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Research Article

Prediction of Pork Color Grade using Image Two-tone Color Ratio Features and Support Vector Machine

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Abstract: The objective of this study was to investigate the usefulness of pork loin color image features in predicting pork two-tone color grade according to objective L* value. Nine image color features (specifically, the means for two-tone ratios of R, G, B, L*, a*, b*, H, S and I) were extracted from 3 different color spaces (RGB (Red, Green and Blue), CIE LAB (L*: luminance; a*: green to red; b*: blue to yellow) and HIS (Hue, saturation and Intensity)). Color features were extracted from a laboratory-based high-quality camera imaging system. Objective color (CIE L*, a* and b*) was measured using a Minolta Colorimeter, calibrated using both white and black tiles. Boneless, 2.54-cm thick sirloin chops (enhanced, n = 541; non-enhanced, n = 232) were collected. K-means clustering technique was used for grouping pork into two color grades based on Minolta L* value. The image color features were used as predictors for multivariate classification of the samples using machine learning method (Support Vector Machine, SVM). For establishing the model, each data set was separated into training (70%) and testing (30%) sets. Ten-fold cross validation was used to set up the model and test for the best model parameters. The results showed that, for both enhanced and non-enhanced chops, the SVM machine method predicted 100% correct for both grades. Therefore, color image features can be used to correctly classify pork chops by SVM model according to the Minolta L* value.

Keywords: Color grade, image processing, k-mean, pork sirloin, SVM

INTRODUCTION

Pork quality has been shown to impact consumer eating satisfaction (Moeller *et al*., 2010) and attributes of marbling, color, firmness and package purge have been shown to impact consumer purchase intent (Brewer *et al*., 2001). Brewer *et al*. (2001) showed that consumers preferred lower marbled pork and rated pork with less marbling as more desirable in color, leanness and appearance. However, when consuming the product either in a central location or at home, consumers preferred the juiciness, tenderness and flavor of more marbled pork. According to previous research (Berg *et al*., 2004; Brewer *et al*., 2006; Chmiel *et al*., 2011; Girolami *et al*., 2013), color is one of the most important features influencing evaluation of meat by the consumer. Currently there is little or no technology used in commercial pork production that automatically sorts, certifies, or 'grades' pork color grade. In practice, when pork color attributes are assessed or sorted for a particular market, it is done subjectively by a trained color grader or by controlling swine genetics and sorting at the plant. This method relies on human skills, can be highly subjective and is time consuming. The outcome of subjective color grading may vary between different graders and processing plants and could not meet on-line requirements due to its cumbersome and inefficient process. Therefore, it is necessary to develop an efficient and rapid inspection method for evaluating pork color grade that can be done rapidly with a non-invasive technique for the pork industry.

Computer vision based methods have been confirmed useful in evaluating meat quality including color and tenderness of beef, pork, or lamb (Chandraratne *et al*., 2006; Chmiel *et al*., 2011, 2012; Jackman and Sun, 2012, 2013; Sun *et al*., 2012; Girolami *et al*., 2013). For the pork industry, a computer vision system for on-line application could be useful to assess pork color grade attribute without sensory panels or other subjective/objective measurements.

Support Vector Machine (SVM) method was approved as a useful classification technique based on machine learning theory in various research areas (Hua and Sun, 2001; Nandi *et al*., 2014; Wen *et al*., 2014). SVM method is well suitable for data which are high dimensional and was originally introduced by Vapnik (1998). For the meat quality industry, researchers

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already found the SVM method to be an effective method of analyzing both surface and internal muscle protein properties (Sun *et al*., 2011, 2012, 2014; Wang *et al*., 2012; Liu *et al*., 2014).
The objectives of this study are to:

- Investigate the computer vision system technique to measure and analyze the color features of various color grades of enhanced and non-enhanced pork sirloin
- Establish pork color grade prediction model using machine learning technique

MATERIALS AND METHODS

Sample collection: Sirloin chops of thickness 2.54 cm (or closest available) were randomly selected (enhanced (n = 541) and non-enhanced (n = 232)), purchased, placed on blue ice and shipped overnight to North Dakota State University.

