVA (Reynders, 2004).

1.5.3 TCP/IP

TCP stands for transmission control protocol and IP stands for industrial protocol. TCP is responsible for the connection between the client and the server. It's job is to ensure proper transmission of the packets which consist of Modbus frames with commands to read/write in the memory of the device (Reynders, 2004).

1.5.4 Socket Communication

The socket communicates messages between two computerized processes connected to a different network by using one communication port and one IP address. The communication port is defined by a number between 0 and 1023 which are encoded on 16 bits. The IP address is typically linked to an IP network to identify a computer. The IP address is composed of an integer of 32 bits which is written as a decimal number in a four bytes format separated by a point. The numbers used are between 0 and 255. For example, “192.168.0.143.” A socket is used in two modes, connected and non-connected mode which uses TCP and UDP transport protocol respectively.

1.6. Transformation and Robot Reference Frames

For the identification and measurements of objects, a 2D vision system utilizes a 2D camera. To ensure measurement accuracy and usefulness in a robot application, the measuring functions are first established by the programmer in the vision system and the robot. This is then integrated into the robot application program.

The robot and the objects position measurements in a work cell are established mathematically and manually using Cartesian coordinate reference frames and its transformations which includes robot base frame, tool frame and work object frame.

1.6.1 Frame Transformation Matrix

The representation of 4x4 transformation matrix ${}^{A}T_{B}$ for the position measurement of Cartesian coordinate frame B Relative to Cartesian coordinate frame A is shown in matrix (1).

$${}^{A}T_{B}=\begin{bmatrix} n_x & o_x & a_x & P_x \\ n_y & o_y & a_y & P_y \\ n_z & o_z & a_z & P_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (1)$$

In equation (1), the orientation and location of frame B related to frame A is represented by the elements in the first three columns and the fourth column respectively. The Transformation of frame A relative to frame B is represented as ${}^{B}T_{A.}$ The inverse of ${}^{B}T_{A}$ is denoted as $({}^{B}T_{A})^{-1}$. By using available frame transformation matrices, the frame transformation equations can be formulated which are used to solve one unknown frame transformation.

1.6.2 Robot World Frame and Default TCP Frame

Every robot manufacturer establishes a fixed world frame for its industrial robots. Generally, the frame starts along the first robot joint and the frame orientation is defined based on its z-axis which is usually upward from the robot. The x-axis is established along the front side of the robot while the y-axis follows the right hand rule. The default end-point of the robot arm is denoted as the tool-center-point (TCP) which originates at the center of the robot wrist faceplate.

1.7 RelTool function in ABB Rapid Programming

RelTool stands for Relative Tool, who’s function is to add up the displacement and rotation from a robot position in an active tool coordinate system. The example of this is as follows:

Example: MoveL RelTool (Target_P0, 10, 15, 20\Rz: - 30), v100, fine, tool0;

After giving the above command the robot moves 10mm in X direction, 15mm in Y direction and 20mm in Z direction from the position Target_P0.

2. LITERATURE REVIEW

Ware house automation has attached additional attention to the research community. In the year 2012, Amazon deployed Kiva systems in to Amazon's warehouse, which has been one of its biggest achievements. Robots which can autonomously grasp items from shelf is still a challenging and active research topic (Zhang, 2016). Previously, warehouse automation mainly focuses on autonomous transport, like delivering packages by using Automated guided vehicles (AGV) (Barbera, 2003). The research done by Andrea and Wurman talks about the new approach used by the Kiva pods for order fulfillment. The Kiva Mobile Fulfillment System (Kiva MFS) has proven to improve productivity, speed, accuracy and flexibility. This system has automated the warehouse, in that, the products are transported to the operator who is stationed at a desk. Various items are stored in assigned inventory pods which are picked up and moved to the nearest operators depending on the orders. Till the year 2008, 500 robot systems were installed for an office supply company in the United States (Wurman, 2008).

Beyond that, Cosma et.al, describes an autonomous robot for indoor light logistics with partial manipulating skill (Cosma, 2004). This robot is designed for transporting packages to the destination in the pharmaceutical warehouses, which can pick up the packages from the ground. This robot's manipulation has limited capability, so it is not suitable for the e-commerce application, which requires grasping several objects from shelves and tables. High dimensional motion planning problems are usually developed for manipulating in the restricted spaces such as boxes and shelves (Cosma, 2004). To mitigate the difficulty Pan et.al. put-forth a sample-based motion planning algorithm that has the capability to accomplish local spline refinement to calculate smooth and collision free trajectories (Pan, 2012).

In order to completely automate the warehouse, in the year 2015, Amazon introduced the Amazon Picking Challenge (APC) which targeted at replacing the job of the operator with an automated robot. The main goal of this challenge is to initiate research efforts at addressing appropriate and potentially transformative technology of shelf-picking and self-restocking. The first APC simulated a simplified version of the general picking and restocking problem. The work space provided was of 2x2 meters in front of a shelving unit with a few objects. The challenge was to autonomously pick as many objects as possible in 20 minutes. The objects had different dimensions and their arrangement was fairly simple for the first attempt of this kind. Each team was given a list of 25 items before the competition. The exact 12 items that had to be retrieved from a shelf were not revealed until 2 minutes prior to the competition. The robot had to discover the position and configuration on real run time (Correll, 2016).

The team RBO, utilized single arm Barret base mobile platform with a suction gripper with, 3D imaging on Arm, laser on base, pressure and force torque sensors. To increase the perception the team used multiple features for detection and filtering 3D bounding box for grasp selection without any motion planning. Using suction gripper alone limits the chances of grasping the objects. The team MIT operated on single arm ABB 1600 platform with Suction cups, two-finger gripper and spatula with both 2D and 3D imaging on Head and Arm sensors. The team used 3D RGB-D object matching without motion planning. The team Grizzly used dual arm Baxter and mobile base data speed platform with suction cups and two finger grippers and 2D imaging at end effector, 3D imaging for head and laser for base sensors. The team utilized 3D bounding box segmentation and 2D feature based localization for perception with custom motion planning algorithm. The team NUS smart Hand operated on single arm Kinova platform with two-finger stripper and 3D imaging on robot sensors. The team utilized foreground subtraction and color histogram classification perception and predefined path to reach online Cartesian planning inside the Movelt motion path planning method. The team C^2M used a single arm (MELFA) on custom gantry with a custom gripper, 3D imaging on End-effector and force sensor on arm. The team used RGB-D data to identify object and carryout prehension. There was no motion planning used. The team Rutgers U with dual arm Yaskawa Moto man platform with a vacuum gripper and Robotiq 3-finger hand gripper and 3D imaging on Arm sensors. The team used 3D object pose estimate perception with Grasp It motion planning. Team K used Baxter dual arm platform equipped with a suction cup gripper, 3D imaging sensor and for perception Bayesian Occupancy Filtering (BoF) was used. Many other teams participated in APC 2015. Every team had its own robot platform, end-effector, perception and motion planning methods which are shown in Table 1 (Correll, 2016).

Table 1: Strategies taken in selected teams in APC 2015 (Correll, 2016).

Team	**Platform**	**Gripper**	**Sensor**	**Perception**	**Motion Planning**
RBO	Single arm (Barrrett) + mobile base (XR4000)	Suction	3D imaging on Arm Laser on base,Pressure sensor, Force-torque sensor.	Multiple features (color, edge, height) for detection and filtering 3D bounding box for grasp selection.	No

Table.1 Continued.

MIT	Single arm (ABB 1600ID)	Suction + gripper + spatula	Both 2D and 3D imaging on Head and Arm	3D RGB-D object matching	No
Grizzly	Dual arm (Baxter + mobile base (Dataspeed)	Suction and gripper	2D imaging at End-effector,3D imaging for head, and laser for base	3D bounding box segmentation and 2D feature based localization.	Custom motion planning algorithm
NUS Smart Hand	Single arm (Kinova)	Two-finger gripper	3D imaging on Robot	Foreground subtraction and color histogram classification	Predefined path to reach and online cartesian planning inside the bin using MoveIt.
Z.U. N	Dual arm (Custom)	Suction	(respondent skipped response)	(respondent skipped response)	MoveIt RRt planning for reaching motion and use pre-defined motion inside bin
C^2M	Single arm (MELFA) on custom gantry	Custom gripper	3D imaging on End-effector and force sensor on arm	RGB-D to classify object and graspability	No
Rutgers U.Pracsys	Dual arm (Yaskawa Motoman)	Unigripper vacuum gripper & Roboting 3-finger hand	3D imaging on Arm	3D object pose estimation	Pre-computed PRM paths using PRACSYS software & grasps using GraspIt
Team K	Dual arm (Baxter)	Suction	3D imaging on Arm and Torso	Color and BoF for object verification	No

Table.1 Continued.

