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LAMB CARCASS CLASSIFICATION SYSTEM BASED ON COMPUTER VISION PART 1: TEXTURE FEATURES AND DISCRIMINANT ANALYSIS

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Abstract

This paper presents a lamb carcass classification system based on image and texture analyses together with multivariate statistical techniques (principal component analysis, cluster analysis and discriminant function analysis). Texture analysis is based on grey level co-occurrence matrix. A set of ninety texture features has been used to extract the texture information from the acquired images. In addition, twelve image area and thickness (geometric) variables have also been calculated.

Principal component analysis was used to reduce the dimensionality of the original data set. Two feature sets were generated based on the results. These feature sets comprised of principal component (PC) scores calculated from the original variables and 14 (6 geometric and 8 texture) variables selected from the original set of variables. Both feature spaces were used for discriminant analysis.

From the experimental results, it was established that the system enabled 66.3% and 76.9% overall classification based on 6 geometric PC scores and 14 (geometric and texture) PC scores, respectively. The system also enabled 64% and 79 % overall classification of lamb carcasses based on 6 geometric and 14 (geometric and texture) variables, respectively. This study shows the predictive potential of combining image analysis with texture analysis for lamb grading. The addition of carcass weight improved the overall classification accuracy, of both feature sets, to 85%.

Key words: Image analysis, Texture features, Lamb grading, Computer vision, Discriminant function analysis, Co-occurrence matrix

1. Introduction

Visual assessment has become the principal component of several meat classification and grading systems. Furthermore, the meat industry, in response to consumer demand for the products of consistent quality, strongly emphasises on quality assurance issues. Instrument grading of animal carcasses has been studied to meet the demand for increased accuracy and uniformity of meat grading.

Computer vision has enormous potential for evaluating meat quality as image processing techniques can quantitatively and consistently characterize complex geometric, colour and textural properties. In New Zealand, the assignment of lamb carcasses to specific quality grades has been an integral part of a lamb carcass classification system (Figure 1). The current classification is based solely on carcass weight and fatness measurements. There are five weight ranges which are: A (very light and lean), L (light), M (medium), X (heavier) and H (heavy). There are also five fatness classes which are: A (devoid), Y (lean), P (prime), T (trimmer) and F (overfat). The fatness classes are specified according to the measured carcass GR (New Zealand Meat Board, 1992), which is defined as the total fat tissue depth over the 12^{th} rib at a point 11 cm from the midline of the carcass. GR is usually measured only on carcasses judged as marginal between fat classes P and T or T and F. In all the other cases it is visually estimated which is largely subjective. The final assigned grade is a combination of fatness class and weight class, eg. YM, PX etc.

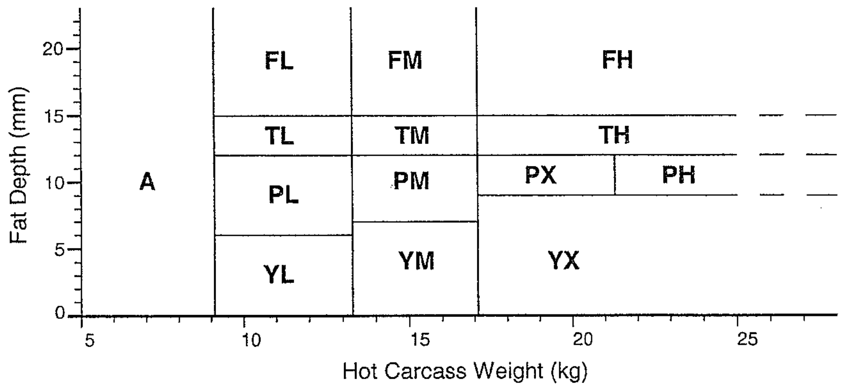

Figure 1. New Zealand lamb carcass classification system

Texture is an important characteristic of many types of images. A precise definition of image texture does not exist. It can be quantitatively evaluated as having one or more of the intrinsic properties of fineness, coarseness, smoothness, granulation, randomness, lineation or being mottled, irregular or hummocky (Haralick, 1979). A variety of techniques for analysing image texture have been proposed over the past three decades. Most of the approaches compute the features that are capable of capturing textural properties. Such features contain information representative of visual characteristics and also characteristics that cannot be visually differentiated.

Haralick (1979), Reed & Du Buf (1993) and Van Gool et al. (1985) present a detailed survey of texture analysis methods used in image analysis. Tuceryan and Jain (1999), classified texture analysis methods into four categories as statistical, structural (geometrical), model based and signal processing.

Statistical approaches, better suited for micro textures, analyse the spatial distribution of grey values and derive a set of statistics. Depending on the number of pixels defining the local feature, statistical approaches can be further classified into first-order, second-order and higher-order statistics. Structural texture analysis techniques assume that textures are composed of well-defined texture elements. In the structural techniques, the primitives and the placement rules describe the texture elements and the spatial organization between the elements, respectively. Structural methods are of limited utility as many textures violate the assumption of texture elements. Signal processing techniques are based on the properties of the Fourier spectrum. Model-based methods are based on the construction of an image model, which can be used to describe and synthesize texture.

A class of simple image properties that can be used for texture analysis are first-order statistics. It measures the possibility of observing a grey value at randomly chosen location in the image. The features calculated using the first order statistics of an image, such as mean and variance, are not textural features because they depend only on the intensity of individual pixels, independent of their neighbouring pixels. These features simply describe the grey level histogram of an image. Texture is essentially a neighbourhood property. It is an innate property of virtually all surfaces and contains important information about the structural arrangement of surfaces. Second-order and higher-order statistics estimate properties of two pixels and three or more pixels, respectively, occurring at specific locations relative to each other.

Statistical approaches commonly used include the grey level co-occurrence matrix (GLCM) method (Haralick et al., 1973), the grey level difference method (GLDM) (Weszka et al., 1976) and the grey level run length matrix (GLRM) method (Galloway, 1975). The other statistical approaches include autocorrelation functions, optical transforms, digital transforms, textural edgeness, autoregressive models and structural elements (Haralick, 1979).

Model based approaches like Markov random field model (Tuceryan and Jain, 1999), autoregressive models and fractal based modelling (Pentland, 1984) have also been widely used in image texture characterization. Signal processing methods include spatial domain filters, Fourier domain filters, Gabor filters and wavelets. Researchers have attempted to compare methods for texture discrimination and classification (Conners and Harlow, 1980; Ohanian and Dubes, 1992; Ojala et al., 1996; Weszka et al., 1976).

Since the texture of muscle images can reflect muscle fibre characteristics such as size, it may be directly or indirectly related to meat quality characteristics. During the last two decades, several authors have proposed different systems based on image analysis technology. Early studies have shown that image analysis technology has great potential to improve the current human grader based meat quality operation (Cross et al., 1983; Wassenberg et al., 1986).

