Vision Guided Robotics Research Study

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Abstract

With the demands of quality management and process control in the industry, machine vision is becoming an important tool to improve inspection quality and speed. It is predicted that the vision inspection techniques may replace traditional inspection methods soon. Machine vision is the automatic extraction of information from digital images for process or quality control. An automated machine vision is better suited to repetitive inspection tasks. Measurement, counting, location, and decoding are some of the most common applications for machine vision. The research project work presented here is based on the faculty led undergraduate student "hands-on" research sponsored by the university grant. Four different colored gear models are analyzed using an image processing software. A vision guided industry type robot is used to make the quality control decision by picking the good part from the bad parts based on image processing criteria. This research work enhanced the research experience for the student as well as for the faculty and improved the class room pedagogy for the mechanical engineering courses. The gear models, robot programming software, hardware setup, and vision tool software are presented in this article. The vision guided robot performed the quality control function consistently.

Keywords:
Vision Tools, Machine vision, Robotics, Robot Studio, In-Sight, Integrated vision, Robot programming

1. Introduction

According to one market research report -the Machine Vision Market is expected to grow from $8.08B in 2015 to $12.50B by 2020. With the demands of quality management and process control in the industry, machine vision is becoming an important tool to improve inspection quality and speed. It is predicted that the vision inspection techniques may replace traditional inspection methods in the near future. Machine vision is the automatic extraction of information from digital images for process or quality control. An automated machine vision is better suited to repetitive inspection tasks. Measurement, counting, location, and decoding are some of the most common applications for machine vision. Machine vision can inspect hundreds or even thousands of parts per minute and provides more consistent and reliable inspection results.

Industry 4.0, or "The Industrial Internet of Things," will rely upon machine vision to revolutionize industrial automation. One of the most hotly discussed topics in the manufacturing world today is Industry 4.0, or "The Industrial Internet of Things." Industry 4.0 refers to a set of emerging innovations in advanced automation, machine vision, Big Data, cloud computing and machine learning which will revolutionize manufacturing. Industry 4.0 demonstrates tremendous potential to bolster productivity, reduce waste, refine product quality, enhance manufacturing flexibility, decrease operating costs and deliver myriad other benefits to the factory floor. Industry 4.0 is associated specifically with an increase in the use of cyber-physical systems (CPS), such as sensors, which have the ability to collect data for manufacturers and producers in order to identify and trace parts and subassemblies. This data collection process enables devices to autonomously exchange information, as well as control and interact with each other independently. The vision guided robotic system is one the enablers of Industry 4.0.

The robotic vision systems should be robust, reliable, and stable. Machine vision systems rely on digital sensors protected inside industrial cameras with specialized optics to acquire images, so that computer hardware and software can process, analyze, and measure various characteristics for decision making. A machine vision system built around the right camera resolution and optics can easily inspect object details too small to be seen by the human eye. In removing physical contact between a test system and the parts being tested, machine vision prevents part damage and eliminates the maintenance time and costs associated with wear and tear on mechanical components. Machine vision brings additional safety and operational benefits by reducing human involvement in a manufacturing process. Moreover, it prevents human contamination of clean rooms and protects human workers from hazardous environments.

The research project work presented here is based on the faculty led undergraduate student "hands-on" research sponsored by the university grant. Four different colored gear models are analyzed using an image processing software. A vision guided industry type robot is used to make the quality control decision by picking the good part from the bad parts based on image processing criteria. This research work enhanced the research experience for the students as well as for the faculty and improved the class room pedagogy for the Mechanical Engineering courses. The gear models, robot programming, vision tools, robot hardware setup and the robot programming and vision tool software are presented in this article.

The outline of this research paper consists of several sections. In Section1, the introduction is presented. Section 2 review the literature available on the topic and in section 3 image processing methodology is presented. In sections 4 & 5 the vision hardware and robot programming software development are presented. Finally, in section 6, the results are presented with discussion.

2. Literature Review

There are lot of literature available on machine vison and vison guided robot's applications. There are many approaches used for validation and verification of the machine vision systems.

