COMPUTER VISION FOR LAMB GRADING: STATISTICAL AND NEURAL NETWORK ANALYSES

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Background

Visual assessment has become the principal component of several meat classification and grading systems. Furthermore, the meat industry, in response to consumer demand for products of consistent quality, is placing more and more emphasis 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 because image-processing techniques can quantitatively and consistently characterize complex geometric, colour and textural properties.

The assignment of lamb carcasses to specific quality grades has been an integral part of the New Zealand lamb classification system. The current classification is based solely on measures of carcass weight and fatness. There are five weight (A, L, M, X or H) ranges and five fatness (A, Y, P, T or F) classes (New Zealand Meat Board, 1992). The fatness classes are specified in the New Zealand meat board classification guide in terms of GR measurement. GR 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 followed by weight class (eg. YM, PX etc).

Artificial neural networks are information processing systems which implement simplified models of their biological counterparts, biological neural networks. An Artificial neural network (ANN) contains many simple processing elements (neurons) and they are capable of learning from the environment in which they operate and adapting their responses according to the feedback that they receive.

Objectives

The objectives of the present study were: a) to identify the suitable geometric and textural variables for effective classification of lamb carcasses; b) to develop a method to evaluate lamb carcass grade using geometric and textural data extracted from lamb chop images and c) to compare the statistical approach with the ANN approach.

Methods

Samples: The data was from samples of mid loin chops taken at 13^{th} rib from randomly selected sides of 160 lamb carcasses. The animals were from Dorset Down x Coopworth and Merino x Coopworth breeds. 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 analysis (imaging and tenderness evaluation) and the other set was aged at 1^0C for 3 weeks.

Imaging system: The imaging system consisted of a Digital Camera (Sony® colour digital camcorder DSR-PD150P), Lighting system (RSX Copy Stand with two sets of RB 5004 HF Copy Lighting units, Kaiser®, Germany), Personal Computer (850 MHz AMD Athlon processor, with 512 MB RAM), Image processing and analysis software (Image-Pro® Plus, Media Cybernetics, USA).

Image Capture: The samples were all bloomed for 30 min. and surface moisture removed with a paper towel prior to image capture. For imaging, lamb chops were placed flat on a non-glare black surface and illuminated with standard lighting. 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.

Image Processing and Analysis: Image processing and analysis were accomplished in the Windows 98 environment using Image-Pro Plus. 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 9 image geometric (thickness and area) variables (*lean area, marbling area, subcutaneous fat area, lean ratio* (lean area/(lean area + marbling area)), *number of marbling specks, 3 measurements of subcutaneous fat thickness (average, maximum, minimum)* and *fat thickness at 11 cm from the midline of the carcass*) were measured.

Textural Properties: Gray level co-occurrence matrix (Haralick, et al, 1973) was used to extract texture features. The number of texture parameters calculated from gray level co-occurrence matrix was 18 (Haralick et al., 1973; Unser, 1986).

Statistical Analysis: Data were analysed using Principal Component Analysis (PCA), Discriminent Function Analysis (DFA) and Cluster Analysis procedures on Minitab™ (Minitab release 13.1, Minitab Inc.).

Neural Network Analysis: Neural network analysis was performed with NeuroShell® 2 (Ward Systems Group, Inc., Frederick, MD).

Results and Discussion

Table 1 shows mean, standard deviation and coefficient of variation of the image geometric data. Variation of all the variables, except lean area and lean ratio, were high.

Some of the variables measured are highly correlated with others and carry no additional information, making them redundant. PCA and Cluster Analysis together with correlation coefficients and analysis of variance (ANOVA) were used to identify the redundant variables. According to the results of PCA, 96% of the total variance of image geometric variables can be condensed into six variables (Table 2). The results were confirmed by cluster analysis. ANOVA and correlation coefficients were used to select the most suitable candidate in cases where selection was needed. The final set of six variables included were lean area, marbling area, fat area, lean ratio, subcutaneous fat thickness average and 11 cm fat thickness.

In a similar way, 18 variables calculated from co-occurrence matrix were condensed to six (homogeneity, entropy, contrast, cluster prominence, difference entropy and information measures of correlation 2) whilst retaining 99.5% of the total variance (Table 2).

More than 30% of the New Zealand lambs produced for the export market belong to the YM grade (Meat New Zealand, 2001). The YL, YX, PM and PX grades together account for nearly 50% of the export lamb production. The PH, TH and FH grades comprise about 5% and the other grades (PL, TL, TM, FL and FM) contribute 1%. The majority of carcasses fall, therefore, into YL, YM, YX, PM and PX grades. Thus higher classification accuracy is required for these grades.

