USING POSTMORTEM PROTEOLYSIS AND IMAGE TEXTURE FEATURES TO PREDICT BEEF TENDERNESS

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Abstract – The objective was to use digital color image texture features, tristimulus color scores, hue angle, and saturation of raw steak, as well as carcass weight and marbling and troponin-T (Tn-T) degradation (steaks aged 3 and 10 d) as indicators to predict cooked beef tenderness. Image texture features, including 88 gray level co-occurrence and 48 Gabor wavelet filter texture features were extracted from digital images of beef steaks aged for 10d [longissimus thoracis (ribeye roll; n = 91, tender n = 82, tough n = 9)] obtained using a laboratory-based color camera (Model S2100HD, Fujifilm Corporation, Japan) imaging system. Longissimus thoracis steaks were classified as tough and tender based on Warner-Bratzler shear force (WBSF) values whereby a WBSF of 4.0 kg or less was considered tender. Statistics analysis method (STEPWISE regression model) and artificial neural network model method (support vector machine, SVM) were designed to classify beef steak tenderness. The STEPWISE model was 93% accurate while the SVM model 79% accurate in predicting cooked beef tenderness. Image texture features, tristimulus color scores features and protein degradation features isolated through the development of SVM and STEPWISE models show potential as a means to predict tenderness of cooked beef steaks.

Key Words – image texture features, STEPWISE, SVM, western blotting.

I. 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 [1]. Computer system processing of images of fresh meat have been analyzed for a number of years for their utility in building predictive models of palatability attributes [2-5]. The degradation of myofibrillar proteins such as titin, desmin and troponin-T (Tn-T) have shown to play an important role in the development of meat tenderness [6]. One of the most common determinates of protein degradation during aging is appearance of a 30-kDa Tn-T degradation product [7]. Support vector machine (SVM) proposed by Vapnik *et al*. [8] is a new state-of-the-art classification technique, which is based on the statistical learning theory and is designed to solve classification problems. It has been proven to be a powerful tool to perform non-linear classification, multivariate function estimation, or nonlinear regression. Compared with other methods, SVM does not need a large number of training samples for developing a model and is not affected by the presence of outliers [9]. The objective of this study was to: use digital color image texture features, tristimulus color scores, hue angle, and saturation of raw steak, as well as carcass weight and marbling and troponin-T (Tn-T) degradation (steaks aged 3 and 10 d) as indicators to predict cooked beef tenderness.

II. MATERIALS AND METHODS

Ninety one crossbred (Angus x Piedmontese) heifers used for this study were part of a separate study on the effects of various field pea (*pisum sativum*) components included in a complete finishing diet on growth and carcass traits [10]. A color image acquisition technique system (Fig. 1) was developed to acquire images of steaks.

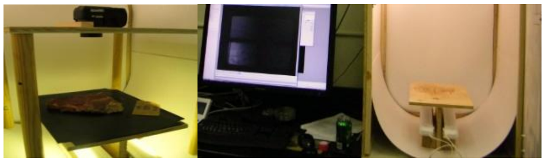

Figure 1. Color image acquisition system

It 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, 60Hz input and 150W 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). 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. 2).

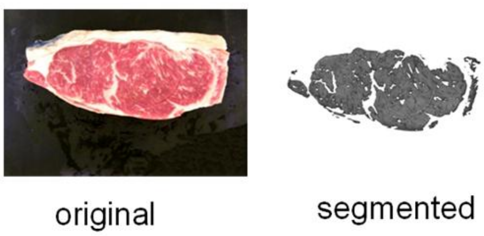

Figure 2. Segmentation of subcutaneous fat from a representative beef longissimus thoracis steak

Two extracting textural features methods were used in this study: 88 image texture features were extracted by the grey level co-occurrence matrix (GLCM) method [11]. Another 48 image texture features were extracted by Gabor wavelet method [12] for a total of 136 color image texture features. Some features cannot be uniquely determined from observed data. This problem can be solved by either providing a large number of training samples to satisfy the requirement of the model or by reducing the number of useless (low effect to model predict) features. Therefore, an effective method for reduction of dimensionality of the input feature space was desired. So, principal component analysis (PCA) method was used to reduce the number of color image features. Carcass data such as weight and marbling, meat color features including L* (luminance), a* (green to red), b* (blue to yellow), and hue, saturation were also used as predictors for the classification model.

For Tn-T degradation product features, whole muscle protein was extracted from steaks (n = 91) aged 3 and 10 d as described by Huff-Longergan *et al.* [6] and further quantified by Western analysis. The use of SVM is gaining favor for its ability to utilize polynomial, radial based functions as a means to reach multilayer perception classifications. The SVM system fixes the classification decision function on the basis of the structural risk minimum mistake instead of the minimum mistake of misclassification based on the confines of the data presented through the training set. In our study, the Gaussian kernel was used for the SVM to obtain appropriate classification of a two-class model through the use of a separating hyperplane. The hyperplane is developed by estimating the maximum distance to the closest data points (termed support vectors) within the training set presented to the SVM. If these data points are not linearly separable in the input space, they can be transformed to a high dimensional space (HDS) through nonlinear transformation. This HDS is called feature space. Once data has been projected in the feature space, an algorithm that constructs the optimal separating hyperplane is developed by the SVM.

The STEPWISE discriminant was conducted by statistical software (SPSS 16.0) using a level of significance value of 0.05 for entering including prediction and a level of significance value of 0.15 for excluding prediction from the model. Both STEPWISE regression and SVM models were set up to predict beef tenderness. Beef longissimus thoracis steaks were divided into a training set and a test set (approximately a 4:1 split).

