BEEF QUALITY GRADING WITH COLOR VIDEO IMAGE ANALYSIS

By

NISHA BIJU

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BEEF QUALITY GRADING WITH COLOR

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Thesis Approved:

Glenn A. Kranzler

Thesis Advisor

Marvin Stone

Gerald H. Brusewitz

Wayne B. Powell

Dean of the Graduate College

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CHAPTER I

INTRODUCTION

Background

The beef industry is currently one of the largest agricultural industries in the U.S. In recent years, it has comprised more than 20% of the total agricultural market. Total retail value of beef consumed in 1996, was $51.4 billion (USDA Cattle and Beef Statistics, 1996). However, changing consumer preference and the need to be competitive have driven the rapid shift from a commodity-oriented to a consumer-oriented industry (Cross et al., 1989). Increased consumer awareness of health and food relationships has initiated strong signals from meat packers to beef producers to place more emphasis on carcass quality (Park et al., 1994).

In the U.S., beef has traditionally been graded by trained United States Department of Agriculture (USDA) personnel. USDA developed standards for the grading of beef carcasses as early as 1926. The 1986 National Consumer Retail Beef Study showed consumer preference for closely trimmed products (Fielding, 1994). The marketing system, however was tolerating and even encouraging the production of excess fat. There was no objective, reliable way to determine the value of individual carcasses.

This situation, in turn, prevented the packer from passing the right signals to the feeders by offering monetary incentives to produce cattle that would yield products with the quality and composition desired by consumers. There was a reduction of confidence in the accuracy of USDA graders, who make visual, subjective determination of carcass quality and yield. USDA graders maintain a level of trust, not because they are infallible, but because they are an impartial third party in the marketing chain (Fielding, 1994). The incorporation of an accurate automatic grading system for beef carcasses would eliminate subjective bias from the grading procedure and would be more desirable to both the feeders and the packers.

Beef carcass grading assesses two factors; yield and quality. Yield grade defines the amount of lean meat obtainable from a carcass, whereas the quality grade is more closely related to taste or palatability of the meat. Physical characteristics of the longissmus dorsi (l.d.) muscle, or ribeye, like size and the amount and distribution of intramuscular fat (marbling) are important factors in the determination of carcass yield and quality grades. The ribeye area, rib-fat thickness, and carcass weight are used to estimate the yield grade of the carcass. Visually discernible characteristics such as muscle color and marbling indicate "eating" quality of the meat and are used to assign quality grade (Gerrard et al., 1995).

A human grader generally estimates these visual characteristics from observation of the cross-sectional surface of the l.d. muscle. Although highly trained, these graders are subject to fatigue, emotional strain, and other stresses, which can affect their decisionmaking process. Further, the working environment and the high rate of inspection demanded are tiring and can cause inconsistencies in judgement of quality. Because this grading decision establishes the value of the carcass, a methodology providing objective quality assessment would be desirable. Automation of the grading process suggests the need for computer-based simulation of the observational and reasoning skills of a human grader.

Machine vision and digital image processing have great potential for automating machines and quality control processes. Machine vision technology in the form of video cameras, image digitizers, and computer processing best matches the human eye for automated grading. Over the past 10 to 15 years, work has been done to apply video image analysis to the automation of grading various agricultural products, including beef. Today's advanced video imaging technology offers much in the area of color and morphological quality evaluation.

Objectives

This study is intended to develop a system to assess the quality grade of beef. The objectives of this research are to:

1. Extract relevant grading parameters using USDA Marbling Standards and the Iowa State University Color Standards as reference.
2. Develop an algorithm to separate and isolate the ribeye from beef steak images, measure marbling and color parameters, and assign quality grades.
3. Train the system with tests using sample steaks and information from the standards.

4. Evaluate performance by comparing quality parameters and grades determined by the machine vision system with those assigned by the expert graders.

Assumptions

Certain assumptions about the handling and grading environment were required to put a reasonable limit on the extent of this research and study.

The first assumption was that the steaks would be chilled for at least 24 hours before grading. This procedure is required to accentuate the distinction between the fat and the lean in the ribeye (Lenhart and Gilliland, 1985).

The second assumption was that only one steak at a time would appear in the field-of-view (FOV) of the camera. The image processing procedure is much simpler if the algorithm must identify only one object per image. Orientation of the steak was not a constraint.

Lighting adequate for color definition was assumed. A dedicated lighting chamber was designed to provide uniform, diffuse lighting throughout the imaging area.

The final constraint was the presence of a dark background to provide contrast with the steak image. A pan with a non-reflective black surface was used to position the steak beneath the camera.

CHAPTER II

REVIEW OF LITERATURE

Introduction

Goals of the U.S. beef industry are to become more competitive in the marketplace and to regain and enhance consumer demand, confidence, and profitability (Cross and Whittaker, 1992). The industry has been rapidly transitioning from a commodity-driven to a consumer-driven industry (Park et al., 1994). The need for instrument-based, objective assessment of carcass value has grown, because the cattle producers feel that the present subjective grading system does not give sufficient confidence to the consumers or themselves.

Carcasses are graded, based on degree of development of specific desirable physical characteristics. The most important considerations are differences in the proportion of the more desirable to less desirable components. The important beef carcass quality attributes are (Thane and Whittaker, 1990):

1. Degree of marbling
2. Level of skeletal maturity
3. Texture of lean muscle

4. Firmness of lean muscle and fat
5. Color of lean muscle and fat

Quality of a carcass can be defined as the relative desirability or expected palatability (tenderness, flavor, and juiciness) of the meat (Thane and Whittaker, 1990). In determining the final quality grade of a carcass, the level of marbling and muscle color are the most important parameters (USDA, 1989).

Carcass maturity is determined by evaluating the skeletal characteristics; the size, shape and degree of ossification of the bones and cartilage (Thane and Whittaker, 1990). The color and texture of the ribeye surface between the 12^{th} and 13^{th} rib cross-section is believed to be equally important in determining the maturity of the carcass. Color of the lean may be divided into eight different classes (Iowa State University, 1989) as shown in Figure 1.

1. Bleached red
2. Very light red
3. Moderately light cherry red
4. Cherry red
5. Slightly dark red
6. Moderately dark red
7. Dark red
8. Very dark red

The USDA beef grading standards recognize five levels of carcass maturity for beef,

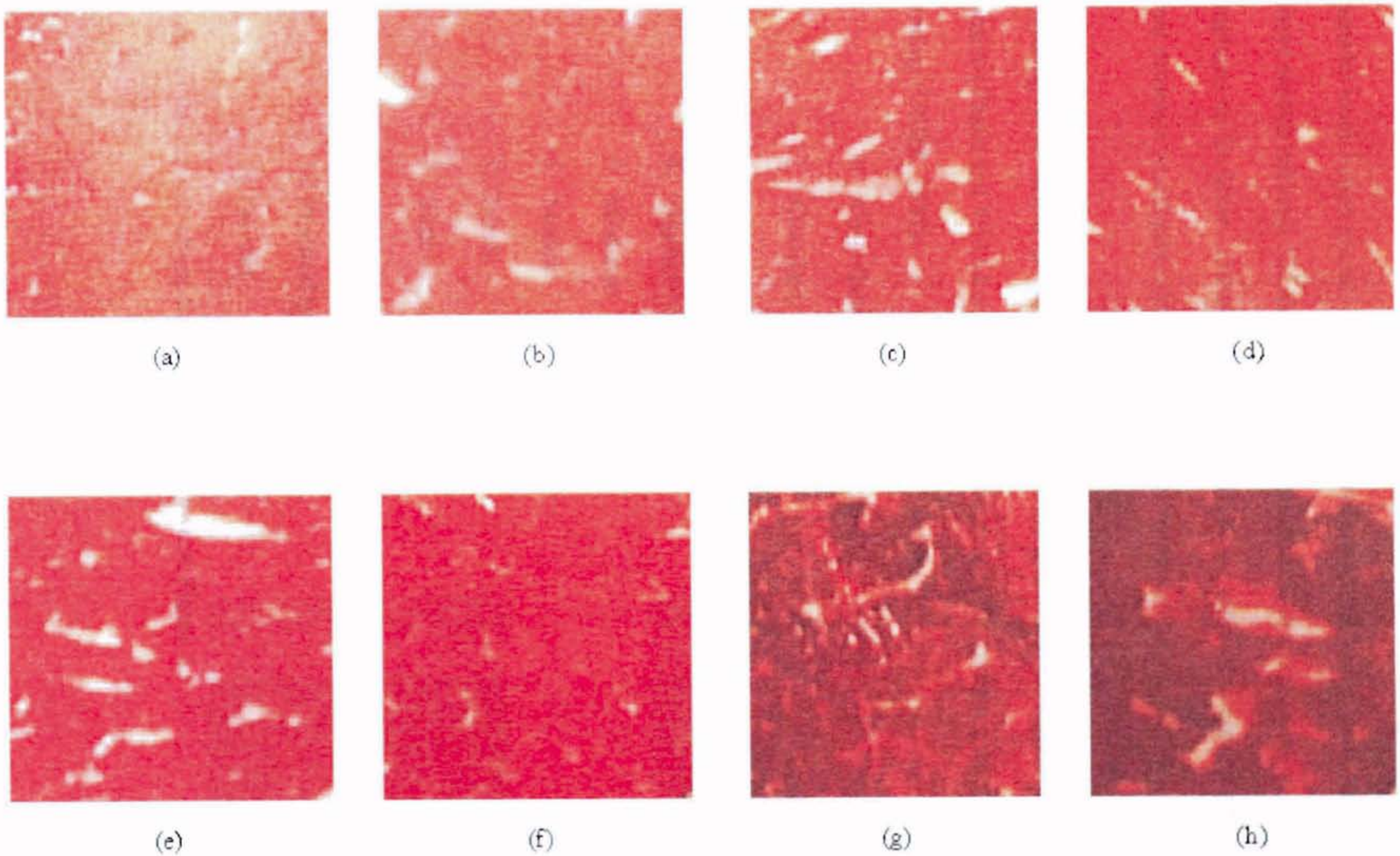

Figure 1. Lean color standards based on Iowa State University standards. (a) bleached red, (b) very light red, (c) moderately light cherry red, (d) cherry red, (e) slightly dark red, (f) moderately dark red, (g) dark red, (h) very dark red.

represented by levels A, B, C, D, and E (USDA, 1989). In evaluating the overall maturity level, expert graders combine the scores suggested by the lean color of the ribeye section between 12th and 13th ribs and by the skeletal characteristics, with more emphasis on the latter. Maturity levels D and E are not relevant in quality grading, since their presence would place the overall grade below acceptable range.

Marbling is the visible fat found on the surface and distributed throughout the ribeye muscle (Thane and Whittaker, 1990). Eleven degrees of marbling are used in beef grading (USDA, 1989):

1. Very Abundant
2. Abundant
3. Moderately Abundant
4. Slightly Abundant
5. Moderate
6. Modest
7. Small
8. Slight
9. Traces
10. Practically devoid
11. Devoid

Some of the most common distributions are shown in Figure 2.

