COMPUTER VISION SYSTEM FOR TRANSLUCENT MEDICAL DEVICES MONITORING DURING MANUFACTURING PROCESS

by

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ABSTRACT

Computer vision is one of the most important technologies for monitoring and control used in the manufacturing industries and is fast emerging in recent applications. The processes that include automatic computer vision techniques are generally faster, more reliable, deterministic, and productive. These systems avoid some human limitations like fatigue and errors.

This project, investigates one important part of the automation strategy to enable the automatic assembly and test of deformable life critical medical device such as catheters. The project is focused on developing and implements a visual inspection computer system and the algorithms necessary to monitor the catheter device unit during the assembly process. The device unit is dispensed and placed into the "initial stage" during a previous manufacturing step. A robot picked up the device unit and transports it to the next manufacturing stage for additional processing. The visual inspection computer system is designed to monitors the robot movement through a controlled predefined path and reacting when the device unit falls from the robot arm into the controlled environment. The designed vision system was able to detect and acquire an image when the device under test falls. Then, it passes this image through the "skeleton track", which is the designed image processing algorithm to identify the coordinates of the extremes (end points) at the image plane. An Associative Neural Network system was used to estimates the coordinates of the device unit extremes at the

robot 4D plane based on the image coordinates plane. Finally, the robot coordinates values are transmitted to the robot which move the gripper until it is placed on the appropriate location at the corresponding device unit extremes.

RESUMEN

Visión por computadora es una de las más importantes tecnologías para el monitoreo y control utilizados en las industrias de manufactura y está creciendo rápidamente en las aplicaciones recientes. Los procesos que incluyen técnicas de inspección de visión por computadora automáticos son generalmente rápidos, más confiables, determinísticos y productivos. Estos sistemas evitan algunas de las limitaciones humanas como la fatiga y los errores.

En este proyecto se investiga una parte importante de la estrategia de automatización para facilitar el proceso de ensamblaje automático y las pruebas de objetos deformables y dispositivos críticos médicos en el cuidado de la vida tales como catéteres. El proyecto está enfocado en desarrollar e implementar un sistema de inspección de visión por computadoras y los algoritmos necesarios para el monitoreo de catéteres durante el proceso de ensamblaje. Los componentes son entregados y colocados en la etapa inicial durante procesos de manufactura previos. Un robot debe recoger la unidad y transportarla a la próxima etapa de manufactura para procesamiento adicional. El sistema de inspección visual por computadoras esta diseñado para monitorear el movimiento del robot a través de un área determinada previamente y controlada, de tal manera que el robot pueda reaccionar si la unidad se cae del brazo del robot al área controlada. El sistema de visión diseñado fue capaz de detectar y adquirir la imagen cuando la unidad bajo prueba cayó. Luego, pasó la imagen a través de un algoritmo llamado "Skeleton track" que es el algoritmo de procesamiento de imagen

diseñado para identificar las coordenadas de los extremos de la unidad (puntos finales) en el plano de la imagen. Un sistema de Red Neuronal Asociativa fue utilizado para estimar las coordenadas de los extremos de la unidad en el plano del robot 4D, basado en la información de las coordenadas en el plano de la imagen. Finalmente, los valores de las coordenadas en el plano del robot son transmitidas al robot quien mueve el brazo hasta colocarlo en el lugar apropiado que corresponde a los extremos de la unidad.

To my wife Ivelisse, my daughter Johannie, and

my daughter Keydaliz who provided me with all the

support needed during completion of this degree.

Also to my father David and mother Evelyn

for being my inspiration and motivation.

You are the most important people in my life.

"To God be the Glory"

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1 INTRODUCTION

1.1 Motivation

Medical devices and pharmaceutical companies are significant profitable industries in the world, because of the high amount of money they earn, and most importantly because they are focused on human health care. Therefore, the more research and work we address to solve the problems occurring in this industry, the better support we will be providing to improve people's and society's life style.

Many manufacturing activities related to medical devices combine manual and automated processes. Manual processes have been used for a long time, and it has been proved that it allows for many problems to occur. The human response is relatively inconsistence. This means that the manual process output is affected by the person's speed, fatigue, interpretation, and other subjective criteria conducting to errors. Companies spend much effort and cost to maintain procedures for standardization and to mitigate risks introduced by human factors that affect their performance. For this reason, manual processes are being targets for automation. The researchers are more concentrated everyday on how to automate the manufacturing and packaging processes and how to remove or identify human errors.

The manufacturing process for a catheter is a manual process where an operator inserts a solid material through a thin and flexible plastic tube. This process has been studied and analyzed by engineers because it is desired to be improved and automated. One of the challenges on the automation of this process is how to handle the parts when undesired falls occur during the operation. The solution will require that the system have the capability of detecting when the part falls, and then, to identify the position of the part and the location of its extremes. Finally, the part must be recovered and returned to the manufacturing line for rework.

Machine vision technology represents a real alternative to deal with these problems. Machine vision hardware (cameras, lens, computers, and others) are of high capacity and can provide a high level of confidence. The software and analysis algorithms have also been improved during the last decades [19], [20]. Machine vision technology can allow companies to perform those manual operations without the fatigue, inconsistencies and limitations of humans. Also, the machine vision equipment can be located in harsh environment not recommended for humans like non typical temperatures or product exposure areas.

All of these mentioned criteria represent a high level of motivation to be involved and work with this project.

1.2 Problem Statement

Manufacturing process of deformable life critical medical device such as catheters, endoscopes, and medical cables have been based on human manual activities that are subject to low speed, fatigue, interpretation and other subjective criteria conducting to errors. It is highly desired to automate these processes and eliminate human behaviors and errors. The problem must be separated into small parts to be properly handled.

One important part is to design and develop a machine that controls the manufacturing process. This machine must handle the plastic tube during the insertion of the metal part, cut the parts, and release the product to begin a new assembly. This mentioned process is out of the scope of this project. However, a problem occurs if during this recommended automated assembly process, a device being manufactured fell down into the controlled environment. This project will focus on this problem.

1.2.1 Objectives

In this project, we proposed to use an automated visual inspection system and develop the method and algorithm necessary to monitor and react when an assembly unit falls from the robotic arm at the manufacturing process into the controlled robot trajectory area. The system will be able to detect the part when it falls, identify the position of the part, and transfer the position information to a robot which will move the arm until reaches the parts end points.

The identification of the device end points will enable a future "Pick and Place" operation that is not part of this project. The experiments will be performed in a controlled environment that simulates the manufacturing process environment.

1.3 Project Overview

This project is structured in four main parts: Chapter 2 begins with a literature review regarding theory, previous work, and information about vision systems. Chapter 3 introduces the methodology and equipment employed for the creation of the system. Chapter 4 presents the results obtained from this research. Finally, chapter 5 summarizes the project and illustrates the main contribution of the machine vision system in the research. Also, some recommendations for future work are included on Chapter 5.

2 LITERATURE REVIEW

2.1 Image Acquisition

2.1.1 Camera Calibration

The camera is one of the critical components in a machine vision system. Several cameras types and models are available in the industry. There are two basic types of cameras: analog and digital. The analog signal consists of a low-voltage signal containing the intensity information for each line, in combination with timing information that ensures the display device remains synchronized with the signal. In analog cameras, the lines of the CCD (Charged Coupled Devices) are interlaced to increase the perceived image update rate. Using these method odd numbered rows is scanned before even numbered rows. The two scanned rows make up one frame. Analog cameras are low cost and easy to interface with a standard analog acquisition device. Therefore, they can solve numerous applications at an attractive price [5].

Digital cameras digitalize a signal at the CCD array, rather than at the image acquisition board, the signal to noise ratio is typically higher, which results in better image resolution. A digital camera can support larger image sizes and faster frame rates, as well as higher pixel resolutions [5].

Independently of what type of image is used in a machine vision system, the relation between the physical space and the image location needs to be determined. This relation is established during the camera calibration process.

Camera calibration in the context of three-dimensional machine vision is the process of determining the internal camera geometry and optical characteristics (intrinsic parameters) and/or 3-D positions and orientation of the camera frame relative to a certain world coordinate system (extrinsic parameters) [1]. Several methods for geometric camera calibration are presented in the literature. Many of those methods required several computational processes, memory, CPU utilization and time. Other methods worked around these conditions by performing simplifications of the camera models and approximations using linearization techniques [1], [2], [4], [6], [7].

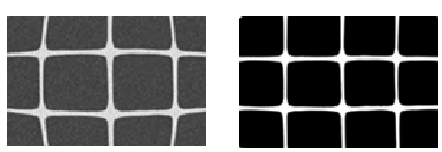
The physical camera parameters are commonly divided into intrinsic and extrinsic parameters. The intrinsic camera parameters usually include the effective focal length, scale factor and the image center also called the principal point. Extrinsic parameters are needed to transform objects coordinate to a camera centered coordinate frame.

Using a camera's pinhole model, the projection from the 3-d space to the image plane can be described by:

$$\lambda\begin{bmatrix}\upsilon\\ \nu\\ 1\end{bmatrix}=\begin{pmatrix}\alpha & \gamma & \upsilon o\\ 0 & \beta & \nu o\\ 0 & 0 & 1\end{pmatrix}\begin{bmatrix}R & \vec{t}\end{bmatrix}\begin{bmatrix}X^w\\ Y^w\\ Z^w\\ 1\end{bmatrix} \qquad (2.1)$$

Where (R, t) represents the transformation between the camera frame and the world coordinate system. The 3x3 matrix denote the camera's intrinsic matrix (α, γ, β, υo, νo) are the camera's five intrinsic parameters, with (α, β) being two scalars in the two ages axes (υo, νo) the coordinates of the principal points and γ describing the skewness of the two image axes. The principal point is assumed to be at the center of the distortion [2].

In (2.1), (υ, ν) is not actually the observed image point, since virtually all imaging devices introduce certain amount of nonlinear distortions (refer to Figure 1). Among the nonlinear distortions, radial distortion, which is performed along the radial direction of the center of distortion, has been recognized to be the most severe part. Notice that, the objective of the coordinate transformation is not computing [R, t] specifically, but to find an accurate mapping from the metric information, (x, y) or (υ, ν) on the image plane, to (*Xw, Yw*) on the 2D platform.



(a) (b)

Figure 1: (a) Distorted Image, (b) Corrected Image

Before any quantitative information from the vision system can be used, we have to know the relationship between the robot and the camera coordinate system, in addition to the camera intrinsic parameters. The extrinsic parameters need to be calibrated many times during the operating periods to compensate environmental noise and disturbance. There are many camera calibration techniques available and this topic is still an area of interest for researchers and engineers.

In this project, the extrinsic camera calibration is required to be performed successfully to ensure an accurately robot movement once the Object Under Test (OUT) end points are identified. As a result of the image processing, the end points of the UOT will be identified at the image plane, and the robot arm will locate those end points at the world plane.

Three camera calibration techniques were evaluated including the 6 point calibration method based on the solution of the inverse kinematics problem, the Labview NI Vision calibration tool and, an Associative Neural Network system approach.

Inverse Kinematics Problem

The kinematics problem usually consists of two sub-problems: direct and inverse problems [25]. The direct kinematics problem is to find the position and orientation of the end-tool of a manipulator with respect to a reference coordinate system, given the joint variable vector **q** of the robot arm and the various geometric links parameters, where n is the number of degree-of-freedom.

$$q = (q_1, q_2 ... q_n)^t \qquad (2.2)$$

The inverse kinematics problem (arm solution) is to calculate the joint variable vector **q** for positioning the end-tool of the robotic arm at the desired position with the desired orientation, given the position and orientation of the end-tool with respect to the reference coordinate system and the various geometric link parameters. The position of the robot can determine by applying the classic kinematics model [24].

