Computers and Electronics in Agriculture 70 (2010) 27–32

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

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

Color grading of beef fat by using computer vision and support vector machine

K. Chen[a,*], X. Sun[a], Ch. Qin[a], X. Tang[b]

[a] The College of Engineering, Nanjing Agricultural University, Nanjing 210031, PR China
[b] Institute of Quality Standard & Testing Technology for Agro-Products, CAAS, Beijing 10081, PR China

ARTICLE INFO

Article history:
Received 23 December 2008
Received in revised form 28 May 2009
Accepted 10 August 2009

Keywords:
Beef fat
Color grading
Image processing
SVM

ABSTRACT

Machine vision and support vector machine (SVM) were used to determine color scores of beef fat. One hundred and twenty-three of beef rib eye steaks were selected to sensory evaluation and image processing. After fat color score was assigned to each steak by a five-member panel according to the standard color cards, images were acquired for each steak. The subcutaneous fat was separated from the rib eye by using a sequence of image processing algorithms, boundary tracking, thresholding and morphological operation, etc. Twelve features of fat color (six features were extracted from the subcutaneous fat images and the other six were calculated) were used as input for SVM classifiers. The best SVM classifier was chosen according to percentage of correct classified samples based on the training set and then was validated by a nondependent test set. The proposed SVM classifier achieved the best performance percentage of 97.4%, showing that the machine vision combined with SVM discrimination method can provide an effective tool for predicting color scores of beef fat.

1. Introduction

Color is one of most important quality traits of meat in the decision to purchase by the customer (Mancini and Hunt, 2005). In the customer's views, freshness is related to bright red in red meats. Fresh pork or beef is expected to have a homogeneous reddish color. Thus most customers discriminate against beef that is dark red or purple which they think is less fresh. Fat color, although less important than the muscle color, is also one of important factors in predicting the ultimate red meat quality. According to the official beef quality grading systems in China and in Japan, which is respectively carried out by China Department of Agriculture and Japan Meat Grading Association, fat color is a primary attribute on which quality grades for beef steaks are based. The China Department of Agriculture has defined nine grades of beef fat color and issued a set of standard color cards illustrating beef fat scores. With the standard color cards as reference, graders assign fat color scores to a beef steak by specially checking this beef rib eye cross-section between the 12th and 13th ribs against these color cards. Since the determination of beef fat color grade largely depends on subjective experience of graders, it is possible that different graders might give different scores to the same beef steak. This will lead to non-consistency in beef quality across one country and increase labor cost. Therefore, developing an objective grading system of beef fat color which does not depend on visual inspection has been a longtime demand of the industry.

Image analysis technology has significant promise for assessing meat quality objectively and effectively. Many efforts on using image analysis technique for pork or beef color assessment (Larraín et al., 2008; O'Sullivana et al., 2003; Ringkob, 2001; Lu et al., 2000; Van Oeckel et al., 1999), marbling measurement (Faucitano et al., 2005; Yoshikawa et al., 2000; Gerrard et al., 1996) and quality evaluation (Jackman et al., 2008; Tan, 2004; Shiranita et al., 1998) have been reported. Several works have also been introduced so far aiming at analyzing and assessing pork fat color by computer vision. Ringkob (2002, 2003) has evaluated image analysis for measuring fat color of pork. They found that image analysis was a useful tool for determining color score of pork fat, particularly, for detecting differences between yellow and white fat. However, little work on the color classification of beef fat by computer vision or digital image analysis has been reported.

Because the computer vision measures the entire surface of a sample, it is more representative of sensory descriptors than the colorimeter, which is based on point-to-point measurements. Furthermore, with the digital image processing, the beef rib eye image can be segmented into exclusively fat and muscle images. As a result, fat color can be evaluated solely over the fat of interest without the influence of other tissues. This resultant information will result in more objective and precise determining for color score of beef fat in comparison with the colorimeter or the visual sensory means.

Support vector machine proposed by Vapnik et al. (1995) is a new state-of-the-art classification technique, which is based on the statistical learning theory and is designed to solve classifica-

* Corresponding author. Tel.: +86 25 58606571; fax: +86 25 58606699.
E-mail address: kunjiechen@njau.edu.cn (K. Chen).

0168-1699/$ – see front matter © 2009 Elsevier B.V. All rights reserved.
doi:10.1016/j.compag.2009.08.006

Fig. 1. Standard color cards of beef fat.

tion problems. It has been proved to be a powerful tool to perform non-linear classification, multivariate function estimation or non-linear regression. Compared with other methods, SVM has such advantages as it does not need a large number of training samples for developing model and is not affected by the presence of outlier (Burges, 1998). Therefore, machine vision combined with SVM method was proposed for the rapid and simple estimation of beef fat color.

