Development of Automated Non-Contact Inspection Methodology through Experimentation

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By

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Declaration

I hereby declare that the entire work embodied in this dissertation has been carried out by me and no part of it has been submitted for any degree or diploma of any institution previously.

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Date: 4th May, 2010

Advisor: Prof P.K. Ray

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Abstract

Computer vision applies to industry and manufacturing in order to control or analyze a process or activity. Typical applications of computer vision are the inspection of produced goods like electronic devices, automobiles, food and pharmaceuticals. Computer vision systems form their judgement based on specially designed image processing softwares. Therefore, image processing is very crucial for their accuracy.

Automated non-contact inspection of food products is of prime requirement when 100% inspection is preferred over sampling inspection, high speed inspection is needed, and bad consequences of physical contact between the measurement system and the food items being inspected are required to be avoided. Research carried out in this area is directed to proposition of several approaches, mainly based on computer vision technology, coupled with prediction models, for inspection of size, shape, colour, presence of blemishes and textures on the surface of food products. Computer vision has been successfully adopted for the quality analysis of meat and fish, pizza, cheese, and bread. Likewise grain quality and characteristics have been examined by this technique.

Food industry is among the industries that largely use image processing for inspection of produce. Fruits and vegetables have extremely varying physical appearance. Numerous defect types present for apples as well as high natural variability of their skin color brings attracts us for major research work.

The report describes a computer vision and 100% inspection-based generic methodology for non-contact measurement and evaluation of quality characteristics of food products with a special emphasis on quality characteristics of food products.

Keywords: *computer vision, quality inspection, apple, image processing, pattern recognition, segmentation, feature extraction, classifiers, neural networks*

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Chapter 1: Introduction

1.1 Introduction

The increased awareness and sophistication of consumers have created the expectation for improved quality in consumer food products. This in turn has increased the need for enhanced quality monitoring. Quality itself is defined as the sum of all those attributes which can lead to the production of products acceptable to the consumer when they are combined. Quality has been the subject of a large number of studies. The basis of quality assessment is often subjective with attributes such as appearance, smell, texture, and flavour, frequently examined by human inspectors. Consequently Francis (1980) found that human perception could be easily fooled. Together with the high labour costs, inconsistency and variability associated with human inspection stresses the need for objective measurements systems. Automatic inspection systems, mainly based on camera-computer technology have been investigated for the sensory analysis of agricultural and food products. This system known as computer vision has proven to be successful for objective measurement of various agricultural and food products. Computer vision includes the capturing, processing and analysing images, facilitating the objective and non-destructive assessment of visual quality characteristics in food products. The potential of computer vision in the food industry has long been recognised and the food industry is now ranked among the top 10 industries using this technology (Gunasekaran, 1996). Recent advances in hardware and software have aided in this expansion by providing low cost powerful solutions, leading to more studies on the development of computer vision systems in the food industry. As a result automated visual inspection is undergoing substantial growth in the food industry because of its cost effectiveness, consistency, superior speed and accuracy. Traditional visual quality inspection performed by human inspectors has the potential to be replaced by computer vision systems for many tasks.

Computer vision systems are largely employed for automatically controlling or analyzing processes or activities in many industries like automotive, electronics, food & beverages, pharmaceutical, textile, etc. One of the most popular applications of computer vision is to inspect qualities of produced goods based on form, color and presence of defects. Computer vision systems benefit from specially designed image processing softwares to perform such particular tasks; therefore image processing plays a very crucial role in their performance.

Physical appearances of fresh fruits and vegetables extremely vary causing difficulties for computer vision systems. Apple fruits, in particular, have numerous kinds of defects and highly varying skin colour. Hence, they pose even more problems for computer vision-based quality inspection systems.

Taking all these facts into account, this thesis will address computer vision and pattern recognition techniques and their application on quality inspection of apple fruits.

1.2 Need for Automated Non-Contact Inspection

It was during the 1970s that computers were introduced for automating the task of product quality control. Before the advent of computer-aided automated inspection of product quality, the only alternative was manual inspection, which suffered from a large number of drawbacks. Operating a full-fledged quality control department manually with a large number of inspectors and data handlers along with constant supervision is an extremely costly and difficult affair. The fatigue and other psychological factors associated with the personnel involved in a manual inspection process, make the performance of these personnel less than satisfactory which in turn results in inspection errors. More importantly, performance of the human inspectors is generally subjective and variable since inspectors may have their own standard of inspection and classifying products and defect. Thus, it is possible that the same item or defect may be classified into different pre-defined classes by different inspectors.

Furthermore, a single human inspector may make different judgements on the same product at different instances. All these drawbacks make manual inspection slow, expensive, erratic, and subjective and thereby render it unsuitable for meeting today's demand.

1.3 Outline of the Thesis

A computer vision system for apple quality inspection has to address and correctly solve the following three major problems to be accurate and acceptable:

A. Stem and calyx concavities of apples should not be confused as defects.
B. Defected skin of apple fruit should be accurately segmented.
C. Fruits should be correctly classified into predefined quality categories.

This thesis is organized as follows: Chapter 2 presents the Review of Literature on the topic. Chapter 3 states the problem description and chapter 4 gives the details of experimentation. The following chapter 5, provides with the solution methodology to be followed for automated inspection by computer vision. In chapter 6, we provide insights on the results obtained. Finally, we draw conclusions from the proposed works and provide some directions for future studies in chapter 7.

Chapter 2: Review of Literature

2.1 Introduction

Computer vision systems are being used increasingly in the food industry for quality assurance purposes. The system offers the potential to automate manual grading practices thus standardising techniques and eliminating proven successful for the objective, online measurement of several food products with applications ranging from routine inspection to the complex vision guided robotic control. In the following sections, we discuss the advancement in automated inspection of food products by computer vision for various food items.

One of the most common applications of computer vision is the inspection of goods such as electronic devices, automobiles, food and pharmaceuticals. In order to judge quality of such goods, computer vision systems use digital cameras and image processing software. Hence image processing is very for accurate inspection.

Among food products, fruits and vegetables extremely vary in physical appearance, therefore their inspection is necessary to discriminate the undesirable, acceptable and outstanding individual pieces and to guarantee the uniform quality required by the industry.

2.2 Bakery Products

The appearance of baked products is an important quality attribute, correlating with product flavour and influencing the visual perceptions of consumers and hence potential purchases of the product. Features such as the internal and external appearance contribute to the overall impression of the products quality. Scott (1994) described a system which measures the defects in baked loaves of bread, by analysing its height and slope of the top. The internal structure (crumb grain) of bread and cake was also examined by machine vision (Sapirstein, 1995). Digital images of chocolate chip cookies were used to estimate physical features such as size, shape, baked dough colour and fraction of top surface area that was chocolate chip (Davidson, Ryks, & Chu, 2001). Colour of 200 muffins were examined using the vision system with a classification algorithm used for separating dark from light samples using pre graded and ungraded muffins.

2.3 Meat & Fish

Visual inspection is used extensively for the quality assessment of meat products applied to processes from the initial grading through to consumer purchases. McDonald and Chen (1990) investigated the possibility of using image-based beef grading in some of the earliest studies in this area. Image analysis was also used for the classification of muscle type, breed and age of bovine meat (Basset, Buquet, Abouelkaram, Delachartre, & Culioli, 2000). Jamieson (2002) used an X-ray vision system for the detection of bones in chicken and fish fillets.

2.4 Vegetables

The necessity to be responsive to market needs places a greater emphasis on quality assessment resulting in the greater need for improved and more accurate grading and sorting practices. Shape, size, colour, blemishes and diseases are important aspects which need to be considered when grading and inspecting potatoes. The colour and shape of the cap is the most important consideration of fresh mushrooms. Location of stem roots in carrots is an important quality characteristic of carrots. Two algorithms for analysing digital binary images and estimating the location of stem root joints in processing carrots were developed by Batchelor and Searcy (1989).

2.5 Fruits

External quality is considered of paramount importance in the marketing and sale of fruits. The appearance i.e., size, shape, colour and presence of blemishes influences consumer perceptions and therefore determines the level of acceptability prior to purchase. Fruits like apples, peach and tomatoes may be used with computer vision for automated 100% inspection.

2.6 Grains

Cereal quality requirements differ with respect to the end users such as the preparation of varieties of bread, cakes, cookies and pasta products. Zayas et al. (1996) found that the physical characteristics of wheat could be used as the basis for the development of an objective wheat classification method. Wan, Lin, and Chiou (2000) developed an online automatic Rice inspection system using computer vision. The Quality characteristics under consideration for grains are kernel shape, colour, and defects. The following figures show the different levels in image processing (Fig 2.1), segmentation techniques (Fig 2.2) and segmentation of pizza (fig 2.3).

