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Classification of lamb carcass using machine vision: Comparison of statistical and neural network analyses

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Abstract

In this study, the ability of artificial neural network (ANN) models to predict the lamb carcass grades using features extracted from lamb chop images was compared with multivariate statistical model (discriminant function analysis (DFA)) with respect to the classification accuracy. Twelve geometric features were extracted from each of the acquired lamb chop images. In addition, 136 texture features (90 co-occurrence, 10 run length and 36 grey-level difference histogram) were also extracted from the acquired images.

Four sets of reduced features comprising six geometric, eight co-occurrence texture, four run length texture and four grey-level difference histogram features were generated based on the results of dimensionality reduction. The four sets of reduced features, individually and in different combinations, were utilised for classification using ANN and DFA.

Several network configurations were tested and the classification accuracy of 96.9% was achieved from the three-layer multi-layer perceptron (MLP) network. Its performance was 12% better than that from the DFA. Geometric features play a very important role in classification. Co-occurrence features also play an equally important role in classification.

Keywords: Computer vision; Machine vision; Image analysis; Texture features; Lamb grading; Meat quality; Artificial neural networks; Co-occurrence matrix; Run length matrix; Grey-level difference histogram

1. Introduction

Quality assurance is one of the most important goals of the meat industry. The ability to meet consumer expectations by providing quality products and maintaining the consistency of products is the basis for success in today's highly competitive market. In New Zealand, the assignment of lamb carcasses to specific quality grades has been an integral part of a lamb carcass classification system (Chandraratne, Kulasiri, Frampton, Samarasinghe, & Bickerstaffe, 2006). The current classification is based solely on carcass weight and fatness measurements. There are five weight ranges which are: A (very light), 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 final assigned grade is a combination of fatness class and weight class, e.g. YL, YM, PX, etc. 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.

Visual assessment has become the main component of several meat classification and grading systems. Visual assessment is subjective, inconsistent and highly variable. It is not capable of detecting commercially important attributes of carcasses. The development of an accurate, reliable and robust inspection system is essential to improve the current visual grading approach. Instrument grading of animal carcasses has been studied to meet the demand

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for increased accuracy and uniformity of meat grading. Computer vision has potential for evaluating meat quality.

Early studies have shown that image analysis technology has great potential to improve the current human grader based meat quality operation (Cross, Gilliland, Durland, & Seideman, 1983; Wassenberg, Allen, & Kemp, 1986). In the last two decades, image analysis technology has been developed and tested for beef, lamb and pig carcass quality evaluation purposes. Several studies on automated grading and classification of beef, pork and lamb carcasses based on image analysis have also been reported (Allen, 2003).

The importance of image texture in the analysis of images has been well accepted (Ojala, Pietikainen, & Harwood, 1996; Wechsler, 1980). Despite its importance, a rigorous definition of the image texture does not exist. Texture is composed of visual and tactile surface characteristics. It is an innate property of virtually all surfaces and contains important information about the structural arrangement of surfaces. Texture is recognised as a key to human visual perception and plays a very important role in computer vision tasks (Ohanian & Dubes, 1992).

A variety of techniques for analysing image texture have been proposed over the past three decades. Haralick (1979), Reed and Du Buf (1993) and Van Gool, Dewaele, and Oosterlinck (1985) present a detailed survey of texture analysis methods used in the analysis of images. Texture analysis methods have been classified into three categories as statistical, structural and spectral (Gonzalez & Woods, 2002) and into four categories as statistical, geometrical, model-based and signal processing (Tuceryan & Jain, 1999). Depending on the number of pixels defining the local feature, statistical methods can be further classified into first, second or higher-order statistics. The grey-level difference method (GLDM) (Weszka, Dyer, & Rosenfeld, 1976) calculates first-order statistics. The spatial grey level co-occurrence matrix (GLCM) (Haralick, Shanmugan, & Dinstein, 1973), one of the first methods used in the texture analysis, is a second-order statistical approach and the grey level run length matrix (GLRM) (Galloway, 1975) is a higher-order statistical approach. Other statistical approaches include autocorrelation functions, optical transforms, digital transforms, autoregressive models, textural edgeness and structural elements (Haralick, 1979).

Texture features extracted using GLCM (Li, Tan, Martz, & Heymann, 1999; Shiranita, Miyajima, & Takiyama, 1998), GLRM (Li et al., 1999; Li, Tan, & Shatadal, 2001), fractal approach (Ballerini & Bocchi, 2001) and wavelets (Li et al., 2001) have been used in meat quality evaluation exercises.

Statistical modelling methods have been used in the past for image classification. However, ANN could be a promising alternative method for classification when classification boundaries are non-linear and the interactions of input variables are complex. ANNs are capable of performing complex prediction and classification tasks. ANNs have been widely used in meat evaluation purposes. In the study of Li et al. (1999), an ANN model has been used to predict beef tenderness. Chandraratne, Samarasinghe, Kulasiri, and Bickerstaffe (2006) used three-, four- and five-layer multi-layer perceptron (MLP) networks to predict lamb tenderness. In the study of Tian, McCall, and Tan (1997), a three-layer feed forward ANN with back-propagation (BP) algorithm have been used for the prediction of tenderness. A feed forward BP neural network model has been developed for prediction and classification of beef quality attributes (Park, Chen, Whittaker, Miller, & Hale, 1994). An MLP network with a BP algorithm has been used for pork colour classification (Lu, Tan, & Gerrard, 1997). ANNs have also been used to estimate the marbling score from ultrasound images (Brethour, 1994) and to implement a meat quality grading system (Shiranita, Hayashi, Otsubo, Miyajima, & Takiyama, 2000).

The aim of the present study was to investigate the use of image processing and texture analysis techniques in the classification of lamb chop images. The specific objective was to develop a method based on ANN approach to evaluate lamb carcass grade using image and texture features extracted from lamb chop images. Furthermore, the classification performance of neural networks was compared with results from the DFA. Fig. 1 shows a flow chart of the general methodology used.

2. Materials and methods

2.1. Image system and image acquisition

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. Six common lamb grades (FH, PM, PX, TH, YM and YX) were selected for this analysis. These grades represent more than 90% of the total volume of lamb graded in New Zealand for export market (Meat New Zealand, 2001, 2002).

The imaging system consisted of a 3 CCD colour digital camera (model DSR-PD 150P, Sony) 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 4.1, Media Cybernetics, USA) with its development environment.

The samples were all bloomed[1] for 30 min. and surface moisture was removed with a paper towel before capturing images. 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 (Chandraratne, Kulasiri, et al., 2006).

[1] Blooming is the process that converts the surface colour of freshly cut meat to bright red when meat is exposed to air. This usually requires at least 30 min