Elias et al. (2003**)** presented the state of the art in machine vision inspection research and technology in their study. They classified vision inspection according to the measured parameters (i.e., dimensions, surface, assembly and operation) and the system's "Degrees of Freedom". In the paper, they also reviewed wide range of software and hardware products including integrated image processing software packages, image processing libraries, neural network, fuzzy, neuro-fuzzy tools, genetic algorithms as well as hardware tools.

Dillmann (2004) presented an approach for teaching a humanoid robot that will enable the robot to learn typical tasks required in everyday household environments. Our approach, called Programming by Demonstration, which is implemented and successfully used to teach a robot system. First, an analysis of human actions and action sequences that can be identified when watching a human demonstrator. Secondly, sensor aid systems are introduced which augment the robot's perception capabilities while watching a human's demonstration and the robot's execution of tasks respectively. The focus is then laid on the knowledge representation to be able to abstract the problem solution strategies and to transfer them onto the robot system.

Agrawal et al. (2010) presented a complete vision-guided robot system for model-based three-dimensional (3D) pose estimation and picking of singulated 3D objects. Their system employed a novel vision sensor consisting of a video camera surrounded by eight flashes (light emitting diodes). By capturing images under different flashes and observing the shadows, depth edges or silhouettes in the scene are obtained. The silhouettes are segmented into different objects and each silhouette is matched across a database of object silhouettes in different poses to find the coarse 3D pose. The database is pre-computed using a computer-aided design (CAD) model of the object. The pose is refined using a fully projective formulation of Lowe's model-based pose estimation algorithm. The estimated pose is transferred to a robot coordinate system utilizing the hand—eye and camera calibration parameters, which allows the robot to pick the object. The system outperformed conventional systems using two-dimensional sensors with intensity-based features as well as 3D sensors under complex ambient illumination conditions, challenging specular backgrounds, diffuse as well as specular objects, and texture-less objects, on which traditional systems usually fail. They demonstrated the effectiveness of the technique with real experimental results using our custom designed sensor mounted on a robot arm.

Belongie and Perona (2015) developed a Visipedia resource for machine vision seekers. Visipedia is a network of people and machines designed to harvest and organize visual information and make it accessible to anyone who has a visual query. They discussed the technical challenges arising from Visipedia and discuss their implications for pattern recognition, computer vision, machine learning and visual psychology. An important realization is that the study of 'computer vision' and 'machine learning' has to be broadened to include the process of information discovery and the dynamic interaction of people and machines in this context. Human-machine systems with no oracle are now within the scope of pattern recognition, machine learning and computer vision.

Malika et al. (2016), argued the importance of the interaction between recognition, reconstruction and re-organization, and proposed that as a unifying framework for computer vision. In this review, recognition of objects is reciprocally linked to re-organization, with bottom-up grouping processes generating candidates, which can be classified using top down knowledge, following which the segmentations can be refined again. Recognition of 3D objects could benefit from a reconstruction of 3D structure, and 3D reconstruction can benefit from object category-specific priors. They showed that reconstruction of 3D structure from video data goes hand in hand with the reorganization of the scene. They demonstrated pipelined versions of two systems, one for RGB-D images, and another for RGB images, which produce rich 3D scene interpretations in this framework.

Acquiring ground truth 3D shapes of objects pictured in 2D images remains a challenging feat and this has hampered progress in recognition-based object reconstruction from a single image. Carreira et al. (2016) proposed to bypass previous solutions such as 3D scanning or manual design that scale poorly, and instead populate object category detection datasets semi-automatically with dense, per-object 3D reconstructions, bootstrapped from: (i) class labels, (ii) ground truth figure-ground segmentations and (iii) a small set of key point annotations. Their proposed algorithm first estimates camera viewpoint using rigid structure-from-motion and then reconstructs object shapes by optimizing over visual hull proposals guided by loose within-class shape similarity assumptions. The visual hull sampling process attempts to intersect an object's projection cone with the cones of minimal subsets of other similar objects among those pictured from certain vantage points. Their method is able to produce convincing per-object 3D reconstructions and to accurately estimate cameras viewpoints on one of the most challenging existing object-category detection datasets, PASCAL VOC.

