Design and Development of Sensor Integrated Robotic Hand

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Design and Development of Sensor Integrated Robotic Hand

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by

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I dedicate my dissertation to my beloved ***Parents*** *& my daughter* ***Ovi.***

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I, *Om Prakash Sahu*, bearing the Roll Number 512ID101 hereby declare that this dissertation entitled "*Design and Development of Sensor Integrated Robotic Hand* " represents my original work carried out as a postgraduate student of NIT Rourkela and, to the best of my knowledge, it contains no material previously published or written by another person, nor any material presented for the award of any other degree or diploma of NIT Rourkela or any other institution. Any contribution made to this research by others, with whom I have worked at NIT Rourkela or elsewhere, is explicitly acknowledged in the dissertation. Works of other authors cited in this dissertation have been duly acknowledged under the section " Reference ". I have also submitted my original research records to the scrutiny committee for evaluation of my dissertation.

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Om Prakash Sahu

Abstract

Most of the automated systems using robots as agents do use few sensors according to the need. However, there are situations where the tasks carried out by the end-effector, or for that matter by the robot hand needs multiple sensors. The hand, to make the best use of these sensors, and behave autonomously, requires a set of appropriate types of sensors which could be integrated in proper manners.

The present research work aims at developing a sensor integrated robot hand that can collect information related to the assigned tasks, assimilate there correctly and then do task action as appropriate. The process of development involves selection of sensors of right types and of right specification, locating then at proper places in the hand, checking their functionality individually and calibrating them for the envisaged process. Since the sensors need to be integrated so that they perform in the desired manner collectively, an integration platform is created using NI PXIe-1082.

A set of algorithm is developed for achieving the integrated model. The entire process is first modelled and simulated off line for possible modification in order to ensure that all the sensors do contribute towards the autonomy of the hand for desired activity.

This work also involves design of a two-fingered gripper. The design is made in such a way that it is capable of carrying out the desired tasks and can accommodate all the sensors within its fold. The developed sensor integrated hand has been put to work and its performance test has been carried out. This hand can be very useful for part assembly work in industries for any shape of part with a limit on the size of the part in mind.

The broad aim is to design, model simulate and develop an advanced robotic hand. Sensors for pick up contacts pressure, force, torque, position, surface profile shape using suitable sensing elements in a robot hand are to be introduced. The hand is a complex structure with large number of degrees of freedom and has multiple sensing capabilities apart from the associated sensing assistance from other organs. The present work is envisaged to add multiple sensors to a two-fingered robotic hand having motion capabilities and constraints similar to the human hand. There has been a good amount of research and development in this field during the last two decades a lot remains to be explored and achieved.

The objective of the proposed work is to design, simulate and develop a sensor integrated robotic hand. Its potential applications can be proposed for industrial environments and in healthcare field. The industrial applications include electronic assembly tasks, lighter inspection tasks, etc. Application in healthcare could be in the areas of rehabilitation and assistive techniques.

The work also aims to establish the requirement of the robotic hand for the target application areas, to identify the suitable kinds and model of sensors that can be integrated on hand control system. Functioning of motors in the robotic hand and integration of appropriate sensors for the desired motion is explained for the control of the various elements of the hand. Additional sensors, capable of collecting external information and information about the object for manipulation is explored.

Processes are designed using various software and hardware tools such as mathematical computation MATLAB, OpenCV library and LabVIEW 2013 DAQ system as applicable, validated theoretically and finally implemented to develop an intelligent robotic hand. The multiple smart sensors are installed on a standard six degree-of-freedom industrial robot KAWASAKI RS06L articulated manipulator, with the two-finger pneumatic SHUNK robotic hand or designed prototype and robot control programs are integrated in such a manner that allows easy application of grasping in an industrial pick-and-place operation where the characteristics of the object can vary or are unknown. The effectiveness of the actual recommended structure is usually proven simply by experiments using calibration involving sensors and manipulator. The dissertation concludes with a summary of the contribution and the scope of further work.

Key Words: Sensors integration; intelligent robotics hand; parts identification; grasping points.

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Abbreviations

ABS	Acrylonitrile Butadiene Styrene
BF-SIFT	Bag of Features Shape Invariant Feature Transform
CAD	Computer Aided Design
CATIA	Computer Aided Three Dimensional Interactive Application
CCD	Charge-Coupled Device
COG	Centre of Gravity
COM	Centre of Mass
CPU	Central Processing Unit
DOF	Degree of Freedom
HSV	Hue Saturation Value
LTS	Light Touch Switch
NN	Neural Network
OLP	Off Line Programming
PC-ORC	PC based Open Robot Control
RAM	Random Access Memory
RGB	Red Green Blue
ROI	Region of Interest
SQDIFF	Square Difference

Chapter 1

INTRODUCTION

1.1 Overview

Robots have extensive applications in modern industries such as inspection, materials handling, machine tending, picking and placing, palletizing, and assembling. Now a day, the production cycles are getting shorter, and the changes of industrial environs happen everywhere. Industrial robots are usually inflexible and expensive to apply for manufacturing industries. Most of the automated robotic grippers were designed for accumulation of specfic tooling system. End of Arm Tooling (EOAT) is a nonspecific model, capable to work for several applications.

The research on flexibility of industrial robotic hand or end-effector is in developing stage for intelligent grasping. In order to increase the flexibility of intelligent robot gripper for assembling or manufacturing industries, rapidity response and intelligence level play an important role. Achieving such manipulator is still a challenging task for most industrial applications. The near future intelligent assembling system should be versatile and able to adopt for any change that economizes the process. The robotic system needs to improve the perception according to the industrial environment. A lot of research has been carried out for intelligent grasping of the industrial robot for the unstructured workspace. There are still certain errors encountered in recognising the amorphous parts with high accuracy. This problem motivated, to carry the research on identifying the uncertain objects with high accuracy. In order to achieve this problem, intelligent robotic end-effector was integrated with sense, think, and react capability. To integrate sense, think and react capability the industrial robot needs multiple types of sensors, control system and algorithms. The sensor incorporation is for the purpose of robotic hand control, real-time learning, interacting with surrounding, and capturing unknown structure of parts.

Several robotic hands are directly related to the purposes of assembly operations. They are not really ideal and suitable for this research. Thus, plan of a robotic hand suited to serve as an investigation platform for a specific purpose, with which intelligent grasping can be explored. To be able to explore the intelligent robotic hand application, a new universal composition of tactile sensory information, part identification, decision-making and gripper control to accomplish intelligent gripping is essential. With all the platform of intelligent robotic hand may be produced like a hierarchical design capability of sensing, decision making and react for grasping control.

The grasping procedure is as per the distinguishing of part position, orientation alignment, in addition, its geometry according to sensory information. The geometry of parts to be grasped differs from object to object. The choice of the gripping surfaces and positions affects the stability as well as consistency regarding grasping method. For a multi-sensor program framework, tactile sensors information might be involving inconsistency sometimes. So that, an efficient methodology and algorithm is essential to develop instrumented intelligent robotic hand for real-time operations.

Intelligent robotic operations can be achieved by the utilization of sensor integration which makes the robot more intelligent at workspace. To associate with their surroundings as far as automated part identification, observation of the status of the object grasping, control and real-time acquisition from tactile sensors information, sensor integration play an importent role. As is valid in humans, vision abilities invest a robot with a complex detecting instrument that permits the machines to react with its surroundings in an "intelligent" and flexible manner.

This thesis provides a sensor integrated intelligent robotic hand and easy control algorithms to carryout robotic assembly operations efficiently in unstructured environment with unique capabilities of part identification, grasping and part insertion. **LaValle (2006)** proposed a planning algorithm for unstructured assembly environments imposing a number of additional difficulties for motion generation. This suggests the capacity to manage critical unpredictability and is also expected to have much more prominent adaptability than it does now. Such systems would be sparse and of a progressive nature. In this context, the intelligent robots can meet the necessities.

1.2 Background

Numerous attempts have been made operators to make an industrial robot more intelligent and also trying to replace human entirely. The robots should have the capacity to sense the surroundings like a human does. The actual robots are generally getting really good at mimicking the actual motions of the human being hand yet at the same time do not have the actual sensing ability that it includes.

In general, robotic hands or end-effectors or (EOAT), play a privileged role in the field of industrial automation and assembly manipulation operation. They intelligently communicate with the real world. That character contributes them a valuable position to convey the handling problem, moreover by utilization of their intelligent actions or by utilization of their smart design. Presently most of the robotic hands employed in the industrial environments usually are designed to complete a particular job along with the ability to accomplish additional tasks beyond the predefined limitations. Most act on the uncomplicated open/close method without having proper opinions of the object grasped. With a percentage of the detecting capacities of the human hand implemented on them, they would have the capacity to perform more perplexing and various assignments. One of the critical sensing abilities is to have the capacity to sense if some workplaces are unstructured. Multi-sensory integration system with a control of robotic system was introduced and discussed as a structure aimed at leading sensory system for robotic intelligence techniques by **Eccles et al., (1991)** and clarified the current status of the art of sensory skills in automated assembly system. **Santochi (1998)** and **Micheli (2009)** described the integrated sensor systems to evolution of assembly systems in the unstructured environments. The principal evident thing this prompts the capacity to identify when an object picked in completely unstructured environment and have the opportunity to take activities according to industrial tasks.

The other things, which are not noticeable, are for the robotic hand to grab and hold an unshaped object without knowing previously what amount grasping power is expected to hold it, by detecting the real slip of the parts. This is much like how the human hand knows the best possible holding force on amorphous and unknown objects.

1.3 Sensor Integrated Industrial Robotic Hands

Manufacturing industries demands an intelligent robotic hand to perform the various industrial tasks such as identifying the objects as well as to perform pick and place operation. Acquiring the information from the robotic hand for accurate placemen of the object is difficult. So, servo motors are used to control the robotic hand motion using intelligent sensors for achiving desired accuracy.

The thought of utilizing sensors mounted to enhance the evaluation was initially proposed in 1985. Despite the fact that this methodology has not yet been widely adopted by industry, a lot of research and analysis continues to be accomplished of this type of problem. A new imaginative and prescient vision sensor is often thought to be a suitable option for this purpose. On the other hand, smart sensors, for example, force/ torque sensor, proximity, and tactile sensors can be used to enhance the intelligent performance.

1.3.1 Industrial robotic hand: a brief review

With robot users requesting more adaptability in their procedures, researchers are under pressure to deliver versatile, intelligent robot hand that increases the value of the entire technique. Today's robot hand is not only easier to implement and also easier to work with, but it is also absolute intelligence. Applications of particular grippers are bringing robotics technology inside of a safe distance of a more extensive group of users. The latest strain of end-effector does not merely perform wonderfully in the research; it is obtaining the technique on top of the particular application of end-effector. Robotic hand with electric, servo-driven 2-finger and 3-finger grippers empower the client to control getting a handle on components. For example, the opening/closing rate of the fingers, force on the subject becoming handled, along with exact fingertips make it possible for just a few available along with in close proximity with regard to quick process durations. The versatile 2-finger grippers are intended for everyday assembling operations, where engineers need to automate 2-finger griper with high accuracy. It is very difficult to grasp different parts with a single end-effector which is a costly process. In order to reduce the cost as well as to decrease the time of the operation, multiple sensors are integrated to a single end effector. The commercial available grippers in the market are briefly explained in the form tree diagram, which is shown in the figure 1.1.

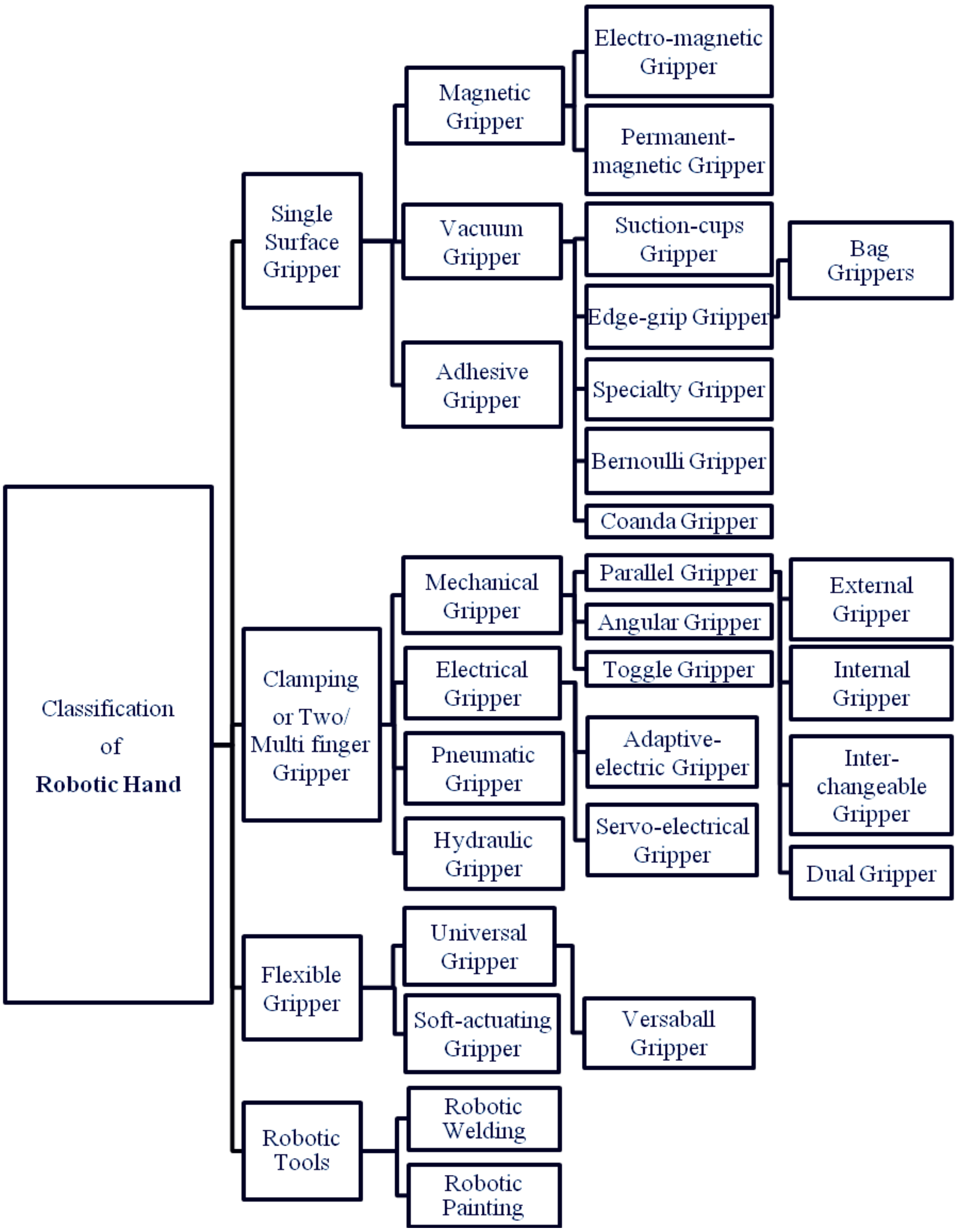


Figure 1.1: Classification of industrial robotic hands

I. Single surface gripper

At the point when one and the only surface of the part is accessible, the single-surface grippers' suits ideal for gripping this particular forms of components. These types of grippers are useful for grasping light and heavy and level parts which are hard to handle by different means. The gripper varieties which have been a part of single-surface grippers usually are magnetic and adhesive grippers.

i. Magnetic gripper

The magnetic gripper shown in Figure 1.2 is regularly utilized as a part of an end-effector to handle the ferrous materials. It can be classified into two types, one is electromagnetic gripper and second one is permanent magnetic gripper.

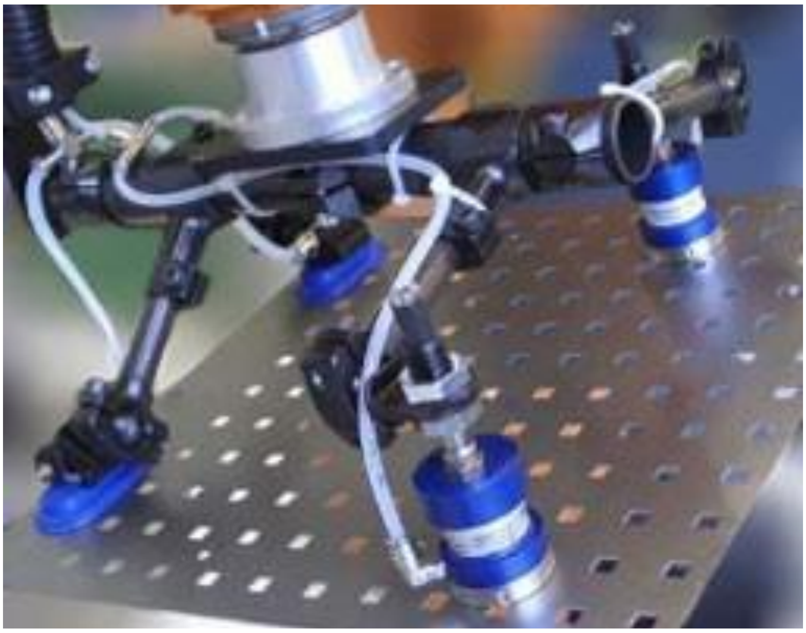


Figure 1.2: Magnetic gripper (in.schmalz.com)

ii. Electromagnetic gripper

Electromagnetic grippers shown in Figure 1.3, incorporate a controller unit and a DC power unit to take care of the materials. These types of grippers are difficult to control and extremely viable in discharging the part towards the end of the operation. In order to slow up the continuing magnetism about the part, the particular polarity levels will be reduced from the controller model before the electromagnet will be switched off to push out the particular part.

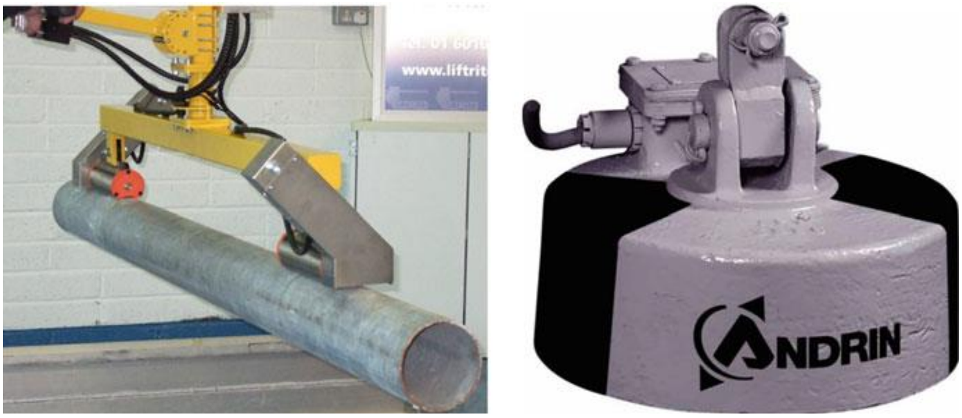


Figure 1.3: Electromagnetic gripper (http://www.liftrite.ie/)

iii. Permanent magnetic gripper

Compare to the electromagnetic based gripper, the permanent magnetic based grippers do not require any outside force for handling the materials, shown in Figure 1.4. To release the part from the gripper a push pin is required. The push pin pushes the grasped material to separate from the magnetic gripper.

Figure 1.4: Permanent magnetic grippers (http://www.liftrite.ie/)

The main advantage of the permanent magnetic based gripper, which usually used in dangerous environments and also in explosion proof apparatus. These magnets reduce maintenance and zero accidence caused by power failures.

iv. Vacuum gripper

Machine grippers utilize the vacuum cleaner pressure to hold materials. This type of grippers provides beneficial controlling on the objects having surface smooth and flat. Its functionality will depend on the surface properties of the object being grasped shown in

Figure 1.5: Vacuum gripper and suction cups (http://www.piab.com/)

Figure 1.5. Vacuum cups, typically referred to as suction cups, and are utilized as the grasping objects. Typically, the vacuum cups (suction cups) are of circular shape, constructed with rubber as well as elastomeric materials. At times, it is also made of soft plastics. Vacuum grippers are regularly utilized in manufacturing industries and automobile industries. It is additionally utilized for marking, fixing, packaging, and box producing.

v. Adhesive gripper

Adhesive grippers are used to grasp the object by sticking to it. This gripper performs grasping action to handle the fabrics and other lightweight materials. These grippers will

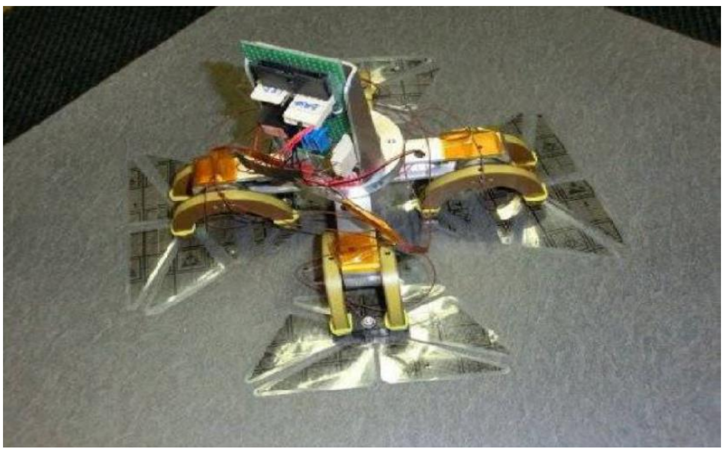


Figure 1.6: Adhesive Gripper (http://www.piab.com/)

work without maintenance as long as the adhesive keeps its sickness.

II. Clamping or two/ Multi-finger gripper

Clamping gripper is of two-jaw or three jaw gripper, used to grasp the objects. As this type of gripper is of simple design, therefore cheaper in price. These grippers hold the objects by applying pressure internally or externally to more than one surface. These grippers generally use pneumatic or hydraulic technic to hold the objects. To grasp the lighter weight object pneumatic technic is used and to grasp the heavier objects hydraulic technique is used

i. Mechanical gripper

Mechanical grippers are actuated by a mechanism to grasp the object. Mechanical grippers consist of fingers, sometimes called as jaws, which are the integral part of the mechanism

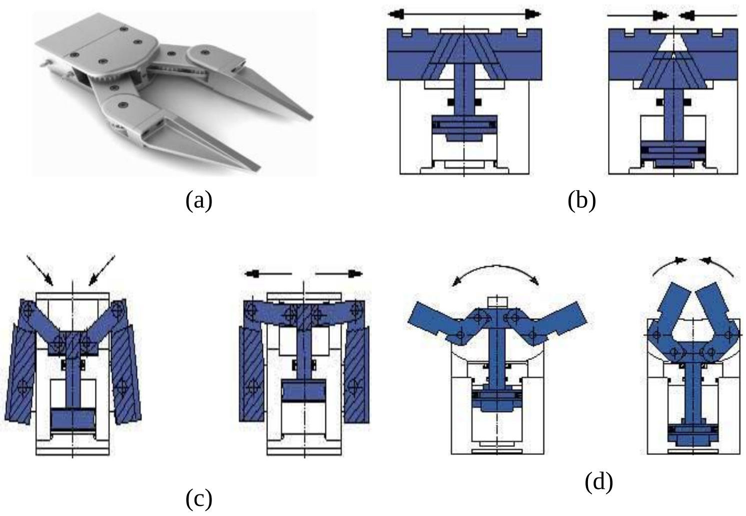


Figure 1.7: (a) Mechanical grippers (b) Parallel Grippers
(c) Angular Gripper (d) Toggle Gripper.

are attached to the mechanism. Mechanical grippers can be further classified into electric grippers and pneumatic grippers. An example of the mechanical gripper is shown in Figure 1.7. Parallel Grippers, Angular Gripper, Toggle Gripper.

ii. Electrical gripper

Electric gripper uses actuator to move their fingers. In these grippers electric motor

Figure 1.8: Commercial electric grippers (http://www.robotiq.com)

controls the movement of the fingers using electrical input from the robot controller. Stepper or servo motors are generally used as the actuators to move the fingers to the respective position to pick or hold the required object. The commercial grippers used in the market are shown in Figure 1.8.

iii. Pneumatic gripper

Pneumatic gripper works on the pressurised air to hold the object. In the pneumatic grippers pressurised air is responsible for the movement of the fingers. As the construction is simpler and straightforward use of pneumatic grippers are of less expense. The commercial pneumatic gripper is shown in the figure 1.9.

Figure 1.9: Commercial pneumatic grippers (http://www.festo.com/)

iv. Hydraulic gripper

Hydraulic grippers uses hydraulic oil to creat the presure for the movment of the fingers. In general hydraulic grippers are used to hold or pick the objects having heavey weights. Hydraulic grippers uses a cilender having diameter made with less area pushes the oil at higher pressures to actuate the fingers of the grippers. The comercial hydoulic gripper shown in Figure 1.10.

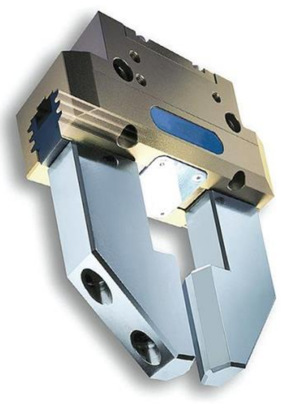


Figure 1.10: Commercial hydraulic gripper (http://www. mobilehydraulictips.com/)

III. Flexible gripper

Flexible grippers are used to hold the differente shape objects without changing the gripper. These gripper compriesed of links, having individual controlling to hold the objects. These gripper reassembles like human hand and having individual control over fingers during picking.this gripper are classified as universal gripper and soft actuating grippers.

i. Universal gripper

Universal Grippers replaces the finger grippers to handle the complex shape objects. However, finger grippers are not suitable to hold the complex objects like glass and unstructured objects because of hardware and software complexities to calculate the stress that is required for individual fingers to hold the object. Universal grippers replace the individual fingers by a single mass of granular materials. This material when pressed against the target object, the granular material flows around it and confirms the shape of the object. By the application of vacuum, the granular material contracts and hardness quickly to hold the object. The commercial universal gripper is shown in the Figure 1.11

Figure 1.11: Universal Gripper (www.brucebot.com)

ii. Soft-actuating gripper

Soft-actuating gripper uses soft materials for the fingers to hold the breakable objects softly. This gripper fingers uses flexible material, which deforms according to the object shape during holding, the commercial soft-actuating gripper is shown in Figure 1.12.

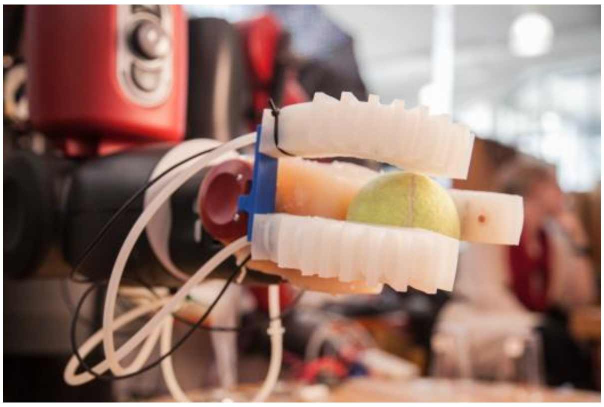


Figure1.12: Soft gripper (http://robohub.org)

IV. Robotic tools

i. Robotic welding

Welding is one of the difficulty task that can perform accurately without error. The welding becomes much complicated in the hazardous condition and at risk areas. Robots play a key role for such type of environments for welding. The end effector is replaced with the welding tool during welding operation. A robotic end tool for welding is shown in Figure1.13.

Figure1.13: Robotic end tools for welding. (http://www.weld-it-right.com/)

ii. Painting

Painting is one of the difficulty tasks because of chemicals presents in the paint, which leads severe health problems for the humans. Robots replace the human's especially in automobile industries for spray painting. In this manner, painting robots are of great resource for doing quality painting and decreasing dangers for the humans. A robotic end tool for painting is shown in Figure1.14.

Figure1.14: Robotic end tools for painting. (http://www.weld-it-right.com/)

1.3.2 Classification of industrial sensors

Robots are capable of doing greater jobs with the integration of intelligent sensors to the various parts of the robots. Sensors provide the information about the environment by sensing the objects to the robot through feedback control system. For guiding the robot, different type of sensors like proprioceptive sensors, exteroceptive sensors and expproprioceptive sensors are used to locate the position of the object in the unstructured environment. Advancements in the sensors encourage mechanical autonomy, which makes the robot smart and intelligent. Development of sensors for the robots replaces the humans especially in the areas like bio medical rehabilitation, nuclear power plants and in hazardous areas.

I. Proprioceptive Sensors

These sensors generally used to measure the velocity, position and acceleration of the internal links of the robot. These sensors control the motion of the internal links based on the information gathered from the outside environment to reach to the require position in the work space. Controlling the motion includes kinematic and dynamic parameters such as joint positions, speeds, velocities, force, torques, and inertia force. Along with these parameters these sensors have to control the angle of rotation of the link according to the position of the object present in the environment.

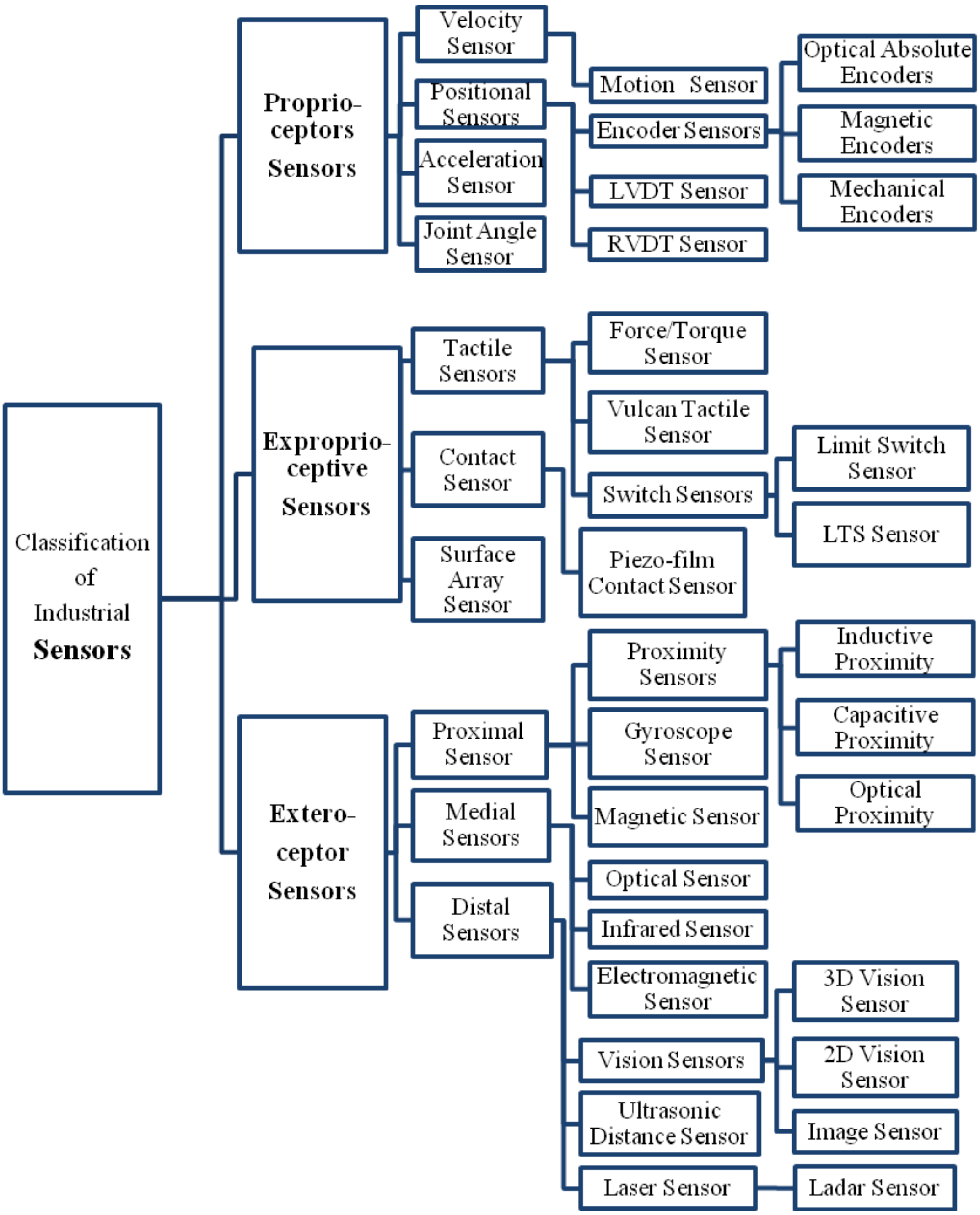


Figure 1.15: Classification of industrial sensors

II. Exteroceptive Sensors

Exteroceptive sensors are used to estimate the position of the objects present in the work space with respect to robot motion. This kind of sensors avoids the collisions with the objects present in the workspace during movement of the robot.

III. Exproprioceptive Sensors

Exproprioceptive sensors utilize a combination of proprioceptive and exteroceptive sensors. These sensors measure the position of the robot body or parts with respect to the surroundings and actuate the internal links according to it to reach the required position of the robot. Among the all the sensors, for the proposed work selected sensors like contact sensors, force/torque sensors, tactile sensors, proximity sensors, range sensor, vision sensors are explained in detail in chapter 2. The broad classifications of the different types of sensors used in the robots are shown in the figure 1.15.

1.4 Application of Sensor Integrated Robotic Hands

In the early stage of robotics robot hands are meant for specific task or operation. But advances in the sensors allow the robot gripper to gather the information more accurately from the workspace. Present days grippers are mounted with multiple sensors to improve the flexibility of the robotic hand to perform the industrial task.

1.4.1 Industrial applications

The expense and simplicity are the two vital variables in the configuration of end effectors for industrial robots. The simple equipment including open/close grippers are generally used as end effectors. With expansion in industrial sectors in commercial ventures like assembling, automobile and so on, robots with multiple sensors integrated hands are being utilized for some specific tasks. The commercial robotic hand with multiple sensors integration is shown in Figure1.16.

Figure1.16: Robotic hands used for industrial applications. (https://www.robots.com/)

1.4.2 Pick and place operation

Robotic pick and place operation speeds up the procedure of lifting parts up and setting them in new area. With numerous end-of-arm-tooling pick and place robots can utilized to any shape of objects. Moving the expensive materails, overwhelming, or difficult-to-handle items can easily automate in the industrial facility line by using pick and place robots. Consistency is additionally an advantage of utilizing a pick and place robot. The commercial pick and place robot is shown in Figure1.17.

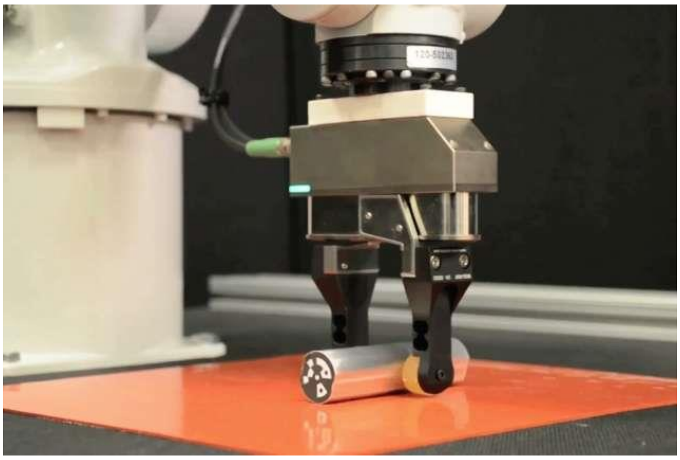


Figure1.17: Robotic hand for pick and place operation. (https://www.robots.com)

1.4.3 General material handling

Material handling and managing robots automates the material handling in the production industry. Material handling robots boost the productivity of the production industry and improve client satisfaction by giving high-quality products on time.
The definition of parts assembling and material handling encompasses a wide variety of solution activities for the retail outlet. Part identification, transporting, packing, palletizing, loading, unloading, stacking and emptying are the operations that are to be performed during material handling and parts assembling. Engaging the labour for all these operations increases the cost of the handling and also time consuming. Using the robots for these operations will automate the process as well as increases the productivity. A robot performing material handling is shown in Figure1.18.

Figure1.18: Robot is performing material handling. (https://www.robots.com)

1.4.4 Role in hazardous environments

An effective tool for ALARA, robots are able to go into the radiation control area and perform operations, recording critical data and protecting persons at safe standoff distances. PackBot and Warrior are another two example robots, have been performing operations in the areas of disabled power plant where radiation levels and temperatures are too high and unsafe for people. An example of ALARA Robot hand for hazardous environments is shown in Figure1.19.

Figure 1.19: ALARA Robot hands for hazardous environments. (http://www.irobot.com)

1.5 Motivation

Now-a-days robots are playing a key role in all engineering applications. The existing robots are only designed for the particular type of task only. It is imperatively critical that the robotic hand is intended to match its workplace. However, neither can effectively check irregularities inside of the robot's workspace. Different sensor information can be utilized to change the development of the interfacing joint; a combination connected with map planning and sensor information helps in removing the drawbacks. Involvement of additional sensory devices to improve robustness, flexibility and performance of common robot applications are aimed at **Jorg et al., (2000)**.

For the robotic hand, the reaching and grasping problems without knowing the precise area of a target involve utmost importance in regards to the control of a robotic hand inside joint space. Consequently, current research described in this thesis is concentrated in this area of sensor integrated control.

Till now there is no such type of gripper which can carry different shape and different material objects. This problem motivated me to carry the research work in that area. The work is mainly focused on design and development of sensors integrated intelligent robotic gripper which handles different types of objects with different material during assembly operation in industries.

1.6 Broad Objective

The main objective of the research work is to design and develop an instrumented robotic hand with the aid of multiple sensors for assembly work in the industrial environment. Precisely the objectives of the present research work are;

1) To carry out a critical study of different sensors and actuators for the robotic assembly related problems.
2) To adopt some existing sensors according to their suitability in term of specifications such as their shape, size, response behavior for the intended actions.
3) To integrate all adopted sensors with the motion of the robot and to conduct an experiment and check the result for real implementation of the system in industrial environments.
4) To analyze the efficiency of adopted sensors and comparison with the other existing result for other sensors.
5) To recommend the appropriate techniques for sensor integration to real-time application.

1.7 Methodology

The research methodology consists of a number of discrete stages leading to development of an intelligent hand for robotic assembly.

Stage -1: In this stage involves the study of the literature review.

Stage -2: Formulation of the research problem.

Stage -3: Determination of sensor requirements robotic assembly in the work environment.

Stage -4: Selection of appropriate sensors.

Stage -5: Carrying out experiments with individual sensors to ensure their suitability for the purpose.

Stage -6: Integration of sensors with Industrial Robot.

Stage -7: Implementation of the developed system for various assembly operations.

A complete chapter (Chapter 3) is devoted to explaining the research methodology.

1.8 Organization of the thesis

The present chapter 1 is the introduction chapter gives a brief idea about the history of an industrial robot, classification of robotic hand or gripper, classification of robotic sensors and application of industrial robotic hand in the various field. Apart from this introduction chapter, the thesis organized as follows:

Chapter 2 provides a review of literature based on different aspects of the multi-fingered hand like structure, control, optimization, gasping etc. Some of the important literatures are presented in a table and a brief analysis is made on the outcomes and shortfalls with respect to multi-fingered hands. The objective of the research work is also defined and presented based on the analysis of the review of literature.

Chapter 3 discusses about the research methodology. It provides a brief idea about the different steps should be carried out during the research work. In this chapter different activities, research methods and tools used for the present research work are presented briefly along with the scope of the present work.

Chapter 4 discusses the design; control and stability of the feedback system from integrated sensors, and implementation of individual subsystem DAQ modules with experimental set-up are briefly explained.

Chapter 5 explained about the intelligent vision system to recognize the perfect grasping parameters, and the objects are considered to identify feature depiction along with methodologies and algorithms.

Chapter 6 devoted to design and development of prototype robotic hand, in order to increase the intelligence level, sensors integrated robotic hand has been designed, simulated and developed.

Chapter 7 introduces the vision sensor affects which is mounted on the robotic hand is presented to extract the grasping points along with the results and discussion of geometrical structure for the unknown objects.

Chapter 8, base grasping strategies to find the grasping point in unknown objects has been discussed.

Chapter 9 results from the research have been discussed.

Chapter 10 concluded the overall research methodologies to design and developed sensors integrated intelligent robotic hand.

Chapter 2

Literature Review

2.1 Overview

Sensor-augmented 'intelligent' system is the state-of-the-art of present day robotics research. A multi-sensory robotic system allows the manipulator to accomplish any specified assembly task in the specified workspace with desired position and orientation of the respective joints and end-effector. A review of the available literature indicates that comprehensive research has been endeavoured in past two decades in the domain of multi-sensory robotic systems. Therefore, day by day more researchers are joining into this challenging research area with a peerage of developing a multiple sensors integrated robotic hand which will mimic the human hand. In this chapter, the various research works in the area of multiple sensors integrated robotic hands and their grasping capability analysis are presented.

2.2 Literature Survey

A chronological development of some important multiple sensors robotic hands is given in chapter-1. Based on the extensive survey of previous literature, a list of some important work done in this area is presented in Table 2.1.

Table 2.1: List of some important literatures

Sl. No.	TITLE	YEAR	AUTHOR	CONTRIBUTION	SENSOR USED
1	An adroit robot gripper for tactile sensor research	1991	Russell	Gripper was designed to investigate the use of touch sensing in object identification and for manipulation tasks.	Vision sensors
2	Intelligent gripper using low cost industrial sensors	1998	Nkgatho	Presented a unique gripper design with an efficient sensing system for electronic component manipulation.	Multiple sensors

3	Sensor system for controlling a multi fingered gripper on a robot arm	1998	Fischer et al.,	This sensor provided the control system with information about the object to be grasped.	Laser scanner, force
4	Sensor-based controlling of the objects' pose for multi finger grippers	1999	Fischer et al.,	An object-pose controller with feedback from an object-pose sensor is presented, to control an objects' movement in applications of a multi finger gripper.	Force sensor, laser Sensor
5	Implementation of sensory motor coordination for robotic grasping	2003	Hyoung and Kim	SMC algorithm is implemented on robotic grasping task. To characterize various grasping objects, pressure sensors on hand gripper were used.	Multi-sensor
6	Robotic grasping of novel objects using vision	2008	Saxena, et al.,	Proposed an algorithm for enabling a robot to grasp a 3-d model of the object. Applied a learning algorithm to process.	Vision sensor
7	Design and implementation of efficient intelligent robotic Gripper	2010	Zaki et al.,	A new sensor adapted to detect slippage is described. Intelligent gripper structure had been modeled. A new algorithm similar to human behaviour for the grasping process is presented.	Fingertip sensors, slip sensor, force sensor
8	Development of intelligent robot hand using proximity, contact and slip sensing	2010	Hasegawa et al.,	Through integrating proximity, tactile and slip senses, detection from approach to contact was seamlessly carried out, and an intelligent robot hand that could reliably grasp/seize was proposed using integrated tactile and proximity sensor	Tactile and proximity sensors
9	Highly sensitive sensor for detection of initial slip and its application in a multi-fingered robot hand	2011	Teshigawar et al.,	Designed a slip detection sensor for a multi-fingered robot hand and examine the influence of noise caused by the operation of such a hand. And described the gripping force of a multi-fingered robot hand equipped with the developed sensors.	Tactile, slip detection sensors

10	Guiding a robotic gripper by visual feedback for object manipulation tasks	2011	Kouskouridas et al.,	Novel visual feedback technique that is able to guide a robotic gripper in object manipulation tasks has been presented. Object's distances from the camera distribution alters and is computed.	Laser sensors
11	Development of vision-based sensor of smart gripper for industrial applications	2012	Hasimah et al.,	Vision sensor based of smart gripper for industrial applications is presented along with the ability to detect and recognize the shape of the object by adopting image processing techniques.	Vision Sensor
12	Development of an adjustable gripper for robotic picking and placing operation	2012	Soh et al.,	Sensor integrated gripper is designed for pick and place operation.	Multiple Sensors
13	Model of tactile sensors using soft contacts and its application in robot grasping simulation	2013	Moisio et al.,	Addressed the problem of creating a simulation of a tactile sensor as well as its implementation in a simulation environment and response methods using soft contacts as well as a full friction description.	Tactile, touch sensors
14	A 3d-grasp synthesis algorithm to grasp unknown objects based on graspable boundary and convex segments	2015	Ala et al.,	An algorithm is developed for two-fingered gripper to grasp objects regardless of their shape, texture, or concavity. The proposed algorithm overcomes the issues associated with the analytical approach, such as long computation times.	Vision, sensors

It is evident from the study of large number or research publications that appeared in various journals, conference proceedings and technical articles that the various aspects of sensor integrated robotic hand research can be classified into following sub areas: 'Industrial robotic hand'; 'Sensors for robotic hand'; 'Control of sensor integration' and 'Grasping and part recognition'.