The selection of the pork samples are based on Fresh-look syndicated grocery data that lists both sirloin chops and shoulder blade steaks as being two of the top ten minimally processed pork cuts by dollar sales. The list can be seen in the Table 1. After blooming 10 to 15 min, objective color (CIE L*, a* and b*) was measured using a Minolta Colorimeter (CR-410, 50 mm diameter head, 10° standard observer, D65 light source; Minolta Co., Ramsey, NJ), calibrated using both white and black tiles (Fig. 1).

Image acquisition systems and image processing: The imaging system consisted of (Fig. 2); a three Charge-Coupled Device (CCD) color digital camera (Model S2100HD, Fujifilm Corporation, Japan) with supporting lighting system consisting of two white light (Model FL8WW, Toshiba, Japan) and two tungsten halogen (Model MK II, 115v, 60 Hz input and 150 W output) lamps, computer (850 MHz AMD Athlon processor, with 512 MB RAM) and image processing and analysis software (MATLAB Version 7; The Mathworks, Natick, MA, USA).

After acquiring the original color picture (RGB) with black background, the image processing method was performed as follows:

- Background segmentation was first performed with a threshold value auto calculated to segment the background area (Fig. 3a) utilizing the boundary tracking algorithm method reported by Otsu (1979).
- After removing the background, separation of the lean muscle area from the extraneous tissues (Fig. 3b) was performed utilizing the algorithm method developed by Sun *et al*. (2011).
- Three areas were selected from the sirloin chop and the average RGB values calculated. Two areas were selected from the bright muscle area and one area was selected from dark muscle area (Fig. 3c).
- Calculate the ratio of area RGB values (two-tone ratio) Two-tone color ratio= $\frac{(\text{Area \#1+Area \#2})/2}{\text{Area \#3}}$.

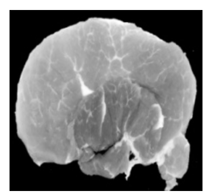
Table 1: Fresh-look syndicated grocery data 2012-sourced from the national pork board

1: Top loin chop boneless	6: Loin whole/half boneless
2: Mixed assorted chops bone-in	7: Shoulder blade steak bone-in
3: Country style ribs bone-in	8: Top loin roast boneless
4: Sparerib bone-in	9: Rib chop bone-in
5: Shoulder blade roast bone-in	10: Sirloin chop boneless

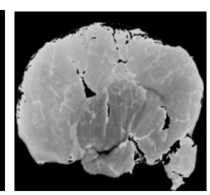
Total U.S. top 10 minimally processed pork cuts by dollar sales, July 2010 through June 2011

Fig. 1: Pork sirloin chop samples

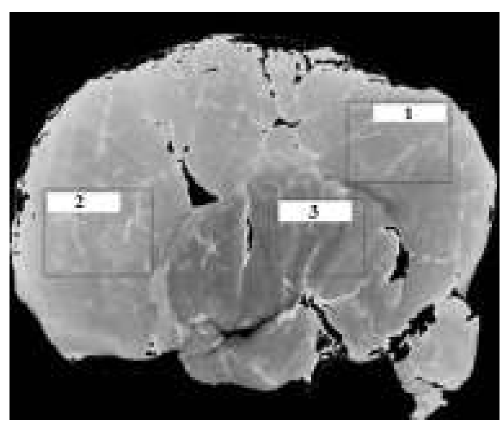
Fig. 2: Color image acquisition system



(a)



(b)



(c)

Fig. 3: Image segmentation step for two-tone ratio

Color features extraction: After the two-tone color ratio method was established, three pork image color features (mean values of R, G and B) were extracted from each image in order to calculate two-tone color ratios. CIE L*a*b* and HSI color space were also used for image color feature extraction. The transformation from RGB color space to CIE L*a*b* and HSI color spaces was performed. The H, S and I computation equations were as follows:

$$I = \frac{1}{3(R+G+B)} \tag{1}$$

$$S = 1 - \frac{3}{(R+G+B)}[\min\{R,G,B\}] \tag{2}$$

$$H = \arccos\{\frac{\frac{1}{2}[(R-G)+(R-B)]}{[(R-G)^2+(R-B)(G-B)^{1/2}]}\} \tag{3}$$