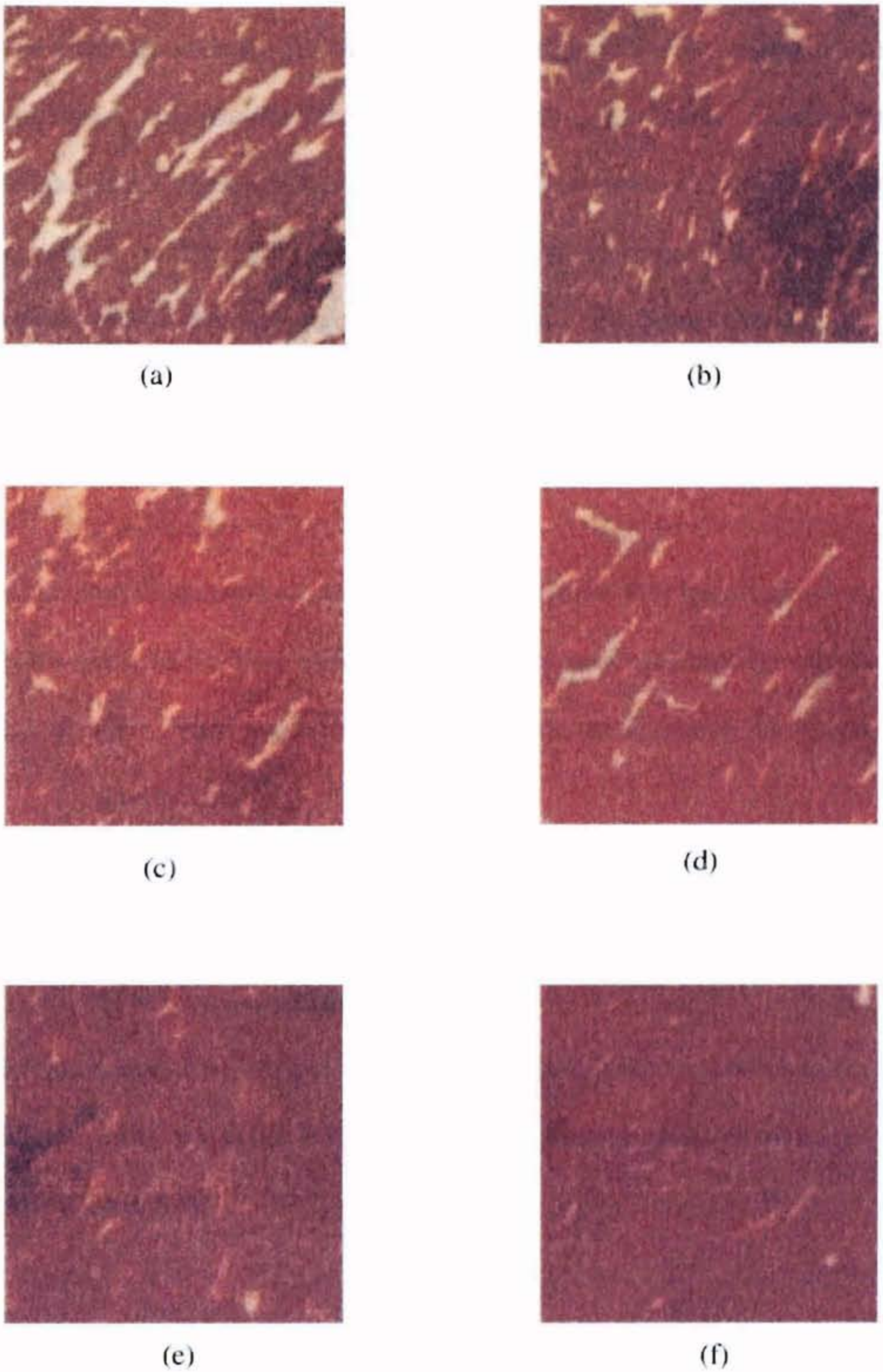

Figure 2. Degrees of marbling according to USDA standards: (a) moderately abundant, (b) slightly abundant, (c) moderate, (d) modest, (e) small, (f) slight.

Historical Background

The USDA adopted standards for grading beef carcasses in 1927. The inspection assigns two different grade types to the carcasses; yield grade and quality grade. Quality grade is based on the marbling, texture, and maturity of the carcass. Research has shown that these factors correlate with the palatability of beef to a limited extent (Lenhert and Gilliland, 1985). The USDA quality grades are; Prime, Choice, Select, Standard, Commercial, Utility, Cutter, and Canner, in order of decreasing palatability (Thane and Whittaker, 1990).

Yield grade indicates the amount of usable meat present in the four major primal cuts of a carcass after the waste fat has been trimmed. The grades are represented by the numbers; USDA 1, 2, 3, 4, and 5. Yield grades are determined from the following four parameters:

1. Fat thickness
2. Ribeye area
3. Percent of kidney, heart, and pelvic fat
4. Warm carcass weight.

Yield grade is computed as: yield grade = 2.5 + (2.5 * fat thickness in inches) + (0.2 * percent of kidney, heart, and pelvic fat) - (0.32 * inches squared of ribeye muscle) (Lenhert and Gilliland, 1985).

Before a carcass can be graded, it should be chilled for at least 24 hours. This treatment enables the marbling to become more visually apparent. In actual on-line grading operations, the USDA grader has approximately 10 to 15 seconds per carcass to evaluate all the criteria and assign the yield and quality grades. Because of this critical constraint, the grader has insufficient time to manually measure the parameters. Hence, the grading becomes a visual judgement process, instead of an objective process. The system carries an inherent error rate due to this subjectivity.

Cross et al. (1983) indicated that about 21 percent of carcasses were graded incorrectly by the trained USDA graders. Apart from grading inaccuracies within a supervisory mainstation, there was inconsistency in interpretation of marbling levels among mainstations. Even though the yield grading process was more objective, the report concluded that in actual applications, the error was greater for yield grading than quality grading. This result encouraged the USDA to seek a more objective means for grading carcasses.

Demands for automated grading had also been felt in other agricultural areas like fresh produce quality evaluation. Machine vision was the technology of choice in most of the suggested and implemented systems. Developments in the field of image processing have been instrumental in building systems that grade produce like fruits and vegetables. Notable examples are the automation of a cucumber processing line, which sorted according to shape and length (Nakahara et al., 1979) and the apple sorting technique outlined by Rehkugler and Throop (1986). This has encouraged the development of similar systems to grade beef, using advanced image processing techniques and grading schemes.

One of the earliest serious efforts to develop an objective means of grading beef carcasses was carried out by the National Aeronautics and Space Administration (NASA). In 1978, research was conducted at the NASA Jet Propulsion Laboratory (JPL) to determine if NASA technology could be applied to beef grading (Cross and Whittaker, 1992). They concluded that ultrasound and video image analysis were the best available methods for the automation of beef grading (JPL Invention Report, 1987). Image analysis was judged to hold the most direct and immediate application to assist the grader, while ultrasound had the advantage of being useful on live animals or intact carcasses. The Agricultural Research Service was subsequently funded to develop an instrument to provide quality and yield grading of beef carcasses (Cross and Whittaker, 1992). A technical committee was formed to develop a Request for Proposals. Among the eight different proposals based on imaging analysis and ultrasound, Kansas State University was awarded the contract in 1980.

From 1981 to 1983, the Roman L. Hruska USDA Meat Animal Research Center cooperated with Kansas State University to develop and test a video image analysis (VIA) unit (Cross et al., 1983). The system consisted of a camera, video monitor, data terminal, and computer. The camera was positioned at a controlled distance and angle, with respect to the beef carcasses. The angle of the camera appeared to influence the results. The system took approximately 10 to 14 seconds to grade a carcass. The subcutaneous fat thickness was measured at several points and averaged. The VIA measured the following parameters:

1. Total fat area

2. Total lean area
3. Number of, and area occupied by, marbling flecks

Cross et al. (1983) reported that the system had more potential as a yield-grading than a quality-grading device.

In 1984, the USDA invited industry representatives to discuss the status of instrument grading (Cross and Whittaker, 1992). Five state-of-the-art-technologies were identified and assessed:

1. Nuclear Magnetic Resonance (NMR)
2. Near Infrared Reflectance (NIR)
3. Real-time Ultrasound
4. Video Imaging
5. Computerized Axial Tomography (CAT) Scan

The NMR and CAT technologies were eliminated because they were too expensive. Research in NIR had not progressed far enough to be useful in determining marbling. Video imaging had limitations because of its need for unribbed, unchilled carcasses. Ultrasound, which at that time had an edge because of the advances made in the medical field, was judged the best choice to automate beef grading.

In 1984 and 1985, research was conducted to determine the potential of ultrasound for beef grading (Cross and Whittaker, 1992). Staff from the National Livestock and Meat Board, the American Meat Institute, National Cattlemen's Association, Texas A & M University, and Cornell University met and combined their efforts for this purpose.

Texas A & M University investigated the usefulness of ultrasound in measuring the yield traits. Studies were conducted at Cornell University to measure marbling content. Results on fat thickness and ribeye muscle were promising, but the results on marbling were marginal. Results did suggest that ultrasound had potential for grading beef.

In 1989, the Australian Meat and Livestock Corporation and the Australian Meat and Livestock Research and Development Corporation hosted a symposium in Sydney on the "Automated Measurement of Beef." State-of-the-art activities were discussed, and ultrasound was identified to have the greatest potential for grading beef (Cross and Whittaker, 1992).

In a project initiated in 1983, the Danish Meat Research Institute developed the Beef Classification Center (BCC) (Petersen et. al., 1989). The prototype instrument, using VIA technology, was tested in 1989. The output of the unit consisted of an index for muscularity and an index for the value of the carcass, based on carcass composition determination. The system included a reflection probe measuring device and an electronic weighing system. The BCC was installed after regular meat inspection on the slaughterline. The carcass was illuminated from the back and a camera placed about 3 m away. Information gathered was used to measure the carcass length and width. Later, a green light was used to illuminate the front to achieve good discrimination between the fat and lean. A probe was used manually to measure fat thickness. Weight was measured automatically.

Work proceeded in the U.S. at the same time, with concentration on the VIA method. Many advances were made in the image-processing field. Chen et al. (1989) developed an algorithm to segment and isolate the ribeye from the cut surface of the 12^{th} and 13^{th} cross-section of the carcass. The gray-scale image was first binarized using a simple threshold. There was a large difference between the gray scale values for the intermuscular fat and lean. That range easily facilitated the process of choosing a threshold. Next, a chain-coding algorithm (Ali and Burge, 1988) was used to define the boundary of the ribeye. Some extraneous tissue was normally included with the actual ribeye. The next step was to separate the intramuscular fat from the lean. Because gray values in the histogram were not clearly separated, a minimum error method was used to pick an optimal threshold. This method had limitations, because it required the background illumination to be uniform throughout the image for correct thresholding.

McDonald and Chen (1990a) developed two algorithms to remove the extraneous tissues that normally were segmented along with the ribeye. Quality grade may be affected if the marbling properties of external portions are significantly different from the l.d. itself. Meyer (1979) developed an algorithm to separate component parts from a union of convex sets. The algorithm was based on sequential shrinking of overlapping components causing the connecting points to erode away and thus leaving two disjointed blobs (McDonald and Chen, 1990a). This algorithm had limitations in separating the l.d. muscle because of the concavities present in its shape. McDonald and Chen (1990b) modified the algorithm by limiting the number of image erosions. It was justified by the assumption that there is a limit in size to the connecting pieces. This method performed well on images, except when the connection between the ribeye and the unwanted tissue was relatively long. The second method, called the removal algorithm, used binary opening procedures. Binary opening is similar in function to mechanical sieving. It removes all the bridges connecting external pieces to the largest blob, and thus everything except the largest blob disappears from the image. The only constraint was that the structuring element had to be larger than the largest piece of extraneous tissue. The algorithm produced good results in most cases. However, for both algorithms, time consumed for the operation made it almost impractical to be used for real-time grading.

Zhuang et al. (1992) reported developing a neural network to segment pork images using the color information from the red, green, and blue spectral channels. It showed satisfactory results for segmenting pork ham images.

