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PREDICTION OF RETAIL BEEF YIELD FROM VIDEO IMAGES USING WAVELET ANALYSIS AND **MULTIVARIATE CALIBRATION**

C.R SMITH¹, S. HARDEN², J.M. THOMPSON¹, R. MURISON³ and D.M. FERGUSON¹

¹ Cooperative Research Centre for the Cattle and Beef Industry (Meat Quality), University of New England, NSW, 2351, Australia

³ Dept. of Statistics, University of New England, Armidale, 2351, Australia

Summary

Wavelet coefficients (WC's) were used to capture colour information at increasing levels of resolution from a video image of domestic weight carcasses. Individual wavelet components compressed the colour information from the carcass into a small subset of WC's. The WC's, which had the strengest line of the strengest had the strongest linear relationship with beef yield, were combined in a multivariate calibration to predict the percentage retail beef yield (RBY%). The multivariate calibration had an adj-R² of 40.3% and an RSD of 1.85 when predicting the RBY%. When cross validated, ^B adj-R² fell to 30.9% and the RSD increased to 2.29. The 'best' WC's demonstrated that there was an advantage to go beyond the present part average, but there was little benefit to go beyond a 4x4 grid within a patch.

Introduction

The whole carcass video image analysis system (VIASCAN[®]) is used on-line in abattoirs to predict the meat yield of beef carcasses and the set of the set capturing lateral images, from which colour parameters and linear dimensions are measured (Ferguson *et al.*, 1995). The colour parameters provide a crude description of the fat coverage by assessing the average red, green and, blue (r,g,b) values within 8 patches over the carcal Since r, g and b parameters exist in a three-dimensional space and are highly correlated, a variety of statistical techniques such as new pretworks and principal asymptotic techniques such as n^{ab} networks and principal component analysis have been used to analyse the colour data for the prediction of saleable meat percentage (Fergue et al., 1995; Boggaard et al., 1996; Smith et al., 1996). The Australian VIASCAN[®] system was able to predict the percentage of saleable meat within market categories with a standard array of view of the percentage of saleable meat within market categories with a standard array of view of the percentage of saleable meat within market categories with a standard array of view of the percentage of saleable meat within market categories with a standard array of view of the percentage of saleable meat within market categories with a standard array of view of the percentage of saleable meat within market categories with a standard array of view of the percentage of saleable meat within market categories with a standard array of view of the percentage of saleable meat within the percentage of meat within market categories with a standard error of estimate (SEE) between 0.98 and 1.76, and generally performed better than carcass weight and fat depth (Ferguson *et al.*, 1995; Smith *et al.*, 1996). Similarly, the Danish VIA system (SEE = 1.34) out performed \mathbb{E} combination of subjective conformation and fat scores (SEE = 1.63) to predict the percentage of saleable meat (Boggaard et al., 1996).

Although the patches traced by the VIASCAN[®] over the carcass are convenient from a carcass jointing perspective, they may not be optimized in number, size and/or location, thus compression the entry of the provide the second in number, size and/or location, thus compromising the prediction of retail beef yield percentage (RBY%). In contrast to the Australia VIASCAN[®], the Danish VIA system divides the carcass into 60 patches (Boggaard *et al.*, 1996). A simple average of r, g and b parameters within a stable parameter a and b parameters a and bwithin a patch may discard information which could influence yield prediction. The statistical tool of wavelets (Nason and Silverman, $\frac{19}{100}$ is capable of capturing localised information at increasing levels of resolution within the patches. Furthermore, individual wavelet components are orthogonal for each patch colour and compresses all the colour information from the patch into a small subset of wavelaction (WC's). Multivariate calibration can then be used to relate the city of the patch into a small subset of wavelaction control of the patch into a small subset of the patch into a smal coefficients (WC's). Multivariate calibration can then be used to relate the significant WC's to RBY%. This paper demonstrates a practical application of the wavelet analysis for support demonstrates a practical definition of the wavelet analysis for support demonstrates and the significant WC's to RBY%. application of the wavelet analysis for summarising video image data and the use of WC's to predict RBY% in a multivariate model.