III. RESULTS AND DISCUSSION

Fig. 3 shows a representative Western blot of d 3 and d 10 aged steaks. A molecular weight marker was used to estimate the molecular weights of each immunoreactive band. Bands 1 to 4 (41, 39, 37, and 32 kDa, respectively) correspond to intact Tn-T. Band 5 (30 kDa) corresponds to proteolytic degradation products of Tn-T. Assessment of blots showed that intact Tn-T (bands 1-4) decreased in abundance over time post mortem and band 5 increased over time. All measurements were compared back to a standard sample to eliminate differences between blots. Band 5 area values at d 3 and d 10 and the difference of d 3 and d 10 were calculated as predictors for classification models.

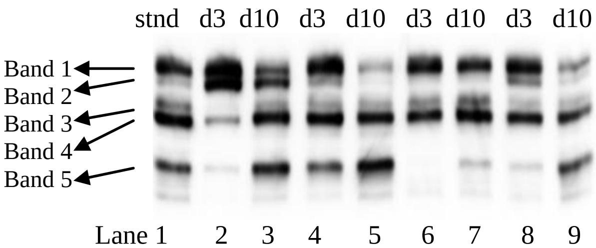

Figure 3. Representative western blot of whole muscle protein extracted from longissimus thoracis steaks aged for either 3 d or 10 d. Each lane was loaded with 15 µg of protein. Lane 1 is a standard sample. Bands 1, 2, 3, and 4 represent intact troponin-T while band 5 (30-kDa) is the measurement of degraded products.

The results of the Principal Component Analysis (PCA) for GLCM, Gabor wavelet color texture features are presented in table 1. The analysis shows that 64.54% of the total variation is explained by the first principal component (PC), 85.83% of the total variation is explained by the first two PC, and finally 98.71% of the total variance of GLCM features can be condensed into six PC. Then six GLCM features were selected according the results of rotated component matrix analysis. These features are: inverse difference (θ = 0°), inverse difference moment normalized (IDN) (θ = 0°), inverse difference moment normalized (IDN) (θ = 45°), sum variance (θ = 90°), maximal correlation coefficient (θ = 135°), and inverse difference moment normalized (IDN) (θ = 135°). In a similar way, 48 features calculated from Gabor wavelet method were condensed to 10 whilst retaining 85.20% of the total variance. According the results of rotated component matrix analysis, the 10 Gabor features selected are: F3, F4, F20, F25, F30, F32, F36, F37, F40, and F47. So, a total of 16 out of 136 image texture features were used as predictors for model.

Table 1 Results of Principal Component Analysis (PCA) for grey level co-occurrence matrix (GLCM) and Gabor wavelet color texture features

	Principal Component	Eigen value	Variance (%)	Cumulative (%)
GLCM features	PC1	56.80	64.54	64.54
	PC2	18.74	21.29	85.83
	PC3	5.94	6.74	92.58
	PC4	2.30	2.62	95.19
	PC5	1.96	2.23	97.42
	PC6	1.13	1.29	98.71
Gabor features	PC1	15.25	31.78	31.78
	PC2	6.92	14.42	46.20
	PC3	4.89	10.20	56.39
	PC4	3.54	7.37	63.76
	PC5	2.69	5.60	69.36
	PC6	1.934	4.03	73.39
	PC7	1.642	3.42	76.81
	PC8	1.533	3.19	80.00
	PC9	1.343	2.80	82.80
	PC10	1.148	2.39	85.20

In all, there were a total of 26 features (7 color and carcass data features, 16 image texture features, and 3 western blotting features) which were input to the STEPWISE and SVM model as predictors for predicting the tenderness of cooked beef steak. With the 26 selected predictors, STEPWISE regression model predicted 100% correct for the tender group, for the tough group, the accuracy was 75%, with an overall accuracy of 93% for beef longissimus thoracis tenderness. The SVM model predicted 100% correctly for the tender sample testing set. For the tough sample testing set, it was 25% accurate. Totally accuracy for the SVM model for predicting tenderness was 79%. Both STEPWISE and SVM have low prediction results on tough group. The number of tough samples needs to be increased for model training sets in future studies. STEPWISE and SVM model predicting results of cooked beef longissimus thoracis steaks are shown in Fig. 4.

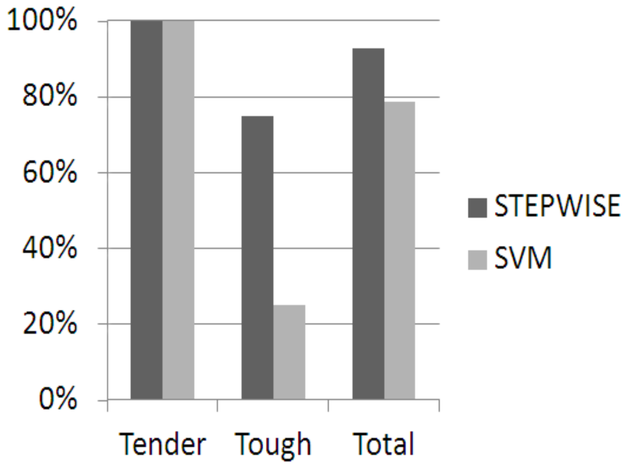

Figure 4. The accuracy of STEPWISE and SVM models for predicting cooked beef longissimus thoracis steak tenderness.

IV. CONCLUSION

STEPWISE and SVM models are suitable for classification of beef steak tenderness using surface factors (image texture features and color features) and internal factors (postmortem degradation of Tn-T). Combined image and protein degradation features as predictors can improve the model accuracy up to 100% on tender group of beef steaks.

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