Gerrard et al. (1995) pioneered the use of color image processing techniques for assessing beef muscle color and marbling. The muscle was segmented from fat based on three-dimensional color space (red, green, and blue). Marbling flecks were then segmented from the muscle. The means and variances of the red, green, and blue components were used to score the color of the lean. It was found that the red and green means were better predictors of color than the blue mean. The areas as well as the density of the small flecks were found to strongly influence the marbling score. Their research suggested that the size and number of flecks biased the perception of marbling by manual graders, even though USDA standards mandate considering flecks regardless of their size. Apart from color and marbling, work has also been conducted to extract the texture features from the beef images. The texture features were found to be good indicators of beef tenderness, which is considered important in quantitative palatability evaluation (Li et al., 1997). They attempted to utilize machine vision techniques, including neural networks, to extract texture features that are difficult for graders to capture. It also allowed characterization of color and marbling in a more efficient manner.

Most recently, the Canadian Computer Vision System was developed by the Canadian Cattlemen's Association and Canadian Meat Council in conjunction with the Lacombe Research Station. This system incorporated neural networks, used two separate cameras to measure carcass and ribeye characteristics, and produced a combined yield grade which was found to be twice as accurate as their current yield ruler method.

A vast amount of research aimed at developing an objective method for grading beef has been conducted over the past 10 to 15 years. Recent advances in the field of color image processing can make contributions toward this goal. This research is intended to investigate the use of color information from the l.d. muscle to determine the quality grade of the carcass.

CHAPTER III

METHODS AND PROCEDURES

Chapter Overview

This chapter discusses the design and development of beef grading system based on video image analysis. System design was accomplished and implemented primarily in software. The goal of the VIA unit was to reproduce human grader's skills and judgement in meat grading. The algorithm was hence based on the methods used by a professional grader to grade meat according to quality standards. However, there were constraints regarding the grading environment that could be recreated in the lab that had to be accommodated.

The beginning of this chapter is divided into two sections, the first one describing the hardware design and the second software design. This development description is followed by an account of the testing procedures used.

Hardware Design

A VIA unit capable of grading beef requires simulation of the human grader's vision and image processing capabilities. Therefore, the basic requirements for the system were a color camera, an image digitizer board, and a computer. The color camera captured the image, and the digitizer converted the analog image signal to digital format. This digital image was processed and analyzed by the computer.

A MicroImage A209 RGB color video camera and 8-mm lens were used. Lens aperture was selected to avoid saturation of the red, green, and blue components in the image. Focus of the camera was fine-tuned when the first steak was presented.

An Integral Technologies Flashpoint 128 digitizer board was installed in a Pentium Pro 200MHz computer equipped with 64Mb of RAM, 4GB of hard disk space, and Windows NT operating system. These features ensured the sufficient speed and memory for the application. Images were regularly backed up on CD ROM.

A vaulted lighting chamber was designed for uniform and diffuse distribution of light. The white interior of the arched cover directed base lighting to a 20 x 30 cm imaging area. Light was supplied by six 50-watt halogen lamps powered by a feedback controller, to stabilize illumination level.

The camera was mounted above the lighting chamber, viewing the imaging area through an observation port. A removable pan with a non-reflective black surface was used to center the steak beneath the camera. Distance from the camera lens to the pan was approximately 0.3 m.

Software Design

Optimas Ver. 6.1 was used for software development (Optimas, 1997). This image processing software supports a substantial library of image acquisition and processing functions. Custom macros were created in the Optimas proprietary programming language, Analytical Language for Images (Appendix B).

Algorithm

An algorithm was designed on the basis of procedures used by a trained grader. The quality grading scheme is defined by the chart shown in Figure 3 (Dolezol et al., 1996). The two most important factors in deciding quality grade are the marbling level and the carcass maturity. Expert graders assess the marbling and maturity by observing the carcass after sectioning between the 12^{th} and 13^{th} ribs. In this study, ribeye steaks cut between the 12^{th} and 13^{th} ribs were used in place of a ribbed carcass (Fig. 4).

Fat percentage on the ribeye surface was determined by segmenting and measuring the area of the fat flecks within the ribeye. The arrangement in Table I was adopted, after preliminary studies, to convert the actual fat area percentage to marbling class levels. The chart shown in Figure 3 requires the marbling to be represented as a level in a marbling class.

Carcass maturity is assessed by the grader by observing the lean color on the sectioned carcass and specific skeletal characteristics. VIA used only the lean color between the 12^{th} and 13^{th} rib-sections to gauge the carcass maturity, because it was not designed to

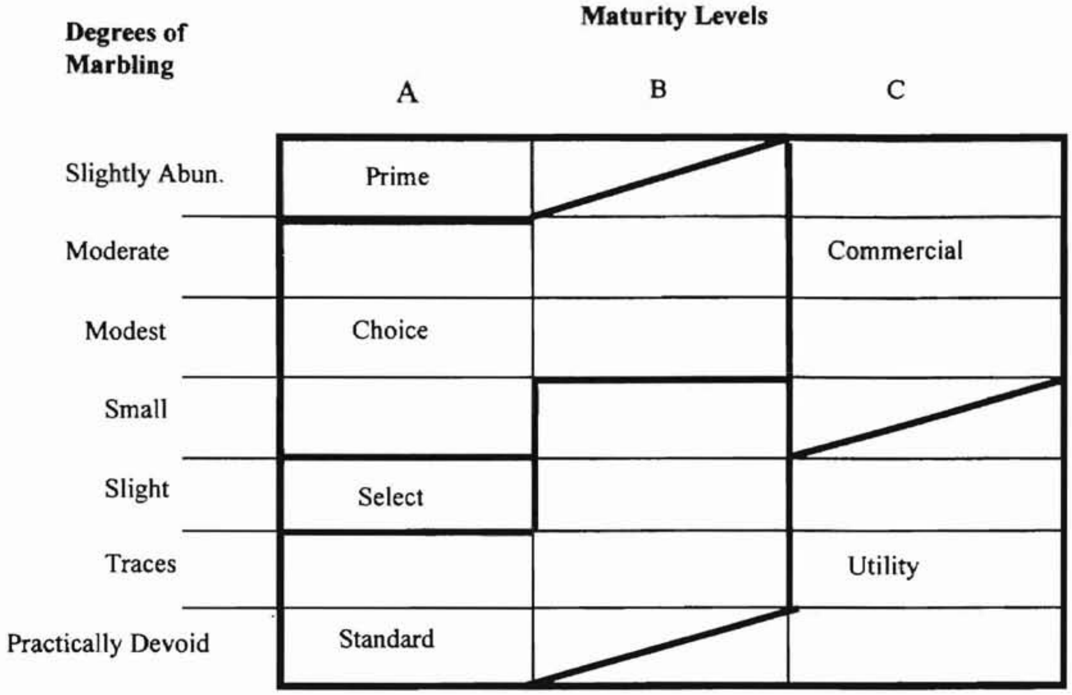

Figure 3. Relationship between marbling, maturity and carcass quality grade.

measure other parameters. The algorithm was developed to distinguish only between maturity levels A, B, and C. Levels D and E were not considered, because they are outside of acceptable quality standards. The lean color was divided into eight different classes and then converted into a carcass maturity score. Tables II and III show the values used for this purpose.

When the marbling level and the carcass maturity were decided, they were combined to generate a quality grade based on the chart in Figure 3.

Program

The program began by spatially calibrating the system. The height and position of the camera were decided before the imaging process began, after sample steaks were presented. A standard calibration grid was then placed beneath the camera, and the image was used to calibrate the system. The settings were saved into a calibration configuration file. The program used this configuration file to calculate the area in centimeters.

Proper color calibration of the machine vision system was ensured by imaging color standards for red, green, and blue and by camera aperture adjustment to avoid saturation under current light settings.

The first and the most difficult of the image processing tasks was to segment and isolate the ribeye from the steak. Images were acquired and saved in the red, green, blue (RGB) format. The software supported conversion between RGB and hue, saturation, intensity (HSI) formats. Both of these models were analyzed to determine which could provide more information for segmentation. By comparison, the red band information from the RGB model was found to be most definitive for segmenting the lean from the intermuscular fat and the background. The green band, however, separated the fat effectively from the lean and the background. Thresholding based on color band intensity was implemented to segment the lean using the red band and the fat using the green band.

The first task was to remove the intermuscular fat from the steak image. This operation was required in order to isolate the ribeye from the image. On some of the sample steaks, a certain amount of intermuscular fat had been trimmed. This effect challenged the initial program, which defined the ribeye as the largest lean area enclosed by the intermuscular fat. Removing the intermuscular fat from the image before isolating the ribeye solved this problem.

The green band was used to threshold the fat. The program was designed to define areas based on this threshold as fat pieces. These fat pieces were spatially filtered to choose those with an area larger than 0.6 sq. cm. This precaution ensured that no intramuscular fat was eliminated along with intermuscular fat. The intermuscular fat pieces were then removed from the image. These steps are shown in Figures 5 and 6.

The resulting image consisted of only the ribeye and a few extraneous tissues. The extraneous tissues were a result of incomplete separation by fat, between the ribeye and the tissues. Morphological operations were required to isolate the ribeye. Several available algorithms were considered. Processing time involved with each of these algorithms was the primary selection criterion. A trade-off was required between the level of segmentation and the processing time required.

McDonald and Chen (1990b) had developed two algorithms for this purpose. The first was a modification of the Meyer's algorithm (Meyer, 1979). Meyer's algorithm suggested binary erosions (shrinking) of the image until the touching blobs were separated. This sequence was followed by dilations (expansions) to regrow the image to original size. The second algorithm, called the Removal Algorithm, involved binary "opens". A binary open consists of consecutive erosions and dilations and is similar to mechanical sieving in effect. It removes the bridge connecting blobs and generally smoothes the boundaries. This process, even though very effective, consumed considerable processing time. To compromise between processing speed and segmentation quality, the modified Meyer's algorithm (McDonald and Chen, 1990b) was chosen. These image processing steps ensured the isolation of the ribeye from all the extraneous tissues (Fig. 7 and 8).

The next task was to determine marbling percentage on the ribeye. Only fat flecks satisfying the constraint that surface area be less than 1 sq. cm were considered while computing the fat percentage. This limit followed the assumption that the human graders would disregard the larger fat pieces when assigning the marbling level.

Uniformity of fat distribution was also accounted for in determining the marbling score. After calculating the centroid of the ribeye, the image was divided into quadrants. Green-band thresholding was applied, and the marbling pieces were identified. Marbling percentage for each quadrant was then computed separately and the average taken. Total fat percentage for the ribeye was also computed. These two values were compared and the lower value was chosen. This selection ensured that when fat distribution was highly non-uniform, the quadrant average (being lower) would be chosen for the final marbling score (Fig. 9).

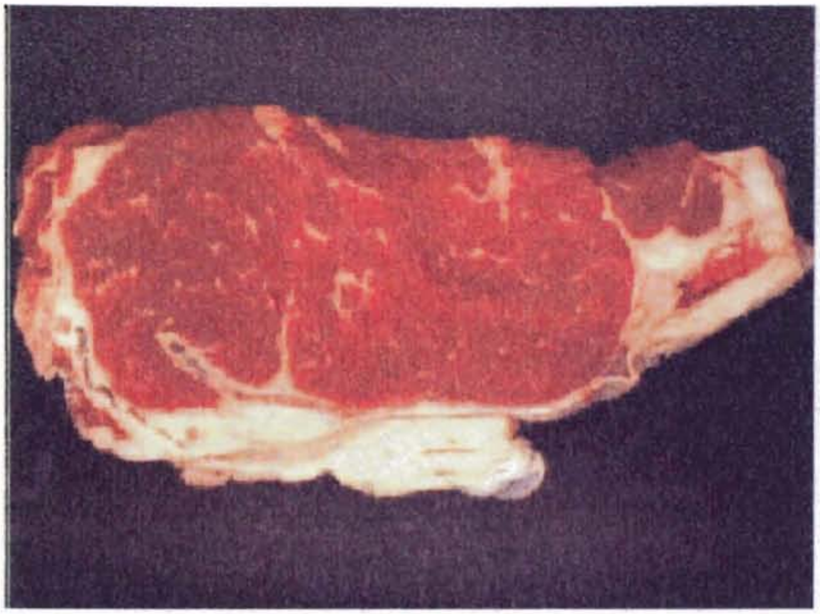

Figure 4. Ribeye steak cut between the 12^{th} and 13^{th} ribs of the carcass.