To investigate whether image processing could improve classification accuracy, DFA was performed with the reduced set of variables. The variables used in each classification attempt and the results are shown in Table 3. Different classification accuracies were observed for

different grades. A reasonably high (more than 80%) classification rate was obtained for TH and FH grades. The overall classification success was 50% using six texture parameters and 60% with image geometric variables alone. A combination of texture and geometric variables increased the overall classification accuracy to 71.3% and that for YM grade to 77.4%.
Artificial neural networks are capable of performing complex prediction and classification tasks. An ANN is trained to do these tasks by repeatedly presenting it with known input vectors and corresponding outputs (Tarassenko, 1998). After training, the network can perform the task for new inputs that it has never seen before.
To avoid any hierarchy among grades, the symbols representing six grades were translated into six variables, one for each grade, that is coded 1 for belonging to the grade and 0 for not belonging to the grade. ANN analysis was also performed with the reduced set of variables. The 12 variables in this set were used as inputs and the grades were used as outputs. The multiplayer perceptron (MLP) with back propagation algorithm was performed to train the network with one layer of hidden nodes. Several different neural networks and learning schedules were tested to select the best neural network.
The results from neural network models are shown in Table3. The neural network classification accuracy also varies with the grade. The 3 layers MLP network with overall classification success of 83.8% was the best out of all neural network models tested. A reasonably high (77.7 – 86.7%) classification rate was obtained for YM, YX, PM and PX grades. In all attempts classification was perfect for FH grade.

Conclusion

The results indicate that the data extracted from images of lamb chops can be effectively used to predict the lamb carcass grades. However: 1). The accuracy of prediction using the statistical approach is 71.3%, 2). The neural network approach is superior to the statistical method and improved the overall classification accuracy by 12.5%.

Pertinent Literature

1. Haralick, R. M., Shanmugan, K. and Dinstein, I. (1973). Texture features for image classification. *IEEE Trans. on Systems, Man and Cybernetics*, SMC-3 (1), 610 - 621.
2. Meat New Zealand (2001). Annual Report 2000-2001. Meat New Zealand, Wellington, New Zealand.
3. New Zealand Meat Board (1992). New Zealand meat guide to lamb and mutton carcass classification. Reissued 1995. New Zealand Meat Board, Wellington, New Zealand.
4. Tarassenko, L. (1998). *A Guide to Neural Computing Applications*. London: Arnold.
5. Unser, M. (1986). Sum and difference histograms for texture classification. *IEEE Trans. on Pattern Analysis and Machine Intelligence,* PAMI-8 (1), 118 – 125.

Table 1. Image area and thickness data

Variable	Mean	SD	CV
Lean area (cm^2)	11.56	1.52	13.10
Marbling area (cm^2)	0.35	0.29	83.98
Fat Area (cm^2)	6.02	1.53	25.48
Lean Ratio	0.97	0.02	2.43
No. of Marbling specks	81.61	39.53	48.45
Fat thickness average (cm)	0.61	0.16	26.99
Fat thickness minimum (cm)	0.44	0.15	33.19
Fat thickness maximum (cm)	0.83	0.22	26.37
11 cm fat thickness (cm)	0.80	0.32	39.21

Table 2. Principle components

	Principal component	Eigen value	% Variance	Cumulative variance %
Image area and thickness variables	PC1	3.600	40.0	40.0
	PC2	2.316	25.7	65.7
	PC3	1.051	11.7	77.4
	PC4	0.714	7.9	85.4
	PC5	0.608	6.8	92.1
	PC6	0.366	4.1	96.2
Co-occurrence texture variables	PC1	9.558	53.1	53.1
	PC2	3.505	19.5	72.6
	PC3	2.495	13.9	86.4
	PC4	1.203	6.7	93.1
	PC5	1.037	5.8	98.9
	PC6	0.117	0.7	99.5

Table 3. Results of classification

	Variables	Analysis method	No of images correctly classified (%)						
			YM	YX	PM	PX	TH	FH	total
1	LA+MA+FA+LR+FAV+11Fat	DFA	58.1	58.7	53.3	59.3	80.0	85.7	60.0
2	Hom+Ent+Cont+Pro+DEnt+IMC2	DFA	58.1	45.3	60.0	37.0	80.0	85.7	50.6
3	LA+MA+FA+LR+FAV+11Fat+ Hom+Ent+Cont+Pro+DEnt+IMC2	DFA	77.4	68.0	73.3	63.0	80.0	100	71.3
4	LA+MA+FA+LR+FAV+11Fat+ Hom+Ent+Cont+Pro+DEnt+IMC2	4 layer MLP network	80.6	78.7	13.3	70.4	0.0	100	70.0
5	LA+MA+FA+LR+FAV+11Fat+ Hom+Ent+Cont+Pro+DEnt+IMC2	3 layer MLP network	77.4	86.7	86.7	81.5	60.0	100	83.8

Abbreviations: LA (Lean area); MA (Marbling area); FA (Fat area); LR (Lean ratio); FAV (Fat thickness average); 11Fat (11 cm fat thickness) Hom (Homogeneity); Ent (Entropy); Cont (Contrast); Pro (Cluster Prominence); IMC2 (Information Measure of Correlation 2); DEnt (Difference Entropy)