Several applications of image analysis in meat quality evaluation have also been published. These include quantification of intramuscular fat content in the beef ribeye (Chen et al., 1989), prediction of beef carcass lean meat yield using images of 12th rib interface (Gardner et al., 1995), evaluation of marbling percentage and colour scores in beef (Gerrard et al., 1996; Schutte et al., 1998) and enhanced image segmentation (Lu and Tan, 1998; McDonald and Chen, 1989; McDonald and Chen, 1990).

Prediction of carcass composition using the information extracted from carcass cross section by image analysis have also been reported (Karnuah et al., 1995a; 1995b; 1996; 2001). Shackelford et al. (1998), used image information in combination with tenderness classification to predict carcass cutability and tenderness. Attempts for automatically grading of beef marbling by image analysis have also been published (Kuchida et al., 1992; Yoshikawa et al., 2000).

Several studies on automated grading and classification of beef carcasses, based on image analysis have been reported (Borggaard et al., 1996; Karnuah et al., 1995a, 1995b, 1996, 2001; Kuchida et al., 1992; Lu et al., 1998; Shiranita et al., 2000). Only a few applications have been reported for sheep grading and classification (Hopkins et al., 1997; Horgan et al., 1995; Stanford et al., 1998).

Texture features extracted using GLCM (Li et al., 1999; Shiranita et al., 1998), GLRM (Li et al., 1999; 2001), fractal approach (Ballerini and Bocchi, 2001) and wavelets

(Li et al., 2001) have been used in meat quality evaluation exercises. Colour, marbling and image texture features have been used to develop tenderness prediction models for beef (Li et al., 1999). They performed statistical as well as neural network analyses to relate image features to tenderness score. In the work of Li et al. (2001), multi-scale texture analysis based on wavelets was used to classify beef samples into tender and tough categories. In the work of Shiranita et al. (2000), the concept of "marbling score[1]", image processing, neural networks and multiple regression analysis were used to study the implementation of a meat quality grading system.

The aim of this research was to investigate the use of image processing and texture analysis techniques in the classification of lamb chop images, with the specific objective was to characterize lamb chops from the features provided by image and texture analyses.

In section 2, we describe the materials used. Section 3 presents the methods used, which includes, calculation of geometric and texture features and data analysis. Section 4 describes the results and the conclusions are in section 5.

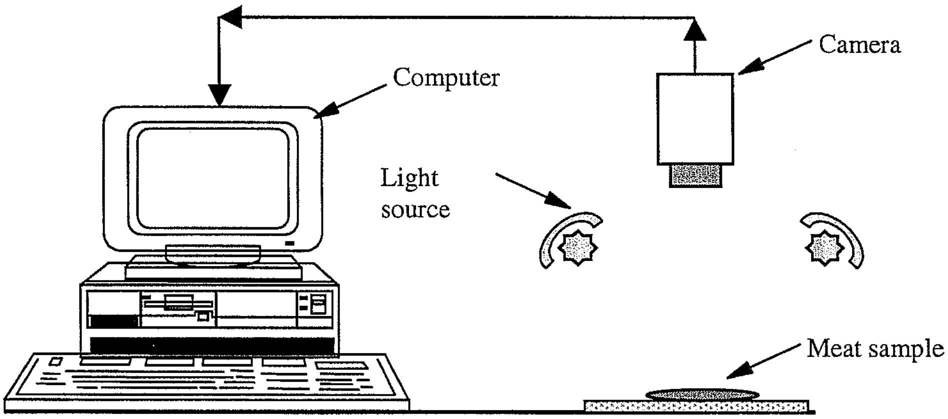

Figure 2. Equipment set up for image capture and analysis

2. Materials

2.1. *Source of Lamb Chops*

The data were collected from 160 digital images of lamb mid loin chops taken at 13th rib from randomly selected sides of 160 lamb carcasses. The animals were from Dorset Down x Coopworth and Merino x Coopworth breeds. Six common lamb grades (FH, PM, PX, TH, YM, YX) were selected for this analysis. These grades represent about 90% of the

[1] marbling score is a measure of the distribution of marbling.

total volume of lamb graded in New Zealand for export market. After 24 hrs of aging, two sets of mid loin chops were removed from both sides of the carcass. One set of samples was used for 24 hrs tenderness evaluation and imaging. The other set was aged at 1^0 C until 21 days post-mortem and then used for tenderness evaluation.

2.2. *Imaging System*

The imaging system (Figure 2) consisted of a 3 CCD (Charge Couple Device) colour digital camera (Sony, DSR-PD150P) mounted on a stand (RSX copy stand, Kaiser, Germany), lighting system (two sets of RB 5004 HF copy lighting units, Kaiser, Germany), personal computer (850 MHz AMD Athlon processor, with 512 MB RAM) and image processing and analysis software (Image-Pro Plus, Media Cybernetics, USA) with its development environment.

2.3. *Image Acquisition*

The samples were all bloomed for 30 min. and surface moisture was removed with a paper towel before capturing images. For imaging, lamb chops were placed flat on a nonglare black surface and illuminated with standard lighting (Kaiser lighting system). The still images of lamb chops were later transferred to the PC for storage and analysis. The images included lean area, marbling, subcutaneous fat, intermuscular fat and bone.

3. Methods

3.1. *Image Processing and Analysis*

Image processing and analysis were accomplished using Image-Pro Plus software. Processing algorithms for determining lean and fat areas, marbling, fat thicknesses and texture parameters were developed using Image-Pro Plus with Image-Pro Basic (IPBasic) programming language. IPBasic is the language in which Image-Pro macros are written and interpreted. IPBasic commands conform to Visual Basic syntax. Automation of routine procedures was achieved with Auto-Pro scripting facility. The images were first segmented into lean (dark) and fat (light) areas. Thresholding was done through trial and error by observing and selecting the best value. Initial values for thresholding were selected from the plot of pixel intensities.

A total of 12 image geometric variables were measured.

1. area of lean in cm^2 (*lean area*)
2. area of marbling within lean in cm^2 (*marbling area*)
3. subcutaneous fat area in cm^2 (*fat area*)
4. lean ratio - the ratio of areas between lean and lean + marbling (*lean ratio*)
5. number of marbling specks (*no of marbling specks*)
6. average, minimum and maximum thickness values of subcutaneous fat (*sub fat average, sub fat maximum, sub fat minimum*)
7. thickness of fat layer at a point 11cm from the midline of the carcass (*fat* 11)
8. average, minimum and maximum of fat thickness values between 10 cm and 12 cm from the midline of the carcass (*fat* 11 *average, fat* 11 *minimum* and *fat* 11 *maximum*)

3.2. *Extraction of Texture Features*

Image texture contains statistical information of grey level image in the spatial domain and can be analysed by studying the spatial dependence of pixel values. Since the textural properties of images appear to carry useful information, it is important to extract features from images. Texture analysis is a well-developed technology and has been used for the analysis of a wide variety of images ranging from microscopic images to satellite images. In this research we use grey level co-occurrence matrix to extract texture features.