In this project, the six-point calibration method was unsuccessful because of the depth limitation. The robot setup uses a table that only has two dimensions because the depth information is the same for all points. This eliminates the third dimension related to the depth.

Labview Camera Calibration Tool Kit

To calibrate an imaging setup, this calibration software uses a set of known mappings between points in the image and their corresponding locations in the real world. The calibration software uses these known mappings to compute the pixel to real-world mapping for the entire image. The resulting calibration information is valid only for the imaging setup that you used to create the mapping. Any change in the imaging setup that violates the mapping information compromises the accuracy of the calibration information [23].

This calibration software requires a list of known pixel to real-world mapping to compute calibration information and create a mapping for the entire image.

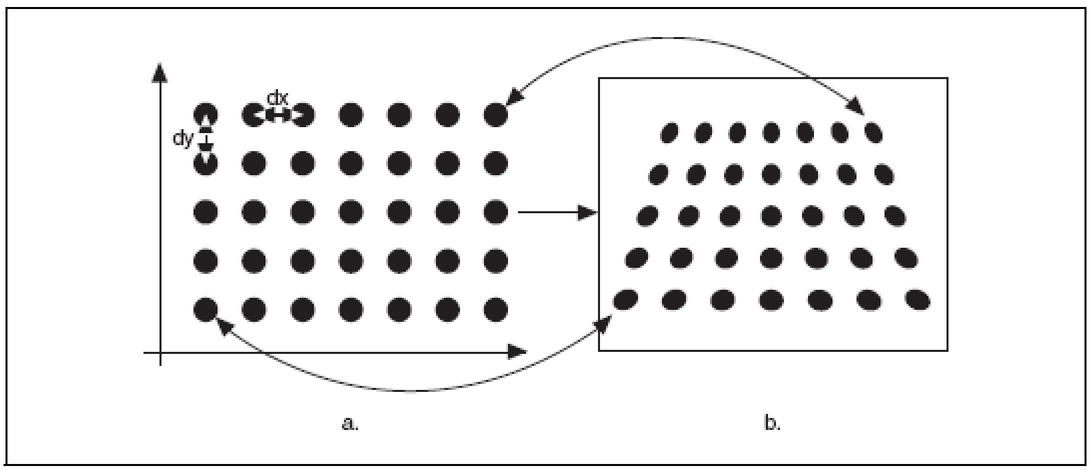


Figure 2: (a) Real World (b) Image

Associative Neural Network approach

An associative neural network was used to create a correlation between the image plane coordinates and the robot plane coordinates and compensates for the camera and robot disturbance and noise. An artificial neural network (ANN), usually called "neural network"

(NN), tries to simulate the structure and functional aspects of the system and make a model of the planes relationship. It consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation. In most cases, an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase [15].

The intention is to model the relationship between the Image plane and the robot plane using the following equation:

$$\begin{bmatrix} Rx \\ Ry \\ Rz \\ \phi \end{bmatrix} = \begin{bmatrix} N11 & N12 & N13 \\ N21 & N22 & N23 \\ N31 & N32 & N33 \\ N41 & N42 & N43 \end{bmatrix} \begin{bmatrix} \operatorname{Im} x \\ \operatorname{Im} y \\ \delta \end{bmatrix} \tag{2.3}$$

Where the input vector [Imx, Imy, δ] contains the image plane coordinates and the output vector [Rx, Ry, Rz, Φ] contains the robot plane coordinates. The robot's parameter, **Φ,**represents the gripper rotation angle, and the image's parameter, **δ,** represents the altitude (distance between the Image plane and the center of the camera lens. The neural network is the matrix M that contains the relationship information in its neurons [N11, N12…N43].

The learning phase for the neurons in this Associative network required a single interaction training using the following general equation:

$$M = R * PseudInverse(\mathrm{Im}) \tag{2.4}$$

Once the neurons in the matrix M are trained, the relationship between the planes are established, and no additional training is required.

2.1.2 *Illumination Techniques*

When implementing an image processing solution, the selection of suitable illumination is a crucial element in determining the quality of the captured images, and can have a huge effect on the subsequent evaluation of the image [21]. Strictly speaking, image processing tools do not inspect the object itself, but instead examine the visual image of the object as captured by the system. Astable andreproducible illumination conditions must be in place to ensure constant image quality for identical objects or similar conditions. Therefore, fluctuations in illumination must be avoided if strict quality criteria are to be applied to the inspection of objects.

It is possible to evaluate them using image processing software when it is possible to view the specific features or faults with sufficient contrast. Many illumination techniques are currently used in today's machine vision implementation to accomplish the desired contrast.

LED illumination has taken an increasing share of the market compared to other light sources. This trend is explained by the large number of benefits offered by LED technology. These benefits include a considerably longer service life of up to 50,000 hours, extremely simple control facilities, the mechanical resilience and small physical size of the units, design flexibility, lower operating costs and excellent value for money. As far as ring lights and similar illumination shapes are concerned, the LED has already become well established as the light source of choice.

Figure 3: LED Ring Lights; Free Publication from Stemmer Imaging web site.

Laser illumination has a special role to play in image processing. Using a laser-generated light structure and a camera plus downstream image analysis makes it possible to measure differences in height and profiles, if the angle between the camera and the object is known.

Figure 4: Laser Illumination; Free Publication from Stemmer Imaging web site.

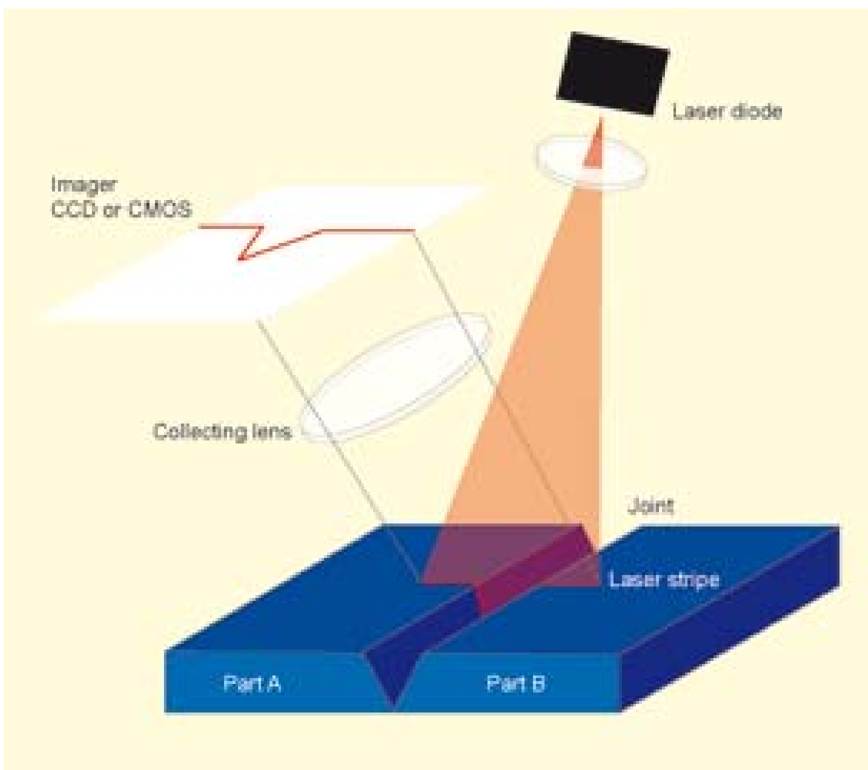


Figure 5: Principles of cut measurement with laser light; Free Publication from Stemmer Imaging web site.

The angle of incidence of light on the object also influences the result. There are several different techniques, such as front illumination or backlighting, direct or diffuse illumination, bright-field or dark-field illumination.

Direct front illumination (a ring light illuminates the objects directly, more or less parallel to the optical axis of the camera). The image appears non-uniform and mottled

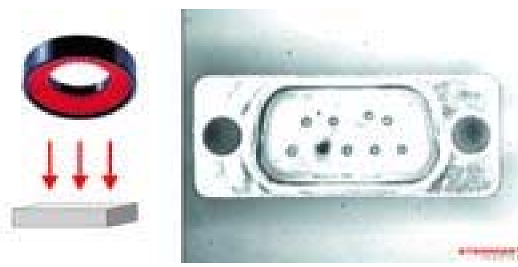


Figure 6: Direct Front Illumination; Free Publication from Stemmer Imaging web site.

In Backlighting, the light is aimed towards the camera from the rear of the object. The light only penetrates where there is nothing to obstruct it. This technique allows the drill holes on each side of the connector to be measured accurately. An easily detected bright spot appears in place of the missing pin.

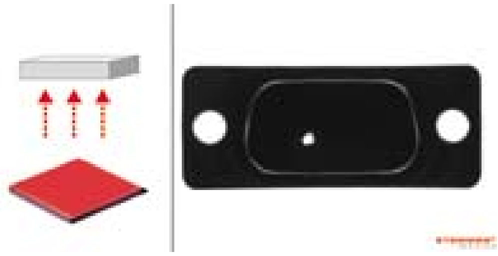


Figure 7: Backlighting Illumination; Free Publication from Stemmer Imaging web site.

2.2 Image Processing

2.2.1 Edge Detection

Edge detection is a common image processing task that identified abrupt changes in intensity indicating the boundary between two regions in an image. The purpose of detecting sharp changes in an image is to capture important events and changes in relation of the world. Discontinuities in image brightness are likely to correspond to discontinuities in depth and surface orientation, changes in material properties, variations in scene illumination and others. The result of applying an edge detector to an image may lead to a set of connected curves that indicate the boundaries of objects, the boundaries of surface markings as well curves that correspond to discontinuities in surface orientation. Thus, applying an edge detector to an image may significantly reduce the amount of data to be processed and may therefore filter out information that may be regarded as less relevant, while preserving the important structural properties of an image. If the edge detection step is successful, the subsequent task of interpreting the information contents in the original image may therefore be substantially simplified [15].

Edge detection has been an active research area for more than 35 years. Several reviews of work on edge detection are available in literature. Surface fitting approach for edge detection is adopted by several authors. Bergholm's edge detector applies a concept of edge focusing to find significant edges. Detectors based on some optimality criteria are developed in [8], [12], [13], [15]. Use of statistical procedures is illustrated in [9]. Other approaches on edge detection include use of genetic algorithms, Neural Networks, the Bayesian approach and residual analysis based techniques.

In this work, we used the Laplacian Operator which is recommended over the Gradient techniques (based on first order derivative) especially for slow changed in gray levels. The Laplacian operator is based on the second order derivative of the wide edge. It produces a zero crossing in the middle of edge, and therefore, the location of the edge can be obtained by detecting the zero-crossings of the second order difference of the image.