For CIE L*a*b* color space, the image was first transformed to CIEXYZ color space:

$$\begin{cases} X=0.40R'+0.325G'+0.265B' \\ Y=0.234R'+0.656G'+0.110B' \\ Z=0.048R'+0.108G'+1.279B' \end{cases} \tag{4}$$

where, $R' = 100\ (R/255)^{1/4}$, $G' = 100\ (G/255)^{1/4}$ and $B' = 100\ (B/255)^{1/4}$. From CIE XYZ color space, the image was then transformed into CIE L*a*b*:

$$\begin{cases} L^* = 116 f(Y/Y_0) - 16 \\ a^* = 500[f(X/X_0) - f(Y/Y_0)] \\ b^* = 200[f(Y/Y_0) - f(Z/Z_0)] \end{cases} \tag{5}$$

where, $f(t) = t^{1/3}$, $t > 0.008856$ and X_0, Y_0 and Z_0 are the CIE XYZ tristimulus values of the reference white point.

Classify pork sirloin two-tone color grade using K-mean clustering method: K-mean clustering method (MacQueen, 1967) was used to separate the pork into 2 color grades according to Minolta L* value. The procedure follows a simple and fast way to classify the given data set into two clusters. First we defined k centroids, one for each cluster. These centroids were placed in a cunning way because different locations cause different results. The second step is to take each point belonging to a given data set and associate it with the nearest centroid. When no point is pending, the first step is completed and an early groupage is done. A 10-step loop was generated. As a result of this loop, the k centroids change their location step by step until no more changes are done. Finally, this algorithm aimed at minimizing an objective function, in this case a squared error function. The objective function equation was:

$$J = \sum_{j=1}^{k}\sum_{i=1}^{n}\left\|x_i^{(j)} - c_j\right\|^2 \tag{6}$$

where $\left\|x_i^{(j)} - c_j\right\|^2$ is a chosen distance measure between a data point, $x_i^{(j)}$ and the cluster center, c_j, is an indicator of the distance of the data points from their respective cluster centers. In this study, the analysis of K-mean clustering algorithm was performed by SPSS 20.0 statistical software (SPSS Inc., Chicago, IL, USA). The values for enhanced and non-enhanced pork loin samples were separated into two groups according to the Minolta L* values by K-mean clustering method.

Support Vector Machine (SVM) classifier for pork two-tone color grade: The use of SVM is gaining favor due to the ability to utilize polynomial, radial based functions as a means to reach multilayer perception classifications. As described in Sun *et al*. (2012), there are two important steps when constructing the SVM model. The first step is choosing an appropriate kernel function. Polynomial kernel function, sigmoid kernel function and Radial Basis Function (RBF) kernel function are the usual functions which are used in data analysis. According to research by Howley and Madden (2005), the RBF kernel is the best and most widely used in SVM research. Therefore in this study, we used RBF kernel as the SVM classifier kernel function. The RBF kernel function is written as:

$$K(x_i, y_i) = \exp(-\gamma\left\|x_i - x_j\right\|^2) \tag{7}$$

where, $x \in Rn$ is n-dimension vector; $y_i \in (-1, +1)$ is the class label; and γ is a parameter which is specified by the model user.

The second step for SVM modeling is choosing the proper kernel parameter γ and soft margin parameter C, which determines the trade-off between the training error and VC dimension (Vapnik-Chervonekis) of the model. In this study, we established an automatically method for selecting the best γ and C. We defined ranges for γ (Log_2 (-5, 5)) and C (Log_2 (-5, 5)); and cross-validation was used to test the best γ and C.

Enhanced and non-enhanced pork sirloin sample imaging data were divided into training (model establishing) and testing (model validating) sets. For both enhanced and non-enhanced pork sirloin data, data sets were divided into 70% (enhanced -n = 379; non-enhanced -n = 163) and 30% (enhanced -n = 162; non-enhanced -n = 69) into the training and testing sets, respectively.

RESULTS AND DISCUSSION

Descriptive statistics and correlation analysis: There were nine two-tone ratio image color features extracted from the pork sirloin images. Descriptive statistics analysis for both enhanced and non-enhanced pork sirloin samples were first performed. As shown in Table 2, all color features exhibited large variation, with the Minolta L*, a* and b* values having greater variation than the nine color ratio features (ΦR, ΦG, ΦB, ΦL*, Φa*, Φb*, ΦH, ΦS, ΦI) (Table 3).