2.2.1 Structure of industrial robotic hand

The robotic hand is one of the most important parts in robotic industries. The robotic hand is the device between the robotic manipulator and the work piece. The selection of the robotic hand in a robotic system is therefore very important.

In robotics hand is a device at the end of an automatic arm, designed to interact with the surroundings. The basic nature of the robotic hand is determined by the intended job. Although robotic hand might be broadly described in two main categories: grippers and tools, in robotics they are additionally known to as grippers.

There are different types of robotic hand, where the robotic gripper can be classified in three categories. The first one is single surface gripper, second is clamping or two/multi finger gripper and the third is flexible gripper, as explained in chapter 1.

Devol and Englberge (1959) invented the initial robotic hand for professional applications, pertaining to use with their professional 'Unimation', the first robotic hand. Robotic hands and automated professional devices were developed in parallel. This kind of gripper was designed for simply grasping and for releasing the objects in the workspace; a two finger manipulator that is still utilized in professional applications today.

Bell et al., (1996) attempted about the most typical industrial applications for automatic grippers in production are packaging and assembling, these applications being well suitable for robotic manipulators as they require precise grasping and accurate position. Robotic hands are used in packaging for the shifting of products, usually from a conveyor belt to packaging box for shipping and delivery. Robot hand is the mechanical component and should have the capacity to control the objects without harming it and place it in right position.

In addition, **Koditschek and Rizzi (1996)** described robot hand for handling the assembly line securely. The other industrial application of robotic hand is usually assembly operation. In these procedures, robotic hand is able to perform the task such as move the objects from one workspace to another workspace or according to the steps of assembly task. Another achievement of this work is the development of suction cups type of robotic hands. An illustration of a robotic application to industry is the uses of robotics technology for assembling for large scale manufacturing, such as assembly of circuit board. The aim of the thesis is to develop a perfect platform with sensor integrated, i.e.

sensitive robotic hand which is capable of working in an unstructured dynamic environment.

Hinrich (1961) introduced the first sensor integrated robotic hand developed in MIT, Massachusetts (USA), such as the manipulator 'Unimate', The aim of the proposed idea was that by using two clamped fingers, the object should be grasped. The robotic hand applies the force, and senses at the contact point using tactile sensors. Previously, if the robotic hand failed to perform the task on an object or the object slipped out from the robotic hand, then the hand would not know the situation and process will continue to fulfil the steps of movement task. To solve this problem by including affectability, the robotic hand should have to be ready to distinguish the measure of constraints it is applying to the object.

Step by step changes in improvement and development of the robotic hand from the last 51 years as a historical summary are present in the Table 2.2. Robotic hand was created to perform more unpredictable industrial task using intelligent advances in both design and controls. Robotic hand with multiple numbers of sensors to increase the sensitivity and adaptability based on the requirements of fingers has been investigated for many applications.

Table 2.2: Historical summary of robotic hand

Sl. No.	Year	Invention	Summary
1	1959	Unimation	First industrial gripper
2	1961	MH-1	First sensitive mechanical robotic hand
3	1961	Unimation	First industrial gripper installed in a facility
4	1963	Rancho Arm	First gripper not made for industrial applications
5	1974	Silver Arm	First autonomous gripper that used feedback from touch and pressure
6	1976	Shigoe Hirose	First soft gripper that could conform to shape of grasped object
7	1978	Nachi	First electromotor-driven robot hand
8	1982	Salisbury hand	Three finger hand build at Stanford university
9	1987	Shadow hand	First commercially available humanoid robotics hand
10	1991	Haptic hand	First haptic system implemented on a multi finger hand
11	2005	Luke Arm	First fully functional prosthetic arm and hand
12	2008	Robotiq	First flexible and adaptive three finger gripper on commercial market
13	2009	Switzerland	First prosthetic hand that can 'feel'
14	2010	Universal Gripper	First gripper that doesn't have digits

At present, generally industrial robotic hands are intended to focus on industrial purposes and must be redesigned in order to perform additional tasks as briefly introduced by **Okada (1979).**

Chen (1982) provided an overview of mechanisms for the grasping in industrial robots. Also described the variety of conventional grasping plans used for industrial robots, and classified these according to kinematic pairs. Many gripping mechanisms containing linkages, gears, cams, screws and flexible bands scattered from various sources are also presented. Several types of versatile grippers including the mouldable grippers, the inflatable grippers, the soft fingers, and the anthropomorphic three-finger grippers are also presented.

Crisman et al., (1996) demonstrated the grasping process by using the control strategy. They also demonstrated fingertip grasping plane when the object was positioned with the finger- tips creating contact with the objects. The limit switch sensors were used with certain limitations. The inadequacy of the sensors becomes more evident when the object under consideration has a large length to diameter ratio, and attempts are made at manipulating the grasped objects. Superior sensors such as tactile sensors would improve the performance of the hand, especially for the purpose of manipulation are briefly explained.

Almost every robotic hand is required to be modified by the manufacturer to provide an accurate measured value of new object geometries and exact shape specifications. In general, mechanical robotic hands with two parallel fingers closing/ opening method in many cases are synchronised to offer good functionality. In professional applications, selection of robotic hand is determined by the tasks, specific parts, and requirements, as proposed by **Wolf et al., (2005)**

Mock (2009) performed the operation for a variety of object geometries and shapes; a specific robotic hand is required is explained in brief**.** However, the state of the art and latest changes in the robotic hand requires increasing the motion capacity for essential time, resulting in redirection of production delays, as presented by **Laliberte and Gosselin (1998)**.

Belter et al., (2011) described the low-cost level robotic hands are essential to customize the requirement of industrial robotic hand needs in order to give flexible openings of manipulator/end-effector.

Aukes et al., (2012) described an under-actuated robotic hand, which is able to conform to objects of various shapes and utilize selective locking to achieve grasping that is possible with the given transmission. In addition, also explained the selective locking allows the hand to perform certain manipulations of objects within the fingers.

Laliberte et al., (2002) described the advanced and modular robotic hands equipped with the smart sensors are latest research focus for engineers to be able to design multi usage flexible robotic devices. In addition, multi-fingered robotic hands are also popular regarding grasping solutions on things that need holding and controlling the industrial operation.

Birglen et al., (2008) explained multifunctional robotic hand enables robots to grasp the dissimilar parts in different geometries; in this way increasing the flexibility of the robotic hand and provides the ideal opportunity for the changes in today’s devices. Generally, the quantity of actuators present in a gripper decides its degrees of freedom (DOF). Higher number of actuators build the flexibility of the holding device.

Herder and Kragten (2010) described and developed a platform to perform the symmetrical grasping by compliant or under-actuated gripper, and experimentally assessed in an effective, the way to measure frictionless grasping of cylindrical objects achieved by using objects consisting of separate disks, which can independently rotate about the same vertical axis.

Krut et al., (2010) evaluated the amount of manipulator positioning error that results in a successful grasp. They also described with experiment, how this hand autonomously grasps a wide range of spherical objects positioned randomly across the work space, guided by only a single image from an overhead camera, using feed-forward control of the hand.

Belter and Dollar (2011) presented a novel method of under-actuated grasp coupling, utilizing friction and allowing increased stability and adaptability of robotic grippers. They explained the variable friction within the coupling element helps the system maintain kinematic form closure while not affecting non-closure forces during grasp acquisition.

Also a prototype system was demonstrated to increase the stability of objects within the grasp as compared to traditional coupling mechanisms.

Odhner and Dollar (2011) presented the design of under-actuated robot hands capable of performing manipulation tasks, and explained about elastic elements at its joints. Then the velocity of the actuators was mapped onto the velocity of the grasped object using elastic averaging. They also demonstrated that holonomic-ally constrained grasping analysis to determine the manifold of stable object configurations that can be reached from some initial grasp.

Odhner et al., (2013) designed and developed a grasping method for precision grasping and manipulation of small objects. They introduced the flip-and-pinch task, in which the hand picks up a thin object by flipping it into a stable configuration between two fingers. They also demonstrated the hand and fingers interaction with the table surface to produce a set of constraints that results in a repeatable quasi-static motion trajectory. In this manner, under-actuated gripper is provided a more significant grasping adaptability. They are more proficient, expend less power, and are less complex. An attempt was made by **Zhao (2007)** to interface and design sensor integrated robotic hand in a complicated procedure, which includes individual parts of mechanics, activation system, and controller.

2.2.2 Sensors for robotic hand

Most robot manipulater applications require a robotic hand to take action acording to the industrial operation or move the objects from one space to another worksapce with rapid speed and precision. To indentifiy the exact position of object and proper speed of the robotic hand, smart sensors play an important role to achieve the objective.

Richtsfeld and Vincze (2008) explained the evolution in robot industries to utilize the sensors mounted on the robotic hand to improve intelligence level and measuring the unknown variables for automatic industrial execution. It was initially proposed more than twenty decades ago. Figure 2.1 presents the review of the approximate figures for various type of sensors used in robotic applications.

Saxena et al., (2008) approached for the intelligent robotic device to handling the object and performing the tasks. They claim that smart sensors are widely adopted by researchers and industry. Many research institutes are involved in a new era of research in the field of sensor integrated robotic system and automation industries.

Huebner and Kragic (2008) presented an idea and focused on the box representation itself, using grasp hypotheses from box face methodology. To determine the exact grasping position, they applied a heuristic selection integrating task by using off-line trained neural network.

Popovic et al., (2010) described that many smart sensors are regularly considered for this same reason. Then again, inexpensive sensors, for example accelerometers and gyros can be used to enhance the payload estimation for precise execution. These kinds of sensor measurements are generally contaminated via environmental noise. Researchers **Bodenhagen et al., (2009)** and **Bohg et al., (2011)** explained the best way to use these kinds of sensors is to improve capability and sensitivity of industrial robotic hand.

Dragiev et al., (2011) presented a novel object representation for robotic grasping and sensor fusion based on implicit surfaces and couples it with a robot movement control system. The overall scheme was able to approximate a large variety of object shapes, and to achieve fluent reach and grasp movements; a redundant robot with a tactile multi-finger hand was used.

Jiang et al., (2011) addressed the issue of end-effector tracking control planning of robot hand with high flexibility. Indirect method for link deflection sensing using vision sensor was presented. Also vision feedback based control method was demonstrated to increase the effectiveness of proposed system.

Aleotti (2011) presented a novel method for robot manipulation planning that enables semantic grasping of unseen objects. The approach was based on programming by demonstration in virtual reality and 3D shape segmentation. The proposed manipulation planning system learns from human demonstration and was capable of performing intelligent grasps of objects by their parts.

Rollies (1975) discussed the purpose of the vision sensor in verifying and finding the location of object and total number of objects by searching within small "Region of Interest (ROI)" inside in the captured picture.

Weiss and Sanderson (1987) extracted feature from image and identified the control parameters of robotic system. The captured image was used for image segmentation which helps in determining the feedback signal for controlling the robot manipulator.

Kent (1984) proposed an idea of world model as a sensor independent interfacing for the robot, which is used to integrate sensors along with various algorithms to increase the intelligence of robot.

Howe and Cutkosky (1990), explained about the adaptability and strength of a controller with a mounted tactile sensor in the end of the robotic manipulator. A two fingered robotic hand system was utilized to decide the grasping point and applied force on object. Investigation of both robotic hand and the grasping manipulators were evaluated by researchers on the basis of flexibility and controllability. And the research outcomes showed that the feedback control system was very accurate and precise for the grasping and manipulating using multiple sensors.

Bergqvist (1996) explained the detection of errors during assembly. The sensors used were a combination of accelerometers, force/torque, and electrical contact with electrical contact indicator. The design and development of the instrumented robotic hand and the integrating position of the tactile sensors affected the industrial operation. Also the movements of robotic manipulator gave some sensing error during experimental testing. After the comparison of human grasp planning on the moved objects, they found designing limitations in the robotic manipulator. An integration approach of vision sensor is used to control the system structure for grasping and handling the objects.

Caicedo (1996) described a hardware and software infrastructure for carrying out tasks assembly and combination of four ultrasonic transducers with two force sensors in unstructured environments.

Ishikawa (1996) proposed a method for sensor fusion of vision and force to estimate contact position between a grasped object and the other objects in the environment.

Bell et al., (1996) simplified that vision sensor system are capable to control the feature position and orientation of unknown objects in the work space. To estimate the geometrical model of the target, captured images were used to identify the position and orientation of objects. The error between the required position and actual position of robotic hand were evaluated. They conclude that, the process of sensor integrated robotic hand has the limitation to calibrate the sensor's feedback signal error; they calculated the estimated values to function the control system. The same problem is further cleared up by the work of **Koditshek and Rizzi (1996)**.

Malcom (1996) additionally examined the method of control system was based on image processing, where the estimated error signal was determined by comparing the position of the extracted image with the current captured image, done by using the method of feature extraction, the feedback signal provides the location of ROI in the present image. Then the matrices of the system are represented by a Jacobian matrix which relates the modifications in the processed image to the robotic manipulator position. The movement of the object in the image was processed to be used for inverse kinematics. Thus, the accurate position of the robotic hand is less sensitive as compare to camera calibrated error.

Kelly (1996) explained the utilization of visual information in the methodology of a robot controller to grasp parts and discussed about the visual servo for robot controller to handing the robotic hand for desired target utilizing an integrated vision sensor. Speed of the joints in the robotic hand are the prime input to control the main system to execute the vision processing by which the exact position of the robotic hand can be calculated.

The same work is extended by the **Cojocaru and Tanasie (2008),** who examined the implication of vision sensor calibration for accurate positioning and precise orientation in the process of image extraction to control the robotic arm.

Eggenberger (1997) discussed the specific favourable conditions to formulating a neural network system to enhance the operation of a robot hand. The experimental work was examined by the researcher to utilize a vision sensor to focus onto the workspace and concludes that, the robotic controllers are able to figuring out an object position at the central point of the field. This approach allowed higher accuracy, level of precision and less calibration issues when the robotic hand performed the assembly operation in the workspace. However, the time taken by robotic hand to execute the operation in the real-time environment to achieve the target in a specific region of interest (ROI) can be estimated, and it is possible to control the positioning error by using vision sensor.

Giovanni and Santochi (1998) described multiple sensor integrated systems for evaluation of assembly systems in unstructured environments. **Norberto (2000)** demonstrated the integration of force/torque sensor capabilities into user applications, especially industrial robotics applications.

Horaud and Skordas (2001) explained the methodology to identify the unknown objects by using digital image or binary image. Using this proposed method captured image was extracted and universal features are evaluated. The procured image of object is recognised whenever a complete set of captured features matches along with the pre-stored image features to identify the targeted object. They found that by installing a vision sensor system, robotic industries are capable to identify the object when they touch or somewhat overlap each other, to identify more than one object and are also able to control the robotic hand with higher flexibility.

Agarwalla and Hutto (2004) explained about the combining of acquired information of sensors from multiple sources to enhance the capability and efficiency of robotic hand. They also explained the necessity to integrate the internal and external sensor and their information of the estimated error to be evaluated by feedback control system. They considered that the sensor integration on robotic hand is the one of the needs to increase the intelligence level of automated robotic system. This is later required in application field of nuclear industry to complete the task in hazardous environments.

Bach and Jordan (2002) explained and described about multiple numbers of sensors were integrated into a system such as vision, proximity and tactile sensors to give abilities that single sensor alone can't give. This research work is continuously figuring and enhancing the efficiency of sensor integrated robotic hand.

Gomez and Helgenberger (2004) proposed the learning algorithm to recognize contrast of the colour difference among the objects under detection process. A vision sensor is mounted at the fixed position in workspace, and monitors the movement of the robotic hand in the workspace. With the vision sensor, the robotic hand is capable to recognise the difference in colour contrast by using Hubbian learning methodology. The matrices are formed for the three basic colours that are for red, black and white, and then the contrast of colour differences are compared with each other.

Harri (2004) used an idea to control the robotic system by involving input signal based software control devices. He also explained that this completely depends upon the extraction of the sensors information, to enhance the speed of the robotic hand in real-time operation. These procedures were utilized as a part of this technique in the current research with some accomplishment.

LaValle (2006) proposed a planning algorithm using multiple sensors for unstructured assembly environments imposing a number of additional difficulties for motion generation. An object detection system to work in real-time is addressed by **Zhang (2007)** by using image processing at various resolutions.

Lee et al., (2007) conferred on multiple ultrasonic sensors are integrated via dissimilar widths of beam array for robot navigation. To identify the environmental condition using ultrasonic sensor through minor beam-width provides decent resolution and here still we need more sensors to recognize obstacles in unstructured working environments.

Eggenberger and Ashutosh (2008) enhanced the same work, utilized a fixed vision sensor mounted in the work-space and another vision sensor was integrated in the robotic controller wrist. The robotic controller gained positional data from the fixed vision sensor and then utilized another vision sensor to recognise the grasping point of the object. After calibration of both vision sensors, two separate coordinate systems obtained the error for grasping objects.

Driemeyer and Saxena (2009) found the problem regarding integrating grasp using vision sensor, and researched on the problem to grasp the object using vision sensor system. In the proposed methodology, the vision sensor was integrated in wrist of the robotic hand. The robotic hand estimates the exact location and orientation, using probabilistic model to grab the unstructured objects in the work-space. The capability, to recognise the objects by captured image using two-dimensional representation, and to identify the grasping orientation by robotic hand were explained with various concepts. Sensory data measurement schemes that can be integrating the three-dimensional touch sensor with huge amount of force range are proposed by **Mei et al., (2011)**. Force/tactile sensor for intelligent gripper robotic applications are briefly explained by **Maria et al., (2012)** and **Kim et al., (2007)**.

2.2.3 Control of sensor integration

From the perspective of intelligent robotic hand, various types of robot platforms have been developed and proposed on different grasping systems, robotic systems, and sensing algorithms and their implementation with various control systems. A sensors integrated intelligent robot hand system to adapt in unstructured environments automatically is explained by **Zhou and Wang (1989)**. The sensor integrated robotic control system is basically divided in two categories. The first one depends on the industrial robot while the other one depends on the specially developed robot system for a particular task.

Lee and Park (1999) determined the previous work was related to the closed loop control system, which was completely based on the two individual systems, i.e. robot control system and sensor integrated intelligent robotic hand system. Today, industrial robot is common, where the human operator can control the robot motion for desired orientation and position using tech-pendant. This procedure was understood and controlled via online teaching schemes. Thus, a more flexible system was demanded. In order to adapt with these industrial demands, the automotive industrial developments have increasingly intelligent and flexibile systems using sensors integrated robotic hand as well as off-line programming (OLP).

OLP has been extended and different methods have been introduced in this way. Virtual environmental robotic system is a conceivable solution in encouraging OLP. In this control system of charge-coupled device (CCD), for example vision sensors or cameras are utilized to recognize position of the desired object in uncertain workspace, and generate the virtual model of the robotic system. National University of Pusan formulated a programmed off-line teaching platform for teaching a robotic operation using OLP with the sensors for vision data. Captured image data of the object is delivered to an operator that inputs the desired position and orientation of the image. In order to achieve the sensitive and flexible robot system, control system architecture (Chapter 3) should be able to perform the operation directly in the workspace. Therefore, the specific object can be assembled or moved from one space to another space.

Hong and Choi (2001) projected a plane to integrate the combination of software and hardware for object orientated architecture to control a robot hand. However, the controller of system depends on the PC based open robot control (PC-ORC) method, which can be reprogrammed to control the robotic system for different unstructured environments with higher flexibility and intelligence.

Friedland et al., (1973) proposed the idea to applying the Kalman filter in acceleration measurement, estimation of the velocity, position and modelling of the kinematics. They demonstrated that the positional and velocity errors in a sampled information system can be saved to estimate the characteristic errors of the sensors.

Shim et al., (1998) extended the KKF that fuses accelerometer estimations was initially proposed for a calibrated motor system. The encoder and accelerometer measurements were synchronized to estimate the velocity of an object. They experimentally estimated and proved that the Kinematic Kalman Filter (KKF) produced the perfect estimate values to control the action of integrated sensors system without any delay.

Nam and Dickerson (1999) explained the various robotic hand sensing and detecting procedures, the Kinematic Kalman Filter (KKF) was the most usable filter for fusing the sensors and estimates of errors. The primary thought of the KKF is to apply Kalman filter to an acceleration measurement, estimation of the velocity and modelling of the kinematics.

This same thought was further improved by **Lee and Tomizuka (2003)** to estimate the multiple values of proposed system, where the sampling rates of the accelerometer and encoder are individually estimated. They exhibited that the multiple rate KKF performed superior as compared to the single rate KKF.

Jeon et al., (2009) described the intelligent sensor technologies to enhance the efficiency and sampling rate of control system to fulfil the requirements in the robotic industries. Therefore, to estimate the multiple rate of KKF, the various sensors such as vision, gyroscope and accelerometer were used to recover the estimated values, and to provide the state estimate errors of the robotic hand precisely in real-time.

Over all there was a considerable amount of research information for KKF, they mostly concentrated on the integration of various types of sensor measurements to be able to estimate the error state for robotic hand. Also they discussed about the feedback control loop signals for KKF estimation are described by **Cheng and Tomizuka (2010)**.

2.2.4 Grasping planning

One of the most significant challenges of robotic hand system is grasping and manipulating the objects in unstructured environments, where geometrical properties of object are usually unknown. The uncertainty relation between robotic hand and object can be evaluated, for successful grasp, if the grasping point and contact force of gripper is fit to the task. Another approach to resolve such grasping domain can be illustrated by the environment structured to handle the industrial operations of an assembling sequential system required the area, dimension, and properties of the object along with sensory feedback system. An "unstructured" grasping task can be performed with a learning methodology to recognise the properties of the objects and environment, such as - object size, shape, mass, surface properties, position along with orientation, using smart sensors.

Stansfield et al., (1991) presented a robotic control system for grasping 3D objects using a six DOF PUMA automated arm along with a mechanical robotic hand. Initially each object was kept on workspace and on conveyer belt, then the object was moved and the object structure acquired using a laser scanner to create 3D point cloud. These data were then used to shape a 3D model of the object in the robot control system. The model was then evaluated into the (top, left, front, back) viewpoints by the controlling devices. The 3D model and the information of orientation angles to grasp the object were calculated.

Taylor et al., (1994) discussed about a method for picking an object from the top of an object. The hardware consisted of an ADEPT-1 robot having a parallel jaw gripper and a wrist mounted vision sensor. The vision sensor was moved around the object, measuring the curvature of the object boundary and looking for increasingly better grasping point based on its image extraction.

Bendiksen and Hager (1994) considered a parallel jaw gripper as well as a grey scale camera to recognise the edge details regarding objects in the workspace. Then they applied a search using polar coordinate centred process to find the grasping points on the grasping object.

In another grasp arranging strategy "Oct-Trees" were utilized to demonstrate the object. Oct-Trees represent the object as a binary 3D matrix involving cubes of (x, y dimension, and perpendicular to the z dimension). Moreover, every objects of 3D Square can be separated into eight sub-3D squares, and then using binary added matrices grasping points are calculated as explained by **Jackins and Tanimoto (1980)**

A Microsoft stereo vision system was developed to capture the unstructured objects; captured images were stored for reference. This is taken from workspace using fixed vision sensor and these images stored to create 3D depth matrices. A heuristic method transformed the depth map into the 3D virtual map, which can be segmented in to individual objects. Then the Oct-tree representation was used to grasp the object.

Bard et al., (1995) found the drawback of this vision studio system is that it cannot provide sufficiently good modelling of object. To resolve this problem, a CAD model can be used for the grasp planning of objects. To achieve the grasping procedure, the developed model was sliced in to thin layers and the area occupied in elliptical shape was compressed. The shapes of ellipses were segmented around the object till the robotic hand fingers were able to grasp around them. Then, each slice was recalculated to construct a three-dimensional model of the object for accurate grasping**.**

Trobina and Leonardis (1995) described utilizing a Mitsubishi MV R1 robot with a two finger parallel robotic hand. A range sensor and two integrated strip projectors were used to develop a model of the unknown objects. The largest object was picked and placed first, and then a new 3D model was reconstructed. To explain the results - a milk container, coffee mug, and liquid jug are tested as objects. Utilizing an automated robotic arm Motoman SV3X equipped with a two finger robotic hand and a JAI M70 vision sensor.

Sanz et al., (2005) considered an assumption to create Z-axis coordination for the objects. This was then combined with x-y axis coordination, which reduces the problem of 3D grasping. Finally, from the captured image, the exact grasping points were found using visual centroid and least inertial axis. Grasping process was based on the circumstance of the contextual points, which make the contacts between robotic hand fingers and unknown objects.

Miller (2004) proposed a novel methodology to improve the shape models of 3D object was described. Construction of the 3D model was split into basic simple shapes by the operator. These shapes involved circles, triangular, cylinders and rectangular. The reorganized shapes were then filtered by using grasping methodology using heuristics grasp generation model. These grasps were assessed with the simulation of unreleased 'Grasp It!' They did not validate the methodology with physical experiments.

Bone et al., (2008) described the six degree of freedom robotic manipulator integrated with two finger robotic hands, vision sensor and a laser sensor was used for the same purpose. **A** pillar model was used to recognise the view of image outlines. Using laser sensor, the object model was refined. Grasping points were evaluated using the location of the parallel surface of object area within certain threshold values. They used some experimental results for objects on levelled workspace.

Richtsfeld and Vincze (2003) described about the grasp planning used bounding volume of rectangle boxes using shape and size primitives of object. Each unknown object was split into a combination of bounding boxes. Boxes were described simply by properties line volume and centre of gravity, which could be effectively calculated. It was noticed that specific tasks, for example, "demonstrate the object" could be refined by grasping the object. For every bounding box the methodological vectors were taken, and the four edges of the front object were utilized for grasping orientation or position of the robotic hand.

Goldfeder et al., (2009) demonstrated a methodology that utilized partial information from integrated sensors mounted on a robotic hand, and reference image models of similar objects data were stored for grasp planning. These captured images were extracted to evaluate the depth map using the 'bag of features', shape invariant feature transform (BF-SIFT) algorithm described **Ohbuchi et al., (2008).** The algorithm of BF-SIFT finds the object model in 3D from the referred stored database that must closely matches the coordinate of scanned object.

Miller and Allen (2004) explained the selection of 3D model; the sensor information was compared with the coated model. Because of the deficiency of sensor information, the model from database and the physical object are not necessarily the same, so a few grasps will fail. To reduce this error, the grip competitors were assessed utilizing the 'GraspIt!'. The proposed system was tested with a Barrett hand.

In order to decide for grasps, **Popovic et al., (2010)** planned for a Power Cube parallel jaw robotic hand mounted on six-degree of freedom Staubli RX60, utilizing the Bumblebee2 stereo vision program to figure the contours of 2D images from each vision camera. The exhaustive search was intended to compare each figured contour with corresponding contours in the different images.

Bodenhagen et al., (2009) described a novel procedure for grasping, which was enhanced with a learning algorithm that assessed every grasp view for success at the first touch of the object with parallel gripper. This information was passed to a neural network that was prepared utilizing both offline and online learning. For the learning and subsequent testing, assessment of the grasp failed for three arrangements of objects: cylindrical, non-cylindrical, and combination of both.

Bohg et al., (2011) conclude the grasping planning in various methodologies used was explained in brief. They utilized a six-axis Kuka manipulator with an Armar III automated robotic hand integrated with two stereo vision sensor and a three fingered Schunk Hand; and additionally a Tombatossals middle system with a 7-axis Mitsubishi PA10 robotic manipulator equipped with a 4-axis Barrett Hand, two head mounted DFK 3 BF03-Z2 vision cameras and a mid-section attached Videre DcSG-STOC stereo vision camera. Stereo pictures of the unknown object were captured. To evaluate the unobserved area of objects put on a table, they accepted that most objects are symmetrical. Grasping planning depended on the algorithm introduced, where the centroid in addition to the boundary of an object were measured along with the fingertip positions. They evaluated their modelling system after performing the experiments with seven different shape and size objects located at various locations, and noted the difference between the created models and accurate visual centroids.

To design the model of object for grasping, **Dragiev et al., (2011)** utilized a Schunk seven degree of freedom manipulator, and a Bumblebee stereo vision camera. Every object was modelled utilizing surfaces estimated, based on sensor information along with Gaussian process for certain surface possibilities. Their grasp planning algorithm utilizes the typical vector, and the potential field made by the Gaussian surfaces model to choose the grasping point, and the robotic hand orientation.

Jiang and Saxena (2011) utilized a six-axis Adept Viper S850 robotic manipulator equipped with a parallel jaw robotic hand and a Bumblebee2 stereo vision camera. Grasping points were created using the orientation pose of the object; as well as the data on robotic hand finger widths and finger separations. Individually obtained grasping points were created by a two-step method. Possible grasping point are first formed from the vision stereo image information using histogram filters, and then the grasping contacts were selected based on an image set of grasping points, produced by the operator.

2.3 Review Analysis and Outcome

An exhaustive survey presented in the above section on multiple sensors integrated robot hands considered different aspects like: structure of the robotic hand, smart motion of the robotic hand and the workspace generation, control, application and grasping ability. It is observed that many researchers tried to develop a sensor integrated robotic end-effector from late 80’s to till date in order to increase the smartness of industrial robotic hand. Initially robots were used for industrial applications for performing repetitive work like pick and place same types of objects. So the prime requirement was to grasp the object firmly for which parallel jaw grippers are best option. Today, parallel jaw grippers are also used for similar purposes like transporting heavy objects on shop floor in unstructured area. But, with the widening of the area of application of robots along with industrial application to human environment for performing human like operation, and along with grasping flexibility, manipulation has become a need of robotic industry. From the literature it is concluded that, to accomplish the intelligent level of flexibility and manipulability along with precise grasping, the need of smartness arises. Figure 2.1 presents the review of the approximate figures for various type of sensors used in robotic applications.

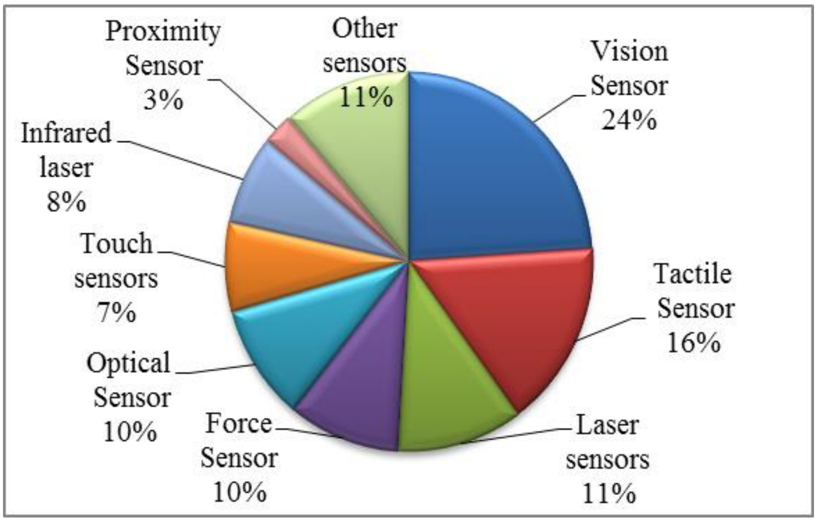


Figure 2.1: Various types of sensors used in robotic application

Almost all the research articles state that intelligence and smartness is the main focus of inspiration and design to develop a sensor integrated robotic hand. Many have tried to design and develop a hand which is structurally similar to human hand which consists of two to multi-fingers. The multi-fingered hands are used as the end-effector in robotic system, where each individual finger is considered as an open loop kinematic chain or independent robot manipulator. The main properties of the robotic hand which researchers tried to mimic are: flexibility, anthropomorphic appearance, manipulability and control. It is observed that depending on the use of the particular robot hand, specific properties are given priority. The flexibility and intelligent manipulation capability of the hand is more when the number of sensors and actuators are more, which leads to more complex control system of the robotic hand. As a result, the load carrying capacity decreases. Many hands are developed and commercialized already, which are used as part of industrial robots, service robots, humanoids and for rehabilitation.

Even many different types of sensors integrated robotic hands are developed, but this is still considered a beginning. The main objective of the research is to mimic the robotic hand as close as possible to humanoid hand. But from literature it is observed that none of the product processes all the properties of human hand simultaneously, as it is very hard to design all at the same time. Sense, think and act are the three important properties of the intelligent robotic hand, which increases the control complexity of the proposed system. To reduce the control complexity, intelligent sensors and the actuators should be integrated to increase the capability of the robotic hand. Most of the work done on grasping planning strategy for different types of grasps considers the number of contact points only. There are various algorithms proposed in the area of grasping of a robot hand, most work has been done with respect to two and three finger robotic hands. Also many works are found in the area of force exerted at contact points on the object for grasping.

2.4 Problem Statement

In the wake of reading several research works carried out in areas under investigation and considering the pattern, the results and challenges and the targets of the present work, the following problem statement and hypotheses are made:

Robotic hand is a focus point for improvement at this moment. It's also a standout amongst the most basic parts of any automated application. Industry specialists can't overstate the significance of robotic hand. It is the immediate interface between the robot and the part that it's processing or handling.

The robotic hand has its restrictions and limitations**,** "In the event that you attempt to pick an object from the side, the object is generally not heavy enough to be able to resist that force, thus the object will slide and you won't go anywhere. You need to pin it against something."

It is imperatively critical that the robotic hand is intended to match its workplace. However, neither can effectively check irregularities inside of the robot’s workspace. Different sensor information can be utilized to change the development of the interfacing joint; a combination connected with map planning and sensor information helps in removing the drawbacks. The problem of fast and programmed automatic grasping of unidentified objects are extracted the scanned data for catching point determination explained by **Liu et al., (2011)**. For the robotic hand, the reaching and grasping problems without knowing the precise position of the target, involve utmost importance with regards to the control of a robotic hand inside the workspace. Consequently, the research described in this thesis is concentrated in this area of sensor integrated control.

Problem statement:

"This research investigates the feasibility of development of a sensor integrated robotic hand to be used in an unstructured environment for assembly operations. It's easy to choose a robotic hand to handle one part, but problem arises for the cases where multiple parts are involved, or, where the parts are similar but of different sizes. Serious challenge lies in figuring out how a single robotic hand can handle such complex situations".

Hypotheses:

Hypothesis 1: Grasp intelligence might be accomplished through robotic hand design, part identification, gasping points, intelligent algorithm pertaining control of the robotic hand, and learning and decision making based on sensor feedback information.

Hypothesis 2: To integrate the sensors on robotic hand for further processing, a data acquisition system and wide range of intelligent control algorithms are proposed. This application structure will assist upgraded adaptability, flexibility, and advance user interaction process in relation with the program and coding.

Hypothesis 3: Intelligent grasping systems for object identification, as well as grasping system, grasping contact points on objects recognition may be achieved by exploiting LabVIEW experimental setup, DAQ controller's modules, and extracting object features through OpenCV using Microsoft visual library.

Hypothesis 4: A robotic hand control system can be developed using sensor information to identify and relocate the target, in addition to control the reach as well as orientation of the robotic hand.

2.5 Summary

A broad study of literature has been conducted. A portion of the more pertinent work has been detail reviewed to help learn the scope and direction of research in the area of the present work. Literature going back to 1980 till the present time were investigated and considered to comprehend the presence of extension for abetting the present work. Through this research work, the development of a near-autonomous robotic hand using multiple sensors has been attempted. A comprehensive presentation has been endeavoured through the present work for the advantage of the readers.

Chapter 3

MATERIALS AND METHODS

3.1 Overview

This chapter is dedicated to enumerate the materials required for abetting this piece of research work and the technology followed to achieve the objectives. The details of materials and methodology include hardware and software components essential for carrying out the proposed research work. The same is discussed.

3.2 Materials

The present work is essentially an experimentally intensive research work. It requires components of two types the basic components and the augmenting components. The basic in the present work are an i) industrial robot, ii) robotic hand and essential peripherals to control the robot, whereas the augmenting components are i) Sensors, ii) interfaces of NI, iii) control system and iv) motor.

The details of these components are as follows.

3.2.1 Industrial robot (Kawasaki RS06L)

In the present work an available industrial robot, Kawasaki RS06L has been used for carrying out the experiments. It is a 6-dof articulated robot with a payload of 6kg.

Figure 3.1: Kawasaki RSO6L robots

The technical specification and image of selected robotic manipulator are shown in Table 3.1 and Figure 3.1 respectively.

Table 3.1: Technical specification of Kawasaki RSO6L robot

WASAKI RSO6L	Specification
Type of arm	Articulated
Degree of freedom	6 axes
Payload capacity	6 kg
Horizontal reach	1,650 mm
Vertical reach	2,982 mm
Repeatability	±0.05 mm
Maximum speed	13,700 mm/s
Mass	150kg

3.2.2 Industrial robotic hand

There is a wide range of robotic hands to perform various operations in industry such as part assembly, welding, painting and so on.

For the present work a SCHUNK robotic hand is selected to develop an intelligent robotic hand. The technical specifications and image of selected robotic hand are shown in Table 3.2 and Figure 3.2 respectively.

Figure 3.2: SCHUNK End-effector

Table 3.2: Technical specification of SCHUNK end-effector

SCHUNK	Specification
Description	PGN-lus100-1-AS
ID	10 mm
Stroke per finger	0371452
Closing force	900N
Weight	1 kg
Min. /max. pressure	4/6.5 bar
Closing/opening time	0.05/0.09 sec
Min. /max. temperature	-10/90 °C
Repeat accuracy	0.01mm

3.2.3 Sensors components

This section discusses the augmenting components such as sensors, interfaces NI components and control systems.

The following sensors were used to achieve the required task using robotic hand;

i. Vision Sensor
ii. Ultrasonic Sensor
iii. Capacitive Proximity Sensor
iv. Inductive Proximity Sensor
v. Force/ Torque Sensor
vi. LTS Sensor

i. Vision sensor

Vision sensors are the most widely used sensors in robotics to recognise an object. It uses the processes of feature extraction and image segmentation by image processing to identify object's position and grasping point in the work environment. A vision sensor (camera) converts pixel information into the electrical signal for subsequently sampling through feature extraction as a digital image. The technical specification and image of the vision sensor used are shown in Figure 3.3 and Table 3.3 respectively.

Figure 3.3: Vision sensor

Table 3.3 Specification summary of the vision sensor

Selected Sensor	Model	Supply Volt.	Product Mass	Size (mm)	Location in the hand	Measurement Purpose
Vision Sensor	BASLER SCA640-70fm/fc	2.5 W	160 g	73.7 x 44.0 x 29.0	In the parallel position of robot hand	Acquiring an image

ii. Ultrasonic sensor

Ultrasonic sensors measure the distance of the objects in the workplace. They are utilized for robot navigation, obstacle prevention or healing the third dimension for monocular vision.

Figure 3.4: Ultrasonic sensor

The technical specification and image of selected ultrasonic sensor are shown in Figure 3.4 and Table 3.4 respectively.

Table 3.4: Specification summary of the ultrasonic sensor

Selected Sensor	Model	Supply Volt.	Product Mass	Size (mm)	Location in the hand	Measurement Purpose
Ultrasonic Sensor	HC-SR04	5V	20 g	45x20x15	Palm of the hand	Distance measurement

iii. Proximity sensors

Proximity sensors identify objects which are close without any contact. These sensors are utilized for the close field robotic functions. Proximity sensors are classified by working guidelines; such as inductive, Hall Effect, capacitive, ultrasonic and optical sensors. Inductive sensors depend on the change of inductance because of the existence of metallic objects. Hall Effect sensors depend on the connection which exists between the voltage in a semiconductor material and the magnetic field over that material. The technical specification and images of selected proximity sensors are shown in Figure 3.5 and Table 3.5 respectively.

(a)

(b)

Figure 3.5: (a) Capacitive and (b) inductive proximity sensors

Table 3.5: Specification summary of the proximity sensors

Selected Sensor	Model	Supply Volt.	Product Mass	Size (mm)	Location in the hand	Measurement Purpose
Capacitive Proximity Sensor	CR30-15DP	12-24 V	212 g	35x71	Parallel of finger	Metal, plastic, stone, wood properties
Inductive Proximity Sensor	E2A-M08-S02 Omron	12-24 V	65 g	13x40	Parallel of finger	Metallic properties

Inductive proximity and Hall Effect sensors recognize just the vicinity of ferromagnetic objects. Capacitive sensors are conceivably fit for distinguishing the vicinity of solid or liquid materials.

iv. Force/Torque sensor

The Force/Torque sensors are used to measure the force or torque during the operation of assembly operation such as material handling, screwing and pressing in page-in-holes. These sensors are also used to distinguish the positive contact between two mating parts and to measure the contact forces and torques which show up while the robot carries out the part mating operations. The technical specification and image of the vision sensor used are shown in Figure 3.6 and Table 3.6 respectively.

Figure 3.6: Forces/torques sensors

Table 3.6: Specification summary of the force/torque sensor

Selected Sensor	Model	Supply Volt.	Product Mass	Size (mm)	Location in the hand	Measurement Purpose
Force/Torque Sensor	ATI- 9105-GAMA IP65 - SCHUNK	5V	1.09 kg	111 x 52.3	On the Wrist of end-effector	Applied Force/Torque

v. LTS sensor

Tactile light touch switch (LTS) sensor gives the information about whether the robot fingers are in contact with the object or not. The technical specification and image of the LTS sensor are used shown in Figure 3.7 and Table 3.7 respectively.

Figure 3.7: Light touch switch (LTS) sensor

Table 3.7: Specification summary of the LTS sensor

Selected Sensor	Model	Supply Volt.	Product Mass	Size (mm)	Location in the hand	Measurement Purpose
LTS Sensor	EVPAA-B3FS	15 V	6 g	4.7 x 3.5	On fingers contact points	Contact information

3.2.4 Interfacing components

After the selection of industrial robot manipulator, robotic hand and sensors, the control system should be selected according to the essential interfacing and communication of peripheral device with each other.

Table 3.8: Technical specification of interfaces NI components

Control System	Model
PXI platforms	NI PXIe-1082
X series Multifunctional DAQ	NI PXIe- 6341
Motion Controller	NI PXI-7340
1394 Host Adapter	NI PXI-8252
NI CompactRIO	NI cRIO-9074
Dual GB Ethernet	NI 8234
4-Ch Universal Analog Input DAQ	NI 9212
16-Ch, 24 DI/DO DAQ modules	NI 9375
8-Ch, TTL High speed DIO DAQ	NI 9401
ATI DAQ Module	FTPS1
SCB DAQ	SCB-68A

The controlling system is to command the robot manipulator, which is going to be controlled via Digi-matrix Kawasaki library. This controlling software integrates and communicates along with Kawasaki robotic manipulator. The module library of LabVIEW VI 2013 features is used to control and command the robots directly from a front panel graphical environment. LabVIEW 2013 uses different modules to program and integrates all aspects of automation from robot control measurements, inspection as well as machine vision. Using this approach, the intelligent system is prepared to control the robotic hand. The entire application is developed in National Instrumentation (NI) powerful LabVIEW graphical design tool.