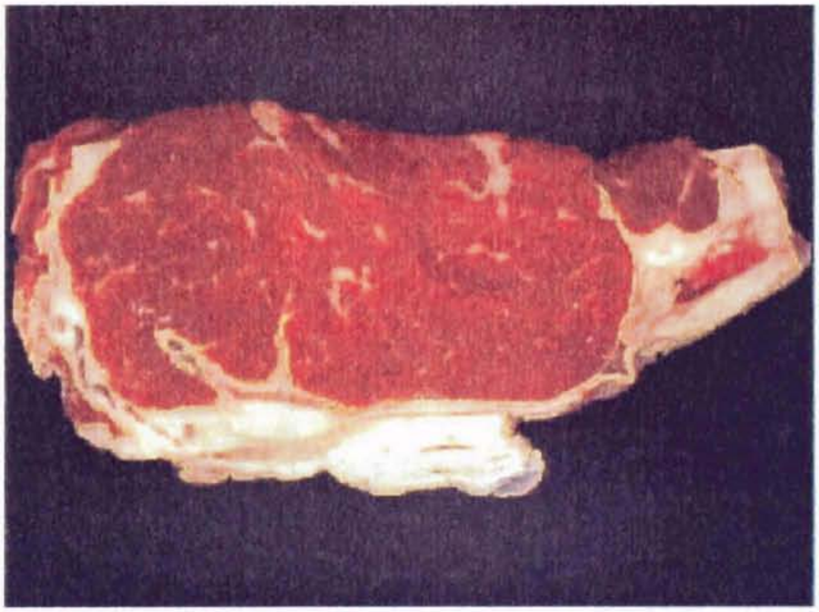

Figure 5. Intermuscular fat identified and shown with yellow border.

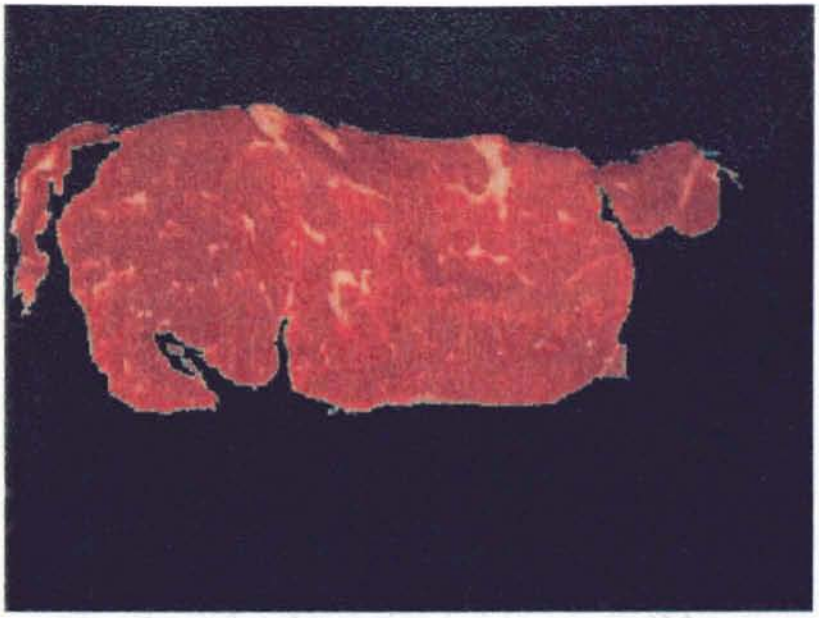

Figure 6. Ribeye and extraneous tissue, after intermuscular fat is identified and removed.

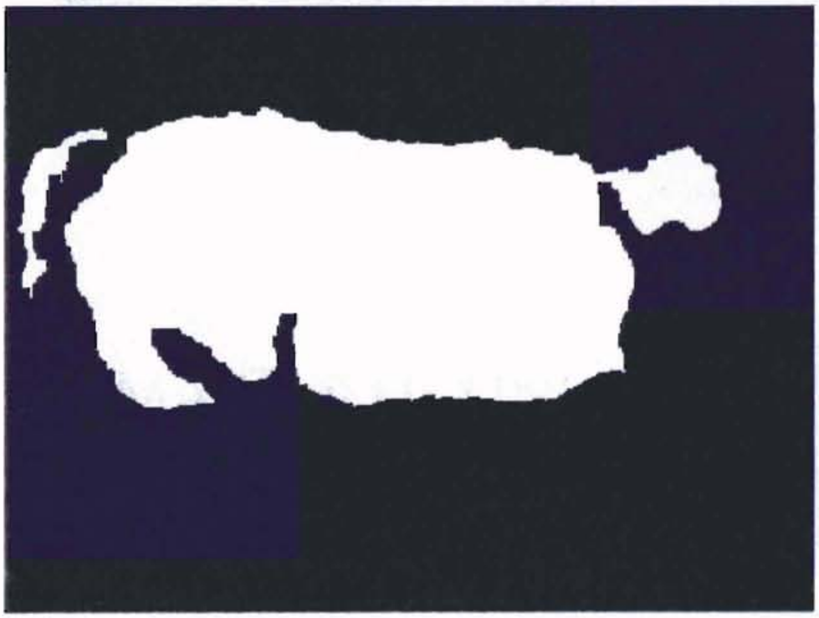

Figure 7. Intermediate stage in separation of extraneous tissue.

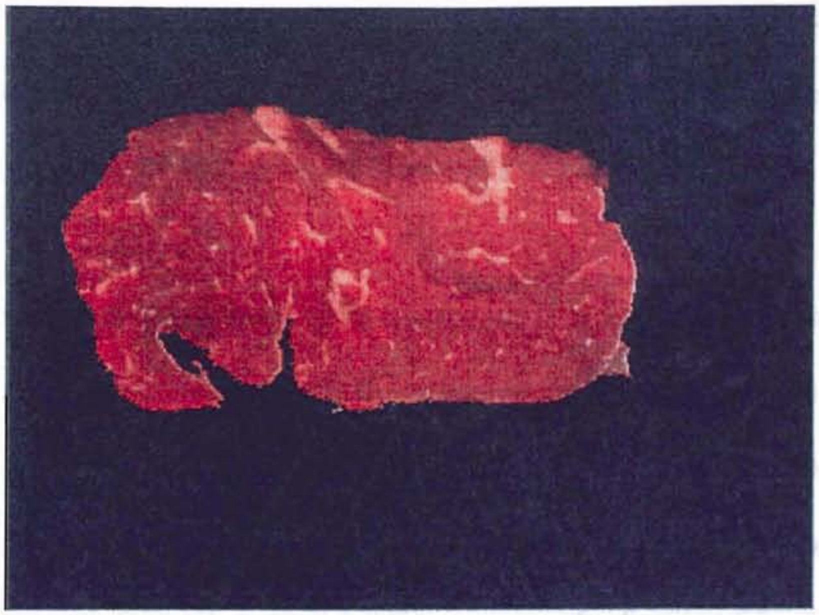

Figure 8. The isolated ribeye.

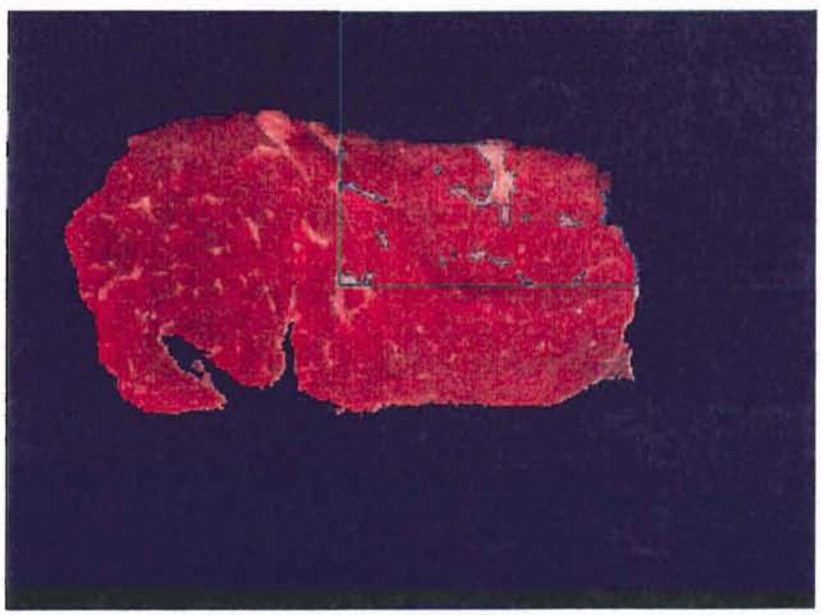

Figure 9. Fat flecks identified with blue border in second quadrant.

Marbling scores are normally represented in terms of their marbling level in each class. The percentage of fat computed thus needed to be converted into standard USDA marbling class values (Table I). By repeated comparison, the percentage values classifying each of the marbling levels were bracketed and implemented.

The final relevant information to be obtained was the lean color. The Iowa State University standards were used to calibrate the color range (Fig. 1). These standards divided the lean color into eight different classes. Lean color is an indirect indicator of carcass maturity. Graders normally assign carcass maturity as perceived average of the lean color of ribeye and bone color. In this study, because ribeye steaks were used instead of ribbed carcasses, maturity was computed from the lean color alone.

Instead of the means of the three color bands (red, green, and blue), their peaks or modes were used to generate a color score. It was determined by comparison that giving equal weights to the red, green, and blue contents resulted in closer matching of scores with human grading. The color scores were then converted to levels on one of the three maturity classes. Lean colors 1 to 4 were classified as A, 5 to 7 as B, and 7 to 8 as C.

Once marbling and maturity scores were determined, the grader's chart (Fig. 3) was used as reference for computing the quality grade. This chart is normally used by expert graders to assign quality grade. The chart was logically implemented in the processing software. A quality grade was then determined by the program, based on the image analysis, scores, and the chart.

Procedure

The system was designed and trained with the standard photo cards for marbling and lean color used by manual graders. After this procedure, three different sets of 10 to 15 sample steaks graded by an expert grader were used to fine-tune the system.

Performance evaluation of the VIA system was conducted with a new set of 40 pairs of ribeye steaks obtained from an area commercial packing plant. Steaks presenting a broad range of marbling and color levels were removed from the 12^{th} and 13^{th} ribs of carcasses that had been chilled for bloom development. One steak in every pair was used to conduct proximate chemical analysis to determine the total fat percent. The remaining half were imaged individually by the VIA system for marbling, color, and grade as described earlier.

Prior to imaging, each steak was evaluated by two beef grading experts from Oklahoma State University Animal Science Department who assigned color scores, marbling scores, and quality grades according to standards the same as those used by the VIA system. For further comparison of marbling, results from the proximate chemical analysis for fat content were analyzed against grades assigned by the experts and the system.

CHAPTER IV

RESULTS AND CONCLUSIONS

A sample set of 40 steaks was evaluated for marbling, color, and quality grade by the VIA system and by two expert meat graders. Scores and grades generated by the experts were averaged for comparison with machine vision assessment. For further marbling comparison, matched steaks were analyzed chemically for fat content.