Team Nanyang	Single arm (UR5)	Suction and gripper	3D imaging on End-effector	Histogram to identify object and 2D features to determine pose	No
Team A. R	Single arm (UR-10)	Suction	3D imaging on End-effector	Filtering 3D bounding box and matching to a database	No
Georgia Tech	Single arm	SCHUNK 3 finger hand	3D imaging on Head and Torso	Histogram data to recognize and 3D perception to determine pose	Pre-defined grasp using custom software and OpenRave
Team Duke	Dual arm (Baxter)	Righthand 3 finger hand	3D imaging on End-effector	3D model to background subtraction and use / histogram data	Klamp't planner to reaching motion
KTH/CVAP	Dual arm + mobile base (PR2)	PR2 2 finger gripper with thinner extension	3D/2D imaging on head, Tilting laser on Torso and laser on base	Matched 3D perception to a stored model	Move to 6 pre-defined working pose and use MoveIt to approach and grasp object
PickNick	Single arm (kinova) on custom gantry for vertical motion	Kinova 3 finger hand	Fixed pair of 3D imaging sensors	3D bounding box-based segmentation	MoveIt! RRT for motion generation and custom grasp generator
SFIT	Multiple miniature mobile robots on gantry	Customer gripper	2D imaging and distance sensor	2D features and color	Visual servoing

Cheng and Pleasant explain how machine vision is crucial in detecting an object, common problems encountered and solutions to the issues (Cheng, 2017). The objects that are placed in front of a 2D camera for detection are 3D objects. Recognizing the object, measuring the object, and picking and placing the object in desired location has always been a challenge in the robotic industry. This study clearly explains common problems encountered in the course of recognizing and picking an object. In addition, a detailed solution is provided for every identified problem. Issues have been identified at different levels such as calculating robot reference frames and their transformations, 2D camera view positions and calibrations, vision measurements and programming needed for vision-guided robotic motions and operations. For all the above-mentioned levels and issues, a 2D vision guided FAUNC robot project results are used for solution (Cheng, 2017).

Fan. X. et.al, in their study explore a more advanced picking system, which uses 2D and 3D vision technique (Fan, 2014).2D vision technique is a known and simplistic technology used in robotic industry to recognize and pick the objects perfectly. Picking an object from a shelf that has equidistant bins is simple and fairly straight forward. However, that is not the case in the real world where things get messy. This study addresses the issues faced when an object is expected to be picked by a robot from clustered scenes. An algorithm is written and used for the purpose of identifying the object from a cluster scene using 2D vision technology. Initial measuring of the object, calculating the frames, position of the object and calibrations are made using 2D vision technique. Then the robot transfers the data obtained using 2D vision technique to 3D vision technique for further analysis (world coordinate). With the utilization of initial 2D vision technique, the analysis of object recognition is simple, and this method increases the efficiency of processing time. The algorithm used for this technique is a three-axis XYZ Cartesian robot and this algorithm helped the researchers to prove the effectiveness of the method. Further research and testing are necessary with different 2D and 3D acquisition technologies for full use of the proposed method (Fan, 2014).

Robot study and robot intelligence is constantly under research to come up with improved technology and methods. The research by Cheng. F and Denman elaborates how robotic intelligence is improving robustness, flexibility and intelligence to serve the robotic industry better (Cheng, 2005) Robot engineering started using 2D vision technology to properly identify the object placed in the bin and successfully pick the object. There are several concerns to use 2D vision technology while picking an object. This study addresses the concerns and provides solutions of using a 2D vision system on a 3D object placed on a surface. A FANUC VisLOC 2D vision camera is mounted on a robot FANUC M6i and algorithm is written to study an unknown 3D object. The results of the study are successful as the 2D vision camera identified the 3D object without inaccuracy. The algorithm is written to accurately measure the system calibration and frame conversion in both the vision and robot systems, which helped in picking the object successfully (Cheng, 2005).

Researchers Andhare. P and Rawat. S used 2D vision camera and a robot to pick up objects (Andhare, 2015). However, their research study is different as the 2D vision camera is not mounted on the robot instead placed independently on the area where object to be picked. The 2D camera placed near the object reads the x, y coordinates required to identify the position and calibrations of the object. The identified measurements are scaled in pixel coordinates by 2D vision camera and then transformed into world coordinates by robot. By using socket communication, the coordinates are sent to controller and the controller will take the action of picking an object. The respective servo motors in the controller are allowed for picking the object and placing into defined place successfully (Andhare, 2015).

Huaiyuan et. al, in their study explain how machine vision detection system is used in pharmaceutical bottle packaging, inspection and classification work (Huaiyuan, 2013). The quality details and requirements of products developed in pharmacy industry are very precise. This study proposes a new vision detection methodology for bottle recognition and package control. Using the vision detection methodology, the contact detection technology detects the object with speed, accuracy and detection results. In real time, the glass bottle detection and packaging at this speed with accuracy is significant improvement and breakthrough. Without this method, the labor cost is high, and productivity is low, which is not a Good Manufacturing Practice (GMP). The computer integrated control system and digital management of bottle recognition and packaging is supported by the vision technology embodied in the detection system. The research study proves that the machine vision detection system could greatly improve the labor costs, productivity, and quality of the product developed (Huaiyuan, 2013).

Kim et. al conducted study on vision-based bin picking systems and its application on industrial robots (Kim, 2012). In the bin picking system, the object shall be recognized first from a pile of objects obstructing each other and pose an estimation on the object and detect the grasping point for picking. Measuring an object’s pose is crucial in the bin picking system. While measuring the pose most frequently encountered issues such as lighting variation or reflection, overlapping parts, and picking from randomly piled parts. This research study uses multiple vision sensors to identify the object from bin to estimate pose accurately and successfully perform the pick and place task by a robot (Kim, 2012).

The robotic industry is constantly improving, and more advances are made each day. However, robots lack the perception characteristic that humans hold in accurately performing the job in warehouses or industries. Researchers Xia and Weng conducted research on the workpieces sorting system (Xia, 2016). Sorting is an extensive and time-consuming work, which often requires large labor support. In order to improve the robotic technology in workpiece sorting system, the researchers in this study used machine vision method to recognize the shape of the object and successfully pick and place. Canny algorithm is used to acquire the edge information of workpieces and images of the workpieces are taken. Hough transform and Freeman chain code are combined to identify shapes of workpieces. The center spatial coordinates of workpieces are calculated to help the robot identify workpieces and complete sorting job. Using the algorithm and vision detection system the time applied for sorting the workpieces have reduced drastically. The results obtained by the research method are observed to be accurate and robust (Xia, 2016).

The 2D/3D vision- based mango extraction and sorting study has been conducted by authors Chalidabhongse, Yimyam, and Sirisomboon (Chalidabhongse, 2006). The authors used 2D and 3D vision mechanism to identify, extract, and sort mangoes. The method used by the researchers is as follows. Initially, several images and silhouettes of different mangoes are obtained and uploaded in to the system. The physical properties of the image silhouettes are used to analyze by using image processing and vision techniques. The properties of mangoes such as length, width, thickness, volume, and 3D surface area. The 2D vision techniques calibrates the properties initially and then the 3d volume reconstruction is done suing computer vision techniques and volumetric carving. A coarse 3D shape is obtained and then volume and surface area are calculated. Then back-propagation neural networks are employed for mango sorting. The results of this technique are proven to be more efficient than human manual sorting mechanism. The time consumed for sorting the mangoes using 2D/3D vision mechanism has greatly reduced (Chalidabhongse, 2006).