To perform the operation in real-time, system requires NI hardware peripherals like smart sensors, cameras, NI cRIO, DAQ modules and NI PXI platforms to achieve industry proven speed and reliable outcomes. Table 3.8 presents the various control modules used in the present work.

3.2.5 Control system

An intelligent robotic hand control system is usually prepared by arrangement of five key modules that execute data acquiring, part recognition, grasping point, manipulator positioning, and robotic hand control. The grasping system is able to take decision intelligently and it usually comprises of sensory data acquisition module, interfaces of NI

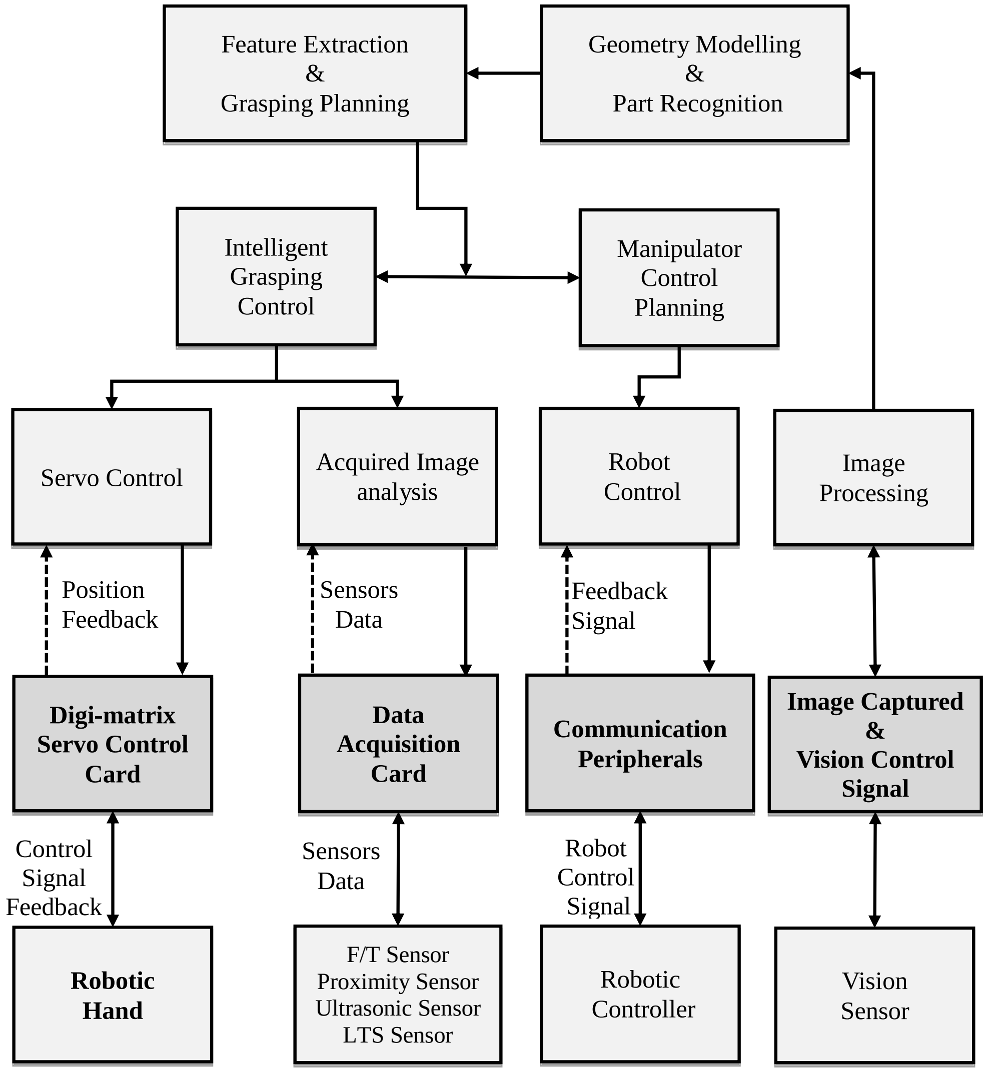


Figure 3.8: Control system architecture.

analysis module. The basic idea of control system is to design intelligent grasping robotic hand. Intelligent robotic hand control system architecture is shown in Figure 3.8.

3.3 Methods

The proposed research work aims at designing and developing a sensor integrated robotic hand. This section presents detailed chronological steps planned for completing this piece of work. It describes the methodology adopted for plan and use of the sensors, their selection and integration in to the robot hands.

Stage -1: This stage involves study of literature. A broad spectrum of the literature by almost all available sources is studied. A portion of the more pertinent work is extravagantly reviewed to learn the scope as well as direction regarding research in the area of the work.

Stage -2: After getting to know about breadth and depth of the previous research work in the relevant area the research gap is identified. Based on the study and analysis thereby the problem formulation is done.

Stage -3: Determination of the sensors requirements in various assembly operations is performed. For wide range of industrial application such as electronics parts assembly, pick and place assembly operation, and assembling semiconductors devices, the combination of sensors and their ranges are defined.

Stage -4: Appropriate sensors to identify and recognize the parts, part properties and part parameters of unknown objects are selected.

Stage -5: Robotic hand receives data from sensors. It is converted from sensor coordinate system by using DAQ to the coordinate of hand motion system. The exact size, shape, area and exact points for grasping along with material properties of targeted object are found.

Stage -6: Experiments with individual sensors to ensure their suitability for the desired tasks are carried out. Each sensor is integrated in defined range and calibrated to determine the intermediate feedback information using LabVIEW.

Stage -7: In the final stage, the developed sensor integrated instrumented robotic hand is implemented in several industrial tests for various assembly operations. Next line of the proposed research work shown in Figure 3.9.

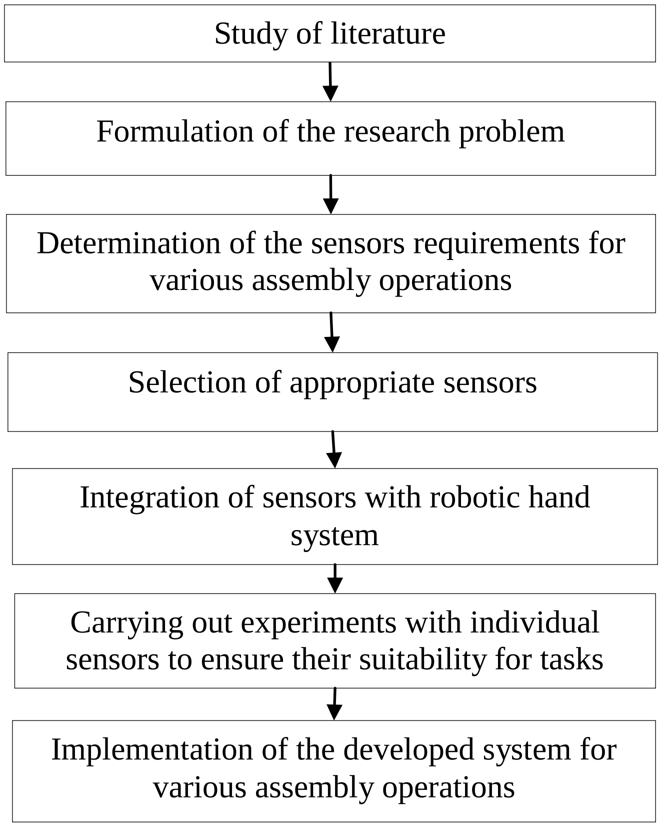


Figure 3.9: Stage of the research work

3.3.1 Interfacing and data collection technique

These sensors are mounted on the wrist, palm and finger of the proposed robotic hand. The mounted multiple sensor system is interfaced using LabVIEW 2013 hardware as well as DLL file of MS visual studio software control system. The planned interfacing block diagram of integrated sensors in the robotic hand is shown in Figure 3.10.

During the interfacing of electronic components and devices to communicate with PC or control system, there are various types of connectors and protocols, is important to interconnect with sub-systems, equipment, power supplies and memory/display units. Therefore, several types of analog or digital input/output parameters are required such as Binary signal, which is the simple 0/1 signal signified with two different voltage potentials. They are important to use as input/output for micro light touch switch (LTS) sensor or to display the signal in digital format.

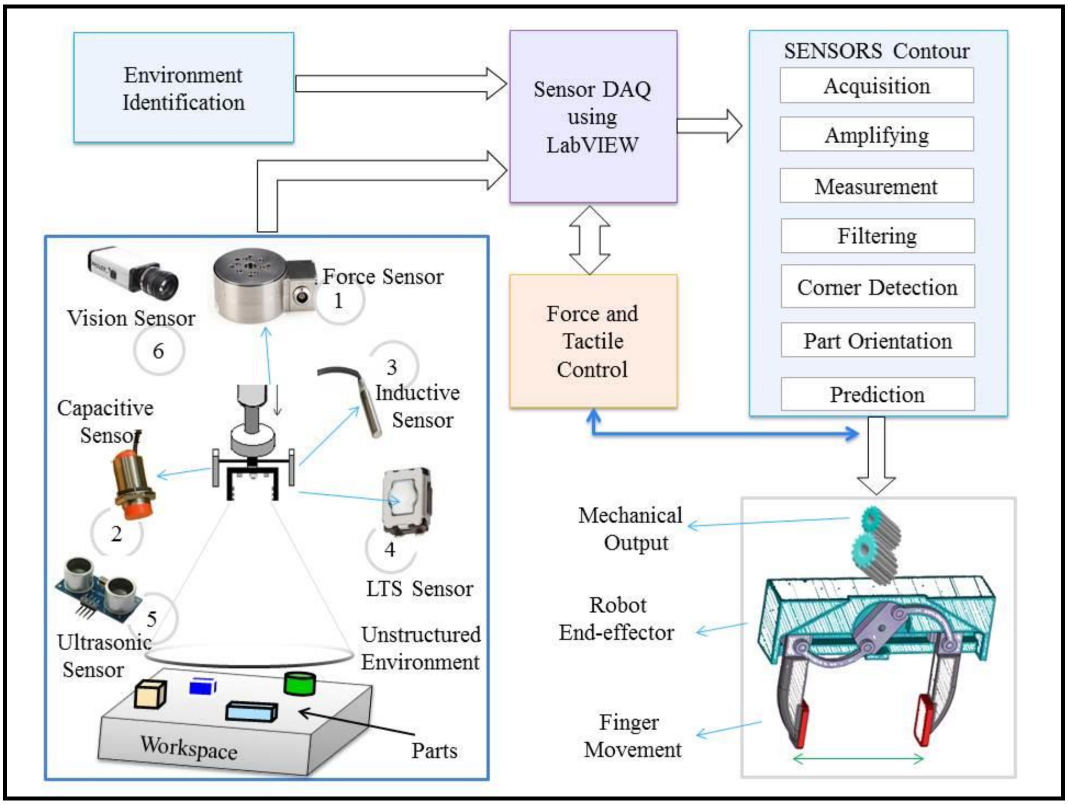


Figure 3.10: Interfacing block diagram of integrated sensors in robotic hand

Similarly, Analog signals are essential for application like distance measurement using proximity or range sensor where the variable voltage is delivered by various types of sensors. Also to control the robot hand action a specific range of voltage is required for analog output signals. This voltage can then be served to an amplifier or used straight away to drive servo motors as well as specific power supplies. On the other hand, serial or parallel interfaces also play an impotent role for peripheral equipment such as disk drives and display system. Today Ethernet connections are widely used to control robot's system. Also these are used for program development and storage within a robot control system in order to creating feedback from interfacing to the sensors. Applications such as intelligent robotic hand require a large number of analogue and digital signals in order to control the sensor's power supply.

3.3.2 Data utilization

In order to grasp an object using robotic hand detailed information about the object like metallic properties, shape and size should be required. The proposed models need the following data:

- Metallic and Non-metallic properties of object

- Size and shape of the object
- Position of the objects in workspace

Table 3.9 represents the experimental assembly task performance datasheet; first one is the identification of the part with material properties. For this operation it is required to measure the weight of the part in considered tolerable range. Similarly, for another assembly task like pushing and screwing, the weighting and picking and manipulation of the correct part for assembly, and carrying out the operation for mating the parts may be required. So this kind of performance is applicable for n numbers of tasks.

Table 3.9: Experimental task performance datasheet

S. No.	Parts	Weight of parts	Tolerable range	Material properties	Assembly task
1	a	2.5 N	1%	Metallic	Identification
2	b	4 N	0.50%	Metallic	Pushing
3	c	1.5 N-m	1%	Metallic	Screwing
:	:	:	:	:	:
n	n	n	n	n	n

3.3 Scope of Work

The present thesis aims to propose a sensor integrated flexible intelligent robotic hand model which is mechanically similar to humanoid hand, so that the robot can perform tasks with smartness and higher precision. The scope of the present work is stated as follows:

- Increase the flexibility and sensitivity levels of the robot hand in order to acquire the movement parameters that could be optimized.
- Enhanced recognition ability of the system to analyze and identify the geometric and material properties of unknown objects in unstructured environments.
- Intelligent control using physical appearance and easy assessment of various features.
- Precise grasping point identification for 2D view of unstructured objects, for pick up approaches.

- Use of standard tools/platforms and creating generic and user friendly algorithms.

3.4 Summary

The material and methodology along with brief summary of the system structures regarding hardware and software components essential for research methodology is presented in this chapter. The different activities performed during this research work along with the methods used for achieving the objectives are also discussed.

Chapter 4

DATA ACQUISITION AND SYSTEM CONTROL

4.1 Overview

Precise and perfect information is essential to control the unstructured environment using smart sensors. This chapter discusses the design, control and stability of the feedback system from integrated sensors along with LabVIEW2013 VIs and NI PXIe-1082 based intellectual grasping framework structures. Sensors based perception and fusion, incorporation of intelligent algorithms into the control systems, as well as implementation of individual subsystem DAQ modules are explained with experimental set-up.

4.2 Data Acquisition and System Control

LabVIEW has empowered researchers and inventors to improve the quality of industrial autonomous control system. At its core, LabVIEW is generally utilized for sensor and actuator connectivity along with more than thousands of drivers for measurement device to combine the graphical as well as programming code**. Masumoto et al., (1993)** proposed a sensory information processing system that can solve the ill-posed problem of sensory information processing. This system also provides a single platform environment in order to integrate multiple methodologies intended for programming, analysis and algorithm development. Furthermore, LabVIEW offers each of the required tools pertaining to robotics development. Robotics Module supports NI cRIO embedded hardware, PXIe series along with Windows-based PCs. Every single independent robot has to sense their environs, make a final decision, and then react on the workspace. The new LabVIEW Robotics module gives coding on projects to every progression of the sense - think - act process as presented in Figure 4.1.

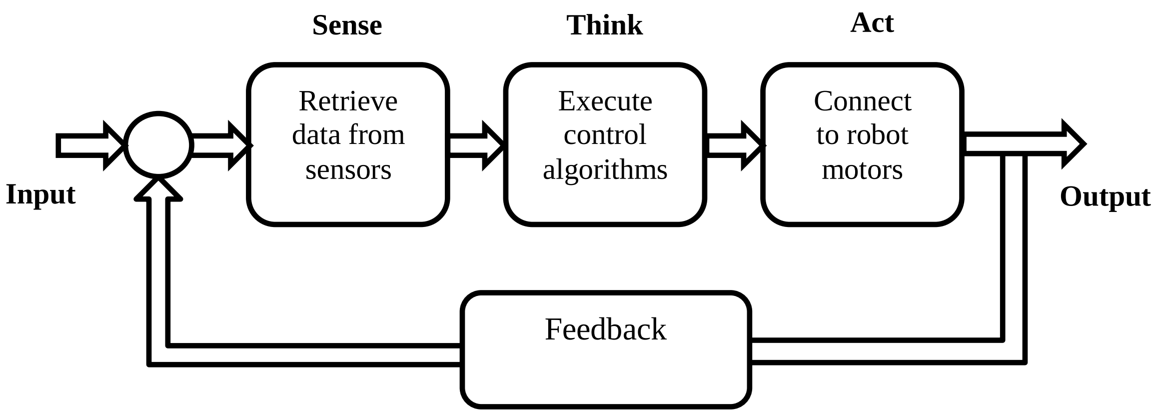


Figure 4.1: Step of the sense - think - act for DAQ system

SENSE: retrieve data from sensors

The used LabVIEW 2013 and NI cRIO instruments devices make it easy to attach to any kind of sensor signal. In addition to simple analog and digital I/O, LabVIEW robotics includes tasks for interfacing with signals using low-level protocols such as PWM, I2C and SPI. Additionally, LabVIEW 2013 Robotics contains a novel set of VIs to arrange, control, and retrieve data from the sensors.

THINK: control a robotic arm

Many robots use a robotic arm or manipulator for completing a task. LabVIEW Robotics offers many functions that are useful for robotic arms such as kinematics, dynamics, and trajectory generation. Here robotic Kawasaki libraries are used for simulation as well as final analysis of results. Once the pertinent data are acquired from sensors and robotic hand movements are controlled the next step is to apply an algorithm for further tasks. The module of LabVIEW 2013 Robotics contains innovative VIs for industrial application based on sensor feedback.

ACT: Control Actuators and Motors

LabVIEW Robotics includes drivers for connecting to a variety of actuators and motor controllers. The software module helps in controlling the actuators and motor drives, LabVIEW Robotics integration is very easy to communicate with real-time and FPGA based hardware systems, NI cRIO embedded architecture enables robot designers to implement hardware interfaces, signal processing, and real time critical control algorithms in FPGA logic, which frees up the processor to handle high-level tasks such as navigation or mission planning. Object detection systems work in real-time is addressed by **Zhang and Zelinsly (2007)** by uses images processing at various resolutions.

4.2.1 Sensors interfacing using Lab-VIEW modules

The multiple sensors can be graphically interfaced using LabVIEW 2013 through essential analog and digital data acquisition system modules. Experiments are conducted to show the correct behaviour of the sensors. As discussed previously, the innovative architecture consists of a multi-sensor system composed of a Kawasaki robot manipulator shown in Fig.4.2.

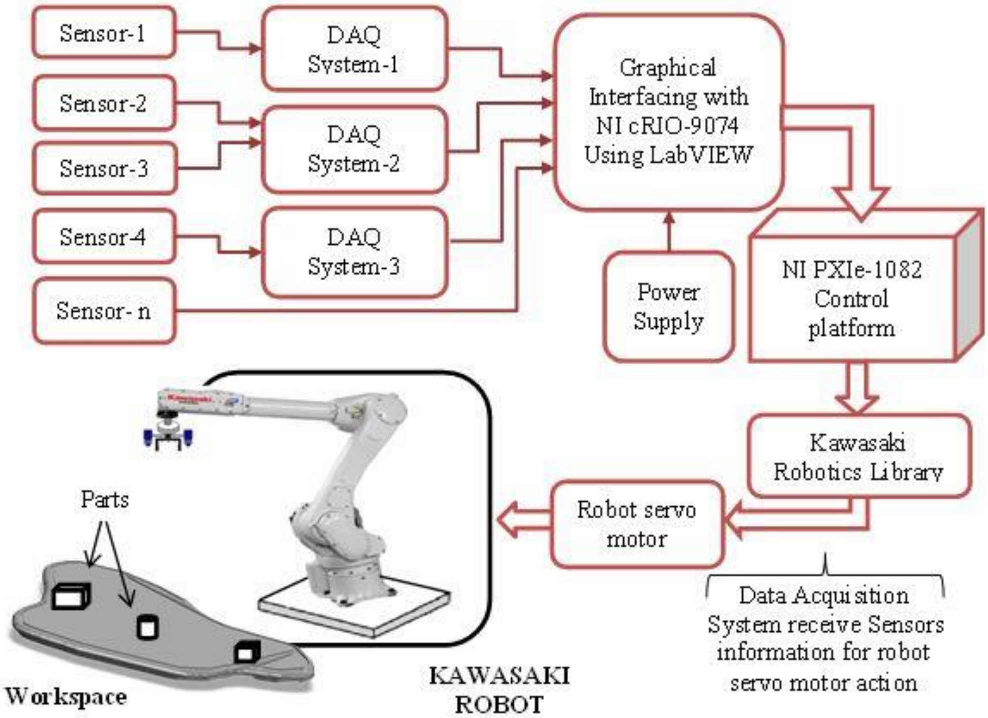


Figure 4.2: Scheme of interfacing of multiple sensors to control the robot hand using LabVIEW

The end-effector of the robot manipulator consists of a robotic hand with selected sensors and controller NI PXIe-1082. The preliminary operations depend on the communication protocol of the end-effector that is chosen to be compatible with the robot. At the moment, the designed and simulated 2-Finger Robot end-effector is consistent with three communication protocols viz. Ethernet cable, TCP/IP, IEEE-1394 and RS232. Fig.4.3 and Fig. 4.4 show the final experimental front panel and block diagram of Main DAQ VI.vi setup respectively along with all incorporated sensors.

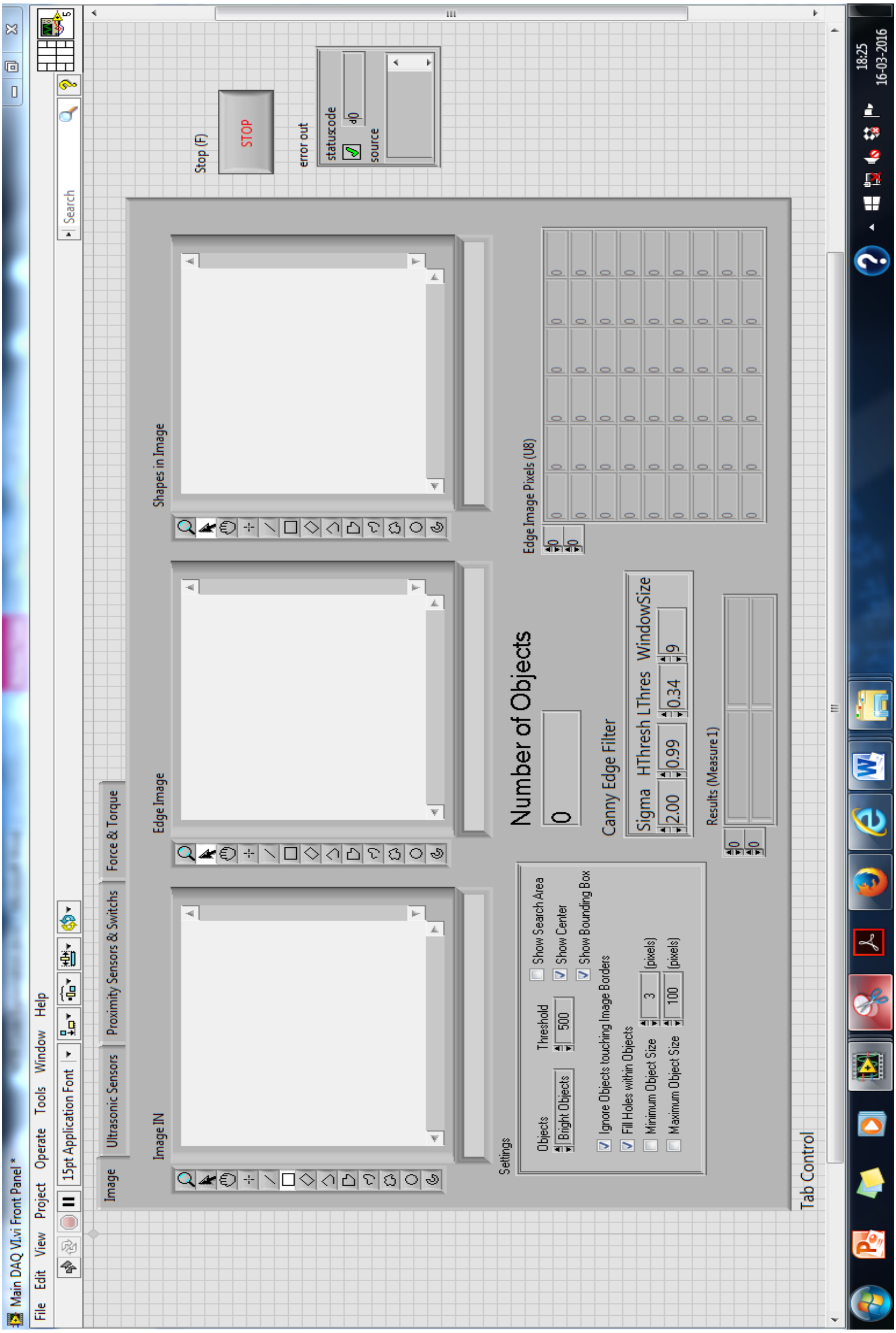


Figure 4.3: Interfacing and control front panel of Main DAQ VI.vi setup using LabVIEW

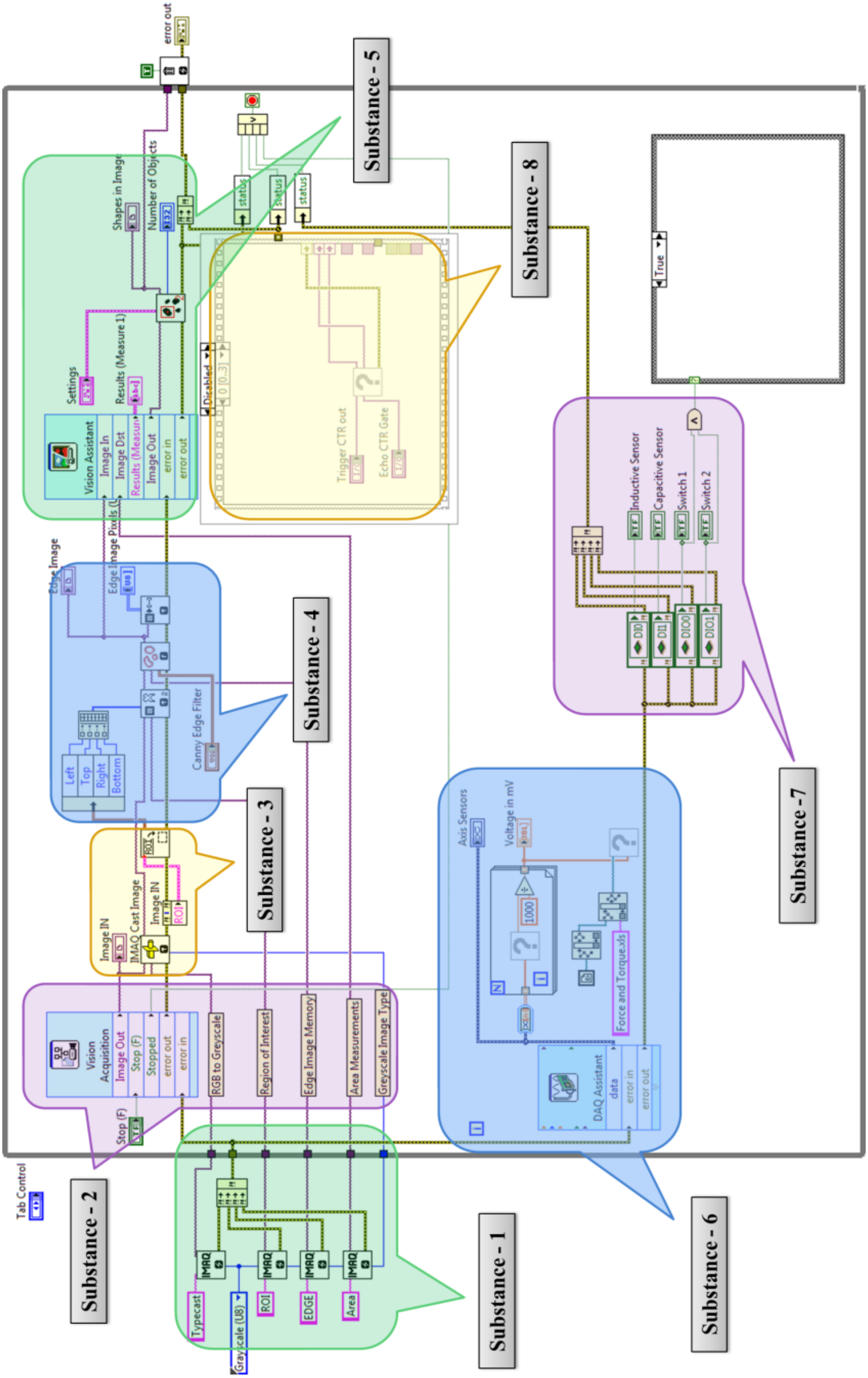


Figure 4.4: Sensor interfacing and control block diagram of Main DAQ VI.vi setup using LabVIEW

Figure 4.4 shows the complete interfacing of sensors used in the experiment using Main DAQVI.vi LabVIEW. The entire scheme can be controls to consist of eight substances are briefly explained.

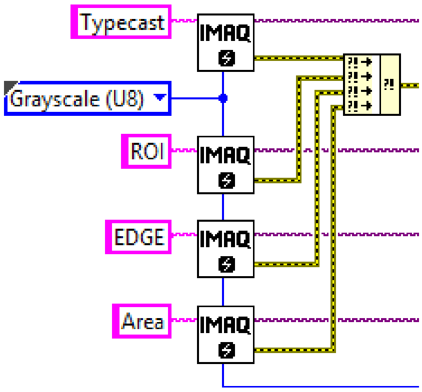


Figure 4.5: Substance 1

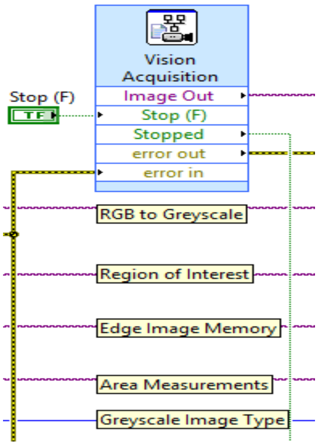


Figure 4.6: Substance 2

Substance 1: This portion is used to create a temporary memory for acquiring and analysis of informatics data of vision sensor images shown in Figure 4.5.

Substance 2: This portion is used to acquire image from the camera, which is interfaced and connected to the workbench of NI PXIe 1082 control system shown in Figure 4.6.

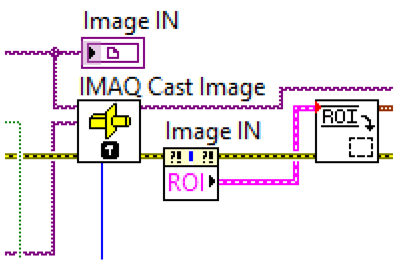


Figure 4.7: Substance 3

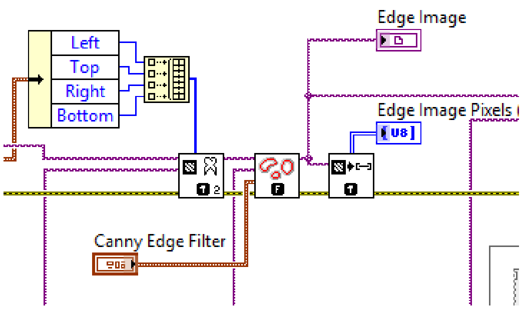


Figure 4.8: Substance 4

Substance 3: This is used to convert the image into greyscale and to identify the find the region interest to select the material shown in Figure 4.7.

Substance 4: This is used to extract the portion of the specified ROI and taking canny edge detection and converting their image into pixels shown in Figure 4.8.

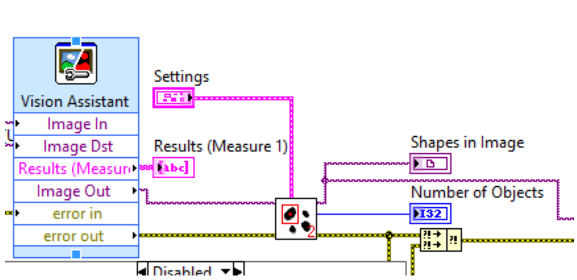


Figure 4.9: Substance 5

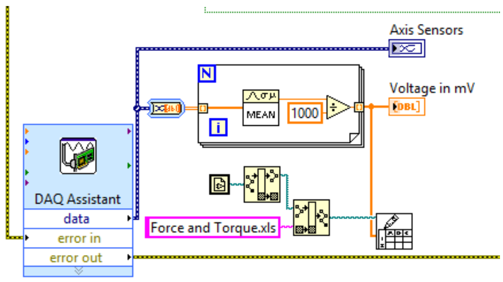


Figure 4.10: Substance 6

Substance 5: This is used to find the measurement of the object present in the selected ROI and to identify how many numbers of objects are available in the ROI specified shown in Figure 4.9.

Substance 6: This portion is used to get data signals from 6 axis Force and Torque sensors using ATI DAQ system along with central controller NI PXIe 1082 shown in Figure 4.10.

Substance 7: This portion is used to find the touch or detection information of object using proximity and LTS sensors. These sensors are interfaced using NI DAQ system along with NI cRIO-9074 Modules shown in Figure 4.11.

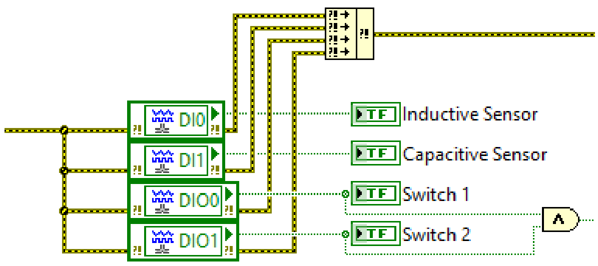


Figure 4.11: Substance 7

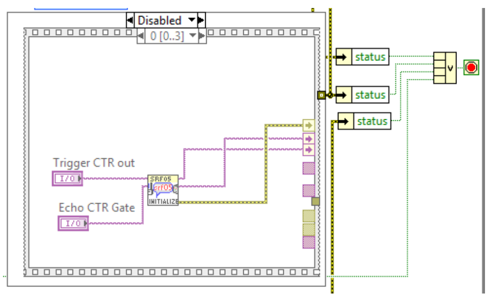


Figure 4.12: Substance 8

Substance 8: This portion is used to acquire informatics data of distance of objects for grasping from ultrasonic sensors interfaced with SCB and controller NI PXIe1082 shown in Figure 4.12.

4.2.2 KAWASAKI RS06L robot control system

Digi-Metrix Kawasaki Robotics Library v0.2.0.59 is used to control the robotic manipulator and programed in LabVIEW2013 that integrates all sensors and DAQ system with controller NI PXIe-1082 for controlling part handling and machine vision. This method is convenient to do programming on this software to complete the crucial tasks with higher precision in less time. Figure 4.13 shows the front panel and block diagram of

Kawasaki robots current position of joint displacement and transformation variable along with the communicated IP address 192.168.0.1.

The whole experimental setup is developed in NI's powerful LabVIEW 2013 graphical design environment. Integration of all proposed sensors through DAQ system is explained in real-time operation like smart cameras, NI cRIO, and PXI platforms to achieve accuracy and consistency.

Robotics Library for Kawasaki plays very important role in designing intelligent robotic hand directly using NI LabVIEW. It is convenient to control the motion with higher accuracy and it is easy to calibrate the whole system along with vision guided system. In order to test real time setup for execution of operations, all the desired experiments are conducted.

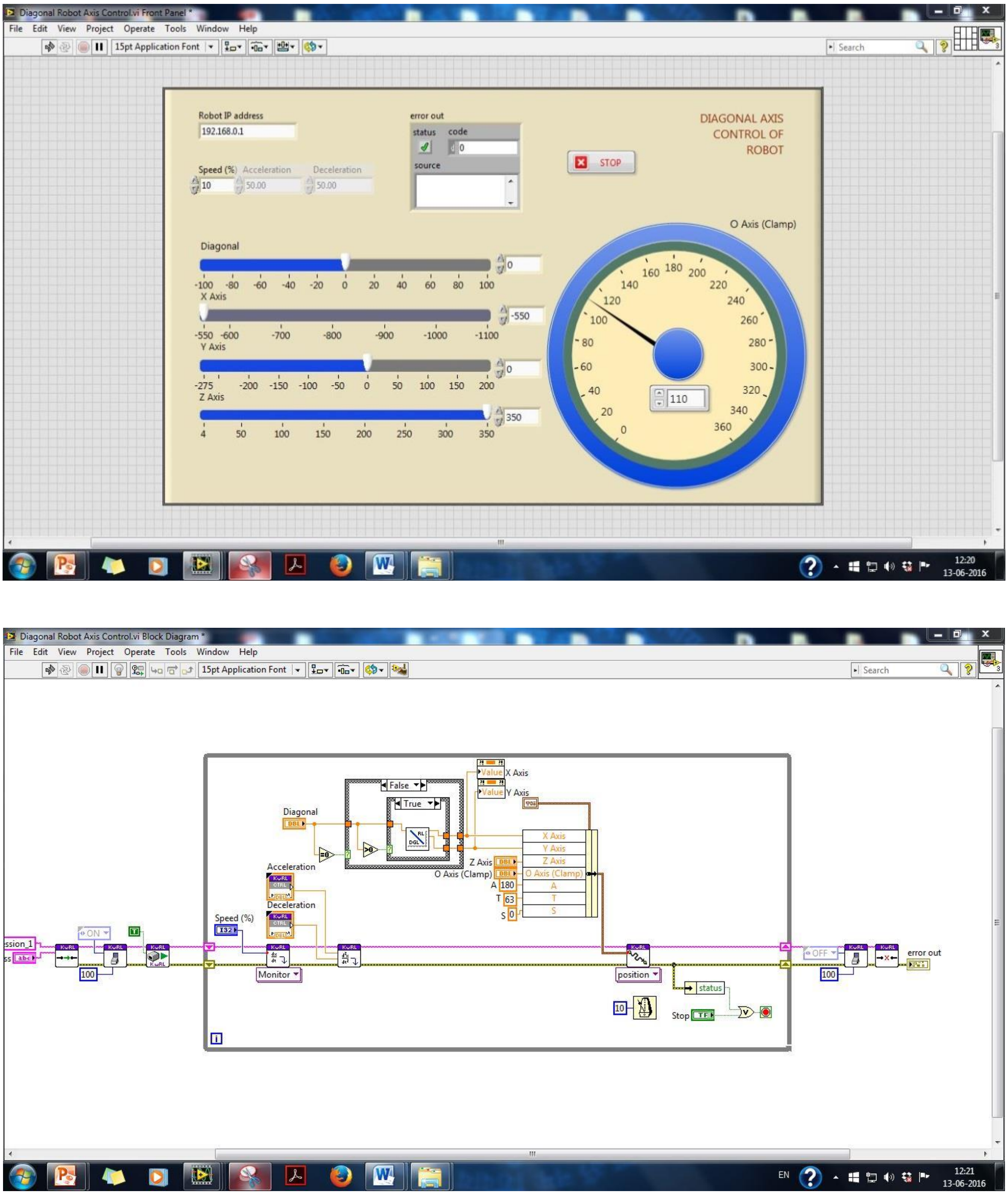


Figure 4.13: Kawasaki RS06L robots servo actuator control using Digi-Metrix Library v0.2.0.59

4.2.3 Robot vision system control

LabVIEW 2013 simulation and program coding is used to support proficient image processing and control of the robot arm or manipulator. In order to detect that the part lies within the workspace is analysis of captured image is essential.

The NI LabVIEW 2013 Virtual Instrument software and hardware units are designed to execute the servo motors of robotic manipulator to control the system architecture. Each servo motor is controlled using Digi-matrix library of Kawasaki robot. The IMAQ driver supports the NI vision module for further hardware processing, and connects to PXIe-1082 via Ethernet for real-time operation.

4.3 Summary

In this chapter, LabVIEW 2013 with robotics module and vision module are embedded with real-time operation. FPGA based hardware such as NI cRIO- 9074 and control platform NI PXIe-1082 central processing unit can interface with sensors and control system of the robot’s motion. This chapter is intended to develop the data acquiring controller for the theory of multi-sensor integrated robotic hand. This process will provide an algorithm for the integration of sensors to acquire the unstructured information to control the robotic hand in the workspace.

Chapter 5

VISION SYSTEM FOR THE ROBOTIC HAND

5.1 Overview

Vision sensors play an important role in increasing the intelligence level of robot. It starts with collection of visual information, and then does feature extraction for image interpretation, part shape determination etc. In the intelligent vision system, geometrical information and their feature extraction are significant matters to solve the problem in desired application domains. Under the present chapter objects are considered to identify the feature along with methodology and development of necessary algorithm.

For the perfect grasping of object with the help of intelligent robot vision system, the following subjects are essential for consideration:

• Robot Vision System

• Processing system for Image

• Algorithm for part recognition

• Algorithm for grasping System

This particular research work concentrates on feature extraction, explanation and understanding of those structures that are important for the grasping purpose and enabling grasping arrangement. For intelligent and smart grasping, the position, orientation as well as the actual structure of objects must be identified precisely.

Hence, a vision sensor or camera is employed to acquire visual data of the target to be gripped. For the real-time grasping operations, and to signify the objects successfully, the structural techniques and pattern recognition methods are considered to compute contacts between features or edges of an object.

5.2 Robot Vision System

The usage of vision sensing system is encouraged via the ongoing necessity to improve the flexibility of industrial applications. Robotic vision system is defined as the method of extracting, describing, and understanding the captured images in the 3-D workspace. This method, also mentioned as computer or machine vision in universal applications. The entire process can be partitioned into the six principal zones: sensing, pre-processing, segmentation, description, recognition, and interpretation. Structure modules of robot vision system are shown in Figure 5.1.

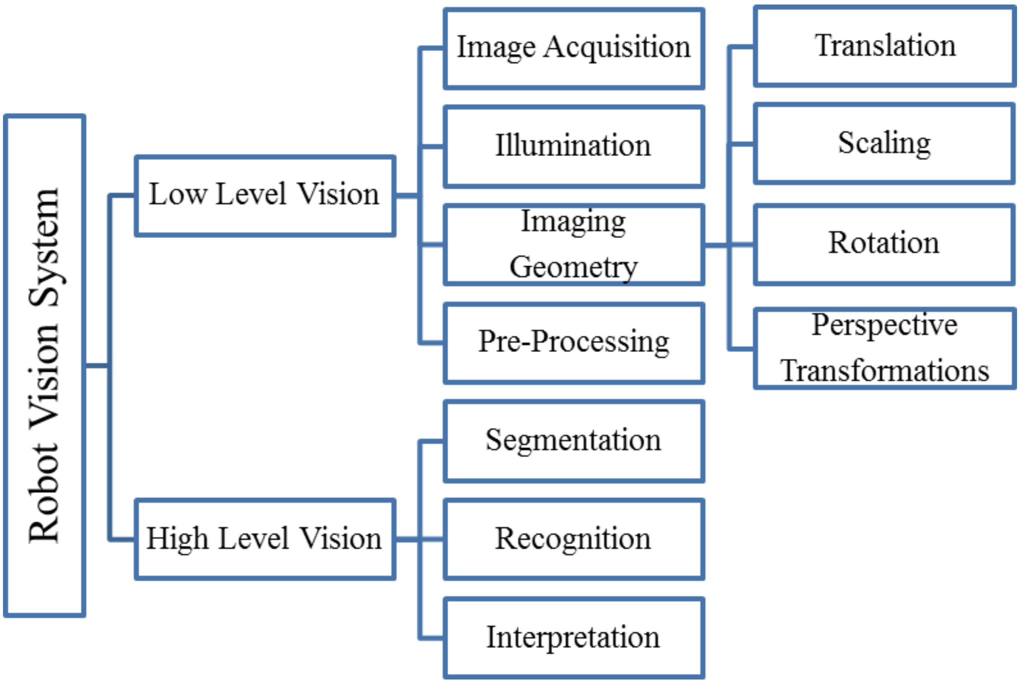


Figure 5.1: Structure modules of robot vision system

Part identification is a vital procedure in the multiple sensor integrated robotic system. The purpose of identification algorithms is to recognize individual segmented object in a workspace and to allocate a tag to that object. Recognition methods in today's research aspects may be separated into two groups specifically: structural and decision. A structural method depends on representative metaphors, while decision methods depend on statistical metaphors. Part recognition is the origin, in addition to the core of computer vision or machine vision.