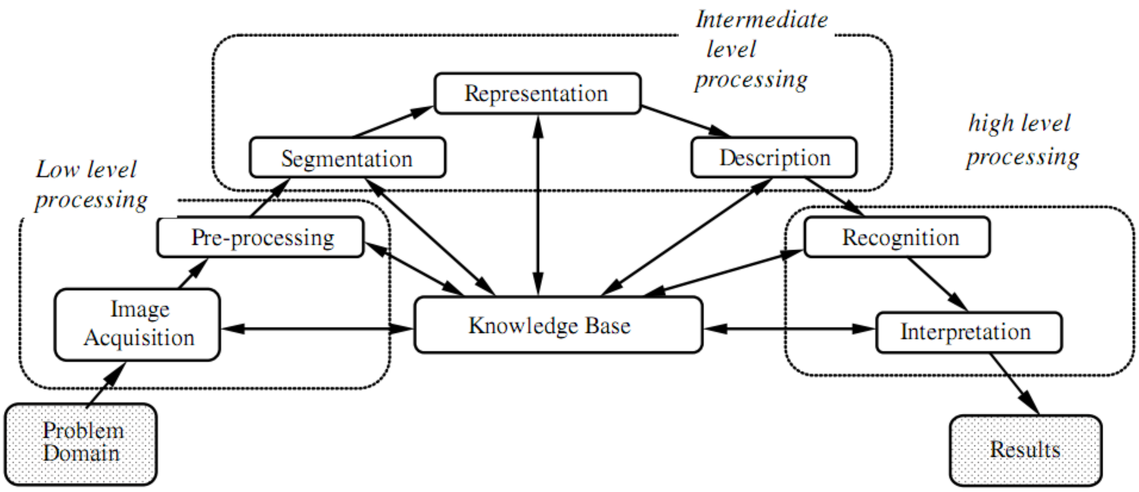

Fig 2.1: Different levels in image processing

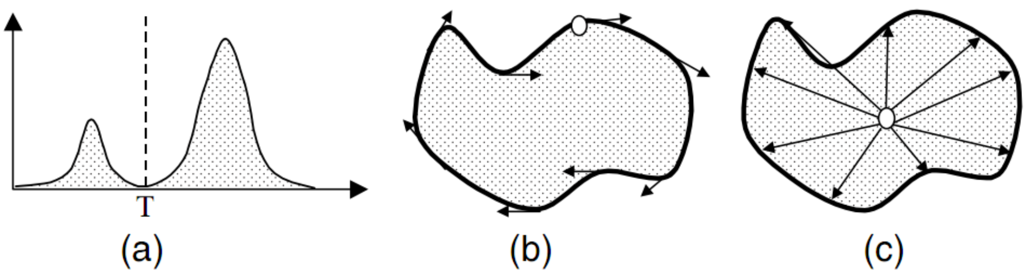

Fig 2.2: Typical segmentation techniques, a) thresholding, b) edge based segmentation, and c) region based segmentation

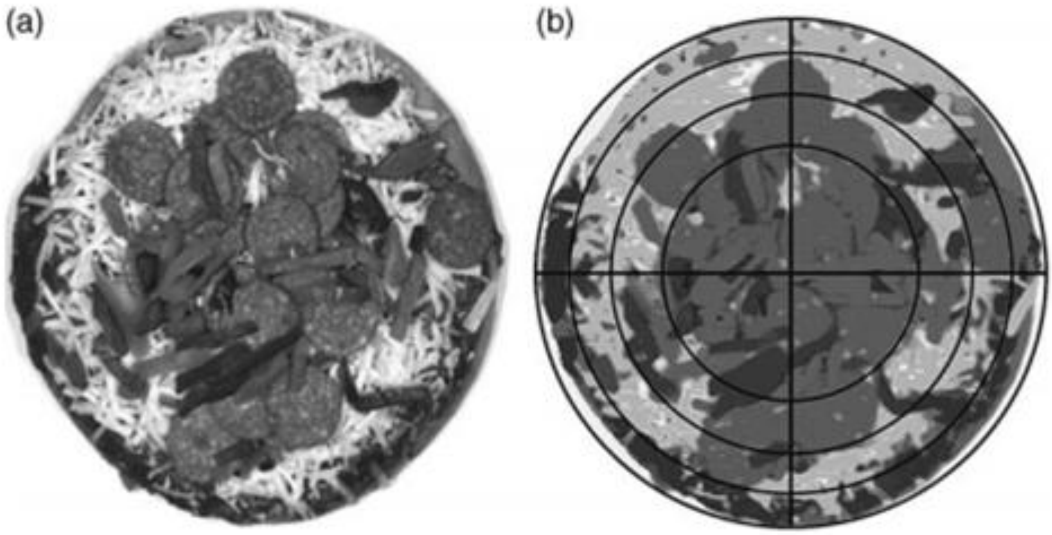

Fig 2.3: Pizza images, a) original image, and b) segmented image

2.7 Apples

Apple fruits, in particular, present large number of defect types and have highly varied skin colour. According to European Commission, quality of apples depends on size, colour, shape and presence/type of defected skin. Their visual inspection is traditionally performed by human experts. Even so, automating this process is necessary to increase speed of inspection as well as to eliminate error and variation by human experts.

2.7.1 Stem and Calyx Recognition

Computer vision systems for apple sorting are mostly confused in discriminating stem/calyx (SC) areas from true defects due to their similarity in appearance. Hence, accuracy of sorting is diminished by false identification of SCs.

Several approaches have been introduced to recognize SCs using mechanical approaches. Mechanical approaches include systems in which orientation of fruit, therefore positioning of SCs are known. However in reality, adjusting and preserving orientation reliably while acquiring images of whole apple surface is problematic. Moreover, in the image acquisition system used in this research as well as in most other systems introduced by researchers, orientations of apple while imaging are not known. Other techniques include placing illumination in such a way that the concave areas automatically get dark.

Apart from mechanical approaches, other techniques include software based works. Software based groups can also be divided into two sub-groups: those applying statistical pattern recognition and those using classifier based approaches. Pattern matching method is widely used for object recognition, but its main disadvantage is its high dependency on the pattern (template) used. For the classifier-based approaches, researchers have proposed to use artificial neural networks to recognize SCs.

2.7.2 Defect Detection

Apple fruit is susceptible to numerous kinds of injuries caused by natural or handling factors. In order to detect these injuries researchers have explored different sensing techniques like X-Ray imaging, magnetic resonance imaging (MRI) and thermal imaging.

Injuries of apple fruit can be sub-grouped as internal and external ones, roughly. Several works have been proposed to detect internal defects of apple fruit, but they will not be considered in this thesis because such defects originate inside the fruit and do not become visible until some mature state, which makes them very difficult to detect by any ordinary computer vision.

Segmentation is the process of extracting important objects by partitioning an image into foreground and background pixels. In order to accurately perform quality inspection of defected skin is crucial. Therefore, defect segmentation is our main objective. Du and Sun (2004) have divided image segmentation techniques used for food quality evaluation into four groups:

1. <u>Thresholding-based:</u> These techniques partition pixels with respect to an optimal values (threshold). They can be further categorized by how the threshold is calculated (simple-adaptive, global-local). Global techniques take

a common threshold for the complete image. Adaptive threshold calculate different threshold for each pixel within a neighbourhood.

2. Region-based: Region-based techniques segment images by finding coherent, homogeneous regions subject to a similarity criterion. They are computationally more costly than thresholding-based ones. They can be divided into two groups: merging, which is bottom-up method that continuously combines sub-regions to form larger ones and splitting, which is the top-down version that recursively divides image into smaller regions.
3. Edge-Based: These techniques segment images by interpreting gray level discontinuities using an edge detection operator and combining these edges into contours to be used as region borders. Combination of edges is a very time consuming task, especially if defects have complex textures.
4. Classification–based: Such techniques attempt to partition pixels into several classes using different classification methods. They can be categorized into two groups, unsupervised and supervised. In unsupervised, desired input output pair for learning is not there, whereas in supervised, it is there. Desired outputs are very difficult and time expensive to determine.

2.7.3 Fruit Grading

One of the earliest works in apple grading by computer vision was introduced by Davenel et al (1988). They used a black and white camera. Apple were manually oriented to avoid stem-calyx view in the images. 230 Golden Delicious apples were graded into 4 quality categories (3 acceptable, 1 reject) by geometric features and thresholding according to the size of defected skin. Correct classification rate achieved was 69%.

Rennick et al (1999) presented a computer vision system with a color camera to grade 200 Granny Smith apples into two categories (1 bruised, 1 not-bruised). Orientation of fruit was controlled in their system. After background removal, fruit area was divided into predefined sub-regions, from which statistical features are extracted.

2.8 Comparison of Existing Methodologies

The following table presents the accuracy of X-Ray imaging in Computer Vision

Application	Accuracy (%)	Reference
Detection of bones in fish and chicken	99	Jamieson (2002)
Internal defects of sweet onions	90	Tollner, Shahin, Maw, Gitaitis, and Summer (1999)
Spit pits in peaches	98	Han, Bowers, and Dodd (1992)
Water core damage in apples	92	Kim and Schatzki (2000)
Pinhole damage in almonds	81	Kim and Schatzki (2001)

Table 2.1: Applications using X-Ray imaging in computer vision

The following table presents a comparison of existing methodologies for computer vision adopted for food products.

Area of use	Speed	Accuracy (%)	Reference
Pork lion chops	1 Sample/s	90	Tan et al. (2000)
Fish identification	0.21 m/s conveyor	95	Storebeck and Daan (2001)
Detection of bones in fish and chicken	10,000/h	99	Jamieson (2002)
Estimation of cabbage head size	2.2 sec/sample	-	Hayashi et al. (1998)

Location of stem root joint in carrots	10 joints/second	-	Batchelor and Searcy (1989)
Apple defect sorting	3000/min	94	Tao and Wen (1999)
Sugar content of apples	3.5 s/fruit	78	Steinmetz et al. (1999)
Pinhole damage of almonds	66 nuts/s	81	Kim and Schatzki (2001)
Bottle Inspection	60,000/h	-	Anon (1995)

Table 2.2 Comparison of existing methodologies for computer vision.

2.9 Conclusions

The review of the literature as carried out helps in identification of some potential research issues pertaining to the areas of automated non-contact inspection of defects and physical dimensions of engineering products as well as food. It is observed that although several approaches for accomplishing the above-mentioned inspection tasks have been proposed by the researchers in the existing literature, research is required from the perspective of adequately addressing a few critical issues, such as integration of inspection for many inspection situations, and propositions of generic approaches applicable to a variety of materials, shape and products.

Chapter 3: Problem Description

The objective of the study is to develop a methodology to classify different grade of food items with the help of computer vision.

The model is formulated to work upon a specific case of food item, i.e., Apple. The specific objective is to develop a novel automated apple surface defect detection experimental system based on computer vision technology.

Chapter 4: Details of Experimental Setup

4.1 Introduction

An experimental setup is necessary to gather data for inspection. In the experimental setup, we are taking a specific product, which is apple. We go for automated non-contact inspection for apples. It is to be observed that, however we are taking a specific food product, the same experimental setup and methodology can be followed for visual inspection of other items where blobs and defects are to be distinguished.

4.2 Components of Experimental Setup

The basic hardware components of industrial computer vision systems include:

i) A part handling system,

ii) A light source,

iii) An Image sensor, and

iv) A computer

The laboratory experimental setup used here is shown in figure 4.1.