Nicola et.al studied a 2D motion detection and estimation vision system (Nicola, 2008). A CMOS camera is used to detect the motions of a moving object in different frames. Within two subsequent frames, number of matching edges moving over less than one pixel are counted to estimate x-y motion vector components. An algorithm is implemented on the FPGA and uses a 20x20 pixel binary image. On a random sized pattern, the system computes up to 350 motion vector estimation. The FPGA is connected to the PC using USB interface. A real moving pattern with different speed components has been successfully tested with embodied algorithm in the system (Nicola, 2008).

Bellandi et. al introduced 2D vision system into drink serving robotic cell (Bellandi, 2012). This experiment is conducted to prove the flexibility and robust results using the 2D vision technique. The robot cell is integrated into the drink pouring system and the robot cell is based on two Denso robots that interoperate to simulate real human perception. Algorithms are used in this method to conduct blob analysis, template matching, and edge detection with fast motion detection. It is observed through this experiment that fast motion detection and flexible adoption is possible using 2D vision system integrated robotic cell. The challenges faced in motion detection system such as defocusing, lighting conditions, and noise have been overcome by the implemented method (Bellandi, 2012).

Harada et. al propose a method of placement plan after the object has been picked up by robot (Harada, 2014). The pick-and-place task can be challenging when the robot gripping plan and placement plan is not efficient enough for successful completion of the task. The authors of this study use the polygon models of object used and the environment used. The clusters of both the object and environment are approximated by a planar region. By utilizing the clusters, the position or orientation of an object placed on the environment surface. The researchers used convexity test, contact test, and stability test to further determine the position of the object accurately. The results of the study prove that using polygon model of environment, the position or orientation of the object can be successfully identified and placed in desired place (Harada, 2014).

The robotic industrial application is advancing everyday with new inventions. Ali et. al explore the application of vision detection technology in object sorting. The research is around Scorbot-ER 9 robot and its advancement for robust sorting (Ali, 2018).. The Scorbot robot is integrated with vision detection system to widen the capability of camera-robot system. Many difficulties have been encountered during the research such as developing proper communication, establishing sequence of operations, and integration of system components into Scorbot. The objective of integrating the camera onto robot is to determine the object specification, establish interface between Matlab and ACL, and pick and place objects based on size, color, and shape. Despite the challenges faced during the research, the digital data obtained from Matlab was processed by Visual Basic and Robocell. After image processing, the robot was successful in performing pick-and-place operation based on shape, size, and color (Ali, 2018).

Presently, the manufacturing industries are struggling with object handling system. The industry is striving towards minimizing human efforts in the picking and restocking processes. The main challenge is to integrate robots with vision system to facilitate object recognition and orientation. Previous research has tried to solve this problem using grippers and vision system specific to their study making it hard to generalize the model for random objects. To resolve this issue, we propose a system which will be developed by using commercially available systems to ease the integration and configuration for the end customers. In this study an ABB IRB 120 robot is integrated with Cognex 7000 series 2D vision system and Robotiq-2 finger gripper is used to grasp the objects placed randomly in the shelf for warehouse automation.

3. PROPOSED SOLUTION

The main objective of this research is to develop a commercial application for object handling in warehouses by using commercial products such as ABB robots,
Robotiq gripper and Cognex vision system for randomly located objects. The robot should be able to perform stocking and restocking tasks in warehouses by recognizing the objects and its location in the shelf.

During the study the following limitations are considered.

- there are some situations where the vision system can recognize the location of the object, but the robot is unable to pick it because of the structural limitations of the gripper;
- the manipulator has some difficulties to reach some positions due to its singularity issues.

The proposed solution includes the camera to image calibration steps and the proposed model which are explained in the following section.

3.1 Calibration Steps

To find the accurate transformation, the object is placed at a reference position and trigged the image from the camera to get the x, y and theta values in calibration steps, which are as follows.

Step 1: Move robot to a desired location P_0

Get sensor information S_0= (Xs_0, Ys_0, Θ_0)

Get robot information P_0= (Xp_0, Yp_0, Zp_0)

Step 2: Move robot to grasp the object

Get robot information G_0= (X_{G0}, Y_{G0}, Z_{G0})

Step 3: Move robot to a different position along X direction.

Get sensor information S_1= (Xs_1, Ys_1, Θ_0)

Get robot information P_1= (Xp_1, Yp_1, Zp_1)

Step 4: Move robot to a different location along Z direction.

Get sensor information S_2= (Xs_2, Ys_2, Θ_0)

Get robot information P_2= (Xp_2, Yp_2, Zp_2)

Step 5: Calculate the Transformation (T) Matrix

P_1-P_0 =T [S_1-S_0]

Where T = $\begin{bmatrix} T_1 & T_2 \\ T_3 & T_4 \end{bmatrix}$

$$\begin{bmatrix} X_{P1} - X_{po} \\ Z_{P1} - Z_{P0} \end{bmatrix} = [T] \begin{bmatrix} X_{S1} - X_{So} \\ Y_{S1} - Y_{S0} \end{bmatrix}$$

There will be 4 unknowns with 2 equations now,

P_2-Po=T (S_2-S_0)

$$\begin{bmatrix} X_{P2} - X_{p0} \\ Z_{P2} - Z_{P0} \end{bmatrix} = [T] \begin{bmatrix} X_{S2} - X_{So} \\ Y_{S2} - Y_{S0} \end{bmatrix}$$

By Using above 4 Transformation matrix equations the Transformation matrix (T) will be found.

3.2 For Real object picking

Step1: Move robot to position P_0 and trig the image

Get Sensor information S= (X, Y, Θ)

Step2: Find OFFSET (T*S) by using the vision data and calculated Transformation

$G - G_0 = T(S - S_0)$

Where G is Current Object location, Go is Object reference location and $T(S\text{-}S_0)$ is calculated OFFSET from reference object location.

Therefore $G = G_0 + T^*S$

Step3: Use Relative function Tool in Rapid to go to object position and grasp the object.

3.3 Proposed Model

The robot controller receives the vision information from the Cognex In-Sight software, where the type of the object is recognized and by using the in-built transformation data the location of the object is calculated. By using this data, the robot will be able to pick the object placed in a certain bin in the shelf. If the vision system did not find the object in the first bin, then the robot will automatically search for the object in the other bins. If the vision system does not find the object in the entire shelf, it indicates that the object was not found in the entire shelf and so the robot will go back to its home position. The proposed model is shown in the figure 6.