5.3 Image Processing

The processing of image starts first with sensing the image, then pre-processing of acquired image, at the ends of boundary or edge finding along with several filters and templates to improve the accuracy of original image. Then it continues to extract and conclude with a pixel values.

5.3.1 Sensing of image

The acquired image quality ought to have a remarkable effect on the vision system. A vision sensor of higher resolution along with a frame grabber is important to obtain an image with sensible intensity, contrast and perceptiveness, etc. To enable image processing and to improve accuracy of intelligent vision system, a vibrant contrast among the targeted object and the background is constantly desirable.

Figure 5.2: Acquired image

In addition, the lightning brightness is essential for the intelligent vision system in some cases. To remove shallow and amorphous brightness and all disadvantages that cannot be compensated by regulating restrictions of vision sensor or camera, a lightning system is intended and set up to form an impeccable image sensing structure. Figure 5.2 shows the acquired image of an object. The computer program for achieving this is given in Appendix D. The comprehensive integration and data arrangement is described in Section 4.3.1.

5.3.2 Pre-processing of image

In order to extract the contour of the object, image pre-processing is carried out with filtering, noise cleaning, and thresholding operations. There are three types of filters (high level filter, median filter, and low level filter) available in this structure.

Figure 5.3: Grayscale level of acquired image

Usually the high level filtering is employed to sharpen images that are out of focus, which gives emphasis to grayscale level of image pixel in the framework. Subsequently in high level filtering, the captured image is improved and low occurrence modules in the image are filtered. Figure 5.3 shows the grayscale level of acquired image of an object.

5.3.3 Thresholding

Thresholding is a principally suitable technique for finding boundaries in images which contain solid objects on a contrasting background or vice-versa. The procedure of thresholding is that a greyscale level image is designated primary and then all pixels under that greyscale level are allocated to the background while all pixels with greyscale level at or above the threshold are considered as the object to be identified.

Figure 5.4: Threshold level of acquired image

In this research, the thresholding outcomes are put into usage. Figure 5.4 shows a vibrant and precise digital image accomplished by using image processing unit and thresholding.

5.3.4 Edge or boundary detection

The procedure of edge finding using vision sensing systems can make things easier and extremely accelerate the method of image processing. The edge structure has a piercing greyscale level conversion. If the boundaries are consistently clear, and the level of noise value is small, then threshold of a boundary image and tiny subsequent digital image reduces the single pixel value near to the linked edges.

Figure 5.5: Detected edge level of acquired image

Hence, boundary recognition process is applied via inspecting each pixel value and counting the gradient directions. Spatial convolution templates are always employed. In this research, options of edge detection are offered. The main edge recognition operators employed in this application is “Canny’s operator edge detector” and its results is shown in the Figure 5.5.

5.4 Part Recognition

Structure identification and illustration is the origin in object feature extraction. The aim of this research is to grasp unknown parts smartly. Hence, part identification process must capture all essential geometrical information for intelligent grasping. **Faugeras and Hebert (2011)** presented a number of ideas and results related to the problem of recognizing and locating 3-D and discussed the need for representing surface information, specifically curves and surface patches. Essential structures of parts are always unstructured with respect to conversion, revolution, and measurement.

5.4.1 Parts features

Amongst all structural features, centre of gravity is the most significant feature that must be found out in part identification, since it has excessive outcome on reliability and consistency of grasping points. The exact area of a part has a direct contact to the mass W of part to be gripped, i.e. the grasping force that should be applied. In addition, the distance D and size are also desirable for grasping planning. Figure 5.6 shows the calculation of centre of gravity, in binary image processing, COG (xc, yc, zc) can be calculated simply by analysis of static moments and consideration of pixel values that stand for the parts. Similarly, for calculation of area, in binary image processing, area A can be found out just by calculating calibrated pixel value of the object.

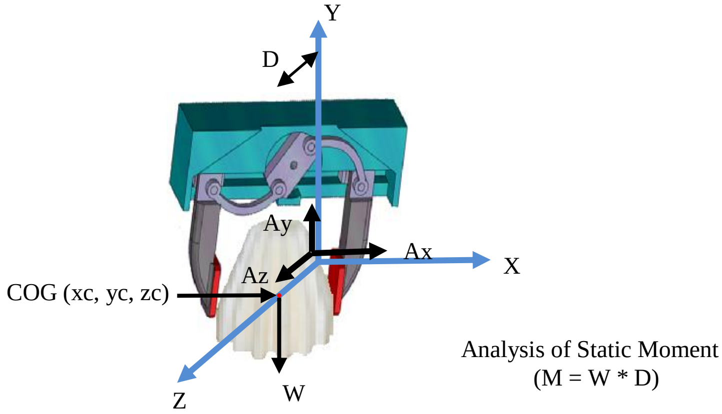


Figure 5.6: Calculation of center of gravity

The length and breadth of the object in centimetres are calculated for a particular height of the object, and this is used in the program to map/proportionate the length and breadth

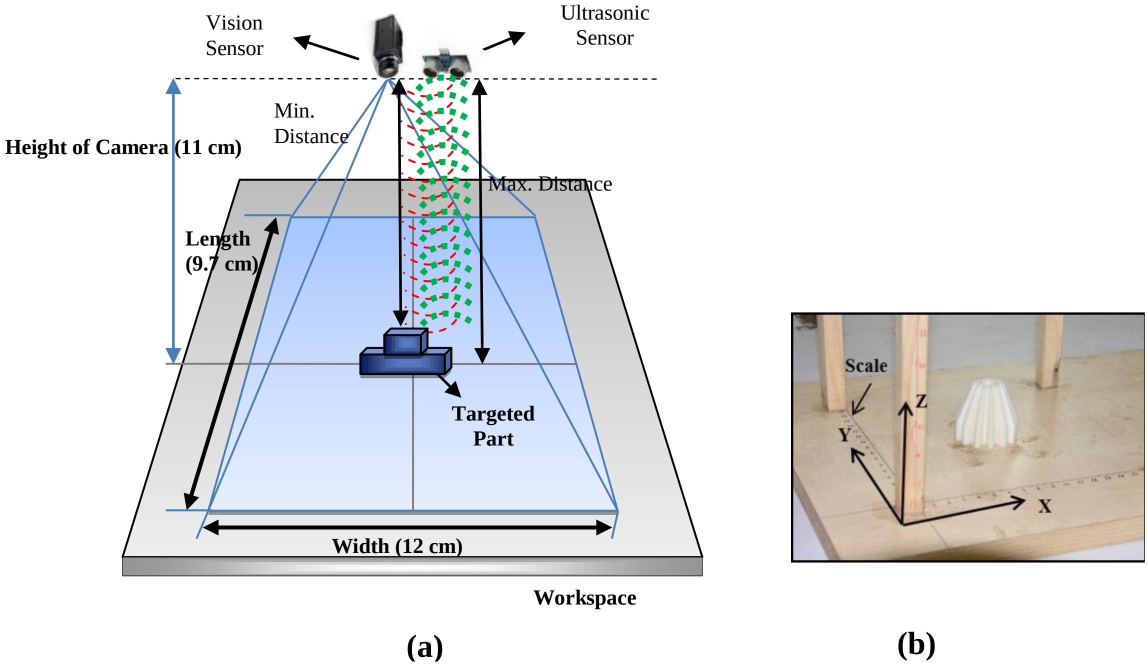


Figure 5.7: Calibration of vision and ultrasonic sensor (a) grid size functions of the camera and target in centimeters. (b) The depth of an object from the camera is found out using ultrasonic sensors

values for the heights detected. Therefore, a calibration of vision and ultrasonic sensors is demonstrated in Figure 5.7. If the height is 11cm, then width and height detected is 12cm and 9.7cm respectively. The product of the width and height gives the object area as shown with the explanation of length L and width W. **Lee et al., (2007)** conferred on multiple ultrasonic sensors are integrated via dissimilar widths of beam array for robot navigation. To identify the environmental condition using ultrasonic sensor through minor beam-width provides decent resolution and here still we need more sensors to recognize obstacles in unstructured working environments.

5.4.2 Parts classification

In locations of the alignment of the two fingered gripper, the part of geometrical identification must be found out so as to make suitable grasping point. In this study, a pattern recognition methodology is utilized to recognize the geometry part. Different shapes of geometrical parts classification are shown in Figure 5.8 and each part is explained individually in the chapter 8.

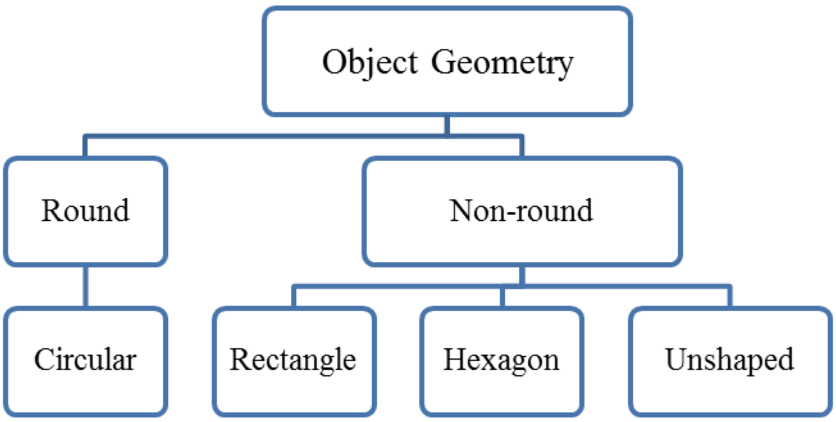


Figure 5.8: Object classification

5.5 Intelligent Grasping System

The research aims on "Intelligent" grasping system using integration of vision system on robotic hand and manipulator to assemble amorphous parts of different shapes and sizes. At the initial stage of grasping, vision outcomes and visual information provides a nonlinear structure from workspace to control the system. In the stage of post grasping, robotic hand is used to obtained precise information for accurate grasping. Geometrical information of objects and workspace is used to measure the exact value of the grasping point. **Markus et al., (2010)** presented a novel grasp planning algorithm based on the medial axis of 3D objects. And proposed an algorithm to be met by a robotic hand is the capability to oppose the thumb to the other fingers which is fulfilled by all hand models. The intelligent system is executed within low cost virtual combined environs, where the intelligent gripper system planning is composed of the next five key modules segments:

5.5.1 Module of image processing

This module implements image pre-processing system to make usage of diverse filters, such as: Low pass filter, high pass filter, median filter, and smoothing, etc. It then executes thresholding process to get a reliable digital image, contour recognition and edge linking is utilized to identify and extract the edge of the part strongly.

5.5.2 Module of part recognition

This module accomplishes edge lines to crop individual pixel dense boundary and then extracts the geometrical structures from the edge. It signifies the border of the parts with a grasping point vectors and finally defines the object structures. **Nicholas and Faugeras (1986)** designed to identify and locate objects lying on a flat surface and described a new method for the recognition and positioning of 2-D objects. To recognize and locate objects lying on a flat surface and a novel technique for the identification and positioning of two-dimensional objects are designed by **Ayache et al., (1986)**.

By this we would be able to verify the position of the object irrespective of orientation and scale. The software's used were Python 2.7, Opencv libraries for python. Using two vision sensors in the workspace, we have taken two images where one image is known as the template image of the images of objects that requires being located within another group of images. After that the template matching is done on the basis of correlation of two images. There are five methods to perform template matching (Appendix D) have used Square Difference (SQDIFF) methodology to perform this. The point at which, getting a global least value is declaring, it as the point where the object is located.

5.5.3 Module of grasping planning

This module extracted geometrical structures of object images such as edge length, the symmetrical view of two edges, border, area and centre of gravity (COG), which is created in part recognition module. Then carry out all imaginable combinations of aspects which are properly placed for grasping points in positions of the shape of the two fingered robotic hand. Laser range data and range from a neural stereoscopic vision system is presented by **Stefano et al., (2005)** and explained the estimate robot position is used to safely navigate through the environment. Appendix C: code for the area and grasping points. Grasping point is the position at which the robotic arm can grasp the object, which is generally be nearer to the center of mass of the object. OpenCV is an open source library written in C++ which helps mainly for real-time operations. A working environment is required to use this library as per our requirements. So software called "Microsoft Visual Studio 2013" is used, which is interfaced with OpenCV. And finally create a DLL file to import the code in the LabVIEW 2013 for interfacing of camera using LabVIEW in front panel and vision assistant function coded.

5.5.4 Module of trajectory planning

This module generates the co-relations between image synchronise system, robot coordinate system and robotic hand coordinates system. Then it constructs up on the grasping track, and finally produces the robot database. This database is transmitted to the robot control system to execute the operation in real-time. **Zhaojia et al., (1996)** described the problem of fast and automatic grasping of unknown objects with minimum number of robots features which are extracted from the scanned data are used for grasping point determination. Considered the contour with largest area, which is the contour of interest. Draw the bounding rectangle around that contour. Using the canny edge detection, the edge of the contour is found out. The total no of black pixels in the image is calculated. Total no of pixels in the image is the product of width and height of the image and the number of black pixels are counted and subtracted to get the total number of pixels on the object is contributing in the image (Appendix A). Now the centroid of the image is found out using cvMoments and the centre is marked with green colour. And the corners of the object are found out using the command approxpolyDP and are also marked with green colour. Now the edge pixels of the image are found out and the image is divided into the pixels towards the left and those pixels towards the right making the first detected pixels as the reference. We found out the pixel of minimum length on the left side and also on the right side. These two points are the minimum or gasping point of the object.

5.5.5 Module of grasping control

This module produces suitable control systems to enhance and improve the controller process. It manages robot motion, image exploration and servo motor control, to achieve the intelligent grasping system by regulating the applicable control components in terms of the feedback of sensors and manipulator position. Important progress has been made toward applying learning techniques to the grasping problem explained by **Sahbani et al., (2012)**. The system hardware such as vision sensors, robot, sensors, and servo motors are interfaced along with Ethernet cables, DAQ card, and controller respectively.

5.6 Summary

Intelligent vision system plays an important role in system intelligence. In this chapter, object or part oriented intelligent vision system is defined for grasping purposes. Overall, intelligent vision system is a challenging real-time image processing application, which is reliant on the significant algorithms and methodologies. Extraction and illustration of part structures are the important topics to which a grasping point must be obtained for industrial application. Meanwhile edges of the parts may provide satisfactory data for their explanation and illustration. This presentation, as an intelligent vision grasping system, takes advantage of boundary information and parts of geometrical structures are extracted step by step using image segmentation.

Chapter 6

DESIGN AND DEVELOPMENT OF PROTOTYPE ROBOTIC HAND

6.1 Overview

The robot hand being designed and developed through this work is different in construction from ordinary robot hands already developed so far. Since the objective is to build an intelligent robot hand, the design of the hand must facilitate accommodating the intended sensors. In other words, the hand must be capable of containing all the necessary sensors in such a way that they are not undesirably obstructed and at the same time, the hand must work to perform its desired action without any hindrance. This chapter is devoted to present the design and development of the prototype of the hand.

6.2 Conceptual Design

The proposed prototype robot hand design procedure can be defined as a five stage systematic process, as shown Figure 6.1. A set of necessities must be recognized by identifying the design problem. The first stage of the design process, titled as “conceptual design”, which includes establishing a set of specifications and design substitutes are

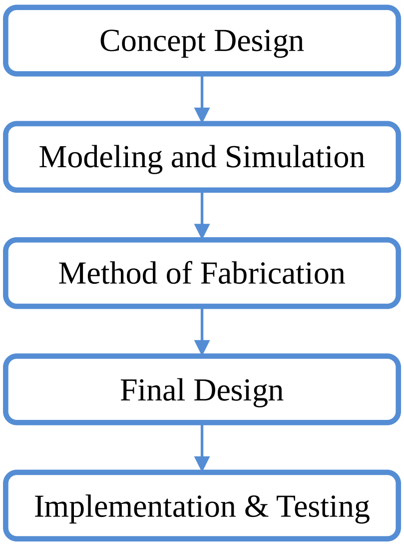


Figure 6.1: A scheme for a design procedure of a product

shown in the Table 6.1. In the initial design part, the concept was 3D modelled, simulated and analysed. The next step is fabrication. The next stage, entitled as "final design", consists of designing the parts that produce a set of manufacturing specifications for an optimised design. Finally, the "implementation & testing" stage involves validation of the final design by testing the developed prototype structures.

Table 6.1: Conceptual design specification of robot hand

Prototype robot hand	**Considered specification**
Type	Mechanical hand
Shape	Rectangle
DOF	1
Finger	Two-fingers
Actuators	Servo motor
Hieght (cm)	13.8
Widht (cm)	5.5
Weight (gm)	358 gm
Closing/opening time	0.4/0.6 sec
Payload capacity	0.3kg
Material	ABS plastic

6.2.1 Modeling and simulation in CATIA

Primarily, the designing process of proposed prototype robot hand involved the modelling according to desired specifications as shown in the Figure 6.2. After the modelling, the specific assembly is simulated by using "CATIA V5R17". The six parts palm basement, rotational motor mechanism, two-clamp fingers, two-joints and a covering box are simulated. Design simulation of the proposed robotic hand screenshot of CATIA V5R17 running on Windows 7 platform is shown in the Figure 6.3.

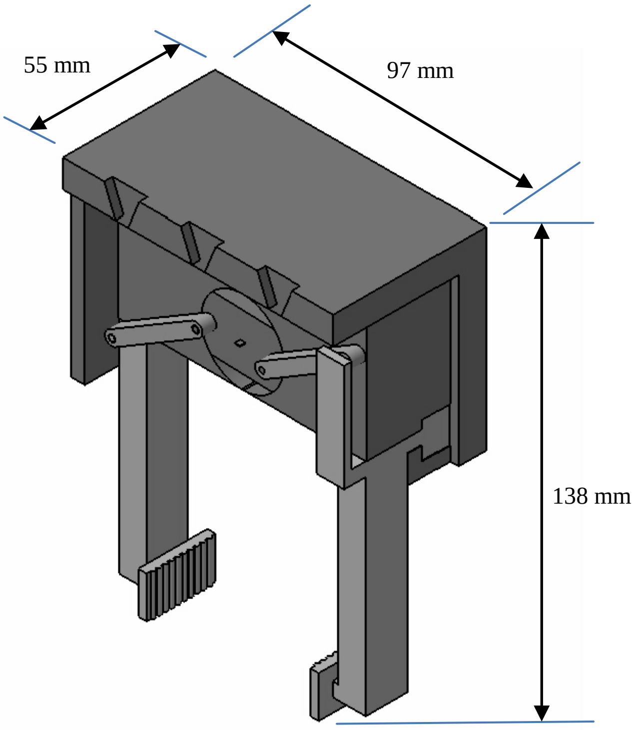


Figure 6.2: Modeled prototype of robot hand

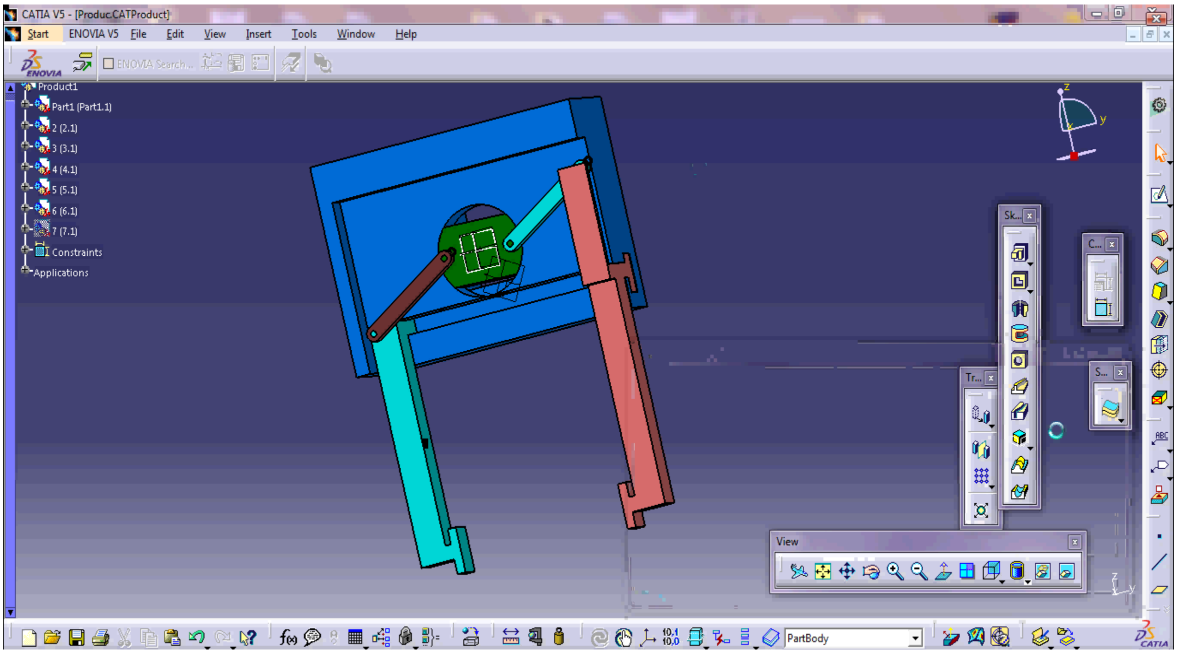


Figure 6.3: Modeling and simulation of the prototype robot hand

6.2.2 Method of fabrication

The modelling and simulated six parts of the robot hand are now converted in to '. STL' files and are developed on Dimension SST 1200ES 3D printing machine. Acrylonitrile Butadiene Styrene (ABS) plastic was the material for 3D printing. It has a higher melting point than PLA plastic. It's also stronger and harder than the same. Because of these characteristics, ABS is widely used as 3D printing raw material, resulting in components suitable for machine or parts with longer lifespan than many plastics. The 3D printed structural components of the robotic hand between the palm basement part-A, rotational motor mechanism Part-B, clamp finger Part-C, joint Part-D, clamping finger Part-E and covering box Part-F are shown in the Figure 6.4 to Figure 6.9.

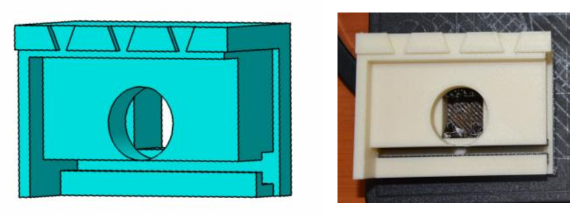


Figure 6.4: Palm basement part-A

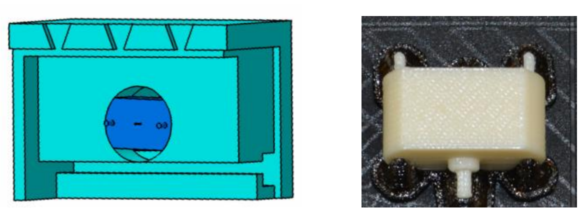


Figure 6.5: Rotational motor mechanism part-B

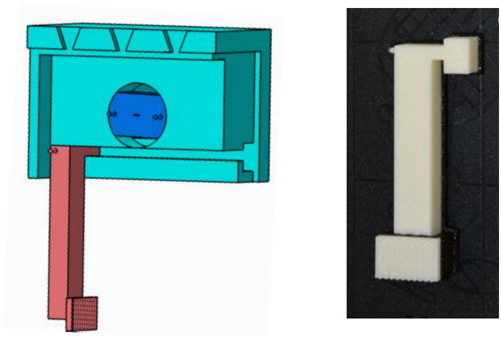


Figure 6.6: Clamping finger part -C

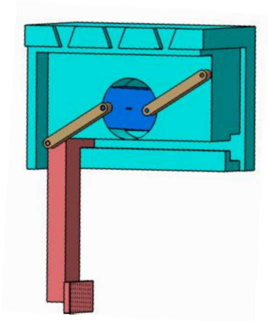



Figure 6.7: Joints mechanism part-D

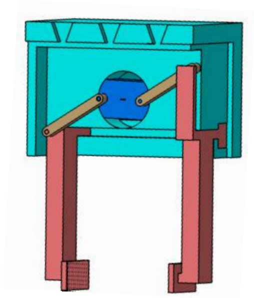



Figure 6.8: Clamping finger part - E

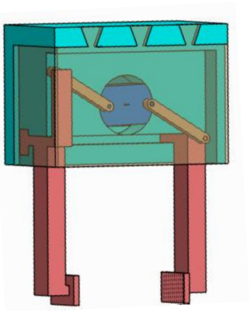
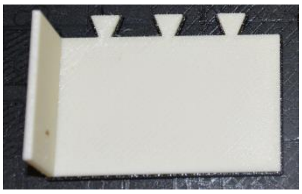



Figure 6.9: Cover box part-F

The two finger robotic hand is designed and developed using parts A to F (Figure 6.4-6.9) for assembly fitted with sensors. The step by step process to assemble the six designed parts are presented and highlighted by green arrow are shown in the Figure 6.10, together with assembled robotic hand. The designed parts such as palm basement is used as part that accommodates the two fingers, joint section, and a rotational gear and a covering box.

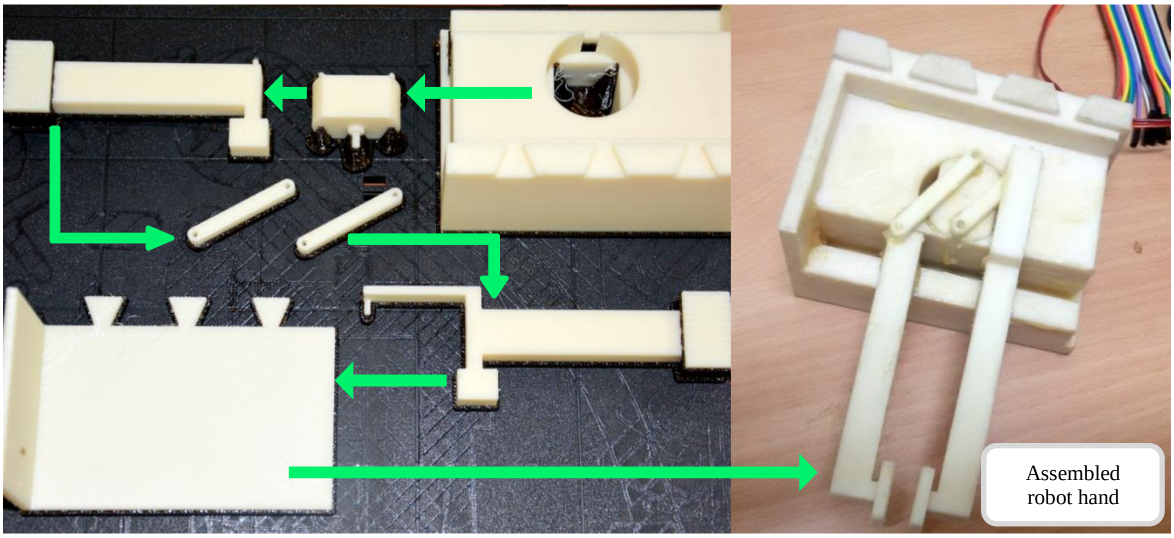


Figure 6.10: Assembled prototype of robotic hand

As with the Kawasaki robotic manipulator the developed prototype robotic hand will be attach, are explained in the chapter-7.

6.2.3 Robotic hand control using servo motor in LabVIEW

The simplest process to control robotic hand fingers is to have a servo motors with open and close system. Selected servo motor along with plastic gear and their accessories are shown in the Figure 6.11. The servo motors are controlled by a Pulse Width Modulated (PWM) waveform, with 180^0 of movement, integration of servo motor with prototype

Figure 6.11: Servo motor with plastic gears

robotic hand shown in Figure 6.12. The servo motor specification required for proposed robotic hand is also shown in the Table 6.1. Integration of economy standard servo motor with plastic gears is controlled by DAQ SCB-68A using LabVIEW are presented in the Figure 6.12.

Table 6.2: Technical specification of servo motor

Servo motor	Specification
Operating Voltage	4.8V
Operating Speed	0.20sec/60degree
Stall Torque	3.8kg/cm
Temperature Range	-20°C ~60°C
Dimension	41mmx20mmx38mm
Weight time	41g
Cable Length	30cm

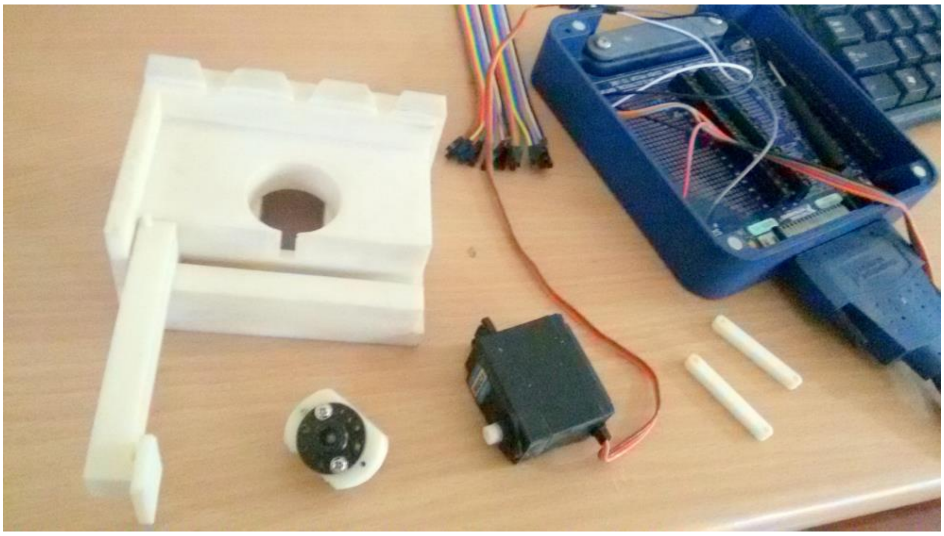


Figure 6.12: Integration of servo motor using DAQ SCB-68A hardware in LabVIEW

Servo motors for the finger motion were selected based on pulse drive and maximum static torque to assemble for jaw movement along with specific location of the palm. This motor is controlled via PWM pulses as corresponding to open/close situation for jaw movement to convert into the applied torque in to targeted object. The required speed of the motor is also calculated in order to help with the motor and grasping feedback process. The torque and speed requirements for the two finger joints are identical because they are in-line and assemble with each other.

The servo motor to be controlled separately to ensure that the object is in the centre of the field of view in observed environment. Then take measurements feedback from each sensor to determine the correct location of the object in the robot's workspace.

Figure 6.13: Front panel diagram of virtual clamp control system using LabVIEW

Measurements can be taken and controlled by using LabVIEW, the screen shot of front panel virtual clamp control system is shown in Figure 6.13. And the screen shot of block diagram of clamp control system is shown in Figure 6.14.

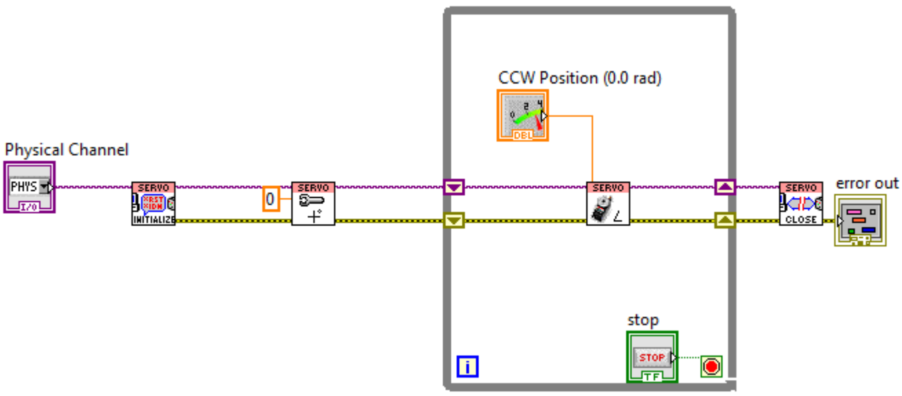
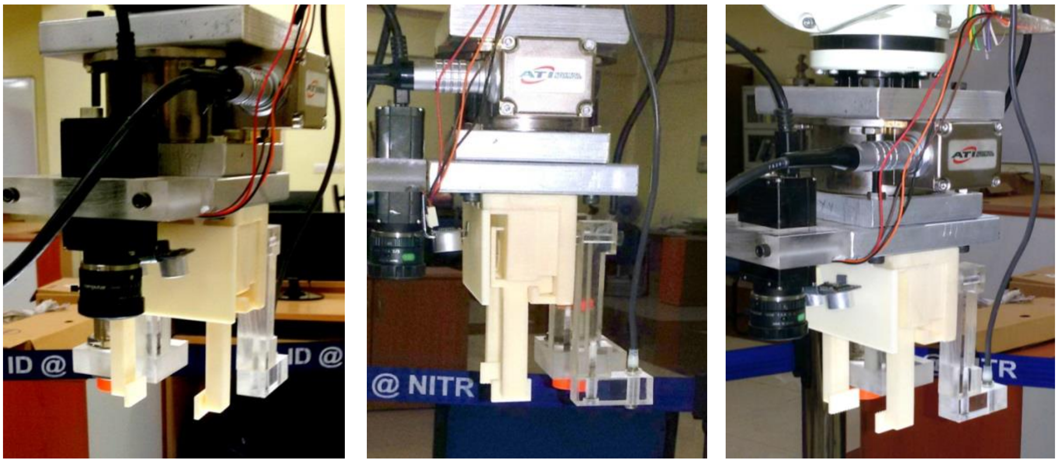


Figure 6.14: Block diagram of clamp control system using LabVIEW

6.3 Final Designed Prototype of Robotic Hand

At the end, selected sensors are integrated with prototype of robotic hand, and able to perform the operations. Figure 6.15 shows the manufactured prototype of robotic hand with attached sensors presented in front, side and 3D views.



Front -view Side-view 3D- view

Figure 6.15: Manufactured prototype of robotic hand with integrated sensors

Smart sensors are integrated in the middle and side of the prototype robotic hand mechanism and the feedback of sensor system hold the key to operate the ABS hand. This robotic hand is used to conduct experiments on the intelligent grasping control system. Implementation and testing to validate the proposed system is explained in Chapter-7.

6.4 Design Validation of the Hand

6.4.1 FE Modeling

For the Finite Element Analysis, the following procedure was followed. Import robot hand into the geometry to the 'static structural module' of ANSYS by right clicking on geometry and selecting the file. Right click on geometry and click update to import the geometry and update it for analysis. Figure 6.16 shows the imported robot hand. After insertion of IGES file into geometry, the next step considered is material selection for the imported geometry. For material selection as shown in Figure 6.17, click on the geometry and then on the solid. A dialogue box will open at bottom and provide material as structural steel as per requirement.

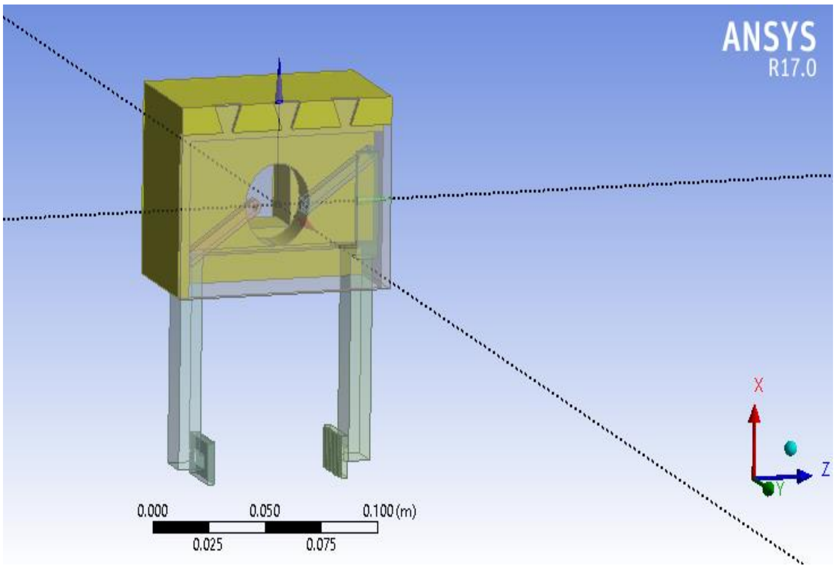


Figure 6.16: Imported robot hand

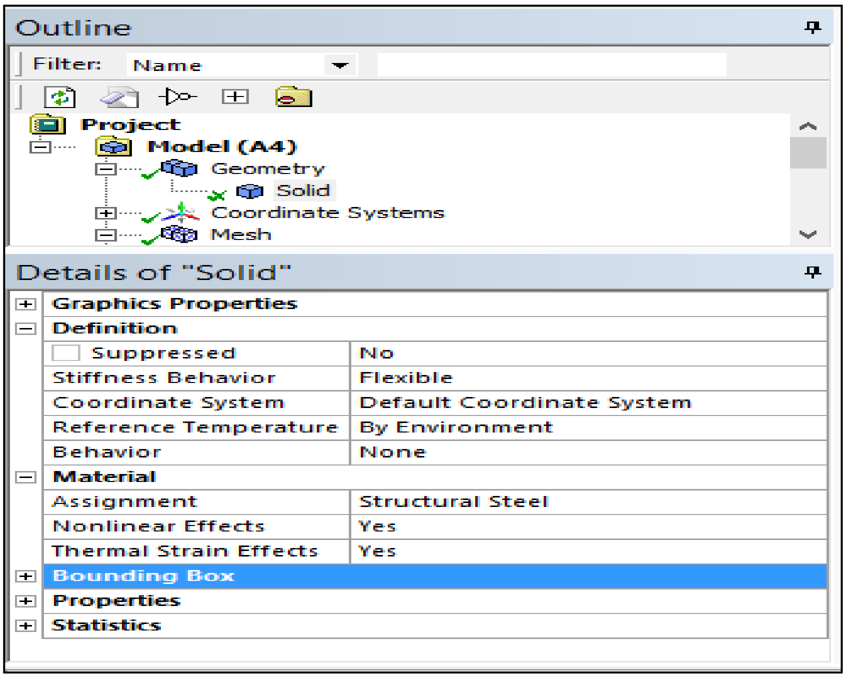


Figure 6.17: Material Selection

The next step is to provide mesh to the geometry. For achieving this double click on the geometry in static structural module to open static structural analysis window. As shown in Figure 6.18, right click on the mesh option and select the method for meshing as tetrahedron, the algorithm as patch conforming.

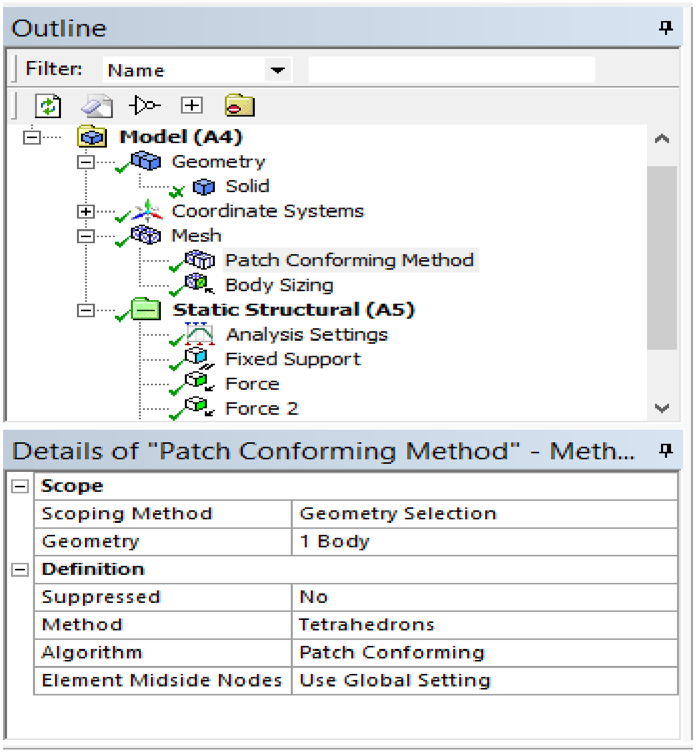


Figure 6.18: Details of meshing

The mesh method of robot hand sizing is carried out for distribution of mesh element on the part body shown in Figure 6.19.

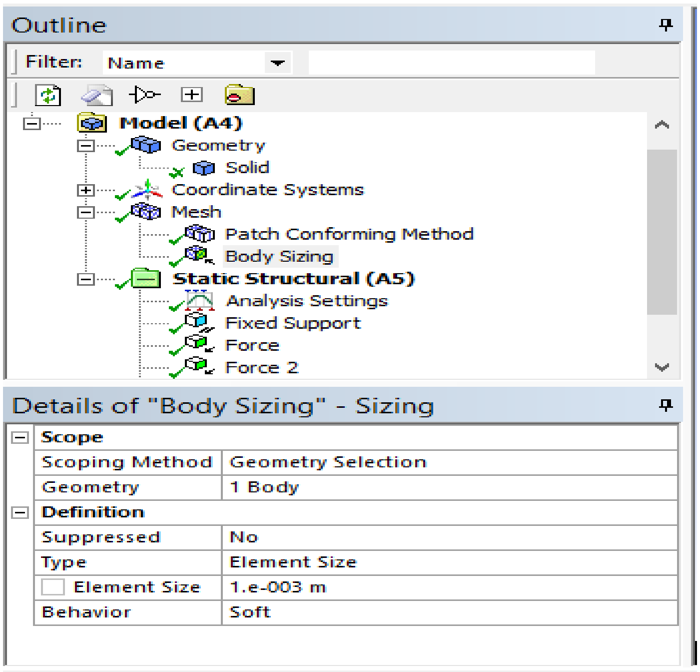


Figure 6.19: Body sizing

For the robot hand mesh sizing, finally select ‘generate mesh’ option. Pick the default mesh element size. Complete mesh on specified body will be obtained as shown in Figure 6.20.

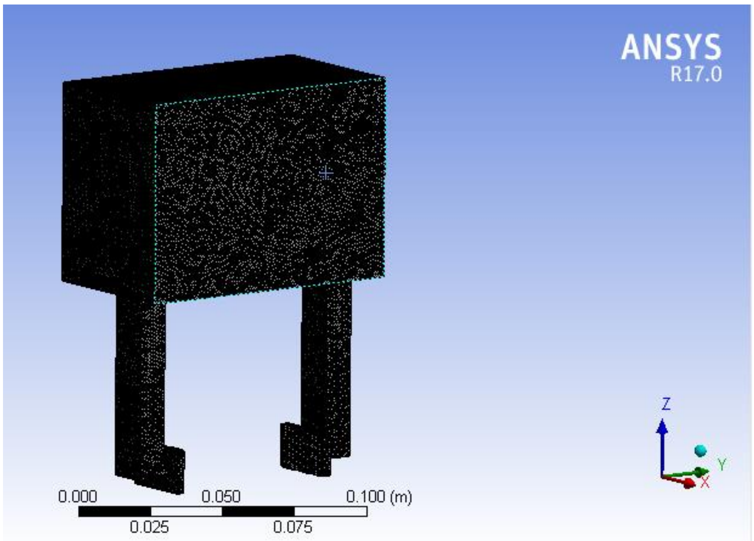


Figure 6.20: Details of meshing

6.4.2 FE Analysis

Next step is to provide the boundary conditions like fixing of supports and application of force at respective points as per the requirement. Before fixing the supports, change the analysis settings and initial sub-steps, minimum sub-steps and maximum sub-steps as 20, 20 and 100 respectively as shown in Figure 6.21.

