SEGMENTATION AND CLASSIFICATION OF FOUR COMMON
COTTON CONTAMINANTS IN X-RAY
MICROTOMOGRAPHIC IMAGES

by

SRI-KAUSHIK PAVANI, B.E.

A THESIS

IN

ELECTRICAL ENGINEERING

Submitted to the Graduate Faculty
of Texas Tech University in
Partial Fulfillment of
the Requirements for
the Degree of

MASTER OF SCIENCE

IN

ELECTRICAL ENGINEERING

Approved

Co-Chairperson of the Committee

Co-Chairperson of the Committee

Accepted

Dean of the Graduate School

December, 2003

ACKNOWLEDGEMENTS

I gratefully acknowledge the intelligent and resourceful guidance of my research advisors, Drs. Hamed Sari-Sarraf and Eric Hequet. Their untiring support and seemingly unlimited belief in me eased the pressure and made this work an enjoyable experience. Without them I could not have attempted this work. I am forever indebted to Dr. Sunanda Mitra, first for introducing me to the field of image processing and then for agreeing to be a part of my thesis committee.

My gratitude to Ajay Pai, for his well-documented research work. Following his footsteps has indeed been easy. I would also like to thank the staff of International Textile Center for their support.

I am always indebted to the long list of people who do their best to improve on my best. Thanks especially to my loving parents, my brother, my friends Arun, Sanju and Sandhya. The many hours we spent together have led to many fruitful developments. It is to them I dedicate this work.

TABLE OF CONTENTS

ACKNOWLEDGEMENTS.....	ii
ABSTRACT.....	v
LIST OF TABLES.....	vi
LIST OF FIGURES.....	vii
LIST OF ABBREVIATIONS.....	ix
CHAPTER	
1. INTRODUCTION.....	1
2. METHODOLOGY.....	5
2.1 Introduction.....	5
2.2 Image Acquisition.....	5
2.3 Preprocessing.....	7
2.3.1 Median Filtering.....	7
2.3.2 Background Subtraction.....	10
2.4 Segmentation.....	18
2.4.1 A Closer Look at Artifacts.....	22
2.4.2 Volume Generation.....	27
2.5 Feature Extraction and Analysis.....	29
2.5.1 Uniformity Ratio.....	30
2.5.2 Aspect Ratio.....	33
2.5.3 Mean Attenuation Coefficient.....	35
2.5.4 Solidity.....	36
2.6 Fuzzy Classification.....	39
3. EXPERIMENTAL RESULTS.....	44
3.1 Fidelity of Segmentation.....	44
3.2 Fuzzy Classification Results.....	48
3.3 Comparison with AFIS measurements.....	51
4. CONCLUSIONS AND FUTURE WORK.....	55

4.1	Summary.....	55
4.2	Future Work.....	56
4.2.1	Image Contrast Enhancement using Ross Filters.....	56
4.2.2	Extending theory to practical use.....	59
4.2.3	Validation.....	60
4.2.4	Process Optimization.....	60
BIBLIOGRAPHY.....		62
APPENDIX.....		64

ABSTRACT

Technologies currently used for cotton contaminant assessment suffer from some fundamental limitations. These limitations result in the misassessment of cotton quality. This may have a serious impact on the evaluation of the economic value of the cotton crop. This thesis work reports on the recent advances in the use of a 3D x-ray microtomographic system that employs image processing and pattern recognition algorithms to accurately detect and classify trash present in cotton. The proposed method offers a slow but attractive alternative to existing trash evaluation technologies, because of its ability to produce 3D representations of the samples, to robustly segment the trash from its background, and to accurately classify the contaminant types. A correct classification rate of 89% was achieved, when the classification algorithm was tested with 93 trash samples. This procedure, when realized in real time, could have a serious impact on the process control technologies (cotton lint cleaning), and indeed on the economic value of cotton.

LIST OF TABLES

2.1	Statistics of x-ray attenuation coefficients observed for cotton and trash before and after background subtraction.....	17
2.2	Mean Attenuation coefficients observed for common cotton contaminants.....	36
3.1	Confusion matrix resulted from classifying 93 trash samples.....	52
4.1	Results of using Fe-Ti Ross filters with Aluminum foil.....	57
A.1	Fuzzy classification results for 93 known trash samples.....	65

LIST OF FIGURES

1.1	Comparison between surface scanned image and x-ray image.....	3
2.1	Description of SkyScan-1074®	6
2.2	Example of cross-sectional slice obtained from SkyScan-1074®	7
2.3	Effect of median filtering on cross-sectional slices.....	9
2.4	Attenuation coefficient profiles obtained after median filtering.....	10
2.5	3D plot of attenuation coefficients in a cross-sectional slice.....	11
2.6	Histogram of attenuation coefficients for cotton and trash.....	12
2.7	Histogram of variance of attenuation coefficients.....	14
2.8	Example of high-variance regions generation.....	15
2.9	Effect of subtraction.....	16
2.10	Histograms of cotton and trash after subtraction.....	17
2.11	Histograms of x-ray attenuation coefficients for four commonly found trash types.....	19
2.12	Example of ideal and observed intensity profile.....	20
2.13	Effect of CT artifacts on segmentation.....	21
2.14	Profile of a high-density trash.....	22
2.15	Example of Canny's edge detector output.....	24
2.16	Example of Delaunay triangulation on edge points.....	25
2.17	Example of a segmented cross-sectional slice.....	26
2.18	Formation of bounding box around regions of high-variance.....	26
2.19	Example of volume generation using synthetic cross-sections.....	27
2.20	The 26 neighborhood of a pixel in a 3D image.....	28
2.21	Example of segmented output in 3D.....	29
2.22	Distribution of attenuation coefficients.....	31
2.23	Examples of uniformity ratio calculations on x-ray attenuation coefficient histograms.....	32
2.24	Principal components of the coordinates of segmented trash.....	33

2.25	Examples of aspect ratio calculations of different trash types.....	35
2.26	Example of a broken Bark.....	37
2.27	Examples of Solidity measurements on different trash types.....	38
2.28	Inputs and outputs of the classifier.....	39
2.29	Input membership function for Uniformity Ratio.....	41
2.30	Input membership functions of all four features.....	43
3.1	Comparison of radiographic and 3D segmented images.....	46
3.2	Segmentation on cotton sample with varying packing density.....	48
3.3	Feature space observed in 3 dimensions.....	50
3.4	Feature space observed in 2 dimensions.....	50
3.5	1D feature space observed for Solidity measurements.....	51
3.6	VFM comparison chart.....	54
4.1	Spectral Sensitivity for Al foils with varying Carbon.....	56
4.2	Transmission curves obtained using Ross Filters.....	59

LIST OF ABBREVIATIONS

USDA	United States Department of Agriculture
AFIS	Advanced Fiber Information System
HVI	High Volume Instruments
1D	One-Dimensional
2D	Two-Dimensional
3D	Three-Dimensional
CT	Computed Tomography
PCA	Principal Component Analysis
VFM	Visible Foreign Matter
Fe	Iron
Ti	Titanium
Al	Aluminum
C	Carbon
O	Oxygen
N	Nitrogen

CHAPTER I

INTRODUCTION

Even under ideal field conditions, cotton lint becomes contaminated with leaf fragments and other trash. Although most foreign matter is removed by cleaning processes during ginning, total trash extraction is impractical and can lower the quality of ginned fiber. The amount of foreign matter present in the cotton after ginning plays an important role in determining the price of the cotton lint. The U.S. Department of Agriculture (USDA) cotton grading and classing program facilitates commerce in cotton by providing official quality determinations that aid in marketing. Grading is the process where cotton is inspected and certified according to the official standards. The grade is given by the visual appearance of the cotton lint and is determined on the basis of its brightness and yellowness of the fibers as well as by presence of extraneous matter [1]. Improper grading causes lot of resentment amongst producers and spinners. Precise measurement and identification of trash particles in cotton can improve the accuracy and repeatability of the grading process, and can provide vital feedback for optimizing both the ginning and spinning process.

Trash can easily be detected and identified by visual inspection, because the trash usually has different color than the white cotton lint. The main drawbacks of manual inspection are the high cost of trained labor and their poor repeatability of cotton quality assessment. It is precisely for this reason, that the USDA is interested in exploring techniques that would facilitate automatic detection and identification of cotton contaminants. Initially, methods that involve physical separation of trash from cotton were developed. Shirley analyzer and AFIS (Advanced Fiber Information System) accomplish their goal by physically separating, weighing and counting (AFIS only) the contaminants. Even though these systems can determine the amount of trash in a cotton sample with high degree of accuracy, they lack the capability to distinguish between various trash types and to give accurate trash size distribution. One other drawback of physically separating the trash is that it is an irreversible process; once a cotton sample is

tested using such machines, that sample cannot be used for other tests. The above-mentioned drawbacks underline the need for more sophisticated systems that do not destroy the cotton samples during testing. To this end, systems that employ image analysis techniques were developed. In HVI (High-Volume Instruments) cotton classing, a black and white camera takes a picture of raw cotton, and the trash data are reported in terms of the total trash area in the image and trash particle counts. The obvious drawback of this system is that, the visible light rays used to capture the image, cannot penetrate the cotton sample and so the trash particles present deep inside the sample are left undetected. The precision and accuracy of HVI measurements are highly sensitive to sample preparation and handling, and, hence cannot be used as a reliable means to quantify the amount of trash present. Recent research efforts for improving the sensitivity of these systems have generated only incremental improvements. These include better separation machinery [2], use of color scanners and more sophisticated image analysis techniques [3], and more effective sample preparation mechanisms [4].