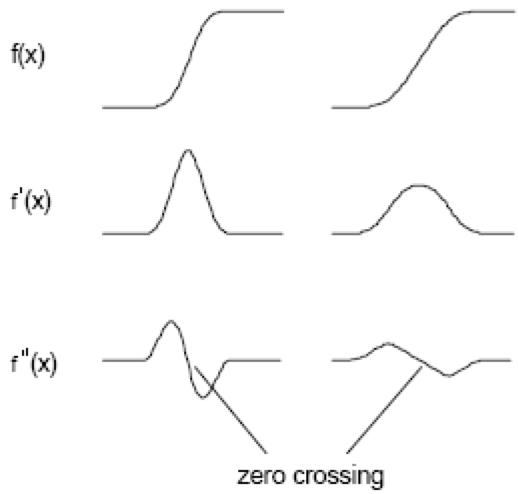


Figure 8: Free publication from University of Haifa in Israel

The Laplacian operator equations are as follow:

$$\frac{\partial^2 f}{\partial x^2} = f[i, j+1] - 2f[i, j] + f[i, j-1] \qquad (2.5)$$

$$\frac{\partial^2 f}{\partial y^2} = f[i+1, j] - 2f[i, j] + f[i-1, j] \qquad (2.6)$$

$$\nabla^2 \approx \begin{matrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{matrix} \qquad (2.7)$$

Results of the Laplatian operator is included in the next figure.

(a) (b)

Figure 9: (a) Original, (b) Laplacian Operator Result; Free publication from Bill Green, Edge Detection Tutorial

2.2.2 Binarization

Binarization is a simple image processing technique used to separate each image pixels in two groups based on their gray values (2.5). As a result, the binary image will contain two classes (clusters) or regions – the white one and the black one. Binary images are typically obtained by thresholding a grey level image [16]. Pixels with a grey level above the threshold are set to 1 (equivalently 255), and the rest are set to 0. This produces a white object on a black background (or vice versa, depending on the relative grey values of the object and the background). Binary images are used in many applications. They are the simplest to process, and are useful where all the information you need can be provided by the silhouette of the object. Binarization makes possible the formation of the silhouette of objects in images.

$$New\,\mathrm{Im}(i,j) = \begin{cases} 1 \rightarrow \mathrm{Im}(i,j) \geq Threshold \\ 0 \rightarrow Otherwise \end{cases} \tag{2.8}$$

Many techniques to perform image binarization process had been researched and recommended. The K-Mean clustering [17] is a popular method for thresholding between two groups (clusters) and for performing image segmentation. One important part of the binarization algorithms is the selection of the threshold value. Many techniques had been recommended for this value selection which can affect the algorithm performance [14].

3 METHODOLOGY AND EQUIPMENT

3.1 Vision System

The Machine Vision system setup consists in the following tasks: camera selection, illumination techniques, camera calibration, and image processing analysis software.

3.1.1 Machine Vision Setup Critical Parameters

There are many machine vision parameters requirements that define the type of camera needed. The most important are the field of view (FOV), the pixel resolution, measurement accuracy, the camera resolution, the depth of field, and the working distance. The FOV is the area of the object that is going to be viewed by the lens and the camera sensor. For our system, we used a field of view of 190 mm. This parameter was determined after performing several trials adjusting the distance between the camera and the object and also considering the robot operating range. The pixel resolution can be calculated using equation 3.1 and the FOV as follow:

$$P_{resolution} = \frac{FOV}{426} = 446\mu m / pixel \qquad (3.1)$$

There is always an error introduced by the measurement instrument limitations. In our case, we can assume one pixel error for high contrast image and estimate the measurement error using 3.2: [10].

$$Measurement\ Accuracy(\mu m) = \frac{Pixel\ Error * FOV(Horizontal) * 1000}{\#\ of\ Pixels\ in\ Image} \tag{3.2}$$

$$Measurement\ Accuracy(\mu m) = \frac{1*190*1000}{640} = 296.87\ \mu m \tag{3.3}$$

We can also calculate the camera resolution using 3.4 [10] as follow:

$$Cam\,Res = \frac{Tv\ line\ horizontal * 1.33}{2 * sensor(horizontal)} = 570 * \frac{1.33}{2 * 6.4\ mm} = 16.8\ \mu m \tag{3.4}$$

3.1.2 Camera and Lens Selection

The camera selected for our system was the LCL-902K from WATEC American Corporation.

3.1.3 Illumination

Two fluorescent linear lights were used for the diffuse and linear array light illumination techniques. The selection was performed by analyzing the histogram of several images that resulted from several experimental trials. Table 1 summarizes the experimental trials performed, where P_x indicates Performed illumination test number x.

Table 1: Illumination selection matrix (by experimentation)

	Room Illumination On			Room Illumination Off		
	Lights Placed at the floor, 8 inches from the object	Lights elevated 8 inches, 8 inches from the object	Lights elevated 8 inches, 16 inches from the object	Lights Placed at the floor, 8 inches from the object	Lights elevated 8 inches, 8 inches from the object	Lights elevated 8 inches, 16 inches from the object
No Illumination	P_15	P_1	P_8			
Right Side Only	P_16	P_2	P_9	P_19	P_5	P_12
Both Sides	P_17	P_3	P_10	P_20	P_6	P_13
Left Site Only	P_18	P_4	P_11	P_21	P_7	P_14

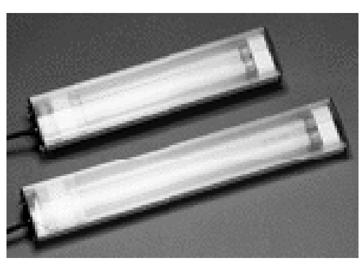


Figure 10: Fluorescent High Frequency Linear Lights.

Note that P_3 in Table 1, for example, means that the picture # 3 was acquired with the room illumination turned on, using both fluorescent high frequency linear lights turned on (right and left), located at 8 inches from the object and elevated 8 inches from the table. The Better results were obtained when both illumination sources were used in all cases. The best contrast result was obtained by using two Fluorescent High Frequency Lights one at the right side and one at the left side. The lights were placed at a 14 cm altitude and around 45 degreed of inclination. The distance between them was 22 cm. The lamps were 27 cm and 34 cm long respectively. The final system setup is presented in the next figure:

Figure 11: System Setup

The contrast obtained between the object and the background is as illustrated in the following pictures.

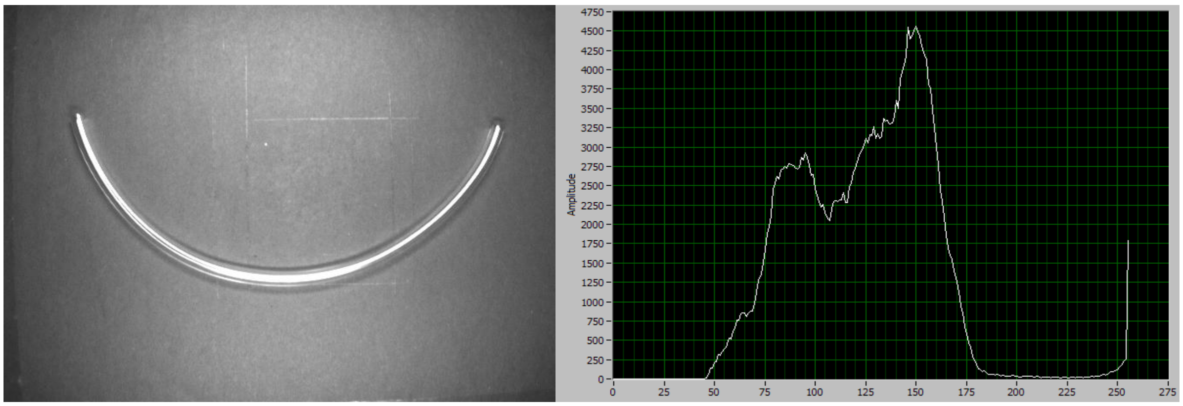


Figure 12:: Image from P_3 and the respective Histogram.

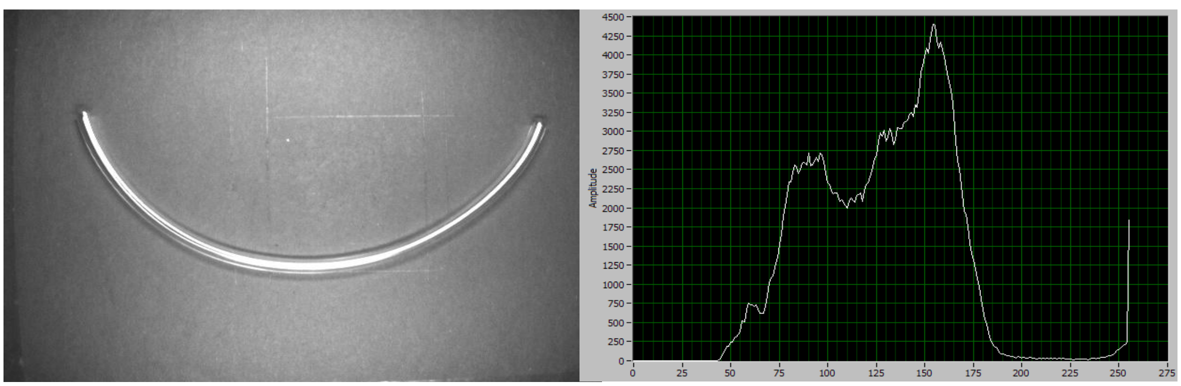


Figure 13: Image from P_6 and the respective Histogram.

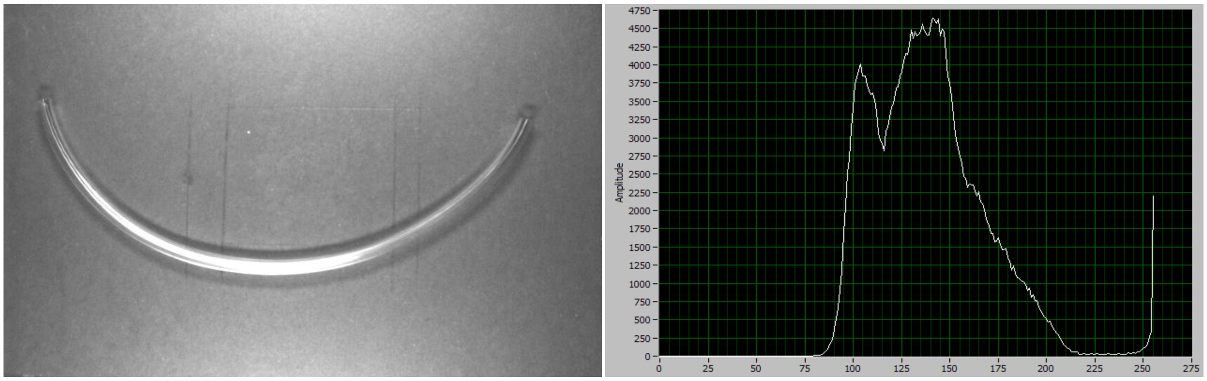


Figure 14: Image from P_10 and the respective Histogram.

By evaluating the histogram we can easily notice that the illumination reflection from the object has a strong gray level component around the area of 150 for an 8 bit representation. This is a very important picture characteristic that will be used during the image processing algorithm.

The ring light was also evaluated as well as the back light, and the ring illumination techniques, but the best results were obtained by using the two fluorescent linear lights.

The selected final system setup was the two fluorescent linear lights elevated at 14 cm from the table, with an inclination of 45 deg, and at a distance from the object of eight inches (8”) one at the left side and one at the right side [5].

3.1.4 Image Processing Analysis

Once we selected the appropriate system elements we started the image processing analysis. The analysis strategy is discussed in the next figure and consists of three main parts as follows: Image Acquisition & Identification, Pre-Processing and End Points detection.