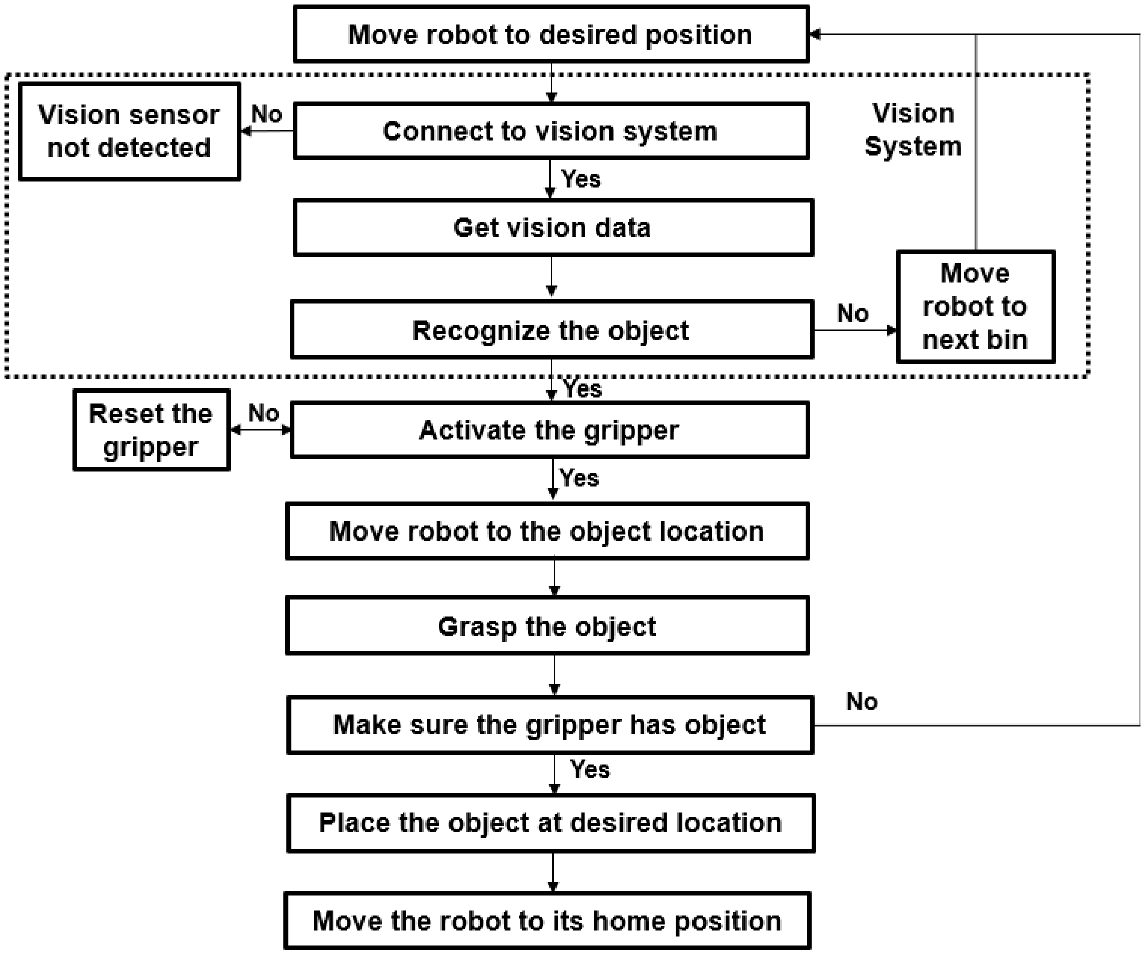

Figure 6: Flow chart of proposed model

4. HARDWARE AND SOFTWARE SETUP

In this study the main purpose is to build an automated robot for warehouse picking and restocking. The experimental system shown in figure 7 consists of an ABB IRB 120 industrial robot with an IRC5 compact controller and teach pendant, the end arm of the robot is equipped with Robotiq-2 finger adaptive gripper and a Cognex 7000 series vision system which is controlled by a master computer. In addition, a standard Kiva pod is placed in front of the robot consisting of individual bins called the shelf, which is used in Amazon warehouses.

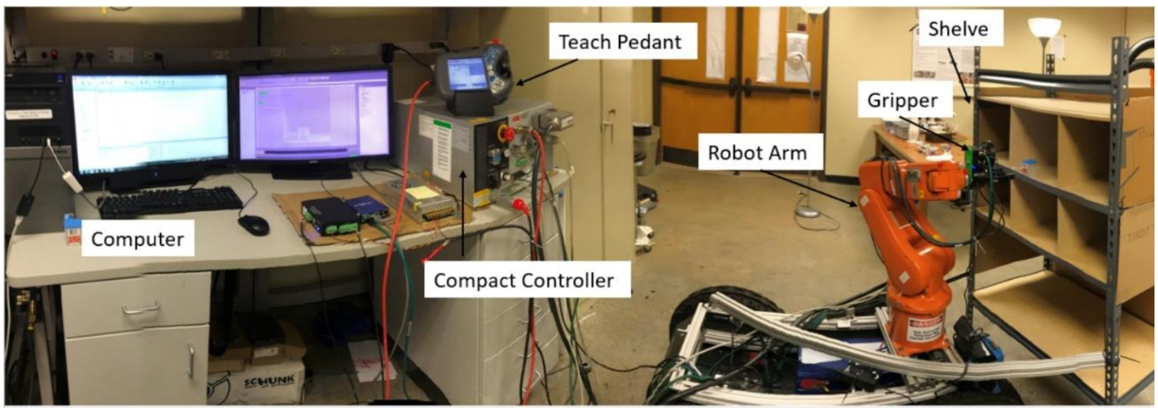

Figure 7: Autonomous object picking and restocking system

4.1 The Shelf

The shelf that is selected for this research study is a standard Kiva pod shelf. The shelf standards are replicated to represent the standards used in Amazon warehouses, which contains individual bins and its structure is rigid. The standard shelf used for the study has 12 bins in the center to reduce the reachability requirements. The shelf outlines a cuboid of 1 meter high, depth of each bin is 43 cm and the width by 87 cm.

To diverge from perfect arrangement of walls and shelves the structure of the shelf comprises of inconsistencies, asymmetries, tolerances and construction artifacts. The below arrangements are made to the shelf used for the study.

- The shelves and walls are not equally distributed. The height of each bin ranging between 19 and 22cms and width between 25 and 30 cm to allow differences in the nominal sizes of the opening of the bins
- To obstruct the ability of exposing an object by sliding, a lip is arranged on the bottom and top edges of each bin.
- To obstruct the ability of exposing an object by pulling it, a lip is arranged on the exterior edge of the lateral bins.

4.2 Integration of Robotiq-2 finger gripper with ABB IRB 120 Robot.

Modbus RTU protocol is the default gateway to communicate with Robotiq-2 finger gripper, to establish communication with ABB's robot controller the gripper's signal should be converted into DeviceNet protocol. To achieve this Robotiq Universal controller with Devicenet communication protocol is used as a gateway between the 2-finger gripper's Modbus RTU protocol and DeviceNet protocol for ABB Robots.

Robotiq-2 finger gripper for ABB IRB 120 comes with 2-finger gripper (AGC-GRP-002), universal controller (UNI-CTR-001-DNET), Device cable (COM-CBL-2067-10) and coupling for ABB IRB 120(AGC-CPL-063-002). The mechanical installation is as follows.

Coupling is mounted on the end of robot wrist and screwed, and gripper is attached on to its coupling using suitable screws provided. Device cable is linked to the pigtail and the cable is secured along the robot arm. Wiring is done according to the schematics shown in figure 8.

Initially, a connection has been established between device cable and Robotiq device connector of universal connector as shown in figure 10a. Since the Robotiq's universal controller has proper connection with the device cable, power and communication is formed between them. Utilizing the front DeviceNet connector, connection is established between universal controller and ABB's controller as shown in figure 9. Finally, the power supply is connected to universal controller.

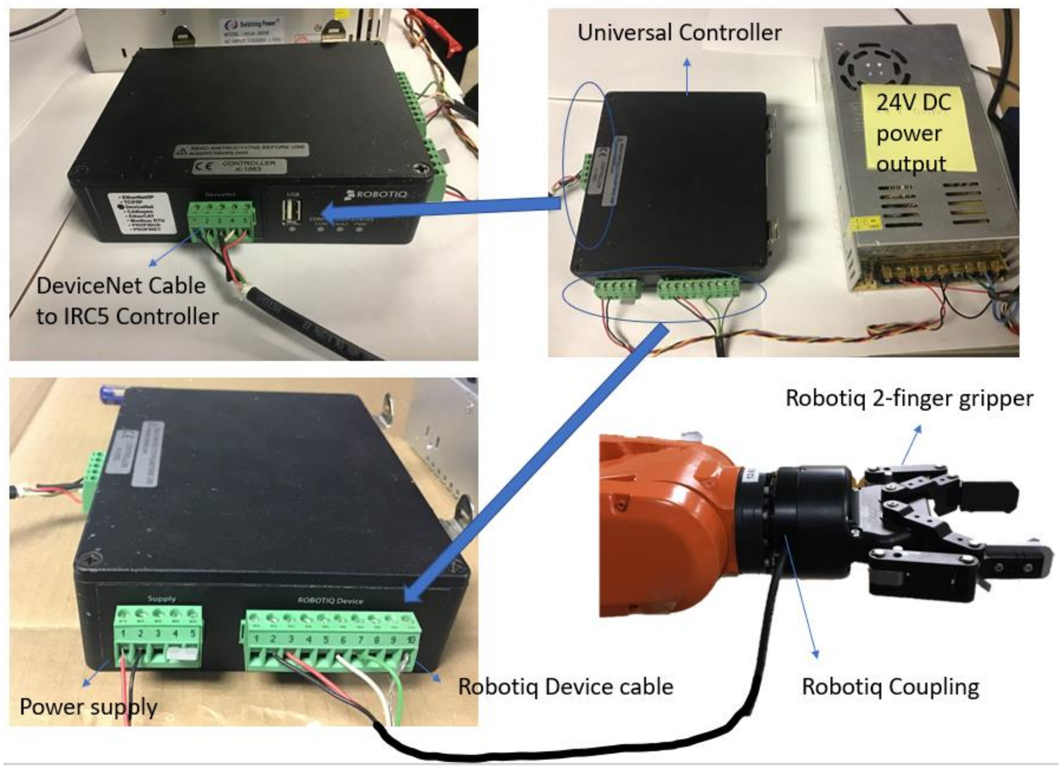

Figure 8: Wiring schematics of Robotiq-2 finger gripper.