X-ray imaging provides a viable alternative and overcomes the above-mentioned shortcomings. X-rays can easily penetrate the cotton sample and can detect trash particles present deep within the sample (Figure 1.1), thus enabling the accurate detection and estimation of the trash particles. Computed tomography (CT) [5] is an ideal examination technique whenever the goal is to locate objects of interest in three dimensions. An x-ray CT system requires an x-ray source, one or more x-ray detectors, and means (scanning apparatus) to move the components so as to collect the needed projections. The tube and detector assembly is first translated to collect a set of projection measurements through the object. The assembly is then rotated to a second angle and the attenuation offered to x-rays is recorded. The rotation is repeated until sufficient measurements are obtained. Then, a computer reconstructs the attenuation coefficients into an image using Radon transform [5]. The main advantage of CT as compared to projection imaging is its inherent ability to separate objects according to their position in the projection direction, i.e., it avoids the confusion that arises when the shadows of multiple objects are

superimposed. This, combined with high precision measurements and digital displays, gives CT the ability to resolve objects with extremely small contrast.

Figure 1.1. Surface scans of cotton (a) do not detect the trash inside the surface of cotton, whereas an x-ray image (b) clearly shows the presence of trash even within the sample.

Characteristics such as shape, internal defects, dimensions and density of the object of interest are readily available from the CT images. Later, it will be shown that, with x-ray CT technology as the mode of obtaining images, trash particles can not only be detected but also their size and shape can be estimated with high accuracy. The main drawback in using an x-ray microtomography system is its high image acquisition time. With the advent of faster scanners, x-ray CT proves itself as an attractive alternative to the present day image acquisition systems for cotton trash assessment.

Earlier work [6], done using a 3D x-ray microtomographic system has been successful in detecting Bark, Polypropylene and Seedcoat fragments in cotton. In segmenting these common trash types from the tomographic images, this work assumes uniform density for cotton, which is seldom true. In this work, we report on our recent

advances in the use of a 3D x-ray microtomographic system that employs image processing and pattern recognition algorithms to accurately detect and classify trash, also overcoming the aforementioned shortcomings. The main objectives of this work are to

1. Add Leaf to the already studied trash classes.
2. Develop a robust segmentation technique to separate trash from cotton lint.
3. Identify features to recognize trash.
4. Evaluate the performance of the classing system to identify trash types.

The subsequent chapters present the methodology, results and the conclusions of this work. Chapter II presents the theory of the segmentation and classification methods used. Chapter III describes the results of the segmentation and classification algorithms when applied to 3D tomographic cotton images. Conclusions of this work as well as suggestions for future work based on this research are detailed in Chapter IV

CHAPTER II

METHODOLOGY

2.1 Introduction

This chapter is an attempt to provide a concise volume containing the descriptions of the techniques and methods used. Here, the five major components of the image classification system, namely, image acquisition, preprocessing, segmentation, feature extraction and classification will be discussed and the methods used at each step will be justified.

2.2 Image Acquisition

The hardware used in this project consisted of the SkyScan μ -CT 1074 portable microtomography system (refer Figure 2.1) [7], which is connected to a desktop computer through a Pico Frame Grabber PCI card [8]. The desktop computer used in this project consists of a Pentium II 400 MHz dual-processor CPU with 512 MB RAM. This system can be used to produce radiographic as well as tomographic images of the sample. In the tomographic mode, the sample is rotated, and the data are collected from multiple angles. The computer then reconstructs the data to obtain cross-sectional slices (Figure 2.2(a)). A number of slices can be stacked up together to provide a 3D view of internal and external structural details (Figure 2.2(b)). The Radon transform and its inverse provide the mathematical basis for reconstructing tomographic images measured from the projection data. Analysis of Radon transform is beyond the scope of this thesis. However, interested readers can find a detailed report in [5]. The x-ray tube operates at 20-40 kV and 0-1000 μ A. The CCD camera has a resolution of 768 x 576 pixels with 256 gray levels. Reconstructed cross-sections have a maximum size of 732 x 732 pixels. This system can achieve a maximum pixel resolution of 40 μ m and can accommodate objects smaller than 30 mm in size. The reconstruction of the data is accomplished using the fan-beam, convolution back-projection technique [5].

Figure 2.1. Description of the SkyScan-1074[®], x-ray scanner

The cross-sectional images resulting from the reconstruction procedure represent a quantitative measure of the linear x-ray attenuation coefficient at each point in the axial plane of the 3D object. These coefficients characterize the rate at which the x-ray photons are attenuated (either by absorption or scattering) from the incident ray as it propagates through the object. The difference between these measured values at two points within an object (i.e., perceived contrast) depends directly on the density and the effective atomic number of the comprising material at those two points, as well as the energy of the incident x-ray beam. A study of how the contrast between the commonly found cotton contaminants varies with voltage and current was made by Ajay Pai [6] et al, and the optimal operating voltage and current were experimentally determined and set at 20kV and 1000mA, respectively.

Figure 2.2. Images obtained from SkyScan-1074[®]. (Operating voltage: 20kV, Current: 1000mA) (a) Shows a cross sectional slice of a rat vertebra, the internal structures of the bone can be clearly seen. (b) Shows a 3-D image after many cross-sections were stacked up.

2.3. Preprocessing

2.3.1. Median Filtering

Pre-processing the reconstructed CT images is essential, because, noise gets introduced while these images are generated. The primary source of noise in CT images is the finite number of x-ray photons measured by the camera. Often, the magnitude of noise is high enough to cause improper segmentation, thus increasing false positives. Therefore, reducing the magnitude of noise, before processing these images, is of utmost importance. Some of the ways to reduce noise in CT images are detailed here.

1. Increasing the x-ray operating voltage: By increasing the operating voltage, x-rays of higher energy can be produced, thus effectively reducing the statistical noise generated. However, high-energy x-rays tend to be transparent to low-density contaminants such as polypropylene and leaf. The operating voltage needs to be set considering both the contrast between contaminants and the amount of noise.

As stated earlier, the optimal operating voltage was experimentally determined [6] and the scanner was operated at 20kV.

2. Increasing the exposure time/scan time: Increasing the exposure time as similar effect as increasing the operating voltage, in the sense that, more x-ray photons are captured by the camera per scan and so the net statistical noise decreases. However, in industry, scan time is given much importance, as it directly affects the throughput. The optimal exposure time was experimentally determined and set at 1000 ms.
3. Increasing the detector size: By increasing the detector size, i.e., the size of the CCD array elements, more x-ray photons are captured per scan, but, in general, it will reduce the spatial resolution of the reconstructed image, which is undesirable.

Even if proper trade-off among operating voltage, scanning time and the detector size is achieved, the statistical noise observed in the CT images cannot be completely eliminated. However, its magnitude can be effectively reduced with the help of simple median filtering [9]. This class of filters belongs to the class of edge preserving smoothing filters, i.e., they smooth the data while keeping small and sharp details. In the median filtering process, the magnitude of each pixel is determined by the median value of the magnitudes of all pixels in a selected neighborhood around that pixel. Shown below (Figure 2.3) are the original cross-sectional image and the image obtained after median filtering.

Figure 2.3. Effect of median filtering on cross-sectional slices. (a) Shows a noisy cross-sectional image obtained after reconstruction. (b) Shows the median filtered image, where the magnitude of the noise has been significantly reduced.

This procedure is extremely simple to implement and is also very robust. However, the performance of this filtering technique is dependent on the size of the mask used in the filtering process. Large masks may smooth the image to a great extent such that, sharp details in the images may be lost, whereas, small masks may not be effective in reducing the noise. Also shown in Figure 2.4 are the median filtering results obtained using 5x5, 7x7 and 9x9 masks. Hundreds of such results were visually examined and it was agreed upon that 9x9 mask produces the best results for this application.

(a)

(b)

(c)

(d)

Figure 2.4. Attenuation coefficient profiles obtained after median filtering. (a) Shows original profile; (b) 5x5 median filtered profile; (c) 7x7 median filtered profile; (d) 9x9 median filtered profile.

2.3.2. Background Subtraction

Cotton harvested from the field, is subject to many mechanical forces. Further, during the ginning process, cotton bales are compressed, thereby making the packing density of cotton in a given volume non-uniform. A sample of cotton, which has inherent

density variations, was scanned and one of the reconstructed slices is shown in Figure 2.4. The 'x' and 'y' coordinates are the image axes and the 'z' coordinate represents the magnitude of attenuation coefficients recorded.

Figure 2.5. 3D plot of attenuation coefficients observed in a cross-sectional slice.

From Figure 2.5, it can be seen that, the attenuation coefficients observed within the cotton is not uniform. This means that the packing density of cotton within a given sample volume varies widely. The x-ray attenuation coefficient values observed for the high packing density cotton overlap with the x-ray attenuation coefficient values observed for low-density trash (such as polypropylene and leaf), thus making segmentation using a global threshold a major problem. To verify this, 100 cross-sectional slices of contaminated cotton were taken and the trash particles in them were segmented manually. The normalized histogram of attenuation coefficients observed for cotton and that observed for trash are shown in Figure 2.6.

Figure 2.6. Shows the normalized histograms of cotton and trash.

Any global threshold for attenuation coefficient cannot completely segment the trash from cotton (Figure 2.6). This poses a very difficult segmentation problem, and may require the use of complex segmentation techniques to isolate trash. One way to overcome this problem is to model the variations observed in cotton and subtract it from the given cross-section. This technique is called background subtraction [10].

Background subtraction attempts to remove slowly varying regions in an image. This is done by first approximating the slowly varying components (analytically or experimentally) by creating a background image $[f_b(x,y)]$ and then subtracting this from the original image $[f(x,y)]$. The new image $[f_n(x,y)]$ can be expressed as:

$$f_n(x,y) = f(x,y) - f_b(x,y). \quad (2.1)$$

There are many ways of generating this background image. Functional forms can be used to analytically represent the slowly varying components. The problem with such analytical models is that, the order of these equations must be known a-priori to model

the background accurately. Also, higher order equations require greater processing time to estimate the constants of the equation, and so, were not found suitable for this application. Similar problem was observed when piecewise polynomial approximations (splines) were used to approximate the variations in cotton. A workable alternative to generate the background slice is to use a low-pass filtered variant of the original image:

$$f_b(x,y) = F^{-1}[H(u,v)F(x,y)]. \quad (2.3)$$

where $H(u,v)$ is the low-pass filtering function. The only problem with this technique is that it is global; it treats high variance regions (cotton with trash) and low variance regions (cotton) alike. This means that, both high-variance and low-variance regions will be equally smoothed. Therefore, some parts of the trash will be left behind in the background image, and after subtraction, the magnitude of attenuation coefficients observed in the trash regions reduces considerably, which is undesirable. To solve this problem, we initially split the given cross-sectional slice into regions of high and low variance, and then selectively apply the low-pass filter only to the regions of low-variance. High variance regions are substituted with values extrapolated from the neighboring low-variance regions. Thus obtained background slice is subtracted from the median filtered cross-sectional slice to obtain the subtracted image.

