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Prediction of beef eating quality from colour, marbling and wavelet texture features

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ABSTRACT

Beef *longissimus dorsi* colour, marbling fat and surface texture are long established properties that are used in some countries by expert graders to classify beef carcasses, with subjective and inconsistent decision. As a computer vision system can deliver objective and consistent decisions rapidly and is capable of handling a greater variety of image features, attempts have been made to develop computerised predictions of eating quality based on these and other properties but have failed to adequately model the variation in eating quality. Therefore, in this study, examination of the ribeye at high magnification and consideration of a broad range of colour and marbling fat features was used to attempt to provide better information on beef eating quality. Wavelets were used to describe the image texture of the beef surface at high magnification rather than classical methods such as run lengths, difference histograms and co-occurrence matrices. Sensory panel and Instron analyses were performed on duplicate steaks to measure the quality of the beef. Using the classical statistical method of partial least squares regression (PLSR) it was possible to model a very high proportion of the variation in eating quality ($r^2 = 0.88$ for sensory overall acceptability and $r^2 = 0.85$ for 7-day WBS). Addition of non-linear texture terms to the models gave some improvements.

1. Introduction

Prediction of beef palatability is required at abattoir level to ensure beef is distributed to an appropriate market. The quality of beef can be determined by trained expert graders at abattoir level (Li, Tan, & Shatadal, 2001). This is achieved by examining the properties of the *longissimus dorsi* (LD) muscle including colour, marbling and surface texture (USDA, 1997). This system can provide immediate and non-invasive measurements of the expected palatability of the beef. However the decisions of expert graders suffer from being subjective, tedious, costly and laborious (Du & Sun, 2004). Furthermore these decisions do not always correlate strongly with sensory panel assessments (Tian, McCall, Dripps, Yu, & Gong, 2005). An alternative prediction of palatability to expert grading that is fast, objective and non-destructive is required. Park, Chen, Hruschka, Shackleford, & Koohmaraie (2001) describe this necessity in beef tenderness prediction.

Current alternatives to expert grading commonly used involve taking palatability measurements on a meat sample and using the result to predict the expected palatability of the whole carcass and possibly similar carcasses. This has the major drawbacks of being heavily time consuming and expensive. Consumer panel evaluation will give the best measurement of palatability but is impractical in most cases. Consumer panel scores can be approximated with those of a trained sensory panel, yielding savings in both time and cost, however, time and cost remain a problem and furthermore skilled panellists can be scarce. Consumer panels and sensory panels can measure a range of sensory qualities including overall acceptability, tenderness, juiciness and flavour. Both types of panel require the consumption of samples of meat that could otherwise be sold adding to the costs involved. Meat tenderness is the most important attribute in determining eating quality for consumers (Chandraratne, Samarasinghe, Kulasiri, & Bickerstaffe, 2006; Park et al., 2001; Tian et al., 2005), and it is possible to measure meat tenderness objectively and more rapidly using a test such as the Warner Bratzler shear force (WBS). However WBS results must be treated with caution as previous studies (Shackleford, Wheeler, & Koohmaraie, 1995) have shown that the correlation between sensory panel tenderness judgements and WBS is not complete ($r^2 = 0.73$). This is expected as the WBS test cannot completely replicate the chewing action of the human mouth. Furthermore the WBS test can only estimate one aspect of palatability. Objective measurement for attributes other than tenderness is a challenge. Park et al. (2001) also assess these alternatives for tenderness prediction.

As an alternative, computer vision can offer immediate, non-invasive and objective predictions. Models can be built to predict consumer panel, sensory panel, WBS or other experimental palatability measurements using image features. These models can then be used to predict the palatability of new meat carcasses. Many

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benefits of computer vision in the prediction of food quality are described by Tan (2004), Sun and Brosnan (2003) and Aguilera and Briones (2005).

Previous studies have shown that a significant proportion of meat tenderness variability can be attributed to classical analyses of image texture (Li, Tan, Martz, & Heymann, 1999; Tian et al., 2005). When combined with colour and marbling features a good proportion ($r^2 = 0.70$) of beef tenderness variability can be modelled with a neural network (Li et al., 1999). Chandraratne et al. (2006) using classical texture and geometric features modelled a good proportion ($r^2 = 0.75$) of lamb tenderness variability with a neural network. These and many other recent studies have been focussed on developing predictive models of tenderness. While tenderness is the most important attribute of palatability other attributes such as juiciness and flavour also play an important part in palatability assessment (Warriss, 2000). Thus tenderness should not be the sole focus of research. Furthermore the most complete measure of palatability is overall acceptability. Accurate modelling of overall acceptability should be the main goal.

In previous studies colour had been efficiently described in the RGB colour space which is common for digital cameras and computer monitors. Each pixel has a certain amount of red, green and blue. The simplicity of the RGB space makes it highly suitable for arithmetic manipulations. Alternative colour spaces such as HSI may better represent the workings of the human eye but are not as convenient, for example red has a hue of 0 and 1. In addition to the features used by Li et al. (1999) and Tian et al. (2005) histogram Kurtosis and Interquartile range are included in the current research as the red, green and blue histograms may deviate strongly from a normal distribution.