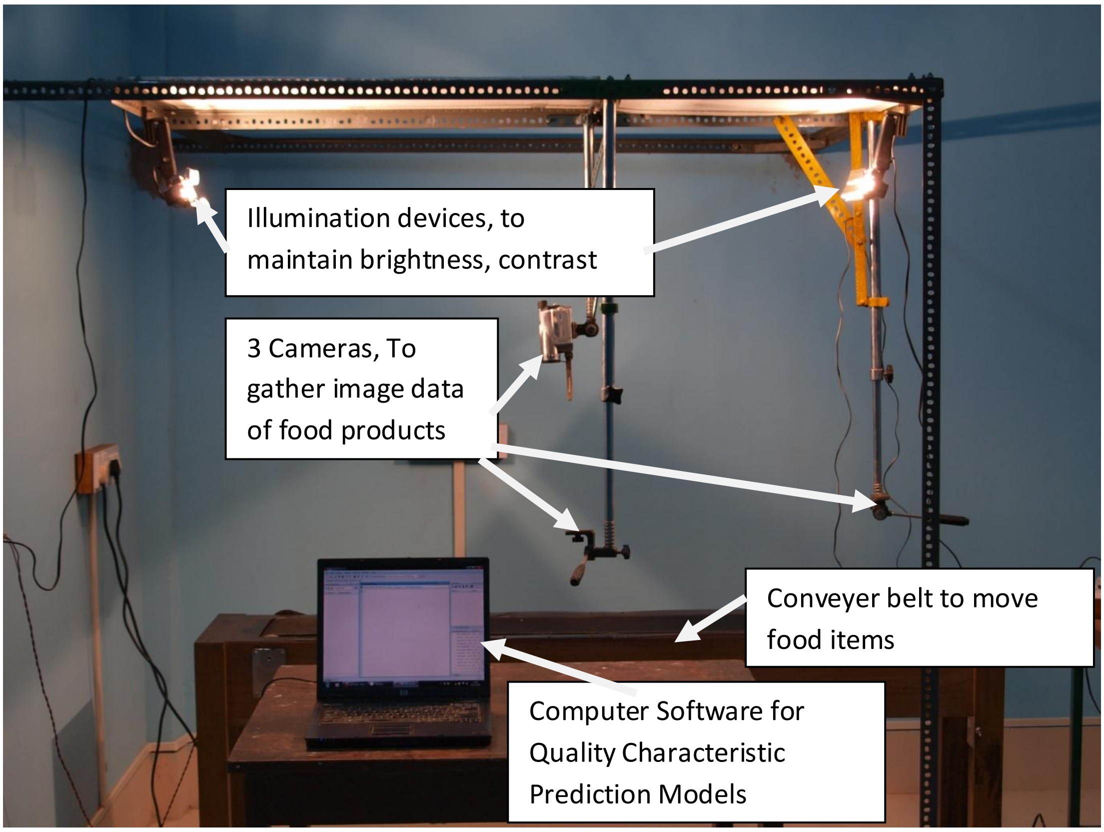

Fig 4.1: Experimental setup for Automated 100% inspection by computer vision.

A robotic arm can be introduced as shown in Fig 4.2 to automatically grade apples.

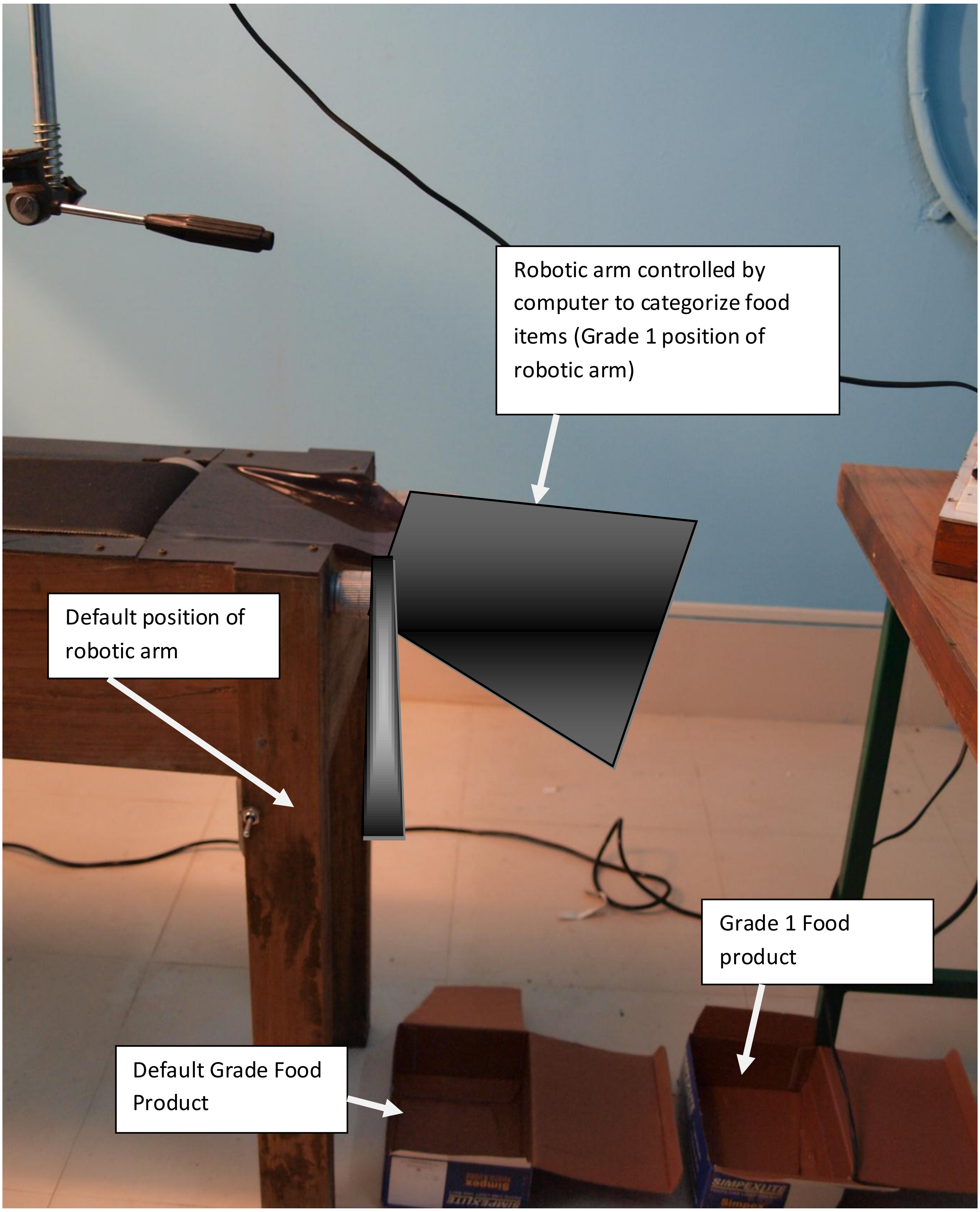

Fig 4.2: Adding a robotic arm controlled by computer software to categorize Food item into different categories.

4.3 Part Handling Sytem

A part handling system is used to place the items under observation in front of the camera. A part handling system can be a conveyer belt, which may have additional grooves that further orient the item. A part handling system is a must in computer vision technique, as a single item appears different at different angles. The size and dimensions of the item change with the change of orientation of the item. Hence the part handling system is a must in the computer vision technique to increase the accuracy of the observations. Here we are using a conveyer belt as a part handling device.

Fig 4.3: Capturing side view of an apple with the help of camcorder

4.4 Light Source

A proper illumination device is used in computer vision technique for uniform lightning, throughout the experiment. The illumination device ensures that the item under consideration is illuminated consistently at any time of the day. The illumination device also helps in maintaining the contrast and brightness levels of the item while the inspections are conducted. Front lighting is used when surface feature extraction is required. Back lighting is used for the production of a silhouette image for critical edge dimensioning. Light sources also differ but may include incandescent, fluorescent, lasers, X-ray tubes and infrared lamps. It is an important component as it affects colour, brightness and contrast of the item in consideration. Here in the experiment we are using flash lights as illumination device.

Fig 4.4: Capturing live data of the apple using IEEE connector with MATLAB

4.5 An Image Sensor

An image sensor is required to capture frames of items, in order to post process it to give results. Image sensors are basically Charge Coupled Devices (CCD). A CCD sensor is used for the conversion of image data to digital signals. It is to be noted that two scientists, Williard S. Boyle and George E. Smith at Bell Laboratories, USA are awarded the Noble Prize in Physics 2009 for the invention of CCD sensor. The image frames captured by the image sensor are then transferred to the computer via standard IEEE cable. The IEEE cable enables fast exchange of data and is faster than the normal USB interface. The camera used for the experimentation is Panasonic MiniDV Camcorder (Model: NV-GS70EN). Fig 4.3 shows the side view of an apple being captured by the camcorder.

4.6 A Computer

The computer consists of computer hardware and computer software. The specific hardware we are using in the computer is an IEEE card which helps in quick transfer of data from the camera to the computer. For the image processing, we are using Matlab™ Software, version R2009a. The software is pre-customized and includes Image Processing Toolbox™ that eases image processing steps. Additional software required is device driver of IEEE cable for the installed operating system. The operating system used is Windows XP service pack 2. Fig 4.4 shows live data being captured from the camera to the computer.

4.7 Conclusions

The experiments are conducted in the Department of Industrial Engineering & Management, IIT Kharagpur. The experimental setup is sufficient for the research work. In the further subsections, we discuss the methodology for processing the captured data.

Chapter 5: Solution Methodology

5.1 Introduction

Traditional inspection of apple fruits is performed by human experts. But, automation of this process is necessary to reduce error, variation, fatigue and cost due to human experts as well as to increase speed. Apple quality depends on type and size of defects as well as skin colour and fruit size. Stem and calyx are natural parts of apple fruit that are highly confused with defects in computer vision systems. Therefore, an automatic inspection system should accurately discriminate between these areas and defected skin. The steps followed in solution methodology are:

i) Stem and Calyx Recognition

ii) Defects Detection

iii) Fruit Grading

5.2 Stem and Calyx Recognition

In apple fruit, stem and calyx areas highly resemble surface defects in appearance. This resemblance may lead to incorrect grading of fruit if they are not accurately discriminated by sorting systems.