This procedure assumes that the variation of attenuation coefficients observed in cotton is, in general, less than the variation observed in the regions where both trash and cotton is present. To test the goodness of the above-mentioned premise, 100 cross-sectional slices of contaminated cotton were taken and each one of them was split into 8 by 8 blocks. These blocks were then classified manually into two classes, one where only cotton is present, and another where trash and some cotton are present. In each of the 8 by 8 blocks, variances of attenuation coefficients were computed and their histograms were analyzed. Figure 2.7 shows the plot of histogram of variances. A block size of 8 by 8 was chosen based on the assumption that, in general, the size of the contaminants observed in CT slices is not more than that of an 8 by 8 block, i.e., the probability of an

event that an 8 by 8 block is completely contained within a large trash piece is very small. (For an 8 by 8 block completely contained in a large trash piece, the computed variance may be low.)

Figure 2.7. Histogram of the variance of attenuation coefficients.

Observations made on the histogram of variances are as follows:

1. As expected, the variance values observed for blocks with both cotton and trash is in general greater than the variance values observed in blocks only with cotton. This may be attributed to the inhomogeneity of attenuation coefficient values since two dissimilar materials (cotton and trash) are present in the same block.
2. One other interesting feature of this plot is that there is minimum overlap between the variance values observed for blocks with cotton and the variance values observed for blocks with both cotton and trash. This means that the low-variance and high-variance blocks can be easily split with the help of a simple threshold.

What is now required is a completely automated thresholding procedure which will separate cross-sectional slices into high-variance and low-variance regions (Figure 2.8). The aim of this thresholding procedure is to adaptively determine the value of threshold variance. The algorithm for determining the threshold is as follows:

1. Each cross-sectional slice is split into 8 by 8 blocks and the variance of attenuation coefficients in each of the blocks is calculated.
2. Histogram of the variances of attenuation coefficients is generated and is smoothed using a Gaussian filter and median filtering. Then the peaks and troughs (local maxima and minima) in the histogram are determined.
3. The minima, whose variance value is the lowest, is chosen as the threshold.

Figure 2.8. A cross-sectional slice (a) and its corresponding binary image (b) Shows the regions of high-variance

Thus obtained threshold variance value is used to classify the previously generated 8 by 8 blocks into high-variance and low-variance blocks. To generate the background slice, the x-ray attenuation coefficients found in the low-variance blocks are substituted with the median of their value. Further, the x-ray attenuation coefficients

found in the high-variance blocks are substituted with the mean of the attenuation coefficients found in the four nearest low-variance blocks.

Figure 2.9. Effect of Subtraction. (a) Shows a median-filtered cross-sectional slice (b) shows the background slice. (c) Shows slice after subtraction

It can be seen from Figure 2.9 (c) that the density variations observed in cotton have been compensated without affecting the regions where trash is present. To test the usefulness of this background subtraction, the same 100 slices used to prove that the x-ray attenuation coefficients in the median filtered image overlaps for cotton and trash

(Figure 2.6) were taken and the density variations observed in cotton were compensated by background subtraction. Thus obtained background compensated images were manually segmented and the histogram of x-ray attenuation coefficients found in the regions of trash and cotton was plotted (Figure 2.10).

Figure 2.10. Shows the normalized histograms of cotton (blue) and trash (red) for a (a) median filtered image (b) background subtracted image.

Observations made on the histogram of attenuation coefficients found in background compensated image (Figure 2.10(b)) were as follows:

1. Very high degree of uniformity was observed in cotton.
2. There is minimal overlap between the attenuation coefficient distribution of background cotton and the trash classes.
3. X-ray attenuation coefficients alone can be used to segment trash from cotton.

Table 2.1 Statistics of x-ray attenuation coefficients observed for cotton and trash before and after background subtraction

	Before Background Subtraction		After Background Subtraction	
	Cotton	Trash	Cotton	Trash
Mean AC (Attenuation Coefficient)	0.0216	0.1878	0.00047	0.1694
Max. AC	0.1031	0.6977	0.0537	0.6863
Min. AC	-0.1569	0.00138	-0.0876	0.0182

2.4. Segmentation

Thus far, we have examined techniques that can be used to correct artifacts in the images or to enhance certain features of interest. Now, we focus on techniques that try to discover the objects that constitute an image. Segmentation is generally the first stage in an attempt to analyze the contents of an image automatically. This involves first locating and then isolating the objects of interest present in the image. Image segmentation process can be defined as the one that partitions a digital image into non-overlapping regions, where a region is nothing but a set of adjacent pixels.

The role of segmentation is crucial in most tasks involving image analysis. The success and failure of the task is a direct consequence of the success or failure of the segmentation. There is no “cure-all” segmentation technique that can isolate any object of interest in any image. To choose the appropriate segmentation technique out of the myriad “possible” algorithms, first of all, one must have prior knowledge on the characteristics of the object to be segmented and secondly, other factors such as complexity of the algorithm and execution time should be taken into account. For example, in an application to identify solid rectangles in an image, it would be of much help, if we knew that all the rectangles are painted red. In this case, a simple red filter would effectively do the job. Similarly, the first step in the process of designing an effective segmentation technique to identify the cotton contaminants is to collect as much prior information about the trash types as possible.

It was decided to design the segmentation process for four commonly occurring trash types, namely, Bark, Seedcoat fragments, Polypropylene and Leaf. These four trash types constitute about 95% of the trash found in the natural cotton and hence their selection is justified. In order to determine the characteristics of these four trash types, 93 volumes of “synthetic” cotton samples were scanned and analyzed. These samples were prepared by inserting known trash types into clean and uniformly dense cotton. These slices were manually segmented and the magnitude of attenuation coefficients produced by each type of trash was recorded. Some of the scanned samples and their corresponding x-ray attenuation coefficients histograms are shown in Figure 2.11.

Figure 2.11. Four commonly found trash types and their corresponding histogram of x-ray attenuation coefficients

The histograms shown in Figure 2.11 also reflect the density of the four trash types analyzed. Bark and Seedcoat fragments, which are usually dense, generally register higher x-ray attenuation coefficients than Polypropylene and Leaf. High density trash

particles pose an additional problem in the sense that, they promote the formation of image artifacts [11] in CT images. An artifact can be defined as an event in the image that does not correspond to the physical feature of the test object. These artifacts are prominent in the interfaces of different density materials, i.e., in the boundary of a high-density trash particle like Bark and Seedcoat fragments and the low-density background like cotton. The interface between low-density trash particle and cotton also produces artifacts, but they can be safely ignored as the extent of distortion they produce is negligible. Figure 2.12 shows the plot of ideal and observed intensity profiles in the interface of high and low-density materials. Undershoots and overshoots characterize the intensity profile at such a boundary. Because, the intensity profiles are not properly characterized, defects in CT images are bound to occur and they ultimately surface in the segmented output. This is precisely the reason why the trash particles that produce artifacts must be analyzed before deciding on the segmentation algorithm.

Figure 2.12. Plot showing the ideal and the observed intensity profiles [5].

In the previous section, as Figure 2.10(b) shows, there is minimal overlap between the histograms of x-ray attenuation coefficient for trash and cotton. Ideally, a threshold applied at the valley between the two histograms, should outline the shape of the trash to perfection. But because, the boundary of high density trash and the low-

density cotton is blurred due to the formation of artifacts, the shape of the trash gets distorted. A median-filtered slice, containing a high-density trash and its corresponding thresholded output (ideal and observed) are shown in Figure 2.13.

Figure 2.13. Effect of CT artifacts on segmentation by thresholding (a) shows a subtracted slice with bark. (b) Shows the segmented output obtained by thresholding. (c) Shows the desired/ideal output.

The goal of the segmentation algorithm is now well defined: It must be able to successfully outline the regions where trash is present, ignoring the artifacts. To solve this challenging segmentation problem, we use different approaches to segment low-density and high-density trash. Low-density trash particles, as previously stated, produce negligible artifacts, and so they can be effectively segmented by simple thresholding. Only high-density trash particles require a more sophisticated technique. An advantage of using different approaches for segmentation is the net reduction of the execution time. Thresholding, being a very simple operation, requires very little time to run, where as, the sophisticated techniques that the high density trash particles require, consume a lot of time. Using one technique to segment all types of trash particles means unnecessary processor time on low-density trash, which can be avoided.

2.4.1. A closer Look at Artifacts

Figure 2.14 shows the attenuation coefficient profile of a high density trash

Figure 2.14. Profile of a high-density trash. (a) Shows a subtracted slice with high density trash. (b) Shows the attenuation coefficient profile along the white line shown.

Several hundred profiles such as the one in Figure 2.14(b) were examined and from them, it could be inferred that:

1. The magnitude of the artifacts produced is generally less than 10% of the magnitude of the trash.
2. The magnitude of the attenuation coefficient gradient in the regions of cotton and artifacts is much smaller than the gradient value observed for trash.

As we know, in the median filtered image, intensity discontinuities are caused both by trash and artifacts. The basic idea of this segmentation process is to capture all the intensity discontinuities, whose gradient values are greater than those normally observed for artifacts. This means that only intensity discontinuities produced by trash will be captured and the rest will be omitted. In computer vision, edge detection [12] is a process that attempts to capture the discontinuities in the intensity values in the image. For this purpose image derivatives are computed. Assuming that, median filtering effectively removes most of the statistical noise, it can be safely stated that the differentiated image contains gradient values primarily from trash and artifacts. Cotton produces negligible gradient values. Most edge detection schemes include these three operations [13]: differentiation, smoothing and labeling. Differentiation is nothing but

evaluating the numerical differential of the image. Smoothing is done in order to remove noise and to regularize the differentiated coefficients. Labeling involves localizing the edges and increasing the signal-to-noise ratio of the edge image by suppressing false edges.

