Meat Science 92 (2012) 386–393

Contents lists available at SciVerse ScienceDirect

Meat Science

journal homepage: www.elsevier.com/locate/meatsci

Predicting beef tenderness using color and multispectral image texture features

X. Sun [a,b], K.J. Chen [b], K.R. Maddock-Carlin [a], V.L. Anderson [c], A.N. Lepper [a], C.A. Schwartz [a], W.L. Keller [a], B.R. Ilse [c], J.D. Magolski [a], E.P. Berg [a,*]

[a] Department of Animal Science, North Dakota State University, Fargo, ND, USA
[b] Department of Engineering, Nanjing Agriculture University, Nanjing, Jiangsu, People's Republic of China
[c] North Dakota State University Carrington Research Extension Center, North Dakota State University, Carrington, ND, USA

ARTICLE INFO

Article history:
Received 29 February 2012
Accepted 25 April 2012

Keywords:
Beef
Tenderness
SVM
Color
Multispectral image
Stepwise

ABSTRACT

The objective of this study was to investigate the usefulness of raw meat surface characteristics (texture) in predicting cooked beef tenderness. Color and multispectral texture features, including 4 different wavelengths and 217 image texture features, were extracted from 2 laboratory-based multispectral camera imaging systems. Steaks were segregated into tough and tender classification groups based on Warner–Bratzler shear force. The texture features were submitted to STEPWISE multiple regression and support vector machine (SVM) analyses to establish prediction models for beef tenderness. A subsample (80%) of tender or tough classified steaks were used to train models which were then validated on the remaining (20%) test steaks. For color images, the SVM model correctly identified tender steaks with 100% accurately while the STEPWISE equation identified 94.9% of the tender steaks correctly. For multispectral images, the SVM model predicted 91% and STEPWISE predicted 87% average accuracy of beef tender.

1. Introduction

The tenderness, juiciness, and flavor of beef are important factors that affect consumer's evaluation of beef quality and influence their decision relative to making a repeated purchase (Shackelford et al., 2001). Among these factors, Huffman et al. (1996) found that tenderness was the most important palatability attribute for beef consumers in the United States. Most consumers are willing to pay a higher price for tender beef.

The main methods currently employed to predict beef tenderness are sensory analysis and shear force assay. The former is usually determined by trained or consumer taste panel assessment while the latter utilizes the Warner–Bratzler shear force (WBSF) method. Sensory panel analysis is a subjective evaluation method which heavily reckons on specialized training of taste panel personnel. This artificial taste method is time-consuming, has poor repeatability, and often results in strong subjective evaluation. The WBSF, method which was proposed more than half a century ago, can be used to objectively determine mechanical beef tenderness. Despite being objective and accurate, it is difficult to employ in the industry due to the necessity of removal of a steak from the high-cost portion of the carcass, cooking, coring, and application of the WBSF methodology. Therefore, it is necessary to develop an efficient and rapid inspection method for beef tenderness which can realize non-destructive on-line testing for beef quality.

Computer system processing of images of fresh meat has been analyzed for a number of years for their utility in building predictive models of palatability attributes (Jackman, Sun, Du, & Allen, 2009; Jackman, Sun, Du, Allen, & Downey, 2008; Li, Tan, Martz, & Heymann, 1999; Shackelford, Wheeler, & Koohmaraie, 2011a, 2011b; Tian, McCall, Dripps, Yu, & Gong, 2005). Computer vision-based beef quality evaluation has shown that texture features computed from muscle images are useful indicators of beef tenderness (Li et al., 1999) compared with using only color and marbling features previously reported (Gerrard, Gao, & Tan, 1996; Lu, Tan, Gao, & Gerrard, 1998). The addition of image texture features significantly improves the accuracy of tenderness prediction (Huang et al., 1997).