In order to recognize SCs, researchers have introduced different approaches based on mechanical solutions. Mechanical systems try to orient the fruit along stem-calyx axis during grading, however reliable adjustment and preservation of this orientation while acquiring images of whole apple surface is difficult. Computer vision based solutions include different equipments like special illumination or cameras, and image processing techniques like statistical pattern recognition methods and artificial neural networks.

5.2.1 Ideal Methodology for Stem Calyx Recognition

The ideal system to recognize SCs of apples is composed of the following steps: background removal, object segmentation, feature extraction, feature selection and classification as represented in fig 5.1.

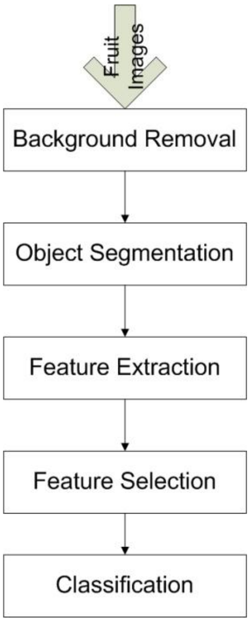

Fig 5.1: Steps in stem/calyx removal

5.2.2 Methodology Followed for Stem Calyx Recognition

Due to complexities of pattern recognition algorithm, we for the time being have resorted to mechanical methods of placing the apples in a definite orientation, so that stem and calyx are barely visible. Fig 5.2 shows a proposed system.

Fig 5.2: A mechanical system of grooves on conveyor belt to hold and orient apples.

The advantages of mechanical system are:

i) It orients the apples automatically.

ii) It also ensures that apples are uniformly placed so that frames can be grabbed at regular intervals.

iii) Requires less effort while developing algorithms

The disadvantages of mechanical system are:

i) It incurs cost of installing grooves on the conveyor belt.

ii) The groove blocks a small part of the apple under investigation.

5.3 Defects Detection

Apple fruit is susceptible to numerous kinds of injuries that affect quality. External injuries, specifically, appear on the surface of fruit and directly affect consumers' perception. Thus, their detection is essential for fresh fruit market. Here we introduce image processing techniques employed to find the defects in the apple. Segmentation techniques employed widely vary from global thresholding approaches to local ones and from statistical classifiers to artificial neural networks and decision trees.

5.3.1 Basic Operations of Digital Image Processing

The images once acquired from the image sensor are transferred to the computer where digital image processing is carried out. The basic operations of digital image processing are shown in Fig 5.3.

5.3.1.1 Steps for Image Acquisition Algorithm adopted in Research Work

Development of an image acquisition algorithm is the first step in the software development process. Image acquisition concerns with the acquisition of digital image. An image is a snap shot of visual information and is composed of many picture elements called pixels. The steps followed for image acquisition algorithm in the research work are described in Fig 5.4.

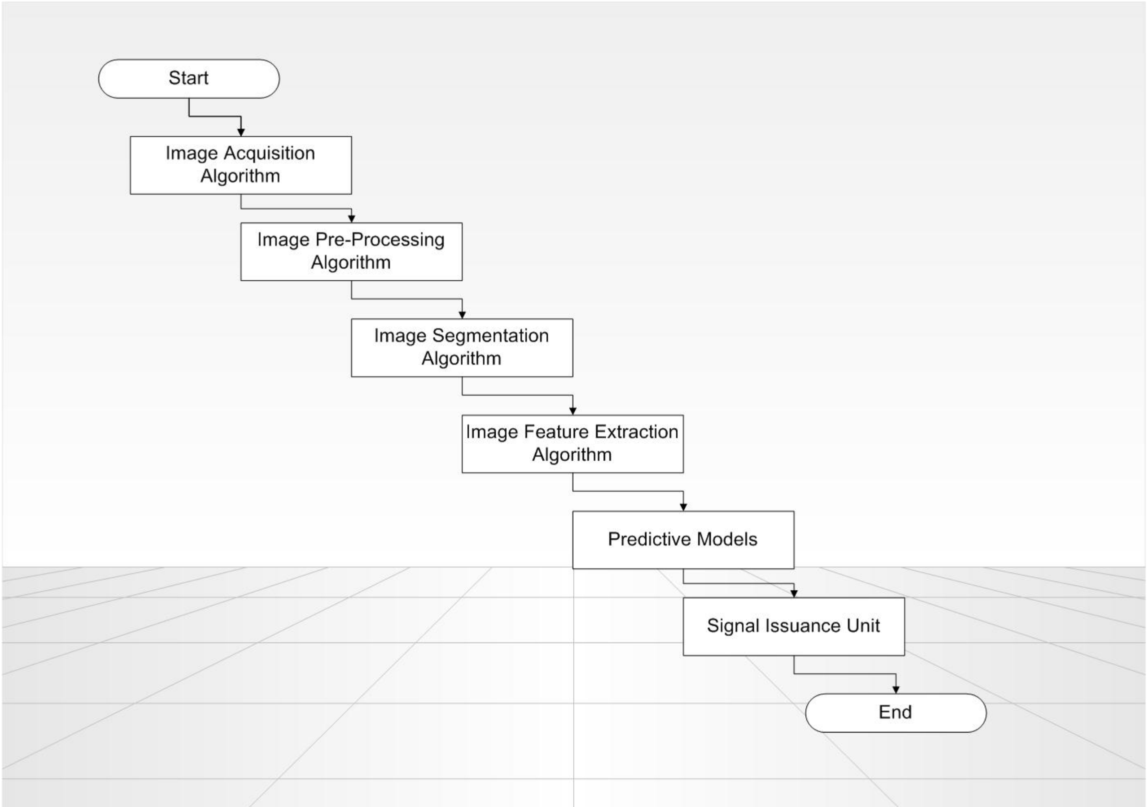

Fig 5.3: Basic Operations of Digital Image Processing in Quality inspection by Computer Vision

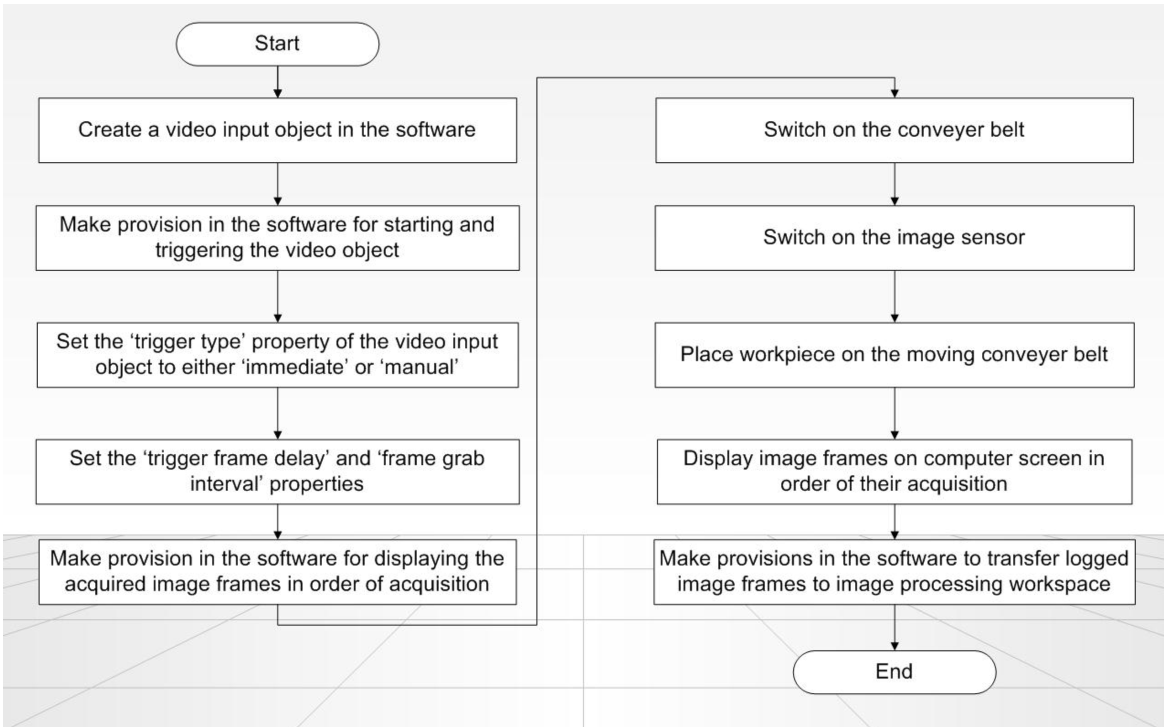

Fig 5.4: Steps for Image Acquisition Algorithm adopted in Research Work

5.3.1.2 Development of Image Pre-Processing (Image Enhancement) Algorithm

Once the image acquisition algorithm is developed, the next step is to develop an algorithm for image-preprocessing. The key function of image pre-processing is to improve the acquired image in ways that increase the chances for success of subsequent image processing operations. Image pre-processing basically aims to improve the quality of the acquired image by suppressing undesired distortions or by enhancing the features of interest. Supression of undesired distortions refers to corrections of geometric distortions, blurring as well as removal of noise. Enhancement of features of interest includes enhancing image contrast. The following steps are followed during image pre-processing:

i) Saving the acquired frames to disk and load it in the memory to operate
ii) Converting the frames to grey scale to ease computation
iii) Removal of noise from greyscal images
iv) Creation of a structuring element
v) Performing morphological opening operations on the noise-removed greyscale images
vi) Performing background subtraction
vii) Adjusting the contrast of the background-subtracted greyscale images

5.3.1.2.1 Saving and Reading Image Frames

The first step in the development of image pre-processing algorithm is to make a provision in the software to save the acquired image frame to disk and read it again from disk, and load it into memory to perform operations. The file format used in the research work is JPEG (Joing Photographic Experts Group). An example of a saved image frame is shown in Fig 5.5.