Statistical tests were conducted to compare results obtained from these three evaluation sources. Source data are included in Appendix A.

Results

<u>Comparison of color scores</u> Color scores were compared using paired t-tests and r^2 values. The paired t-test results showed a significant difference between the expert grader's color scores and the machine's computed color scores. The t-computed had a value of 6.389 and exceeded the t-critical 2.021 at a 95 % confidence interval (Table V). However, the r^2 value obtained when the machine scores were regressed against the expert grader's scores was 0.80. This result suggested relatively high correlation ability of the VIA system to predict expert color scores.

Comparison of marbling scores Apart from the expert graders' scores and the machine vision system's scores, another set of marbling data was available from the proximate analysis procedure. Proximate marbling percentages were converted into marbling levels using the classification criteria developed for the machine scores. The expert graders' scores were available in marbling class levels, only. Analysis of variance statistics (Anova) tests were used to compare the three sets, as well as every combination as a pair. The three sets of data were found to be significantly different (95 % confidence), with an F-computed of 3.74 and F-critical of 3.073. The F-computed for Anova applied to expert grader scores and machine vision system scores was 0.842. It was concluded that the two sets were not different from each other, since the F-critical was as high as 3.96. The machine vision system data was, however, determined to be significantly different from the proximate analysis data with F-computed of 7.021 and F-critical of 3.96 at a 95 % confidence level. The last comparison was made between the human graders' scores and proximate analysis data. The F-computed was 3.043 and the F-critical was 3.96. The two sets were thus concluded to be not significantly different from each other. The Anova test results are shown in Table VI.

Paired t-test comparisons were also performed on the three pairs of marbling data (Table V). The t-computed was 1.186 for the grader scores vs. machine scores and indicated that the two groups were not different at a 95% confidence level. Proximate analysis scores were found to be different from the machine scores with a t-computed of 3.668, and from the human grader's scores with a t-computed of 3.44. Confidence level used in both cases was 95%. The t-critical in all the cases was 2.021.

The r^2 value for the machine-human pair was 0.55, the machine-proximate pair was 0.23, and the human-proximate was 0.16 (Table IV).

Comparison of grades The average of the human graders' scores was compared with the machine scores. A paired t-test was conducted. The t-computed was 0.813 as opposed to a t-critical of 2.021 (Table V). Therefore, the two sets were concluded to be not significantly different. The r^2 was only 0.18, suggesting a low predictative correlation between the two data sets (Table IV).

Conclusions

Statistical tests performed on the data obtained from the test steaks were used as the basis for the following conclusions.

The machine vision system's scores were found to be reasonably close to the human grader's scores regarding the color, marbling, and quality grades. The high r^2 of 0.8 for the color comparison means that the system was able to very closely predict the human grader's judgement.

The proximate analysis results for the marbling score were found to vary considerably from the human grader's as well as the machine's assessment. This result could be attributed to the fact that the proximate analysis assesses the fat content based on the whole ribeye, rather than surface appearance. Machine results were found to be closer to the expert grader's marbling scores. The paired t-test as well as the Anova test results showed that the two sets were not significantly different. Also, the r^2 value for this pair is higher than either of the other two combinations.

The r^2 for the grade comparison was relatively low, but the paired t-test results indicated that they were not significantly different. Hence, we can say that the total quality grade computed by the machine followed the expert graders' assignments. Performance of the system in marbling prediction did not achieve the level shown for color prediction. Overall, it can be concluded that the machine vision system was able to successfully simulate a human grader's skills in quality grading of beef.

Further Research

The results from testing the VIA system showed promising results in substituting or assisting a human grader for quality inspection of beef. Color image processing appears to offer a system that is better and more efficient. Algorithms can be developed to assess additional parameters such as the distribution of fat specks, intermuscular fat thickness, skeletal muscle color, etc., to provide more useful information in deciding the quality grade of beef. This would in turn assist in simulating the human grader's complex processing and grading procedure.

Table I - Conversion from fat area percentages to marbling levels.

Fat area percentages	Marbling levels assigned
0 - 1.5	Practically Devoid
1.5 - 3	Traces
3 - 5	Slight
5 - 7.5	Small
7.5 - 10	Modest
10 - 13	Moderate
13 - 15	Slightly Abundant
15 - 18	Moderately Abundant
18 - 21	Abundant

Table II - Conversion from color scores to color classes.

Color scores (R+B+G)	Color classes
518 - 468	Bleached red
468 - 418	Very light red
418 - 368	Moderately light cherry red
368 - 318	Cherry red
318 - 293	Slightly dark red
293 - 268	Moderately dark red
268 - 243	Dark red
243 - 218	Very dark red
218 - 0	Dark cutter (out of acceptable range)

Table III - Conversion from color classes to maturity levels.

Color classes	Maturity levels
Bleached red	A
Very light red	A
Moderately light cherry red	A
Cherry red	A
Slightly dark red	B
Moderately dark red	B
Dark red	C
Very dark red	C
Dark cutter (out of acceptable range)	D

Table IV - Regression of machine color scores, marbling scores, and quality grades vs. expert evaluation.

Sensory scores	r-squared
Color	0.80
Marbling	
Expert vs. Machine	0.55
Machine vs. Proximate	0.23
Expert vs. Proximate	0.16
Quality Grades	0.18

Table V - Paired t-test results for the machine color scores, marbling scores, and quality grades vs. expert evaluation.

Sensory scores	t-critical	t-computed
Color	2.021	6.389
Marbling		
Expert vs. Machine	2.021	1.186
Machine vs. Proximate	2.021	3.668
Expert vs. Proximate	2.021	3.44
Quality Grades	2.021	0.813

95% confidence level

Table VI - Comparison of the expert, machine, and proximate analysis marbling scores.

Marbling scores	F-critical	F-computed
Expert, Machine, and Proximate	3.073	3.74
Expert vs. Machine	3.96	0.842
Machine vs. Proximate	3.96	7.021
Expert vs. Proximate	3.96	3.043

95 % confidence level

REFERENCES

Ali, S.M. and R.E. Burge. 1988. A new algorithm for extracting the interior of bounded regions based on chain coding. Computer Vision, Graphics, and Image Processing, 43: 256-264.

Chen, Y.R., T.P. McDonald and J.D. Crouse. 1989. Determining percent intra-muscular fat on ribeye surface by image processing. ASAE Paper No. 89-3009, ASAE, St. Joseph, MI 49085.

Cross, H.R., D.A. Gilliland, P.R. Durland and S. Seideman. 1983. Beef carcass evaluation by use of a video image analysis system. J. of Animal Science, 57(4): 910-917.

Cross, H. R., A. D. Whittaker and J. W. Savell. 1989. The objective measurement of value in meat animals. The Automated Measurement of Beef: The Australian Meat and Livestock Corporation.

Cross, H.R. and A.D. Whittaker. 1992. The role of instrument grading in a beef value-based marketing system. J. of Animal Science, 70: 984-989.

Dolezol, H.S., C.P. Foutz, C.S. Nick, B.A. Gardner, J.S.Nelson, and B.R. Schutte. 1996. Meat Grading and selection. Department of Animal Science, Oklahoma State University.

Fielding, W. G. 1994. Carcass tracking, computer assisted vision grading as tools for value based marketing. Proceedings of the International Congress of Meat Science and Technology, 40: 153-155.

Gerrard, D.E., X. Gao and J. Tan. 1995. Determining beef marbling and color scores by image processing. J. Food Science, 61(1): 145-148.

Iowa State University. 1989. Standards for Beef Color. Iowa State Extension Publication, #515.

JPL Invention Report. 1987. Electronic inspection of beef. NASA Tech Brief 11(6).

Li, J., J. Tan and F.A. Martz. 1997. Predicting beef tenderness from image texture features. ASAE Paper No. 97-3124, ASAE, St. Joseph, MI 49085.

Lenhert, D.H. and D.A. Gilliland. 1985. The design and testing of an automated beef grader. ASAE Paper No. 853035, ASAE, St. Joseph, MI 49085.

McDonald, T. P. and Y. R. Chen. 1990a. Application of morphological image processing in agriculture. Trans. of ASAE, 33(4): 1345-1352.

McDonald, T.P. and Y.R. Chen. 1990b. Separating connected muscle tissues in images of beef carcass ribeyes. Trans. of ASAE, 33(6): 2059-2065.

Meyer, F. 1979. Iterative image transformations for an automatic screening of cervical smears. J. Histochemistry and Cytochemistry, 27(1): 128-135.

Nakahara, S., A. Maeda and Y. Norma. 1979. Automatic cucumber sorting using pattern recognition technique. IEEE, Tokyo, Proceedings Denshi Tokyo, No. 18:46-48.

Optimas. 1997. Optimas 6.1 image analysis software. Optimas Corporation, Bothell, WA.

Park, B., Y.R. Chen, A.D. Whittaker, R.K. Miller and D.S. Hale. 1994. Neural network modeling for beef sensory evaluation. Trans. of ASAE, 37(5): 1547-1553.

Petersen, F., S. Klastrup, N.T. Madsen and S.E. Sorensen. 1989. Beef Classification Center. Proceedings of the International Congress of Meat Science and Technology, 35: 49-52.

Rehkugler, G.E. and J.A. Throop. 1986. Apple sorting with machine vision. Transactions of ASAE, 29(5): 1388-1397.

Thane, B.R. and A.D. Whittaker. 1990. Automated assessment of marbling in ultrasonic images of beef animals. ASAE Paper No. 90-7055, ASAE, St. Joseph, MI 49085.

USDA. 1989. Official United States standards for grades of beef carcasses. Agricultural Marketing Service, US Dept. of Agriculture, Washington, DC.

USDA Cattle and Beef Statistics. 1996. *http://www/usda/gov/statistics*.

Zhuang, X., A. Hetzroni, C.J. Precetti, B.A. Engel and G.E. Miles. 1992. Neuro-segmentation of color images in quality evaluation of pork hams. ASAE Paper No. 923595, ASAE, St. Joseph, MI 49085.