Correlations between traits were estimated as shown in Table 4 and 5. Strong, positive correlations (r>0.85) were observed between many traits, specifically Φa*, Φb* and ΦI with each other and with ΦR, ΦG, ΦB and ΦL* and ΦH with ΦS. In the case of non-enhanced samples, the correlations of ΦI with ΦR, ΦG, ΦB and ΦL* were equal to 1.00. Correlations between ΦR, ΦG, ΦB and ΦL* were equal to 1.00 for both enhanced and non-enhanced samples.

Prediction of pork two-tone color grade by Support Vector Machine (SVM) based classifier.

Instead of performing a dimensionality reduction step, we used the SVM technique to pool all color features in the model. The reason for pooling all the y color features into the model is that we can typically use the SVM technique without dimensionality reduction and still get effective classification results, as it is fairly immune to over fitting problems. Two independent test data sets were evaluated utilizing the SVM technique. For enhanced pork sirloin samples, the test data sets were 62 and 100 samples for grades 1 and 2, respectively. For non-enhanced pork sirloin samples, the test data sets were 22 and 47 samples for grades 1 and 2, respectively.

Table 2: Descriptive statistics of Minolta and two-tone ratio image color features for enhanced pork sirloin samples

Features[1]	N	Min.	Max.	Mean	S.E.	S.D.	Variance
L*	541	43.60	61.34	51.72	0.13	3.13	9.85
a*	541	13.33	29.47	20.30	0.11	2.71	7.34
b*	541	5.38	20.53	10.00	0.07	1.72	2.98
ΦR	541	0.49	3.45	1.36	0.01	0.40	0.16
ΦG	541	0.48	3.54	1.38	0.01	0.40	0.16
ΦB	541	0.48	3.49	1.36	0.01	0.40	0.16
ΦL*	541	0.49	3.45	1.35	0.01	0.39	0.16
Φa*	541	0.14	1.72	0.72	0.01	0.24	0.06
Φb*	541	0.14	1.81	0.74	0.01	0.25	0.06
ΦH	541	1.77	3.77	2.36	0.01	0.29	0.08
ΦS	541	1.77	3.44	2.34	0.01	0.26	0.07
ΦI	541	0.49	3.49	1.36	0.01	0.40	0.16

[1]: (ΦR, ΦG, ΦB, ΦL*, Φa*, Φb*, ΦH, ΦS, ΦI) = two-tone ratios of R, G, B, L*, a*, b*, H, S and I values; Min.: Minimum; Max.: Maximum; S.E.: Standard error; S.D.: Standard deviation

Table 3: Descriptive statistics of Minolta and two-tone ratio image color features for non-enhanced pork sirloin samples

Features[1]	N	Min.	Max.	Mean	S.E.	S.D.	Variance
L*	232	43.06	63.04	52.14	0.23	3.53	12.47
a*	232	7.17	23.50	18.12	0.16	2.47	6.10
b*	232	4.64	71.78	10.39	0.30	4.55	20.74
ΦR	232	0.52	3.40	1.23	0.02	0.38	0.14
ΦG	232	0.52	3.55	1.24	0.02	0.37	0.14
ΦB	232	0.51	3.39	1.23	0.02	0.37	0.14
ΦL*	232	0.52	3.38	1.22	0.02	0.37	0.14
Φa*	232	0.16	1.58	0.64	0.02	0.23	0.05
Φb*	232	0.16	1.81	0.67	0.02	0.24	0.06
ΦH	232	1.77	3.79	2.45	0.02	0.36	0.13
ΦS	232	1.84	3.33	2.43	0.02	0.30	0.09
ΦI	232	0.52	3.44	1.23	0.02	0.37	0.14

[1]: (ΦR, ΦG, ΦB, ΦL*, Φa*, Φb*, ΦH, ΦS, ΦI) = two-tone ratios of R, G, B, L*, a*, b* H, S and I values; Min.: Minimum; Max.: Maximum; S.E.: Standard error; S.D.: Standard deviation

Table 4: Correlations between Minolta and two-tone ratio image color features for enhanced pork sirloin samples