5.3.1.2.2 Conversion of truecolor images to greyscale images

The images that are taken from the light sensor are in true color. They store the information of Red, Blue and Green (RGB) levels for each pixel in the image. However, it is noted that calculations on RGB is quite time expensive, hence the image is converted to greyscale which has only grey level values. The RGB images also use more of disk space and memory. An example of greyscale converted image is shown in Fig 5.6.

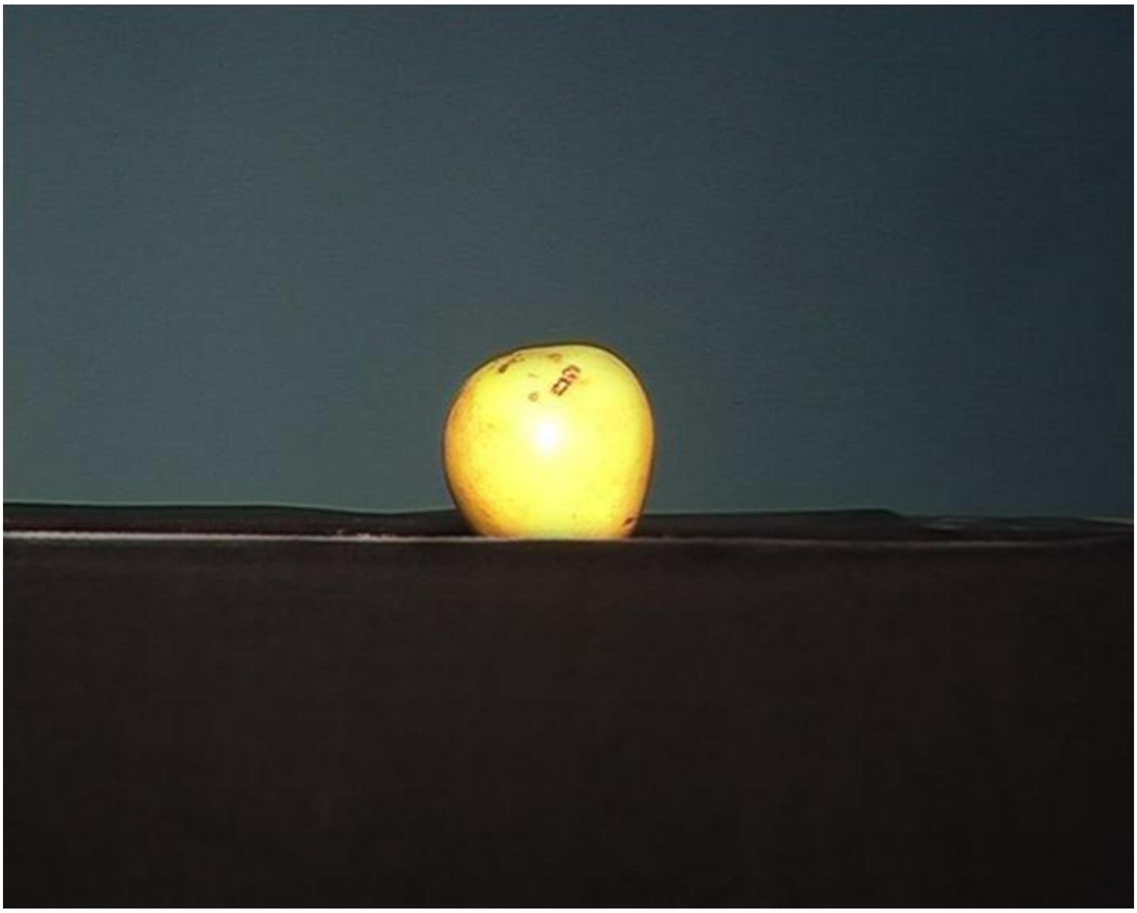

Fig 5.5: An example of a saved image frame.

5.3.1.2.3 Removal of Noise

Once provisions for writing, reading and converting the acquired images to greyscale are created in the software, a provision is made for removal of noises from the greyscale images. Noise in an image is the consequence of errors in image acquisition process and results in image pixel values that do not reflect the true intensities of the real scene concerned. Noises in an image may be reduced or removed by using a filtering technique. Filtering is a technique of enhancing an image for emphasizing certain features or removing other features. Different filtering techniques available for accomplishing removal of noise from a greyscale image are as follows:

i) Linear Filtering

ii) Median Filtering

iii) Adaptive Filtering

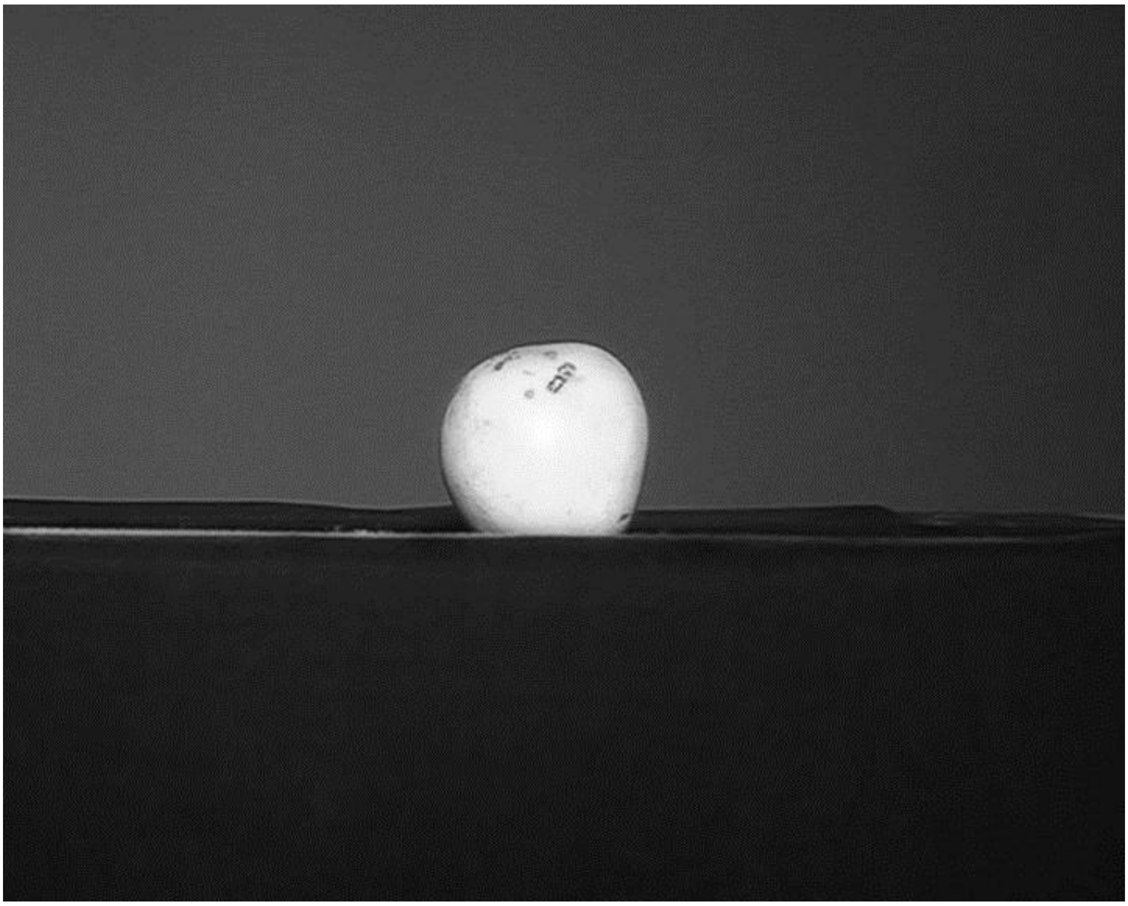

Fig 5.6: An example of greyscale converted image

Linear Filtering

In linear filtering, the value of pixel in the output image is a linear combination of the values of the pixels in the neighbourhood of the corresponding pixel in the input image. These weights in linear combination is determined with Convolution and Correlation techniques. In an averaging linear filter, the weights assigned to neighbours are equal. An example of a greyscale image operated with an averaging filter is shown in Fig 5.7.