The aim of this study is to test the feasibility of using computer vision and SVM for predicting color score of beef fat. The special objectives are to: (1) segment subcutaneous fat from beef rib eye by using digital image analysis; (2) extract color features of beef fat images; (3) develop a SVM-based classifier to determine the color score of beef fat based on the proposed color features.

2. Materials and methods

2.1. Samples and sensory analysis

One hundred and twenty-three wholesale beef rib representing various fat color score of beef typically found in china packing plants were purchased from a local supplier. After having been aged for 72 h at 4 °C. Individual longissimus dorsi (l.d.) muscle was sliced into a 2.5 cm thick sample for sensory analysis and image acquisition. The samples were divided into two groups: 85 was used to train the classifier, and the other 38 was used to evaluate performance of the classifier.

For sensory analysis, a five-member panel was established and trained to assess beef fat color according to an official set of color photographs of beef fat issued by China Department of Agricultural. Each panelist was retrained to evaluate the fat color. Training sessions were terminated when the results given by each panelist were not more than one unit from the group mean color score specified for each sample. China Department of Agriculture defined nine grades (1–9) of beef fat color in the china beef quality standard system. However, as shown in Fig. 1, the published color cards of beef fat contain only five color photographs: 1 = Ivory, 2 = Lightyellow, 4 = PaleGoldenrod, 6 = Khaki and 8 = Golden. Color for each sample was determined by the panelists with this five-point scale in this experiment.

2.2. Computer vision system

The implemented computer vision system has three main components: a dedicated lighting chamber, a color digital camera (Dimage Z1, Minolta Co. Ltd., Japan), with the maximum resolution 2048 by 1536 pixels and output in RGB format, and an image

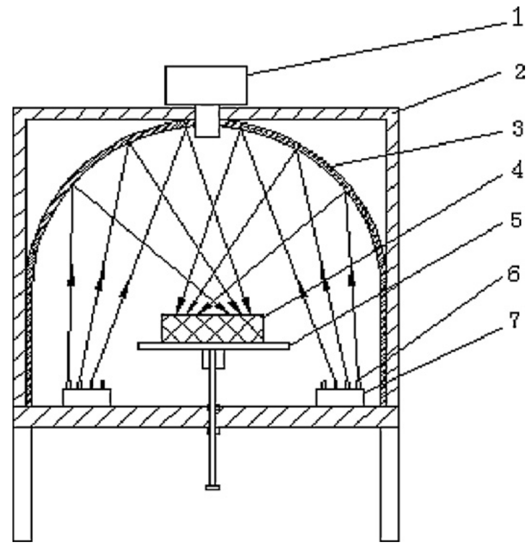

Fig. 2. Schematic diagram of the illumination chamber. (1) CCD, (2) box, (3) arc ceiling, (4) sample, (5) supporting plane, (6) LED lamps, and (7) lamp board.

processing software package. The lighting chamber consists of a devised box, lighting system and a sample supporting plane (Fig. 2). The supporting plane allows easy vertical movement. Samples were placed on it for image acquisition. The light-emitting diode (LED) lamps (model LT564CWC, color temperature 5400 K, China) were used in the lighting system. A total of 240 LED lamps were mounted on two lamp boards. Two lamp boards were on either side of the supporting board and each lamp board was fitted with 120 LED lamps. As shown in Fig. 2, there is an semicircle ceiling inside the box. Most light from the LED lamps reach to the arc ceiling and then diffusively reflect to the sample surface.

2.3. Image acquisition

Image acquisition was conducted immediately after scoring the fat color by the sensory panel under similar conditions. The camera was held on the arc top of the ceiling and the lens faced downwards towards the sample supporting plane. The distance from the bottom of the camera lens to the sample surface was set as 35 cm. After the camera was calibrated (Lu and Chen, 2008 reported in details the calibration procedure) using a standard white card (model LTB-100, Kodak, China), images of beef sample were captured on a matte black background under the following camera settings: manual mode, no flash, resolution of 1024 × 1680 pixels. After zooming the lens to make the sample cover the whole field of view and focusing, the image of each sample was taken and stored in JPEG format for image processing and analysis.

2.4. Image processing

Background segmentation was first performed on the original images. Photometric differences between background and rib eye cross-section were used to develop discriminant functions to remove background from the images. In this experiment, we developed a boundary tracking algorithm to remove background. Details of this algorithm are given by Wang (2006).