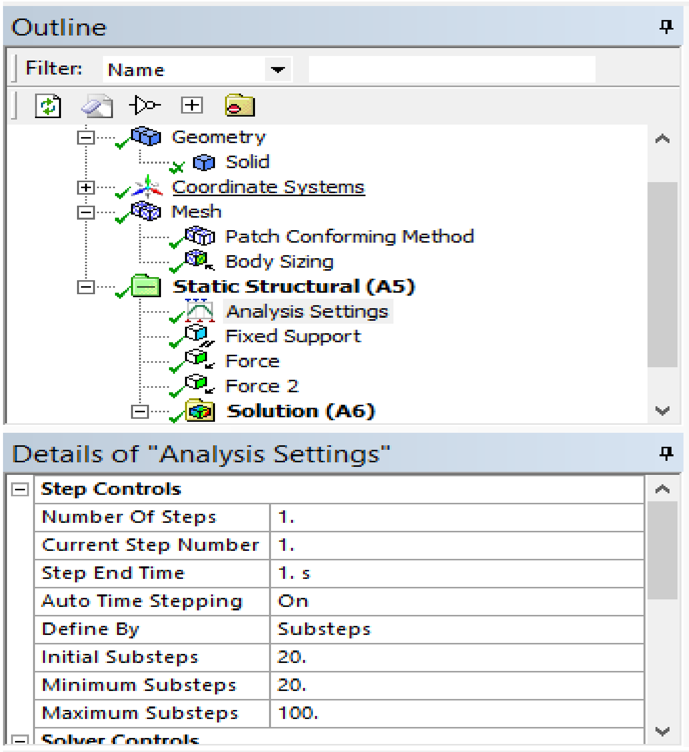


Figure 6.21: Details of analysis settings

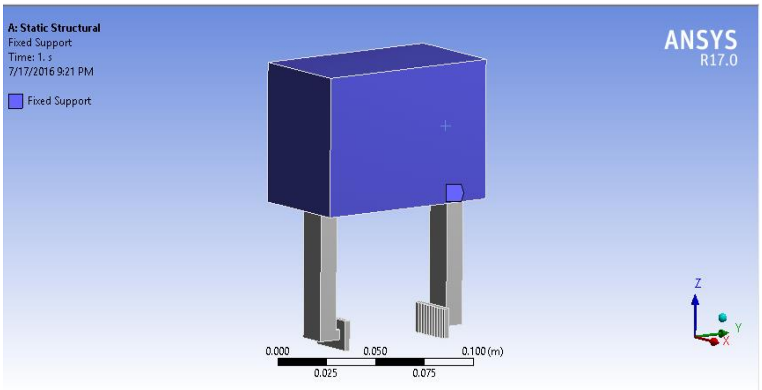


Figure 6.22: Details of fixed support

After support fixing, again click on static structural and select force. Force is selected to provide the value at particular side effector on robot hand shown in Figure 6.22. For assigning the force value select the side effector face and provide the force value as 1000 N in positive X direction. The complete explanation of this step is in Figure 6.23.

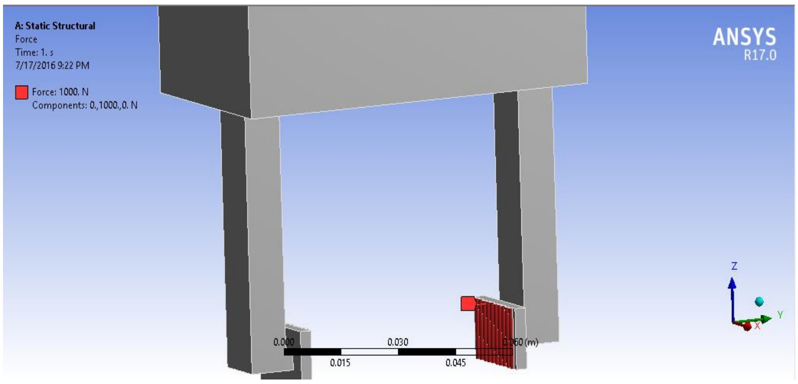


Figure 6.23: Details of force on one side effector

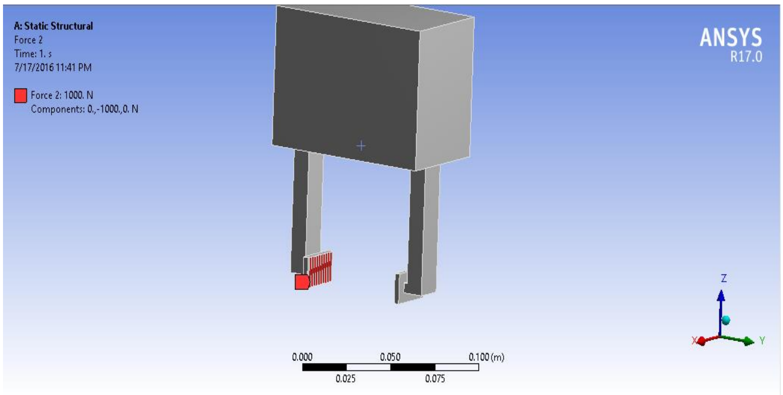


Figure 6.24: Details of force on other side of end effector

Repeat the process for the other finger face and provide the force value as 1000N in negative X direction as per the requirement, shown in Figure 6.24.

6.4.3 Validation

This section presents details of the finite element analysis and validation of the designed robot hand. CAD model for an intelligent robotic hand is designed and developed to be integrated with sensors. To analyse the designed prototype robot hand ANSYS-15 workbench has been used, where the 'transient structural module' is used to conduct a finite element analysis (FEA). Details on (a) Equivalent Elastic Strain; (b) Equivalent Stress; (c) Strain Energy; (d) Total Deformation, are shown in Figure 6.25.

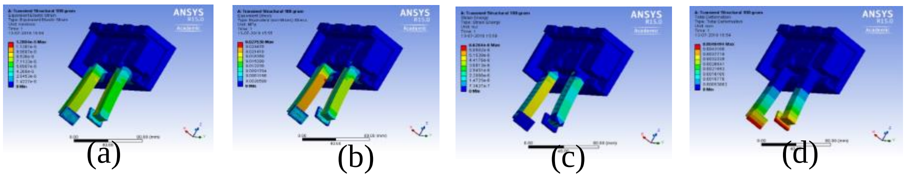


Figure 6.25: FEA analysis of robotic hand (a) Equivalent Elastic Strain (b) Equivalent Stress (c) Strain Energy (d) Total Deformation

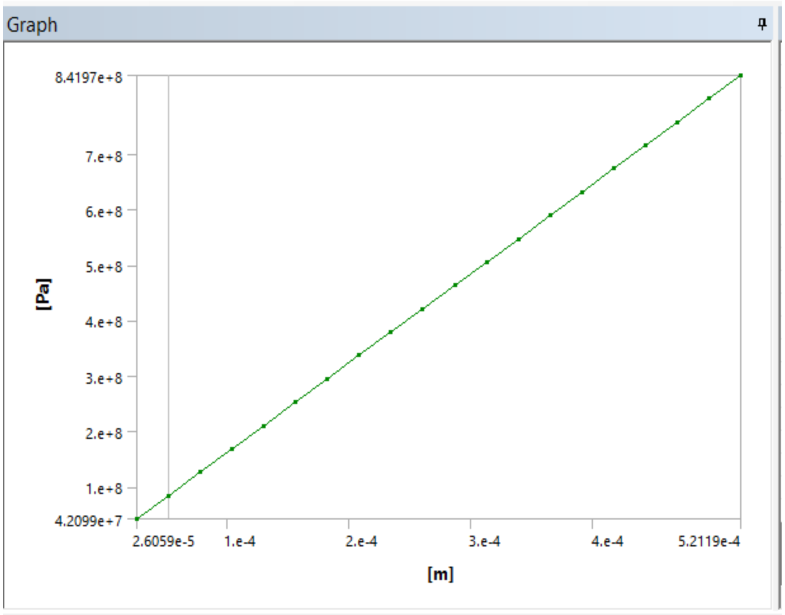


Figure 6.26: Stress vs deformation graph

Stress vs. directional deformation graph of the robotic end effector is shown in Figure 6.26.

6.5 Summary

A method has been proposed and conceptually planned for the process of design and analysis of a two-fingered robotic hand. This methodology is composed of stages that allow a sequentially systematic design of prototype of a mechanical hand. As per the requirement of this research work, the prototype of the proposed sensor integrated robotic hand has been 3D modeled, motion simulated, fabricated and analysed.

Chapter 7

SENSOR INTEGRATION AND CALIBRATION

7.1 Overview

Integration of sensors is bridge between the robotic hand and object that take action from perception. This chapter presents the interfacing of sensors on robotic hand, and the exact location of sensor in the designed prototype hand. This chapter also includes the integration of individual sensors and their calibrations for sensing information on unknown objects.

7.2 Scheme of Sensor Location

In order to increase the intelligence level of proposed prototype robot hand, a sensor interfacing based control system has designed. This scheme combines the control plans along with location of sensors and their integrations. Each sensor is individually integrated and calibrated in the particular locations of robot hand. The schemes for the location of sensors in the robot hand are shown in the Figure 7.1. Where the force/ torque sensor is mounted between Kawasaki robot manipulator and robot hand i.e., on the location of wrist in the end-effector. Then the most important usable vision and ultrasonic sensors are located, on parallel position of the robot hand to observe the workspace along with perfect distance. The capacitive and inductive proximity sensors are located with parallel contextual position of fingers to provide the object properties and their information. At the end Light touch switch (LTS) sensor is located on the both fingers, which will directly interact with objects and provide the digital information, when clamper fingers will pick or releasing the objects, Table 7.1 presents the General specification of prototype robot hand.

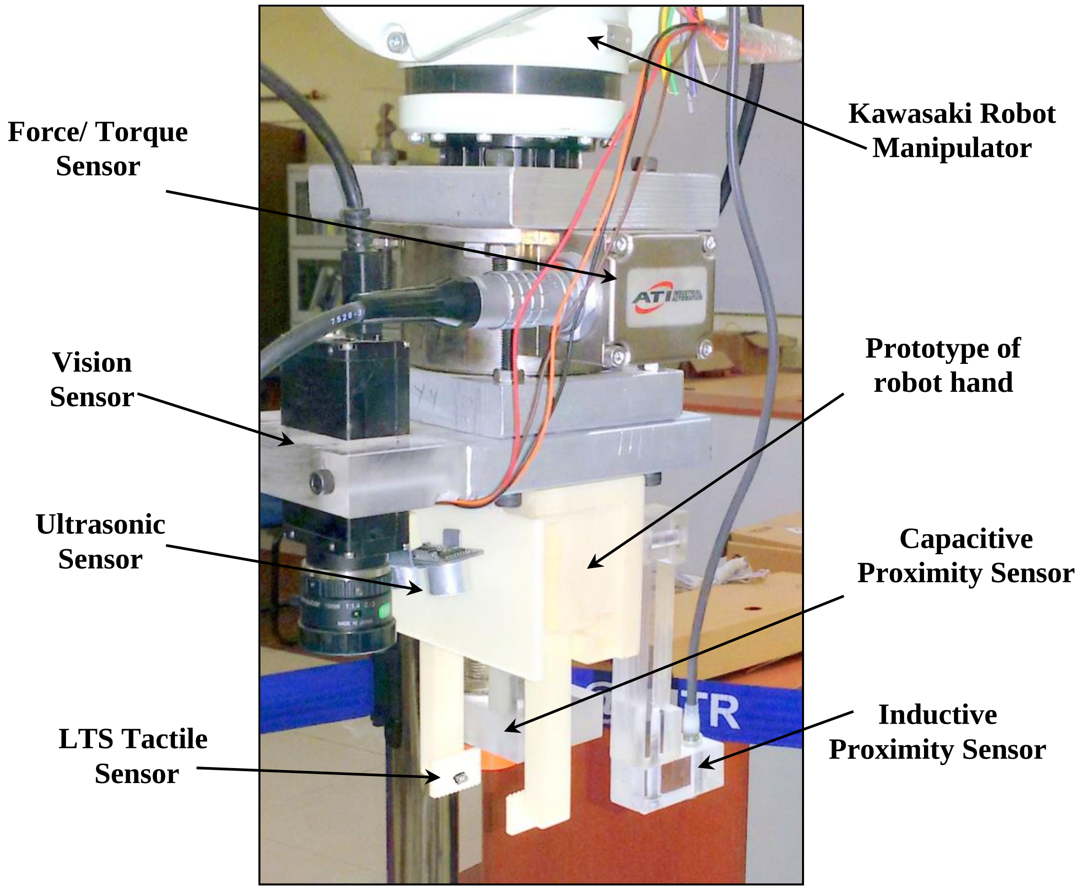


Figure 7.1: Locations of sensors on robotic hand

General block diagram of sensor integration with DAD system is shown in the Figure 7.2.

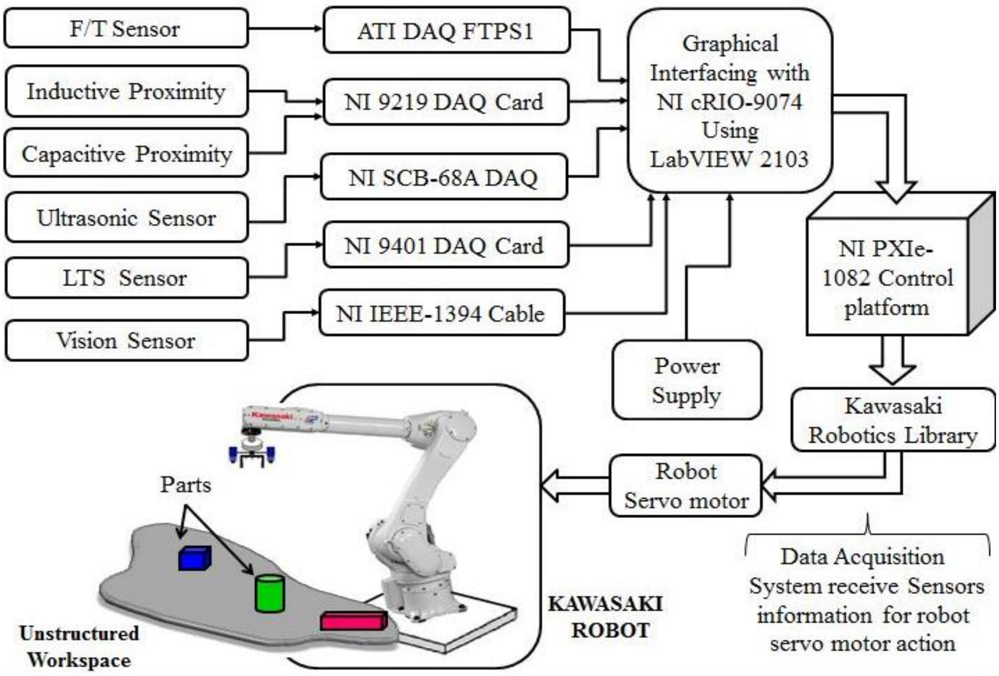


Figure 7.2: Block diagram of sensor integration with DAQ system

Table 7.1: General specification of prototype robot hand

Prototype robot hand	**Specification**
Product weight (gm)	358 gm
Closing/opening time	0.08/0.9 sec
Payload capacity	0.5kg
Object size	4.5 cm (Max.)
Objects shape	Circular, Square, Hex and Unshaped

7.3 Interfacing Circuit Diagram

This circuit diagram introduces another process of designing a single loop control system with feedback of sensors to control the servomotor. The aim of the design is to integrated sensors are mounted on the wrist, palm and finger of the designed and developed prototype robot hand and joint with a six-axis KAWASAKI RSO6L robotic manipulator, through which robotic gripper can control. All the mounted multisensory systems are interfaced using the tool LabVIEW 2013 along with controller NI PXIe-1082 series internal circuit diagram shown in Figure 7.3. And the sensor integrated prototype robotic hand is interfaced to acquiring the real-time information from sensors.

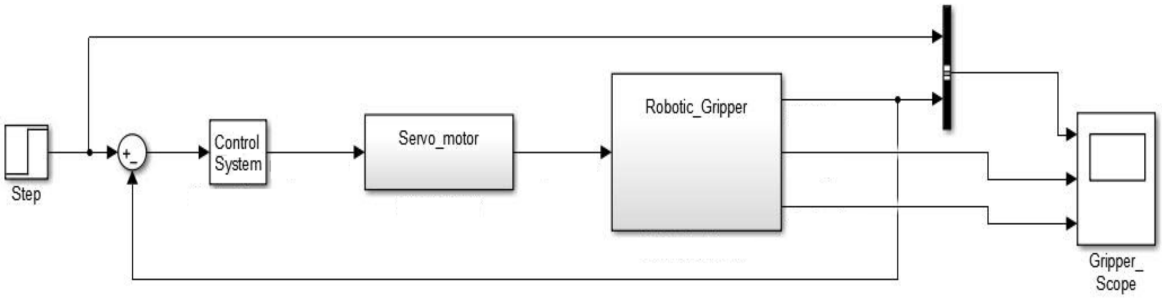


Figure 7.3: Interfacing circuit diagram

7.4 Scheme of Sensor Integration

Figure 7.4 shows the main scheme of sensor integration with DAQ system. In this set up the main DAQ program of virtual instrumentation are interfaced with NI-cRIO, and connections has been deployed in the main control function. It is having three modules Mod-1 Mode-2 and Mode-3. Proximity inductive sensor and capacitive sensor are connected with DO0 and DO1respectively in Mode-2 using NI 9375 DAQ card. And Mode3 is for two LTS switches; switch DOI-0 and switch DOI-1 are connected using NI

9401 DAQ card. Force/ Torque sensor data is acquiring using ATI FTPS1 DAQ card. Ultrasonic sensor is connected through NI-SCB-06A DAQ card to measure the objects distance in the rea-time operations. At the final vision sensor is interfaced directly with NI PXIe-1082 control platform through IEEE-1394 cable to capture the image information. To collect information's of integrated sensors in real-time; all interfaced DAQ cards are

Figure 7.4: Scheme of interfacing of Main DAQ VI.vi setup using LabVIEW

connected with NI PXIe-1082 control unit. Now the collected information's of sensors are processed, using different methodologies, algorithms and calibrations, it is ready to give the intelligent command to Kawasaki robotic library to actuate the servo motors for the further movements and real-time operations in the work space.

7.5 Sensors Integration Testing and Calibrations

Step by step integration of each sensor and their calibration are briefly explained individually. Acquiring the sensors information along with higher precise value is one of the other most significant requirements for the controlling system. The platform of control system is developed along with sensitivity and sensors feedback. Also the two-fingered SCHUNK robotic hand is controlled by pneumatic pressure on which the sensors are integrated is presented in the Figure 7.5.

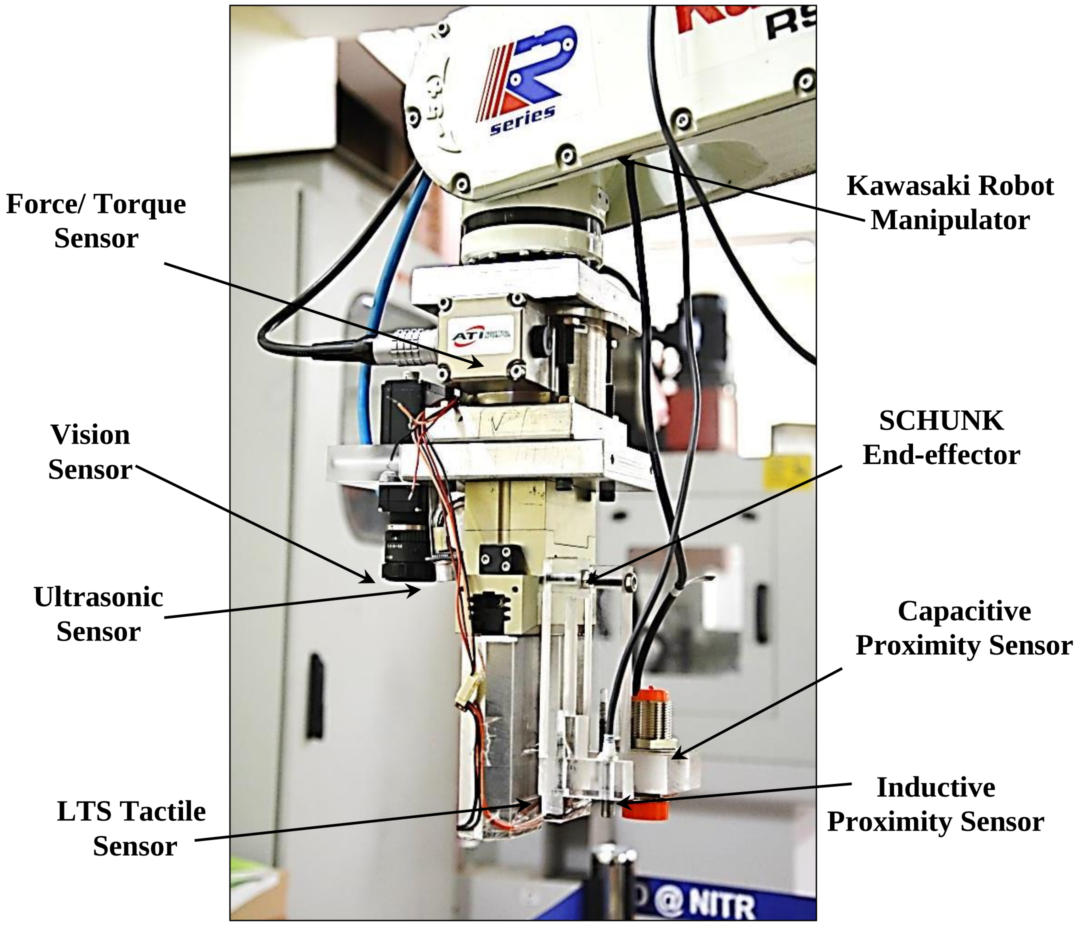


Figure 7.5: Sensors integrated SCHUNK robotic hand

Now, along with this single Main DAQ VI.vi project accessing, there is FPGA based individual separate computer i.e. NI-cRIO 9074 with IP address 169.254.4.42. and a control system platform NI PXIe-1082, both are connected through Ethernet cable. In this program, the processor has used network shared variable structure, where the computer used local variable or global variable, but the system has required communicating with another. So directly it can be identifying and started from the chassis cRIO-9074, where the particular slot, modules and module elements are select as for that has been explained previously. And that particular element will select for another interfacing device to acquire the sensors data. The ideas of world model as a sensor independent interfacing for the robot has been proposed by **Kent and James (1984)**. A complete setup and internal programing of sensors integrated block diagram of Main DAQ VI.vi setup using LabVIEW 2013 are presented in the Figure 7.6.

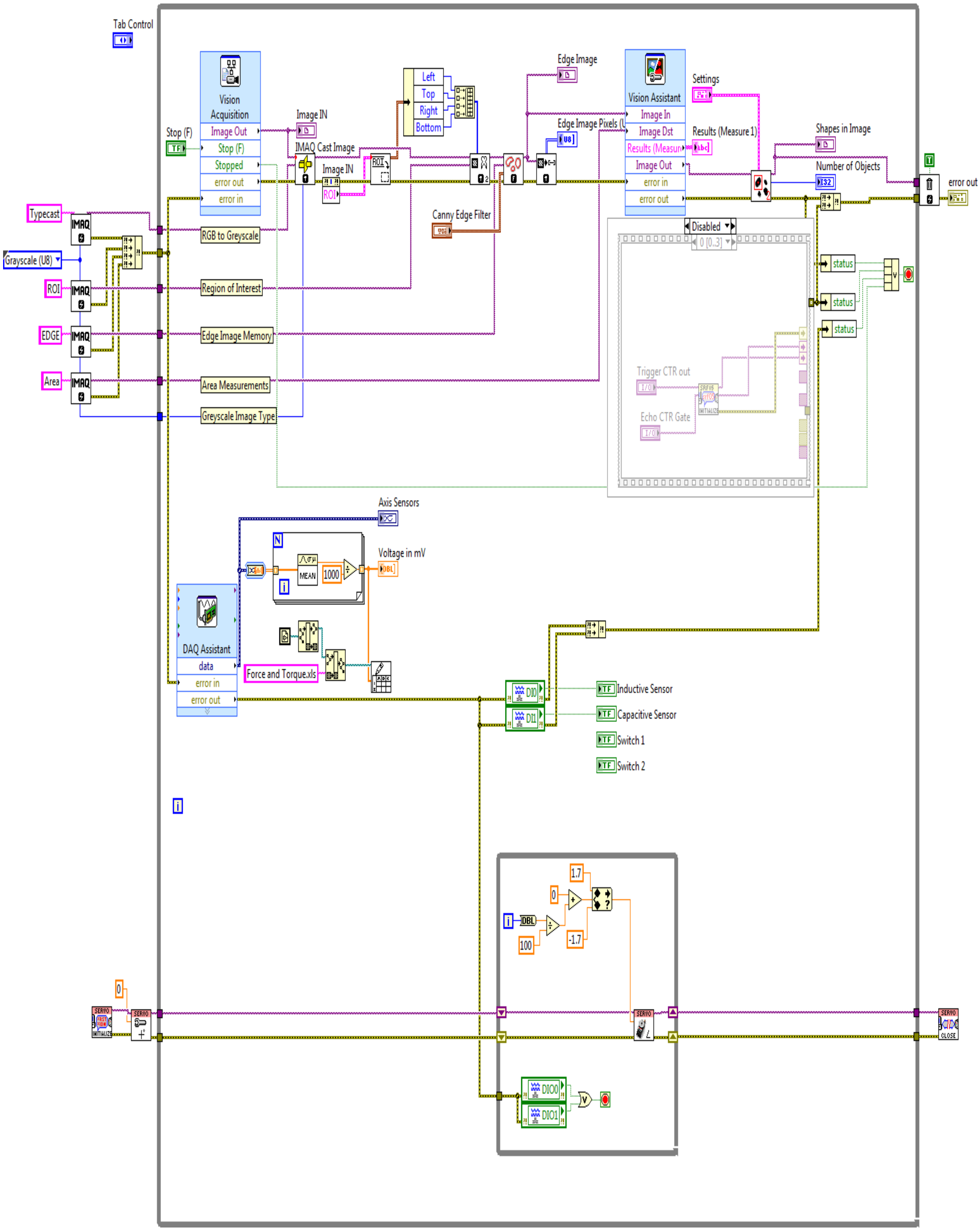


Figure 7.6: Sensors integrated block diagram of Main DAQ VI.vi setup

7.5.1 Integration of vision sensor

The robotic hand being developed through this research work, also used vision sensor along with other sensors. The purpose of the vision sensor is to identify the object, find out its orientation, check for correct object and determine the grasping points for handling it in the desired real-time operations.

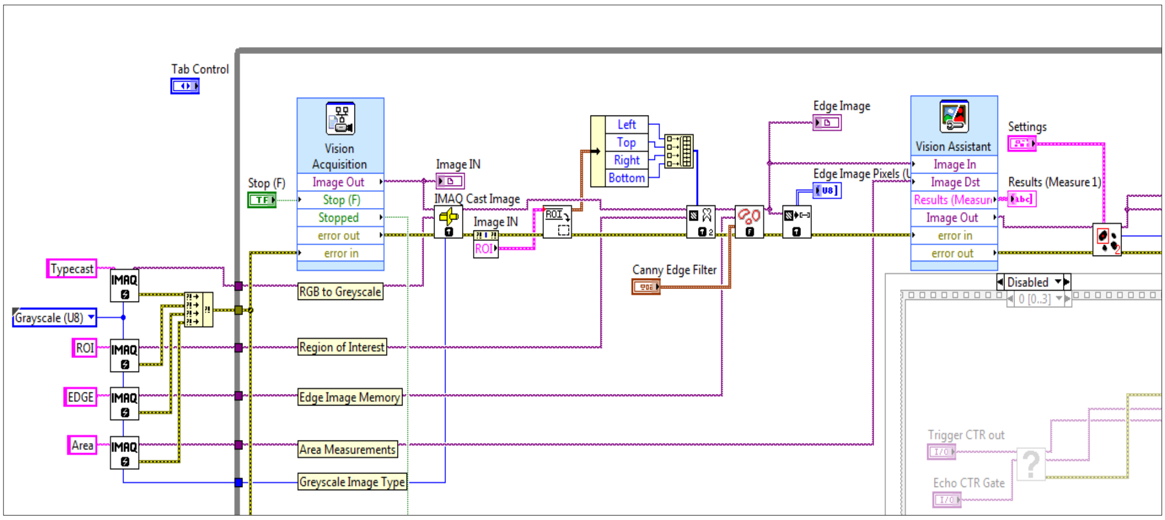


Figure 7.7: Vision sensors integrated VI block diagram using LabVIEW 2013

Figure 7.7 shows the block diagram of the vision sensor modelled in LabVIEW. It can explanation when start the function with main DAQ Vis, and such as vision acquisition, IMAQ created file along with type cast image, stop buttons and vision assistant are used along with several programs. Also used the DAQ assistant in order to acquire vision sensor information, so all the icons entire VIs library files are require to execute this program. An instrumentation library is there, use of this file close.vi, is to convert pulse width.vi, initialize.vi and measures echo pulse.vi, this four VIs has been used, so all libraries is there in the main DAQ. Instrument IO (Input / Output) Library along with VIs library, counts how many VIs has been used, if it is require to convert colours in the RGB or if it is require to convert waveforms to dynamic data type, then there can be built a path in the excel sheet, also they can be remove all the errors. So for all those purpose having six different channels and each channel have pulses and pulse generations. If it keeps on come out, it has required to create task such as read data, so already there is six channels over there to read, furthermore have a timing palate for counters.

Figure 7.8 present the calibrated vision sensor front panel diagram using LabVIEW, which is used to operate the connected devices in the blocks. So finally the image conversion rectangle to ROI, ROI to rectangle, IMAQ dispose, and Image to array along with spreadsheet string file is there, all files has been added under these dependencies. So vision and acquisition outcomes data can be seen in the in particular configuration through camera device, such as which mode of acquisition, how many numbers of object frames has to be present in the workspace.

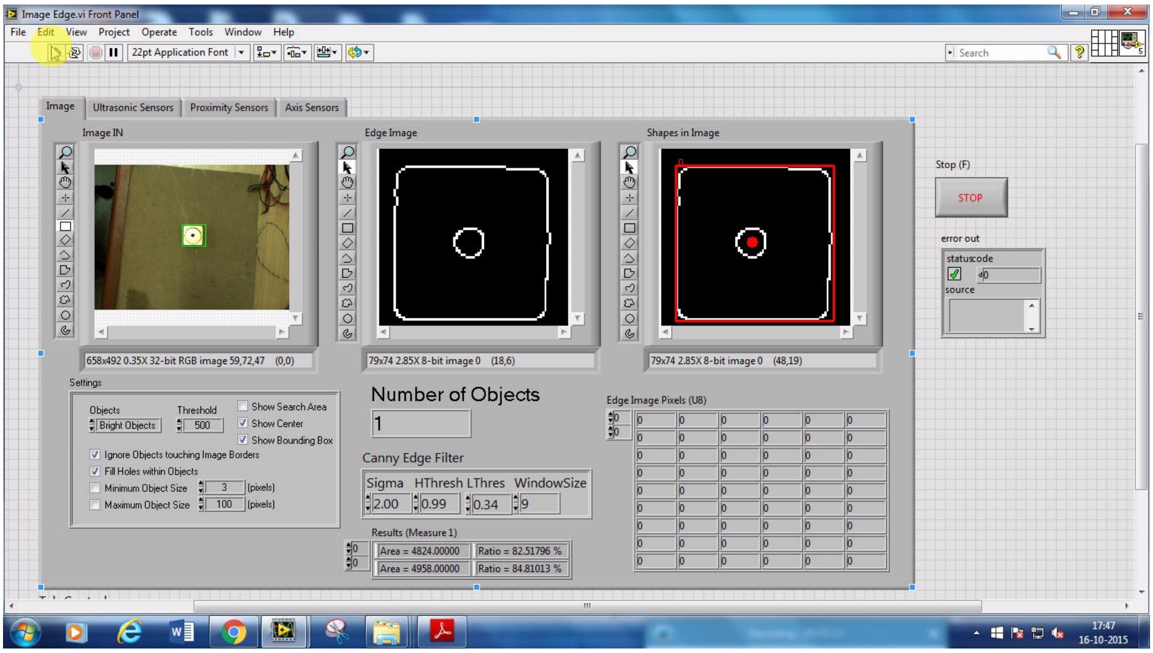


Figure 7.8: Calibrated vision sensor front panel diagram using LabVIEW

Also it can vary the brightness, gamma and gain, once after finish this initial image process, the acquired final image or colour image can be convert in to a grayscale image, then that value is need to take a selected portion for ROI. The ROI has to be extracted, so here using the rectangle from this it is easily able to get left to right and top to bottom values, so it will extract the particular portion and provide the extract image, and that image is require to converted in to the canny edge detector, so this will provide us the detected edge or boundary image to identify the shape and size of the particular object are explained in the chapter-8.

So now here using a vision assistant, before that an icon is used, is image to pixel conversion, which will convert the stored arrays. So inside whichever loaded over there, based on the particular file, we can add several algorithms. If will add multiple algorithm towards, based on that, we can vary the brightness, contrast based on that can apply towards, once it is finish, it will be added or removable easily.

So after specifying, it is require to controls, which data is need to be measures, only to acquire the image or to find out the errors or it can measure the external values, breakdown value or require to enable, then will give finish, it will be automatically created. So once after created, will get respective elements over in the front panel shown in Figure 7.8. Now this is the calibrated icons, which will find out, how many numbers of parts are available in the image of the specified portion on workspace. Also we can specify the minimum number or maximum number of pixels in the area of object.

7.5.2 Integration of force/torque sensor

The vision sensors provide eyes to the robot, force/torque sensors provide touch to the robot wrist. **Pires et al., (2002)** demonstrated the integration of force/torque sensor capabilities into user applications, especially industrial robotics applications. Here the robot uses a force/torque sensor to know the force that the robot is applying with its end of arm tooling. Most of the time, the F/T sensor is located between the robot manipulator and the robotic hand.

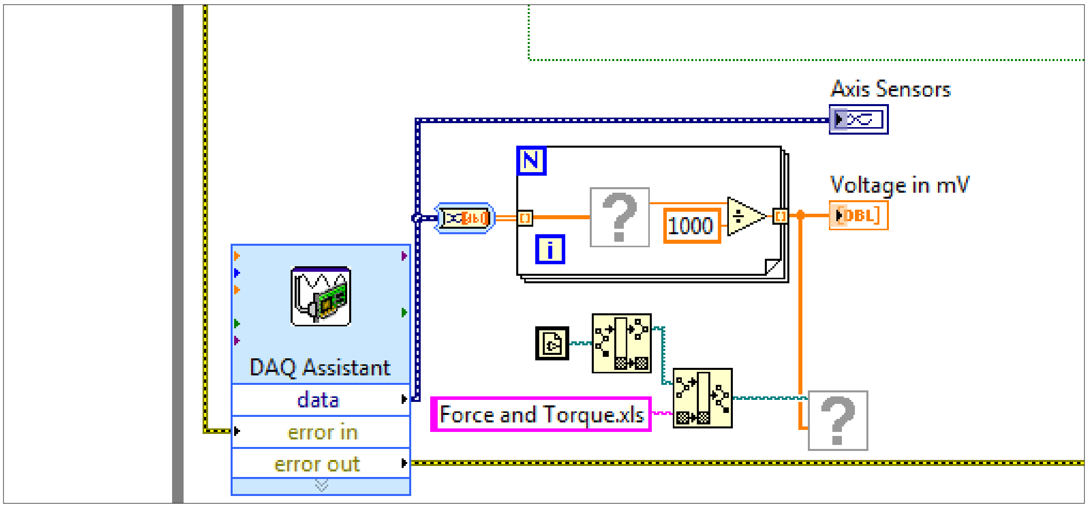


Figure 7.9: Force/Torque sensor integrated VIs block diagram using LabVIEW

This way, all the forces that are applied on the tool are monitored. So proposed F/T sensor integrated VIs block diagram using LabVIEW shown in Figure 7.9, where all the errors line is removed from there, through this DAQ assistant acquiring all the six-axes of force and torque sensor data, and providing the sample rate of continues frequency signal of 10 KHz acquiring out of 1k samples. Now entire samples are require to the voltage values has to be converted in the mv, so here it is converting the entire six axis F/T sensor acquiring data. **Fumihito et al., (1996**) analysed the balance of the adhesive forces between the objects, and proposed reduction method of adhesive force. Every data is providing an array, so each array is converting in to the 2D array and making a mean value, so the values will not change with more differences, the same value can be stored in the excel sheet or directly it can be display in the front panel diagram, so now this particular array value can be save and write to spreadsheet string file, each and every time it is require to save the acquire values in particular location, but if they don't have the particular location, so here they can use a current VI path, which can be locate anywhere in the desktop.

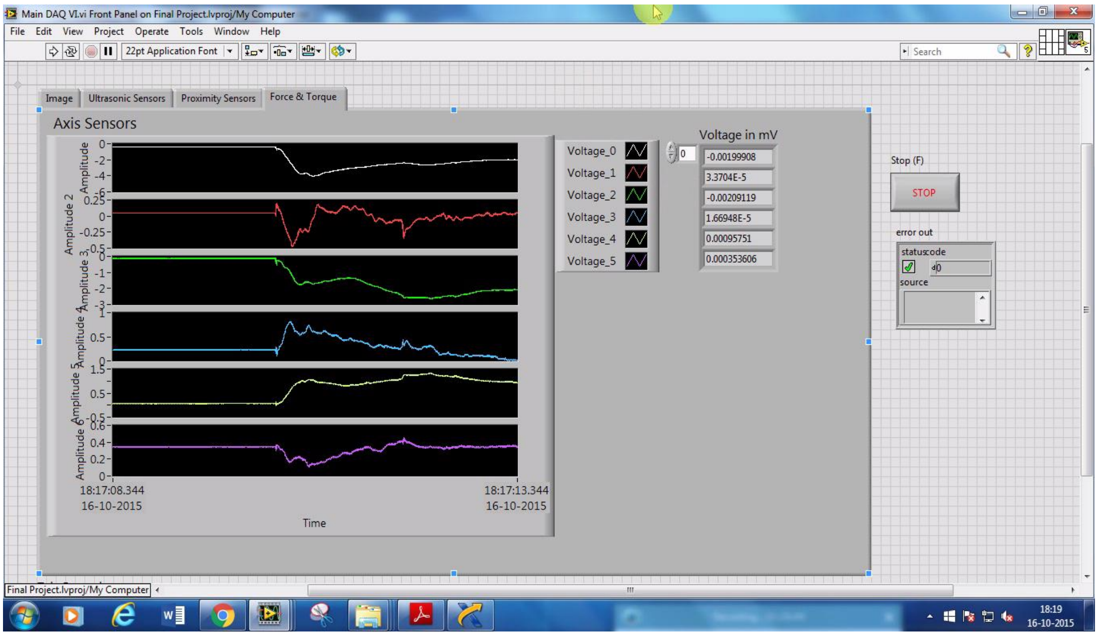


Figure 7.10 Calibrated Force/Torque sensors front panel diagram using LabVIEW

So in the pink box have a string of Force/ Tourque.xls file to build a path for data communication shown in Figure 7.9. Now from the Figure 7.10, it can be seen the calibrated acquiring force and torque outcomes in term of voltage in mv, and figure out the same in the graphical representation, the variation of amplitude with respect to time.

7.5.3 Integration of inductive and capacitive proximity sensors

Now in the integration of proximity sensors are connected with NI cRIO-9074 previously explained. If the proximity has been reached near to the object, the particular sensor is detected, that inductive and capacitive type, the green light will be on. The Proximity

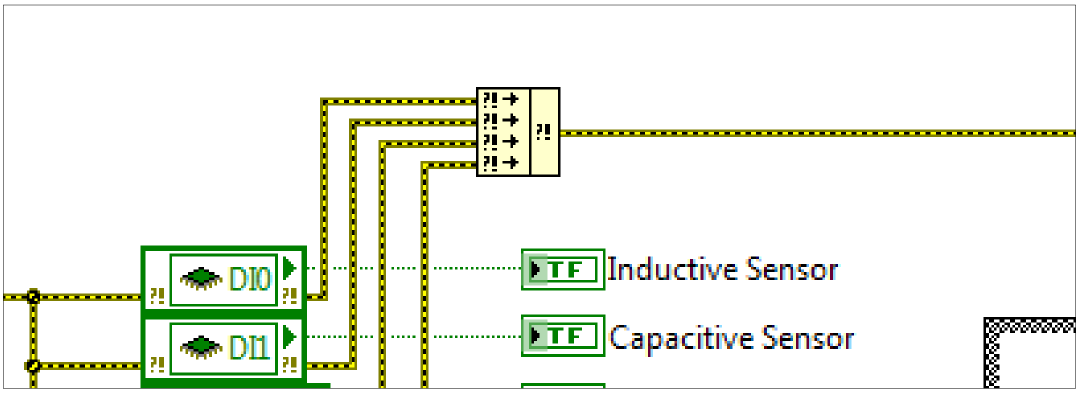


Figure 7.11: Proximity sensors integrated VI block diagram using LabVIEW 2013

sensors integrated VI block diagram is shown in the Figure 7.11. The calibrated capacitive proximity sensor integrated front panel diagram and indicative proximity sensor integrated front panel diagram using LabVIEW 2013 are shown in the Figure 7.12 and Figure 7.13 respectively.

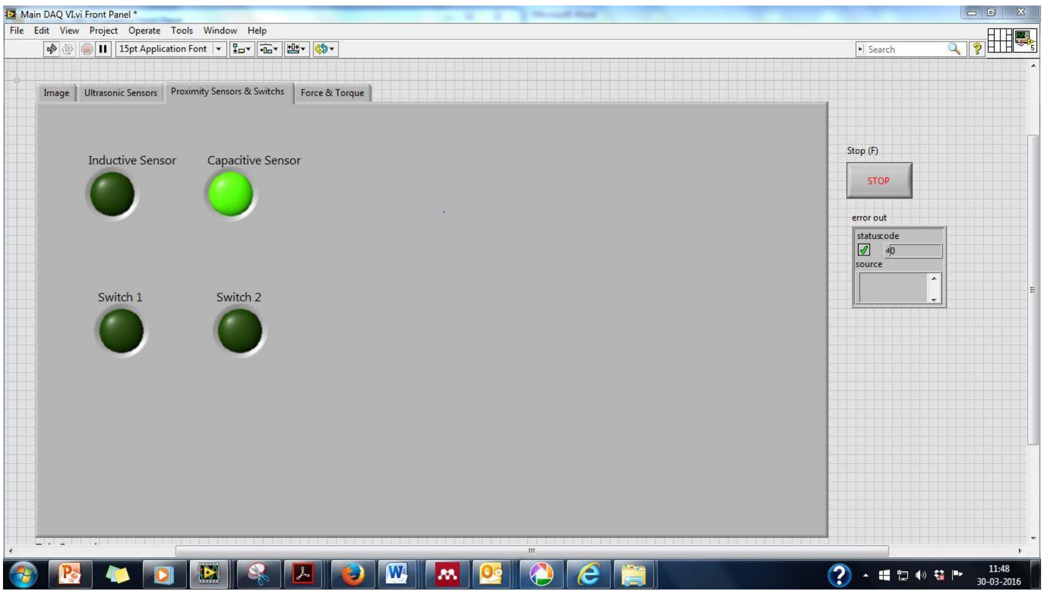


Figure 7.12: Calibrated capacitive proximity sensors front panel diagram using LabVIEW

The sensors are vertical-integrated inductive-capacitive proximity sensor. The advantages of this vertical-integrated inductive-capacitive proximity sensor are enlarge the range of sensing distance, capacitive-sensing remains sensitive for short-distance object and long-distance object remains detectable by inductive-sensing, conductive and non-conductive objects can be detected.