Perez et al. (2016) provided a comprehensive summary of the state of the art and the existing 3D vision techniques used in robotics. Vision techniques for robot guidance have been analyzed in terms of accuracy, range, weight, safety, processing time, and scanning environmental influences. Choosing which type of 3D vision system to use is highly dependent on the parts that need to be located or measured. In addition to this, robot and industrial environments conditions also need to be considered. Each application and each type of robot need a specific vision solution. There is no universal vision technique to perform several tasks.

Savarimuthu et al. (2018) presented a three-level cognitive system in a learning by demonstration context. The system allows for learning and transfer on the sensorimotor level as well as the planning level. The fundamentally different data structures associated with these two levels are connected by an efficient mid-level representation based on so-called "semantic event chains." They described the details of the representations and quantify the effect of the associated learning procedures for each level under different amounts of noise. They also demonstrated that the system has a technical readiness level (TRL) of 4.

This paper is unique because it is developed by using the authors' vast automotive robotics application experience combined with undergraduate student's expertise in robotic programming with ABB robot.

3. IMAGE PROCESSING METHODOLOGY

Typically, an industrial inspection system computes information from raw images according to the following sequence of steps:

a. **Image acquisition:** Images containing the required information are acquired in digital form through cameras, digitizers etc.

b. **Image processing:** Once images have been acquired, they are filtered to remove background noise or unwanted reflections from the illumination system. Image restoration may also be applied to improve image quality by correcting geometric distortions introduced by the acquisition system (e.g., the camera).

c. **Feature extraction:** A set of known features, characteristic for the application domain, is computed, so that better classification can be achieved. Examples of such features include size, position, contour measurement via edge detection and linking, as well as and texture measurements on regions. The set of computed features forms the description of the input image.

d. **Decision-making:** The first step in decision making attempts to reduce the dimensionality of the feature space to the intrinsic dimensionality of the problem. The reduced feature set is processed further as to reach a decision. For example, in the case of visual inspection during production the system decides if the produced parts meet some quality standards by matching a computed description with some known model of the image (region or object) to be recognized. The decision (e.g., model matching) may involve processing with thresholds, statistical or soft classification.

Processing is the mechanism for extracting information from a digital image and may take place externally in a PC-based system, or internally in a standalone vision system. Processing is performed by software and consists of several steps. First, an image is acquired from the sensor. In some cases, pre-processing may be required to optimize the image and ensure that all the necessary features stand out. Next, the software locates the specific features, runs measurements, and compares these to the specification. Finally, a decision is made, and the results are communicated. While many physical components of a machine vision system (such as lighting) offer comparable specifications, the vision system algorithms set them apart and should top the list of key components to evaluate when comparing solutions. Depending on the specific system or application, vision software configures camera parameters, makes the pass-fail decision, communicates with the factory floor, and supports HMI development (Cognex corp.).

4. VISION HARDWARE SET-UP

Vision Guidance may be done for several reasons. First, machine vision systems can locate the position and orientation of a part, compare it to a specified tolerance, and ensure it's at the correct angle to verify proper assembly. Next, guidance can be used to report the location and orientation of a part in 2D or 3D space to a robot or machine controller, allowing the robot to locate the part or the machine to align the part. Machine vision guidance achieves far greater speed and accuracy than manual positioning in tasks such as arranging parts on or off pallets, packaging parts off a conveyor belt, finding and aligning parts for assembly with other components, placing parts on a work shelf, or removing parts from bins. Guidance can also be used for alignment to other machine vision tools. This is a very powerful feature of machine vision because parts may be presented to the camera in unknown orientations during production. By locating the part and then aligning the other machine vision tools to it, machine vision enables automatic tool fixturing. This involves locating key features on a part to enable precise positioning of caliper, blob, edge, or other vision software tools so that they correctly interact with the part. This approach enables manufacturers to build multiple products on the same production line and reduces the need for expensive hard tooling to maintain part position during inspection.

Image processing under controlled lighting condition

Image processing under *controlled lighting* condition

- Setup illuminated back-light table and Cognex IS7010 camera (16 in. focal length) with Easy Builder Cognex

In-Sight software on the laptop.
- Connect the power source: CIO-MICRO COGNEX IN-SIGHT MICRO I/O Expansion module 8 inputs/ 8 outputs, POE, 24 VDC input power.
- Bring camera in *live* mode.
- Calibrate the camera using 10 mm grid rectangular calibration sheet to convert pixel values into real world measurements.
- Utilize four different colored plastic gears for research experiment.
- Place the colored gears under the camera and take static picture under controlled lighting conditions.
- Using "vision tools" analyze the image for grey scale values, and pattern matching.