4.2.1 Configuration of the Robot Controller.

A series of steps are taken to configure the DeviceNet network to accommodate the Robotiq gripper factory settings. For the reason of utilizing other devices there could be an issue in configuring the network baud rate. There is a possibility to change the configuration of gripper using Robotiq User Interface (RUI). Using the IRC5 teach pendant the ABB IRB 120 robot is configured with Robotiq 2 finger gripper by following below steps.

1. From the ABB menu Control panel selected
2. From control panel menu, configuration with the comment "Configures system parameters" is selected.
3. From configuration the Topics menu and I/O submenu is selected.
4. The current topic I/O and its types are displayed. From the available types, BUS is selected.
5. DeviceNet lean menu is selected, which corresponds to the card used to communicate with the gripper.
6. Since the DeviceNet lean used for the study is compatible at 500kbps baud rate, same baud rate is used in the gripper side to match the rate by using RUI.
7. After the completion of above steps, a green LED light on the universal controller starts to blink which is an indication of successful DeviceNet lean BUS configuration.
8. Next steps iterate the configuration of Robotiq's gripper unit type.
9. By using DeviceNet EDS file provided by Robotiq support website the unit type is created accordingly.
10. The connection with the gripper is activated by creating new unit in I/O menu. The unit type named Robotiq_Gripper is created according to the previously defined unit type and DeviceNet lean card to which the gripper is attached.
11. The Gripper IO is mapped using the Signal tab in IO menu.

12. Each digital input/output Boolean variable is defined with a name in signal menu and multi bits variables are defined as group input/output. The defined robot output variables are shown in Table 2 and the Input variables are shown in Table 3 respectively.

Table 2: Gripper Output Variables

Name	Type	Unit Mapping
O_Ract	Digital Output	0
O_Rmod	Group Output	1-2
O_Rgto	Digital Output	3
O_rATR	Digital Output	4
O_rGLV	Digital Output	8
O_rAAC	Digital Output	9
O_rICF	Digital Output	10
O_rICS	Digital Output	11
O_rPRA	Group Output	24-31
O_rSPA	Group Output	32-39
O_rFRA	Group Output	40-47

Table 3: Gripper Input variables

Name	Type	Unit Mapping
I_gACT	Digital Input	0
I_gMOD	Group Input	1-2
I__gGTO	Digital Input	3
I_gIMC	Group Input	4-5
I_gSTA	Group Input	6-7
I_gPRA	Group Input	24-31

4.3 Cognex 7000 Series Vision System Integration with ABB Robot

The hardware setup of the Cognex 2D vision system with ABB robot includes mechanical installation of the camera, ethernet communication, software setup and powerup. The standard vision components used in this study are Cognex In-Sight 7402 camera with C-Mount lens with a focal length of 2/6mm and a lens cover. The camera is mounted on a mounting bracket which is then fitted on the robot arm as shown in Figure 9.

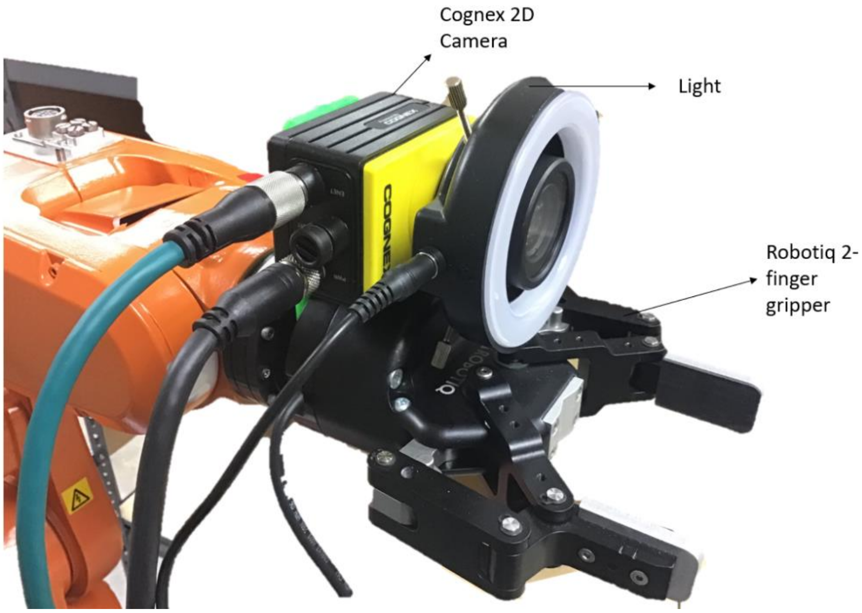

Figure 9: Cognex 7000 series camera mounted on ABB IRB120

Wiring is done according to the schematics shown in Figure.10. To establish communication between the vision system, robot controller and the computer, an ethernet switch is used. One end of the ethernet cable, which is the M 12 connector, is connected to the ENET connector and the other end is connected to the ethernet switch which is connected to the robot controller and the master computer via the RJ-45 ethernet cable. To power up the vision system, a breakout cable's one end is connected to the vision system power connector and the other end is connected to a 24V DC power supply.

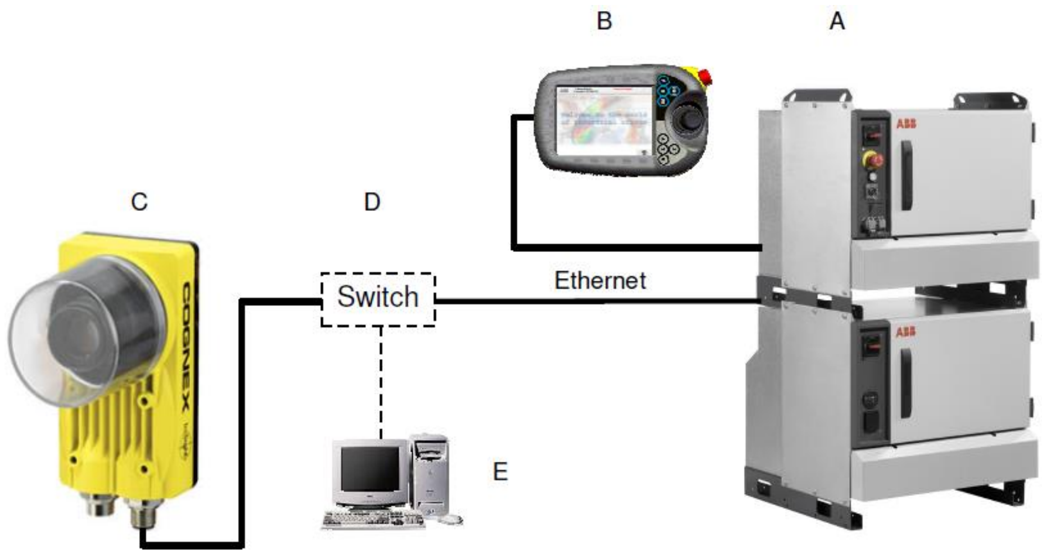

Figure 10: Wiring schematics of Cognex vision system with ABB IRC5 controller (A. ABB IRC5 Controller, B. ABB IRC5 Teach pendant, C. Cognex 2D Camera, D. Ethernet Switch, and E. Computer.)