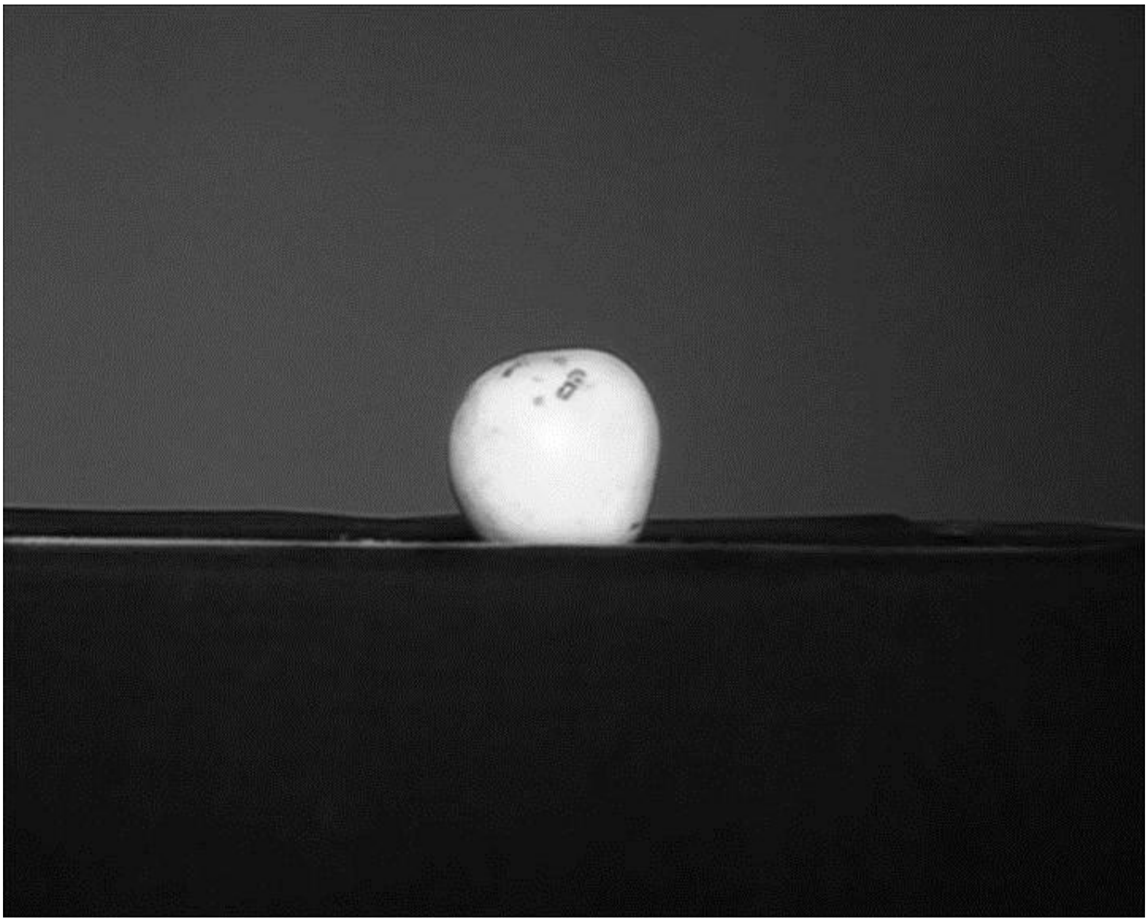

Fig 5.7: A greyscale image operated with a averaging filter.

5.3.1.2.4 Creation of Structuring Element

After creating a provision in the software for removal of noise(s), from the greyscale image, a structuring element is to be created for carrying out a morphological opening operation followed by a background subtraction operation in order to obtain a more uniform background for the concerned image.

A structuring element is a matrix (consisting of only 0s and 1s) which may assume any arbitrary shape (square, rectangle, diamond, disk etc) and size. In order to obtain only the background image by removing the apple from the original image, the structuring element should be large enough so that the concerned apple cannot completely contain the structuring element. Here we use a structuring element with the shape of disk (that resembles an apple the most) and its diameter is 75 pixels.

5.3.1.2.5 Morphological Opening

Using the structuring element mentioned above, a provision for morphological opening is made in the software. Generally, the background illumination is not the same throughout an image. In order to estimate the image background illumination for creating an image with a more uniform background, a morphological opening operation followed by a background subtraction operation is carried out. Basically, morphological opening operation is image erosion followed by image dilation, wherein the same structuring element is used for both erosion and dilation operations.

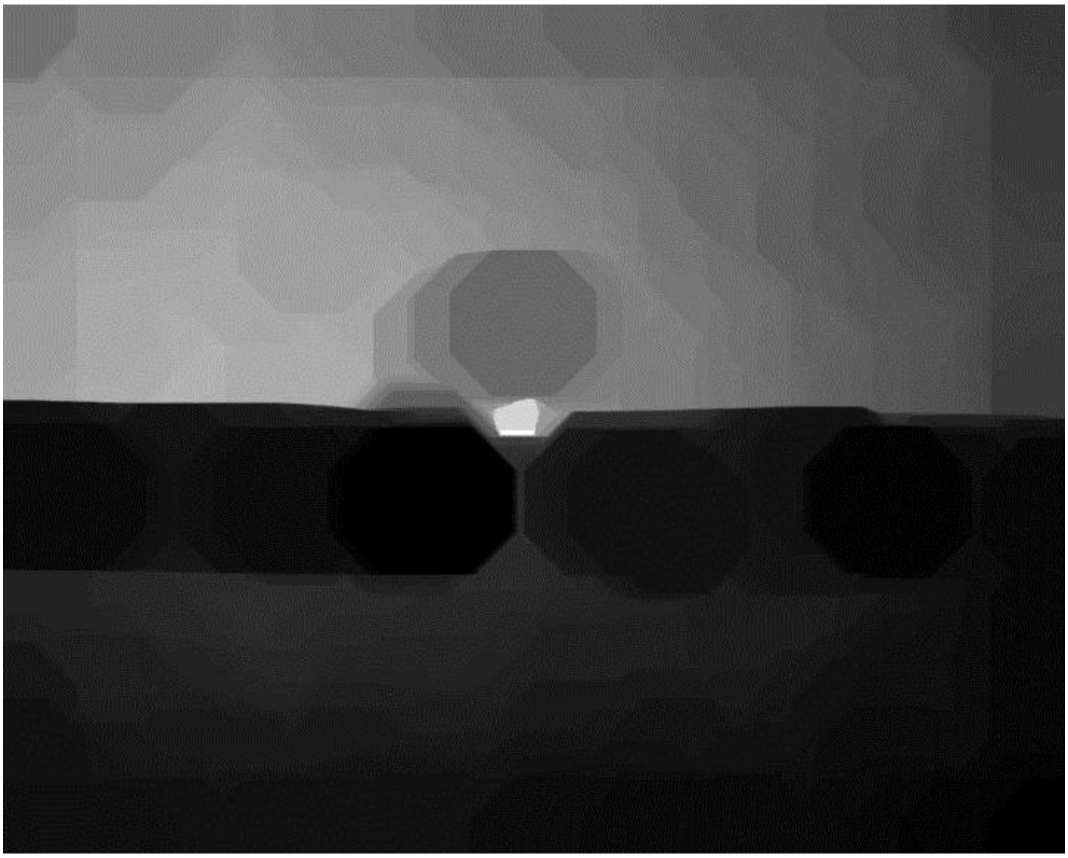

Fig 5.8: Image erosion using a disk structuring element of size 50 pixels

Image Erosion and Image Dilation

Image erosion is a fundamental morphological opening operation, which removes pixels on the boundaries ob objects in an image. Image dilation on the other hand, is another fundamental morphological opening operation, which adds pixels to the boundaries of objects in an image. The number of pixels removed or added from/to the boundaries of objects in an image depends on the size and shape of the structuring element. Examples of image erosion and dilation are shown in Fig 5.8 and 5.9 respectively.

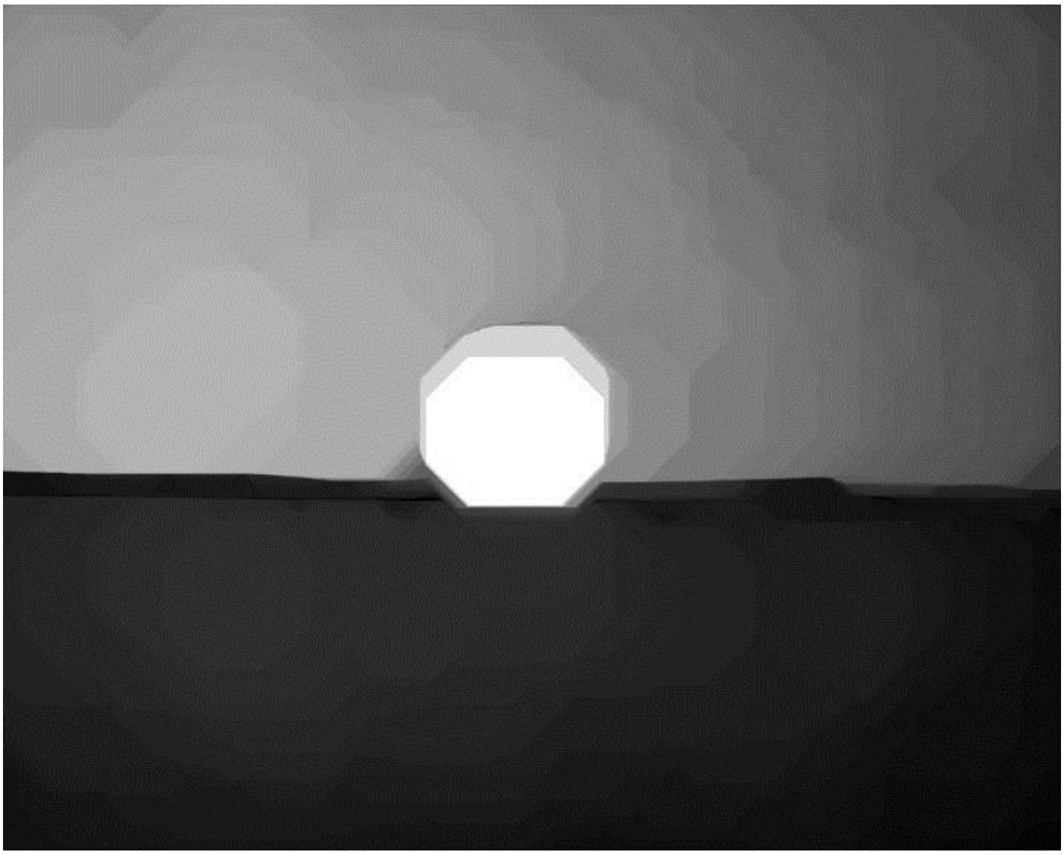

Fig 5.9: Image dilation using a disk structuring element of size 50 pixels

5.3.1.2.6 Background Subtraction

Once a provision for morphological opening operation is created in the software, the next step is to create a provision for background subtraction. Background subtraction concerns with subtracting the background image (image on which morphological opening operations have been performaned) from the original image. An image with a much uniform background in this step. An example of background subtraction is shown in Fig 5.10. It is to be noted that Fig 5.10 has a much uniform background than the original noise removed greyscale image Fig 5.6.