After removing the background, the rib eye image contained l.d. muscle, subcutaneous fat surrounding l.d. muscle and intramuscular fat referring to the fat flecks (marbling) surrounded by l.d. muscle. Because fat color scores are determined based on the subcutaneous fat, separating the subcutaneous tissues from a rib eye is necessary. To achieve this objective, morphological and logical operations were investigated. A representative example of beef

Fig. 3. Original image of a representative beef steak with a uniform background.

steak image (Fig. 3) was selected in random from 128 samples to demonstrate the performance of the proposed algorithms. The adaptive segmentation procedure is illustrated (Fig. 4) and summarized as follows.

After the boundary tracking algorithm was conducted on the original image, a mask image precision covering the objective was obtained as shown in Fig. 4(a). Then a logical operation 'AND' of the mask image with the original image in Fig. 3 resulted in a background-removed beef steak image shown in Fig. 4(b). After the Otsu thresholding (Otsu, 1979) was used to automatically calculate the optimum threshold value (the computing method of optimum threshold value was described in details by Chen and Qin, 2008), the background-removed beef steak image was binarized based on the optimum threshold value. Fig. 4(c) shows the resulting binarized image. Fig. 4(d) presents the result that the binarized image in Fig. 4(c) was erosioned. After deleting intramuscular fat flecks and other tissues by using a labeling algorithm, we dilated the resulting image shown in Fig. 4(d) and obtained the binarized subcutaneous fat image as shown in Fig. 4(e). Finally, we performed a logical operation 'AND' on the binarized subcutaneous fat image with the background-removed beef steak image. As a result, the subcutaneous fat was segmented from the beef steak and presented in Fig. 4(f). Implementing the above operations on other sample images resulted in successful segmentation of the subcutaneous fat for all sample images, indicating that our approach of adaptive segmentations is robust.

Each sample image was preprocessed in the same way and all of resulting images were subjected to extraction of color features.

2.5. Color features extraction

Six features of fat color (mean and SD of red, green and blue, RGB) were obtained from the images, the other six (mean and SD of hue, saturation and intensity, HSI) were calculated. As segmented fat images were represented in RGB color space, a transformation from RGB to HSI was required. Following equations were used to compute S and I (Yang, 2005):

$$I = \frac{R+G+B}{3}$$

$$S = 1 - \frac{\min(R, G, B)}{I}$$

For each of the six color components, their mean and standard deviation were calculated and, consequently, 12 color features including six means ($\mu_R, \mu_G, \mu_B, \mu_H, \mu_S, \mu_I$) and six standards deviations ($\sigma_R, \sigma_G, \sigma_B, \sigma_H, \sigma_S, \sigma_I$) were obtained. The means show the average color properties of fat and the standard deviations represent a measure of color un-uniformity over a fat.

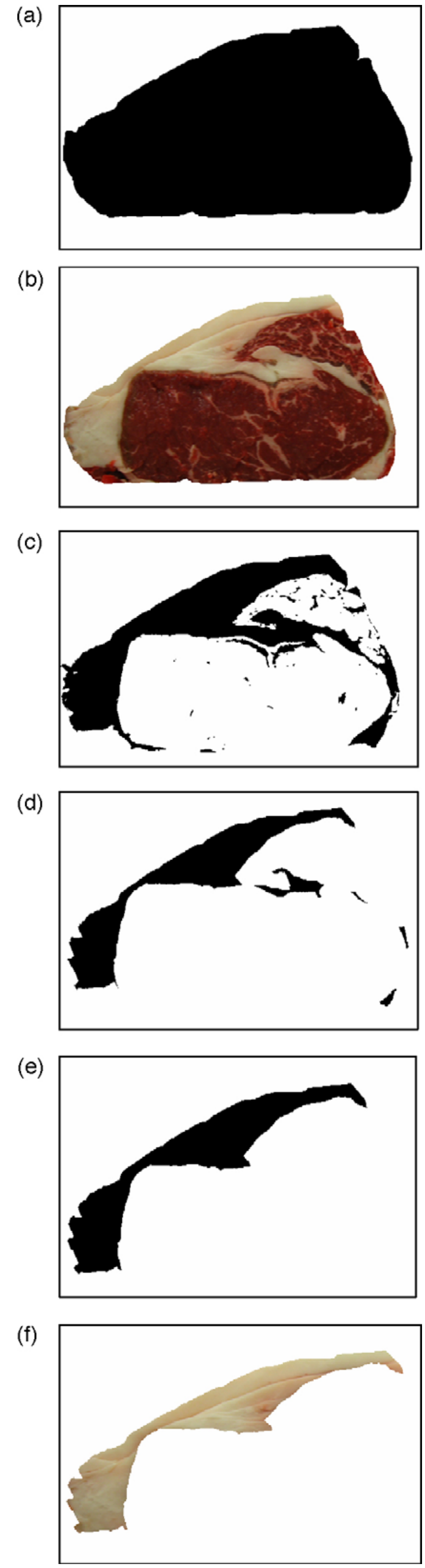

Fig. 4. Segmentation of subcutaneous fat from a representative beef steak.