Support vector machine (SVM) proposed by Vapnik and Cortes (1995) is a new state-of-the-art classification technique based on statistical learning theory designed to solve complex classification problems (Nathalie & Fabrice, 2006; Shutao, James, Hailong, & Wang, 2003). The SVM technique has been effectively used to perform non-linear classification, multivariate function estimation, or nonlinear regression. Compared with other methods, SVM does not require a large number of training samples for model development and is not affected by the presence of outlier (Burges, 1998).

The objectives of this study are to: (1) digitally identify and extract useful color and multispectral image texture features from four diverse cuts of fresh beef and (2) use statistical and neural network models to predict cooked beef tenderness.

* Corresponding author.
E-mail address: Eric.P.berg@ndsu.edu (E.P. Berg).

0309-1740/$ – see front matter
doi:10.1016/j.meatsci.2012.04.030

2. Materials and methods

2.1. Source of beef steaks

All animal procedures were approved by the North Dakota State University Institutional Animal Care and Use Committee. One hundred twenty-six crossbred (Angus × Piedmontese) heifers were weighed and randomly allotted to one of 16 pens at the Carrington Research Extension Center (Carrington, ND). Heifers used for this study were part of a larger evaluation of the effects of various field peas (*Pisum sativum*) components included in a complete finishing diet (Table 1) on growth and carcass traits (Hayes et al., 2011). Cattle were assigned by pen into 1 of 4 dietary treatments (CON = no field peas; WRL = 15% of DM as dry rolled field peas [hulls + seed]; HULL = 15% of DM as field pea hulls; CHIP = 15% of DM as field pea chips [split seed only]) consisting of four pens per treatment. Heifers were fed for 120 d, feed intake was recorded daily, and heifers were weighed individually every 28 days to monitor performance during the feeding period. Heifers were delivered (21 km) for slaughter to a commercial processing facility (North Dakota Natural Beef, New Rockford, ND). The cattle truck-trailer was a standard (16.2 m long) double-deck livestock trailer. All calves were commingled at the feed yard prior to loading and a random gate cut was made during loading, approximately 42 head per load, across three loads, spanning three hours from first load out to last load off. No differences were observed relative to field pea component inclusion on growth performance, carcass characteristics, and (or) tenderness.

Carcasses were chilled overnight (33 °C), loaded onto refrigerated trailers as whole beef sides, and delivered to the carcass fabrication plant (230 km). Four muscle types were identified, tagged, and collected from the fabrication line. Two boneless steaks (2.6 cm thick) were removed from the LT (longissimus thoracis), SM (semimembranosus), BF (biceps femoris), and SP, (supraspinatus). Steaks were then vacuum packaged, aged for 14 days (4 °C), and then frozen until machine vision images and WBSF analyses. Prior to analysis, samples were placed in the cooler (4 °C) to thaw. After acquiring color and multi-spectral imaging, all samples were cooked according to the guidelines published by American Meat Science Association (AMSA, 1995) for WBSF. All steaks were cooked in a fume hood on electric grills (George Foreman Grill, GRP99) with cooking plates on both the top and bottom. Grills were set to 176.7 °C and internal steak temperature was monitored by digital thermometer (Omega HH801B) thermoelectric couple (Omega SMPW-T-M thermocouple connector: Type T, glass-filled nylon with Omega TT-T-36-SLE-200 thermocouple wire: copper/constantan, Type T Neoflon PFA insulation, 36 gage, special limits of error accuracy [0.2 °F at 212 °F]).

Table 1
Finishing rations formulated with field pea and pea components.

Feeds	Diet treatments			
	Control	Pea hulls	Pea chips	Whole peas
	Percent, dry matter basis			
Straw, chopped	16	16	16	16
Corn grain, dry rolled	58	56	55.25	54
Field peas, dry rolled	0	0	0	15
Pea chips	0	0	12.75	0
Pea hulls	0	1.67	0	0
Dry distillers grains	18	18.33	8	7
Calcium carbonate	1	1	1	1
Rumatec sup − 1/3 lb	2	2	2	2
Condensed distillers solubles	5	5	5	5
Total, percent nutrients	100	100	100	100
Dry matter, %	84.88	84.96	84.98	84.89
Net energy gain, Mcal/lb	60.61	60.26	60.87	60.61
Crude protein, %	12.56	12.63	12.60	12.62
Calcium, %	0.62	0.63	0.63	0.64
Phosphorous, %	0.33	0.33	0.34	0.34
Potassium, %	0.61	0.61	0.65	0.65