Grey Level Co-occurrence matrix (GLCM)

The GLCM is based on the estimation of second order joint conditional probability density functions $P(i, j: d, \theta)$. Each $P(i, j: d, \theta)$ is the probability that two neighbouring pixels with grey levels i and j occur for a given distance d and direction θ. This yields a matrix of dimensions equal to the grey levels in the image, for each distance and orientation (d, θ). Consider an image with N_x pixels in the horizontal direction and N_y pixels in the vertical direction. The grey levels of image pixels are quantised into N_g grey levels. Consider a pair of pixels (k, l) and (m, n) in a texture image, that are separated by a distance d and angle θ with respect to the horizontal axis (Figure 3). Let the grey level of pixel (k, l) be of value i and that of pixel (m, n) be of value j.

When GLCM is constructed with symmetry, only angles up to 180^0 need to be considered and this can be done at regular angular intervals. There is no distinction between opposite angles, i.e. $P(i, j: d, \theta) = P(i, j: d, \theta + \pi)$ and therefore $P(i, j: d, \theta) = P(j, i: d, \theta)$. The elements of unnormalized co-occurrence matrix, $P(i, j: d, \theta)$, in the four principal directions (horizontal, first diagonal, vertical and second diagonal or $\theta = 0^0, 45^0, 90^0$ and 135^0) are defined as:

$$\begin{aligned}
P(i, j: d, 0^0) &= \#\{((k, l), (m, n)) \in (L_x \text{ x } L_y) \text{ x } (L_x \text{ x } L_y) \mid \\
&\quad (k - m = 0, |l - n| = d), I(k, l) = i, I(m, n) = j\} \qquad (1) \\
P(i, j: d, 45^0) &= \#\{((k, l), (m, n)) \in (L_x \text{ x } L_y) \text{ x } (L_x \text{ x } L_y) \mid \\
&\quad (k - m = d, l - n = -d) \text{ or } (k - m = -d, l - n = d), \\
&\quad I(k, l) = i, I(m, n) = j\} \qquad (2) \\
P(i, j: d, 90^0) &= \#\{((k, l), (m, n)) \in (L_x \text{ x } L_y) \text{ x } (L_x \text{ x } L_y) \mid \\
&\quad (|k - m| = d, l - n = 0), I(k, l) = i, I(m, n) = j\} \qquad (3) \\
P(i, j: d, 135^0) &= \#\{((k, l), (m, n)) \in (L_x \text{ x } L_y) \text{ x } (L_x \text{ x } L_y) \mid \\
&\quad (k - m = d, l - n = d) \text{ or } (k - m = -d, l - n = -d), \\
&\quad I(k, l) = i, I(m, n) = j\} \qquad (4)
\end{aligned}$$

where

where	$\#$	= number of elements in the set
	(k, l)	= coordinate with grey level i
	(m, n)	= coordinate with grey level j
	$I(k, l)$	= grey level intensity at coordinate (k, l)
	$I(m, n)$	= grey level intensity at coordinate (m, n)
	L_x	= horizontal spatial domain $(1, 2, \ldots, N_x)$
	L_y	= vertical spatial domain $(1, 2, \ldots, N_y)$

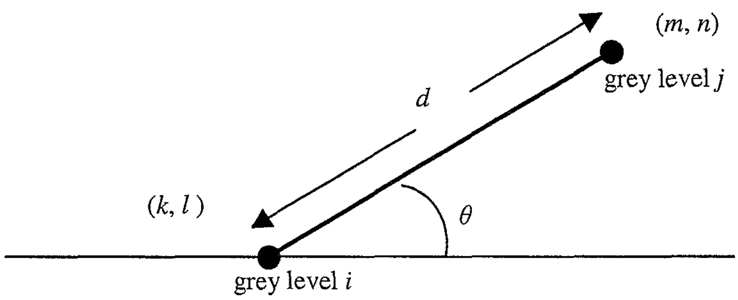

Figure 3. Displacement (d, θ)

Scale is an important aspect of texture. Characterization of image texture depends on the scale of analysis. The scale refers to the size of the textural elements or neighbourhood used for textural analysis. Use of different scales reveals different levels of details of an image texture. A small d results in a P matrix relating to the detailed local properties of an image, while a large d leads to properties in large scale.

There is no known rigorous optimal method for selecting d and θ. Based on the results of preliminary experiments we fixed the value of d = 1 to 10 with angles $\theta = 0^0$, 45^0, 90^0 and 135^0. For each direction, one matrix is computed and thus we have four such matrices ($P(i, j: 1, 0^0)$, $P(i, j: 1, 45^0)$, $P(i, j: 1, 90^0)$ and $P(i, j: 1, 135^0)$). If an image is quantised into N_g grey levels, then the co-occurrence matrix is an N_g x N_g matrix. The GLCM is to be implemented with some rotation invariance. This can be achieved by combining the results of subset of angles ($\theta = 0^0$, 45^0, 90^0 and 135^0). By adding the four matrices we obtained the summation matrix $P(i, j)$.

$$P(i,j) = \sum_{\theta=0,45,90,135} P(i,j:d,\theta) \tag{5}$$

$$i, j = 1, 2, \ldots\ldots\ldots\ldots, N_g$$

In addition $P(i, j)$ and $P(i, j: d, \theta)$ are normalized by dividing each entry of the co-occurrence matrix by the total number of paired occurrences in the image as

$$p(i,j) = \frac{P(i,j)}{\sum_i \sum_j P(i,j)} \tag{6}$$

$$p(i,j:d,\theta) = \frac{P(i,j:d,\theta)}{\sum_i \sum_j P(i,j:d,\theta)} \tag{7}$$

A number of features can be computed from these matrices. A general procedure was presented by Haralick et al (1973) for extracting textural properties of image data in the spatial domain and suggested a set of 14 features for texture characterization. Unser (1986) also defined some texture properties. In this research, a set of 18 features was calculated. These 18 features are *angular second moment*, *contrast*, *correlation*, *variance*, *inverse difference moment* or *homogeneity*, *sum average*, *sum variance*, *sum entropy*, *entropy*, *difference variance*, *difference entropy*, *information measures of correlation* (1 and 2), *mean*, *difference average*, *cluster prominence*, *cluster shade* and *product moment*. These 18 parameters were calculated from the normalized co-occurrence matrices in four principal directions ($p(i, j: 1, 0^0)$, $p(i, j: 1, 45^0)$, $p(i, j: 1, 90^0)$ and $p(i, j: 1, 135^0)$) separately, as well as from the normalized summation matrix $p(i, j)$. There were total of 90 texture variables.