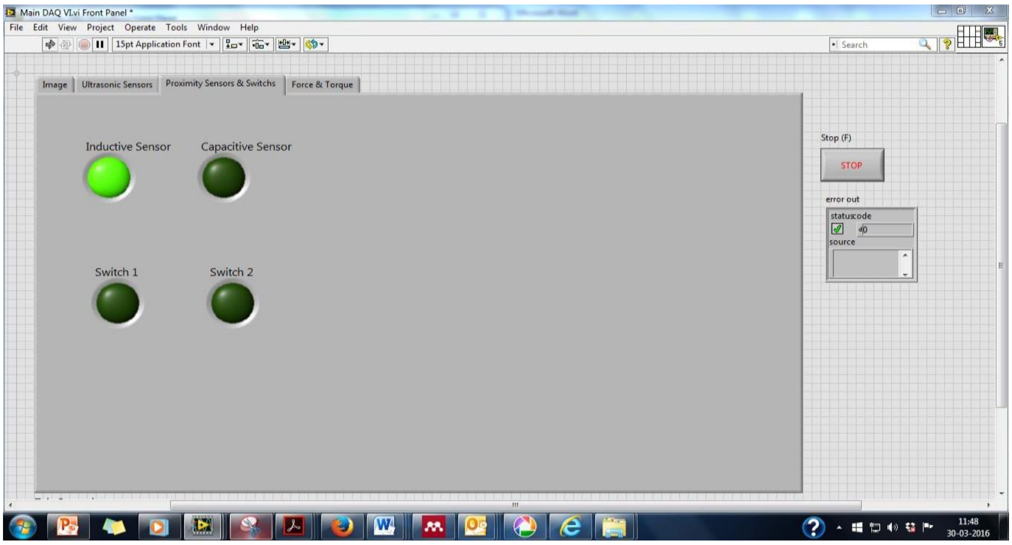


Figure 7.13: Calibrated indicative proximity sensors front panel diagram using LabVIEW

7.5.4 Integration of ultrasonic sensor

For the integration of ultrasonic sensor, there is a SEB card connection in PXI, where PXI have four counters (Ctr0, Ctr1, Ctr2 and Ctr3), where it is selecting the trigger pulse to the counter Ctr0, and taking the echo signal counter gate port to the counter Ctr1, ultrasonic sensor integrated VIs block diagram using LabVIEW is shown in the Figure 7.14.

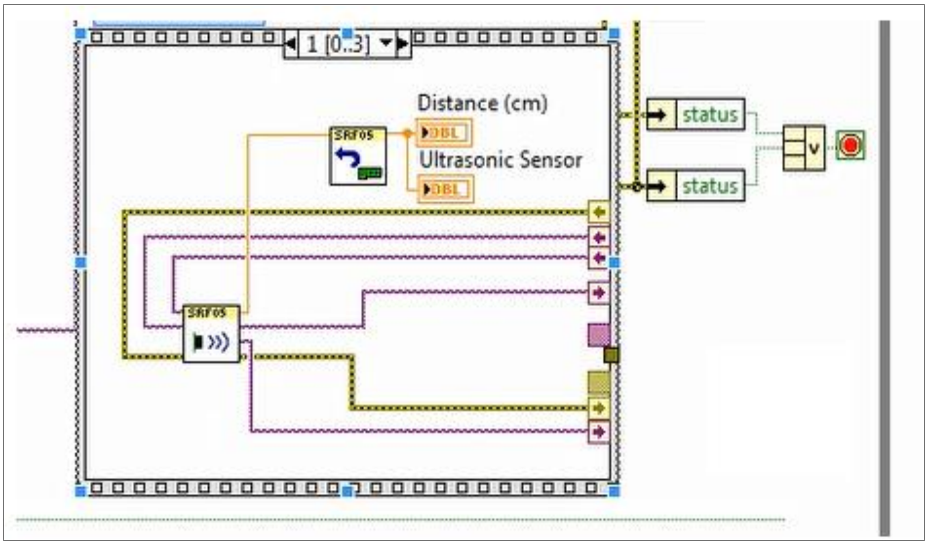


Figure 7.14: Ultrasonic sensor integrated VI block diagram using LabVIEW 2013

Pires (2002), **Lee et al., (1996**) proposed a novel module and a new algorithm which are applied on robot to avoid obstacles using three ultrasonic sensors with different beam

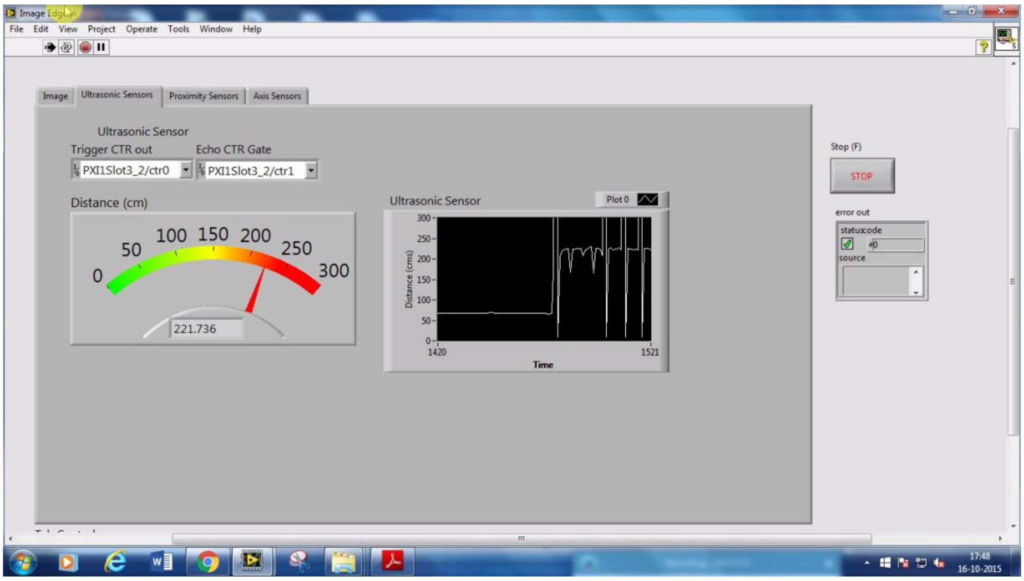


Figure 7.15: Calibrated ultrasonic sensors front panel diagram using LabVIEW

widths. The counter line has to be enabling to initializing the counter with enable counter icon, then measuring the echo pulse and converting the echo pulse, closing the counter pulse Ctr1 up to counter pulse Ctr3 code will be continuously executed to measure the object distances. The Figure 7.15 shows the calibrated front panel diagram of ultrasonic sensor and the icons displays the calibrated acquired distance value of the object in the workspace.

7.5.5 Integration of LTS sensor

Now in the integration of light touch switch (LTS) switch-1 and switch-2, when the end-effector or clamp hold some object or parts, then the switch will be in on, so if both the switch element will be on. The integrated LT Switch Sensors integrated block diagram and calibrated front panel diagram setup using LabVIEW 2013 are shown in Figure 7.16 and 7.17 respectively. So based on the switch condition, if both switch outcomes is high, then there should have the condition, then there have codes for the robotics task, pick the object and move for particular distance. Also there it has to be specifying, if the condition is true, and then do it, else enactive the robot movements.

And secondly using the sequence structure, because each and every time this particular element will execute once, so at the same time all structure should have to execute, these sequence structure in the signal phase, it will occupy the big amount of portion, instead of

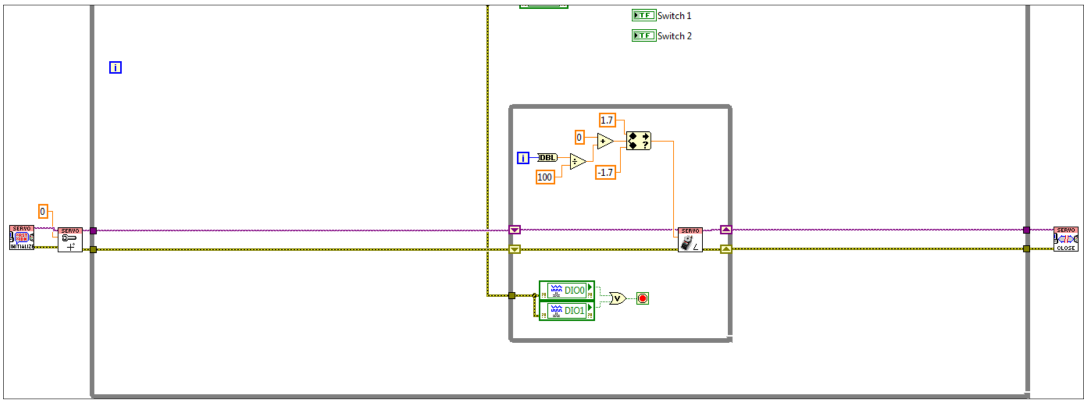


Figure 7.16: LT Switch sensor integrated front panel diagram setup using LabVIEW

that it will convert this flat sequence in to the stack sequence, so anyhow this will be continuously go on, whenever there are any errors, that will be taken out through loop

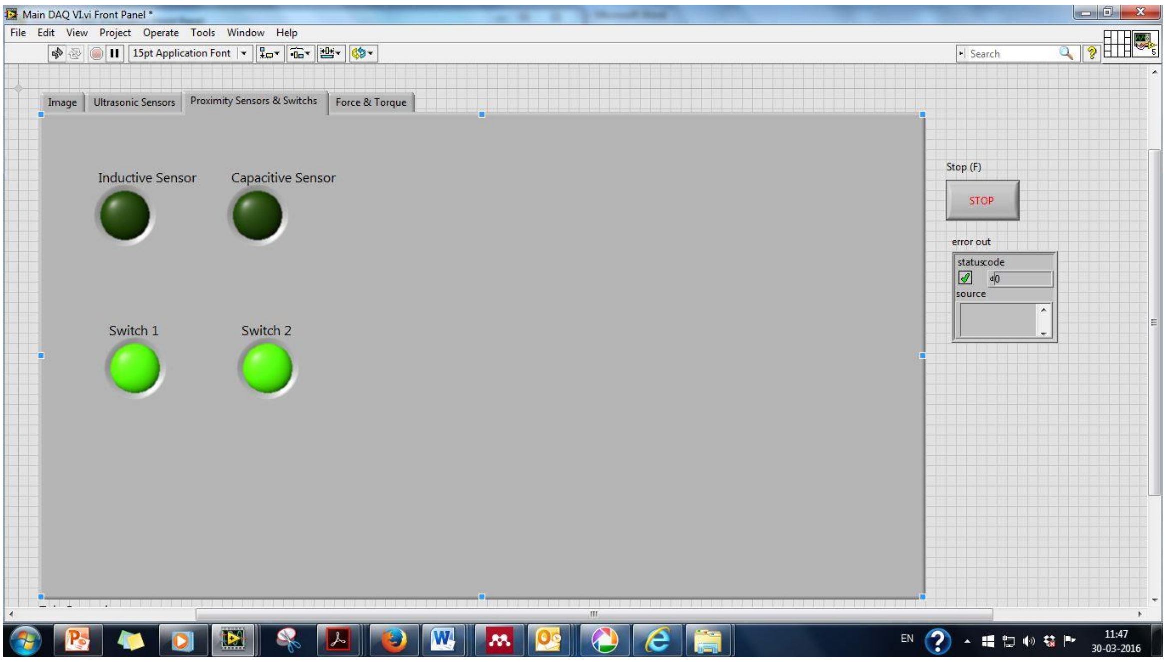


Figure 7.17: Calibrated LTS sensors front panel diagram using LabVIEW

error and can continue with program. And when our program has to be stop or any of the icons throw the logical icon error, then program will be automatically stop. **Girao et al., (2013)** given the brief analysis of the advanced of touch sensing techniques in the context of robotics.

7.6 Summary

In this chapter, LabVIEW 2013 with robotics module and vision module are embedded with real-time operation, and hardware based platforms such as NI cRIO- 9074 and NI PXIe-1082 central processing unit provides all of the necessary hardware and software tools needed for interfacing with sensors and actuators, controlling the robot's motion, implementing proposed methodology along with advanced control, and modelling the robot in a dynamic environment. The interfacing and internal diagram of experimental set-up works are presented in this chapter is intended to develop the data acquiring controller for the theory of multi-sensor integrated robotic hand. This process will provide a methodology for the integration of unstructured sensors data into a robotic hand and reliable evaluation of the state of a robot workspace.

Chapter 8

IMPLEMENTATION OF THE SENSOR BASED ROBOT HAND FOR ASSEMBLY TASKS

8.1 Overview

This chapter presents the implementation of the sensor in the robot hand for assembly tasks. Grasping is bridge between the robotic hand and object that take action from perception. The awareness of grasping is depends on; how to grip the object, find the grasp point, and force to apply on objects Also this chapter presents the applied methodologies, algorithms for grasping the four different objects such as circular, rectangular, hexagonal and unshaped object.

8.2 Extraction of Grasping Points

Furthermost robotic hand has the uncertainty to find the exact gasping point on unknown objects. Extraction of gripping aspects on object is the key issue of this section. Grasping points can be created on the basis of geometrical model of the object. In general, the two fingertips of robotic hand are located at the top of the object surface, in order to find the perfect orientation interaction along with the area of object. The generalized methodology of object model based grasping points can be derived from the information of smart sensors.

An object model based grasping point is depends on three sources of information; geometrical information of unknown object, robotic hand orientation configuration and operational task to be executed. The objects characteristics that impact the grasping point position depend on two aspects; first one is the physical characteristics of objects such as materials properties, texture of surface, inertia and weigh, second one is the geometrical properties of objects such as size, shape, position and COG.

To perform the grasping procedure, following comprehensive strategy is required to enhance the grasping strength: maximize the contact between robotic hand and object, constant COG, minimize the grasping force to optimize the objects contact area, reduce the wrist torque and robotic hand movements.

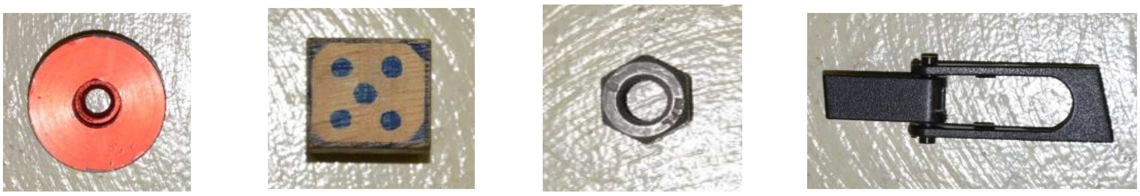


Figure 8.1: Considered four unknown objects

Various grasping modes can be performing from the principles that are applied to satisfy the above criteria. To simplify the explanation and conversation of grasping points some objects are considered shown in Figure 8.1. Experimental setups of integrated sensors with robotic hand are presented in Figure 8.2.

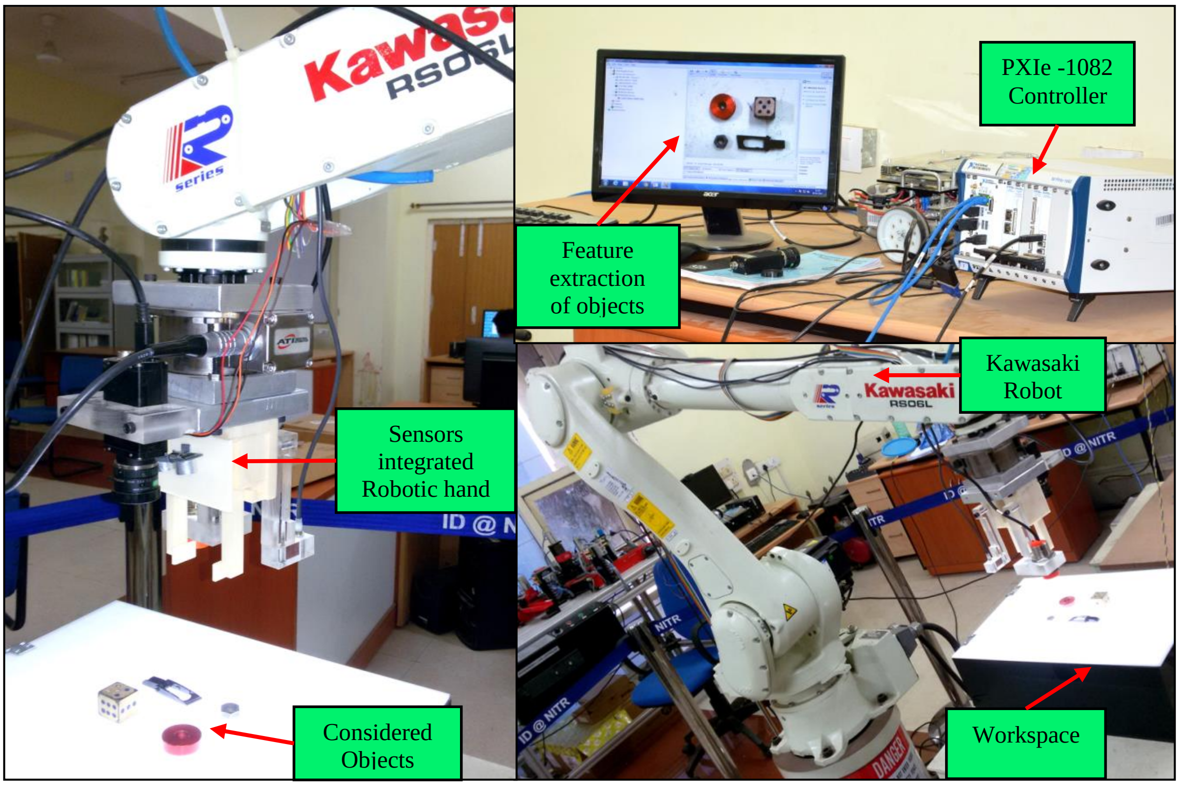


Figure 8.2: Experimental setup of integrated sensors with robotic hand

The geometrical data that is identified with pixel extraction in LabVIEW robot vision module is two-dimensional considered images (top view). Grasping points for each object are predefined in the positions of the geometrical information formed by vision assistant system shown screen shot in the Figure 8.3.

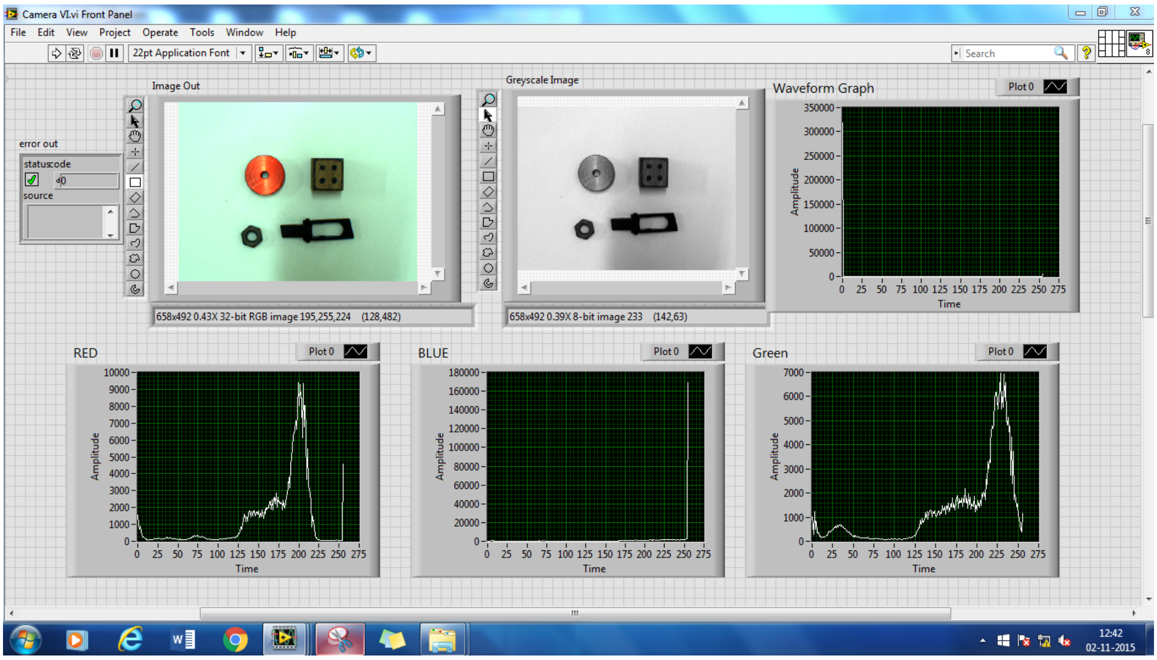


Figure 8.3: Vision assistant interfacing front panel of Main DAQ VI.vi setup using LabVIEW 2013

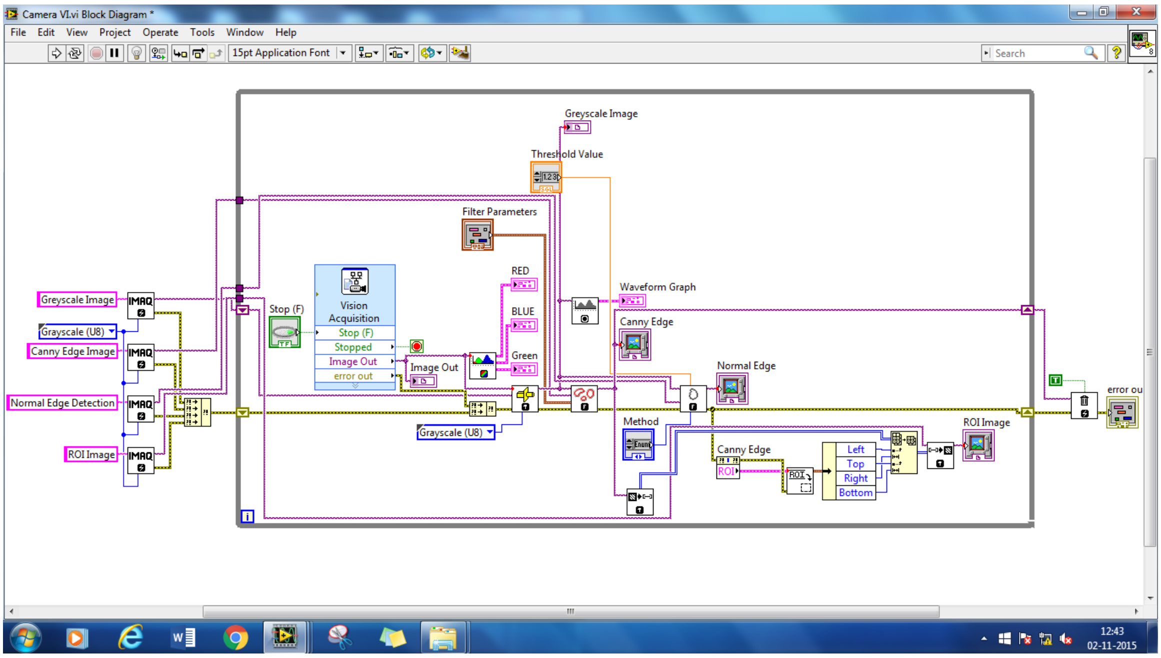


Figure 8.4: Vision assistant interfacing front panel of Main DAQ VI.vi setup using LabVIEW 2013

Figure 8.4 shows the block diagram of vision sensor acquisition system using the module of LabVIEW 2013 vision and motion, where the vision sensor is connected using IEEE cable in NI PXIe-1082, and according to the program here the system is acquiring real-time images of considered unstructured objects. Then for the feature extraction and further image processing, images are converted in the grey-scale image, and finding the edges of unstructured objects using canny edge detection algorithm. A grasping point comprises with reference to the designed prototype configuration of the two-fingered robotic hand.

8.2.1 Feature extraction for circular object

Circular object is defined as an object with sphere profile from the top view. The sensitive contact on circular object is the most significant grip feature in this case. Extraction of images for circular object in real-time operation results is shown in the Figure 8.5.

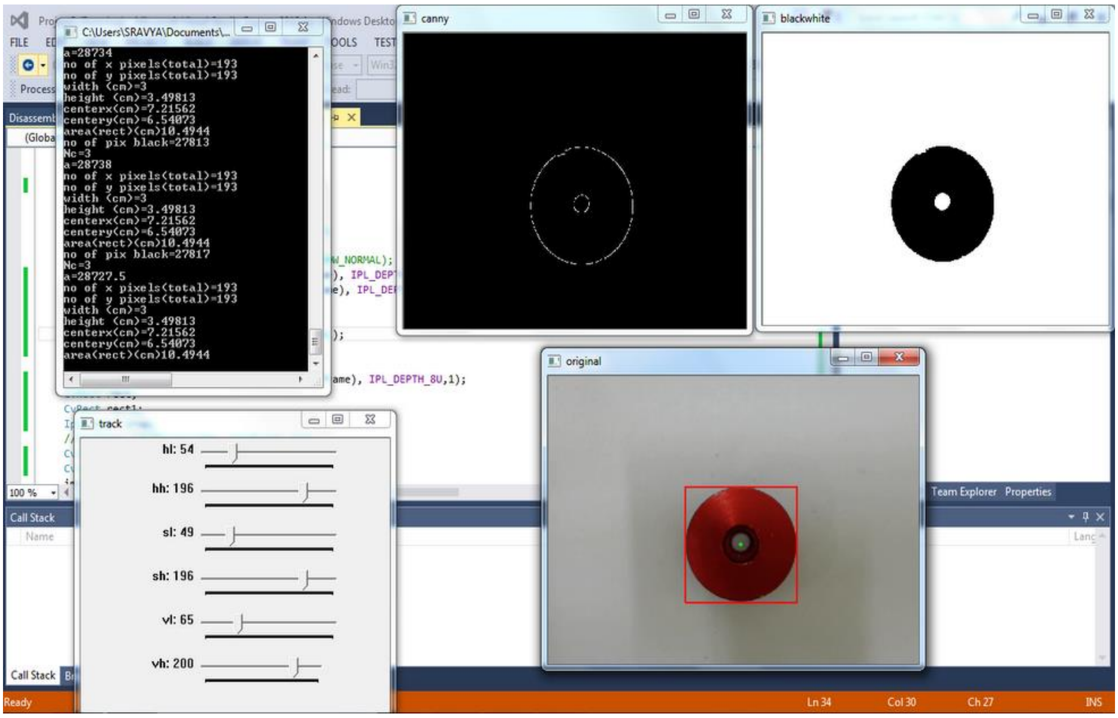


Figure 8.5: Extractions for circular object

The Microsoft visual studio “#include<cv1111.h>” contains all the predefined header files of OpenCV which are used for different purposes can be seen in the programing part in **(Appendix-B).** Using the respective data types, the images frames (IplImage) are captures form the vision sensors or cameras attached, and are processed through importing the OpenCV programmed DLL file in LabVIEW shown in Figure 8.6. These frames are in the RGB colour format which is converted to HSV (Hue Saturation Intensity) colour model because if intensity varies the actual colour of the object cannot be identified in RGB model, whereas in HSV intensity value range can be set using the track bar.

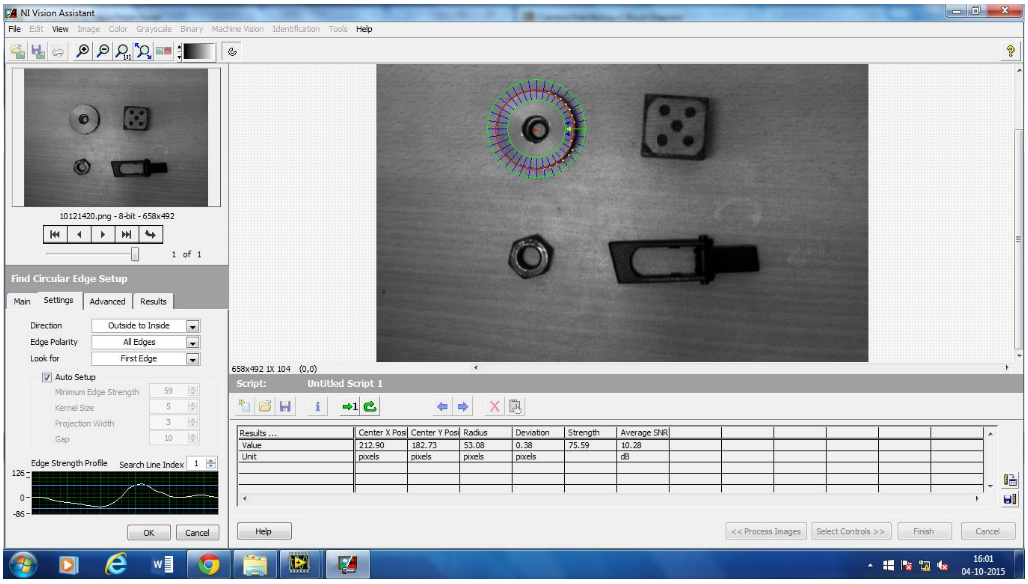


Figure 8.6: Vision assistant extractions for circular object using DLL file in LabVIEW

Hue value range defines the actual colours we are interested in, whereas saturation defines the amount of white colour that is present in that particular object colour and value is the surrounding light intensity.

8.2.2 Feature extraction for square object

Similarly, a wooden block is considered as an object with its contour being a rectangle from the top view. Red box presents the identified object from the group of objects in the

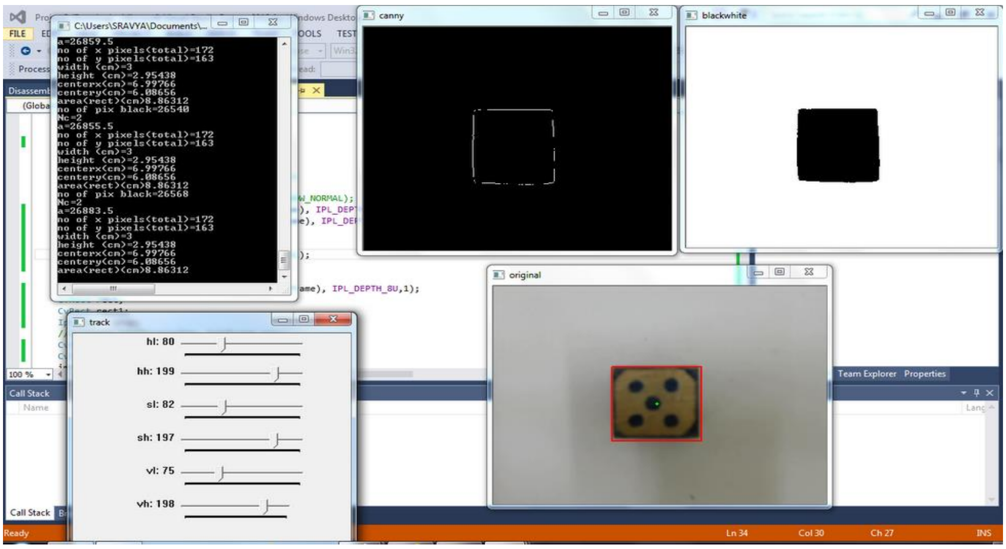


Figure 8.7: Extractions for square object

workspace. In the centre point of object, there is green dot point represent the central orientation from x and y coordinates in the workspace are shown in Figure 8.7.

8.2.3 Feature extraction for hex object

In case of hexagon object, a metallic nut is considered, and same methods or algorithms are applied to extract the features of captured image, defined as an object with hexagon profile from the top view. Black and white icon is used to represents and determines the numbers of pixel values in the objects, as shown in Figure 8.8.

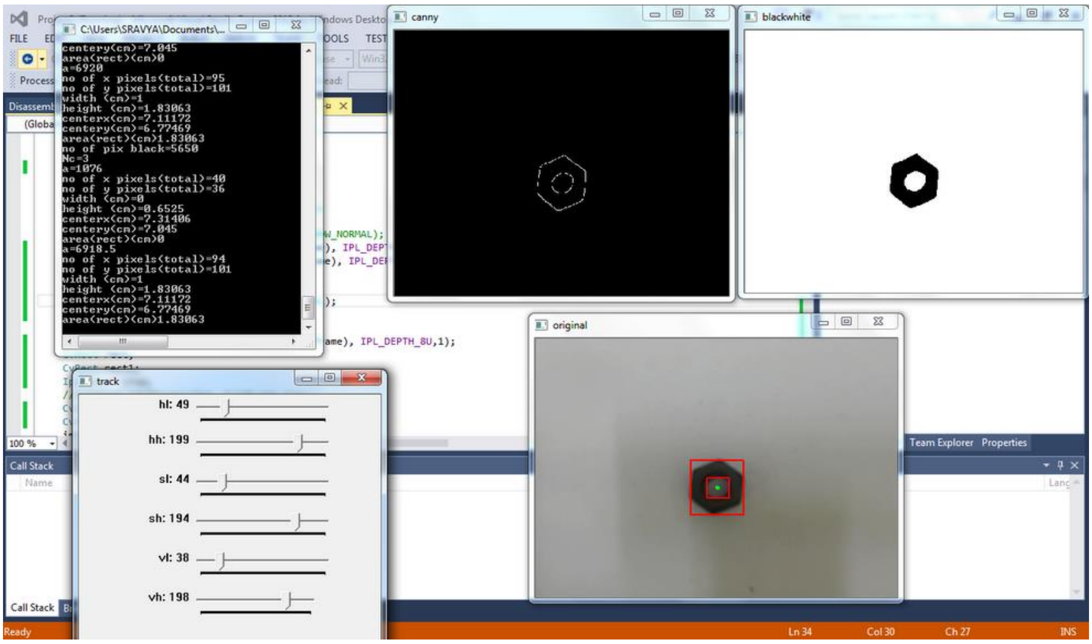


Figure 8.8 Vision assistant interfacing front panel of Main DAQ VI.vi setup using LabVIEW 2013

8.2.4 Feature extraction for unshaped object

Unshaped object of plastic material is considered to extract the feature of identified object, is defined as an object with two parallel edges in its profile from the top view. All the selected objects are experimentally extracted using sensors. The first user icon of each object represents the all the information about objects shown in Figure 8.9, such as pixel values on image, orientation in the workspace and object location from the x and y coordinates. This all acquired information from sensors are applicable to perform the operation in real-time.

8.3 Model-Based Grasping Point

Grasping point is the position at which the robotic hand can grasp the object, which is generally be nearer to the centre of mass of the object. A Kawasaki robot RS06L is used for further experiments in real-time. Developed robotic hand is attached with Kawasaki robotic manipulator. OpenCV is an open source library written in C++ which helps mainly for real-time operations. A working environment is required to use this library as per our requirements. So software called “Microsoft Visual Studio 2013” is used, which is interfaced with OpenCV. And finally create a DLL file to import the code in the LabVIEW 2013 for interfacing of vision sensor using LabVIEW in front panel and vision assistant function coded in block diagram has been explained previously. Experimental setup of sensors integrated robotic hand with Kawasaki robot, there controlling and feature extraction of images. And the preliminary operations depend on the communication protocol of the robotic hand that is chosen to be compatible with the robot Kawasaki manipulator. Where two-finger developed prototype robotic hand is connected with three communication protocols are: Ethernet/IP, TCP/IP, and RS232 are shown in the Figure 8.2.

Now the grasping points on the objects at which the robotic hand can grip the targeted object, which has to be closed to the centre of gravity of the object. When geometrical structures of unknown objects are recognised to find the grasping point, the aforementioned formation of the robotic hand is derived. With reference to the design of the two-fingered robotic hand, the following results are suitable to find the grasping points on considered objects.

8.3.1 Grasping points for circular object

To find the grasping points on considered circular object, real-time operation performed to extract the captured image features for circular object are shown in Figure 8.10. The location and orientation coordinate of the two-fingered robotic hand are completely determined by the configuration of the robotic hand.

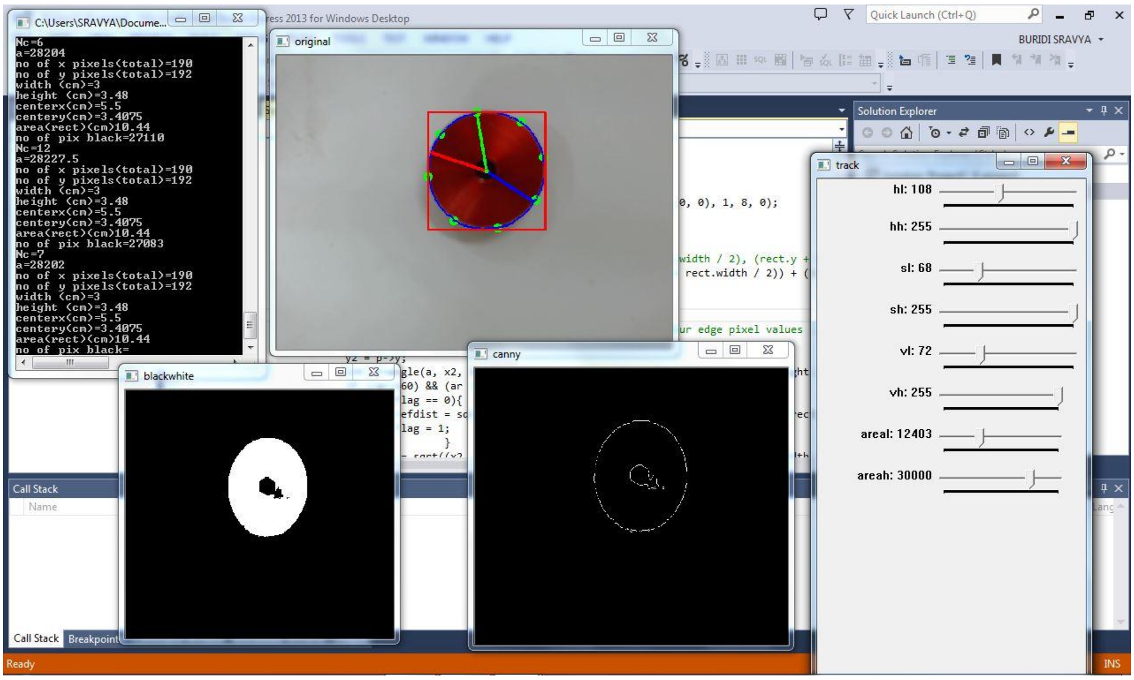


Figure 8.10: Grasping point on circular object.

We considered the contour with largest area, which is the contour or region of interest (ROI). Draw the bounding rectangle around that contour. Using the canny edge detection, the edge of the contour is found out. The total no of black pixels in the image is calculated. Total no of pixels in the image is the product of width and height of the image and the number of black pixels are counted and subtracted to get the total number of pixels on the object is contributing in the image. Now the centroid of the image is found out using cvMoments and the centre is marked with green colour. And the corners of the object are found out using the command approxpolyDP and are also marked with green colour. Now the edge pixels of the image are found out and the image is divided into the pixels towards the left and those pixels towards the right making the first detected pixels as the reference. We found out the pixel of minimum length on the left side and also on the right side. These two points are the minimum or gasping point of the object. These two lines are shown in blue and red colour steps by step, are shown in Figure 8.10 for hexagon object.

8.3.2 Grasping points for square object

To find the grasping points on considered square object, real-time operation performed to extract the captured image features for square object. The two finger grasping points will be function with the grasping structures communicated by the two red and blue dark lines are shown in the Figure 8.11 for Square object.

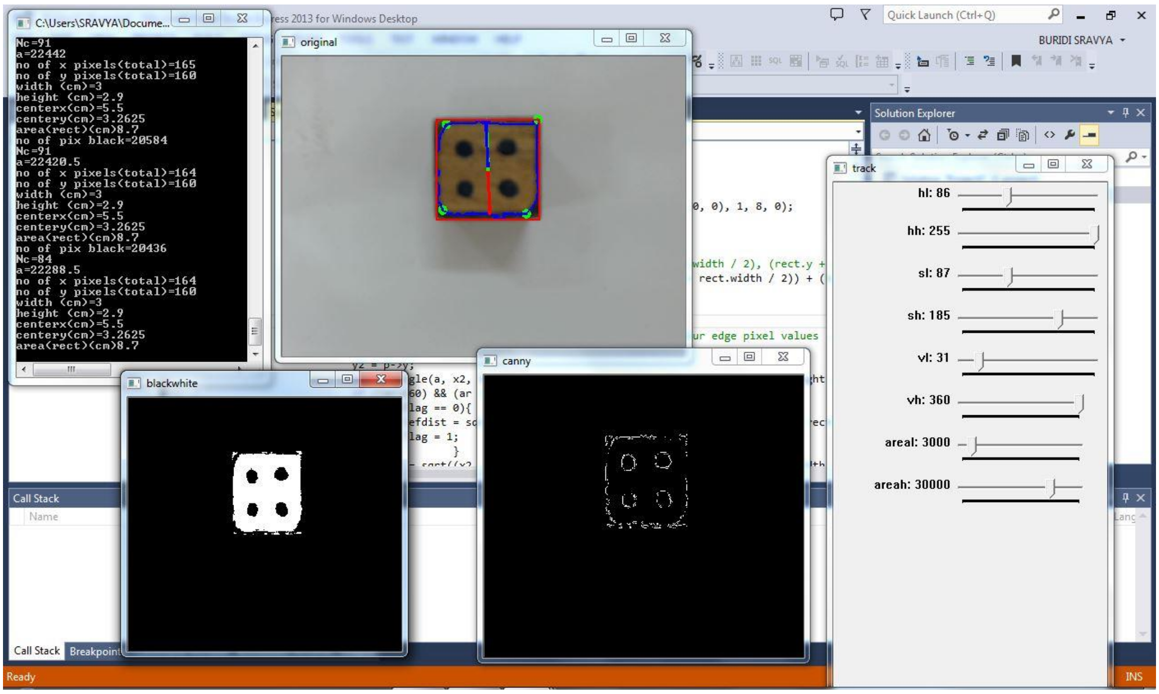


Figure 8.11: Grasping point on square object.

Grasping points are said to be in symmetrical when the resulting forces and torques applied on the object both by the robotic fingers and by outside force is constant.

8.3.3 Grasping points for hex object

The grasping point's algorithm is extracted the features to construct hexagon object and its structures, as shown in Figure 8.12.