Vision Guided Robotic system (VGR)
- Utilize ABB Robot: IRB 120, payload: 3kg. reach:0.58 m; Software: Robot Studio.
- Utilize Integrated vision system: Cognex IS7010 camera; Software: In-Sight.
- Feed the processed image information to the real robot, equipped with integrated vison system.
- Develop the robot program to find the good part among the bad parts based on processed image using the integrated robotic vision system.

In this research work, four different colored gear set is utilized for machine vision inspection techniques. The gear dimensions are shown in Figure 1. The Table 1 compares the measurement data between the actual measurement and the camera measurement using vision tools. The actual gear photos (White, red, green and blue) are presented in Figure 2. The Table 2 lists the proper light intensity and the gray scale values required to set-up for the robotic vision image processing. For this research work 2530 lumens selected as the proper lighting conditions. Figure 3 shows the light table and camera setup.

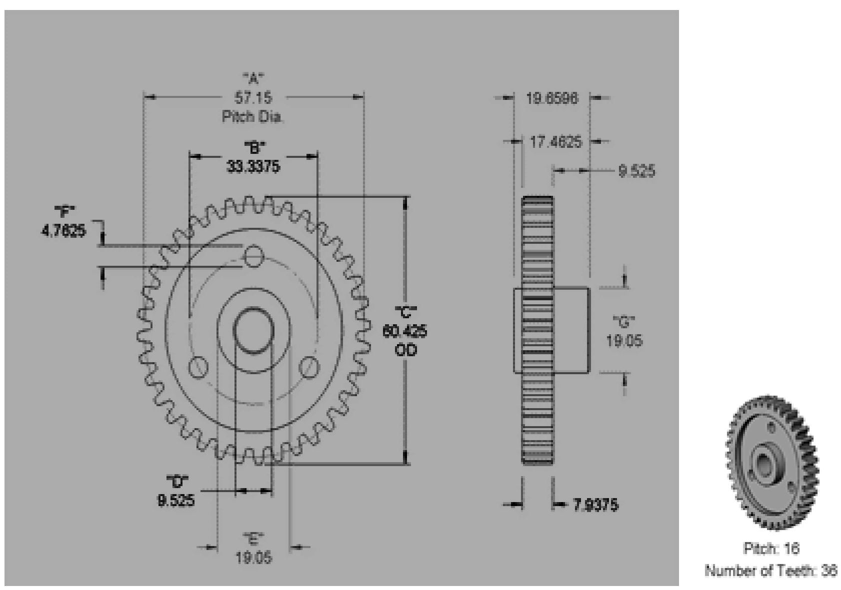


Figure 1. Gear dimensions

Table 1. Actual vs. Camera measurement using vision tools

Dimensions (mm)							
	A	B	C	D	E	F	G
Actual Dimensions	57.15	33.3375	60.425	9.525	19.05	4.7625	19.05

Camera-Vision tools measurement	N/A	35.44	63.464	10.486	20.474	5.181	20.598

Figure 2. Four coloured gears

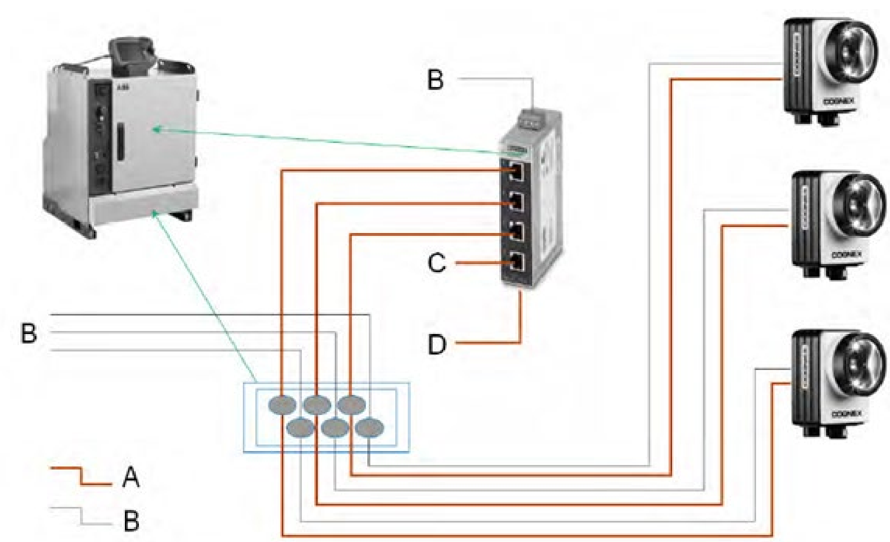
Figure 3. Camera set-up to measure the grey scale values