To configure this vision system with the robot, In-Sight explorer software is installed in the master computer where Cognex 7000 series 2D vision system is connected. To establish a secure communication, the Cognex camera is assigned with an IP address of 192.168.0.144 and the robot controller is assigned an IP address of 192.168.0.140.

4.3.1 Image Processing

The Cognex 7000 Series 2d vision system comes with a default software-Insight Explorer. As mentioned earlier, it has two interfaces namely the easy builder user interface and the Insight spreadsheet interface. To create custom graphical user interface and access complex logic statements, the spreadsheet view is selected.

The camera is connected to the Insight network panel by logging on to it. Once connected, we assigned an IP address of 192.168.0.144 for further communications with the robot controller and the computer. After logging in and establishing communication with the robot and the computer, in cell A0 image properties are modified as shown in Figure 11.

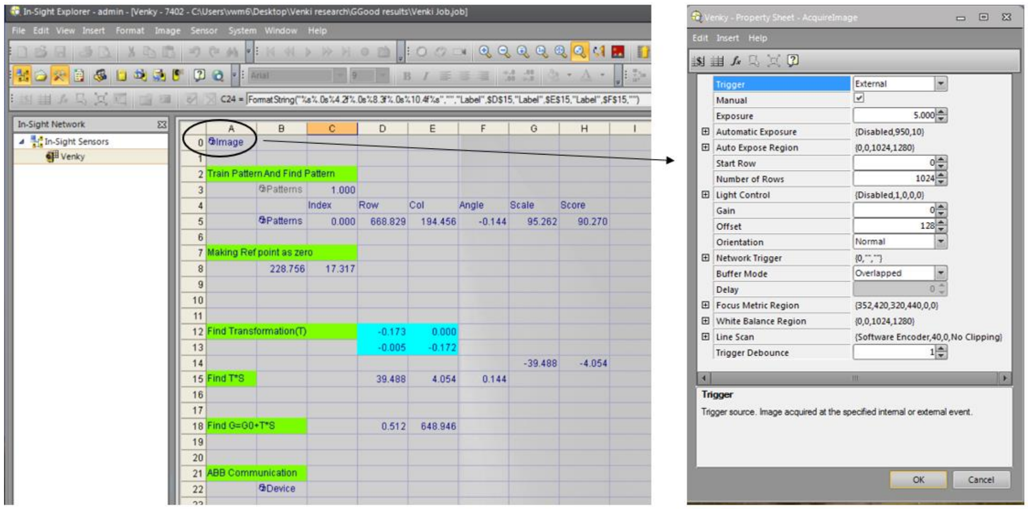

Figure 11: Image Property Sheet for Acquired Image.

The object is trained by using Pattern PatMax tool. This tool is used because of its accurate pattern match feature. In PatMax Pattern match there are two steps: 1) train pattern function where the pattern on the object is trained as a model region which is shown in Figure 12; 2) Find PatMax Patterns function shown in Figure 13 is used where the search region, number of patterns, accuracy and graphical results are trained. In the result the Find Pattern function tool will give x, y and theta values in the form of pixels. A score is given for each image in the range of 0 to 100, with 0 as the least and 100 as the highest level of accuracy of the pattern found. All this data is saved in the vision system.

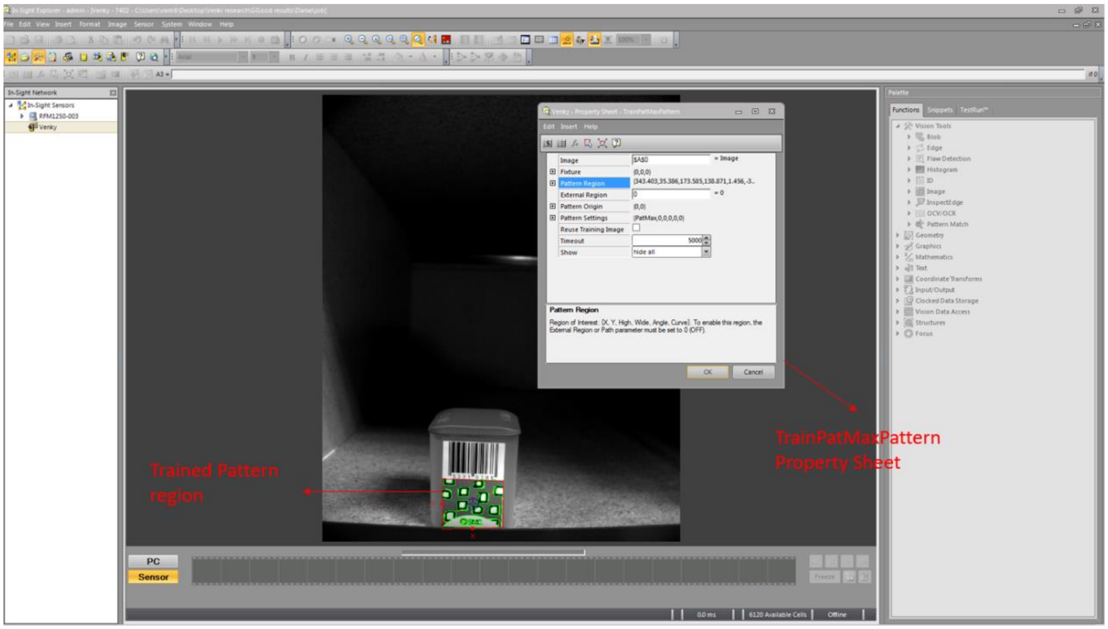

Figure 12: Property Sheet for Train PatMax Pattern.

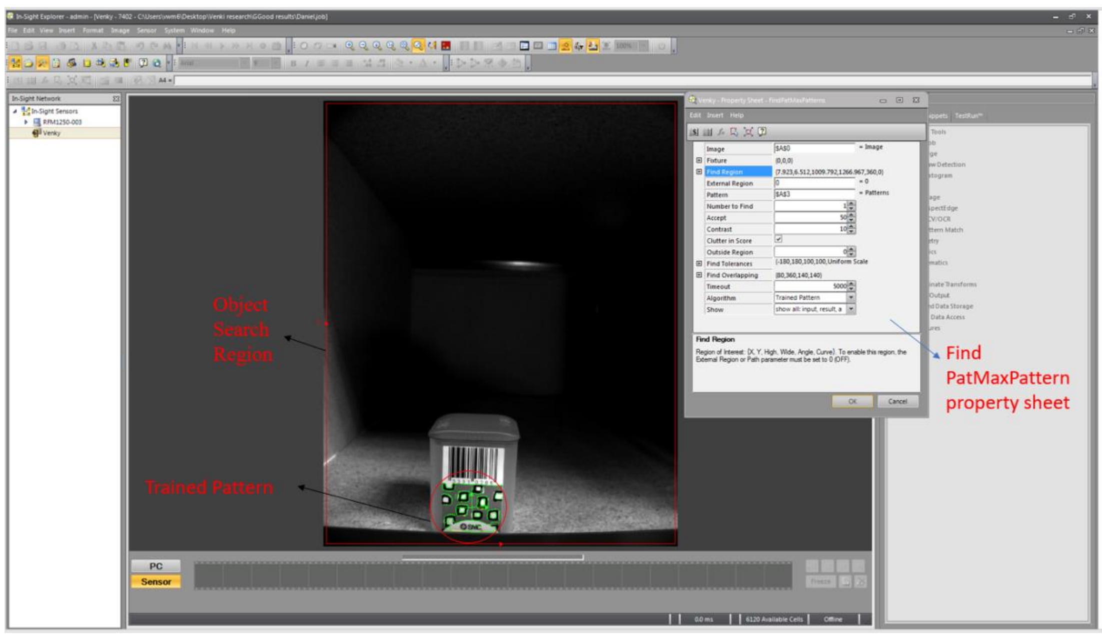

Figure 13: Property Sheet for FindPatMax Pattern.