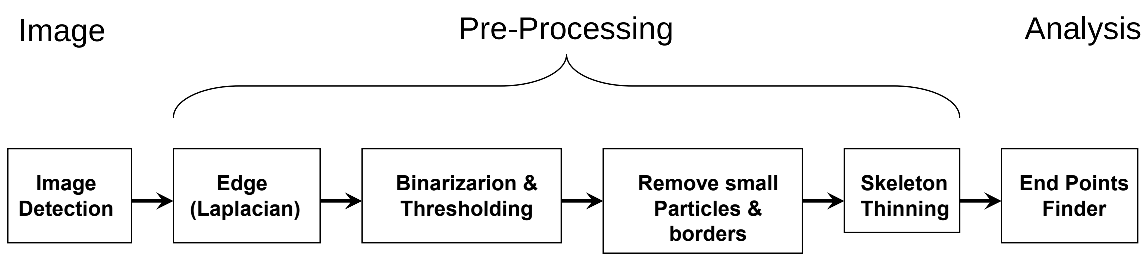


Figure 15: Image Analysis Algorithm.

It was decided to use LabView application to perform the Image Processing Analysis activities. NI LabVIEW is a graphical development environment for creating flexible and scalable design, control, and test applications. With LabVIEW, engineers and scientists interface with real-world signals; analyze data for meaningful information; and share results through intuitive displays, reports, and the Web. LabVIEW is a full-featured graphical programming language that includes all the standard features of a general-purpose programming environment, such as data structures, looping structures, event handling, and object-oriented programming. LabVIEW has a built-in compiler that compiles all code at edit time. However, unlike other general-purpose programming languages, LabVIEW is specifically designed for engineers and scientists and has built-in tools to meet their needs. These high-level functions, assistants, and tools make LabVIEW much more than a programming language [11].

The algorithm to be designed must highlight the contrast between the object and the background while keeping enough information to identify the end to end shape.

Image Acquisition & Identification

The first step in the Image Processing task is to identify when the plastic tube falls from the manufacturing operation area. To perform this task, it is necessary to periodically inspect the area and compare with previous inspections. If no drastic difference is detected between both images (current one and previous one), then it is assumed that no parts fell down. This comparison is performed by subtracting both images and by observing the output image and using a threshold value.

Pre-Processing

The second part in this analysis is to partition the image so that regions representing different objects are explicitly identified. Such partitions may be obtained from the characteristics of the gray values of the pixels in the image. The approach used to partition the image into regions was the boundary estimation using edge detection. Edges are significant local changes and typically occur on the boundaries between two different regions in an image. A common approach is to find the points that have local maxima in gradient values and consider them edges [3]. This means that at edge points, there will be a peak in the first derivative and equivalent, and there will be a zero crossing in the second derivative. Thus, the edge points may be detected by finding the zero crossing of the second derivative of the image intensity.

The Laplacian Operator was used to perform the edge detection and is the two-dimensional equivalent of the second derivative.

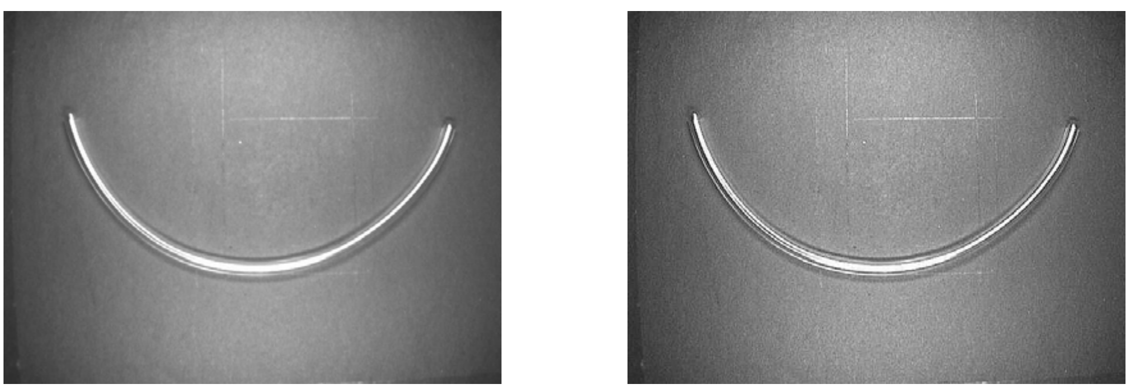


Figure 16: Original Picture at Right, Laplacian result Left.

The Laplacian filter will highlight the edge of all objects in our image that typically are the boundaries between the object and the background. Because we already know that our object reflects the incoming lighting very well, we are able to eliminate from the analysis those areas in our image with low gray scale intensity.

A Thresholding technique will be applied. For binary vision, Thresholding is synonymous of segmentation which is a method to partition an image into sub images called regions. Therefore, each image is an object candidate [3]. The Thresholding is a method to convert a gray scale image into a binary image so that the objects of interest are separated from the background.

$$Ft[i,j] = \begin{cases} 1 \rightarrow F[i,j] \geq T \\ 0 \rightarrow otherwise \end{cases} \tag{3.5}$$

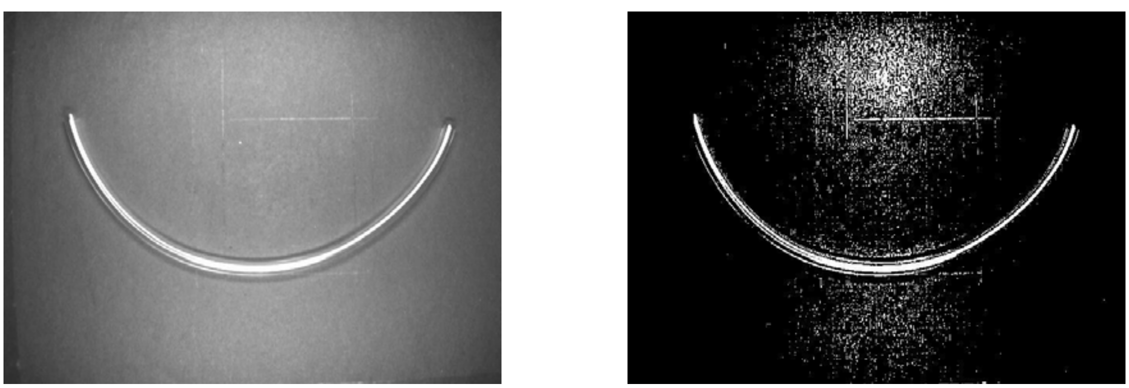


Figure 17:Original Picture at Right, Threshold result Left .

The outcome of the thresholding operation is a binary image where the low gray level intensity was eliminated and the high gray level intensity was highlighted. Additional characteristics of the analyzed-and-processed images can be used to expedite the identification process. The Object Under Test (OUT) is being managed by the robot and the movement is controlled within a certain area. The field of view is set to cover this working area. Therefore, we can make the assumption that once the OUT fell into the working area, it will not be in contact with any of the image boundaries. We also know that the OUT is big, so we can remove from the image the small objects by analyzing each object areas. Labview already includes algorithms to perform both operations, remove objects that touch the image boundaries, and remove small objects.

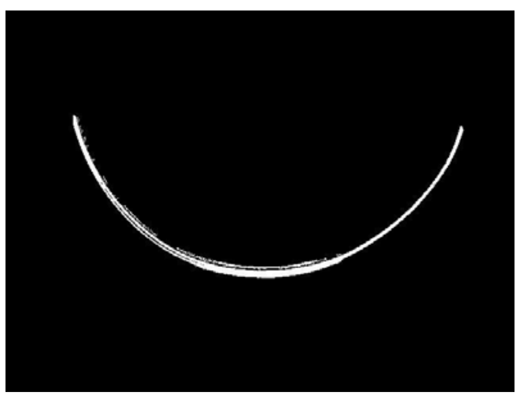


Figure 18: Image resulting from Removing Borders and Particles.

At this point the image processing algorithm was able to identify the OUT which is separated from the background while other undesired sub-images had been removed.

Finally, and to simplify the algorithm, we will perform a thinning operation using Labview Skeleton function to reduce the image components to their essential information so that further analysis and recognition are facilitated. Thinning is an image processing operation in which a binary image regions are reduced to lines that approximate their center lines, also called skeletons or core lines [3]. Now, we are ready to start working with the OUT itself to identify the two end points.

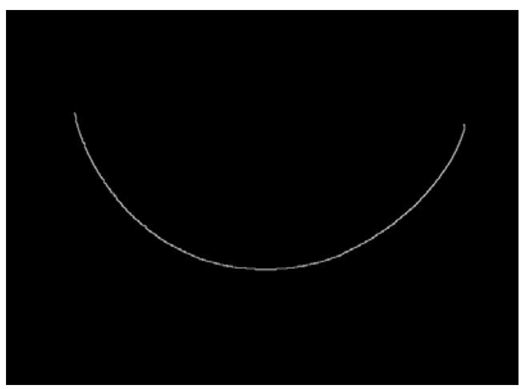


Figure 19: Image Resulting from Skeleton Function (Thinning Processing).

End Points Detection

Several approaches can be used to process this resulting image. Pattern recognitions can be used to find out the ending areas and also analytical methods like statistical characteristics of the OUT and others. In our case, we designed an algorithm to track the skeleton image from the center of the OUT to both ending points.

Skeleton Track Algorithm

The first implemented algorithm started by finding any point of the skeleton. The analysis consist in tracing the skeleton line in both directions, to the left and to the right, until find the two end points. This algorithm basically looked for the 8-neighbors of a pixel in the skeleton (PUA = Pixel under analysis) and check for line continuity. Then, the PUA is replaced by the new found pixel and so on. This procedure is repeated until no more new neighbors are found, which means that the end points had been detected.

The first step is to find out a starting point in the image. Some assumptions were made to simplify the algorithm; however, those mentioned assumptions are supported by the mechanical and physical characteristics of the proposed manufacturing environment. The assumptions are as follow:

1- Because the OUT is a small plastic hose no abrupt corners are formed when it falls but rather smooth curves (can be differentiated in all points).

2- The manufacturing process movement is set in a horizontal form, therefore, when the OUT fell, the line formed by the two ending points will remain in a horizontal form. It does not mean that the OUT will keep a form of a line because it is expected that some curves can be formed as mentioned in the item 1, but the line formed by the two end points will be horizontal. This assumption was confirmed during the experiment.

3- The OUT is big enough when compared to the field of view specified by design, therefore, at least one pixel of the OUT can be found by searching down from the center of the image.

By using the mentioned assumptions, we developed an algorithm to track through the skeleton image until it found out the end points of the line. The Figure 20 shows how the initial point (PUA) is found. Basically, we are working with a picture area about 426 x 300 pixels. The algorithm starts just using the center of the columns which is the pixel (i, 150) and starts searching towards the bottom, increasing the **J** value until it finds a pixel with a level value equal to one. Because the image is Pre-processed at this stage, we know that all background pixels are equal to zero. When the algorithm finds a pixel with a level value equal to one, this pixel is identified as part of the OUT and is used as the first PUA.