Table 2. Effect of background light intensity and gray scale values

		Lumens				
		2530	3060	3570	4050	
Gear Color	White	**179**	191	200	207	**Grey Scale Values**
	Red	**167**	172	178	187	
	Blue	**155**	163	169	178	
	Green	**159**	166	172	177	

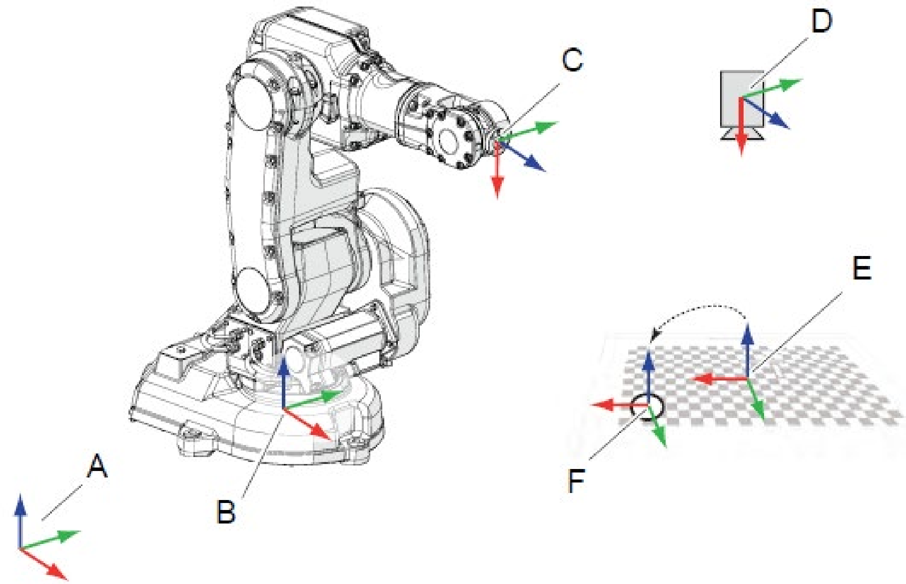
5. Vision Guided Robot (VGR) Hardware and Software Development

The software solution is based on three components – Robot Studio, the IRC5 controller with the RAPID programming language, and the Flex Pendant. Robot Studio presents vision and robot configuration parameters side by side, providing a convenient VGR programming environment. The IRC5 controller enables easy creation of RAPID programs that make maximum use of the camera system's capability. Among other features, the controller has a RAPID interface with a pre-established camera communication interface and vision target queue handling. The Flex Pendant is equipped with an operator interface to allow supervision of the system when deployed in production. Figure 4 shows the robotic vision with 3 Camera set-up with the robot controller cabinet. Figure 5 shows the robot co-ordinate system with fixed camera in space looking at the work object co-ordinate system E and F. Figure 6 shows the robot integrated vision GUI. Figure 7 shows the checker board calibration plate for integrated vision system. Figure 8 shows the program snippet to run the robot vision system. Figure 9 shows the actual robot picking the part using robotic vision system.