5. EXPERIMENTATION AND RESULTS

Calibration steps are followed to find the transformation matrix which is showed below

Step 1: Move robot to desired location P_0 and get Sensor and robot data

Get sensor information S_0= (0,0)

Get robot information P_0= (381,107.2,637.7)

Step2: Move robot to grasp the object

Get robot information G_0= (363.5,240.57,647.31)

Step3: Move robot to different position along x-direction

Get sensor information S_1= (0.167,74.384)

Get robot information P_1= (381,107.2,624.9)

Step4: Move robot to a different position along y-axis

Get sensor information S_2= (152.356, -4.218)

Get robot information P_2= (354.7,107.2,637.7)

Step5: Calculate transformation (T)

P_1-P_0 =T [S_1-S_0]

$$\begin{bmatrix} 381 & -381 \\ 624.9 & -637.7 \end{bmatrix} = \begin{bmatrix} T_1 & T_2 \\ T_3 & T_4 \end{bmatrix} \begin{bmatrix} 0.167 & -0 \\ 74.384 & -0 \end{bmatrix}$$

$$\begin{bmatrix} 0 \\ -12.8 \end{bmatrix} = \begin{bmatrix} T_1 & T_2 \\ T_3 & T_4 \end{bmatrix} \begin{bmatrix} 0.167 \\ 74.384 \end{bmatrix}$$

$0.167\ T_1 + 74.384\ T_2 = 0 \longrightarrow$ Equation 1

$0.167\ T_3 + 74.384\ T_4 = -12.8 \longrightarrow$ Equation 2

P_2-P_0 =T [S_2-S_0]

$$\begin{bmatrix} 354.7 & -381 \\ 637.7 & -637.7 \end{bmatrix} = \begin{bmatrix} T_1 & T_2 \\ T_3 & T_4 \end{bmatrix} \begin{bmatrix} 152.356 \\ -4.218 \end{bmatrix}$$

$$\begin{bmatrix} -26.3 \\ 0 \end{bmatrix} = \begin{bmatrix} T_1 & T_2 \\ T_3 & T_4 \end{bmatrix} \begin{bmatrix} 152.356 \\ -4.218 \end{bmatrix}$$

$152.356\ T_1 - 4.218\ T_2 = -26.3 \longrightarrow$ Equation 3

$152.356\ T_3 - 4.218\ T_4 = 0 \longrightarrow$ Equation 4

By using equation 1 and 3 T_1 and T_2 are calculated

$T_1 = -0.10047$

$T_2 = 0.0003$

By using equation 2 and 4, T3 and T4 are calculated

$T_3 = -0.0047$

$T_4 = -0.1720$

Therefore,

$$T = \begin{bmatrix} -0.1726 & 0.0003 \\ -0.0047 & -0.1720 \end{bmatrix}$$

The Calculated transformation matrix is manually inserted in insight spreadsheet cells to determine the object offset from reference object location with respect to the object data trigged from camera, which is shown in figure 14.

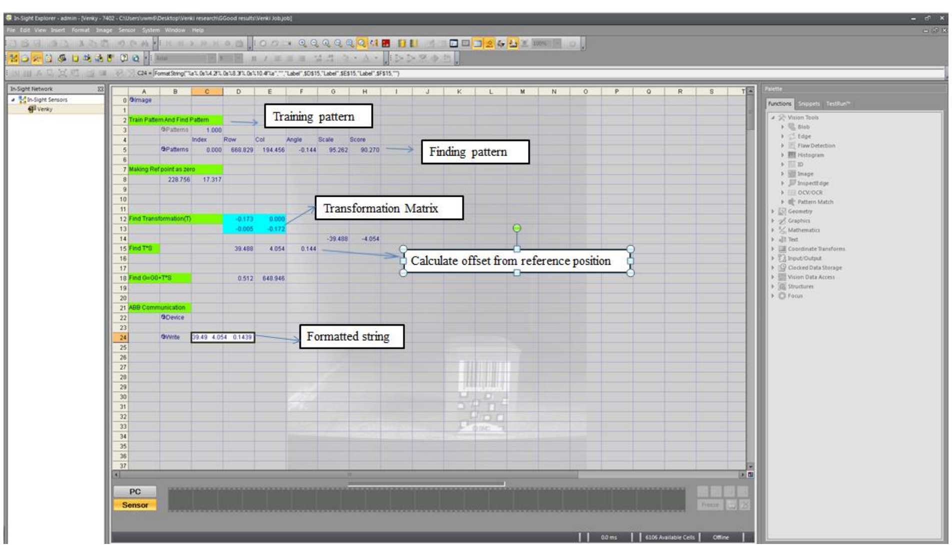

Figure 14: Spread sheet view in insight software

The object offset data (x, y, ϴ) is then converted in to string parse which is then transferred to robot rapid program by using socket messaging. This means of communication is used to deliver object coordinates to the ABB IRB 120 robot with compact controller. A rapid program is implemented to get the vision data in the form of string. The object data ‘x, y, theta’ is transmitted to the IRC5 controller via the vision system. The ABB controller is compatible with the client server socket communication, which allows it to receive the string. It can parse the string with “,” as a delimiter which facilitates the controller in carrying out a movement of the robot to the desired position with respect to string data. As the object recognition and location is completed, the second stage is to grip the object by using Robotiq-2 finger gripper. We developed a rapid program, which helps the robot to comprehend the vision data and the gripper orients itself accordingly to the object in order to pick it. After successful grasp, the gripper will perform certain functions to ensure the object has been grasped. If the object has not been grasped, the gripper communicates to the robot to return to the home position and repeat the vision procedure to capture the object’s current data. We wrote a program which integrates the functions of Cognex vision system, Robotiq-2 finger gripper and the ABB robot. This program has resulted in successful picking and placing of the object which was placed in random positions in the shelf. The system was successfully tested by placing the object in various positions, some of which are shown in Figure, 15, 16 and 17.

Figure 15: Object pickup from the shelf by recognizing the trained pattern

In the trial in figure 15, the object was placed in the left side of the bin. The vision system recognized the object successfully and the robot proceeded to grasp the object by using the vision data string. The gripper verifies if the object has been picked by tightening the grasp around the object. Once it is confirmed that the object has been grasped, the robot then retrieves the object from the bin and places it in the adjacent bin. After placing the object in the desired location, the robot moves back to its home position to rescan for the object. In the next iteration, the object is placed slightly deeper and towards the middle of the bin as shown in Figure 16.

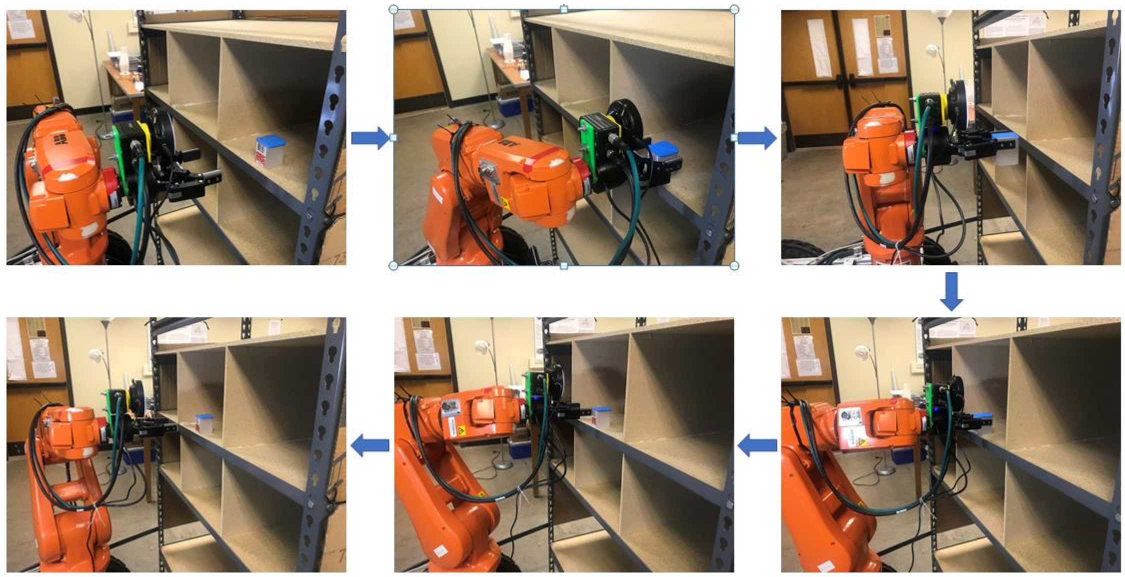

Figure 16: Object placed at the center of a bin with depth.