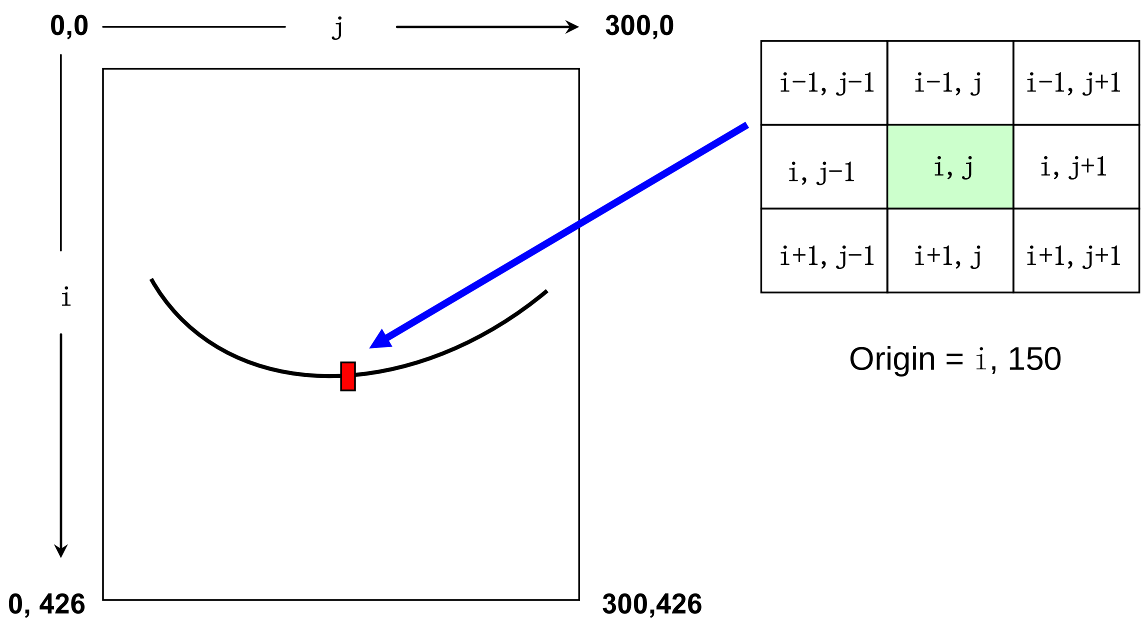


Figure 20: A 426 x 300 FOV Image is used and the PUA is located at Im(i,150). The RED square represents the PUA.

Once the first PUA is determined, this information is transferred to the two tracking Algorithms (Left & Right) to start the End Points Detection. As shown in Figure 21, the routine will search for the PUA neighbors until identify the next OUT pixel. Then, the identified pixel will become the new PUA and the process starts again. The algorithm will continue until it finds a PUA that does not have any additional neighbor pixel with a level value equal to one. At this point, the end point is detected and the algorithm stops. The two routines (used for left and right) are similar except for the neighbor pixels used (Figure 22), which are determined by the direction of the search activities.

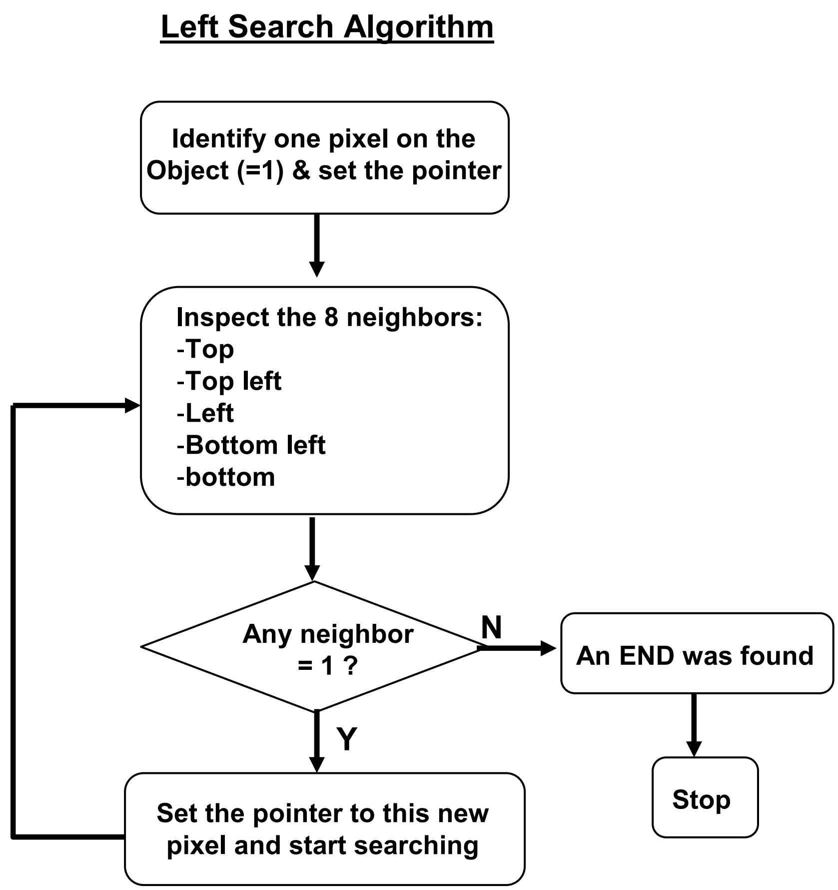


Figure 21: **Tracking algorithm used for left search. Right search algorithm is similar.**

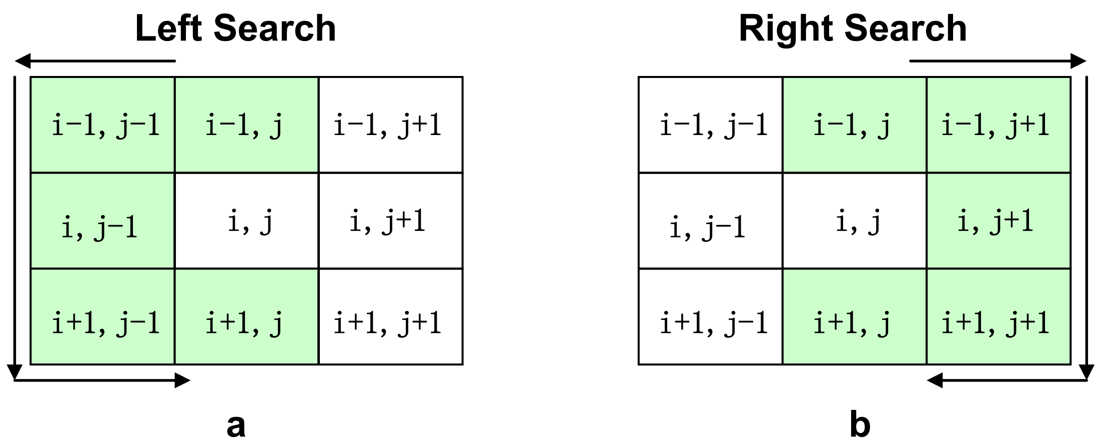


Figure 22: a) Neighbors used for left search, b) Neighbors used for right search.

3.2 Robot Control

3.2.1 Robot Specifications and Control System

The robot control system is shown in the figure 23 and it consist in a Control Unit, a Drive Unit, and a robot Manipulator. The RC520 robot controller consists of one Control Unit and Drive Unit(s). Each Drive Unit controls up to 4 axes/motors simultaneously. Up to three Drive Units can be connected to one Control Unit. The Control Unit is an FA personal computer that includes an MIB (Motion Interface Board) and a system panel. The Control Unit sends commands to the Drive Unit to control the Manipulator motors. The Control Unit also controls such peripheral devices as I/O and stepper motors.

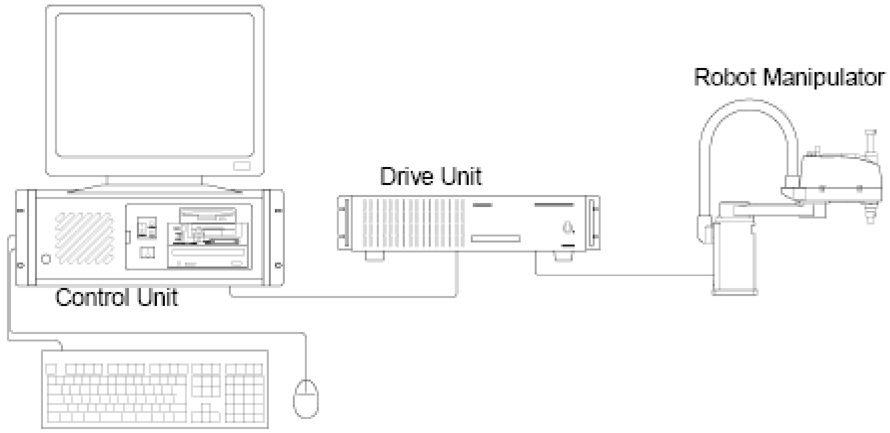


Figure 23: Robot setup; Picture from the EPSON Robor Controller Manual [18]

The Epson RC+ Development environment is used in coordination with the SPEL+ programming language to perform all the robot motions and control activities. The development environment includes an integrated debugger, I/O Monitoring and Robot-teach functions.

3.2.2 Robot Coordinates Vs Image Coordinates

Once the Image processing phase is completed, as discussed in the section 3.1.4 "Image Processing Analysis", the two end points coordinates for the OUT are determined. Those coordinates identify the specific location of the OUT end points at the image plane and need to be converted into the specific location at the robot coordinates (world physical location).

Then, the world coordinates are transmitted to the robot which finally moves to the end points and confirms the conversion.

We used an Associative Neural Network system that model the relation between the 3D Image space and 4D robot space to convert the Image coordinates into the robot coordinates. The equation 3.6 shows the relation between both coordinate systems where, M is the Associative Neural Network defined by a 12 neurons that forms the transformation matrix. The input (*im*) and output (*r*) parameters are defined as follows:

$$\begin{pmatrix} Xr \\ Yr \\ Zr \\ \phi r \end{pmatrix} = M \begin{pmatrix} Xim \\ Yim \\ Zim \end{pmatrix} \tag{3.6}$$

Image

1- Xim and Yim are the Cartesian coordinates that identify the Image area.

2- Zim represents the depth value and is calculated by measuring the distance in pixels from the center of the image to the camera focus.

Robot

1- Xr and Yr are the Cartesian coordinates that identify the robot area.

2- Zr represents the depth value and is calculated by measuring the distance in pixels from the center of the image to the camera focus.

3- Φr is the rotation angle of the arm gripper.

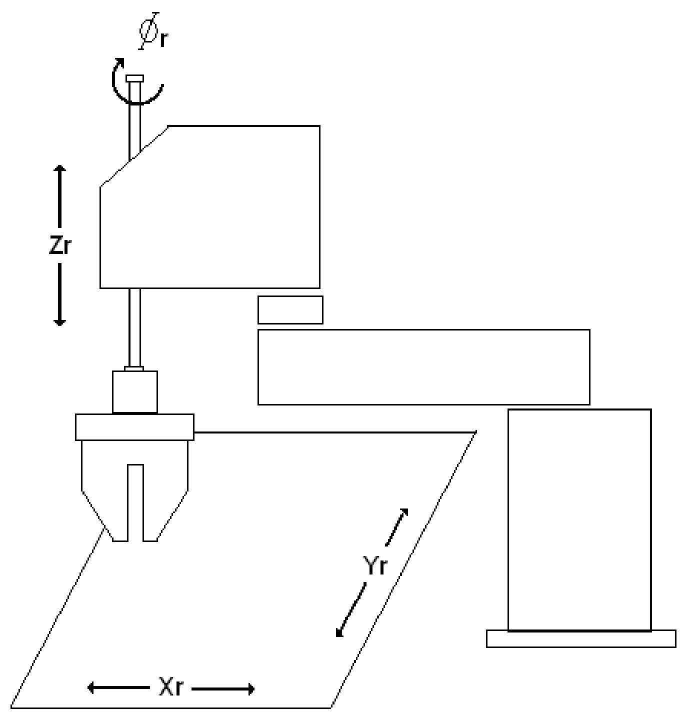


Figure 24: Robot Model and Coordinates.