APPENDIXES

APPENDIX A – STATISTICAL ANALYSIS

Paired Observations Comparisons between the machine and human marbling level prediction

ID#	Human Avg	Machine	Difference
beef1	5.8	5.29	0.51
beef2	7	7	0
beef3	5.55	5.5	0.05
beef4	6.75	7	-0.25
beef5	6.8	5.7	1.1
beef6	5.9	5.04	0.86
beef7	5.9	5.2	0.7
beef8	5.25	6.5	-1.25
beef9	6.5	5.94	0.56
beef10	7.2	5.84	1.36
beef11	6	5.79	0.21
beef12	7.35	5.67	1.68
beef13	6.75	7	-0.25
beef14	5.85	5.15	0.7
beef15	5	5.87	-0.87
beef16	6.35	5.52	0.83
beef17	5.25	6.5	-1.25
beef18	4.75	4.8	-0.05
beef19	4.55	4.4	0.15
beef20	5.35	5.2	0.15
beef21	5.9	5.92	-0.02
beef22	6.2	5.52	0.68
beef23	5.65	5.05	0.6
beef24	6	5.44	0.56
beef25	5.45	5.11	0.34
beef26	5.15	4.8	0.35
beef27	6.25	5.62	0.63
beef28	5.5	7	-1.5
beef29	4	5.3	-1.3
beef30	6.55	5.22	1.33
beef31	5.85	7	-1.15
beef32	5.85	5.35	0.5
beef33	5.9	6.5	-0.6
beef34	6.75	6.5	0.25
beef35	6.8	5.75	1.05
beef36	5.75	4.8	0.95
beef37	4.8	5.27	-0.47
beef38	5.15	6.5	-1.35
beef39	6.85	6.5	0.35
beef40	6.45	6.5	-0.05

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.402650353
R Square	**0.162127307**
Adjusted R Square	0.140078025
Standard Error	0.709604158
Observations	40

Dependent Var	Human Avg
Independent Var	Machine

Sum	6.09
Mean	0.15225
Sum(D sqrd.)	26.6139
CT=(Sum(D))sqrd/40	0.9272025
SS	25.6866975
Var. D	0.658633269
S.D. D	0.81156224
S.D. Dmean	0.128319257
T computed	1.186493777
T critical	2.021

Hence the two sets of observations are not different at error level 0.05

Paired Observations Comparisons between the human and Proximate analysis marbling assessment

ID#	Human Avg	Prox. Anal.	Difference
beef1	5.8	5.98	-0.18
beef2	7	7	0
beef3	5.55	5.86	-0.31
beef4	6.75	7.66	-0.91
beef5	6.8	8.33	-1.53
beef6	5.9	6.5	-0.6
beef7	5.9	5.2	0.7
beef8	5.25	6.5	-1.25
beef9	6.5	5.98	0.52
beef10	7.2	7.66	-0.46
beef11	6	7	-1
beef12	7.35	7.66	-0.31
beef13	6.75	6.5	0.25
beef14	5.85	6.5	-0.65
beef15	5	5.96	-0.96
beef16	6.35	7	-0.65
beef17	5.25	4.8	0.45
beef18	4.75	5.22	-0.47
beef19	4.55	5.26	-0.71
beef20	5.35	5.18	0.17
beef21	5.9	6.5	-0.6
beef22	6.2	5.66	0.54
beef23	5.65	5.62	0.03
beef24	6	5.52	0.48
beef25	5.45	5.47	-0.02
beef26	5.15	5.2	-0.05
beef27	6.25	5.8	0.45
beef28	5.5	6.5	-1
beef29	4	4.8	-0.8
beef30	6.55	6.5	0.05
beef31	5.85	6.5	-0.65
beef32	5.85	5.88	-0.03
beef33	5.9	6.5	-0.6
beef34	6.75	7.66	-0.91
beef35	6.8	7	-0.2
beef36	5.75	5.39	0.36
beef37	4.8	5.66	-0.86
beef38	5.15	6.5	-1.35
beef39	6.85	7	-0.15
beef40	6.45	5.97	0.48

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.7482808
R Square	**0.5599241**
Adjusted R Square	0.5483432
Standard Error	0.5142697
Observations	40

Dependent Var	Human Avg
Independent Var	Prox. Anal.

Sum	-12.73
Mean	-0.31825
Sum(D2)	17.4005
CT=Sum(D2)/40	4.0513225
SS	13.349178
Var. D	0.3422866
S.D. D	0.5850526
S.D. Dmean	0.0925049
T computed	-3.440357
T critical	2.021

Hence the two sets of observations are significantly different (error level 0.05)

Paired Observations Comparisons between the machine and proximate analysis predictions of marbling levels

ID#	Prox. Anal.	Machine	Difference
beef1	5.98	5.29	0.69
beef2	7	7	0
beef3	5.86	5.5	0.36
beef4	7.66	7	0.66
beef5	8.33	5.7	2.63
beef6	6.5	5.04	1.46
beef7	5.2	5.2	0
beef8	6.5	6.5	0
beef9	5.98	5.94	0.04
beef10	7.66	5.84	1.82
beef11	7	5.79	1.21
beef12	7.66	5.67	1.99
beef13	6.5	7	-0.5
beef14	6.5	5.15	1.35
beef15	5.96	5.87	0.09
beef16	7	5.52	1.48
beef17	4.8	6.5	-1.7
beef18	5.22	4.8	0.42
beef19	5.26	4.4	0.86
beef20	5.18	5.2	-0.02
beef21	6.5	5.92	0.58
beef22	5.66	5.52	0.14
beef23	5.62	5.05	0.57
beef24	5.52	5.44	0.08
beef25	5.47	5.11	0.36
beef26	5.2	4.8	0.4
beef27	5.8	5.62	0.18
beef28	6.5	7	-0.5
beef29	4.8	5.3	-0.5
beef30	6.5	5.22	1.28
beef31	6.5	7	-0.5
beef32	5.88	5.35	0.53
beef33	6.5	6.5	0
beef34	7.66	6.5	1.16
beef35	7	5.75	1.25
beef36	5.39	4.8	0.59
beef37	5.66	5.27	0.39
beef38	6.5	6.5	0
beef39	7	6.5	0.5
beef40	5.97	6.5	-0.53

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.486251
R Square	**0.23644**
Adjusted R Square	0.216346
Standard Error	0.635606
Observations	40

Dependent Var	Machine
Independent Var	Prox. Anal.

Sum	18.82
Mean	0.4705
Sum(D2)	34.5232
CT=Sum(D2)/40	8.85481
SS	25.66839
Var. D	0.658164
S.D. D	0.811273
S.D. Dmean	0.128274
T computed	3.667943
T critical	2.021

Hence the two sets of observations are significantly different (error level 0.05)

Anova: Single Factor **Human vs Machine at 0.05**

SUMMARY

Groups	Count	Sum	Average	Variance
Column 1	40	236.65	5.91625	0.585562
Column 2	40	230.56	5.764	0.515527

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.4636012	1	0.463601	0.842077	0.361632	3.9634642
Within Groups	42.942497	78	0.550545			
Total	43.406099	79				

Anova: Single Factor **Human vs Machine at 0.01**

SUMMARY

Groups	Count	Sum	Average	Variance
Column 1	40	236.65	5.91625	0.585562
Column 2	40	230.56	5.764	0.515527

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.4636012	1	0.463601	0.842077	0.361632	6.9713906
Within Groups	42.942497	78	0.550545			
Total	43.406099	79				

Anova: Single Factor **Machine vs Proximate Analysis at 0.05**

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
Column 1	40	230.56	5.764	0.515527
Column 2	40	249.38	6.2345	0.745548

W =	0.35531375
LSD =	0.35511627
Mean Diff =	0.4705

Significantly Different

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	4.427405	1	4.427405	7.021633	0.009746	3.963464
Within Groups	49.18195	78	0.630538			
Total	53.609355	79				

Anova: Single Factor **Machine vs Proximate Analysis at 0.01**

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
Column 1	40	230.56	5.764	0.515527
Column 2	40	249.38	6.2345	0.745548

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	4.427405	1	4.427405	7.021633	0.009746	6.971391
Within Groups	49.18195	78	0.630538			
Total	53.609355	79				

Anova: Single Factor **Human vs Prox. Analysis at 0.05**

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
Column 1	40	236.65	5.91625	0.585562
Column 2	40	249.38	6.2345	0.745548

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	2.025661	1	2.025661	3.043565	0.084997	3.9634642
Within Groups	51.91333	78	0.665555			
Total	53.93899	79				

Anova: Single Factor **Human vs Prox. Analysis at 0.01**

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
Column 1	40	236.65	5.91625	0.585562
Column 2	40	249.38	6.2345	0.745548

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	2.025661	1	2.025661	3.043565	0.084997	6.9713906
Within Groups	51.91333	78	0.665555			
Total	53.93899	79				

Anova: Single Factor **All three treatments at 0.05**

SUMMARY

Groups	Count	Sum	Average	Variance
Column 1	40	236.65	5.91625	0.585562
Column 2	40	249.38	6.2345	0.745548
Column 3	40	230.56	5.764	0.515527

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	4.611112	2	2.305556	3.745546	0.026502	3.073765
Within Groups	72.01889	117	0.615546			
Total	76.63	119				

Significant Test

Anova: Single Factor **At 0.01**

SUMMARY

Groups	Count	Sum	Average	Variance
Column 1	40	236.65	5.91625	0.585562
Column 2	40	249.38	6.2345	0.745548
Column 3	40	230.56	5.764	0.515527

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	4.611112	2	2.305556	3.745546	0.026502	4.791275
Within Groups	72.01889	117	0.615546			
Total	76.63	119				

Color Comparision

Dr. Dolezol	Bilynn	M/C
4.75	3.75	3.36
4.25	3.75	3.38
5.75	5.25	4.52
6.75	4.75	4.24
5.25	3.75	3.72
5.75	4.25	3.98
6.25	4.25	4.36
5.75	3.75	3.24
5.25	3.75	2.94
4.75	3.75	3.38
8.75	8.75	7.2
2.75	2.25	2.58
5.75	4.75	3.96
6.25	4.75	4.24
4.75	3.75	3.2
6.75	5.75	5.52
3.75	3.25	3.08
5.25	4.75	3.94
6.25	6.75	4.8
5.75	5.25	4.68
5.75	4.75	4.68
5.25	4.25	4.52
4.25	3.75	2.76
6.25	5.25	4.84
7.25	4.75	5.2
5.25	3.75	3.7
3.75	3.25	2.78
8	8.75	6.08
4.25	3.25	3.12
6.25	4.25	4.08
6.25	4.75	3.9
5.25	4.25	3.48
4.75	4.25	3.5
3.25	3.75	2.82
4.25	4.75	3.84
5.75	4.75	3.9
4.25	4.25	3.32
4.25	4.25	3.32
5.25	4.25	3.52
4.75	4.75	3.7

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.895039
R Square	**0.801096**
Adjusted R Square	0.795861
Standard Error	0.564945
Observations	40

Dependent var Bilynn
Independent var Machine

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.807596
R Square	**0.652212**
Adjusted R Square	0.643059
Standard Error	0.747036
Observations	40

Dependent var Bilynn
Independent var Dr. Dolezol

Color Comparision using Paired T test

Bilynn	M/C	Diff
3.75	3.36	0.39
3.75	3.38	0.37
5.25	4.52	0.73
4.75	4.24	0.51
3.75	3.72	0.03
4.25	3.98	0.27
4.25	4.36	-0.11
3.75	3.24	0.51
3.75	2.94	0.81
3.75	3.38	0.37
8.75	7.2	1.55
2.25	2.58	-0.33
4.75	3.96	0.79
4.75	4.24	0.51
3.75	3.2	0.55
5.75	5.52	0.23
3.25	3.08	0.17
4.75	3.94	0.81
6.75	4.8	1.95
5.25	4.68	0.57
4.75	4.68	0.07
4.25	4.52	-0.27
3.75	2.76	0.99
5.25	4.84	0.41
4.75	5.2	-0.45
3.75	3.7	0.05
3.25	2.78	0.47
8.75	6.08	2.67
3.25	3.12	0.13
4.25	4.08	0.17
4.75	3.9	0.85
4.25	3.48	0.77
4.25	3.5	0.75
3.75	2.82	0.93
4.75	3.84	0.91
4.75	3.9	0.85
4.25	3.32	0.93
4.25	3.32	0.93
4.25	3.52	0.73
4.75	3.7	1.05

Sum	23.62
Mean	0.5905
Sum(D2)	27.2696
CT	13.94761
SS	13.32199
Var D.	0.341589
S.D. D.	0.584457
S.D. Dmean.	0.092411
T Comp.	6.389953
T critical	2.021

Hence the means are significant ly different

Grade Comparision

Avg	M/C	Q Grade1	Q Grade2	Difference
6	6	6	6	0
8.5	9	8	9	-1
9	6	9	9	0
8	9	8	8	0
8	6	8	8	0
6.5	6	7	6	1
6	6	6	6	0
5.5	8	5	6	-1
7.5	6	8	7	1
9	6	9	9	0
11	11	11	11	0
9	6	9	9	0
8	9	8	8	0
6.5	6	6	7	-1
5.5	6	6	5	1
9	9	9	9	0
6	8	6	6	0
5	5	5	5	0
5.5	5	5	6	-1
9	6	9	9	0
6	6	6	6	0
7	6	7	7	0
6	6	6	6	0
9	6	9	9	0
6	9	6	6	0
5.5	5	5	6	-1
7	6	7	7	0
11	9	11	11	0
5	6	5	5	0
7.5	6	8	7	1
6	9	6	6	0
6	6	6	6	0
6.5	8	7	6	1
8	8	8	8	0
8	6	8	8	0
6	5	6	6	0
4.5	6	5	4	1
5.5	8	6	5	1
8	8	8	8	0
7.5	8	7	8	-1

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.432737
R Square	**0.187261**
Adjusted R Sqr	0.165873
Standard Error	1.460584
Observations	40

Sum	1
Mean	0.025
Sum(D2)	13
CT	0.025
SS	12.975
Var D.	0.332692
S.D D.	0.576795
S.D. Dme	0.091199
T compu	0.274125
T critical	2.021

The means are not different at a 95 % confidence level, between the human avg and individual scores.