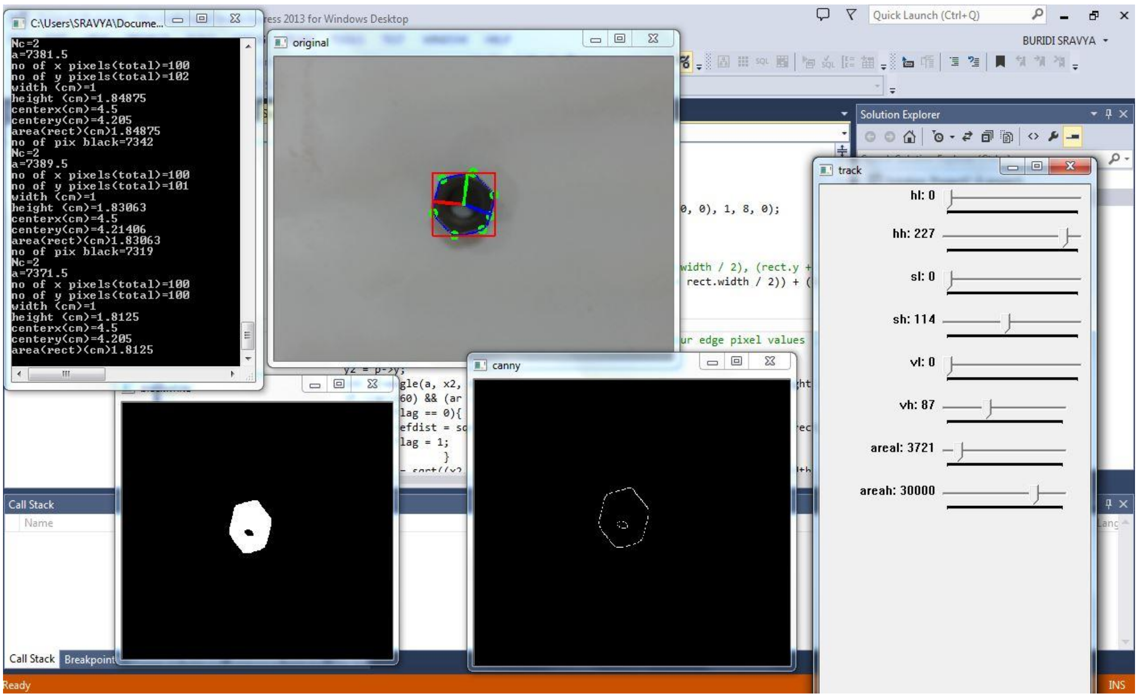


Figure 8.12: Grasping point on hex object.

8.3.4 Grasping points for unshaped object

Grasping skill is described as the capability of a robotic hand to accomplish the object while sustaining the (Cartesian and joint) kinematic relationship. To find the grasping points on considered unshaped object, real-time operation performed to extract the captured image features for unshaped object, as shown in Figure 8.13.

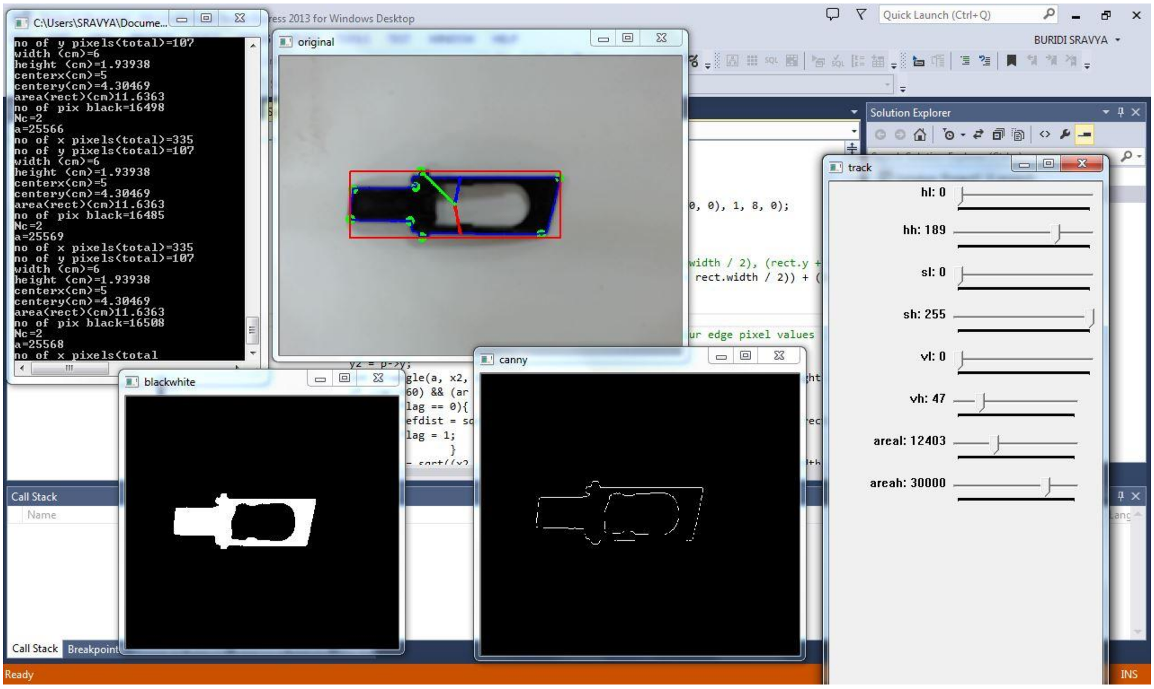
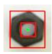


Figure 8.13: Grasping point on unshaped object.

8.4 Results and Discussion

This whole research work proposed an efficient method to control robotic hand grasping position combining a constant 2-D vision sensor with information of another acquired sensor mounted in a two-fingered developed robot hand. This sensor arrangement is a substitute to more difficult and expensive 3-D vision systems for industrial application. In this submission the vision sensor gives the direction vector to originate objects top views or features. Meanwhile the vision sensor is only two dimensional; the perfect range from the vision sensor to the object is desired in order to guesstimate the precise part parameters. This distance can be achieved by the ultrasonic distance sensor, mounted in the robotic hand in such a way that it is calculating the diffidence nearly parallel to the alliance of the vision sensor. The sensory information is used for grasping control and can be used for part identification, part shape, metallic properties, orientaions, parts pixel values, size, parts area and exact grasping points on objects are presented in the Table 8.1.

Table 8.1: Experimental outcomes and results

S N	Name of Object	Shape of Object	Orientation	Width of the Rectangular Box		Distance from the centre cordinate		Pixel value of object	Object area in Rectangular	Threshold Value					
										Hue Value		Saturation Value		Intensity of Light	
				X-axis	Y-axis	X (cm)	Y (cm)		cm^2	H_L	H_H	S_L	S_H	V_L	V_H
1	Circular		Horizontal	3	3.49	6.54	6.45	27817	10.49	54	196	49	196	65	200
2	Square		Horizontal	3	2.95	6.99	6.08	26568	8.86	80	199	82	197	75	200
3	Hexa		Horizontal	1	1.83	7.11	6.77	5650	1.83	49	199	44	194	38	200
4	Unshaped		Horizontal	6	2.1	6.17	7.82	21611	12.6	192	192	70	194	61	200

8.5 Summary

This chapter introduces the vision sensor affects which is mounted on the robotic hand is presented to extract the grasping points along with the geometrical structure of the unknown objects. This has to be picked or griped the objects by sensing information and continuous perception. Object model based intelligent grasping planning is a real-time solution to figure up the unstructured objects and environments. It's an important exploration and challenges to resolve the grasping planning problem by using sensors integrated intelligent robotic hand. In conclusion the unknown shape and size of the object can be grasped by the robotic hand is determined. The planned robotic hand system is applicable in automatic material handling and assembly operations.

Chapter 9

RESULTS AND DISCUSSIONS

9.1 Overview

This chapter is devoted to presenting the outcomes of the research work and the related discussions. The design and development of the intelligent robotic hand dealt with multiple issues such as design of the mechanical hand, selection of the sensors, integration of sensors and implementations of all the ideas to build an autonomous robotic hand. While dealing with these subtopics, some of the results have already been presented and discussed through the previous chapters. Some broad's results are discussed herewith to enumerate the findings.

9.2 Finite element analysis of robot hand

Before the hand is developed, it is important to assure that the designed hand functions correctly as per the intended tasks. Therefore, finite element modeling and analysis was carried out. As a final result the intelligent robotic hand is designed and developed along with integrated sensors as represent in Figure 9.1.

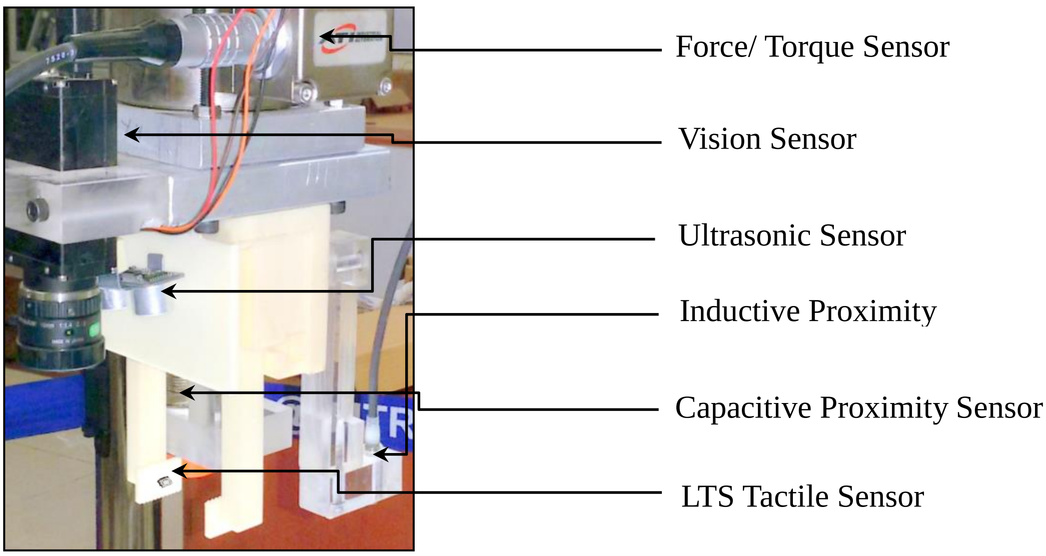


Figure 9.1: Complete robot hand

To analyse the designed prototype robot hand, ANSYS-15 workbench has been used. The transient structural module was used to carry out finite element analysis (FEA) in ANSYS results are shown in Figure 9.2.

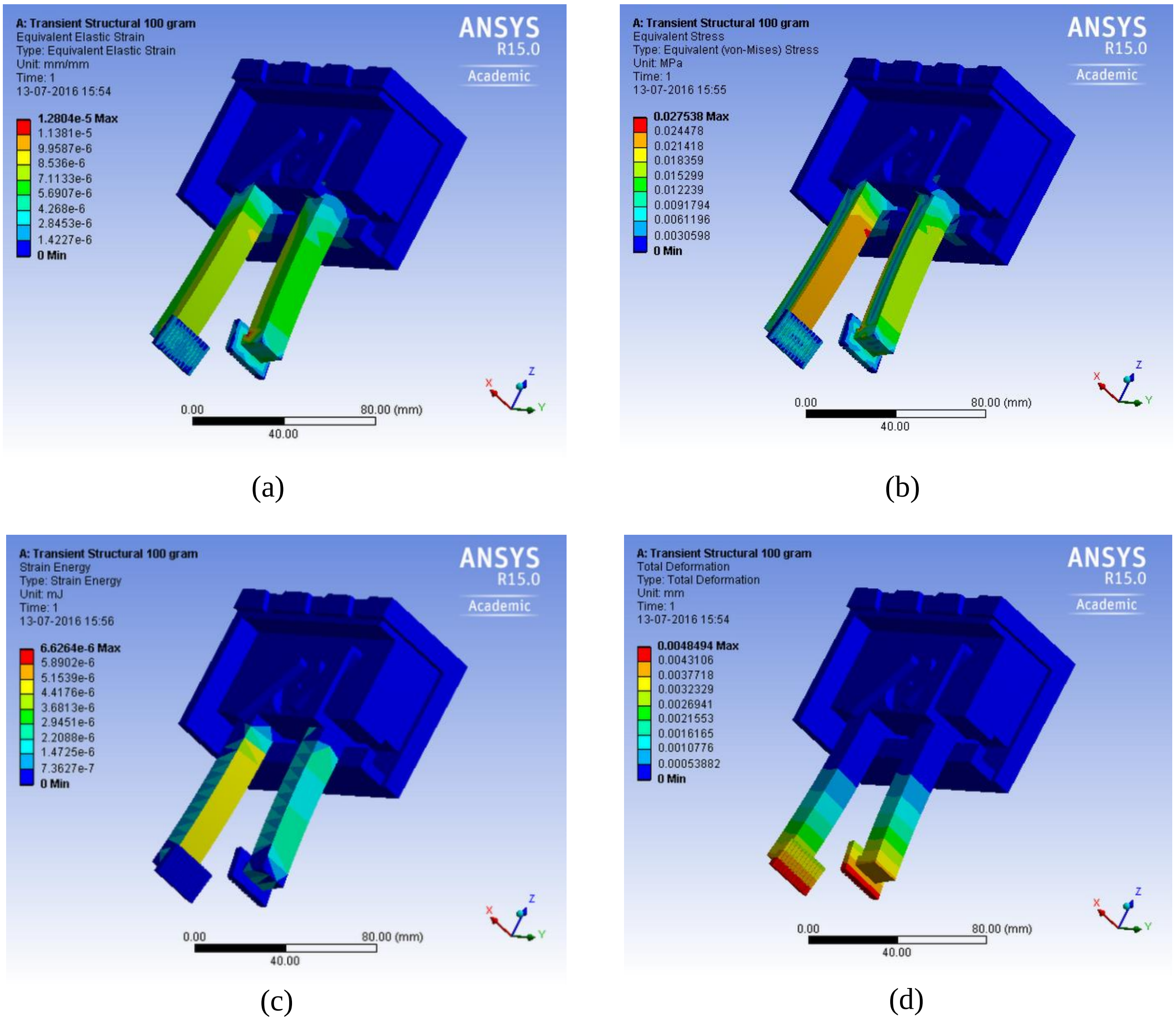


Figure 9.2: FEA analysis of robotic hand (a) Equivalent Elastic Strain (b) Equivalent Stress (c) Strain Energy (d) Total Deformation

A material property of ABS polymer is added in the material library, and then the geometrical model is imported in '.igs' file format in to the workbench of ANSYS. This defines the model mesh properties and applied load. In this model, a fine mesh in proximity and curvature is used.

9.3 The Sensors

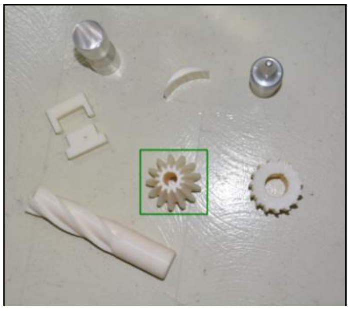
The output of the proposed research work is explained stepwise in this section. First step has to be identifying the objects shape, size and orientations of object in unstructured environments.

9.3.1 Vision sensor

For this purpose, initially images are acquired through vision sensor from the workspace and are processed for feature extraction. First, these images are converted into grayscale images and then the edge detection operator is applied with a fixed threshold value, as represented in Figure 9.1.

Using vision sensors in the workspace, an image template is required to locate the correct image within a group of images. After this, template matching is done on the basis of correlation of image data. There are five different methods to perform template matching, out of which we have used Square Difference (SQDIFF) methodology to perform this. In this method the point at which, a global least value is declared (Figure 9.4), is the point where the object is located. To perform these operations Visual Studio 2012 ultimate edition as the compiler and OpenCV libraries to perform image processing are used. A green rectangle is found over the image to verify the object as shown in Figure 9.9(a) and (b). A captured image, a template image and images of the objects from stored data are taken by vision sensors from the workspace. SURF algorithm to get prominent features of each image is applied for object verification to match the objects individually.

(a) Template Image



(b) Image to search for, from multiple objects

Figure 9.3 Experimental process of template matching using Square Difference (SQDIFF) methodology

By this methodology the system is able to verify the position of the object irrespective of orientation and scale. The software were used Python 2.7, Opencv libraries for Python. Programming and written coding of above work has been briefly explained in **Appendix-A.** Figure 9.5 shows the matching process. This is done by matching the corresponding points of the image acquired with the template image by drawing green lines from point to

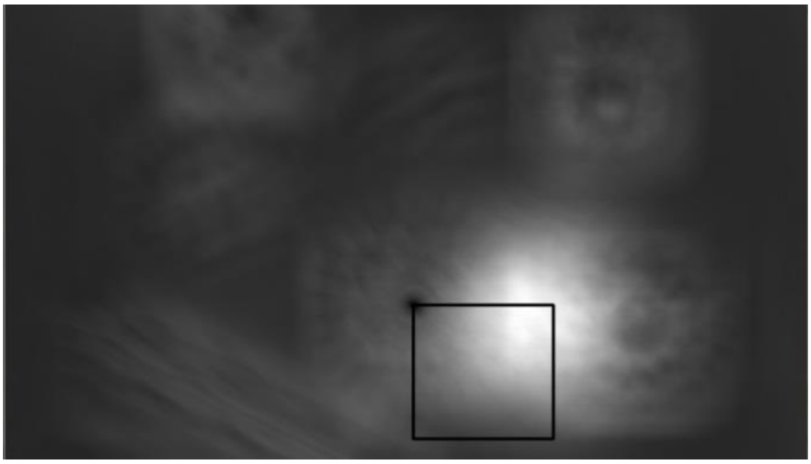


Figure 9.4 Finding the global least value to obtain correlation and match the object

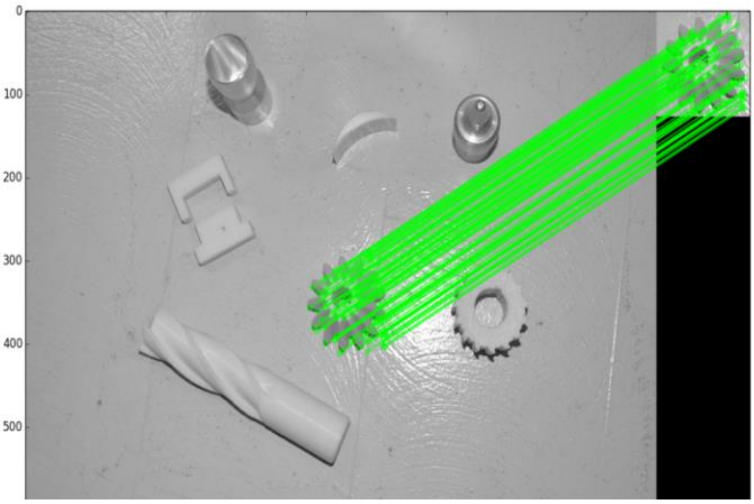


Figure 9.5: Feature matching of object with the template image using SURF algorithm

point. Then the other parameters for recognition are processed by matching the dimension of objects acquired through ultrasonic sensor. This is represented with the help of an experiment.

9.3.2 Ultrasonic sensor

Sensors for distance and position detect are applied for sufficient information acquisition working together with vision sensor and ultrasonic sensor, to judge 2D surface, position, distance and shape of the parts in workspace, and guide the autonomous manipulator as well as the robot hand to recognize the object and parts.

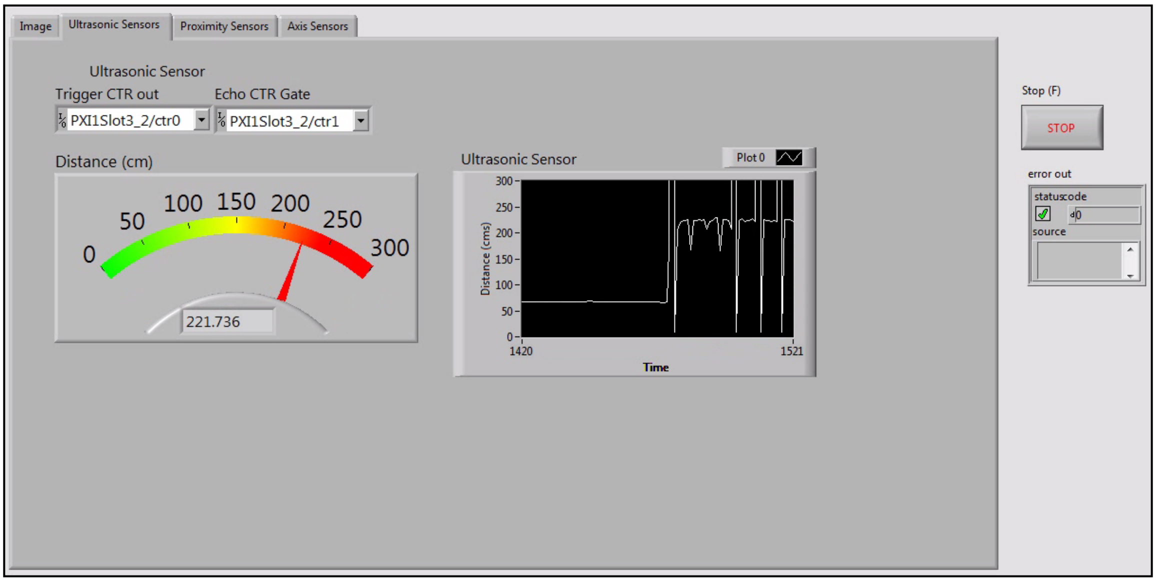
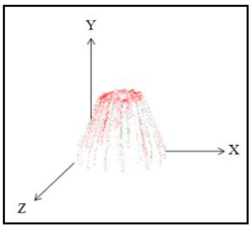


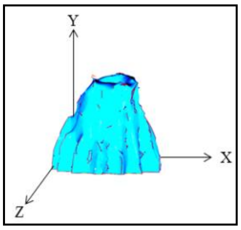
Figure 9.6: Graphical representation of ultrasonic sensors to measure the distance using LabVIEW 2013

Vision sensors are mounted on the robot hand by which we are creating a grid size function of the distance between sensors and the target. This has been explained in the Chapter 5. This grid size function will be stored as a template image by vision sensor for matching. Similarly, an ultrasonic sensor has been mounted parallel along with the vision sensor on the robot hand. It will transmit a 40 KHz square pulse signal when applied with a 5V P-P square wave. Graphical representation of ultrasonic sensors to measure the distance using LabVIEW 2013 is presented in the Figure 9.6. Initially a reference point will be considered on the top of targeted object to calculate the distance using time of flight method.

The ultrasonic sensor matrix will find out the distance of corner point and boundary point in three axes according to the reference point. With respect to the distance data, the reference points of the curve can be plotted. Using curve fitting technique the virtual model of the surface has been generated are shown in Figure 9.7. Generated model will also be stored in another database for further use.



(a) Generated point data plot using ultrasonic sensor



(b) Virtually generated surface using curve fitting algorithm

Figure 9.7: Virtual model of parts recognition by using ultrasonic sensor

By the image data the top surface plane has been generated and with the help of ultrasonic sensor data, other information like dimensions, height from the base plane etc. has been calculated. For height calculation we have to subtract the nearest point distance from the farthest point distance. By considering dimensions, the weight distribution of target objects is calculated. This information is used for generating the exact robotic hand and target object contact point location. In this experiment the present state of the sensor technology in automated assembly system has been analysed. The object identification is performed by integrating the vision sensor with the ultrasonic sensor matrix. The exact shape regarding surface of the target object is obtained by vision sensor. Proper weight distribution and other geometric information regarding dimension and location of the target object are obtained by ultrasonic sensor matrix. By using the ultrasonic database, exact robot hand and target object contact point is determined.

9.3.3 Force/Torque sensor

In order to conduct the experiments and verify the correctness of the instrument setup, the Force/Torque (F/T) sensor has been calibrated. This was done by applying forces and torque of known voltages on the F/T sensor and recording the output in terms of voltage. As many as 25-30 different points were taken on the sensor and the outputs were measured are represented in the Appendix-B.

A correlation between the applied force/torque and the output voltage was established. This correlation was used to determine the weight of the part being manipulated during

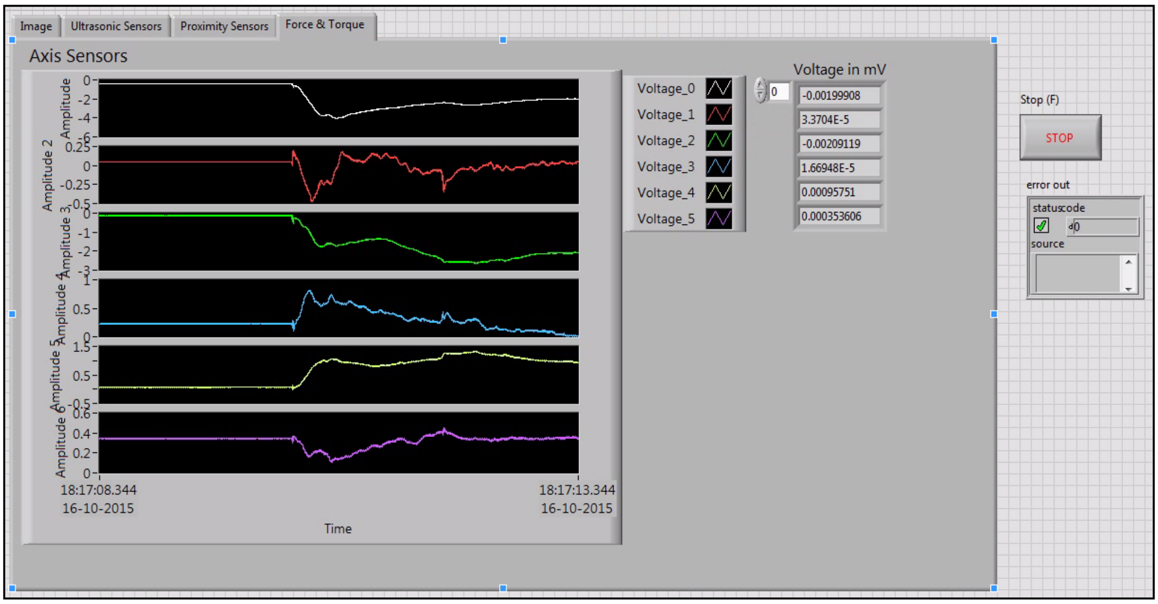


Figure 9.8: Graphical view of the Force/Torque value during operation using LabVIEW 2013

assembly and to do the necessary mating operations for part assembly. The mating operations considered in the present work are simple pushing and screwing. The forced torque required to do the necessary mating operation was also predetermined through experiments. Graphical view of the Force/Torque value during operation in ATI software results are presented and explained in Figure 9.8.

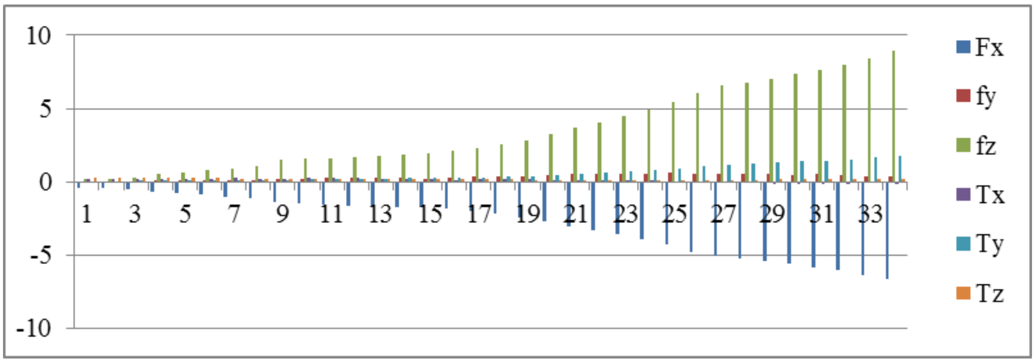
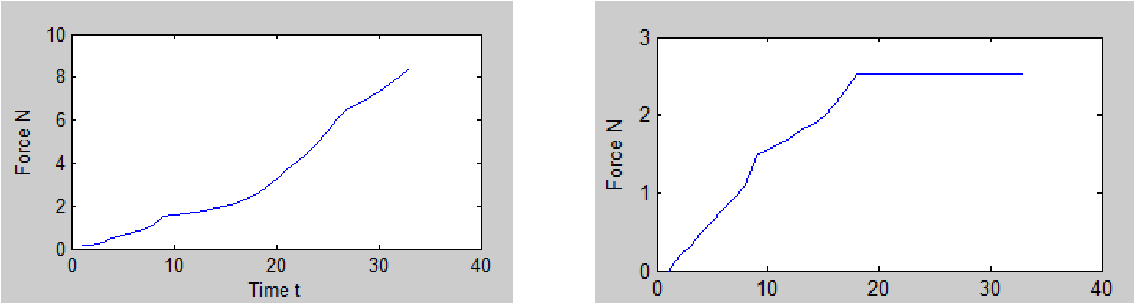


Figure 9.9: Bar Graph of recorded output in volts

It shows that the force/torque is increasing with respect to time. According to this data, the applied force/torque output voltage and correspondingly recorded bar graph is shown in Figure 9.9 respectively.



(a) (b)

Figure 9.10 Weight identification force curve at considered tolerable range

The required forced and torque to do the necessary mating operation is determined through experiments. Result of weight identification force curve show the force applied at considered tolerable range curve, as presented in Figure 9.10 (a) and (b), respectively. Similarly, Figure 9.11 shows the pushing force curve and Figure 9.12 shows the screwing torque curve at considered tolerable range.

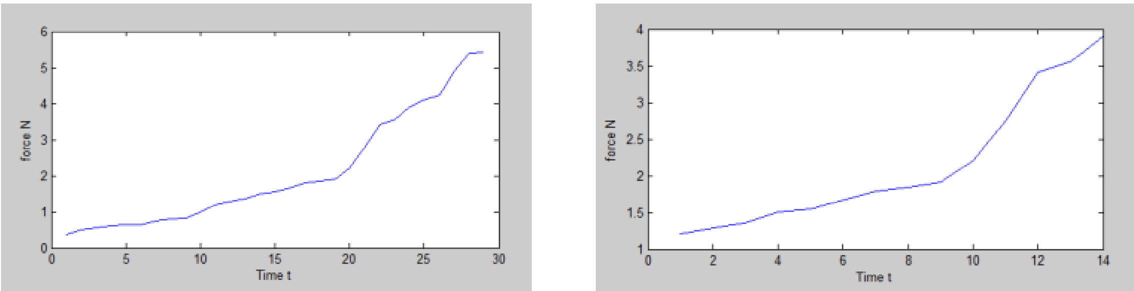


Figure 9.11: Pushing force curve at considered tolerable range

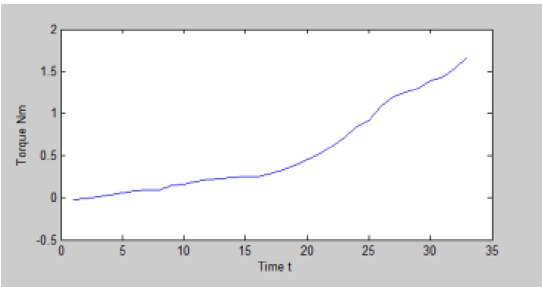


Figure 9.12: Screwing torque curve at considered tolerable range

In this experiment, force/torque sensor technology in automated assembly system has been analysed. Using Matlab2012a the integration of force/torque sensors with applied load have been analysed for the typical mechanical assembly processes to improve reliability and to perform quality inspection in new assembly areas. Results of the entire research of observing system gain ground mostly in robotized systems field with intelligence assembly system.

9.3.4 Capacitive and inductive proximity sensor

A capacitive and inductive proximity sensor has been mounted on the front of each finger, and these two proximity sensors are used to feel the proximity of the finger to the object in 2mm distance and compensate the positioning error of the visual system. This would help the

Figure 9.13: Capacitive and inductive proximity sensor responses using LabVIEW 2013

robot hand to adjust its position and posture to avoid collision with the object parts and determine the metallic and non-metallic properties of four different types of considered objects. Experimental responses using LabVIEW are shown in the Figure 9.13.

9.3.5 LTS sensor

Similarly, two light touch switch (LTS) switches, switch-1 and switch-2 are mounted on the contact points between hand fingers and the object. Whenever the robot hand holds the object, the switch will be turned on if both the switch elements will be in 'on' position. This is shown in Figure 9.14.

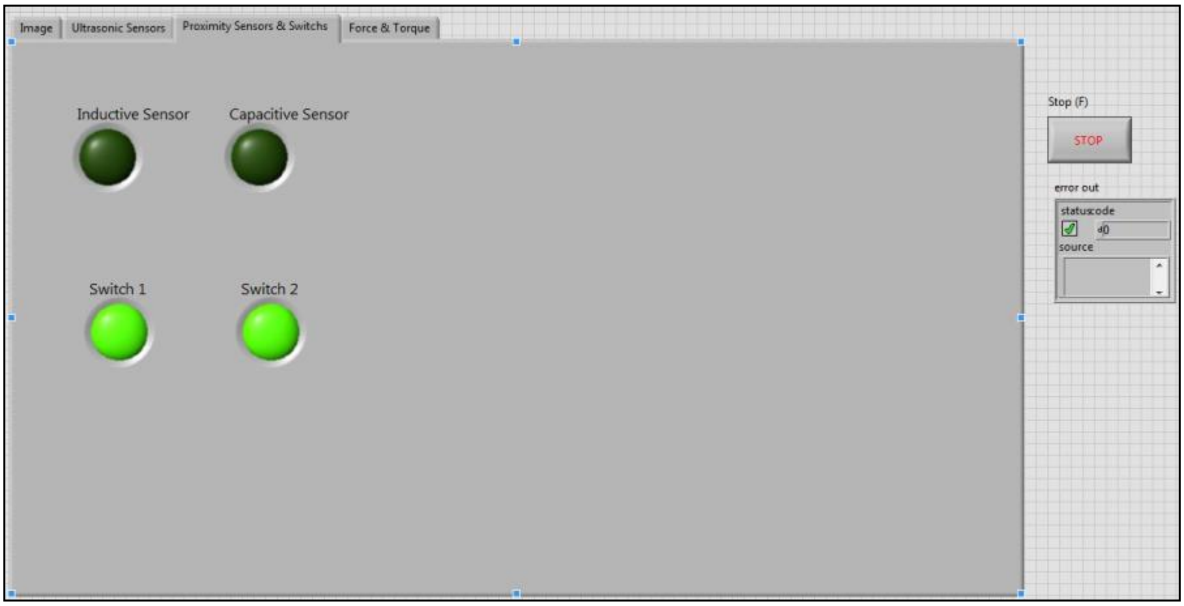


Figure 9.14: LTS Sensors responses using LabVIEW 2013

So, based on the switch condition, if both the switches outcome is high, then the condition for the robotic task to pick the object and move for particular distance is performed.

Table 9.1 Experimental assembly task performance datasheet

Parts	Force(s) to perform assembly task	Tolerable range	Material properties	Inspection of parts	Assembly task
a	2.5 N	1%	Metallic	Touch and Distance	Identification
b	4 N	0.5 %	Metallic	Touch and Weight	Pushing
c	1.5 N -m	1%	Metallic	Touch and Torque	Screwing
:	:	:	:	:	:
n	n	n	n	n	n

Table 9.1 represents the three experimental assembly task performance datasheet. The first one is the identification of part. For this operation, measurement of the weight of the part in considered tolerable range is required. Inspection of parts is also considered via measuring the touch and distance. Similarly, for another assembly task - pushing and screwing, the system has to measure the weight and pick and manipulate the correct part for assembly and carry out the operation for mating the parts.

9.3.5 Grasping points on the objects

Similarly, in the case of vision sensor, captured images are processed in real-time to find the image parameters such as numbers of objects in the workspace, edge of the image, and shape of image, threshold value, HSV range and area of image pixels in the unstructured workspace, as shown in Figure 9.15.

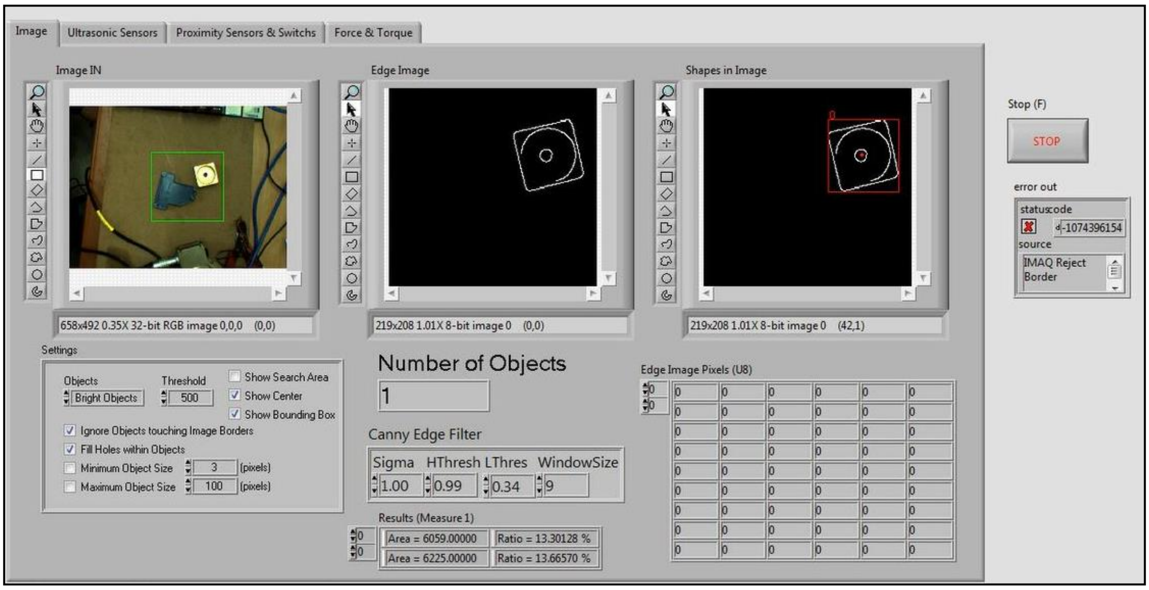


Figure 9.15: Image processing for unstructured workspace of Main DAQ VI.vi setup using LabVIEW

In locations of the alignment of the two fingered robot hand, the part of geometrical identification must be found so as to make suitable grasping point. In this study, a pattern recognition methodology is utilized to recognize the geometry of the part. Four different shapes of geometrical parts are considered to get the grasping points as represented in Figure 9.16.

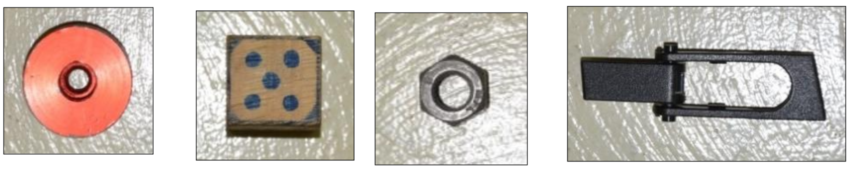


Figure 9.16 Four different types of unstructured parts to recognize

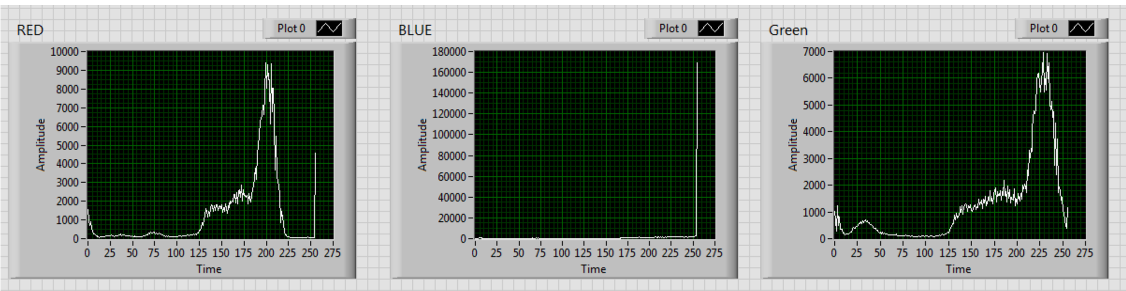


Figure 9.17: RGB graphical representation of captured images

To identify the exact grasping points of considered objects, the image processing of four different parts has been done along with grayscale image by using LabVIEW. The graphical representation in RGB (red, green, blue) of considered objects in real-time operation is shown in the Figure 9.17. The contour with largest area is picked as the contour of interest. A bounding rectangle around that contour is drawn as shown in the Figure 9.18.

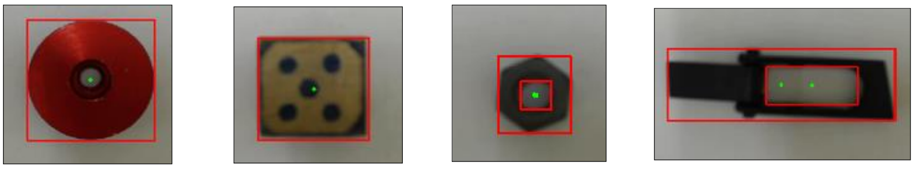


Figure 9.18: The image frame size is found in pixels and converted to centimetres

Using the Canny Edge Detection, the edge of the contour is found, as shown in the Figure 9.19. The total number of black pixels in the image is calculated. Total number of pixels in the image is the product of width and height of the image, and the number of black pixels are counted and subtracted from it to get the total number of pixels the object is contributing in the image. Now the centroid of the image is found out using cvMoments

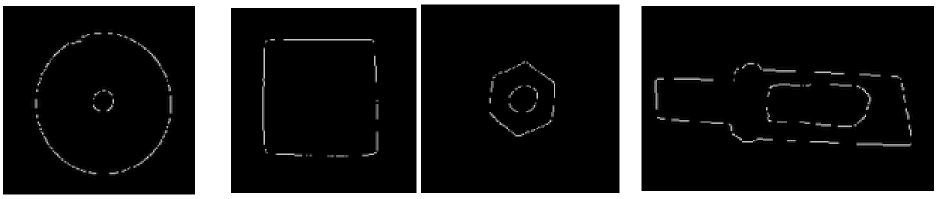


Figure 9.19: Using the Canny Edge Detection the edge of the contour is found

and the center is marked with green color. The corners of the object are found out using the command approxpolyDP and are also marked with green color. Now, the edge pixels of the image are found and the image is divided into - pixels towards the left and pixels

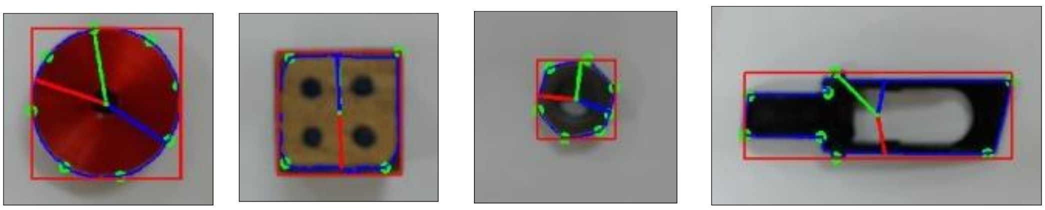
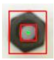


Figure 9.20: Gasping point of the object with two lines is shown in blue and red colour.

towards the right. Right side is used to first detect the grasping point, as a pixel, used for reference. Then the pixel of minimum distance from the centroid on the left side and right side is found. These two points are the grasping points of the object. These two lines are shown in blue and red color, as shown in Figure 9.20.

Table 9.2 Image parameters of unstructured parts

S N	Name of Object	Shape of Object	Orientation	Width of the Rectangular Box		Distance from the centre cordinate		Pixel value of object	Object area in Rectangular	Threshold Value					
										Hue Value		Saturation Value		Intensity of Light	
				X-axis	Y-axis	X (cm)	Y (cm)		cm^2	H_L	H_H	S_L	S_H	V_L	V_H
1	Circular		Horizontal	3	3.49	6.54	6.45	27817	10.49	54	196	49	196	65	200
2	Square		Horizontal	3	2.95	6.99	6.08	26568	8.86	80	199	82	197	75	200
3	Hexa		Horizontal	1	1.83	7.11	6.77	5650	1.83	49	199	44	194	38	200
4	Unshaped		Horizontal	6	2.1	6.17	7.82	21611	12.6	192	192	70	194	61	200

First the image frame size (width and height) is found, which is in pixels and is later converted to centimeters. The contour of the object is found by varying the HSV ranges using the track bars. Now, the numbers of contours that are detected for that HSV range are counted, as represented in Table 9.2.