To perform edge detection, Canny edge detector [14] was chosen. This choice was made because, trash produces step edges in CT images, and Canny edge detector is optimal in detecting such edges. The Canny edge detector first smoothes the image with a Gaussian kernel and eliminates noise. It then finds the image gradient to highlight regions with high spatial derivatives. The algorithm then tracks along these regions and suppresses any pixel that is not at the maximum (non-maximal suppression). The gradient array is now further reduced by hysteresis. Hysteresis is used to track along the remaining pixels that have not been suppressed. Hysteresis uses two thresholds (T_1 and T_2). If the magnitude of the gradient is above the high threshold (T_1), it is made an edge. And if the magnitude is between the 2 thresholds, then it is set to zero unless there is a path from this pixel to a pixel with a gradient above T_2 .

The effect of the Canny operator is determined by three parameters - the width of the Gaussian kernel used in the smoothing phase, and the upper and lower thresholds used by the tracker. Increasing the width of the Gaussian kernel reduces the detector's sensitivity to noise, at the expense of losing some of the finer details in the image. The localization error in the detected edges also increases slightly as the Gaussian width is increased. Usually, the upper tracking threshold can be set quite high and the lower threshold quite low for good results. Setting the lower threshold too high will cause noisy edges to break up. Setting the upper threshold too low increases the number of spurious and undesirable edge fragments appearing in the output.

The gradient magnitude produced by the artifacts is much less compared to that produced by trash (Figure 2.14b). It was decided that a lower threshold value (T_2) be set at 30% of the highest gradient magnitude in any image. This value is optimal in the sense that it effectively omits gradient values produced by artifacts while retaining those

produced by trash. Figure 2.15 shows a subtracted slice and the binary output obtained after edge detection.

Figure 2.15. Output of Canny's edge detector. (a) Shows a subtracted slice. (b) Shows a binary image containing edge points.

What we now have is a set of edge points corresponding to the boundary of the trash. From these edge points, the regions in the image corresponding to the trash need to be identified and isolated. In other words, the image shown in Figure 2.15(b) needs to be split into regions of trash and cotton. To address this problem, we triangulate the edge points using Delaunay triangulation. The Delaunay triangulation of a set of points tends to generate regularly shaped triangles and is preferred over alternative triangulations [15]. A detailed discussion on Delaunay triangles and its properties is out of the scope of this thesis. Interested readers are referred to [16] for a detailed review. The most interesting aspect of the Delaunay triangles is that they adapt perfectly to the structure of the trash, thereby giving us the regions in the slice where trash is present. Once the Delaunay triangles are formed on the edge points (Figure 2.16(b)), what we essentially have is a set of triangles which can be classed into two types: One which is entirely contained in trash and the other which is entirely contained in regions of cotton and artifacts. Our task now is simplified, we just need to identify the triangles which belong to the former category and eliminate the rest.

Figure 2.16. Example of Delaunay triangulation. (a) Shows the edge points (b) Shows the output after Delaunay triangulations.

One important point to be noted is that none of these triangles are completely contained in the regions of artifacts alone. It is either combination of artifacts and cotton or trash. Since we know that cotton registers lower attenuation coefficients than artifacts, the average attenuation coefficient found in the triangles contained in cotton and artifacts will be smaller than the attenuation coefficients registered by artifacts. This information is very useful in classing these two types of triangles automatically. The average attenuation coefficients found in each of the triangles is computed and is compared with the threshold attenuation coefficient. If the average attenuation coefficient in a triangle is greater than the threshold value, then that triangle is classified as the one entirely contained in the region where trash is present, else, it is classified as the one contained in cotton and artifacts. The threshold value can be automatically determined by locating the first minima in the histogram of attenuation coefficients found in that slice.

Once the triangles contained in the trash are identified, a binary image is generated by making the pixels inside the triangles '1' and the rest '0'. Such an image is shown in (Figure 2.17(b)). This image may be compared with Figure 2.13(b) to see how the artifacts have been completely eliminated.

(a)

(b)

Figure 2.17. Example of a final segmented output. (a) Shows a subtracted slice. (b) Shows the final segmented output.

Since the low-density trash varieties such as polypropylene and leaf generally do not produce significant artifacts, such an elaborate segmentation procedure is not necessary. To segment low-density trash simple thresholding may be sufficient, this also means saving valuable processor time. Another way to reduce processor time is the formation of a bounding box around the high-density trash. Once a high-density trash has been identified, a minimum area bounding box is generated around it, and only the region enclosed by the bounding box is processed instead of the whole slice. In section 2.3.2, we discussed about determining the regions of high-variance in an image. Once, these regions are identified, we form a minimum area bounding box around the high-variance regions (Figure 2.18).

(a)

(b)

Figure 2.18. Trash and its bounding box (a) Shows a subtracted slice (b) Shows a bounding box around the regions of high-variance.

2.4.2. Volume Generation

Thus far, our focus has been on segmenting trash from the cross-sectional slices. What is actually required is the 3D representation of the trash. For this purpose, the cross-sectional slices are stacked up one on top of the other to form a 3D array. This 3D array is binary, i.e., it contains only 2 values, either '0' or '1'. '0' represents cotton, whereas '1' represents trash. Once the slices are stacked on top of each other, it is important to identify connected pieces of trash in adjacent slices. For example in Figure 2.19(a), a single piece of trash (animated) is contained in slices 1 to n. The idea is to identify these connected pieces and represent them as a single trash piece (Figure 2.19(c)).

Figure 2.19. Example for volume formation. (a) Shows cross-sectional slices stacked up together. (b) Shows segmented regions of the slices alone. (c) Shows the reconstructed object.

Connected component labeling [9] scans an image and groups its pixels into components based on pixel connectivity, i.e., all pixels in connected component share similar pixel intensity values and are in some way connected with each other. In our application, since we are dealing with 3D images, and we are concerned with 26 immediate neighbors to a pixel. Figure 2.20 shows the 26 immediate neighbors to a pixel.

Figure 2.20. The 26 neighbors of a pixel in a 3-D image

The ultimate goal of this algorithm is to label each pixel in the image as to belonging to a particular class. The algorithm works by initially labeling the first pixel and then scanning rest of the image pixel by pixel, comparing the binary value of that pixel with the binary values of labeled pixels in its 26-neighborhood. If the binary value of the pixel is the same as that of its labeled neighbors, then it is assigned the same label as its neighbors, else, a new label is assigned. Once the scanning is complete, what we have is a labeled 3D image, from which we can determine the (a) pixel coordinates of the connected objects (b) the number of unconnected objects in the image. This means that we can not only determine the 'x', 'y' and 'z' coordinates of the trash particles but also we can determine the number of trash particles present in the scanned volume. MATLAB[®]'s implementation of 3D connected component analysis was used. The result of the application of connected component analysis is illustrated in the figure below.

Figure 2.21. Final Segmented Output

2.5. Feature Extraction and Analysis

In the previous section, we discussed the identification and isolation of trash particles from a 3D image. One other task that remains to be done is that of identifying the trash particle. In other words, the segmented trash particle needs to be classified into Bark, Seedcoat fragment, Leaf or Polypropylene. In this section, we address the different methods we employ to classify the trash particles. If we desire to classify objects in any general scene, we must first study the distinguishing characteristics of the object. The characteristics that are measured from the object are called features of the object. Now, we are faced with the task of identifying the appropriate features which can be used to classify the trash with high accuracy.

Frequently, intuition leads us to selecting appropriate features. For example, in our application, just by looking at Bark and Polypropylene (Figure 2.11) we know that they have long and slender shape, whereas, Seedcoat fragments and Leaf generally tend to be short and compact. If we can somehow come up with a feature to measure the relative width of the segmented object, then we will be able to say if that trash piece belongs to Bark/Polypropylene or Seedcoat fragment/Leaf. Another a-priori information

we have is that, in general, Bark and Seedcoat fragments register higher x-ray attenuation coefficient values than Leaf and Polypropylene. Two primary areas available for feature extraction are x-ray attenuation coefficient values and shape information. Earlier work done [6] in this direction uses uniformity ratio and Aspect ratio as two features. These two features were successful in distinguishing Bark, Seedcoat fragments and Polypropylene. However, in this work, a new trash type (Leaf) has been added, and hence requires additional features for classification. An explanation of the features used to classify trash is as follows.

2.5.1. Uniformity Ratio

Man-made products, in general, are uniformly dense. It is safe to assume that polypropylene strips found in cotton have uniform density. Seedcoat fragments, Bark and Leaf do not exhibit such a property. They tend to have lumps of tissues and are not uniformly thick. The histogram of attenuation coefficients registered by a trash particle provides information about its density. If the histogram shows a low-spread of attenuation coefficients, it can be concluded that the trash particle is uniformly dense and vice versa. Therefore, a feature that measures the uniformity of the histogram can be effectively used to separate man-made trash particles (Polypropylene) from naturally occurring trash particles (Bark, Seedcoat fragments and Leaf). This feature was originally developed by Ajay Pai, et al [6]. However, a short description of the feature is given here. Refer to Figure 2.22. Once the attenuation coefficient distribution curve of a trash sample is obtained, it is truncated so that only the non-zero elements of the curve remain. Therefore, if $f(x)$ represents the distribution curve for the trash, then

$$y = f(x), \quad f(x) \neq 0 \quad (2.3)$$

where $y = \{y_1, y_2, \dots, y_L\}$ is a vector of variable length L . Next, the vector y is normalized so that all its elements lie in the range $[0, 1]$, i.e.,

$$y_{norm} = \frac{y}{\max(y)} \quad (2.4)$$

The vector y_{norm} represents a normalized, truncated version of the attenuation coefficient distribution curve calculated for the given trash sample. The feature then extracted for the purpose of classification is the mean value of the vector y_{norm} , i.e.,

$$\bar{y}_{norm} = \sum_{i=1}^L [y_{norm}(i) \cdot P_{y_{norm}}(i)], \quad (2.5)$$

where

$$P_{y_{norm}} = \frac{y_{norm}}{\sum_{j=1}^L y_{norm}(j)} \quad (2.6)$$

represents the probability density function of the vector y_{norm} .