APPENDIX B – IMAGE ANALYSIS PROGRAM

```
// Open the saved calibration configuration file to initialize and enable the calibration
// settings (to measure in centimeters).

OpenConfiguration("c:/optimas6/config/stkcm.cfg");
Calibrate (stkcm);
CloseWindow ("Calibrate Spatial");

// Define the working variables.

real diff;
real add;
real marbling;
real color;

// Set image to be grabbed in RGB format and save the original image,
// to be retrieved after morphological operations.

SetColorMode (1 : 1 : 8 : 1 : 3 : 3);
saveimage("c:/optimas6/original.tif",,,4);

// Data objects are defined as areas.

DataCollectionType = 2;

// Load file containing parameters defining the selection criteria for the various
// object classes required by the program.
// lean – constraints for ribeye
// fats – constraints for intermuscular fat
// marble1 - constraints for intermuscular fat (area < 0.1 sq.cm.)
// marble2 - constraints for intermuscular fat (0.1 < area <  0.5 sq.cm.)
// marble3 - constraints for intermuscular fat (area > 0.5 sq.cm.)


loadfromoptfile("c:/optimas6/config/grading.cfg","lean");
loadfromoptfile("c:/optimas6/config/grading.cfg","fats");
loadfromoptfile("c:/optimas6/config/grading.cfg","marble1");
loadfromoptfile("c:/optimas6/config/grading.cfg","marble2");
loadfromoptfile("c:/optimas6/config/grading.cfg","marble3");
loadfromoptfile("c:/optimas6/config/grading.cfg","white");
loadfromoptfile("c:/optimas6/config/grading.cfg","meat");

// Enable the intermuscular fat object class and disable everything else.

objectclass (lean, false);
objectclass (fats, true);
```

```
objectclass (marble1, false);
objectclass (marble2, false);
objectclass (marble3, false);
objectclass (white, false);
objectclass (meat, false);
getorsetfield(lean,305,true);
getorsetfield(lean,302,true);
getorsetfield(fats,305,true);
getorsetfield(fats,302,true);
getorsetfield(marble1,302,true);
getorsetfield(marble2,302,true);
getorsetfield(marble3,302,true);
getorsetfield(white,305,true);
getorsetfield(white,302,true);
getorsetfield(meat,302,true);

// Select only the green band and apply autothresholding to pick up the fat in the image.

BandOfInterest = 2;
REAL rPairs[,];
Histogram();
rPairs = GetAutoThreshold(0 : ArROIHistogram[1..(VectorLength(ArROIHistogram)-1)]
: 0,6,2,,ActiveLuminanceRange,);
if ( rPairs && 1 < GetShape(rPairs)[0] )
  {
      Threshold(rPairs[1,0]:rPairs[1,1]);
   }
Delete(rPairs);

// Based on the threshold, find enclosed areas and filter them to include the intermuscular
// fat and exclude the intramuscular fat.

AreaCNVFactors[0..14] = 100.0 : 0.028125 : -1.0 : 64.0 : 100.0 : 0.28125 : -1.0 : 1.0 : 1.0
: 0.0 : 255.0 : -1.0 : -1.0 : 0.0;
CreateArea (, , TRUE);
MultipleMode = true;
MultipleExtract (TRUE);
BandofInterest = 0;

// Remove the intermuscular fat from the image.

RunMacro ("C:/OPTIMAS6/macsrc/cxroi/cmplxroi.mac", );
CMPLX_mAreasToMasks ();
ImageToClipboard (, TRUE);
CloseWindow ("Complex Regions of Interest");
ImageMask (8);
```

```
SelectFullScreen (0);

// Enable the object class to differentiate the ribeye.

Objectclass(fats, false);
Objectclass(lean, true);

// Select the red band and  autothreshold the image.

Bandofinterest = 1;
REAL rPairs[,];
Histogram();
rPairs = GetAutoThreshold(ArROIHistogram[0..(VectorLength(ArROIHistogram)-1)] :
0,6,2,,ActiveLuminanceRange,);
if ( rPairs && 1 < GetShape(rPairs)[0] )
  {
       Threshold(rPairs[1,0]:rPairs[1,1]);
   }
Delete(rPairs);

// Filter the ribeye out from the image.

CreateArea (, , TRUE);
MultipleMode = true;
MultipleExtract (TRUE);
BandofInterest = 0;

// Eliminate everything except the ribeye (along with the extraneous tissue).

RunMacro ("C:/OPTIMAS6/macsrc/cxroi/cmplxroi.mac", );
CMPLX_mAreasToMasks ();
ImageMask (0x1000);
ImageToClipboard (, TRUE);
ImageMask (0x2000);
CloseWindow ("Complex Regions of Interest");
ImageMask (8);
SelectFullScreen (0);

// Convert the image to binary and perform binary erosions and dilations to
// remove the extraneous tissues.

Threshold(5:255::5:255::5:255);
RunMacro ("C:/OPTIMAS6/macsrc/binary/binary.mac", );
GrayToBinary ();
Threshold ( 127.5:255.0::127.5:255.0::127.5:255.0 );
BINB_iIterations = 1;
```

```
// brkapart.mac is a macro provided along with the software that was customized to
// meet the requirements of the progam.  It performs binary morphological operations
// to separate connected blobs.

RunMacro("dialogs/brkapart.mac");
Threshold ( 127.5:255.0::127.5:255.0::127.5:255.0 );
BRK_nHoleDilates = 2;
BRK_nRawErodes = 4;
BRK_nErodesToPoint = 10;
BRK_bAutoAreas = TRUE;
BRK_bAutoPoints = FALSE;
BRK_bAutoNone = FALSE;
BRK_bShowWork = TRUE;
BRK_BreakApartBlobs ();
CloseWindow ("Break Apart Touching Blobs");
CloseWindow ("Binary Morphology");

// Enable the object class 'white' to pick the largest of the separated blobs.

ObjectClass (lean, false);
objectclass (white, true);
MultipleMode = true;
MultipleExtract (TRUE);

// Eliminate everything from the resulting image except the required mask.

RunMacro ("C:/OPTIMAS6/macsrc/cxroi/cmplxroi.mac", );
CMPLX_mAreasToMasks ();
ImageMask (0x1000);
ImageToClipboard (, TRUE);
ImageMask (0x2000);
CloseWindow ("Complex Regions of Interest");

// Fill in any holes that may have been generated as the result of the
// morphological operations.

ImageMask (8);
SelectFullScreen (0);
BINB_iIterations = 1;
FillFilter(,FALSE);

// Determine the centroid of the object.

CreateArea (,, TRUE);
MultipleExtractAll (TRUE);
SetExport ( ArCentroid, 1, TRUE);
```

```
MultipleMode = FALSE;
Select(GetScreenItemHandles());
Extract();
MultipleMode = TRUE;

// Divide the object into four quadrants with the inner corner at the centroid.

REAL WholeROI = ROI;
REAL BottomLeft = WholeROI[0,0]:ArCentroid[1]::
    ArCentroid[0]:WholeROI[1,1];
REAL TopLeft = WholeROI [0,]::ArCentroid;
REAL TopRight = ArCentroid[0]:WholeROI[0,1]::
    WholeROI[1,0]:ArCentroid[1];
REAL BottomRight = ArCentroid::WholeROI[1,];

// Logically AND the original image with the mask to recover the isolated ribeye.

SetColorMode (1 : 1 : 8 : 1 : 3 : 3);
filetolist("c:/optimas6/original.tif");
ArithmeticOp ();
ArithmeticOp ("And", "original.tif", 0.0 : 142.02 ::
189.46 : 0.0, , "Clip", FALSE, FALSE);
CloseWindow ("Arithmetic Operations");

// Enable the object classes to identify the intermuscular fat.

objectclass (marble1, true);
objectclass (marble2, true);
objectclass (marble3, true);
objectclass (white, false);

// Determine the intermuscular fat percentage for the first quadrant.

ROI = TopLeft;

// Use the green band to threshold the fat.

BandOfInterest = 2;
REAL rPairs[,];
Histogram();
rPairs = GetAutoThreshold(0 : ArROIHistogram[1..(VectorLength(ArROIHistogram)-1)]
: 0,6,2,,ActiveLuminanceRange,);
if ( rPairs && 1 < GetShape(rPairs)[0] )
  {
      Threshold(rPairs[1,0]:rPairs[1,1]);
   }
```

```
Delete(rPairs);
CreateArea (,, TRUE);
SetExport(ArArea,1,TRUE);
MultipleMode = true;
MultipleExtract (TRUE);

// Obtain the sum of areas belonging to each fat class.

fat3=Sum( mArArea[ Ar_marble1_Select_C ] );
fat4=Sum( mArArea[ Ar_marble2_Select_D ] );
fat5=Sum( mArArea[ Ar_marble3_Select_E ] );
TOTTL=fat3;

// Shift to the red band information to threshold the lean portion in the quadrant.

Bandofinterest = 1;
REAL rPairs[,];
Histogram();
rPairs = GetAutoThreshold(ArROIHistogram,6,2,,ActiveLuminanceRange,);
if ( rPairs && 1 < GetShape(rPairs)[0] )
  {
       Threshold(rPairs[1,0]:rPairs[1,1]);

   }
Delete(rPairs);
objectclass(marble1, false);
objectclass(marble2, false);
objectclass(marble3, false);
objectclass(meat, true);
CreateArea (,, TRUE);
SetExport(ArArea,1,TRUE);
MultipleMode = true;
MultipleExtract (TRUE);

// Measure the ribeye area, and thus determine the fat area percent in that quadrant

ribarea=sum(mArArea);
marbletl=(TOTTL/ribarea)*100;
macromessage("TL = ",marbletl);

// Determine the intermuscular fat percentage for the second quadrant.

ROI = TopRight;
BandOfInterest = 2;
REAL rPairs[,];
Histogram();
```

```
rPairs = GetAutoThreshold(0 : ArROIHistogram[1..(VectorLength(ArROIHistogram)-1)]
: 0,6,2,,ActiveLuminanceRange,);
if ( rPairs && 1 < GetShape(rPairs)[0] )
  {
      Threshold(rPairs[1,0]:rPairs[1,1]);
   }
Delete(rPairs);
objectclass(marble1, true);
objectclass(marble2, true);
objectclass(marble3, true);
objectclass(meat, false);
CreateArea (,, TRUE);
SetExport(ArArea,1,TRUE);
MultipleMode = true;
MultipleExtract (TRUE);
BandOfInterest = 0;
fat3=Sum( mArArea[ Ar_marble1_Select_C ] );
fat4=Sum( mArArea[ Ar_marble2_Select_D ] );
fat5=Sum( mArArea[ Ar_marble3_Select_E ] );
TOTTR=fat3;
Bandofinterest = 1;
REAL rPairs[,];
Histogram();
rPairs = GetAutoThreshold(ArROIHistogram,6,2,,ActiveLuminanceRange,);
if ( rPairs && 1 < GetShape(rPairs)[0] )
  {
      Threshold(rPairs[1,0]:rPairs[1,1]);
   }
Delete(rPairs);
objectclass(marble1, false);
objectclass(marble2, false);
objectclass(marble3, false);
objectclass(meat, true);
CreateArea (,, TRUE);
SetExport(ArArea,1,TRUE);
MultipleMode = TRUE;
MultipleExtract (TRUE);
ribarea=Sum( mArArea);
marbletr=(TOTTR/ribarea)*100;
macromessage("TR = ",marbletr);
BandOfInterest = 2;
REAL rPairs[,];
Histogram();
rPairs = GetAutoThreshold(0 : ArROIHistogram[1..(VectorLength(ArROIHistogram)-1)]
: 0,6,2,,ActiveLuminanceRange,);
if ( rPairs && 1 < GetShape(rPairs)[0] )
```

```
  {
        Threshold(rPairs[1,0]:rPairs[1,1]);
    }
Delete(rPairs);

// Determine the intermuscular fat percentage for the third quadrant.

ROI = BottomRight;
objectclass(marble1, true);
objectclass(marble2, true);
objectclass(marble3, true);
objectclass(meat, false);
CreateArea (,, TRUE);
SetExport(ArArea,1,TRUE);
MultipleMode = true;
MultipleExtract (TRUE);
fat3=Sum( mArArea[ Ar_marble1_Select_C ] );
fat4=Sum( mArArea[ Ar_marble2_Select_D ] );
fat5=Sum( mArArea[ Ar_marble3_Select_E ] );
TOTBR=fat3;
bandofinterest = 1;
REAL rPairs[,];
Histogram();
rPairs = GetAutoThreshold(ArROIHistogram,6,2,,ActiveLuminanceRange,);
if ( rPairs && 1 < GetShape(rPairs)[0] )
  {
        Threshold(rPairs[1,0]:rPairs[1,1]);
    }
Delete(rPairs);
objectclass(marble1, false);
objectclass(marble2, false);
objectclass(marble3, false);
objectclass(meat, true);
CreateArea (,, TRUE);
SetExport(ArArea,1,TRUE);
MultipleMode = TRUE;
MultipleExtract (TRUE);
ribarea=Sum( mArArea);
marblebr=(TOTBR/ribarea)*100;
macromessage("BR = ",marblebr);
BandOfInterest = 2;
REAL rPairs[,];
Histogram();
rPairs = GetAutoThreshold(0 : ArROIHistogram[1..(VectorLength(ArROIHistogram)-1)]
: 0,6,2,,ActiveLuminanceRange,);
if ( rPairs && 1 < GetShape(rPairs)[0] )
```

```
  {
       Threshold(rPairs[1,0]:rPairs[1,1]);
    }
Delete(rPairs);
objectclass(marble1, true);
objectclass(marble2, true);
objectclass(marble3, true);
objectclass(meat, false);
```