In the trial illustrated in Figure 16, the object was placed randomly at the center of a bin with a depth of about 20mm than the reference object. The object was successfully recognized by the vision system and the data was transmitted to the robot accordingly. Using this information, the robot grips the object by using the gripper, which confirms that the object has been grasped by tightening the fingers around the object. Once it is confirmed that the object has been grasped, it is retrieved and placed in another bin. After placing the object, the robot returns to its home position to rescan for the object's location. In the following iteration, the object orientation is changed by tilting it and placing it on a random height as shown in Figure 17.

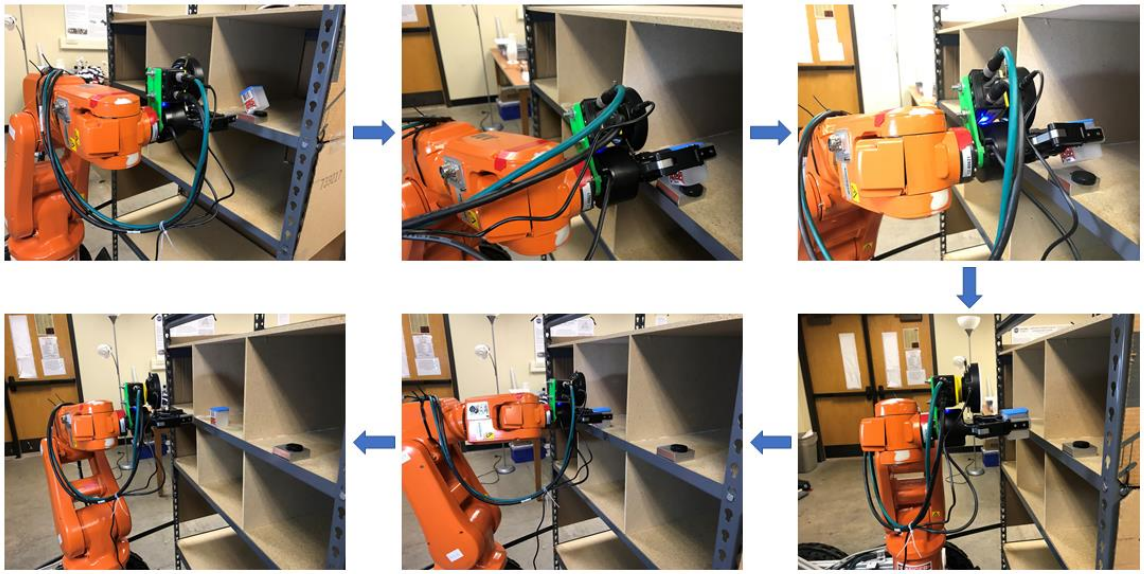

Figure 17: Object placed at a random orientation and height.

In the trial shown in Figure 17, the object is rotated and placed at a random height of about 10mm to15mm. According to the vision data received from the vision system, the robot reorients its gripper to match the object rotation and grasping is achieved as shown Figure 17. After grasping the object, the gripper checks by tightening the fingers around the object to confirm. The robot then retrieves by reorienting the end effector to its home position and places it in the desired location followed by the robot going back to its home position.

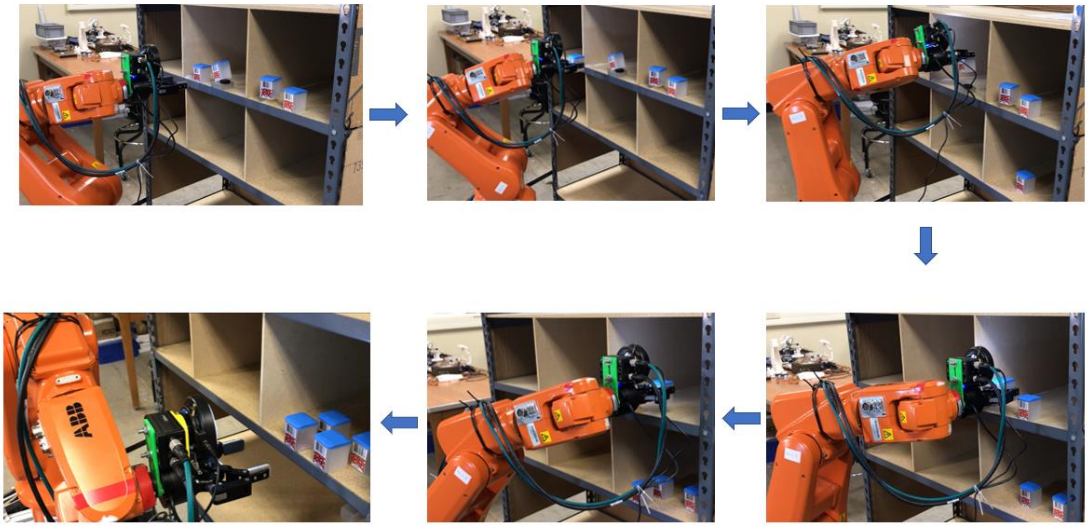

Figure 18: Object placed randomly in shelf

In this iteration, we placed four objects randomly in bins one and two. The job of the robot was to recognize the patterns on the objects and pick it according to the score. The first object was placed in the left corner in bin two, the second object was placed on a height and with an orientation in bin two, the third object was placed in bin one with a slight tilt to the right and on a height, and the fourth object was placed tilted to the left side in bin one. The task of picking the objects from various bins and placing them in bin three was executed using the teach pendant. As shown in Figure 18, the robot successfully recognizes the objects' patterns, picks and places them in bin three according to their score. In this study, there were various trials conducted with the object placed in random positions resulting in the robot successfully handling the object for picking and restocking application.

In addition, the picking and placing tasks were repeated with different lighting conditions such as fixed light exposure, increasing light exposure, decreasing the light exposure and with or without disturbances. With light disturbances include opening the window blinds and doors to allow natural light; without light disturbances include a control setting with no disturbances. The robot successfully recognizes the object and grasps them to place it in the desired locations. The success rate is calculated by dividing the total number of successful iterations by the total number of experiments. The results are recorded in table 4, we can clearly see that the success rate is slightly more without disturbance when compared to the with disturbance condition. Also, fixed light exposure gives high accuracy in pattern recognition to find the object location when compared to the increased and decreased light exposure conditions.

Table 4: Experiments in different lighting conditions

Condition		Sets of Experiments	Number of Experiments in each set	Success Rate
Fixed Light Exposure	Without Disturbance	10	10	100 %
	With Disturbance	10	10	98%
Decreased Light Exposure	Without Disturbance	10	10	95%
	With Disturbance	10	10	94%
Increased Light Exposure	Without Disturbance	10	10	94%
	With Disturbance	10	10	92%

6. CONCLUSION

In this study, a commercial application for object handling in warehouses was developed using commercial products such as ABB IRB 120 robot, Robotiq-2 finger gripper and Cognex vision system for randomly located objects. This study also showed the ease of integrating and configuring the gripper and vision system with ABB robots. In addition, the calibration steps were proposed for accurate measuring functions in both the robot and vision system. The success of the application relied on developing a rapid program in ABB robot studio which initiated the vision and gripper operations, which also enabled the robot for an OFFSET motion command with respect to the vision OFFSET value. In addition, the model was tested using different lighting conditions which resulted in fixed lighting conditions producing highest accuracy. The results showed that the ABB IRB 120 robot with Cognex 2D vision system and Robotiq-2 finger gripper could identify, pick and place a randomly placed object with accuracy every single time. The main objective was to implement this in warehouses for object handling.

7. FUTURE WORK

Future work in this area may include: 1) use of modified grippers with suction cups on the fingertips to reach objects placed deeper in a bin; 2) use 3D cameras for measuring the depth of the object; 3) develop an online system to provide live feedback regarding the object handling.

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