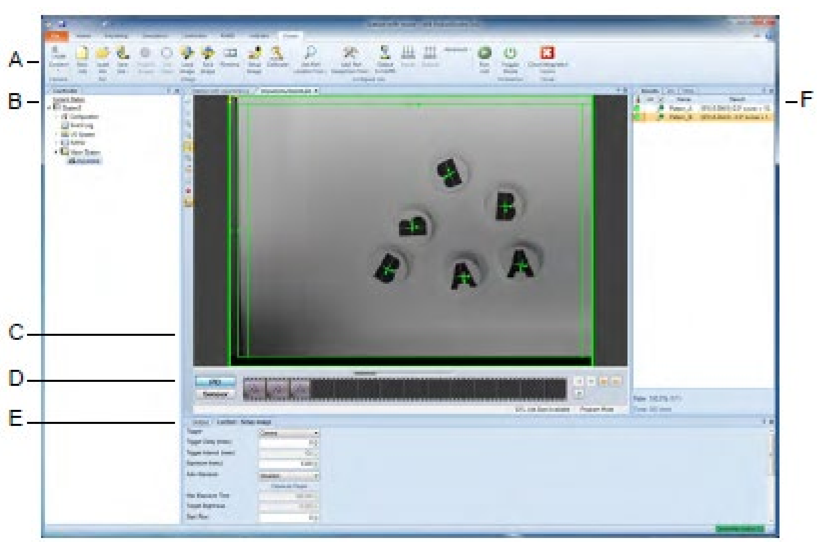
A	Ethernet
B	24V power supply from the customer power supply to the switch and to the cameras
C	Ethernet between the switch and the controller cabinet service port (inside)
D	Ethernet between the switch and the main computer service port

Figure 4. ABB Robotic vision: Three camera set-up (robot not shown)



A	WORLD coordinate system.
B	BASE coordinate system.
C	Tool coordinate system (`tool0`).
D	Fixed camera position in space. The camera position is unknown to the robot controller unless the camera in held by the robot. **Note** If the camera is held by the robot, then the robot must go to the same position (`robtarget`) every time an image is acquired.

Figure 5. ABB Robot co-ordinate system with fixed camera in space



	Parts	Description
A	Ribbon	Displays groups of icons organized in a logical sequence of function.
B	Controller browser	The vision system node displays all vision cameras on the network.
C	Image capture and configuration area	Displays an image acquired by the vision camera with configuration guides for locating and inspecting parts.
D	Filmstrip bar	Used to record a sequence of images for later analysis.
E	Context window	Contains the available properties, settings, and events of the selected controls.
F	Palette window	Following tabs are available: • **Results** tab - displays the setup of the active vision job with a list of all used location and inspection tools. • I/O tab - displays the I/O setup. • Help tab - provides online help.

Figure 6. ABB Robot Integrated Vision GUI

The camera is calibrated to the robot by defining a work object with the same origin of coordinates as the calibration plate.

On a checkerboard calibration plate with fiducial, the origin of coordinates is located at the intersection of the extended X- and Y-arrows as seen in the picture below.