Figure 2.22. Attenuation-coefficient-based feature extraction [6]. The mean value of the normalized truncated distribution curve is a viable feature for use in separating polypropylene from the high-density classes.

It is easy to see that if the curve in question is identical to a uniform distribution, then the mean will be unity. The operation of this feature is demonstrated by a few examples, as shown in Figure 2.23. The four graphs shown in Figure 2.23 represent

distribution curves belonging to the four classes of trash, and are roughly representative of their classes. It is evident from these graphs that the uniformity ratio increases for trash particles that show a low variation on attenuation coefficient numbers, and decreases as the variation within a trash type increases. The compact nature of the polypropylene distribution ensures that the vector $P(y_{norm})$ would produce consistently higher numbers than in the case of Bark, Leaf and Seedcoat fragment distributions.

Figure 2.23. Examples of Uniformity ratio calculations on attenuation coefficient histograms.

2.5.3. Aspect ratio

As discussed earlier, a feature which measures the elongation of the trash particle can be effectively used to classify it into Bark/Polypropylene or Seedcoat fragment/Leaf. Such a feature can be derived by performing principle component analysis (PCA) [17] on the 3D coordinates of the segmented trash. PCA is a statistical technique that finds the directions of maximum variability inherent in a dataset. The mathematical technique used in PCA is called Eigen analysis: we solve for the eigenvalues and eigenvectors of the correlation matrix of the dataset. The eigenvector associated with the largest eigenvalue has the same direction as the first principal component. The eigenvector associated with the second largest eigenvalue determines the direction of the second principal component. Also, the magnitudes of the eigenvalues are representative of the variance observed along each principal component.

Figure 2.24. Eigenvalues and eigen vectors of the segmented trash. λ denotes eigenvalue and P denotes the eigenvector of the data points.

The three-dimensional coordinates of the voxels constituting the trash sample are treated as random variables, and are represented by the three-dimensional vector

$$x = [x \ y \ z] \quad (2.8)$$

where x , y , and z represent the coordinates in the spatial domain. The mean vector of this vector population is defined as

$$m_x = E\{x\} \quad (2.9)$$

where $E\{\}$ is the expected value of the argument. The covariance matrix is calculated as

$$C_x = E\{(x - m_x)(x - m_x)^T\} \quad (2.10)$$

where T indicates vector transposition. Because x is three-dimensional, C_x is a matrix of order 3×3 . Element c_{ii} of C_x is the variance of x_i and element c_{ij} of C_x is the covariance between elements x_i and x_j of these vectors. The matrix C_x is real and symmetric.

The eigenvectors and eigenvalues of the matrix are obtained from the solution of the equation

$$C_x X = \lambda X, \quad (2.11)$$

where X_i $\{i = 1, 2, 3\}$ represents the eigenvectors and λ_i $\{i = 1, 2, 3\}$ represents the eigenvalues of the matrix C_x . The eigenvectors of the covariance matrix represent the directions of the three axes along which the voxels have a maximum spread [greatest variance, see Figure 3.13(a)]. The corresponding eigenvalues give us the relative spread of the object along the three axes in the spatial domain. The ratio of the maximum eigenvalue to the second largest eigenvalue can be thought of as a ratio of the ‘length’ of the object to its ‘breadth’. This ratio is called the Aspect ratio, and is defined as

$$\text{Aspect ratio} = \frac{\lambda_1}{\lambda_2} \quad (2.12)$$

Figure 2.25. Examples of Aspect ratio calculations on different trash types

From Figure 2.25, it can be seen that as the object of interest tends to be long and slender, the calculated value of aspect ratio is generally high and vice versa. Hence this feature can be effectively used to classify trash into long or compact pieces.

2.5.3. Mean Attenuation Coefficient

Bark and Seedcoat fragments provide tough outer covering for the soft tissues present in the cotton plant. By nature, they are hard and dense. It is only natural that they resist the passage of x-rays through them. On the contrary, Leaf and Polypropylene are generally soft and offer much less resistance to the passage of x-ray radiation. The amount of resistance an object offers to the passage of x-rays is indicated by its attenuation coefficient. Therefore, the mean attenuation coefficient offered by a trash particle can be used effectively to classify it into low-density trash (Leaf and polypropylene) and high-density trash (Bark and Seedcoat fragments).

To study the effectiveness of this feature, 10 samples each of Bark, Seedcoat fragments, Leaf and Polypropylene were separately scanned and the mean attenuation coefficient registered by each one of them was noted.

Table 2.2. Mean attenuation coefficients for different trash types

Trash Type	Mean Attenuation Coefficient
Bark	0.2393
Seedcoat fragments	0.2501
Leaf	0.1121
Polypropylene	0.0685

From Table 2.1, it can be seen that the mean attenuation coefficient registered by Leaf and Polypropylene is in general, far lesser than the other two trash types. Hence this feature can be effectively used to classify trash into high-density and low-density trash varieties.

2.5.4. Solidity

Bark pieces, due to their fragile and slender nature, are susceptible to mechanical forces much more than the other trash types. During the harvesting and ginning processes, long bark pieces may break and may resemble the trash piece shown in the Figure 2.26. Since the pieces are broken, the aspect ratio for them becomes very low. For example, the trash piece shown in Figure 2.26 has an aspect ratio of mere 7.9. If the same trash piece were not broken, the aspect ratio would have been many magnitudes greater.

Broken Bark pieces have an adverse effect on the classification system. A broken bark piece, due to its low aspect ratio, may get misclassified as a small and compact trash piece (Seedcoat fragment and Leaf). This underlines the need for a new feature that will be able to differentiate broken barks from small and compact trash varieties. Such a feature can be computed by determining the convex hull of the 3D trash particle.

Performing convex hull on 3D dataset generates a set of triangles which enclose all the points on the dataset and also the total surface area of all the triangles is smaller than all the other combinations. MATLAB[®]'s implementation of convex hull was used here. Interested readers are referred to [2] for a detailed review.

Figure 2.26. Example of a Broken Bark

Solidity [18] is a measure of the interior of any volume being filled with matter. For example, if 0.5 gallons of water is stored in 1 gallon jar, its solidity is 0.5. Similarly, we find solidity of the convex hull. Since a convex hull encloses all the points in the dataset, the volume of the convex hull is always greater than the volume of the trash inside it. Here, the solidity is determined by calculating the ratio of the volume of the trash particle to the volume of its convex hull. Figure 2.27 shows different trash particles and their corresponding convex hulls.

Figure 2.27. Examples of (a) Trash particles and (b) its corresponding convex hulls

From Figure 2.27, it can be seen that the normal trash pieces have convex hulls with a shape consistent with the trash itself. Broken bark pieces have crooked shape and the volume of their convex hull is generally much greater than its volume, i.e., broken bark pieces have much less solidity than the other trash varieties. Hence this feature can be effectively used to classify broken bark from other trash varieties.

2.6. Fuzzy Classification

In the previous section, we focused on extracting useful information out of the segmented trash particles. Here, we will study the design of a classifier whose inputs will be the measured features and the output is a label or a name assigned to the trash particle. In other words, given a trash particle, we will input its Uniformity ratio, Aspect ratio, Mean attenuation coefficient and Solidity values to the classifier and then determine if that trash particle belongs to Bark, Seedcoat fragment, Leaf or Polypropylene.

Figure 2.28. Inputs and outputs of a classifier.

With traditional (crisp) classification methods, each sample is placed into one class or another, i.e., the class membership is binary, a sample is a member of a class or not. Crisp class membership values can be either '1' when that class is the best fit, or '0' (for all other classes). This type of classification works well only if the output classes are well separated. When dealing with continuous datasets, crisp classification methods fail because of the ambiguity surrounding the threshold values. A commonly used example would be helpful at this point. Consider a crisp classification algorithm designed to classify a set of people into either "Tall" or "Short" and the classification rule being, a

person is said to be “Tall” if his height is more than 6 feet or otherwise. Such a classification may prove to be absurd in certain cases. It may be unreasonable to call a person whose height is 5’11” as “Short” Similarly, crisp classification does not provide reasonable results when used to classify cotton trash. We know that most of the trash found in cotton is organic, and hence it is rational to expect large variations in the extracted features. It is impossible to say, for example, if the measured value of uniformity ratio is greater than 0.55, then the sample definitely belongs to Polypropylene. There could always be a uniformly dense bark piece, which has a uniformity ratio value greater than 0.55. What is now required is a classification algorithm which can deal with uncertainty surrounding the threshold values.

In fuzzy classification, a sample can have membership in many different classes to different degrees. Typically, the membership values are constrained so that all of the membership values for a particular sample sum to 1. Fuzzy set theory implements classes or groupings of data with boundaries that are not sharply defined. The benefit of extending crisp theory and analysis methods to fuzzy techniques is the strength in solving real-world problems, which inevitably entails some degree of imprecision and noise in the variables and parameters measured and processed for the application. In fuzzy classification, regions of ambiguity are characterized by smooth membership functions. A membership function is a curve that defines how each point on the input space is mapped to a membership value between ‘0’ and ‘1’ Figure 2.29 demonstrates the use of membership functions in the process of decision making. Here two membership functions (“High” and “Low”) have been used to make decisions. If a uniformity ratio value of 0.55 is given as input to this fuzzy classifier, two outputs are generated. That trash piece belongs to “Low” class with a membership degree of 0.9 and at the same time it belongs to “High” class with a membership degree of 0.32. This provides us information about how “ambiguously” a sample belongs to a particular class.

Figure 2.29. Example of a fuzzy membership function.

Fuzzy if-then rules are used to formulate conditional statements that comprise fuzzy logic. In general, the input to the if-then statements is the current value of the input variable and the output generally is the label of a particular class. The following are the fuzzy conditional statements used in designing the classifier.