The transformation matrix M is calculated by using the equation 3.7, using the Image coordinates (inputs) and robot coordinates (outputs) from the empirical data on the Table 2. To find the data values, we use the pattern showed in the Figure 25. The process started by taking a picture of the Transformation Matrix Pattern and identifies the specific image pixel coordinates of the center of each dot. Then, the robot is moved to the center of each dot at the physical space and the coordinates are identified.

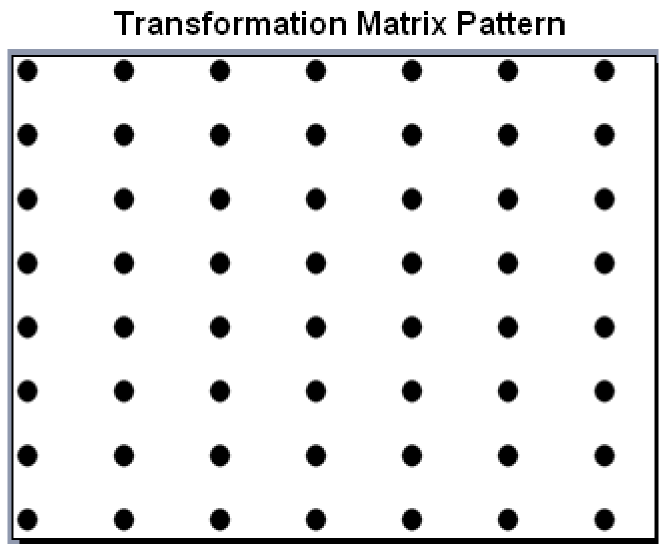


Figure 25: Transformation Matrix Pattern.

To find the Image coordinate, we placed a cursor in front of one specific dot and read the X_{im} and Y_{im} from the Labview display. Then, we moved the robot arm manually and placed the center of the gripper in the center of the dot under consideration. This robot motion was performed using the "Jog and Teach" window from the Epson RC+ GUI (Graphycal User Interface). This option window provides the robot coordinate information and a print screen is shown in the Appendix A. The results of this experimental trial in included in the Table 2.

Table 2: Relation between Image coordinates and Robot Coordinates

Camera Coordinates			Robot Coordinates			
Xim	Yim	Zim	Xr	Yr	Zr	Φr
77	31	1298.5	-47.64	161.98	-80	-875
128	30	1298.5	-39.74	185.56	-80	-875
180	30	1298.5	-31.48	207.64	-80	-875
232	30	1298.5	-23.6	228	-80	-875
284	30	1298.5	-15.83	247.05	-80	-875
76	109	1298.5	-6.74	153.6	-80	-875
127	108	1298.5	0.767	176.23	-80	-875
179	108	1298.5	7.51	198.56	-80	-875
231	108	1298.5	14.52	219.55	-80	-875
284	108	1298.5	21.42	239.45	-80	-875
75	187	1298.5	34.62	143.37	-80	-875
126	187	1298.5	41.25	166.16	-80	-875
178	187	1298.5	47.61	188.03	-80	-875
231	187	1298.5	53.68	209.41	-80	-875
284	187	1298.5	58.96	229.59	-80	-875
74	265	1298.5	77.01	130.09	-80	-875
126	266	1298.5	82.11	154.17	-80	-875
178	266	1298.5	87.27	176.13	-80	-875
231	266	1298.5	92.42	197.94	-80	-875
284	266	1298.5	97.79	218.4	-80	-875
75	344	1298.5	88.99	89.66	-80	-875
126	345	1298.5	97.79	114.41	-80	-875
178	345	1298.5	106.63	139.95	-80	-875
231	345	1298.5	116.11	166.85	-80	-875
284	345	1298.5	126.34	195.64	-80	-875
76	422	1298.5	124.08	83.32	-80	-875
128	423	1298.5	133.98	107.89	-80	-875
179	424	1298.5	142.97	133.14	-80	-875
231	424	1298.5	153.27	159.74	-80	-875

The equation 3.7 defines the single iteration needed to train the 12 Neurons of the transformation matrix M.

$$M = \left(R\_coord\right)^T * PseudInverse\left(\mathrm{Im}\_coord\right)^T \qquad 3.7$$

For the Table 2 data, the neurons values obtained is as follow:

$$M = \begin{bmatrix} 0.126344 & 0.505735 & -0.0537539 \\ 0.413827 & -0.127355 & 0.104883 \\ -1.14654\text{E-}17 & -5.20417\text{E-}17 & -0.0616095 \\ -3.08998\text{E-}17 & -2.6563\text{E-}16 & -0.673854 \end{bmatrix} \qquad 3.8$$

3.2.3 Robot Control

Once the robot coordinates are determined, the information is transmitted from LabView into the robot application. This task is accomplished by using a text file for the handshaking. The file information includes four flouting numbers for the point A coordinates, four floating numbers for the point B coordinates and, two additional critical parameters: the four floating numbers for a point C and the rotation angle Δ. The last two parameters were introduced to the analysis as a contribution to simplify the pick and place operation in the future. The concept is presented in the next figure.

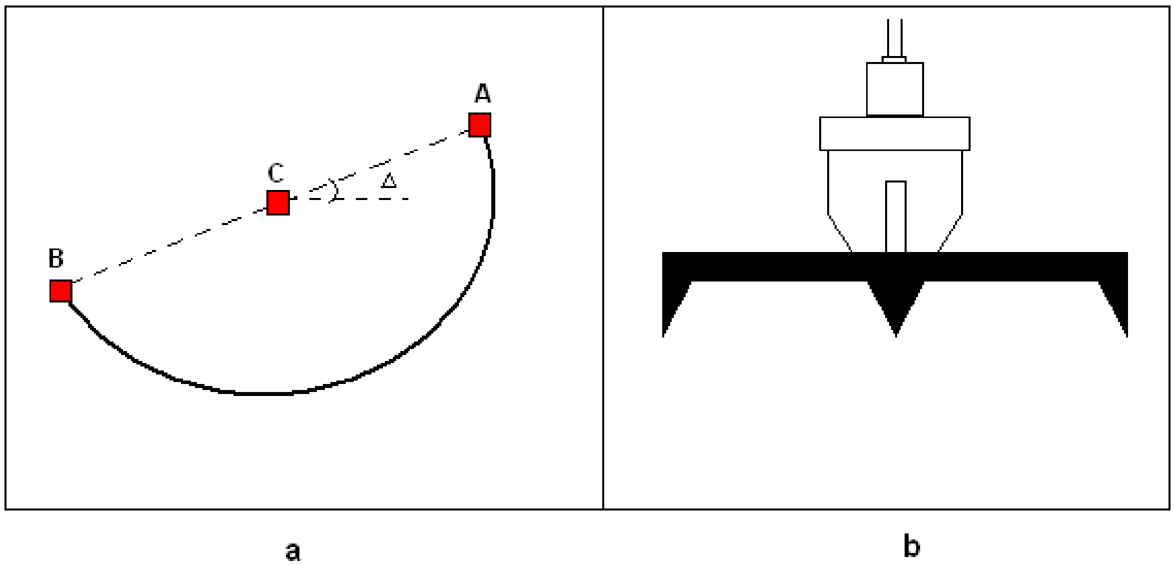


Figure 26: a) Imaginary line between the end points, b) Robot gripper, each corner will be aligned with the points A, B and C respectively.

An imaginary line can be drawn between points A and B, where the Point C defines the center of this line calculated from the Cartesian coordinates at the image plane. The angle Δ can be obtained by using the cosine inverse function. The concept is that in the future, a "mechanical pick up mechanism" can be designed and located in each end of the robot gripper. Once the center of the robot gripper is located and aligned with the point C, the robot gripper will rotates by Δ degrees to align each end of the gripper to the corresponding points A and B. As a result, the two "mechanical Pick up mechanism" located at each end of the robot gripper will be close to the desired UOT end point locations and can complete the pick up process.

All robot parameters are read from the robotic controller application database that was programmed in SPEL+. The robot starts the movement until it aligns the center of the gripper in point A and waits for two seconds. Then, it moves the gripper to the center of point B and waits for two seconds. Finally, it moves the gripper to the center of point C and rotates Δ degrees and aligns each end of the gripper to the corresponding points A and B. The robot Control Code program is included in the Appendix A.

4 OUTCOME AND RESULTS

In this chapter we presented the outcomes and results obtained from this project. The original objective of the project was achieved successfully. All machine vision components including the hardware selection, image processing algorithms, geometric calculations, and robot control were fulfilled. The following sections include a detailed summary of all critical areas development.

4.1 Image Processing

The selected image processing strategy demonstrated to be appropriate for the application. The illumination environment as well as the algorithms used for binarization, edge detections, particle & background identification, and end points detection worked appropriately allowing identifying the OUT as well as determining the specific end points coordinates.

The following is a progressive diagram that compares the image output (left) that results from the corresponding algorithm process stem (right). It also shows the contribution of each step to process to the image until the desired features are highlighted and able to be identified.

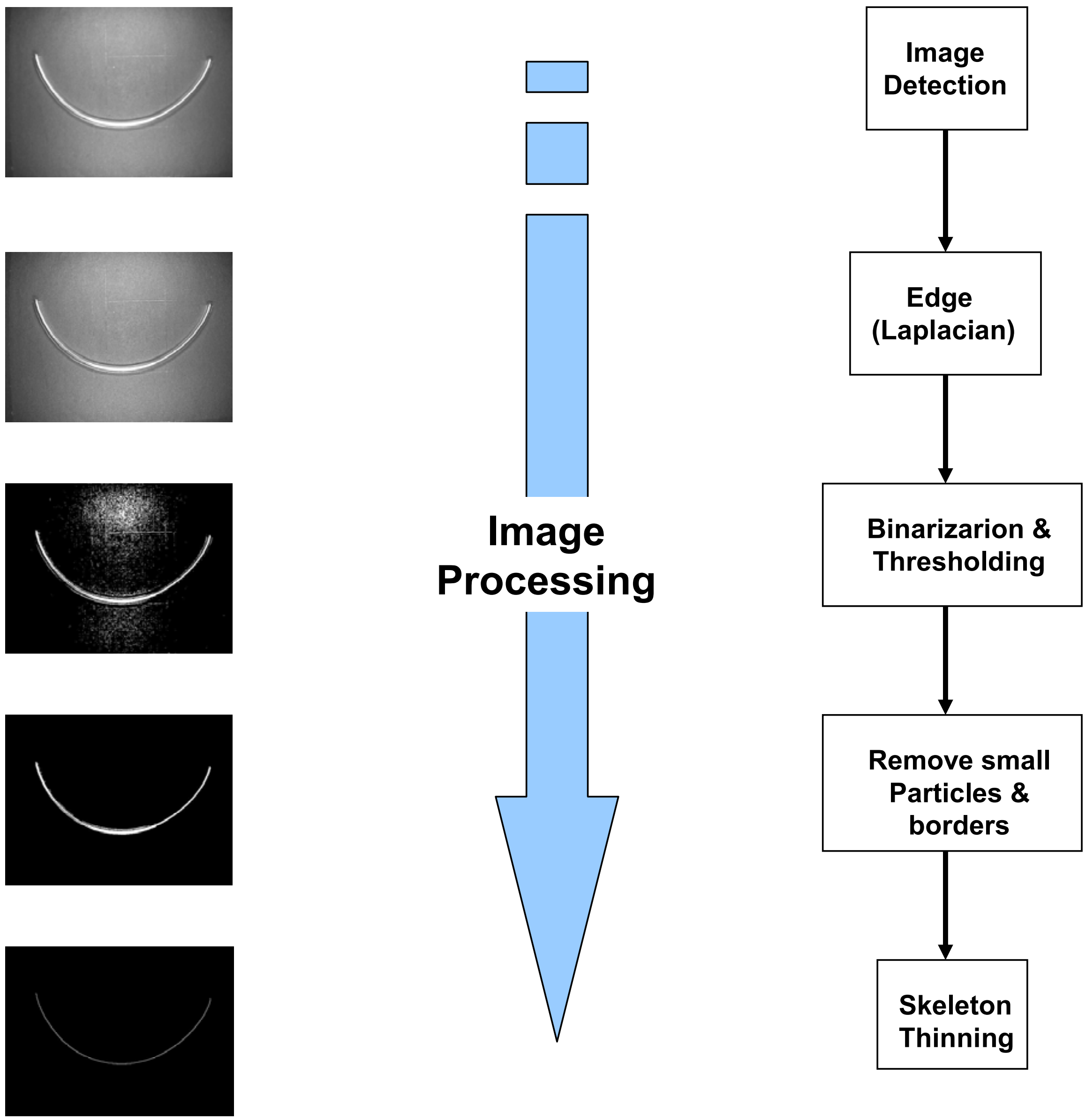


Figure 27: Image processing outcome.