3.3. *Data Analysis*

Principal Component Analysis and Cluster Analysis were used to reduce the dimensionality of the data. The reduced feature spaces were used for the discriminant analysis. Statistical analysis was performed with Minitab (release 13.1, Minitab Inc.) and SPSS (release 10.0.5, SPSS Inc.).

3.3.1. *Principal Component analysis (PCA)*

PCA is a method of data compression, developed to identify the directions of main variability in a multivariate data space. It is an orthogonal transformation that transforms the original set of variables into new axes or principal components (PCs), while retaining as much as possible variation in the original data set. Mathematically, PCs are linear transformations of the original measured set of variables. The calculation of PCs is simply a task of finding these indices of linear transformation.

The PCs are uncorrelated and ordered so that the first PC displays the largest amount of variation and each successively defined PC expresses decreasing amount of variation. The first few PCs contain most of the variation in the original data set. The lack of correlation means that the PCs are measuring different dimensions in the data. The best results from PCA are obtained when the original variables are highly correlated (Manly, 1994; Mardia et al., 1979).

The number of PCs to choose is usually determined by how much variability each of the PC represents; select the smallest number of PCs that the cumulative variance proportion has reached the criterion acceptable. For each principal component a new variable is obtained by projecting the samples onto its space. These new variables are usually called PC scores.

3.3.2. *Cluster analysis*

Clustering analysis is another multivariate analysis technique that classifies objects into clusters. The objects within the same cluster should resemble and objects in different clusters should differ from one another. The resulting clusters of objects should then exhibit high homogeneity within a cluster and high heterogeneity between clusters.

Many algorithms have been proposed for cluster analysis. The two approaches, partitioning and hierarchical techniques, are more common. Partitioning method classifies objects into a specified number of clusters with each cluster containing at least one object and each object belonging to no more than one cluster. In this method objects are allowed to move in and out of clusters at different stages of the analysis.

Hierarchical clustering methods fall into two categories, agglomerative and divisive clustering. Clustering starts with a matrix of distances between individuals (the distances between each individual to all other individuals). In divisive clustering all objects start in a single cluster. This is then split into two clusters. The procedure continues until all objects are in clusters of their own. In agglomerative clustering, each object is considered as a separate cluster and then two clusters that are most similar are merged into a new cluster. The procedure is continued until finally all the objects are in a single cluster. The graphical representation of the results of a hierarchical clustering is called dendrogram.

3.3.3. *Discriminant function analysis (DFA)*

DFA is yet another multivariate technique in which two or more predictors are used in combination. DFA is concerned with the problem of assigning individuals (on whom several variables have been measured) to certain groups that are already identified in the sample. It takes into account the different variables of an object and works out which group the object most likely belongs to. DFA finds a set of linear combinations of the variables, whose values are as close as possible within groups and as far apart as possible between groups. A discriminant function is a linear combination of the discriminating (independent) variables.

A linear discriminant function ($D_i = a_i + b_{i1}X_1 + b_{i2}X_2 + \ldots + b_{ip}X_p$) is created such that the two groups differ as much as possible on *D*, where the *b*'s are discriminant coefficients, the *X* 's are discriminating variables and *a* is a constant.

4. Results and Discussion

For each image, 102 features were calculated: 12 geometric variables and 90 co-occurrence texture variables as described in sections 3.1 and 3.2. The standardised data (mean of zero and variance of one) were then reduced using PCA and cluster analysis and the reduction procedure is described below.

4.1. *Data Reduction*

The results of the PCA for image geometric variables and texture variables are presented in Table 1. The analysis shows that 43.7% of the total variation of the image geometric variables is explained by the first PC, 64.2% by the first two PCs, 79.1% by the first three PCs, 87.8% by the first four PCs, 93% by the first five PCs and the 96.1% by the first six PCs. That means 96.1% of the total variance in all the twelve geometric variables can be condensed into six PCs. Principal components loading (eigen vectors) of geometric variables are shown in Table 2. The loading plot (plot of eigen vectors), shown in Figure 4, can be used for further interpretation of results.

Table 1. Results from the PCA for geometric variables and texture variables

	Principal components	Eigen value	% Variance	Cumulative variance %
Image geometric variables	PC1	5.24	43.7	43.7
	PC2	2.46	20.5	64.2
	PC3	1.79	14.9	79.1
	PC4	1.05	8.7	87.8
	PC5	0.62	5.1	93.0
	PC6	0.38	3.1	96.1
Co-occurrence texture variables	PC1	47.03	52.3	52.3
	PC2	17.67	19.6	71.9
	PC3	11.20	12.4	84.3
	PC4	5.89	6.5	90.9
	PC5	4.89	5.4	96.3
	PC6	1.20	1.3	97.6
	PC7	0.78	0.9	98.5
	PC8	0.59	0.7	99.2

Six new variables or PC scores were calculated as a linear combination of the measured variables. For each sample, PC scores were calculated as the summation of the principal component loading multiplied by respective measured variable. For example,

$$PC1 = \sum(-0.148 \times lean\,area - 0.485 \times marbling\ area - 0.293 \times fat\ area + 0.477 \times lean\,ratio....)$$

These PC scores were used as variables for classification. The other alternative to PC score is that one of the measured variables can be selected to represent the principal component. This is computationally attractive, as we don't have to extract all the variables. Only the selected variables can be extracted. In this research, we used both approaches to examine the effect on classification.