Previously marbling had been described in terms of small, medium and large fleck densities as well as overall fleck densities. Gerrard, Gao, and Tan (1996), Li et al. (1999) and Tian et al. (2005) used this approach. In contrast in this work marbling features were described with five fleck size histogram properties (mean, standard deviation, skewness, kurtosis and interquartile range) as well as overall fleck densities.

Li et al. (2001) proposed that high magnification examination of muscle may better describe surface texture by allowing individual muscle fibre bundles to be seen, yielding better tenderness information. Thus the use of high magnification images may allow more accurate predictive models based on surface texture alone and when combined with colour and marbling. Research by Huang et al. (1997) indicated that wavelet analysis of image texture can give significantly better predictions than classical analysis. Thus wavelet analysis was applied in this work. For comparison a classical texture analysis based on co-occurrence and run lengths similar to that used by Li et al. (1999) and Tian et al. (2005) was also applied. Finally these image texture features were combined with colour and marbling features to create predictive models of a range of important palatability measures.

2. Materials and methods

2.1. Sample preparation

Thirty two heifers were slaughtered at a pilot scale abattoir (Meat Industry Development Unit, Teagasc Ashtown Food Research Centre, Dublin). Each heifer was subjected to the same pre-slaughter treatment, but a variety of post-slaughter treatments were used to simulate the variable chilling conditions found in many abattoirs. Carcasses were dressed, centrally split and chilled as follows for two days post-mortem. The first sixteen carcasses were chilled under normal conditions at ≈2 °C. One side of each of the remaining sixteen carcasses was chilled at higher than normal temperatures ≈5 °C, and the other side was chilled at lower than normal temperatures ≈−5 °C. Thus effectively forty eight carcasses and half carcasses were used. Quartering took place at the 10th rib. An expert butcher cut nine steaks (25 mm thick) from each carcass or half carcass around the 10th rib. Two steaks were for computer vision (One normal magnification and the other high magnification), two were for verification, one for sensory panel analysis at 14 days, one for texture profile analysis (TPA) at 14 days and four for WBS analysis at 2, 7 14 and 21 days. Each steak was immediately vacuum-packed and transferred to a 4 °C fridge for ageing. After the correct ageing the steaks were transferred to a −20 °C freezer for storage (the 2-day WBS steak was frozen immediately after extraction).

2.2. Image acquisition and processing

Two steaks were used for computer vision, the first was examined at normal magnification to extract colour and marbling features, and the second was examined at high magnification to extract surface texture features.

A Dell Workstation 400 with an IC-RGB frame grabber (Imaging Technology Ltd., Quebec, Canada) and a 3-CCD Sony XC-003P camera (Sony Co., Tokyo, Japan) was the main equipment used for acquiring images of the first steak. A stand (RS1, Kaiser Fototechnik, Buchen, Germany) was used to keep the camera in a secure and fixed position. To minimise the specular reflection a multiple and diffuse lighting system was employed consisting of two fluorescent lamps (RB5000, Kaiser Fototechnik, Buchen, Germany) inclined at 45° with plastic light diffusers as well as two fluorescent lamps (RB211, Kaiser Fototechnik, Buchen, Germany) inclined at 90°. To further reduce the specular reflection, the beef surface was dried with paper towels and a polarising filter was used (EX, Sigma, Welwyn Garden City, Hertfordshire, UK). Image acquisition took place after blooming the steaks for one hour at 4 °C. The images of steaks were captured on a blue background to facilitate image segmentation.

The image acquisition system used for the second steak consisted of the above with a high magnification telescope (Infinivar CFM2, Infinity, Boulder, Colorado, USA) attached to the camera to give high magnification images and with the two smaller fluorescent lamps (RB211) inclined at 0°. Steaks for high magnification imaging had five cores extracted with a number 18 cork borer. An image was taken of a spot on each core. Specular reflection was mitigated by drying the core with paper towels. The vision system failed for two samples, thus reducing the total number of samples from 48 to 46.

All images were acquired in the RGB colour space as compressed TIFF (Tag Image File Format) files of size 720 × 574 (413,280 pixels) with 24 bits per pixel. Compressed images cannot be read by the image processing software Matlab (Mathworks, Natick, MA, USA). Thus images were decompressed into bitmap (BMP) format with conversion software (Optimas, Bothell, WA, USA).

The first steak was trimmed of all non-LD muscle and intermuscular fat by the expert butcher to assist image segmentation. Thus all white objects could be presumed to be marbling fat. It is vital that intermuscular fat is not mistaken for marbling fat as considerable errors can result in the computed marbling features (Subbiah, Ray, Kranzler, & Acton, 2004). As some parts of the LD muscle were dark red a blue background was chosen rather than a more typical black background. Preliminary studies showed that the fuzzy-c-means algorithm allocated some very dark LD muscle pixels to the background when a black background was used. Both Barni, Cappellini & Mecocci (1997) and Borggard, Madsen & Thodberg (1996) have shown a coloured background to be effective in assisting the segmentation of meat images.