When the center temperature reached to 70 °C, samples were removed from the grill, cooking time recorded, and reweighed to determine cooking loss. Steaks were cooled to room temperature (20 °C) and four to six cores (diameter = 1.27 cm) were removed from each steak along the direction parallel to muscle fiber. Each core was sheared once perpendicular to the longitudinal orientation of the muscle fiber by shear force instrument (Mecmesin Warner Bratzler Meat Shear: Basic Shear Gauge 13FG5001N, SIB 06-0290-11: G-R Manufacturing Co, Manhattan, KS). The average shear force and standard deviation were calculated for each sample.

2.2. Color image acquisition and processing

The imaging system consisted of three components; a three charge-coupled device (CCD) color digital camera (Model S2100HD, Fujifilm Corporation, Japan) with supporting lighting system consisting of two white lights (Model FL8WW, Toshiba, Japan) and two tungsten halogen lamps (Model MK II, 115v, 60 Hz input and 150 W output), computer (850 MHz AMD Athlon processor, with 512 MB RAM), and image processing and analysis software (Matlab Version 7; The Math-works, Natick, MA, USA). Steaks were removed from vacuum packaging and allowed a 10 min bloom prior to image acquisition. Images were obtained on cross-sectioned steaks cut from the LT (n = 109; n = 86 as tender, n = 23 tough), SM (n = 93; tender classification n = 48 and tough n = 45), BF (n = 77; tender classification n = 67 and tough n = 10), and SP (n = 81; tender classification n = 58 and tough n = 23).

Images were processed for analysis utilizing processing algorithms and analysis (developed using Matlab software) for identification of background from lean and fat texture parameters. The color images were first segmented into background (dark) and meat sample (light) areas. Initial values for textural threshold were selected from the plot of pixel intensities. After image segmentation, the lean muscle area was used for future texture feature extraction (Fig. 1). Each image was resized to 128 × 128 pixel × 8 bit. Before extraction of textural features, median filtering was used to reduce noise.

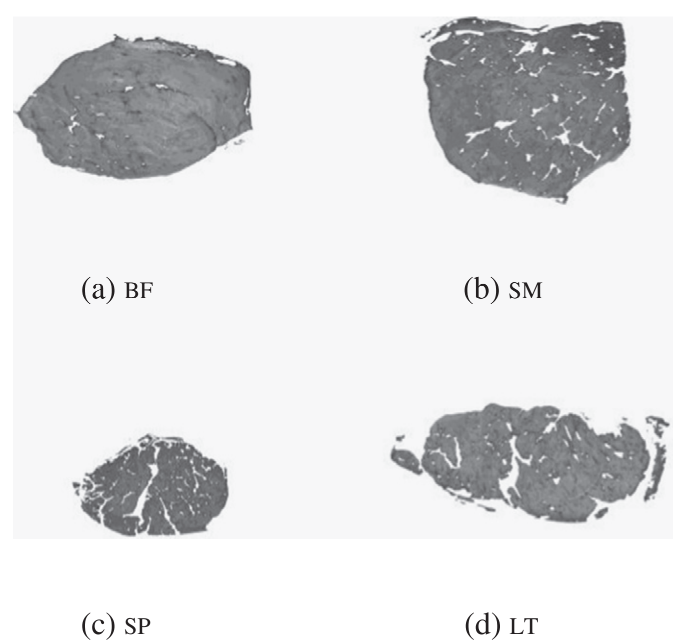

Fig. 1. Muscle lean area of four different beef steaks (LT = longissimus thoracis, SM = semimembranosus, BF = biceps femoris, SP = supraspinatus) after segmentation from a color image.