Table 2. Principal components loading of geometric variables

	Variable	PC1	PC2	PC3	PC4	PC5	PC6
1	lean area	-0.148	-0.097	0.094	**-0.956***#	-0.160	-0.085
2	marbling area	-0.485	**0.828***#	-0.031	0.028	-0.140	-0.220
3	fat area	-0.293	-0.454	0.463	0.225	**-0.664***#	0.031
4	lean ratio	0.447	-0.841*	0.034	-0.170	0.123	**0.193**#
5	marbling specks	-0.239	**0.806***#	-0.060	-0.183	-0.119	0.453
6	sub fat average	-0.743*	-0.023	**0.632**#	-0.013	0.149	0.017
7	sub fat minimum	-0.675*	0.004	**0.579**#	0.089	0.203	0.200
8	sub fat maximum	-0.743*	-0.019	**0.496**#	-0.084	0.182	-0.179
9	fat 11	**-0.895***#	-0.217	-0.359	-0.019	0.014	0.019
10	fat 11 average	**-0.886***#	-0.236	-0.394	0.014	-0.007	0.024
11	fat 11 minimum	**-0.873***#	-0.226	-0.370	0.032	-0.048	0.069
12	fat 11 maximum	**-0.859***#	-0.225	-0.396	0.021	0.025	-0.030

* maximum coefficient # selected coefficient

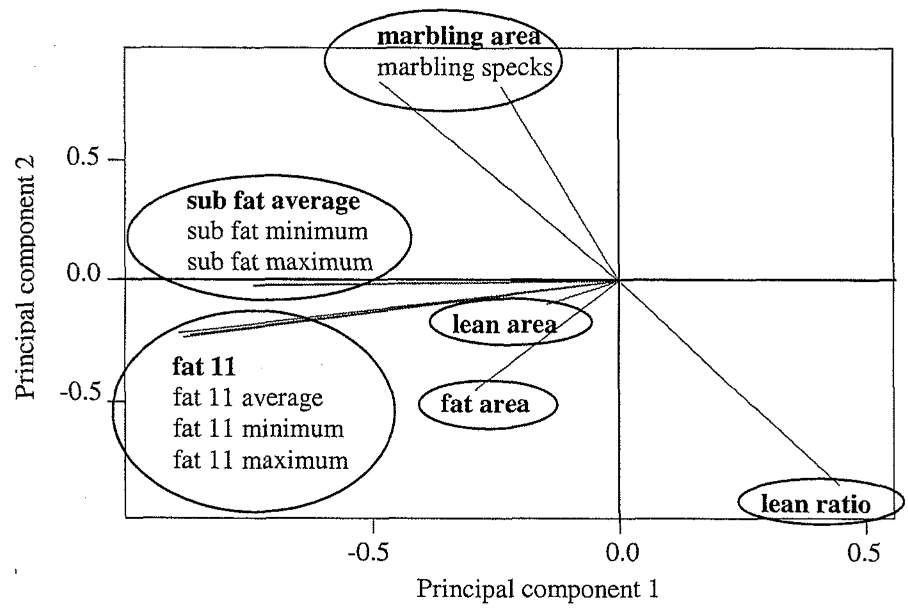

Figure 4. Loading plot of geometric variables

The most important variables for the first PC were *fat* 11, *fat* 11 *average*, *fat* 11 *minimum* and *fat* 11 *maximum* (Table 2). These variables are related to subcutaneous fat thickness at 11 cm (from the mid line of the carcass). So, the first PC is defined by 11 cm fat thickness. These variables, placed to the left in the third quadrant of the loading plot, are close together making a single cluster (Figure 4). The second PC was characterised by two marbling indicators: *marbling area* and *no of marbling specks*. These variables are placed in the second quadrant, form another cluster (Figure 4).

The third PC is characterized by three subcutaneous fat thickness (*sub fat average, sub fat maximum, sub fat minimum*) parameters. These variables placed to the left in the second and third quadrants (close to the x axis) of the loading plot are also close together making another cluster (Figure 4). *Lean area, fat area* and *lean ratio* represented the fourth, fifth and sixth PC, respectively. The variables formed three separate groups in the third and fourth quadrants of the loading plot (Figure 4). First, second and third PCs are characterized by more than one variable. Three variables were selected to represent these PCs. Therefore the original number of 12 variables can be effectively represented by six variables which are: *fat* 11, *marbling area, sub fat average, lean area, fat area* and *lean ratio*.

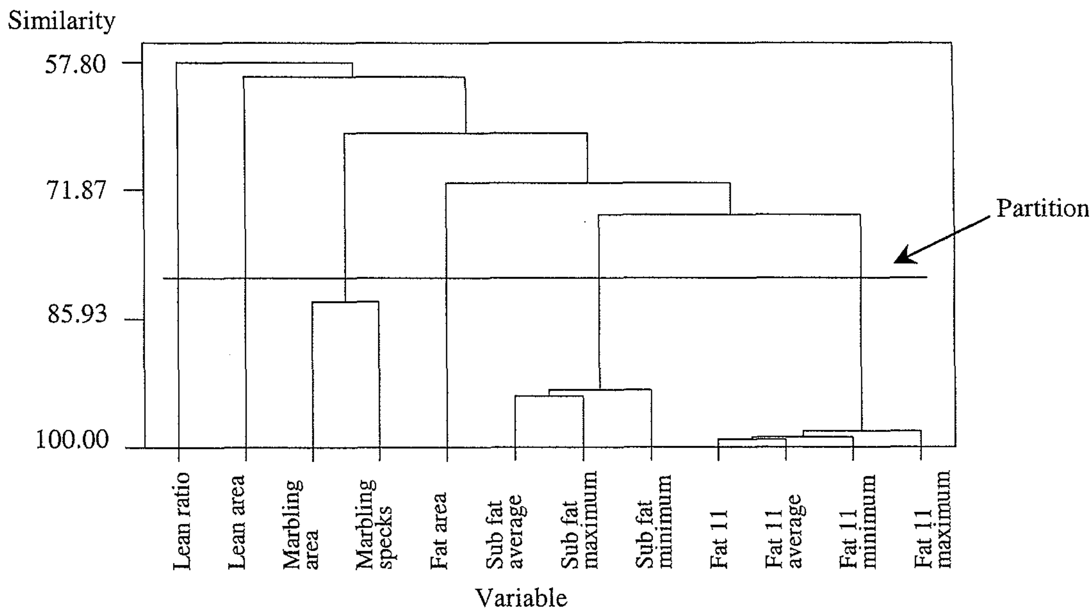

Figure 5. Dendrogram of geometric variables

Cluster analysis of the variables (agglomerative clustering) was carried out using twelve geometric variables. Figure 5 shows the dendrogram. Partition of the six clusters produced *lean ratio, lean area* and f*at area* alone in three separate clusters whilst two variables (*marbling area* and *marbling specks*), three variables (*sub fat average, sub fat minimum* and *sub fat maximum*) and four variables (*fat* 11, *fat* 11 *average, fat* 11 *minimum* and *fat* 11 *maximum*) were in three other clusters confirming the results of PCA.

The analysis of texture variables shows that 52.3% of the total variation is explained by the first PC, 71.9% by the first two PCs, 84.3% by the first three PCs, 90.9%

by the first four PCs, 96.3% by the first five PCs, 97.6% by the first six PCs, 98.5% by the first seven PCs and 99.2% by the first eight PCs (Table 1). That is 99.2% of the total variance in the ninety image texture variables can be condensed into eight PCs. Figure 6 shows loading plot for image texture variables. Visual examination of the loading plot revealed eight clusters of variables. Therefore, eight texture variables were selected using the procedure explained previously, for geometric variables. The texture variables selected are *mean*, *homogeneity*, *entropy*, *contrast*, *cluster prominence*, *cluster shade*, *difference entropy* and *IMC2*. All of them were calculated from the summation matrix, $p\ (i, j)$. Cluster analysis of the variables was carried out on the ninety texture variables and produced similar results to PCA. The reduced set of variables, therefore, included six-image geometric variables and eight co-occurrence texture based variables.