Material and Methods

Left carcass sides from 98 pasture finished *Bos taurus* steers were imaged using VIASCAN[®] system within an hour of slaughter. carcass weight and P8 fat depth of 205.7 ± 24.6 kg and 7.0 ± 3.0 mm respectively). The left carcass side was boned to standard reput specifications (fat cover over each primal cut trimmed to 3mm). Manufacturing meat, was cored and fat content determined using a rap microwave method (Anon. 1983). RBY% was defined as the total weight of trimmed boneless cuts, plus the weight of manufacturing (adjusted to an 85% chemical lean) expressed as a percentence of (adjusted to an 85% chemical lean), expressed as a percentage of recovered side weight. Mean RBY% for the 98 carcasses was 72.3 ± 1.9 % Modifications to the VIASCAN[®] Software The lateral view of a carcass was originally segmented into 9 patches. Of these, 8 were normality assessed for colour, generating average r_{eq} and h values for each metric D_{eq} is the problem. assessed for colour, generating average r, g and b values for each patch. Based on previous analyses, 6 of these patches were selected on the basis that they contained the most useful colour information to the patch. basis that they contained the most useful colour information to predict RBY%, according to their average r, g and b. The selected patches the selected patches are the selected patches are the selected patches and b. The selected patches are the selected patches encompassed the anterior and posterior loin, rump, knuckle, shin and brisket regions. In this study, each of these 6 patches were further divided in to an 8x8 grid (64 sub-patches). All pixels in each sub-patch divided in to an 8x8 grid (64 sub-patches). All pixels in each sub-patch were averaged to give a mean r, g and b values for each sub-patch. Statistical Methods Carcasses were randomly assigned to either a calibration or validation group and the data from the calibration g^{roup} were initially used to construct the model. The model was assessed by using it to predict the DDVC is in the data from the calibration g^{roup} were called a state of the predict the DDVC is in the data from the calibration g^{roup} were called a state of the predict the DDVC is in the data from the calibration g^{roup} were called a state of the predict the DDVC is in the data from the calibration g^{roup} were called a state of the predict the DDVC is in the data from the calibration g^{roup} were called a state of the predict the DDVC is in the data from the calibration g^{roup} were called a state of the predict the DDVC is in the data from the calibration g^{roup} were called a state of the predict the DDVC is in the data from the calibration g^{roup} were called a state of the predict the DDVC is in the data from the calibration g^{roup} were called a state of the data from the calibration g^{roup} were called a state of the data from the calibration g^{roup} were called a state of the data from the calibration g^{roup} were called a state of the data from the calibration g^{roup} were called a state of the data from the calibration g^{roup} were called a state of the data from the calibration g^{roup} were called a state of the data from the calibration g^{roup} were called a state of the data from the data from the calibration g^{roup} were called a state of the data from the initially used to construct the model. The model was assessed by using it to predict the RBY% in the validation group. The major source of an error was due to the measurement of the colour parameters (denoted by (an the validation group). The major source of an error was due to the measurement of the colour parameters (denoted by (an the validation group). error was due to the measurement of the colour parameters (denoted by $\{r,g,b\}$), whilst error in measuring RBY% was of smaller magnitude Given this, calibration was best modeled using the following function: Given this, calibration was best modeled using the following function :-

 $\{r,g,b\} = g(RBY\%) + error, where g(RBY\%)$ was a regression function (see Brown, 1992, pp 23). Prediction was done by inverse regression for a single value of RBY\% for a given response of $\{r,g,b\}$. When $\alpha(RDM)$ to find a single value of RBY% for a given response of $\{r,g,b\}$. When g(RBY%) was a linear regression, the estimate of RBY% for Robserved VIA measurements, $\{r,g,b\}_0$, was given by the following equation

$\overrightarrow{\text{RBY}} = (\beta \Sigma^{-1} \beta^{\mathsf{T}})^{-1} \beta \Sigma (\{r, g, b\}_0, -\mu)$

where β were the regression coefficients, Σ was the variance-covariance matrix for β , and μ was the mean of $\{r, g, b\}$ estimated from the calibration data (see Brown, 1992, pp 88). Six patches were segmented by an 8x8 grid, leading to a potential multivariate response of 6 patches x 3 colours x 64 within patch measurements. The first step in reducing these data was to transform the measurement of each patch colour by the wavelet transformation (Nason and Silverman, 1994). The data from each patch was represented mathematically by

$$f = \phi + \sum_{i=1}^{63} c_i \psi_i \approx \phi + \sum_{i=1}^{4} c_i \psi_i$$

 ϕ - wavelet for the mean colour of the original patch

ci - wavelet coefficient, capturing colour variation at resolutions that increased by powers of 2

 ψ_I - known wavelet bases

² Tamworth Centre for Crop Improvement, New South Wales Agriculture, 2340, Australia

The image was reconstructed with a small subset of WC's which were shown to contain the most important colour information. The remaining WC's were less useful and assumed to represent 'noise'. Calculations were done using the wavethresh package of Nason and Silverman (1994). The individual WC's were expressions of the localised variation at resolutions that increased by powers of 2 thus, ϕ and c_{63} , $c_{10}c_{61}$, summarised the colour data at low frequency whilst $c_1, \ldots c_{16}$ summarised high frequency data.

^helminary plots of WC's and RBY% revealed that simple linear regression was suitable, therefore a robust regression was fitted for each where parameter. The individual calibrations were combined in a multivariate calibration, but not all were necessary. The 'best' combination ^{br} ^{predicting} RBY% was determined from a stepwise selection by adding and dropping individual regression equations. The choices were ^{the d} on the adjusted coefficient of determination (adj-R²) and residual standard deviation (RSD). A colour parameter from the calibration and the adjusted coefficient of determination (adj tc) and restore than $\chi_{2(0.05)}^2$ for a random variable. WC's were generated for the validation data set and were used to predict RBY%.