The image process outcome produced a clean image, without any noise or background, and the OUT is highlighted and ready for the end points determination sequence.

The Image Processing Algorithm was executed more than 300 times using one sample of a translucence device that falls in different orientations. The algorithm demonstrated to be a robust algorithm. The UOT end points were successfully identified in the 100% of the cases whenever the assumptions mentioned in section 3.1.4 were satisfied.

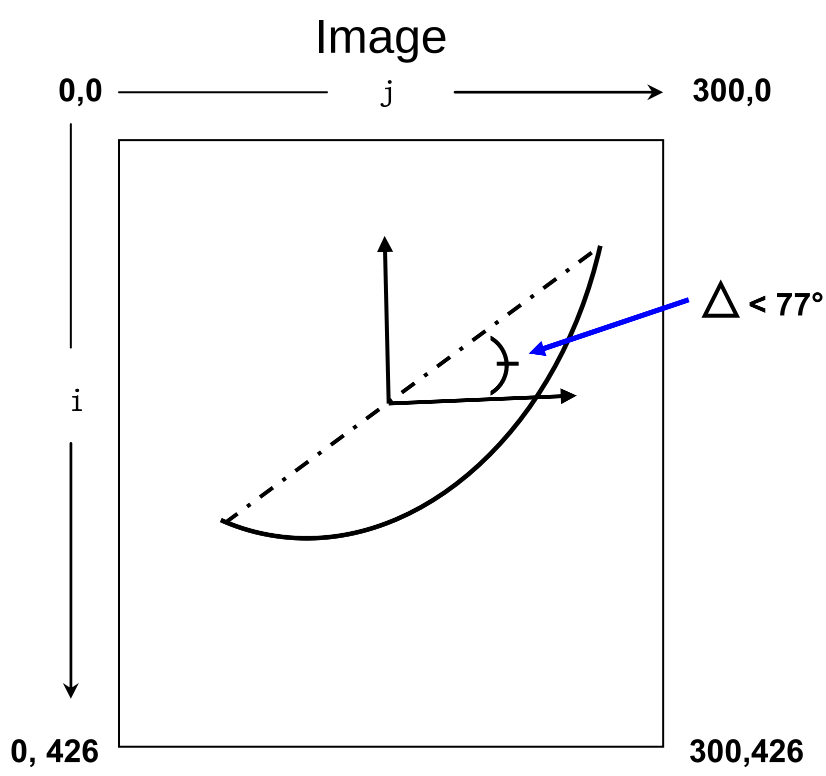


Figure 28: processing outcome.

While the second assumption established that it expected that the imaginary line between Point A and Point B remains in a horizontal form when the object fell, the experimentation demonstrated that the algorithm works appropriate even when the mentioned imaginary line rotates by an angle less than 77 degrees (refer to Figure 27).

Finally, it is important to mention that the thickness of the plastic tube also affect the measurement error. It is expected an inverse proportional relation meaning that if the plastic tube thickness decrease, the error will increase.

4.2 Robot Control

The robot moves and places the gripper at the desired points, once it received the coordinates from the Labview application, The Neural Network system defined a very good correlation model that estimates the final robot coordinates. The experimental results demonstrated that the robot was able to find the end points and locate the gripper with a minimum and acceptable error. The robot control worked properly in all cases without any issues.

5 CONCLUSIONS AND FUTURE WORK

5.1.1 Conclusion

An automated visual inspection system to monitor the assembly process of insertion of solid material as part of the manufacturing process for a catheter was successfully implemented in this project. The method and algorithm necessary to monitor and react when a part fell from the manufacturing process into the controlled workspace of the robot was developed and tested in a simulation environment. The system was able to detect and create an image of the fallen part, pass this image through the designed image processing algorithm, identify the coordinates of the part end points at the image plane by using the "skeleton track" designed algorithm, convert the image 3D coordinates into a robot physical 4D coordinates by using an Associative Neural Network system and, transfer the coordinates information to a robot which moved the gripper until achieved the desired physical location. The following is a summary of the conclusions:

1- The fluorescent linear lights arrangement selected as illumination technique was appropriate and helped to reduce the image noise caused by the reflections. It also increased the contrast between the transparent object and the background. The arrangement includes two lights located at the left and right site of the working environment, elevated at 14 cm and, with an inclination of around 45 degrees.

2- The Laplacian Operator function produced very good results highlighting the gray transitions and edges also in the smooth areas. Taking into consideration that the object was transparent, the low transitions in the gray levels were critical for identification.

3- The Associative Neural Network used to transform between the image coordinates into the robot coordinates produced a very accurate results based on this type of application. With a single interaction, the neurons were trained and the transformation matrix correlates between the image and the robot space compensating for the image/robot errors and fulfilling the geometric calibration requirements.

5.1.2 Future Work

We demonstrated that it is feasible to implement a machine vision system for the purposes defined in this project, and that the image processing algorithm was developed successfully. Some areas for future work, however, were identified.

1- The identification of the end points in the object is still an area of opportunity. While the algorithm used for identification of the end points worked appropriate, it was noticed that it is required a strong pre-processed image to produce the appropriate results. Therefore, the illumination environment became a critical component of the processing algorithm allowing only for small environmental changes.

2- The skeleton-function performance affected the end point detection sequence developed. This sequence fail when false ending points are not removed from the image. The false end points are small lines not filtered by the skeleton sequence and typically located near to a real end point. It was observed those false end points very frequently. Future work should be done in order to achieve better performance on mentioned end points identification function. The future work can incorporate techniques such as pattern matching, statistical information, neural network or others. The algorithm should provide a good performance independent from the skeleton function and reducing the effect of the shadows.

3- While the experimentation demonstrated that the algorithm for end point identification works properly, even when the imaginary line between Point A and Point B rotates from total horizontal up to 77 degrees, a future work should consider improving the algorithm to remove any dependency on the OUT position.

4- Finally, an additional opportunity should be also evaluated in a future work to determine the appropriate solution for the "mechanical Pick Up mechanism" as part of the robot arm.