Features[1]	L*	a*	b*	ΦR	ΦG	ΦB	ΦL*	Φa*	Φb	ΦH	ΦS
a*	-0.22**										
b*	0.55**	0.15**									
ΦR	-0.07	0.02	-0.11*								
ΦG	-0.07	0.02	-0.11*	1.00**							
ΦB	-0.07	0.02	-0.11*	1.00**	1.00**						
ΦL*	-0.07	0.02	-0.10*	1.00**	1.00**	1.00**					
Φa*	-0.09*	0.04	-0.09*	0.89**	0.88**	0.89**	0.89**				
Φb*	-0.05	0.01	-0.07	0.90**	0.90**	0.90**	0.90**	0.99**			
ΦH	0.00	0.02	0.06	-0.71**	-0.69**	-0.70**	-0.71**	-0.63**	-0.64**		
ΦS	0.01	-0.01	0.06	-0.76**	-0.74**	-0.75**	-0.76**	-0.66**	-0.68**	0.92**	
ΦI	-0.08	0.02	-0.11*	0.99**	0.99**	0.99**	0.99**	0.87**	0.89**	-0.69**	-0.76**

[1]: (ΦR, ΦG, ΦB, ΦL*, Φa*, Φb*, ΦH, ΦS, ΦI) = two-tone ratios of R, G, B, L*, a*, b*, H, S and I values

Table 5: Correlations between Minolta and two-tone ratio image color features for non-enhanced pork sirloin samples

Features[1]	L*	a*	b*	ΦR	ΦG	ΦB	ΦL*	Φa*	Φb	ΦH	ΦS
a*	-0.26**										
b*	0.34**	0.07									
ΦR	-0.12	-0.02	-0.03								
ΦG	-0.12	-0.02	-0.03	1.00**							
ΦB	-0.12	-0.02	-0.02	1.00**	1.00**						
ΦL*	-0.12	-0.02	-0.03	1.00**	1.00**	1.00**					
Φa*	-0.12	-0.04	-0.03	0.91**	0.90**	0.91**	0.91**				
Φb*	-0.09	-0.04	-0.02	0.92**	0.91**	0.92**	0.92**	0.99**			
ΦH	-0.03	0.10	0.13*	-0.55**	-0.53**	-0.53**	-0.55**	-0.46**	-0.47**		
ΦS	-0.06	0.06	0.07	-0.63**	-0.60**	-0.61**	-0.63**	-0.53**	-0.55**	0.89**	
ΦI	-0.12	-0.02	-0.03	1.00**	1.00**	1.00**	1.00**	0.91**	0.92**	-0.54**	-0.62**

[1]: (ΦR, ΦG, ΦB, ΦL*, Φa*, Φb*, ΦH, ΦS, ΦI) = two-tone ratios of R, G, B, L*, a*, b*, H, S and I values

Table 6: Prediction of color grade and error rates of support vector modeling using image color two-tone ratio features for enhanced pork sirloin chops[1]

	SVM model predictions		
Test sample set	Grade 1	Grade 2	Error rate
Grade 1	62	0	0.0
Grade 2	0	100	0.0

[1]: Overall correct classification rate: 100%

Table 7: Prediction of color grade and error rates of support vector modeling using image color two-tone ratio features for non-enhanced pork sirloin chops[1]

	SVM model predictions		
Test sample set	Grade 1	Grade 2	Error rate
Grade 1	22	0	0.0
Grade 2	0	47	0.0

[1]: Overall correct classification rate: 100%

As shown in Table 6 and 7, the SVM model was 100% successful at predicting both grades (grade 1 and 2) in enhanced and non-enhanced pork loin samples. This proved the useful of SVM model which can fix the over fitting data set problem and give us an effective classified results based on the k-mean clustering method.

CONCLUSION

In this study, researchers investigated the ability of computer vision and machine learning technique to objectively predict two color grades of enhanced and non-enhanced pork sirloin chops. K-mean analysis was conducted to cluster the different grades of pork samples. Nine color image features were extracted from the pork sirloin sample images and used as predictors for the color grade classification model.

The Support Vector Machine (SVM) classifier was performed to establish the prediction model. The result of SVM classification model presented 100% correct for both enhanced and non-enhanced test samples. Therefore, color grades of pork sirloins can be predicted accurately using machine vision and support vector machine techniques.

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