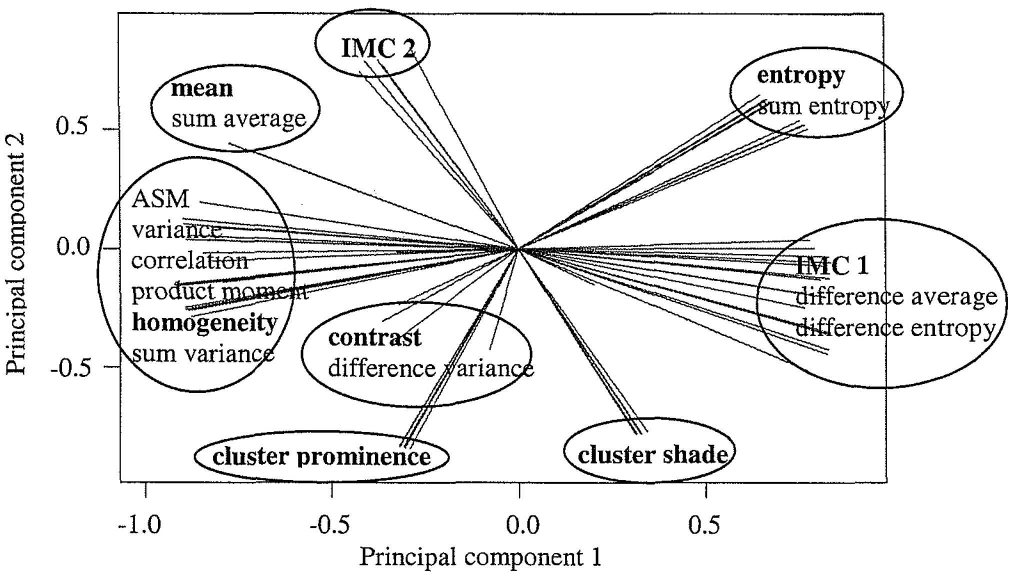

Figure 6. Loading plot of texture variables

4.2. *Classification*

DFA was performed to classify lamb images into different grades. The analysis was carried out using linear and quadratic discriminant functions with and without cross validation. In all cases, linear discriminant functions produced better classification than quadratic discriminant functions. In the analysis, equal prior probabilities (all the groups are treated equally) as well as prior probabilities calculated from group membership sizes were used. Prior probabilities calculated from group sizes account for prior knowledge of probable group membership or bias the allocation procedure in favour of groups with higher membership. Adjustment for prior probabilities will have the greatest impact when the groups overlap or when there are number of cases near the borderlines between the groups (Klecka, 1980). If the groups are very distinct, then the adjustments for prior probabilities will have the least effect.

Table 3. Results of Discriminant Function Analysis

	Variables[#]	No of images correctly classified (%)						
		FH	PM	PX	TH	YM	YX	Total
1	reduced set 1	100.0	73.3	44.4	100.0	58.1	66.7	64.0
2	reduced set 2	100.0	60.0	44.4	80.0	67.7	70.7	66.0
3	reduced set 3	100.0	73.3	63.0	100.0	74.2	85.3	79.0
4	all variables	100.0	66.7	51.9	100.0	74.2	77.3	73.0
5	PC scores set 1	100.0	66.7	48.1	100.0	54.8	72.0	66.3
6	PC scores set 2	100.0	66.7	44.4	0.0	77.4	73.3	67.5
7	PC scores set 3	100.0	66.7	59.3	80.0	77.4	82.7	76.9

[#] reduced set 1 (6 geometric variables); reduced set 2 (8 texture variables calculated from $p(i, j)$); reduced set 3 (reduced set 1 + reduced set 2); all variables (12 geometric and 90 texture variables); PC scores set 1 (6 PC scores of geometric variables); PC scores set 2 (8 PC scores of texture variables); PC scores set 3 (PC scores set 1 + PC scores set 2).

Classification was performed using both the reduced and original data sets. The seven sets of variables used for classification were: three reduced sets (six geometric variables, eight texture variables and 14 geometric + texture variables); all 102 variables (12 geometric variables and 90 texture variables) and three sets of PC scores (six geometric PC scores, eight texture PC scores and 14 geometric + texture PC scores). Table 3 shows classification results. In the analysis, higher overall classification rate was observed with prior probabilities calculated from group sizes.

Both PC scores and selected variables were used to examine the effect of selecting original variables to represent PC scores. Classification with 14 PC scores produced 76.9% accuracy but the classification accuracy with 14 geometric and texture variables were 79%. This clearly shows that selection of original variables to represent PC scores is successful. The original data set was used to observe the effect of data reduction on classification. The results are shown in Table 3. Classification with all variables (12 geometric and 90 texture) produced 73% accuracy but the classification was higher (79%) with the selected set of variables. It undoubtedly indicates that the data reduction is effective and there is no loss of information contained in the data set. In other words, it is clear that some of the variables measured are highly correlated with others and carry no additional information, making them redundant.

More features extracted from images always leads to a better characterization. Normally we would expect a higher classification with more features. But in practical, the contrary was observed indicating the existence of an optimal measurement complexity. The error rate initially drops with an increasing number of features but at a certain point error rate saturate and then it rises if additional features are used (Jain and Chandrasekaran, 1982). This phenomenon is called curse of dimensionality.

Table 4. Details of misclassified images (reduced set 3)

	FH	PM	PX	TH	YM	YX	Total
FH	100.0	0.0	0.0	0.0	0.0	0.0	100.0
PM	0.0	73.3	0.0	0.0	26.7	0.0	100.0
PX	0.0	0.0	63.0	0.0	3.7	33.3	100.0
TH	0.0	0.0	0.0	100.0	0.0	0.0	100.0
YM	0.0	9.7	0.0	0.0	74.2	16.1	100.0
YX	0.0	1.3	6.7	0.0	6.7	85.3	100.0

Table 4 present details of misclassified images with prior probabilities calculated from group sizes. The classification rate of the grade YX was 85.3%, while the corresponding misclassifications into grades PM, PX and YM were 1.3%, 6.7% and 6.7%, respectively (Table 4). The classification rate of grade YM was 74.2%. The misclassification of YMs into grades PM and YX were 9.7% and 16.1%, respectively. This higher misclassification into grade YX is probably due to the influence of high membership population in grade YX, forcing the cases near the borderline between YM and YX to classify as YX. But the YM managed to improve its classification by drawing some misclassified cases from grades PM and PX.