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7 APENDIX A: PROGRAM CODES

7.1.1 LABVIEW FRONT PANEL

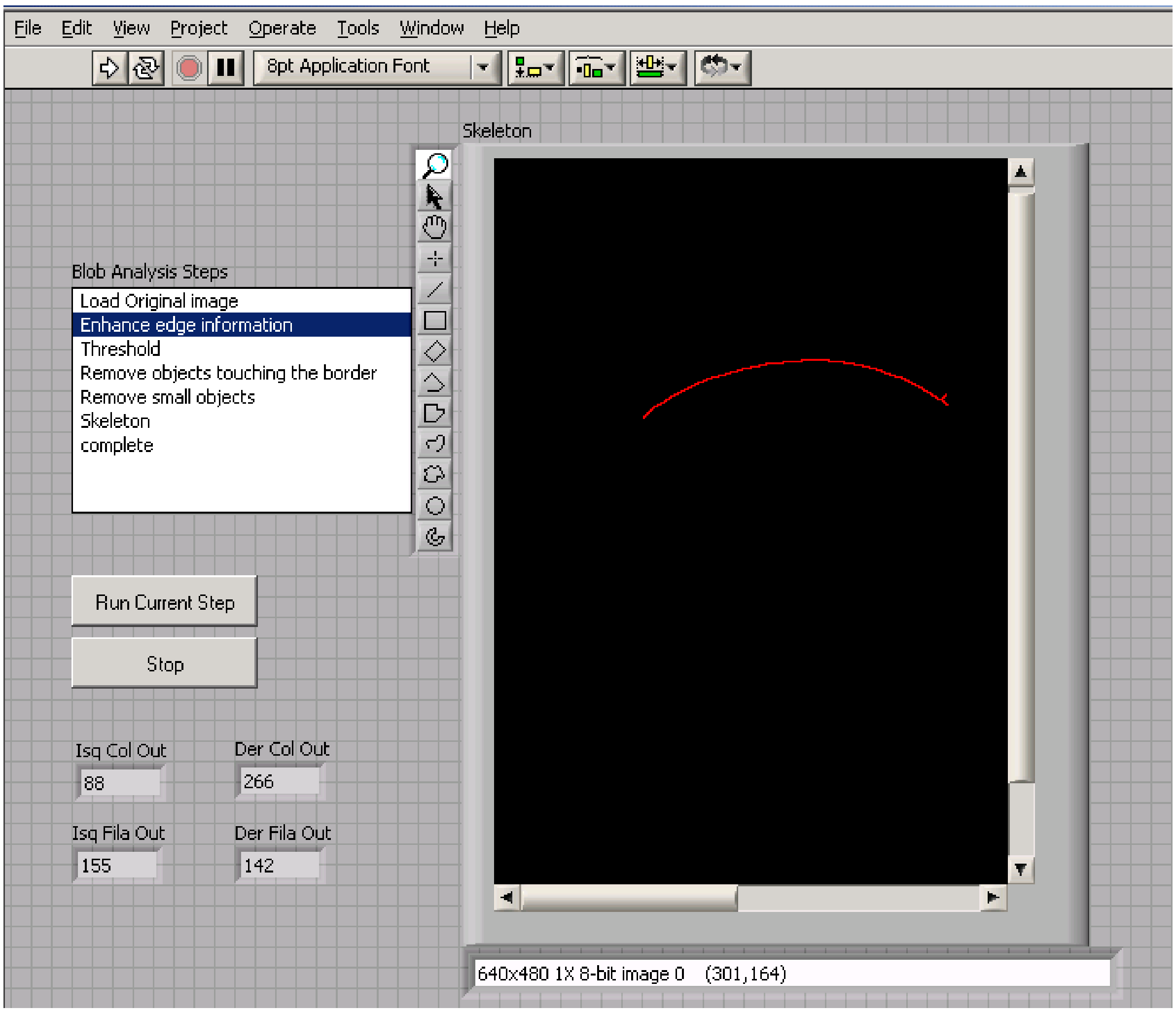

Figure 29: Labview Front Pannel

7.1.2 LEFT SEARCH CODE

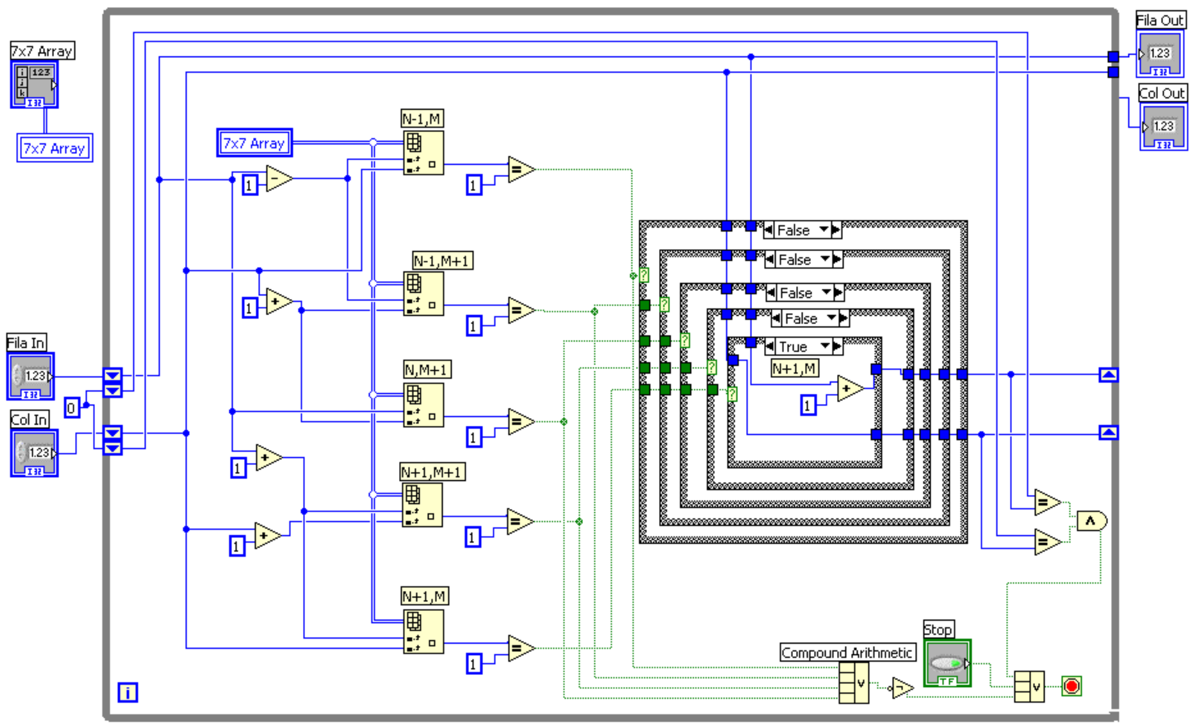

Figure 30: Left Search routine graphical code

7.1.3 LEFT SEARCH FLOWCHART

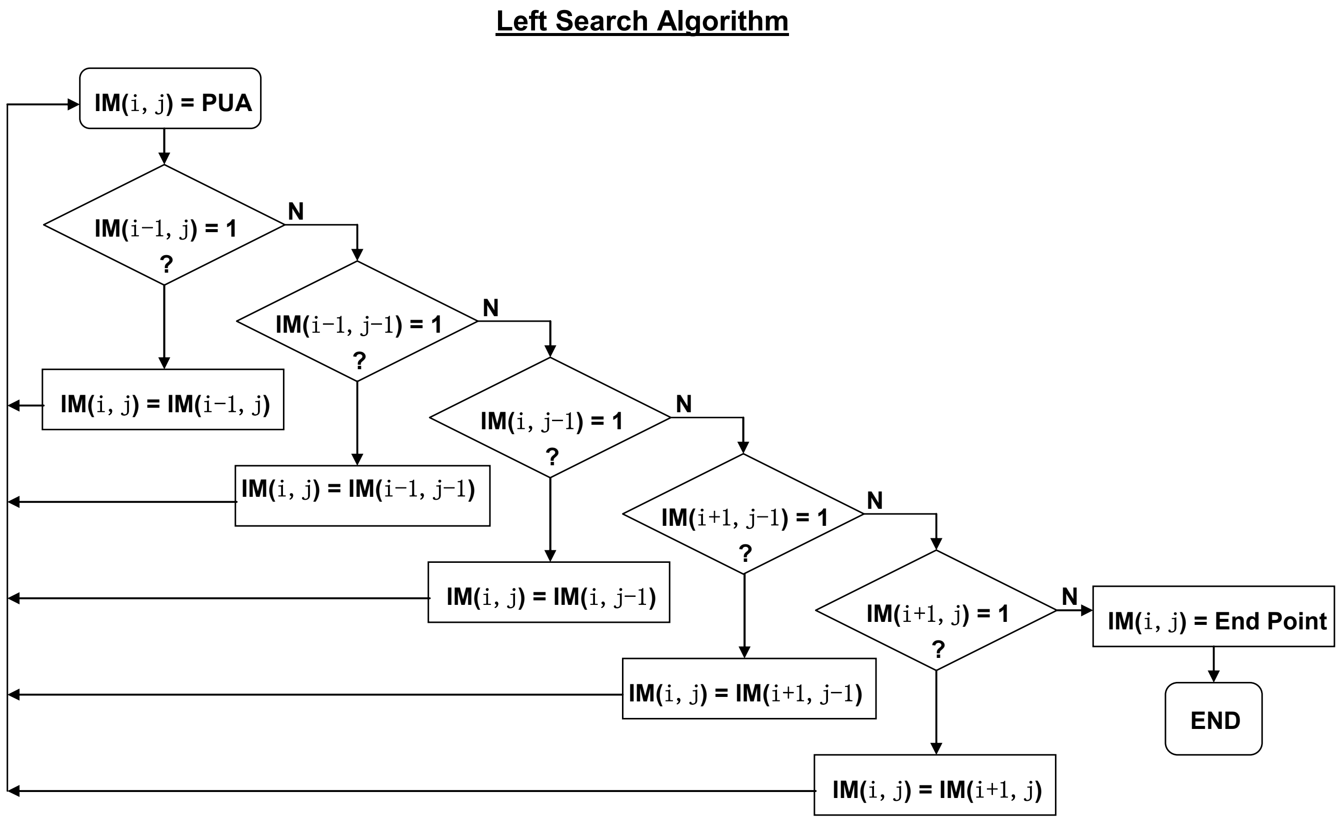

Figure 31: Left Search algorithm from coordinates perspective

7.1.4 ROBOT CODE

```
' ********************************************************
' ******* Robot Application for Master Degree Project ***************
' **************** Ver 2.0, Oct 14, 2010 ************************
' ****************** By. David Aponte *************************
' ********************************************************

Function main
String data1$(17), ans$ 'data1 is used for program controls and error
Integer fNum, i
Double X1(17) 'X1 is the coordinate variable

mainloop:
        Print "press S for start or E for end"
        Line Input ans$
        P0 = -217.5, 120, -65, -875
        If ans$ = "S" Then
                fNum = 30
                'fNum2 = 30
                ROpen "C:\DavidAponte\Robot\coordenadas.txt" As #fNum
                For i = 1 To 17
                Input #fNum, X1(i)
                Print "valor =", X1(i)
                Next i

                If X1(3) > -65 Or X1(7) > -65 Or X1(11) > -65 Then
                Print "valor de Z muy alto", X1(3), X1(7), X1(11)
                GoTo mainloop
                Else
                EndIf

                If X1(15) = 1 Then
                'Robot orientation definition 1 = R, 0 = L
                P1 = X1(1), X1(2), X1(3), X1(4)          'P1 is the Right End
                Else
                P1 = X1(1), X1(2), X1(3), X1(4) /L
                EndIf

                If X1(16) = 1 Then
                P2 = X1(5), X1(6), X1(7), X1(8)     'P2 is the Left End
                Else
                P2 = X1(5), X1(6), X1(7), X1(8) /L
                EndIf
```

```
        If X1(17) = 1 Then
        P3 = X1(9), X1(10), X1(11), -875   'P3 is the center defined by P1 and P2
        P4 = X1(9), X1(10), X1(11), X1(12)
        Else
        P3 = X1(9), X1(10), X1(11), -875 /L
        P4 = X1(9), X1(10), X1(11), X1(12) /L
        EndIf

        Go P1
        Wait 2
        Go P2
        Wait 2
        Go P3
        Wait 2
        Go P4
        Wait 5
        Go P0
        Close #fNum
        GoTo mainloop

        'WOpen "C:\DavidAponte\Robot\start.txt" As #fNum2
        'Print #fNum2, 0
        'Close #fNum2

    Else
        If ans$ <> "E" Then
        GoTo mainloop
        Else
        EndIf
    EndIf
Fend
```

7.1.5 JOG AND TEACH WINDOW

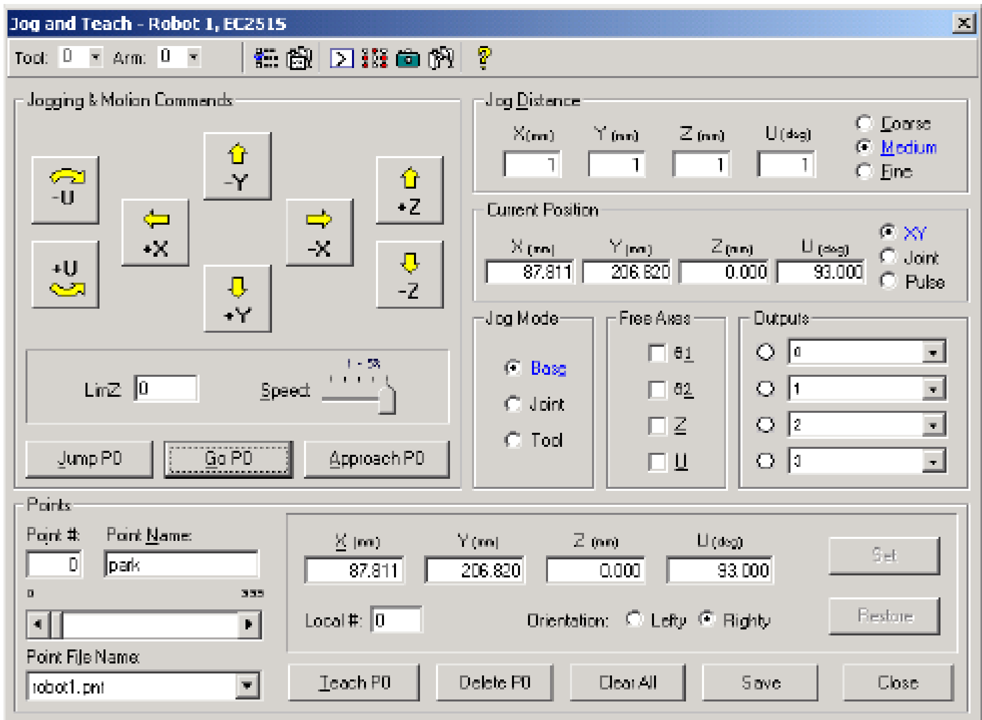

Figure 32: Jog and Teach Window.

Picture from the EPSON RC+ GUI User Manual