1. "If Solidity is Low, then Bark is high, Seedcoat fragment is low, Leaf is low, Polypropylene is low."
2. "If Solidity is high, Aspect ratio is low and Mean attenuation coefficient is not high, then bark is low, Seedcoat fragment is low, leaf is high and polypropylene is low."
3. "If Solidity is high. Aspect ratio is low and Mean attenuation coefficient is high, then bark is low, Seedcoat fragment is high, leaf is low and polypropylene is low."
4. "If Solidity is high, Aspect ratio is high, Mean attenuation coefficient is high and Uniformity ratio is high, then bark is low, Seedcoat fragment is low, leaf is low and polypropylene is high."
5. "If Solidity is high, Aspect ratio is high, Mean attenuation coefficient is high and Uniformity ratio is low, then bark is high, Seedcoat fragment is low, leaf is low and polypropylene is low."

Interpretation of an if-then statement involves three distinct steps [19]: (1) The evaluation of the input(s) [determining the degree of membership (fuzzification) for each input]; (2) The application of the fuzzy operator to the fuzzified inputs; and (3) Application of the result to the consequent (known as implication). The output of each of these rules (the result obtained after the implication process) is usually a fuzzy subset. The next step in any fuzzy system consists of combining the outputs of the fuzzy if-then rules (aggregation) into a fuzzy subset. A defuzzifying procedure is then applied to this fuzzy subset to resolve it into a single number, i.e. the output. The most popular defuzzification method is the centroid calculation, which returns the center of area under the curve. For information about other defuzzification methods, refer to [19].

The membership functions used to define the linguistic variables (*high* and *low*) for the four features are shown in Figure 2.30. When presented with the four features measured for an object, the classifier produces four outputs. These numbers lie in the range [0, 1] and indicate the degree to which the object belongs to each of the four classes.

(a)

(b)

(c)

(d)

Figure 2.30. Input membership functions of the four features used.

CHAPTER III

EXPERIMENTAL RESULTS

This chapter presents the results of applying the new segmentation and classification techniques to cotton samples. The primary goals of this chapter are to (1) Establish the faithfulness of this new segmentation technique. (2) Evaluate the performance of fuzzy classifier on training samples. (3) Compare AFIS trash measurements to the measurements made using this proposed technique.

3.1. Fidelity of Segmentation

One important aspect to be checked is the faithfulness of this segmentation process described in Section 2.4. In other words, we need to check if the physical features of the segmented trash particles correspond to that of original trash samples. To verify this, the radiographic (2D) images and the 3D segmentation results were compared. The 3D segmented volumes were rotated and aligned such that the camera position and angle used to capture the radiographic image corresponds to the observer's eye position while viewing the 3D image. Thus by visually comparing the 2D radiographic image with the 3D segmented image, we can determine the faithfulness of this segmentation process. Figure 3.1(a) shows the radiographic image of a cotton sample, Figure 3.1 (c) shows the corresponding segmented sample. It can be seen that the physical dimensions of the trash in the radiographic image matches the dimensions observed in the segmented image.

(a)

(b)

(c)

(d)

(e)

(f)

(g)

Figure 3.1. Comparison of radiographic and 3D segmented images. (a, d, f, h) Shows a radiographic image of a bark piece. (b) Shows a 3D representation of the segmented sample in (a). (c, e, g, i) Shows a rotated version of the same.

Greatest challenge to the segmentation algorithm is posed by samples which have cotton with non-uniform packing density. As discussed in the previous chapter, the x-ray attenuation coefficient recorded by the highly dense cotton is usually comparable to that observed for low-density trash particles like Polypropylene and Leaf. The success of this technique can be ascertained in its ability to distinguish varying density cotton from low-density trash particles. Shown below (Figure 3.2(a)) is a radiographic image of a cotton sample with varying packing density. Dark areas in the image represent highly dense

cotton whereas lighter areas represent cotton with low packing density. The trash particle observed in the image (Figure 3.2(a)) is a Leaf. The technique performs well for this sample; especially taking into account that some regions of leaf have very low density, i.e., they have attenuation coefficient values similar to that of cotton.

(a)

(b)

(c)

(d)

Figure 3.2. Examples of cotton samples with varying packing density. (a, c, e, g) Shows radiographic images of cotton. (b, d, f, h) Show the segmented output.

3.2. Fuzzy Classification Results

The main issue discussed in this section is the performance of the fuzzy classifier: Given a training set of scanned cotton samples, we seek to design a classifier that is optimal for differentiating the trash particles present in them. The utilized features are the measurements (Solidity, Aspect ratio, Uniformity ratio and Mean attenuation coefficient) made on the segmented trash samples. In this section, it will be shown that these four features provide the necessary discriminatory power for the classification of the four trash

types under study. The estimate of error used in this work is the classification rate, i.e., the ratio of the number of correct classifications to the total number of samples.

The training set was prepared by manually placing the known contaminants into clean cotton. In doing so, care was taken not to disturb the natural density variations present in cotton. If the samples are pressed hard, certain regions of cotton may get compressed and may result in greater value of attenuation coefficients for that region. Also, it was made sure that the physical dimensions of the trash particles used in the training set matched those of the trash particles found in the natural cotton.

Adopting the above-mentioned guidelines, 50 cotton samples were prepared which had 93 known trash pieces distributed among them. On scanning and subsequently segmenting the trash pieces, four features were measured for each of the trash piece. Of the four features, as we discussed in the previous chapter, Solidity is used only to classify broken bark pieces. The impact this feature has on the classifier will be discussed later in this section. Using the other three features (Mean attenuation coefficient, Aspect ratio and uniformity ratio), a 3D feature space was constructed. This feature space is nothing but a 3D plot with these three features as axes. The region occupied by each of the trash type in the 3D space represents the variation of its computed features. From Figure 3.3, it can be seen that each type of trash occupies a distinct region in the feature space, with minimal overlap with other trash types, thus giving the classifier sufficient discriminatory power to differentiate all types of trash except broken bark. Also shown (Figure 3.4) are 2D feature spaces.

Figure 3.3. 3D Feature space constructed from the computed feature values of the 93 trash samples.

(a)

(b)

Figure 3.4. Feature space observed for 2 dimensions. (a) Shows the feature space generated using Aspect ratio and Mean attenuation coefficient. (b) Shows the feature space generated using uniformity ratio and Aspect ratio.

Observations made on the feature spaces shown in Figure 3.4 are as follows:

1. From Figure 3.4(a) it can be inferred that Leaf and Seedcoat fragments have lower aspect ratios than bark and polypropylene.
2. The mean attenuation coefficient observed for Polypropylene is, in general, less than that observed for Bark. Similarly, mean attenuation coefficient for Leaf is less than that for Seedcoat fragment. This feature may be used in combination with aspect ratio to distinguish the four trash types. This requires two thresholds (See Figure 2.29(b)): one for separating Bark and Polypropylene, the other for Leaf and Seedcoat fragments.
3. From Figure 3.4(b), it can be seen that polypropylene (man-made material) generally has uniformity ratio greater than all the other trash types.

As stated earlier, solidity measurement made on a trash piece alone can say if that trash piece is a broken bark or not. For each of the 93 trash pieces used for training, solidity values were computed and plotted in the 1D feature space as shown in Figure 3.5. Broken bark pieces, in general, have much less solidity values than the remaining trash types and hence Solidity serves as an effective feature to classify broken bark.

Figure 3.5. Measurement of solidity values for 93 trash samples of known classification.

These four features, when used according to the “if-then” rules (described in section 2.6), were used to classify the 93 test samples. The classification rate of the

classifier is determined as the ratio of the number of correct classifications to the total number of samples tested. Testing this algorithm with 93 samples, we were able to achieve a correct classification rate of 89%; see Table 3.1.

Table 3.1 Confusion matrix resulted from classifying 93 trash samples

	Bark	Seedcoat fragment	Polypropylene	Leaf
Bark	21	0	5	0
Seedcoat fragment	0	27	0	4
Polypropylene	0	0	12	0
Leaf	0	1	0	23

The rows of Table 3.1 indicate inputs of known classification, whereas the columns represent the classes assigned by the classifier. The sum of any row would indicate the number of samples present in that class. For example, from Row 1 of Table 3.1, we can conclude that there are 26 (21 + 5) samples of Bark. Of these samples 21 were correctly classified as Bark and five of them were misclassified as Polypropylene. The correct classification rate of Bark would be 80.76 % ($\frac{21}{26} * 100$). From Table 3.1, it can be seen that, the total number of correct classifications among 93 trash samples was 83. This translates to a correct classification rate of 89%.

Five Bark pieces were misclassified as Polypropylene; Four Seedcoat fragments were misclassified as Leaf. On closer look at the features computed for these misclassified trash pieces (see Appendix A), it was observed that these samples recorded lower mean attenuation coefficient values than that generally observed for their respective classes. It is believed that these trash pieces were still immature when they were scanned, and so they recorded very low attenuation coefficient values. One of the Leaf samples was misclassified as Seedcoat fragment. This particular Leaf sample was found to contain lots of dried veins, and so, the mean attenuation coefficient observed for that sample was much greater than the remaining samples, thus, getting misclassified as Seedcoat fragment.

3.3 Comparison with AFIS (Advanced Fiber Information System) measurements

In AFIS, the trash content is determined by physically separating trash from cotton. Although AFIS is not capable of classifying the trash particles, they provide accurate information on the weight of the contaminants present in the cotton. The weight of the contaminants and cotton estimated separately and the ratio of the weight of trash to cotton is expressed as VFM% (Visible Foreign Matter). Since VFM measurements accurately indicate the amount of trash in the sample, it was decided to compare VFM measurements with the proposed technique.