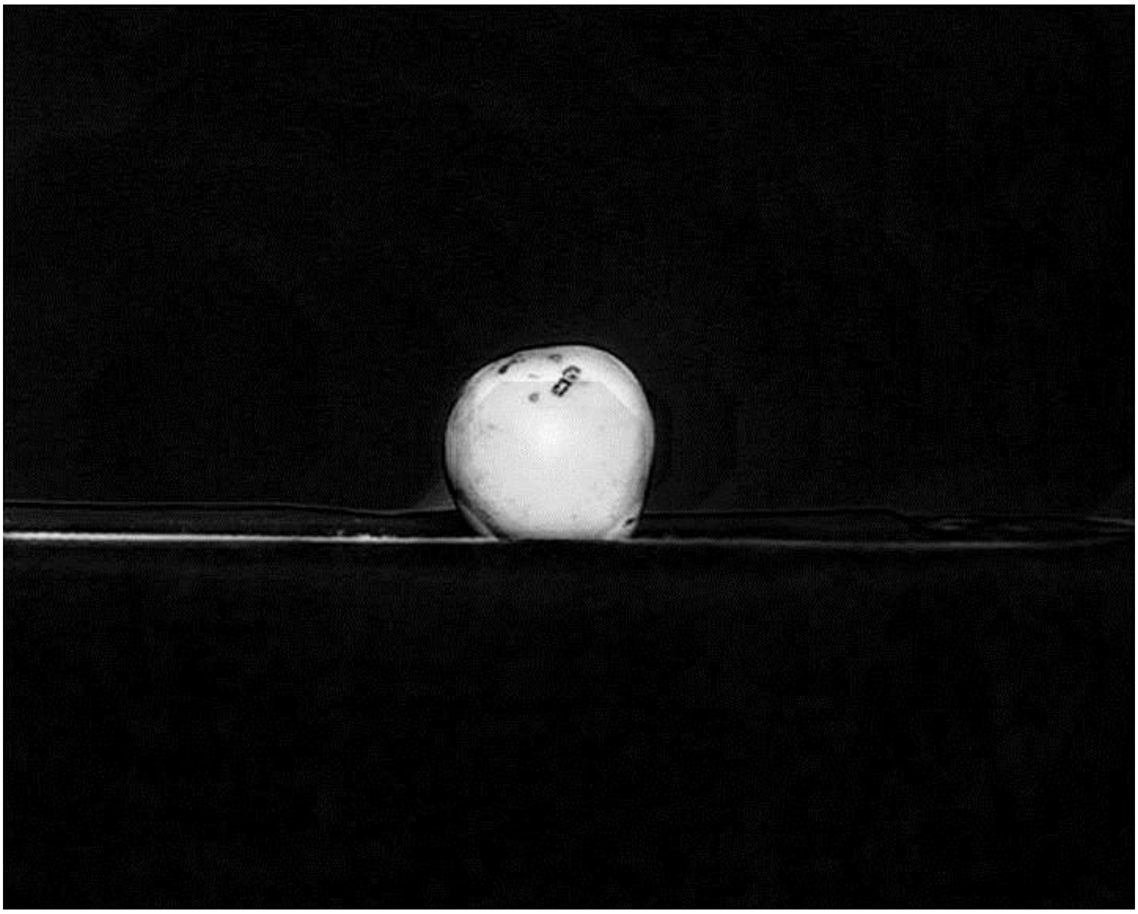

Fig 5.10: An example of background subtracted image

5.3.1.2.7 Contrast Adjustment

During the background subtraction operation, we find that the morphological opening grey values are subtracted from the original image. So, the contrast of the image is reduced. Hence, we go for a contrast adjustment algorithm to enhance the intensity values. Fig 5.11 shows an image whose contrast is adjusted using Adaptive histogram equalization technique.

5.3.1.3 Development of Image Segmentation Algorithm

Once the image pre-processing algorithm is developed for enhancing the quality of the acquired images, the next step is to develop an algorithm for accomplishing segmentation of the pre-processed images. Segmentation is broadly defined as partitioning an object into its constituent parts or objects. The image segmentation algorithm consists of the following steps:

i) **Zooming –in:** Here we zoom in the image so that only the apple to be considered is present.

ii) **Image Thresholding-I:** The zoomed in greyscale image is converted into binary image wherein the defects the defects present in apple get separated.

iii) **Image Thresholding-II**: The conversion of a contrast-adjusted greyscale image into a binary image wherein the workpiece under inspection gets separated from the conveyor belt.

iv) **Hole Filling**: Any holes that are created due to thresholding in binary image are filled.

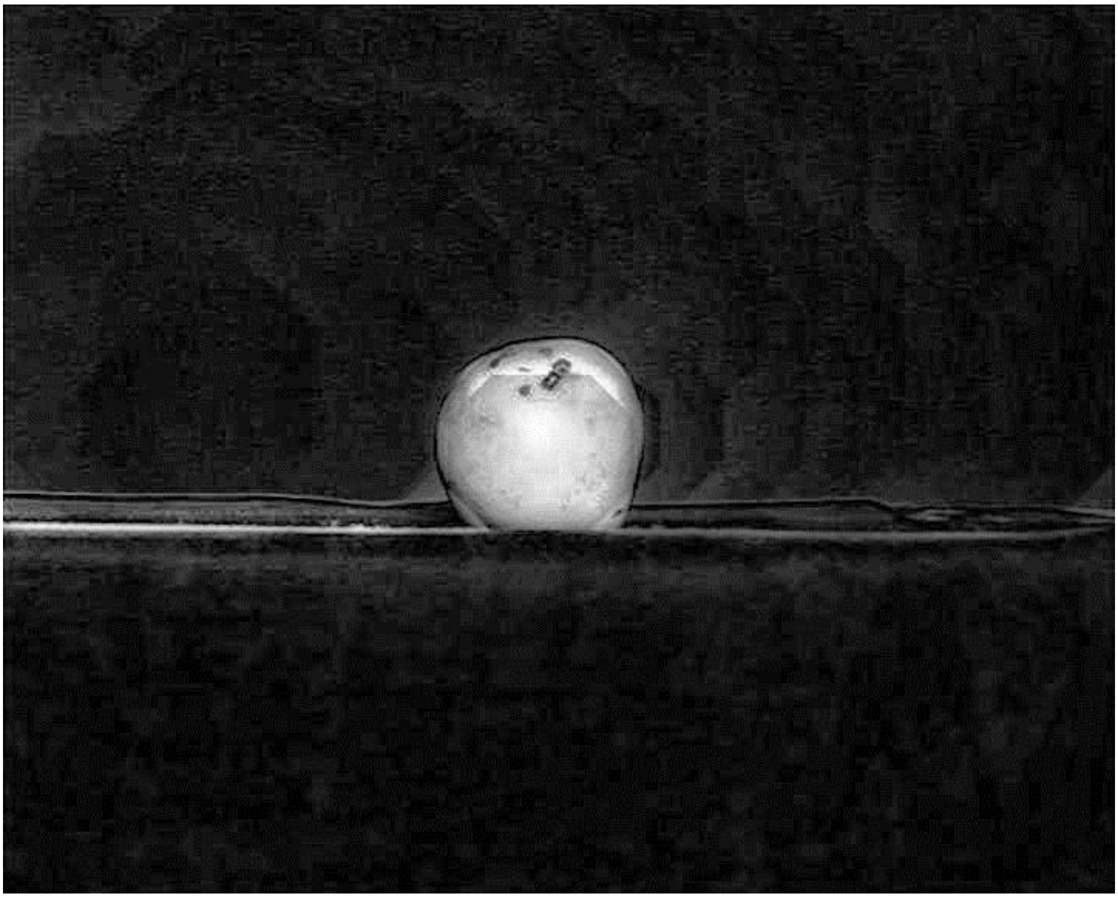

Fig 5.11: An example of contrast adjusted image

5.3.1.3.1 Zooming in Operation

The first step needed in image segmentation algorithm is to zoom in to the concerned apple. This is being done by using the inbuilt matlab functions to calculate edges, and calculating the box surrounding the apple. With the zoomed in image in place, it gets easy to extract features as the conveyor belt, and the background are completely removed. Fig 5.12 shows an example of greyscale zoomed in image of apple.

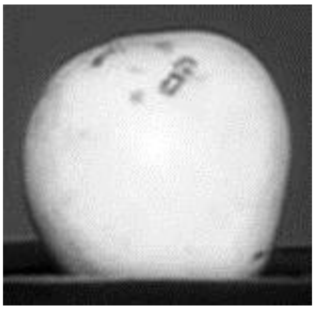

Fig 5.12: Greyscale zoomed in image of apple

5.3.1.3.2 Image Thresholding

Once the provision is made in the software for zooming in operation, the next step is to create a provision for thresholding the pre-processed greyscale image. Thresholding is achieved by determining a threshold value, below which value the pixels may be discarded. An example is presented in Fig 5.13 where an image is threshold using a minimum grey level value of 100. Fig 5.14 shows an example of a multi-level thresholding in which the first level of grey level values < 150 are shown as black and, second level grey values < 200 are shown as grey.

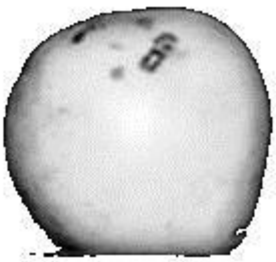

Fig 5.13: An image having a white background. The black background is removed with image thresholding

Fig 5.14: Multi-level thresholding the white substituted background image. Here we can clearly see that the border of the apple is also thresholded because it appears dark in the original frame due to non-uniform lighting.

5.3.1.3.3 Removal of Apple Border

In fig 5.11 we have seen that the border of apple still remains after thresholding. However, this border can't be classified as a true defect as it has come due to non-uniform lightning. So, a provision in the software is necessary to remove this border. This border is removed by connected component analysis. With this analysis, the components in the image are determined. Once these components are determined, the component which has the largest bounding box is removed. Here we can see the border has a characteristic of having the largest bounding box. So, this component is removed from the image. The output of this step is shown in Fig 5.15.

Fig 5.15: Segmented defects with apple boundary removed.