2.6. Construction of SVM classifiers and prediction of color score

2.6.1. Support vector machine

SVM is a method of training polynomial, radial basis function, or multilayer perception classifier. It fixes the classification decision function in the basis of structural risk minimum mistake instead of the minimum mistake of misclassification on the training set to avoid over fitting problem. SVM solve the binary classification problem by finding maximal margin hyperplane between different classes. In the case that the input data are not linearly separatable, SVM firstly maps the data into a high-dimensional feature space, and then classifies the data by the maximal margin hyperplane. After projecting data in the feature space, SVM is, in fact, an algorithm that constructs the optimal separating hyperplane (Chen et al., 2007).

Assume that the training data with k number of samples is represented by $\{x_i, y_i\}$ with $i = 1, 2, 3, \ldots, k$, where $x \in R^n$ is n-dimension vector and $y_i \in \{-1, +1\}$ is the class label. Each pattern x belongs to either of two classes. The aim is to construct the equation $w{\cdot}x + b$ ($w,x \in R^n$, $b \in R$) of the optimal hyperplane that can divide the data leaving all points of the same class on the same side of hyperplane while maximizing the distance between the two classes and hyperplane. This can be expressed by following constraint:

$$y_i(w \cdot x_i + b) - 1 \geq 0, \qquad i = 1, 2, \ldots, k \tag{1}$$

where w is a vector and b is a scalar constant. As the distance is represented in $1/||w||$, the optimal hyperplane can be found by minimizing $||w||^2$ under constraint (1). The minimization problem is solved by introducing Lagrange Multipliers and maximizing:

$$L(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j}^{n} \alpha_i \alpha_j y_i y_j (x_i \cdot x_j) \tag{2}$$

Under constraints: $\alpha_i \geq 0$, $i = 0, 1, 2, 3, \ldots, k$.

If $\alpha^m = (\alpha_1^m, \ldots, \alpha_k^m)$ is an optimal solution of the above maximization problem, then the optimal separating hyperplane can be written as:

$$w^m = \sum_i y_i \alpha_i^m x_i \tag{3}$$

The points for which $\alpha^m > 0$ are the support vector. In most practical problems, such a separating hyperplane may not exist. In this situation, the solution to find an optimal hyperplane can be obtained by introducing a slack variable $\xi_i \geq 0$:

$$\begin{aligned} &\min \frac{1}{2} ||w||^2 + C \sum_{i=1}^{n} \xi_i \\ &s.t. \begin{cases} y_i(w \cdot x_i + b) \geq 1 - \xi_i \\ \xi_i \geq 0 \end{cases} \qquad i = 1, 2, \ldots, k \end{aligned} \tag{4}$$

where parameter C is regularization constant determining the trade-off between the two terms. It is named as penalty constant, which is chosen by the user.

In the case that a hyperplane could not be defined by linear equations, we can map input data into a high dimension feature space by substituting each x_i with its responsible mapping in the feature space $\phi(x)$. Thus Eq. (2) is expensed as following:

$$L(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j}^{n} \alpha_i \alpha_j y_i y_j (\phi(x_i) \cdot \phi(x_j)) \tag{5}$$

It is difficult to compute an optimal hyperplane in feature space when the mapping is unknown. Usually, a kernel function $K(x_i, y_i) = \phi(x_i) \cdot \phi(x_j)$ is introduced to make the computation easier. The optimization problem becomes:

$$\text{Maximize} \quad \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j}^{n} \alpha_i \alpha_j y_i y_j K(x_i, x_j) \tag{6}$$

$$s.t. \begin{cases} \sum_{i=1}^{n} \alpha_i y_i = 0 \\ 0 \leq \alpha_i \leq C, \end{cases} \qquad i = 1, \ldots, n \tag{7}$$