The two grades TH and FH produced 100% classification rates. The classification rate for the grade PM was 73.3%. The grade PM was unable to attract any of the misclassified cases from YM. This may be due to higher membership population of the grade YM compared to the grade PM. Finally, the classification of grade PX was only 63%. This can be explained by analysing misclassified cases. The misclassification into grade YX and YM were 33.3% and 3.7%, respectively. The influence of YX on PX, the grade share common border with YX, is high.

All the misclassified images of grade PM were classified as grade YM (Table 4). These two grades lie between the same weight ranges. A fat depth of 7 mm separates the grades. A fat depth higher than 7 mm is graded as PM and fat depth with 7 mm or less is graded as YM. On the other hand, 9.7% of the misclassified images of the grade YM fell into the grade PM. Similar observations were made between the grades YX and PX. The two grades are separated by 9 mm fat depth. Highest percentage (33.3%) of misclassified images of the grade PX were in the grade YX, while 6.7% of the misclassified images in grade YX are in grade PX.

Inclusion of carcass weight produced higher overall classification in first three cases of Table 5. Apparently, carcass weight seems to have some vital information that does not carry in the geometric and texture variables. The highest overall classification rate without carcass weight was 79% and addition of carcass weight improved the overall classification to 85% (Table 5). In case of all (geometric and texture) variables, the overall classification remained unchanged at 73%, even after the addition of carcass weight indicating that the carcass weight has no additional information. PC scores with carcass weight produced classification accuracy of 85%.

Table 5. Results of Discriminant Function Analysis effect of carcass weight

	Variables*	No of images correctly classified (%)						
		FH	PM	PX	TH	YM	YX	total
1	reduced set 1	100.0	73.3	44.4	100.0	58.1	66.7	64.0
	reduced set 1 + HCW	100.0	86.7	51.9	100.0	58.1	84.0	75.0
2	reduced set 2	100.0	60.0	44.4	80.0	67.7	70.7	66.0
	reduced set 2 + HCW	100.0	60.0	55.6	100.0	87.1	81.3	78.0
3	reduced set 3	100.0	73.3	63.0	100.0	74.2	85.3	79.0
	reduced set + HCW	100.0	80.0	70.4	100.0	80.6	90.7	85.0
4	all variables	100.0	66.7	51.9	100.0	74.2	77.3	73.0
	all variables + HCW	100.0	66.7	51.9	100.0	74.2	77.3	73.0
5	PC score set3	100.0	66.7	59.3	80.0	77.4	82.7	76.9
	PC score set 3 + HCW	100.0	73.3	74.1	80.0	80.6	92.0	85.0

* HCW (hot carcass weight), others similar caption as Table 3

More than 35% of the New Zealand lambs produced for the export market belong to the YM grade (Meat New Zealand, 2001). The YX, PM and PX grades together account for nearly 50% of the export lamb production. The TH and FH grades comprise about 5%, the grades YL and PH account for about 6% and the other grades (PL, TL, TM, FL and FM) contribute about 1%. The majority of carcasses fall, therefore, into YM, YX, PM and PX grades. Thus higher classification accuracy is required for these grades. In this research, we used YM, YX, PM, PX, TH and FH grades. These grades represent more than 90% of the New Zealand export lamb production.

5. Conclusions

In this paper, we have investigated the classification of lamb images using image and texture analysis together with multivariate statistical techniques. Six geometric variables and eight texture variables extracted from grey level co-occurrence matrices of lamb chop images were used for classifying lamb carcasses into different grades. PC scores calculated from geometric and texture variables were also used for classifying lamb carcasses.

The classification showed encouraging results indicating that the data extracted from images of lamb chops can be effectively used to predict lamb carcass grades. The classification accuracy using 14 PC scores were 76.9% and addition of carcass weight produced overall classification of 85%. The accuracy of predicting lamb grades using six geometric variables was 64%. Inclusion of eight texture variables in the analysis improved the overall classification to 79%, which is better than the classification using PC scores. The addition of carcass weight improved the overall classification to 85%.

The classification of lamb images using geometric and texture features have therefore been successful. Certain grades were classified as 100%. The calculated texture features have therefore the potential to be used as indicators of the quality of lamb carcasses. Extraction of texture features with different techniques and further experiments on a larger number of samples, including the grades YL and PH are planned for future studies on lamb carcasses.

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6. References

Ballerini, L. and Bocchi, L. (2001). A fractal approach to predict fat content in meat images. *Second International Symposium on Image and Signal Processing and Analysis* (ISPA 2001), Pula, Croatia, 19 - 21 June 2001.

Borggaard, C., Madsen, N. T. and Thodberg, H. H. (1996). In-line image analysis in the slaughter industry, Illustrated by beef carcass classification. *Meat Science*, 43 (S), S151 - S163.

Chen, Y. R., McDonald, T. P. and Crouse, J. D. (1989). Determining precent intramuscular fat on rib eye surface by image processing. *ASAE Paper No.* 893009, ASAE, St. Joseph, MI, USA.

Conners, R. W. and Harlow, C. A. (1980). A theoretical comparison of texture algorithms. *IEEE Transactions on Pattern Analysis Machine Intelligence*, PAMI - 2 (3), 204 - 222.

Cross, H. R., Gilliland, D. A., Durland, P. R. and Seideman, S. (1983). Beef carcass evaluation by use of a video image analysis system. *Journal of Animal Science*, 57 (4), 908 - 917.

Galloway, M. M. (1975). Texture analysis using grey level run lengths. *Computer Graphics and Image Processing,* 4, 172 - 179.

Gardner, T. L., Dolezal, H. G. and Allen, D. M. (1995). *Utilization of video image analysis in predicting beef carcass lean product yield.* Research Report P 943, Oklahoma Agriculture Experiment Station.

Gerrard, D. E., Gao, X. and Tan, J. (1996). Beef marbling and colour score determination by image processing. *Journal Food. Science*, 61, 145 - 148.

Haralick, R. M. (1979). Statistical and structural approaches to texture. *Proceedings of the IEEE*, 67(5), 786 - 804.

Haralick, R. M., Shanmugan, K. and Dinstein, I. (1973). Texture features for image classification. *IEEE Transactions on Systems, Man and Cybernetics*, SMC - 3 (1), 610 - 621.

Hopkins, D. L., Fogarty, N. M. and MacDonald, B. A. (1997). Prediction of lamb carcass yield using video image analysis. *Proceedings of the 43rd International Congress of Meat Science and Technology*, pp 234 - 235.