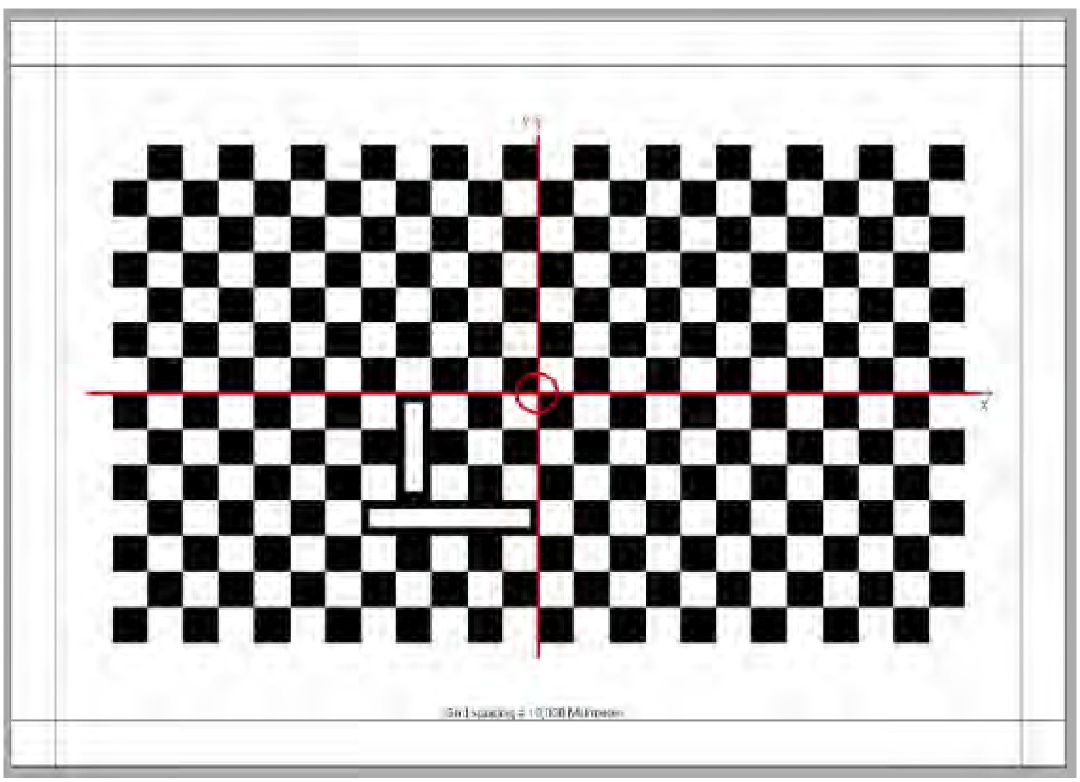


Figure 7. Cognex Checkerboard calibration plate

The purpose of the following **RAPID** program is to move the robot to a position where the robot can pickup a part detected by the vision camera. It is based on the snippet `MoveToDetectedObject` found in RobotStudio.

```
1    ...
2    PERS wobjdata mywobj := ... ;
3    PERS tooldata mytool := ... ;
4    PERS robtarget myrobtarget := ... ;
5    CONST string myjob := "myjob.job";
6    VAR cameratarget mycameratarget;
7    ...
8    PROC MoveToDetectedObject()
9      CamSetProgramMode mycamera;
10     CamLoadJob mycamera, myjob;
11     CamSetRunMode mycamera;
12     CamReqImage mycamera;
13     CamGetResult mycamera, mycameratarget;
14     mywobj.oframe := mycameratarget.cframe;
15     MoveL myrobtarget, v100, fine, mytool \WObj:=mywobj;
16   ENDPROC
17   ...
```

Row	Comment
2 - 6	Declaration of data.
9 - 10	Set the camera to program mode and load the job.
11 - 12	Set the camera to run mode and acquire an image.
13	Get the vision result and store it in a camera target.

Figure 8. ABB MoveToDetectObject snippet

Vision Guided Robot Programming Procedure:

Using calibration grid sheet, calibrate the robotic integrated vision system. Using the robot teach pendent define the work object for the robot vision to pick up the objects. Place the good part on the robot vision area. Acquire image using Pat Max vision tool and model the region. Run the vision job and output the “good” image to the Rapid program in Robot Studio. Using the snippet function in Robot Studio, run the “Move to Detected Object” routine. Also, Set the pick position for the robot to pick the parts. Place all the parts in robot vision area, run the vision job to pick the good part from the bad ones. The program works for all orientation of the parts. Figure 9 shows the robot recognizing thru vision camera, picking the good part from other parts.

Figure 9. VGR pick the good part from other parts.

6. Results and Recommendation

Four different coloured gear models were analysed using vision guided robot (VGR). The VGR is programmed to identify and fixture the good part using Pat Max vision tool. The VGR was able to pick the good part from other parts every time automatically. Even when the parts orientation changed, VGR was able to pick the good part.

This research integrated the quality control process using the VGR technology with robot programming to accept the good part based on part quality control criteria. It is vital to the education of future engineering students to remain up-to-date with this technology. The undergraduate student gained a tremendous “hands-on” research experience working with the faculty.

It is recommended that the robotic vision course should be developed and taught in the universities due to its increasing popularity and projected exponential use in the modern-day quality inspection environment.

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Biography

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Kyle Bruce is an undergraduate student pursuing his Bachelor's degree in Mechanical engineering at Saginaw Valley State University, Michigan, USA. Kyle has a keen interest in pursuing career in Robotics and related field. He is a certified ABB programmer for material handling applications. He also worked with FANUC robots. His research interest includes Robotics and Vision systems.