In order to perform this comparison study, 45 cotton samples were randomly selected from Grades 3, 4 and 5 cotton. (A Grade is assigned to a cotton sample by a composite assessment of three factors – color, trash content, and preparation. The higher the grade assigned to a sample, the lower is its quality.) The randomly selected samples were scanned and subsequently segmented. We know that, the mean x-ray attenuation coefficient offered by any object is proportional to its average density. We also know the volume occupied by trash (The number of voxels in the segmented object). The product of the volume of trash and its mean x-ray attenuation coefficient is assumed to be proportional to the weight of the trash. Similarly, the product of the volume of cotton and its mean x-ray attenuation coefficient will be proportional to the weight of cotton in that sample. Therefore, the ratio of thus computed weight of trash to cotton is assumed be proportional to the VFM measurements.

After determining VFM% for the samples using the proposed technique, the same samples were tested for VFM measurements using AFIS trash analyzer. (Courtesy: International Textile Center) Figure 3.6 shows the comparison chart between AFIS VFM% and that calculated using the proposed technique. A correlation coefficient of 0.7091 was obtained. It is worth noting that the SkyScan 1074-Microtomograph is capable of scanning only a small region of the cotton placed in it, and so trash particles lying outside this region of interest are omitted, whereas, the AFIS trash analyzer can work with the entire sample. This is believed to contribute to the discrepancy between the

VFM measurements. Better correlation coefficient values are expected with the use of bigger scanners, where the entire cotton sample can be scanned.

Figure 3.6. VFM (Visible Foreign Matter) comparison chart.

CHAPTER IV

CONCLUSIONS AND FUTURE WORK

4.1. Summary

The proposed method for identifying trash in cotton is an attractive alternative to present-day trash meters, due to its ability to provide accurate 3D representations and to gather precise shape and size information. Currently used mechanical trash meters, while physically separating trash, reduce big trash particles to smaller ones, and thereby fail to provide reliable information about trash pieces. Further, the proposed technique does not require prior sample preparation and manual handling, which is very appealing to the industry where millions of bales of cotton need to be graded every year.

A major drawback in using an x-ray microtomography system to acquire images is its high image acquisition time. The SkyScan μ -CT 1074 portable microtomography system [14], which was used in this project, takes approximately 20 minutes to scan a sample. This is followed by slice reconstruction, which takes about 5 seconds a slice. This is followed by slice upload into MATLAB[®], where the slices are segmented and the 3D representation of all the trash particles in the sample is generated. This procedure roughly takes 15 seconds a slice on a 1GHz machine. As evident, the current implementation of the proposed technique is unsuitable for real-time cotton evaluation. However, research in the fields of improved CT hardware [22], faster x-ray reconstruction algorithms [20,21], and the ever-increasing computational and storage capabilities of computers provide some assurance that in the near future, x-ray computed tomography will find application in the online assessment of cotton contamination.

Software tools were designed and implemented to streamline this task, including a graphical User Interface (GUI) for automatically loading and processing the scanned data. Because 3D models unavoidably involve huge datasets, the goal in designing this tool was to provide easy-to-use and effective software interface to the user.

4.2. Future Work

4.2.1. Image Contrast Enhancement using Ross Filters

Contrast between organic and inorganic materials can be enhanced by using a Ross-filter. A basic Ross-filter system consists of two identical detectors placed behind x-ray absorbing foils. These pairs of filters are made of elements with adjacent atomic number Z . The foil thickness is adjusted to provide identical absorption except in the energy region between the two K-edges of two metal foil filters (Iron (Fe) and Titanium (Ti)) are good candidates for this application [32]).

The use of Ross Filters in x-ray image enhancement is explained using an example described in [23, 24]. The overall spectral sensitivity of Aluminum (Al) foils with varying amounts of Carbon (C) is depicted below in Figure 4.1, where C at a density of 1g/cm^2 at different thicknesses (0, 10, 100, and 1000 μm). Other constituents of organic material (Oxygen (O), Nitrogen (N)) do not differ much from this behavior. The corresponding recorded intensities (areas under these curves) are 66.65, 66.40, 64.68, and 53.51. The intensity ratio “1000 μm C to “nothing” would be $53.51/66.65=0.803$.

Figure 4.1. Spectral sensitivity for Al with no C, 10, 100, 1000 μm C. Energy scale is in MeV.

Using the Ross-filter combination of 15 μm Ti and 5 μm Fe (Figure 4.2 (a)) provides a difference which coincides with the spectral range showing the highest difference for C-absorption, and a difference measurement should enhance the contrast. The transmissions for the combinations 20 μm Al+5 μFe , 20 μm Al+15 μm Ti, and the same two combinations with 1000 μm C added, are shown in Figures 4.2 (b) and 4.1(c). The difference between the areas under the curves in Figure 4.2 (b) (“nothing”) and the curves in Figure 4.2 (c) (presence of 1000 μm C) were measured and are shown in Table 4.1.

Table 4.1 Results of using Fe-Ti filters with Aluminum foil

Filter Combination	Area	Filter Combination	Area
Al + Fe	46.5	Al + Fe + 1000 μm C	38.44
Al + Ti	41.04	Al + Ti + 1000 μm C	36.10
[Al + Fe] – [Al + Ti]	5.01	[Al + Fe + C] – [Al + Ti + C]	2.34

The corresponding ratio of the “C” to “nothing” signal after difference forming would be: $2.34/5.01=0.46$, which would mean more contrast between pure Al foils and those with 1000 μm C.

(a)

(b)

(c)

Figure 4.2. (a) Transmissions of 5 μm Fe and 15 μm Ti, showing almost identical transmission except for the region between the two K-edges. (b) Transmissions of 20 μm Al + 5 μm Fe and 20 μm Al + 15 μm Ti (c) Transmissions of the same combinations as in Fig. 3, but 1000 μm C added. Energy scale is in MeV.

The elemental composition of cotton and the main constituents of its biological contaminants are C, N, and O. Metallic contaminants, which do not have C, N, and O, can be distinguished from organic contaminants by using a Ross-Filter combination. Preliminary experiments were conducted with Al foils (Metallic contaminant) and Polypropylene (Organic contaminant) using Fe-Ti Ross filter combination. Results of the experiments performed failed to produce favorable results as the SkyScan-1074 microtomography system could not be operated at voltages around 6kV. It is believed that once the scanner is functional at low-voltages, favorable results can be obtained.

4.2.2. Extending theory to practical use

In its current form, the SkyScan-1074 x-ray CT scanner allows only up to 500 milligrams of cotton sample to be scanned at a given time. The industry standards require the test sample to weigh at least 100 grams. Bigger samples mean bigger image size,

which further adds to the computation time. One way to reduce the image size is to sub-sample the image further or to use low-resolution detectors. Further, tests need to be conducted studying the impact of low-resolution detectors on segmentation and classification algorithms.

4.2.4. Validation

Correct classification percentage of 89% was obtained using artificially prepared samples, i.e., samples prepared by manually inserting known contaminant types into clean cotton. It still remains to be proven that similar classification rate would be obtained when the classification algorithm is run on samples of naturally occurring cotton. To accomplish this task, trash particles would have to manually removed from the samples and identified by a human grader and subsequently compared with the classification result produced by the algorithm.

Accurately determining the weight of trash in cotton is of utmost importance to the industry, as it can make the grading process more reliable. Tomographic images indirectly provide density information, which can not only be used to detect objects, but also to estimate the weight of objects. As previously stated, the x-ray attenuation coefficient registered by an object is proportional to its density. The weight of a trash piece can be estimated from the product of its mean attenuation coefficient and its volume. To test how well the devised weight estimation procedure corresponds to the actual weight of the samples, a large study involving hundreds of trash specimens need to be conducted.

4.2.5. Process Optimization

A major area of future research will involve modifying the x-ray based cotton contaminant analysis system to make it a feasible option in comparison to current technologies. This will include research into the implementation of more efficient reconstruction algorithms, and possible methods of interlacing the acquisition and

reconstruction stages. Conversion of the existing MATLAB[®] implementation to C/C++ or using high-performance DSP boards may also form possible avenues for future work.

BIBLIOGRAPHY

- [1] U.S. department of Agriculture, Agricultural marketing Service, The classification of cotton, Agricultural Handbook 566, Washington, D.C. (Revised January 1999)
- [2] M. Siddaiah, M.A. Lieberman, N.R. Prasad, and S.E. Hughs, "Identification of Trash Types in Ginned Cotton Using Neuro Fuzzy Techniques," *IEEE Int. Conf. Fuzzy Systems*, 738-743, 1999.
- [3] F.M. Shofner, and G.F Williams, "Evolution of the Microdust and Trash Monitor for Cotton Classification," *Textile Research J.* 56, 150-156, 1986.
- [4] B. Xu, C. Fang, and R. Huang, "Chromatic Image Analysis for Cotton Trash and Color Measurement," *Textile Res. J.* 67(12), 881-890, 1997.
- [5] A. Kak, and M. Slaney, *Principles of Computerized Tomographic Imaging*, IEEE Press, New York, 1988.
- [6] A. Pai, H. Sari-Sarraf, and E. F. Hequet, "Recognition of Cotton Contaminants via X-ray Microtomographic Image Analysis," To be published in *IEEE Trans. on Industry Applications*
- [7] SkyScan MicroCT: 1074-model Portable Micro-CT Scanner.
http://www.skyscan.be/next/spec_1074.htm
- [8] Euresys Online – Eurecard Picolo Series Frame Grabbers.
<http://www.euresys.com/downloadablefiles/datasheets/PicoloSeriesDataSheet.pdf>
- [9] R. C. Gonzalez and R. E. Woods, *Digital Image Processing*, Reading, MA: Addison-Wesley, 1992.
- [10] M. Nixon and A. Aguado, *Feature Extraction and Image Processing*, Newens, 2002.
- [11] Guide E1441-00, "Standard Guide for Computed Tomography (CT) Imaging," American Society for Testing and Materials, West Conshohocken, PA, Copyright 2000.
- [12] K. R. Castleman, *Digital Image Processing*, Prentice Hall, 1996.
- [13] D. Ziou, S. Tabbone, "Edge Detection Techniques An Overview", *International Journal of Pattern recognition and Image Analysis*, 1998.