Results and Discussion

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 $h_{ahalysis}$ 1, the multivariate calibration incorporated the WC's that described the average r,g or b (denoted by ϕ) from the original $M_{\rm ASCAN}^{\rm source}$ patches. These were the average r and g from the loin patch and b from the rump patch. Analysis 2 augmented this analysis by $\frac{1}{2}$ higher resolution WC's for the g spectrum from the anterior loin patch (c_{62}), the rump patch (c_{55}) and the brisket patch (c_{61}).

 $\mathbb{R}^{\text{light}}$ for the g spectrum from the anterior ioin patch (\mathbb{C}_{62}), the rump patch (\mathbb{C}_{55}) and the order part (\mathbb{C}_{55}) and the order patch (\mathbb{C}_{55} $^{\circ}$ of 40.3% and an RSD of 1.85. When the multivariate calibration was applied to the validation dataset, the adj-R² fell to 30.9% and the $\frac{100.3\%}{100}$ and an RSD of 1.85. When the multivariate calibration was applied to the validation dataset, the enj-spincreased to 2.29 (Table 1). The "best" WC's not only captured localised colour variation from the simple patch average (ϕ), but also higher resolutions, a 2x2 grid (c_{62},c_{61}) and 4x4 grid (c_{55}) .

lable 1: Adjusted coefficients of determination (Adj-R²) and residual standard deviations (RSD) for the

inultivariate calibration of the	he 'b	best' wave	let coefficients	to est	imate	the	RB	Y%	1
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uysis	Prediction parameters	Calibra	tion data	Cross Validation data		
1	Lot a such a such as	Adj-R ²	RSD	Adj-R ²	RSD	
	φ	23.6	2.86	31.3	2.77	
	$\phi, c_{62}, c_{61}, c_{55}$	40.3	1.85	30.9	2.29	

ich was equivalent to the average r, g or b of the original patch, c_{62}, c_{61}, c_{55} - higher resolution WC's

 $\frac{h_{en}}{h}$ the higher resolution WC's were disregarded and only the WC's of the means r, g and b from the original patch were used (ϕ , Analysis the accuracy was substantially reduced, predicting the RBY% with an adj-R² of 23.6% and a RSD of 2.86. When cross validated, the R_{cutracy} improve slightly (adj-R² = 31.3%, RSD = 2.77, Table 1). We concluded that variation in colours at the 4x4 and 2x2 resolution mained important information for the prediction of RBY% not contained in the simple patch average. The WC's c_{61} , c_{62} measured the M_{20} and vertical variation respectively about the patch average, when the patch was resolved into a 2x2 grid. The WC c₃₅ corresponded the horizontal edges from the 4x4 resolution. The role of these WC's are explained in Bruce and Gao (1996). Since the WC's from the there frequency added little to predictive accuracy, it would appear unnecessary to use a resolution higher than 4x4 grid, nevertheless there eclear advantages which go beyond the present patch average.

^{car} advantages which go beyond the present patch average. ^{carcass} fat increased, subcutaneous fat over the rump was late maturing (Kempster *et al.*, 1976). However, our results showed that there ^{a cass} fat increased, subcutaneous fat over the rump was late maturing (Kempster et al., 1976). The week was related to RBY%. The sufficient difference in fat deposition within the rump patch to create variation in the g spectrum which was related to RBY%. The $\frac{1}{100}$ $\frac{1}$ The rump patch that were related to changes in the RBY%. The WC c_{61} captured localised differences in the g spectrum over the brisket $h_{\text{th}}^{\text{uc}}$ rump patch that were related to changes in the KBY%. The we c_{61} captured rotation differences and the second ^{by norizontally splitting the original patch, which would suggest there was a gradient of succumentation of the experimentation of the succumentation of the experimentation of the succumentation of the experimentation of the exp} the caudal end towards the cranial end of the brisket as carcass fatness increased. Vertically splitting the anterior loin patch enabled the $c_{2}^{\text{the caudal end towards the cranial end of the brisket as carcass fatness increased. Vertically splitting the dimensional diminished in a <math>c_{2}$ to isolate variation in the g spectrum that related to RBY%. It is likely that the subcutaneous depth over the loin diminished in a c_{2} to isolate variation in the g spectrum that related to RBY%. $v_{sal-ventral gradient, which corresponded to a shift in the g intensity.$

Conclusion

^{aveston} ^{avelet} analysis determined the level of resolution that was required to extract important colour information from lateral images of a carcass. differences in a colour were summarised by WC's, which was used to predict RBY%. To capture localised colour variation using ³, it was necessary to divide patches into at least 2x2 grids, and on occasion 4x4 grids. Higher resolution WC's were not necessary. The ^{11 Was necessary to divide patches into at least 2x2 grids, and on occasion 4x4 grids. Higher resolution WC's, which would have} overlooked with simple averages.

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