// Determine the intermuscular fat percentage for the fourth quadrant.

```
ROI = BottomLeft;
CreateArea (,, TRUE);
SetExport(ArArea,1,TRUE);
MultipleMode = true;
MultipleExtract (TRUE);
fat3=Sum( mArArea[ Ar_marble1_Select_C ] );
fat4=Sum( mArArea[ Ar_marble2_Select_D ] );
fat5=Sum( mArArea[ Ar_marble3_Select_E ] );
TOTBL=fat3;
Bandofinterest = 1;
REAL rPairs[,];
Histogram();
rPairs = GetAutoThreshold(ArROIHistogram,6,2,,ActiveLuminanceRange,);
if ( rPairs && 1 < GetShape(rPairs)[0] )
  {
       Threshold(rPairs[1,0]:rPairs[1,1]);
    }
Delete(rPairs);
objectclass(marble1, false);
objectclass(marble2, false);
objectclass(marble3, false);
objectclass(meat, true);
CreateArea (,, TRUE);
SetExport(ArArea,1,TRUE);
MultipleMode = TRUE;
MultipleExtract (TRUE);
ribarea=Sum( mArArea);
marblebl=(TOTBL/ribarea)*100;
macromessage("BL = ",marblebl);
```

// Determine the total fat percentage.

```
ROI = WholeROI;
SetExport(ArMajorAxisPoints,1,TRUE);
SetExport(ArArea, 1, TRUE);
```

```
objectclass(lean, true);
CreateArea (,, TRUE);
SetExport(ArArea,1,TRUE);
MultipleMode = TRUE;
MultipleExtract (TRUE);
CreateLine(mArMajorAxisPoints);
ribeye=sum(mArarea);
macromessage(" Ribeye = ", ribeye);
RunMacro ("C:/OPTIMAS6/macsrc/cxroi/cmplxroi.mac", );
CMPLX_mAreasToMasks ();
closewindow ("Complex Regions of Interest");
BandOfInterest = 2;
REAL rPairs[,];
Histogram();
rPairs = GetAutoThreshold(0 : ArROIHistogram[1..(VectorLength(ArROIHistogram)-1)]
: 0,6,2,,ActiveLuminanceRange,);
if ( rPairs && 1 < GetShape(rPairs)[0] )
  {
        Threshold(rPairs[1,0]:rPairs[1,1]);
   }
Delete(rPairs);
objectclass(marble1, true);
objectclass(marble2, true);
objectclass(marble3, true);
objectclass(lean, false);
objectclass(meat, false);
CreateArea (,, TRUE);
SetExport(ArArea,1,TRUE);
MultipleMode = true;
MultipleExtract (TRUE);
fat3=Sum( mArArea[ Ar_marble1_Select_C ] );
fat4=Sum( mArArea[ Ar_marble2_Select_D ] );
fat5=Sum( mArArea[ Ar_marble3_Select_E ] );
ribeye=ribeye-(fat4+fat5); //Eliminating the effect of the larger fat pieces
marble=(fat3/ribeye)*100;
macromessage(" % Fat is ", marble);
avg=((marbletl+marbletr+marblebr+marblebl)/4);
macromessage("%avg fat is ", avg);

BandofInterest=0;
RunMacro ("C:/OPTIMAS6/macsrc/cxroi/cmplxroi.mac", );
CMPLX_mAreasToMasks ();
ImageMask (0x1000);
ImageToClipboard (, TRUE);
ImageMask (0x2000);
CloseWindow ("Complex Regions of Interest");
```

```
// In case of abnormal distribution, choose the average distribution as the
// marbling score.

if (marble>avg)
{
marble=avg;
}

// Determine the marbling class level based on the conversion table shown in Table I.

if (marble>=18)
{
diff=(21-marble);
add=diff/3.0;
marbling=add;
}
else if (marble>=15)
{
diff=(18-marble);
add=diff/3.0;
marbling=1.0+add;
}
else if (marble>=13)
{
diff=(15-marble);
add=diff/2.0;
marbling=2.0+add;
}
else if (marble>=10)
{
diff=(13-marble);
add=diff/3.0;
marbling=3.0+add;
}

else if (marble>=7.5)
{
diff=(10-marble);
add=diff/2.5;
marbling=4.0+add;
}
else if (marble>=5)
{
diff=(7.5-marble);
add=diff/2.5;
```

```
marbling=5.0+add;
}

else if (marble>=3)
{
diff=(5-marble);
add=diff/2.0;
marbling=6.0+add;
}
else if (marble>=1.5)
{
diff=(3-marble);
add=diff/1.5;
marbling=7.0+add;
}
else if (marble>=0.5)
{
diff=(1.5-marble);
add=diff/1.0;
marbling=8.0+add;
}
else
{
diff=(marble);
add=diff/0.5;
marbling=9.0+add;
}

// Determine the red, green and blue band peaks.

BandOfInterest = 1;
histogram();
red=arroihistogramstats[6];
macromessage(" The red mode is ", red);
BandOfInterest = 2;
histogram();
green=arroihistogramstats[6];
macromessage(" The green mode is ", green);
BandOfInterest = 3;
histogram();
blue=arroihistogramstats[6];
macromessage(" The blue mode is ", blue);
BandofInterest = 0;

// Compute the color scores based on the RGB values.
```

```
score=red+green+blue;
if (score>318)
{
diff=(score-318);
add=diff/50;
color=(4.0 - add);
}
else if (score>218)
{
diff=(score-218);
add=diff/25;
color=(8.0 - add);
}
else
{
macromessage("Meat is dark cutter");
}

macromessage("Color score is ",color);
macromessage("Marbling score is", marbling);

// Determine the quality grade by combining color and marbling scores.
// A Maturity

if (color<=5.0)
{
if (marbling>=8)
macromessage("Grade is Standard minus");
else if (marbling>=7)
macromessage("Grade is Standard plus");
else if (marbling>=6.5)
macromessage("Grade is Select minus");
else if (marbling>=6.0)
macromessage("Grade is Select plus");
else if (marbling>=5)
macromessage("Grade is Choice minus");
else if (marbling>=4)
macromessage("Grade is Choice average");
else if (marbling>=3)
macromessage("Grade is Choice plus");
else if (marbling>=2)
macromessage("Grade is Prime minus");
else if (marbling>=1)
macromessage("Grade is Prime Average");
else
macromessage("Grade is Prime plus");
```

```
}

// B Maturity

else if (color<=7.0)
{
subcolor=(color-5)/2;
score=subcolor+marbling;

if (marbling<=1.0)
{
if (score<=1.0)
macromessage("Grade is Prime plus");
else
macromessage("Grade is Prime Average");
}
else if (marbling<=2.0)
{
if (score<=2.0)
macromessage("Grade is Prime Average");
else
macromessage("Grade is Prime minus");
}
if (marbling<=3.0)
{
if (score<=3.0)
macromessage("Grade is Prime minus");
else
macromessage("Grade is Choice plus");
}
else if (marbling<=4.0)
{
if (score<=4.0)
macromessage("Grade is Choice plus");
else
macromessage("Grade is Choice Average");
}
else if (marbling<=5.0)
{
if (score<=5.0)
macromessage("Grade is Choice Average");
else
macromessage("Grade is Choice minus");
}
else if (marbling<=7.0)
{
```

```
macromessage("Grade is Standard plus");
}
else if (marbling<=8.0)
{
if (score<=8.0)
macromessage("Grade is Standard plus");
else
macromessage("Grade is Standard minus");
}
else if (marbling<=9.0)
{
if (score<=9.0)
macromessage("Grade is Standard minus");
else
macromessage("Grade is Utility");
}
}

// C Maturity

else if (color <=8.0)
{
if (score<=13.0)
macromessage("Grade is Commercial");
else
macromessage("Grade is Utility");
}
```

2

VITA

Nisha Biju

Candidate for the Degree of

Master of Science

Thesis: BEEF QUALITY GRADING WITH COLOR VIDEO IMAGE ANALYSIS

Major Field: Biosystems Engineering

Biographical:

Education: Graduated from Nirmala High School, Kerala, India in April 1988; Received Bachelor of Technology degree in Biomedical Engineering from Government Model Engineering College, Kerala, India in July 1991. Completed the requirements for the Master of Science degree with a major in Biosystems Engineering at Oklahoma State University in July 1998.

Experience: Employed as Lecturer in Biomedical Engineering by Mahatma Gandhi University, Kerala, India, February 1995 to November 1995; Employed by Oklahoma State University, Department of Biosystems Engineering as Graduate Research Assistant, September 1996 to December 1997; Employed by Amdocs, Inc., Dallas, Texas as Programmer, February 1998 to present.