- [14] J. Canny, "A *Computational Approach to Edge Detection*", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 8, No. 6, Nov. 1986.
- [15] T. Gevers, "Adaptive Image Segmentation by Combining Photometric Invariant Region and Edge Information", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 24, No. 6, June 2002.
- [16] J. O'Rourke, "Computational Geometry in C", Cambridge University Press, 1994.
- [17] R. O. Duda and P. E. Hart, "Pattern Recognition and Scene Analysis", John Wiley, 1983.
- [18] M. Siddaiah, M. A. Lieberman, S. E. Hughs and N. R. Prasad, "Identification of Trash Types in Ginned cotton", Beltwide Cotton Conference, Feb 2000.
- [19] "Fuzzy Logic Toolbox User's Guide", The MathWorks Inc., Copyright 1995-2001.
- [20] C. Laurent, C. Calvin, F. Peyrin, and J. M. Chassery, "Efficient Implementation of Parallel Image Reconstruction Algorithms for 3D X-ray Tomography," Parallel Computing: State-of-the-Art and Perspectives, Conf. Proc., pp. 109-116, September 1995.
- [21] A. H. Delaney and Y. Bresler, "A fast and accurate iterative reconstruction algorithm for parallel-beam tomography," IEEE Trans. Image Processing, pp. 740-753, May 1996.
- [22] SkyScan, "Microtomography. Part 1: Methods and Equipments," Journal of Microscopy, Vol.147, Part 2, 1987, pp.169-178.
- [23] National Institute of Standards and Technology, Physics Laboratory.
<http://physics.nist.gov/PhysRefData/Xcom/html/xcom1.html>
- [24] E.O. Lawrence Berkeley National Laboratory, Material Science Division, Center for X-Ray Optics.
http://www-cxro.lbl.gov/optical_constants/

APPENDIX A

FUZZY CLASSIFICATION RESULTS FOR 93 KNOWN TRASH SAMPLES

NO.	INPUT TYPE	COMPUTED FEATURES				FUZZY CLASSIFICATION RESULTS
		Aspect Ratio	Mean Attenuation Coefficient	Uniformity Ratio	Solidity	
1	Bark	15.7103	0.16911	0.531	0.88618	Bark
2	Bark	57.4256	0.37211	0.5126	0.27826	Bark
3	Bark	23.098	0.13241	0.573	0.9555	Bark
4	Bark	8.3452	0.043168	0.6112	0.63957	Polypropylene
5	Bark	13.1458	0.037553	0.614	0.63169	Polypropylene
6	Bark	18.06	0.03541	0.6888	0.8926	Polypropylene
7	Bark	9.858	0.085153	0.5187	0.87256	Bark
8	Bark	33.3658	0.2886	0.598	0.92989	Bark
9	Bark	40.6386	0.075271	0.607	0.65131	Bark
10	Bark	12.1505	0.33789	0.572	0.46605	Bark
11	Bark	9.0097	0.0577	0.624	0.51805	Polypropylene
12	Bark	11.556	0.03886	0.5542	0.032008	Bark
13	Bark	11.291	0.0518	0.6262	0.53343	Polypropylene
14	Bark	51.3751	0.21653	0.573	0.3721	Bark
15	Bark	13.1299	0.080392	0.557	0.88652	Bark
16	Bark	14.949	0.061682	0.5866	0.7859	Bark
17	Bark	17.2285	0.19636	0.615	0.87904	Bark
18	Bark	17.5896	0.205	0.622	0.9432	Bark
19	Bark	11.208	0.0944	0.694	0.50091	Bark
20	Bark	2.8502	0.0368	0.7086	0.32082	Bark
21	Bark	3.7895	0.26674	0.5266	0.37846	Bark
22	Bark	33.245	0.235	0.4128	0.7332	Bark
23	Bark	16.654	0.1988	0.5146	0.8566	Bark
24	Bark	28.488	0.2416	0.5368	0.6888	Bark
25	Bark	21.54	0.1546	0.4636	0.8762	Bark
26	Bark	18.3754	0.082	0.602	0.7438	Bark
27	Seedcoat	4.126	0.2593	0.57019	0.91365	Seedcoat
28	Seedcoat	7.74	0.19107	0.6067	0.74482	Seedcoat
29	Seedcoat	1.7162	0.14992	0.52723	0.61782	Leaf
30	Seedcoat	3.8184	0.23444	0.5427	0.68075	Seedcoat
31	Seedcoat	4.6485	0.34399	0.4684	0.5309	Seedcoat
32	Seedcoat	2.2662	0.389	0.57402	0.97126	Seedcoat
33	Seedcoat	2.2476	0.22755	0.56859	0.7931	Seedcoat
34	Seedcoat	3.2965	0.25616	0.4271	0.81466	Seedcoat
35	Seedcoat	5.8345	0.20486	0.57476	0.59485	Seedcoat
36	Seedcoat	2.8931	0.101	0.7148	0.75259	Leaf
37	Seedcoat	2.0176	0.32763	0.3889	0.86084	Seedcoat

38	Seedcoat	4.7004	0.3613	0.3566	0.4362	Seedcoat
39	Seedcoat	3.8137	0.30434	0.5244	0.72733	Seedcoat
40	Seedcoat	4.7717	0.11956	0.609	0.7487	Leaf
41	Seedcoat	7.5118	0.24602	0.6309	0.87323	Seedcoat
42	Seedcoat	7.8958	0.2528	0.5878	0.59483	Seedcoat
43	Seedcoat	7.973	0.27	0.51469	0.60209	Seedcoat
44	Seedcoat	7.4143	0.21387	0.63028	0.7808	Seedcoat
45	Seedcoat	6.0672	0.31362	0.4618	0.6251	Seedcoat
46	Seedcoat	11.4182	0.24019	0.604	0.85883	Seedcoat
47	Seedcoat	4.09	0.18157	0.4841	0.61873	Seedcoat
48	Seedcoat	3.698	0.209	0.5561	0.49648	Seedcoat
49	Seedcoat	4.4882	0.1412	0.598	0.97423	Seedcoat
50	Seedcoat	2.7895	0.26674	0.5618	0.37846	Seedcoat
51	Seedcoat	3.6751	0.32626	0.3636	0.6533	Seedcoat
52	Seedcoat	1.2817	0.20142	0.5594	0.93989	Seedcoat
53	Seedcoat	4.5704	0.19272	0.5124	0.90259	Seedcoat
54	Seedcoat	6.546	0.2088	0.3976	0.6398	Seedcoat
55	Seedcoat	3.9875	0.3465	0.5578	0.7432	Seedcoat
56	Seedcoat	2.6924	0.0985	0.6034	0.6937	Leaf
57	Seedcoat	5.654	0.1969	0.4098	0.8489	Seedcoat
58	Polypropylene	38.6687	0.069722	0.677	0.8227	Polypropylene
59	Polypropylene	26.4599	0.067055	0.8405	0.8921	Polypropylene
60	Polypropylene	75.404	0.043051	0.6043	0.80851	Polypropylene
61	Polypropylene	14.157	0.04269	0.744	0.62886	Polypropylene
62	Polypropylene	60.4137	0.044898	0.597	0.86538	Polypropylene
63	Polypropylene	88.7219	0.0553116	0.563	0.47251	Polypropylene
64	Polypropylene	21.8316	0.047767	0.642	0.95969	Polypropylene
65	Polypropylene	42.007	0.047622	0.649	0.8507	Polypropylene
66	Polypropylene	18.6422	0.030223	0.655	0.49504	Polypropylene
67	Polypropylene	12.9979	0.046019	0.596	0.59314	Polypropylene
68	Polypropylene	88.3075	0.06182	0.731	0.64122	Polypropylene
69	Polypropylene	18.855	0.033442	0.733	0.81404	Polypropylene
70	Leaf	4.0007	0.081854	0.582	0.29709	Leaf
71	Leaf	3.98448	0.16535	0.58	0.5398	Leaf
72	Leaf	1.7922	0.05727	0.5051	0.2908	Leaf
73	Leaf	2.4889	0.046778	0.4326	0.94082	Leaf
74	Leaf	1.449	0.040678	0.5902	0.609	Leaf
75	Leaf	2.2539	0.0463	0.5096	0.54748	Leaf
76	Leaf	6.1556	0.06319	0.618	0.69	Leaf
77	Leaf	2.165	0.04419	0.4663	0.72672	Leaf
78	Leaf	2.245	0.047689	0.4932	0.6646	Leaf
79	Leaf	1.5008	0.058448	0.523	0.85664	Leaf
80	Leaf	2.2479	0.163	0.578	0.51909	Leaf
81	Leaf	1.1557	0.053175	0.471	0.6144	Leaf

82	Leaf	2.4313	0.0387	0.498	0.56792	Leaf
83	Leaf	9.305	0.14326	0.518	0.58549	Leaf
84	Leaf	2.3702	0.04823	0.527	0.49886	Leaf
85	Leaf	3.7809	0.078877	0.412	0.5134	Leaf
86	Leaf	2.9513	0.23583	0.564	0.64226	Seedcoat
87	Leaf	5.8729	0.11492	0.518	0.67433	Leaf
88	Leaf	1.6123	0.12382	0.4008	0.7114	Leaf
89	Leaf	2.1374	0.06891	0.512	0.94727	Leaf
90	Leaf	1.6894	0.13138	0.436	0.96473	Leaf
91	Leaf	1.7438	0.043635	0.566	0.90103	Leaf
92	Leaf	4.3952	0.066432	0.546	0.464	Leaf
93	Leaf	3.368	0.05014	0.597	0.70029	Leaf

PERMISSION TO COPY

In presenting this thesis in partial fulfillment of the requirements for a master's degree at Texas Tech University or Texas Tech University Health Sciences Center, I agree that the Library and my major department shall make it freely available for research purposes. Permission to copy this thesis for scholarly purposes may be granted by the Director of the Library or my major professor. It is understood that any copying or publication of this thesis for financial gain shall not be allowed without my further written permission and that any user may be liable for copyright infringement.

Agree (Permission is granted.)

Student Signature

Date

Disagree (Permission is not granted.)

Student Signature

Date