5.3.1.4 Image Feature Extraction Algorithm

Here we are looking looking for various features in the segmented image so that we can build up the predictive models. The features can be broadly classified as *statistical*, *textural* and *shape*. The statistical features include average (μ), standard deviation (σ), minimum (min), maximum (max), gradient (grad), skewness (skew) and curtosis. The shape features include area (S), perimeter(P) and circularity (C). Fig 5.16 shows the formulae of these features.

$$
\textit{statistical}\begin{cases}
\text{average } (\mu) & = \frac{1}{N}\sum_{i=1}^{N} p_i \\
\text{standard deviation } (\sigma) & = \left(\frac{1}{N-1}\sum_{i=1}^{N}(p_i-\mu)^2\right)^{1/2} \\
\text{minimum } (min) & = min(p_i) \text{ for i=1,...,N} \\
\text{maximum } (max) & = max(p_i) \text{ for i=1,...,N} \\
\text{gradient } (grad) & = max - min \\
\text{skewness } (skew) & = \frac{\sum_{i=1}^{N}(p_i-\mu)^3}{N\sigma^3} \\
\text{kurtosis } (kurt) & = \frac{\sum_{i=1}^{N}(p_i-\mu)^4}{N\sigma^4}
\end{cases}
$$

$$
\textit{textural}\begin{cases}
1^{st} \text{ invariant moment } (\phi_1) \text{ of Hu [42]} & = \eta_{20}+\eta_{02} \text{ where } \eta_{xy} \text{ is the normalized central moment}
\end{cases}
$$

$$
\textit{shape}\begin{cases}
\text{area } (S) & = N \\
\text{perimeter } (P) & = N_p \\
\text{circularity } (C) & = \frac{P^2}{4\pi S}
\end{cases}
$$

Fig 5.16: Details of features extracted for defect recognition.

The current system is looking for statistical and shape features. Currently only 5 apples have been examined, and we have considered average, standard deviation, area, perimeter and circularity features. Table 5.1 summarizes the features extracted with for the 5 apples.

Apple\Features	**μ**	**σ**	**Area**	**Perimeter**	**Circularity**
Apple 1	254.1486	8.7747	3399	585	7.9889
Apple 2	253.2436	6.5930	4316	696	7.3341
Apple 3	249.4506	9.3095	5031	807	7.9840

Apple 4	254.2024	8.8423	3425	553	7.9756
Apple 5	253.2103	9.0256	3902	579	7.9560

Table 5.1: Features extracted from 5 apples.

5.4 Fruit Grading

A quality inspection system for apple fruit will be incomplete if it does not take decisions at fruit level by assigning them to corresponding quality categories. Here in this chapter we classify the fruits on the basis of features extracted from apples.

5.4.1 Apple Grading

In table 5.1, we have extracted features from only 5 apples. Right now, its quite difficult to design a predictive model with this small amount of data. However, we can easily say that if the defect area is greater than a certain amount, we can say that the fruit is defective. On the basis of defect area, we can easily classify apples into various categories. Here in table 5.2 we present the rules for grading of apples on the basis of defect area.

Apple Grade	Defect Area (in pixels)
Class A Apples	Area < 2000
Class B Apples	2000 <= Area < 4000
Class C Apples	4000 <= Area < 7000
Defective Apples	Area >= 7000

Table 5.2: Rules for grading apples on the basis of defect area

Here we can clearly see that a basis for the determination of thresholds apple defect area is not calculated statistically, and these values are assigned intuitively. After collecting a good amount of data, we will be in a position to determine the threshold areas for grading.

5.5 Conclusions

We have developed an image processing technique that can very easily identify an apple in a frame. The apple is zoomed in and the defects are segmented. With the defects segmented out, we can very easily extract a lot of features, which are useful in predicting the grades of apples.

Chapter 6: Summary of Findings & Discussions

Industrial systems benefit more and more from computer vision in order to provide high and equal quality products to the consumers. Accuracy of such systems depend on the performance of image processing algorithms used by computer vision.

Food and beverages industry is one of the industries where computer vision is very popular and widely employed. Among the goods of this industry, fruits and vegetables have a lot of varying physical appearances. Apple fruits, in particular, are even more problematic due to high natural variation of their skin colour and numerous defect types present. Hence, quality inspection of apple fruits by image processing is still a challenging problem for the industry as well as the image processing community.

We discussed upon usage of automated 100% inspection for different items. Then we looked for a specific case of apples and developed a methodology to detect surface defects. Here, in this thesis, we collected data of 5 apples. The data collected is shown in Table 5.1. From the table 6.1, which is developed intuitively, we find that Apple 1, 4 and 5 are Class B apples and apple 2, 3 are Class C apples. By validating this result with manual inspection, we find that apple 2 and 3 have more blobs and are inferior than apple 1, 4 and 5.3

Chapter 8: Recommendations and Scope for Further Work

Here in the research work, we have successfully implemented all the image processing steps required in computer vision, and extracted most of the necessary features. We see that the feature extraction algorithm adopted in the research work is almost complete. But, we find that the predictive models are modelled intuitively. So, there is a need of a better prediction model. Also, we find that the stem/calyx recognition is currently done through mechanical methods. But, an ideal image processing technique should have provisions for automatic stem/calyx recognition. So, a better inspection technique can be made using automatic stem/calyx recognition.

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- PhD Thesis by Deepayan Shome on Automated Non-Contact Inspection of Engineering Products submitted to Indian Institute of Technology, Kharagpur. July 2009. Under the guidance of professor Biswajit Mahanty and professor Pradip Kumar Ray.

Appendix A: Source Code Used in Research Work

```
%initializing the frame trigger properties
vid = videoinput('winvideo');
preview(vid);

%data image
data = getsnapshot(vid);
imwrite(data, 'Originals\data.jpg');

%capturing oringal data image to greyscale and average
filter
img = imread('Originals\data.jpg');
greyimg = rgb2gray(img);
imwrite(greyimg, 'Greyscale\data_greyscale.jpg');
h = fspecial('average');
I = filter2(h,greyimg);
imwrite(mat2gray(I), 'Average\data_average.jpg');

%capturing oringal data image to gaussian filter
h = fspecial('gaussian');
I = filter2(h,greyimg);
imwrite(mat2gray(I), 'Gaussian\data_gaussian.jpg');

%Subtracting the data
se = strel('disk', 50);
I = imread('Gaussian\data_gaussian.jpg');
I2 = imerode(I, se);
imwrite(mat2gray(I2), 'Eroded\data.jpg');
```

```
I3 = imdilate(I2, se);
imwrite(mat2gray(I3), 'Dilated\data.jpg');
I4 = imsubtract(I, I3);
imwrite(mat2gray(I4), 'Subtracted\data.jpg');



%Contrast Adjustment: adaptive histogram equalization
J = adapthisteq(imread('Subtracted\data.jpg'));
imwrite(mat2gray(J), 'Adapt_Hist\data.jpg');

%Contrast Adjustment: histogram equalization
J1 = histeq(imread('Subtracted\data.jpg'));
imwrite(mat2gray(J1), 'Hist\data.jpg');

%Zoom in Operation
Iedge = edge(I4);
se1 = strel('square',5);
Iedge2 = imdilate(Iedge, se1);
% * *Image Filling*
Ifill= imfill(Iedge2,'holes');
se2 = strel('square',15);
Iedge3 = imerode(Ifill, se2);

%Removing the boundary
CC = bwconncomp(Iedge3);
br = regionprops(Iedge3, 'BoundingBox');
Area = regionprops(CC, 'Area');
Curr_Area = 0;
```

```
for i = 1:CC.NumObjects
    if(Area(i).Area > Curr_Area)
        Curr_Area = Area(i).Area;
        index = i;
    end
end

s = br(index);
b = s.BoundingBox;
BoundBox = [b(1)-15 b(2)-15 b(3)+30 b(4)+30];

I = imread('Average\data_average.jpg');
crop = imcrop(I, BoundBox);
crop_ad_hist =  imcrop(J1, BoundBox);
crop_hist =  imcrop(J, BoundBox);
crop_sub =  imcrop(I4, BoundBox);
imwrite(mat2gray(crop), 'Zoom\data.jpg');
imwrite(mat2gray(crop_sub), 'Zoom\subtracted.jpg');
imwrite(mat2gray(crop_ad_hist), 'Zoom\ad_hist.jpg');
imwrite(mat2gray(crop_hist), 'Zoom\hist.jpg');

%white background image
[m,n] = size(crop);

for i = 1:m
    for j = 1:n
        if(crop(i:i, j)< 100)
            L(i:i, j) = 255;
```

```
        else
            L(i:i, j) = crop(i:i, j);
        end
    end
end
imwrite(mat2gray(L), 'White_Background\data.jpg');

%Segmented Image
for i = 1:m
    for j = 1:n
        if(crop(i:i, j)< 100)
            L(i:i, j) = 255;
        else
            L(i:i, j) = crop(i:i, j);
        end
    end
end
imwrite(mat2gray(L), 'White_Background\data.jpg');

[m,n] = size(crop);
L1 = 255;
for i = 1:m
    for j = 1:n
        if(L(i:i, j)< 150)
            L1(i:i, j) = 0;
        elseif(L(i:i, j)< 200)
                L1(i:i, j) = 0;
        else
```

```
                L1(i:i, j) = 255;
            end
        end
end
imwrite(mat2gray(L1), 'Segmented\major_defects.jpg');

%Removing the boundary
CC = bwconncomp(~im2bw(L1));
Area = regionprops(CC, 'Area');
Curr_Area = 0;
for i = 1:CC.NumObjects
    if(Area(i).Area > Curr_Area)
        Curr_Area = Area(i).Area;
        index = i;
    end
end
L1(CC.PixelIdxList{index}) = 255;
imwrite(mat2gray(L1), 'Defects\major_defects.jpg');

%Segmented Major Defects
[m,n] = size(L1);
L2 = 255;
for i = 1:m
    for j = 1:n
        if(L1(i:i, j) == 0)
            L2(i:i, j) = L(i:i, j);
        else
            L2(i:i, j) = 255;
```

```
        end
    end
end
imwrite(mat2gray(L2), 'Defects\segmented_defects.jpg');

%Statistical Features
Mean = mean2(L2)
Std = std2(L2)
Area = Curr_Area
Perimeter = regionprops(L2, 'Perimeter');
Per = Perimeter(255).Perimeter
Circularity = (Per * Per) /(4*3.14*Area)
```