9.3 Summary

The development of the sensor integrated robotic hand consisted of developing/ selecting each active component used in the hand. Every component was carefully chosen and tested for their suitability for the intended job. The hand was also tested with all the sensors on board. It is observed that the sensor integrated robotic hand behaves exactly as intend.

Chapter 10

CONCLUSIONS AND FUTURE WORK

10.1 Overview

The intelligent robotic hand is designed and developed by extracting, analysing, and modelling of sensor data with the self-decision-making systems. In this work, a sensor integrated, configurable and intelligent two-fingered robot hand for grasping is developed. This development presents a novel platform to accomplish research into automated vision system and intelligent robotic hand. This chapter concludes the overall research aimed at the design and development of sensor integrated intelligent robotic hand.

10.2 Conclusions

This thesis, presents designing and development of sensor integrated control schemes for robotic hand that assist robots with a system to grasp the unknown objects in unstructured environments. Intelligent robotic hand with more than six sensors for industrial application is developed first time; it is the novelty of this research work.

In this research dissertation, an intelligent robotic grasping system is developed and combined with a Kawasaki RS06OL industrial robot. Hardware components such as sensors, robot, servo motors and NI interfacing components of LabVIEW and software components were used to accomplish the integration task.

Hierarchical planning for instrumented intelligent grasping was created, which divided the robot functions into two categories. The first one is at a high level – functions such as design, modelling, identifying and development. The second is at a low-level – functions such as sensing, interfacing and executing based on control system.

New experiments have been done along with different sensors, and their output has been explained in previous chapter. A vision sensor system plays an important part in increasing the robot intelligence level. Vision sensor systems need high level process-algorithms computational proficiency in order to operate in real-time operation. Unknown object edges provide suitable grasping orientations using a process that includes extraction of geometric details, explanation and illustration of object structures. This extracted feature provides the essential information for a vision sensor system, such as edges on objects, pixel values, and useful features such as centre of gravity (COG), area of object, etc.

Various challenges have been faced to achieve the goal of proposed research work; such as to integrate the six sensors is a novel achievement but, after integration of sensors, it was very typical to do sensor fusion using LabVIEW. Secondly many time interfaces sensor does not response properly due to the atmospheric and human error, so to handle this kind of problem along higher accuracy is a challenging job. All the integrated sensors are generally activate on low voltage, but to interface the low level of components along with the high level of augmenting components such as control system and Kawasaki robot was the another challenging work to achieve this research goal. A connection that associates perception to action and grasping strategies, resolves the problem of finding points to grasp on objects. Grasping strategy is extremely dependent upon the robotic hand alignment and object geometrical parameters. A prototype grasping robotic hand system and algorithm is developed to create and recognise the operational grasping points on object. The control system architecture integration of the robot controller is done by using Ethernet cable to communicate with each other. Another implementation of the robotic manipulator using Digi-matrix Kawasaki program to control the two fingered robotic hand has been performed. This intelligent grasping method is conducted by analysis of sensor information and creating suitable control system architecture. Several experiments have been conducted for assembly tasks in the real-time workspace. The experimental outcomes validate the developed system and verified its correctness.

Chapter 1, described and explained the introduction of related works in fields such as robotic hands and sensor classification, and also presented the objective of this research. A literature and status of research work from 1975 to till date, and explanation of the research outcomes to achieve the research objective was presented in Chapter 2. In Chapter 3, the materials and components selected for hardware integration, and explanation about the methodology stages to implement research work was provided. The integration of sensors in robotic hand with selected control system and robotic manipulator are briefly explained in Chapter 4. Also, the way to assembling of hardware and software NI control system using LabVIEW is shown. In Chapter 5, description on the vision control system along with various algorithms for feature extraction the captured images of unknown part in real-time operations is provided. In Chapter 6, the conceptual design and development of prototype robotic hand along with integration of sensors is explained. The implementation of sensors for assembly operations has been performed in Chapter 7. In Chapter 8, the considered object model base grasping strategies to find the grasping point in unknown objects has been discussed. In Chapter 9, results from the research have been discussed.

10.3 Specific Contributions

The experimentation outcomes and results are demonstrated to be successful and they fulfil the desired objectives. The activities and contributions of this research work can be summarized as follows:

- A sensor integrated intelligent robot hand has been designed and developed. A prototype model is also designed, developed and simulated to analyse the stress and force in finite element analysis.

- It is the first time, when six types of different sensors are integrated and implemented in robot hand for real-time operation.

- An instrumented intelligent robotic hand system which integrates vision sensor system, proximity sensors, ultrasonic sensor, force/torque sensor and LTS sensor, with the assistance of grasping points and manipulator trajectory planning to a smart grasping control system and Kawasaki RS06L industrial robot has been developed.

- The processing of a captured image using vision sensor to identify the parts and extract the features for modelling the shape and size is formulated with the help of an ultrasonic sensor.

- To enhance the smartness of the system, two proximity sensors are integrated to determine the metallic properties of the objects. A force/torque sensor is integrated on the wrist of the robotic hand to find the applied force and torque on objects during assembly operation.

- The Kawasaki robot manipulator movement algorithm using Digi-matrix library in LabVIEW has been successfully designed.

- Four different model based grasping systems categorize the points extracted from the objects and successfully creates a grasping points for dissimilar objects.

10.4 Scope for Future Work

The intelligent robotic hand developed in this work, that operates using information on grasping points is a novel system. Additional expansion may improve the performance capability and accuracy of the system. Future scope of this research may be summarized as follows:

- To increase the customer interaction along with this system, 3D simulation of intelligent grasping points can be designed with visual structural model.

- 3D vision system enabling geometric and grasp features to be extracted more effectively may be developed which may lead to more efficient grasp schemes.

- Limited to the present experimental setup, the proposed scheme on unstructured environments was verified. A possible future direction is the implementation of this scheme to unplanned environments to show its effectiveness.

- In addition, it is necessary to extend the proposed system to the three dimensional circumstance. In that case, more sensors are essential. To integrate these sensor measurements to obtain robotic hand motion information promptly and accurately will be a challenging problem.

- The validity and effectiveness of the proposed sensor fusion scheme could eventually be demonstrated for articulated six axes industrial robots.

- Neural network prediction technique, rather than a conventional curve fitting algorithm could be used to modify the learning method for this system.

Appendix

Appendix A: Robot program for object pixel value

```
#include <cv1111.h>
#include<iostream>
using namespace cv;
using namespace std;

int hl = 0;
int sl = 0;
int vl = 0;
int hh = 255;
int sh = 255;
int vh = 360; int t = 0;
float width, height, xrect, yrect;
int a = 0, b = 0,c=0,d=0;
//int d[1000], e[1000], f[10], g[10];
int x2 = 0, y2 = 0;
int black_p, white_p;
int lowarea = 3000;
int higharea = 30000;
int a1, b1;
/*void clearchar()
{
        for (int i = 0; i < 1000; i++)
        {
                d[i] = NULL; e[i] = NULL;
        }
        for (int i = 0; i < 10; i++)
        {
                f[i] = NULL; g[i] = NULL;
        }
}
*/

int angle(int x1, int x2, int y1, int y2, int cenx, int ceny)
{
        int d1 = sqrt((x1 - x2)*(x1 - x2) + (y1 - y2)*(y1 - y2));
        int d2 = sqrt((x1 - cenx)*(x1 - cenx) + (y1 - ceny)*(y1 - ceny));
        int d3 = sqrt((cenx - x2)*(cenx - x2) + (ceny - y2)*(ceny - y2));
        if ((d2 == 0) || (d3 == 0))return 0;
        else{
                float a = (d3*d3 + d2*d2 - d1*d1) / (2 * d2*d3);
```

```
            //cout << (acos(a) * 180 / 3.14);
            return (acos(a) * 180 / 3.14);
        }

}

int main()
{
        CvCapture* capture = 0;
        capture = cvCaptureFromCAM(CV_CAP_ANY);
        if (!capture){ return -1; }
        IplImage* frame = 0;

        frame = cvQueryFrame(capture);
        if (!frame){ return -2; }
        cvNamedWindow("original", CV_WINDOW_NORMAL);
        int mindist = 255;
        IplImage* bw = cvCreateImage(cvGetSize(frame), IPL_DEPTH_8U, 1);
        IplImage* bw2 = cvCreateImage(cvGetSize(frame), IPL_DEPTH_8U, 3);
        IplImage* i1 = cvCreateImage(cvGetSize(frame), IPL_DEPTH_8U, 1);
        IplImage* i2 = cvCreateImage(cvGetSize(frame), IPL_DEPTH_8U, 1);
        IplImage* i3 = cvCreateImage(cvGetSize(frame), IPL_DEPTH_8U, 1);
        cvZero(bw);
        cvNamedWindow("track", CV_WINDOW_NORMAL);
        cvNamedWindow("canny", CV_WINDOW_NORMAL);
        cvNamedWindow("blackwhite", CV_WINDOW_NORMAL);
        int Nc;
        IplImage* canny = cvCreateImage(cvGetSize(frame), IPL_DEPTH_8U, 1);
        CvRect rect;
        CvRect rect1;
        CvSize imgSize;
        CvSize bw1Size;
        imgSize.width = frame->width;
        imgSize.height = frame->height;
        cout << imgSize.width << "*" << imgSize.height;
        while (1)
        {
            frame = cvQueryFrame(capture);
            if (!frame)return -6;
            cvCvtColor(frame, bw2, CV_RGB2HSV);
            cvCreateTrackbar("hl", "track", &hl, 255, NULL);
            cvCreateTrackbar("hh", "track", &hh, 255, NULL);
```

```
            cvCreateTrackbar("sl", "track", &sl, 255, NULL);
            cvCreateTrackbar("sh", "track", &sh, 255, NULL);
            cvCreateTrackbar("vl", "track", &vl, 255, NULL);
            cvCreateTrackbar("vh", "track", &vh, 255, NULL);
            cvInRangeS(bw2, cvScalar(hl, sl, vl), cvScalar(hh, sh, vh), bw);
            cvCreateTrackbar("areal", "track", &lowarea, 40000, NULL);
            cvCreateTrackbar("areah", "track", &higharea, 40000, NULL);

            //.......
            /*cvSplit(frame, i2,bw,i3, NULL);
            cvCreateTrackbar("hl", "track", &hl, 255, NULL);

            cvThreshold(bw, bw, hl, 255, CV_THRESH_BINARY_INV);
            cvThreshold(i2, i2, 100, 255, CV_THRESH_BINARY_INV);
            cvThreshold(i3, i3, 120, 255, CV_THRESH_BINARY_INV);
            //.....*/

            cvShowImage("blackwhite", bw);
            CvSeq* contours = 0;
            CvSeq* result = 0;
            CvMemStorage* storage = cvCreateMemStorage(0);
            cvCanny(bw, canny, 10,50, 3);
            cvShowImage("canny", canny);
            //cvCopy(bw, bw1);
            int white = cvCountNonZero(bw);
            cout << "no of pix black=" << white << endl;
            CvMemStorage* circles = cvCreateMemStorage(0);
            Nc = cvFindContours(bw, storage, &contours, sizeof(CvContour),
CV_RETR_LIST, CV_CHAIN_APPROX_NONE, cvPoint(0, 0));
            cout << "Nc=" << Nc << endl;
            for (; contours != 0; contours = contours->h_next)
            {
                   double area = cvContourArea(contours);
                   if ((area>lowarea) && (area<higharea))
                   {
                          cout << "a=" << area << "\n";

                          rect = cvBoundingRect(contours, 0); //extract bounding
box for current contour
                          int rx1 = rect.width, rx2 = rect.x, ry1 = rect.height,
ry2 = rect.y;
                          if ((rx1 < imgSize.width) && (ry1 < imgSize.height))
                          {
```

```
                                    CvMoments *moments =
(CvMoments*)malloc(sizeof(CvMoments));
                                    cvMoments(bw, moments, 1);
                                    double moment10 = cvGetSpatialMoment(moments, 1,
0);
                                    double moment01 = cvGetSpatialMoment(moments, 0,
1);
                                    double area = cvGetCentralMoment(moments, 0, 0);
                                    int x1;
                                    int y1;
                                    x1 = moment10 / area;
                                    y1 = moment01 / area;
                                    CvPoint* p = CV_GET_SEQ_ELEM(CvPoint, contours,
0);     //contour edge pixel values ..
                                    x2 = p->x;
                                    y2 = p->y;
                                    // .... refdist , distace of top most first pixel
detects to the centroid ..
                                    cvDrawLine(frame, cvPoint(x2, y2),
cvPoint((rect.x+rect.width/2),(rect.y+rect.height/2)), cvScalar(0, 255, 0), 3, 8,
0);
                                    cvDrawCircle(frame, cvPoint((rect.x + rect.width
/ 2), (rect.y + rect.height / 2)), 1, cvScalar(0, 0, 255), 1, 8, 0);
                                    result = cvApproxPoly(contours,
sizeof(CvContour), storage, CV_POLY_APPROX_DP, cvContourPerimeter(contours)*0.02,
0);
                                    int corners = result->total; CvPoint *pt[100];
                                    for (int i = 0; i<corners; i++)
                                    {
                                           pt[i] = (CvPoint*)cvGetSeqElem(result, i);
                                           cvDrawCircle(frame, cvPoint(pt[i]->x,
pt[i]->y), 5, cvScalar(0, 255, 0), 3, 8, 0);
                                    }
                                    int refdist = sqrt((x2 - (rect.x + rect.width /
2))*(x2 - (rect.x + rect.width / 2)) + (y2 - (rect.y + rect.height / 2))*(y2 -
(rect.y + rect.height / 2)));
                                    int n = contours->total; int dist;
                                    for (int i = 1; i < n; i++)
                                    {
                                           p = CV_GET_SEQ_ELEM(CvPoint, contours, i);
//contour edge pixel values ..
                                           x2 = p->x;
                                           y2 = p->y;
                                           dist = sqrt((x2 - (rect.x + rect.width /
2))*(x2 - (rect.x + rect.width / 2)) + (y2 - (rect.y + rect.height / 2))*(y2 -
(rect.y + rect.height / 2)));
                                           if (dist < refdist)
                                           {
```

```
                                        a1 = x2; b1 = y2; refdist = dist;
                                }
                                cvDrawCircle(frame, cvPoint(x2, y2), 1,
cvScalar(255, 0, 0), 1, 8, 0);


                        }
                        int flag = 0;
                        //cvDrawLine(frame, cvPoint(a, b),
cvPoint((rect.x + rect.width / 2), (rect.y + rect.height / 2)), cvScalar(255, 0,
0), 3, 8, 0);
                        dist = sqrt((a - (rect.x + rect.width / 2))*(a -
(rect.x + rect.width / 2)) + (b - (rect.y + rect.height / 2))*(b - (rect.y +
rect.height / 2)));
                        refdist = 0;
                        for (int i = 0; i < n; i++)
                        {
                                p = CV_GET_SEQ_ELEM(CvPoint, contours, i);
//contour edge pixel values ..
                                x2 = p->x;
                                y2 = p->y;
                                int ar=angle(a, x2, b, y2, (rect.x +
rect.width / 2), (rect.y + rect.height / 2));
                                if ((ar>160) && (ar < 200)){
                                        if (flag == 0){
                                                refdist = sqrt((x2 - (rect.x
+ rect.width / 2))*(x2 - (rect.x + rect.width / 2)) + (y2 - (rect.y + rect.height /
2))*(y2 - (rect.y + rect.height / 2)));
                                                flag = 1;
                                                        }
                                        dist = sqrt((x2 - (rect.x +
rect.width / 2))*(x2 - (rect.x + rect.width / 2)) + (y2 - (rect.y + rect.height /
2))*(y2 - (rect.y + rect.height / 2)));
                                        if (dist < refdist)
                                        {
                                                c = x2; d = y2;a=a1,b=b1;
                                        }
                                        }
                        }
                        //if (((c>rx2) && (c<rx2 + rx1 / 2) && (d>ry2) &&
(d<ry2 + ry1 / 2)) || (c==rx2) || (c==rx2 + rx1 / 2) || (d==ry2) || (d==ry2 + ry1 /
2))
                        cvDrawLine(frame, cvPoint(a, b), cvPoint((rect.x
+ rect.width / 2), (rect.y + rect.height / 2)), cvScalar(255, 0, 0), 3, 8, 0);
                        cvDrawLine(frame, cvPoint(c, d), cvPoint((rect.x
+ rect.width / 2), (rect.y + rect.height / 2)), cvScalar(0,0,255), 3, 8, 0);
                        cvRectangle(frame, cvPoint(rect.x, rect.y),
cvPoint(rect.x + rect.width, rect.y + rect.height), cvScalar(0, 0, 255, 0), 2, 8,
0);
```

```
                                    cvRectangle(frame, cvPoint((rect.x + rect.width /
2), (rect.y + rect.height / 2)), cvPoint((rect.x + rect.width / 2 + 0.01), (rect.y
+ rect.height / 2 + 0.01)), cvScalar(0, 255, 0, 0), 5, 8, 0);
                                    xrect = rect.x * 12 / imgSize.width;
                                    yrect = rect.y*8.7 / imgSize.height;
                                    width = (rect.width * 12 / imgSize.width);
                                    height = (rect.height*8.7 / imgSize.height);
                                    cout << "no of x pixels(total)=" << rect.width <<
endl;
                                    cout << "no of y pixels(total)=" << rect.height
<< endl;
                                    cout << "width (cm)=" << width << endl;
                                    cout << "height (cm)=" << height << endl;
                                    cout << "centerx(cm)=" << (xrect + width / 2) <<
endl;
                                    cout << "centery(cm)=" << (yrect + height / 2) <<
endl;
                                    cout << "area(rect)(cm)" << (width*height) <<
endl;
                                    //a = 0; b = 0; c = 0; d = 0;
                             }
                      }
               }
               cvShowImage("original", frame);
               //cvShowImage("bw", bw);

               cvClearMemStorage(storage);
               contours = 0;
               char c = cvWaitKey(33);
               if (c == 27) return -5;
       }
       cvDestroyAllWindows();
       cvReleaseCapture(&capture);
       cvReleaseImage(&frame);
       return -9;


}
```

Appendix B: Force and Torque values in volts.

Table 2- Output of F/T sensor at 30 different forces in volts

Fx	fy	fz	Tx	Ty	Tz
-0.39522	-0.015405	0.1576454	0.197348	-0.0212808	0.276148
-0.410214	-0.021139	0.1837634	0.196599	-0.0149185	0.282753
-0.514139	-0.01198	0.3101995	0.231429	0.01551533	0.279045
-0.649936	0.009882	0.5010087	0.217185	0.03719588	0.271508
-0.743284	0.012719	0.6315175	0.221156	0.05863328	0.272643
-0.874239	0.030084	0.8000586	0.227073	0.08321133	0.252684
-0.999115	0.097091	0.9286831	0.238541	0.0886416	0.225796
-1.123261	0.119136	1.0949345	0.221197	0.09589546	0.208817
-1.395606	0.194451	1.4797951	0.188453	0.14687515	0.175384
-1.490615	0.235968	1.5676115	0.240142	0.1631457	0.159114
-1.556022	0.259533	1.6153493	0.264092	0.18910157	0.167988
-1.621529	0.256109	1.7036926	0.263666	0.21526007	0.178484
-1.69425	0.287252	1.8064221	0.234286	0.22871417	0.190094
-1.721868	0.254346	1.8906928	0.194005	0.24249246	0.192668
-1.754895	0.230477	1.9869384	0.164524	0.25112416	0.213903
-1.859773	0.284192	2.1394928	0.118609	0.25400139	0.20367
-2.036054	0.373103	2.3254597	0.152569	0.28646143	0.162234
-2.181517	0.360337	2.5350727	0.185779	0.32945781	0.16193
-2.419841	0.398532	2.8404857	0.173013	0.38349709	0.146125
-2.720614	0.422664	3.2512832	0.127849	0.45702861	0.137818
-3.051983	0.531958	3.710589	0.022425	0.51670078	0.116968
-3.302243	0.548269	4.0309768	0.02976	0.60733358	0.099988
-3.599592	0.536963	4.4804767	0.002244	0.70775303	0.11322
-3.95706	0.577548	4.9497127	0.004047	0.84140249	0.103595
-4.297467	0.662933	5.4390905	-0.0783	0.91548109	0.083454
-4.757666	0.523164	6.0648761	-0.00943	1.07921992	0.101488
-5.071307	0.518322	6.5475086	-0.04302	1.19443079	0.131881
-5.248522	0.547297	6.7651688	-0.06006	1.24559285	0.140999
-5.385233	0.546851	7.0024028	-0.1388	1.29067624	0.153704
-5.584332	0.475751	7.336391	-0.15072	1.39093362	0.186346
-5.813459	0.515708	7.6731557	-0.1558	1.43251166	0.173601
-6.01578	0.442683	7.9879158	-0.11424	1.52752114	0.191817
-6.323608	0.348606	8.3955202	-0.03145	1.67338876	0.225999
-6.673076	0.412492	8.9495039	-0.19319	1.72908957	0.201725

Appendix C: Code for the area and grasping points

```
#include <cv1111.h>
#include<iostream>
using namespace cv;
using namespace std;
#include <Windows.h>
#include <sstream>
#include "opencv2/nonfree/nonfree.hpp"
int hl = 0;
int sl = 0;
int vl = 0;
int hh = 255;
int sh = 255;
int vh = 255;
float width, height,xrect,yrect;
int a, b, c, d;
int main()
{
	CvCapture* capture = 0;
	capture = cvCaptureFromCAM(0);
	if (!capture){ return -1; }
	IplImage* frame = 0;

	frame = cvQueryFrame(capture);
	if (!frame){ return -2;}
	cvNamedWindow("original", CV_WINDOW_NORMAL);
	cvNamedWindow("bw", CV_WINDOW_NORMAL);
	//cvNamedWindow("Difference image", CV_WINDOW_NORMAL);
	IplImage* bw = cvCreateImage(cvGetSize(frame), IPL_DEPTH_8U, 1);
	cvNamedWindow("track");
	cvNamedWindow("crop");
	int Nc;

	CvRect rect;

	//IplImage *differenceImg, *oldFrame_grey;
	CvSize imgSize;
	imgSize.width = frame->width;
	imgSize.height = frame->height;
	cout << imgSize.width << "*" << imgSize.height;

	while (1)
	{
		frame = cvQueryFrame(capture);
		if (!frame)return -6;

		cvCreateTrackbar("hl", "track", &hl, 255, NULL);
		cvCreateTrackbar("hh", "track", &hh, 255, NULL);
		cvCreateTrackbar("sl", "track", &sl, 255, NULL);
		cvCreateTrackbar("sh", "track", &sh, 255, NULL);
		cvCreateTrackbar("vl", "track", &vl, 255, NULL);
		cvCreateTrackbar("vh", "track", &vh, 255, NULL);
		cvInRangeS(frame, cvScalar(hl, sl, vl), cvScalar(hh, sh, vh), bw);
		cvShowImage("blackwhite", bw);
		CvSeq* contours = 0;
		CvMemStorage* storage = cvCreateMemStorage(0);
		Nc=cvFindContours(bw, storage, &contours, sizeof(CvContour),
CV_RETR_LIST, CV_CHAIN_APPROX_SIMPLE, cvPoint(0, 0));
		cout <<"Nc="<<Nc<<endl;
```

Appendix D: Template matching

Code:

```
#include <opencv2/highgui/highgui.hpp>
#include <opencv2/imgproc/imgproc.hpp>
#include<cv.hpp>
#include<cv.h>
#include <iostream>
#include <stdio.h>

using namespace std;
using namespace cv;

/// Global Variables
Mat img; Mat templ; Mat result;
char* image_window = "Source Image";
char* result_window = "Result window";

int match_method;
int max_Trackbar = 5;

/// Function Headers
void MatchingMethod( int, void* );

/** @function main */
int main( )
{
  /// Load image and template
  img = imread( "C:/Users/ranga/Desktop/test.png",0 );
  templ = imread( "C:/Users/ranga/Desktop/test1.png",0 );
  /*Canny(img,img,50,100,3,false);
  Canny(templ,templ,100,100,3,false);*/
  /// Create windows
  namedWindow( image_window );
  namedWindow( result_window );

  /// Create Trackbar
  char* trackbar_label = "Method: \n 0: SQDIFF \n 1: SQDIFF NORMED \n 2: TM CCORR
\n 3: TM CCORR NORMED \n 4: TM COEFF \n 5: TM COEFF NORMED";
  createTrackbar( trackbar_label, image_window, &match_method, max_Trackbar,
MatchingMethod );

  MatchingMethod( 0, 0 );
```

```
  waitKey(0);
  return 0;
}

/**
 * @function MatchingMethod
 * @brief Trackbar callback
 */
void MatchingMethod( int, void* )
{
  /// Source image to display
  Mat img_display;
  img.copyTo( img_display );

  /// Create the result matrix
  int result_cols =  img.cols - templ.cols + 1;
  int result_rows = img.rows - templ.rows + 1;

  result.create( result_cols, result_rows, CV_32FC1 );

  /// Do the Matching and Normalize
  matchTemplate( img, templ, result, match_method );
  normalize( result, result, 0, 1, NORM_MINMAX, -1, Mat() );

  /// Localizing the best match with minMaxLoc
  double minVal; double maxVal; Point minLoc; Point maxLoc;
  Point matchLoc;

  minMaxLoc( result, &minVal, &maxVal, &minLoc, &maxLoc, Mat() );

  /// For SQDIFF and SQDIFF_NORMED, the best matches are lower values. For all the
other methods, the higher the better
  if( match_method  == CV_TM_SQDIFF || match_method == CV_TM_SQDIFF_NORMED )
    { matchLoc = minLoc; }
  else
    { matchLoc = maxLoc; }

  /// Show me what you got
  rectangle( img_display, matchLoc, Point( matchLoc.x + templ.cols , matchLoc.y +
templ.rows ), Scalar::all(0), 2, 8, 0 );
  rectangle( result, matchLoc, Point( matchLoc.x + templ.cols , matchLoc.y +
templ.rows ), Scalar::all(0), 2, 8, 0 );
  imwrite("C:/Users/ranga/Desktop/matched.png",img_display);
```

```
  imwrite("C:/Users/ranga/Desktop/correl.png",result);
  imshow( image_window, img_display );
  imshow( result_window, result );

  return;
}
```

Appendix E: Grasping Points

```
#include <cv1111.h>
#include<iostream>
using namespace cv;
using namespace std;
#include <Windows.h>
#include <sstream>
#include "opencv2/nonfree/nonfree.hpp"
int hl = 0;
int sl = 0;
int vl = 0;
int hh = 255;
int sh = 255;
int vh = 255;
float width, height,xrect,yrect;
int a, b, c, d;
int main()
{
       CvCapture* capture = 0;
       capture = cvCaptureFromCAM(0);
       if (!capture){ return -1; }
       IplImage* frame = 0;

       frame = cvQueryFrame(capture);
       if (!frame){ return -2;}
       cvNamedWindow("original", CV_WINDOW_NORMAL);
       cvNamedWindow("bw", CV_WINDOW_NORMAL);
       //cvNamedWindow("Difference image", CV_WINDOW_NORMAL);
       IplImage* bw = cvCreateImage(cvGetSize(frame), IPL_DEPTH_8U, 1);
       cvNamedWindow("track");
       cvNamedWindow("crop");
       int Nc;

       CvRect rect;
```

```
	//IplImage *differenceImg, *oldFrame_grey;
	CvSize imgSize;
	imgSize.width = frame->width;
	imgSize.height = frame->height;
	cout << imgSize.width << "*" << imgSize.height;

	while (1)
	{
		frame = cvQueryFrame(capture);
		if (!frame)return -6;

		cvCreateTrackbar("hl", "track", &hl, 255, NULL);
		cvCreateTrackbar("hh", "track", &hh, 255, NULL);
		cvCreateTrackbar("sl", "track", &sl, 255, NULL);
		cvCreateTrackbar("sh", "track", &sh, 255, NULL);
		cvCreateTrackbar("vl", "track", &vl, 255, NULL);
		cvCreateTrackbar("vh", "track", &vh, 255, NULL);
		cvInRangeS(frame, cvScalar(hl, sl, vl), cvScalar(hh, sh, vh), bw);
		cvShowImage("blackwhite", bw);
		CvSeq* contours = 0;
		CvMemStorage* storage = cvCreateMemStorage(0);
		Nc=cvFindContours(bw, storage, &contours, sizeof(CvContour),
CV_RETR_LIST, CV_CHAIN_APPROX_SIMPLE, cvPoint(0, 0));
		cout <<"Nc="<<Nc<<endl;

		for (; contours != 0; contours = contours->h_next)
		{
			double a = cvContourArea(contours);

			if ((a > 1500) && (a<20000))
			{
				cout << "a=" << a << "\n";
				rect = cvBoundingRect(contours, 0); //extract bounding
box for current contour
				if ((rect.width < imgSize.width) && (rect.height <
imgSize.height))
				{

					cvRectangle(frame,cvPoint(rect.x,
rect.y),cvPoint(rect.x + rect.width, rect.y + rect.height),cvScalar(0, 0, 255,
0),2, 8, 0);
					cvRectangle(frame, cvPoint((rect.x + rect.width /
2), (rect.y + rect.height / 2)), cvPoint((rect.x + rect.width / 2 + 0.01), (rect.y
+ rect.height / 2 + 0.01)), cvScalar(0,255, 0, 0),5, 8, 0);
```

```
                                    xrect = rect.x*15.5 / imgSize.width;
                                    yrect = rect.y*12.5 / imgSize.height;
                                    width = (rect.width*15.5 / imgSize.width);
                                    height = (rect.height*12.5 / imgSize.height);
                                    cout << "no of x pixels(total)=" << rect.width <<
endl;
                                    cout << "no of y pixels(total)=" << rect.height
<< endl;
                                    cout << "width (cm)=" <<width  << endl;
                                    cout << "height (cm)=" << height << endl;
                                    cout << "centerx(cm)=" << (xrect+width / 2) <<
endl;
                                    cout << "centery(cm)=" << (yrect+height/2) <<
endl;
                                    cout << "area(rect)(cm)" << (width*height) <<
endl;


                                    cout << "area(rect)(pixels)=" <<
(rect.height)*(rect.width) << endl;


              cvShowImage("original", frame);
              cvShowImage("bw", bw);


              //press Esc to exit
              char c = cvWaitKey(33);
              if (c == 27) return -5;
              //waitKey(33);
       }
       cvDestroyAllWindows();
       cvReleaseCapture(&capture);
       cvReleaseImage(&frame);
       return -9;


}
```

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Dissemination

Journal Publications:

- **Om Prakash Sahu**, B K Balabantaray, N Mishra and B B Biswal; “An Integrated Approach of Sensors to Detect Grasping Point for Unstructured 3-D Parts”, International Journal of Engineering and Technology, Vol. 7, No. 6, 2015.
- B.K. Patle1, Dayal Parhi, A. Jagadeesh, **Om Prakash Sahu**, “Real Time Navigation Approach for Mobile Robot” Journal of Computers. Vol 13,4, pp. 135-142, 2017.
- B K Balabantaray, **Om Prakash Sahu**, N Mishra and B B Biswal; “A Quantitative Performance Analysis of Edge Detectors with Hybrid Edge Detector”, Journal of Computers. Vol 13,4, pp. 165-172, 2017.
- N. Mishra, B. K. Balabantaray, **Om Prakash Sahu**, and B. B. Biswal; “Feature based face detection in HRI”, Journal of Image and Graphics. 2015.
- **Om Prakash Sahu**, Bibhuti Bhusan Biswal, Saptarshi Mukharjee, and Panchanand Jha, "Development of Robotic End-Effector Using Sensors for Part Recognition and Grasping," International Journal of Materials Science and Engineering, Vol. 3, No. 1, pp. 39-43, March 2015.
- Panchanand Jha, Bibhuti B. Biswal, and **Om Prakash Sahu**, "Inverse Kinematic Solution of Robot Manipulator Using Hybrid Neural Network," International Journal of Materials Science and Engineering, Vol. 3, No. 1, pp. 31-38, March 2015.

Presented Conferences:

- **Om Prakash Sahu**, B K Balabantaray, B B Biswal; “Part Recognition Using Vision and Ultrasonic Sensor for Robotic Assembly System”, 13th IEEE SCOReD International Conference, IEEE, Kual lumpur, Malaysia, 2015.
- **Om Prakash Sahu**, B K Balabantaray, N Mishra and B B Biswal; “An Integrated Approach of Sensors to Detect Grasping Point for Unstructured 3-D Parts”, ICCSI, NTU Singapore, 2015
- B.K. Patle1, Dayal Parhi, A. Jagadeesh, **Om Prakash Sahu**; “Real Time Navigation Approach for Mobile Robot”, ICCSI, NTU Singapore, 2015
- **Om Prakash Sahu**, Bibhuti Bhusan Biswal, and Panchanand Jha, "Development of Robotic End-Effector Using Sensors for Part Recognition and Grasping", International Conference on Robotics and Mechatronics, Jul 6-7, Nottingham, United Kingdom, 2014.
- **Om Prakash Sahu**, B.B. Biswal, S. Mukharji, “Multiple Sensor Integrated Robotic End-effector for Assembly” , 2nd International Conference on Innovations in Automation and Mechatronics Engineering, Procedia Technology, Elsevier, India, pp. 100-107, 2014.

- **Om Prakash Sahu**, B.B. Biswal, “Design and Development of Multiple Sensor Integrated Robotic Manipulator for Assembly”, Proceeding of ICFM- Sensor and actuators, February 5-7, IITK, pp. 184, 2014.
- **Om Prakash Sahu**, B.B. Biswal, “Force / Torque Sensor Integrated Robotic manipulation for Assembly Operations”, Proceeding of IEEE conference on ICRESE, Coimbatore, India, pp. 955-959, December 5-6, 2013.
- **Om Prakash Sahu**, “Artificial & fabricated Humanoid Robotic Arm” National paper presentation and publication on BETCON, Bhilai Institute of Technology, Bhilai (C.G.) India, 2008.

Book Chapter:

- Panchanand Jha, Bibhuti B. Biswal, and **Om Prakash Sahu,** "Intelligent Computation of Inverse Kinematics of a 5-dof Manipulator Using MLPNN," Proceedings of Springer-Verlag Berlin Heidelberg, TAROS 2014, LNAI 8717, pp. 243–250, 2014.

CURRICULUM VITAE

Om Prakash Sahu

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Education: B.E., M.Tech., Ph.D.
Total Experience: 11 Years (7 Teaching)+(4 R&D)

MOTIVATION OBJECTIVE

Seeking an enriching and challenging opportunity, this will aid in utilize my technical research & administration skills and gaining experience in a challenging environment.

I will bring excellent interpersonal skills, leadership and top notch analytical skills with an enthusiasm for learning technologies. Currently, I did work with design and development of sensors integrated intelligent robotic hand.

EDUCATION

***Ph.D**. (**Sensors & robots, 8.93/10** CGPA)*
Department of Industrial Design, NIT – Rourkela (India) 07/2012 – 06/2016

***M.Tech. (ETC: Instrumentation & Control**, **8.12/10** CGPA)*
BIT – Durg, India 06/2006 – 07/2008

***B.Tech.** (**Electronics & Telecom**, **72.93**%)*
M.P.C.C.E. & T., Bhilai, India 06/2001 – 06/2005

AREAS OF SPECIALIZATION

- Industrial Robots Design
- Autodesk Sketchbook Design
- Engineering Drawing & Design
- Robotics Automation & Control Design
- Industrial Control Systems & Instrumentation
- Intelligent Sensors Technologies and Sensors Fusion
- Mechatronics

PROFESSIONAL MEMBERSHIPS

66043 (LM)	ISTE (Indian Society for Technical Education)
20150828001	SAISE (South Asia Institute of Science and Engineering)
159292	IAENG (International Association of Engineers)
20150827001	SCIEI (SCIence and Engineering Institute)
Regular Member	MIR Labs (Machine Intelligence Research Labs)

RESEARCHER-IDENTITY

ORCID ID	orcid.org/0000-0003-0515-399X
Google Scholar	Om prakash sahu
Research Gate	Om sahu
Edas.info ID	1349193

TEACHING EXPERIENCE

PhD, NIT Rourkela	***Research Scholar***	***25/07/12 – 30/05/16***
G D RCET, Bhilai,(C.G.)	***Asso. Prof. @HOD***	***31/12/10 - 16/07/12***
Rungta College of Engg & Tech. Bhilai,(C.G.)	***Reader***	***01/12/08 - 30/12/10***
Rungta College of Engg & Tech. Bhilai,(C.G.)	***Sr.Lecturer***	***18/09/06 - 30/11/08***
GEC, Jagdalpur (C.G.)	***Lecturer***	***26/07/05 - 17/09/06***

ACADEMIC CAREER CITATIONS

- Qualified for MHRD Gov. of India - Institute fellowship for Ph.D.
- Got the opportunity to visit Robotic Research Centre, 21-25 Dec. 2015, NTU Singapore.
- Achieved 93.93 percentile in GATE 2006 and eligible for UGC aid.
- College campus selection in HCL info-tech system.
- Best paper presentation award in Nanyang Technological University, Singapore.
- Best paper presentation award in BITCON, Durg, India
- Participated and awarded in a QUIZ EXAMINATION-1997 conducted by All India, United School Organisation of India.
- Participated in district level science seminar competition-1999 conducted by District Science Centre.

TECHNICAL SKILL MATRIX

Expertise Skill:

LabVIEW Packages and Real-Time Control System & library, LabVIEW DAQ System, NIcRIO- 9074, Modules and Sensors technologies, interfacing. Automated Material Handling Control System.

Knowledge & worked on:

ROS, MATLAB, C, C++, V.B., Ms- Visual OpenCV Library, PYTHON, SPICE, Multisim.

Graphics Tools:

Sketch-up, Photoshop & Light-room.

Design Tools:

Rhino, CATIA V6, Rhino, DELMIA, FaroArm Fusion, 3D Printer Dimension SST 1200es, Touch tablet.

CONTRIBUTION TO DEVELOP LAB

Mechatronics Laboratory:

LabVIEW DAQ System, NI cRIO- 9074, Module of NI 9219, NI9375 and NI 9401, Workstation NI PXIe-1082, with NI 8234- Dual Gb Ethernet, X series multifunction's DAQ-NI PXIe 6341, NI SCB and NI SXI, Motion controller NI PXI-7340 and Host adopter NI PXI-8252 and Intelligent Sensors.

Industrial Robot and Design Laboratory:

Digi-matrix KAWASAKI RS06L & Denso Robotic library, SCARA Robot, ARISTO robot, Programmable logic controller.

Microprocessor and Microcontroller Laboratory:

Digi-matrix KAWASAKI RS06L & Denso Robotic library, IC coding and development system.

TECHNICAL TRAININGS RECEIVED

- On LabVIEW Software and Sensors DAQ System @ BIT, Durg - 2008.
- On Mechatronics & Robotics Controls @ NIT, Rourkela - 2013.
- On Auto CAD, 3D Modeling & Dynamic Analysis for Mechanical System@ NIT, Rourkela - 2013.
- On 3D Printing through Dimension by Stratasys @ NIT, Rourkela -2013
- On 3D Scanning through Faro Arm by Faro @ NIT, Rourkela -2013
- On PLC & SCADA Software Interfacing and Control @ NIT, Rourkela-2013
- On LabVIEW modules control system calibration and Applications @ NIT, Rourkela-2014
- On Delmia suit for Robotic Applications @ NIT, Rourkela -2014

TECHNICAL AND PROFESSIONAL WORKSHOP

- Workshop on Internet of Things (IOT) for two days, Venue National Institute of Technology, Rourkela, (Odisha) India, 29-30 Jan. 2016.
- Workshop on Solar PV Energy and Future for two days, Venue National Institute of Technology, Rourkela, (Odisha) India, 29-30 Jan. 2016.
- Workshop on LabVIEW and Sensors interfacing for two days, Venue National Institute of Technology, Rourkela, (Odisha) India, 2015.
- Workshop on "Robotics Control and Sensor Fusion" for two days, Venue National Institute of Technology, Rourkela, (Odisha) India, 2014.

- Workshop on "ROBOTICS" for two days, Venue Rungta College of Engg. & Technology, Bhilai, (C.G.) India, 2010.
- Workshop on special training programs in "Trends of Instrumentation & Control System" for two days, Venue Bhilai Institute of Technology, Bhilai (C.G.), India, 2007.

PROJECT EXPERIENCE

25/07/12 – Till date: **Researcher,** Laboratory of Product Design NIT- ID, Rourkela, India.
Developed a real–time control architectures, algorithms and technologies for haptic devices, robotic hands and automatic control systems in several national and international projects.

Winter 2015: **Visiting Research Scholar**, Nanyang Technological University, Singapore.
In the Robotic Research Centre, visited the projects of Denso manipulator along with sensor integration and controllers for industrial assembly operation.

2012- 2014: **Project Assistant**, CSIR Sponsored project, NIT- ID, Rourkela, India.
Design and controlling subsystem of sensor integrated robotic tooling for welding and cutting operations.

2010 - 2012: **Mechatronics Project,** Bhilai,(C.G.) India,
Designed over 13 projects in intelligent robotic control and mechatronics systems. Trained my co-workers and students in the use of special features of the mechatronics design hardware. Accelerated the design process devising automatic servo control of robot and its communication along with various hardware equipment's.

PROJECT UNDERTAKEN

M.Tech- Under the guidance of **Prof. Amitabh Mishra (University of Cincinnati, US),** an Artificial Humanoid Robotic Arm: In this project an artificial **Robotic Arm** is designed and controlled, by using sensors, stepper motor and for the controlling purpose microcontroller has been used, This Humanoid Robotic Arm can be wear by physically handicapped person. And can be used in army as an automated arm, after few modifications.

B.E. – Multi Channel monitoring system using sensors and microcontroller AT89C51.

PROJECT UNDERGUIDANCE DETAILS

58 no. of B.E. Students (U.G.) has been completed their project work.

3 (P.G.) Students completed their M-Tech projects under my guidance.

1. M-tech thesis on Sensor integrated humanoidal robot control.
2. M-tech thesis on quadric robotic flying chopper and remote control.
3. M-tech thesis on moisture measurement control system for soil formation.

ACADEMIC WORK INCHARGE/COORDINATOR

- General Secretary for Cultural & Environment at NIT, Rourkela.
- Coordinator of College Induction Program at GDRCET Bhilai.
- Cultural activities and Annual Function in-charge at GDRCET Bhilai.

- Training and Placement Sub-Coordinator at RCET, Bhilai.
- Vocational Training in-charge at RCET, Bhilai.
- Company visiting & Campus tour in-charge.
- Game & Sports Coordinator at RCET, Bhilai.
- “Value Education” and “YOGA & HUMANITY Classes in-charge at CSVTU Bhilai.
- In-charge of University Discipline Committee.
- In-charge of Anti-Ragging Committee at GEC Jagdalpur.

EXTRA CURRICULAR ACT

- Best Personality Award in pune, India.
- NCC cadet with ‘A’ certificate.
- Member of NSS & 15 days Camp Organizer for NSS.
- Participated in dramatics and did comparing at college
- Senior UN of America Information test certificate.
- National level Stage performance certificate.

PERSONAL DETAILS

Date of Birth	:	13th April, 1982
Father’s Name	:	Mr. G. R. Sahu
Mother’s Name	:	Mrs. Sushila Sahu
Sex	:	Male
Nationality	:	Indian
Languages Known	:	Hindi , English
Permanent Address	:	Qt. No. B-86, Central Avenue Road, Anand Nagar, Smriti Nagar, Junwani Bhilai, Dist. - Durg (C.G.), INDIA
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I hereby declare that all the information furnished if from best of my knowledge and belief.

Place: **NIT, Rourkela, INDIA**

OM PRAKASH SAHU