Horgan, G. W., Murphy, S. V. and Simm, G. (1995). Automatic assessment of sheep carcasses by image analysis. *Animal Science*, 60, 197 - 202.

Jain, A. K. and Chandrasekaran, B. (1982). Dimensionality and sample size considerations in pattern recognition practice. In Krishnaiah, P. R. and Kanal, L. N. (Eds.), *Handbook of statistics (vol 2): Classification, pattern recognition and reduction of dimensionality* (pp 835 - 855). Amsterdam: North Holland publishing Company.

Karnuah, A. B., Moriya, K., Mitani, K. and Sasaki, Y. (1995a). Estimation of beef carcass composition from the cross-section around the longissimus muscle area in Holstein steers by computer image analysis. *Animal Science Technology*, 66 (4), 323 - 329.

Karnuah, A. B., Moriya, K., Mitani, K., Yamasaki, T. and Sasaki, Y. (1996). Estimation of carcass composition by computer image analysis in the cross section of crossbred steers. *Canadian Journal of Animal Science*, 76, 497 - 506.

Karnuah, A. B., Moriya, K., Nakanishi, N., Nade, T., Mitsuhashi, T. and Sasaki, Y. (2001). Computer image analysis for prediction of carcass composition from cross sections of Japanese Black steers. *Journal of Animal Science*, 79, 2851 - 2856.

Karnuah, A. B., Moriya, K., Sasaki, Y., Mitsumoto, M., Mitsuhashi, T. and Ozawa, S. (1995b). Estimation of carcass composition by computer image analysis in the cross section of Japanese black steers. *Animal Science Technology*, 66 (12), 987 - 993.

Klecka, W. R. (1980). *Discriminant analysis*. Sage University Paper Series on Quantitative Applications in the Social Sciences, series no. 07-019. Beverly Hills and London: Sage Publications.

Kuchida, K., Yamaki, K., Yamagishi, T. and Mizuma, Y. (1992). Evaluation of meat quality in Japanese beef cattle by computer image analysis. *Animal Science Technology*, 63 (2), 121 - 128.

Li, J., Tan, J., Martz, F. A. and Heymann, H. (1999). Image texture features as indicator of beef tenderness. *Meat Science*, 53, 17 - 22.

Li, J., Tan, J. and Shatadal, P. (2001). Classification of tough and tender beef by image texture analysis. *Meat science*, 57, 341 - 346.

Lu, J. and Tan, J. (1998). Application of non-linear transforms to beef image processing. *ASAE Paper No.* 983016, ASAE, St. Joseph, MI, USA.

Lu, J., Tan, J., Gao, X. and Gerrard, D. E. (1998). USDA beef classification based on image processing. *ASAE Paper No. MC* 98131, Mid-central conference, ASAE, St. Joseph, MI, USA.

McDonald, T. and Chen, Y. R. (1989). Location and isolation of beef carcass ribeyes in cluttered scenes. *ASAE Paper No.* 893005, ASAE, St. Joseph, MI, USA.

McDonald, T. and Chen, Y. R. (1990). Separating connected muscle tissues in images of beef carcass ribeyes. *Transactions of the ASAE*, 33 (6), 2059 - 2065.

Manly, B. F. J. (1994). *Multivariate statistical methods: a primer*. London: Chapman and Hall.

Mardia, K. V., Kent, J. T. and Bibby, J. M. (1979). *Multivariate analysis*. London: Academic Press.

Meat New Zealand (2001). *Annual report* 2000-2001. Wellington: Meat New Zealand, New Zealand.

New Zealand Meat Board (1992). *New Zealand meat guide to lamb and mutton carcass classification*. Wellington: New Zealand Meat Board, New Zealand. (Reissued 1995).

Ohanian, P. P. and Dubes, R. C. (1992). Performance evaluation for 4 classes of texture features. *Pattern Recognition*, 25 (8), 819 - 833.

Ojala, T., Pietikainen, M. and Harwood, D. (1996). A comparative study of texture measures with classification based on feature distributions. *Pattern. Recognition*, 29, 51 - 59.

Pentland, A. P. (1984). Fractal based description of natural scenes. *IEEE Transactions on Pattern Analysis and Machine Intelligence,* PAMI - 6, 661 - 674.

Schutte, B. R., Biju, N., Kranzler, G. A. and Dolezel, H. G. (1998). *Colour video image analysis for augmenting beef carcass grading*. Research report P 965, Oklahoma Agricultural Experimental Station.

Shackelford, S. D., Wheeler, T. L. and Koohmaraie, M. (1998). Coupling of image analysis and tenderness classification to simultaneously evaluate carcass cutability, longissimus area, sub primal cut weights and tenderness of beef. *Journal of Animal Science*, 76, 2631 - 2640.

Shiranita, K., Miyajima, T. and Takiyama, R. (1998). Determination of meat quality by texture analysis. *Pattern Recognition Letters*, 19, 1319 - 1324.

Shiranita, K., Hayashi, K., Otsubo, A., Miyajima, T. and Takiyama, R. (2000). Grading of meat quality by image processing. *Pattern Recognition*, 33, 97 - 104.

Stanford, K., Richmond, R. J., Jones, S. M. D., Robertson, M., Price, M. A. and Gordon, A. J. (1998). Video Image Analysis for online classification of lamb carcasses. *Animal Science*, 67, 311 - 316.

Tuceryan, M. and Jain, A. K. (1999). Texture analysis. In Chen, C. H., Pau, L. F. and Wang, P. S. P. (Eds.), *Handbook of pattern recognition and computer vision* (pp 207 - 248). River Edge, NJ: World Scientific.

Unser, M. (1986). Sum and difference histograms for texture classification. *IEEE Transactions on Pattern Analysis and Machine Intelligence,* PAMI - 8 (1), 118 - 125.

Van Gool, L., Dewaele, P. and Oosterlinck, A. (1985). Texture analysis anno 1983. *Computer Vision, Graphics and Image Processing*, 29, 336 - 357.

Wassenberg, R. L., Allen, D. M. and Kemp, K. E. (1986). Video image analysis prediction of total kilograms and percentage primal lean and fat yield of beef carcasses. *Journal of Animal Science*, 62, 1609 - 1616.

Weszka, J. S., Dyer, C. R. and Rosenfeld, A. (1976). A comparative study of texture measures for terrain classification. *IEEE Transactions on Systems, Man and Cybernetics*, SMC - 6, 269 - 285.

Yoshikawa, F., Toraichi, K., Wada, K., Otsu, O., Nakai, H., Mitsumoto, M. and Katagishi, K. (2000). On a grading system for beef marbling. *Pattern Recognition Letters*, 21, 1037 - 1050.