Then the optimal hyperplane function can be written as:

$$f(x) = \sum_{i=1}^{k} \alpha_i y_i K(x_i, x_j) + b \tag{8}$$

The b can be computed by solving following equation:

$$y_i(w \cdot x_i + b) = 1, \qquad i = 1, 2, \ldots, k \tag{9}$$

2.6.2. Construction of multiclass SVM classifier

Before construct a SVM classifier, an appropriate kernel function needs be carefully chosen. Popular kernel functions are: polynomial kernel function, sigmoid kernel function and radial basis function (RBF) kernel function, respectively. Of them, the RBF kernel function performs best and is widely used in SVM. Thus we used RBF kernel function to construct the SVM-based classifier in our research work. RBF kernel function can be written as:

$$K(x_i, x_j) = \exp\left\{ -\frac{||x_i - x_j||^2}{\sigma^2} \right\} \tag{10}$$

The optimal hyperplane function becomes:

$$f(x) = \sum_{i=1}^{k} \alpha_i y_i \left(\exp\left\{ -\frac{||x_i - x_j||^2}{\sigma^2} \right\} + b \right) \tag{11}$$

When the number of classes k is larger than 2, a multiclass SVM needs to be constructed. In our experiment, we need to develop a five-output SVM classifier since the panel assigned the beef fat color score in a five-point scale with five standard color cards as reference. A multiclass SVM classifier usually can be developed by combining several two classes SVM classifiers in terms of two strategies: one-versus-one or one-versus-rest (Herbrich, 2004). We adopted one-versus-one method in this study.

To construct a SVM-based classifier which performs well in predicting color score of beef fat, it is important to select appropriate kernel parameter σ and penalty constant C. The kernel parameter σ implicitly defines the non-linear mapping from input space to high-dimensional feature spaces; the penalty constant C determines the trade-off between minimizing the training error and minimizing model complexity. Large C value means assigning a higher penalty to error but simpler model. In order to eliminate any biased performance of the SVM classifier due to the inappropriate parameters, a range of $\sigma \in \{0.1, 0.5, 1, 5, 10, 50\}$ and $C \in \{0.1, 0.5, 1, 5, 10, 50, 100\}$ were selected, respectively, and then a great number of experiments had to be carried out to look for the optimal combination of σ and C values. Firstly, we adopted each possible combination of σ and C, for example, $\sigma = 0.1$ and $C = 0.5$ or $\sigma = 1$ and $C = 50$, e.g., to develop SVM classifiers, then the constructed SVM classifiers were applied to the training set for predicting color scores of the samples in training set. Finally, the optimal combination of σ and C was determined according to correct classification rate.

2.6.3. Prediction of color score

The test set was used to validate the proposed SVM classifier. Twelve color features were input into the classifier and the predicted results by the classifier were compared with that reported by the sensory panel. Correct classification rates were used to evaluate the performance of the classifier.

All the algorithms used in this study for image preprocessing and analysis were developed in C++ language by the authors.

3. Results and discussion

3.1. Color features extraction

Twelve features characterizing color of the entire subcutaneous fat were extracted from the subcutaneous fat images. Table 1 listed descriptive statistics of the fat color feature computed from steak samples. All color features exhibited large variation. The wide variation in mean color features among samples was agreement with the large variation observed in sensory color scores. One hundred and twenty-three of samples were assigned to color score of 1, 2, 4, 6 or 8 by the panel, showing the selected samples were representative of those beef steaks available in the market place. Compared with the means, the standard deviations of color fea-

Table 1
Descriptive statistics of color features of beef fat.

Color features	*N*	Minimum	Maximum	Mean	S.D.
μ_R	123	135	204	175.82	15.0
μ_G	123	118	178	148.94	13.7
μ_B	123	37	130	87.79	20.7
σ_R	123	0.06	0.32	0.14	0.04
σ_G	123	0.07	0.36	0.19	0.06
σ_B	123	0.07	0.36	0.21	0.06
μ_H	123	27.5	50.02	42.76	4.27
μ_S	123	0.19	0.68	0.37	0.11
μ_I	123	0.46	0.70	0.53	0.05
σ_H	123	0.02	0.12	0.06	0.02
σ_S	123	0.14	2.16	0.98	0.41
σ_I	123	0.25	1.20	0.63	0.20

Table 2
Correct recognition percent by SVM with various combinations of *C* and σ on the training set.

σ_I	*C*						
	0.1	0.5	1	5	10	50	100
0.1	63.2	63.2	55.3	55.3	68.4	55.3	55.3
0.5	73.7	84.2	79.0	79.0	81.6	81.6	79.0
1	76.3	89.5	89.5	92.1	89.5	89.5	86.8
5	63.2	76.3	79.0	89.5	94.7	94.7	97.4
10	60.5	63.2	71.1	86.8	86.8	92.1	94.7
50	55.3	47.4	60.5	57.9	63.2	76.3	84.2

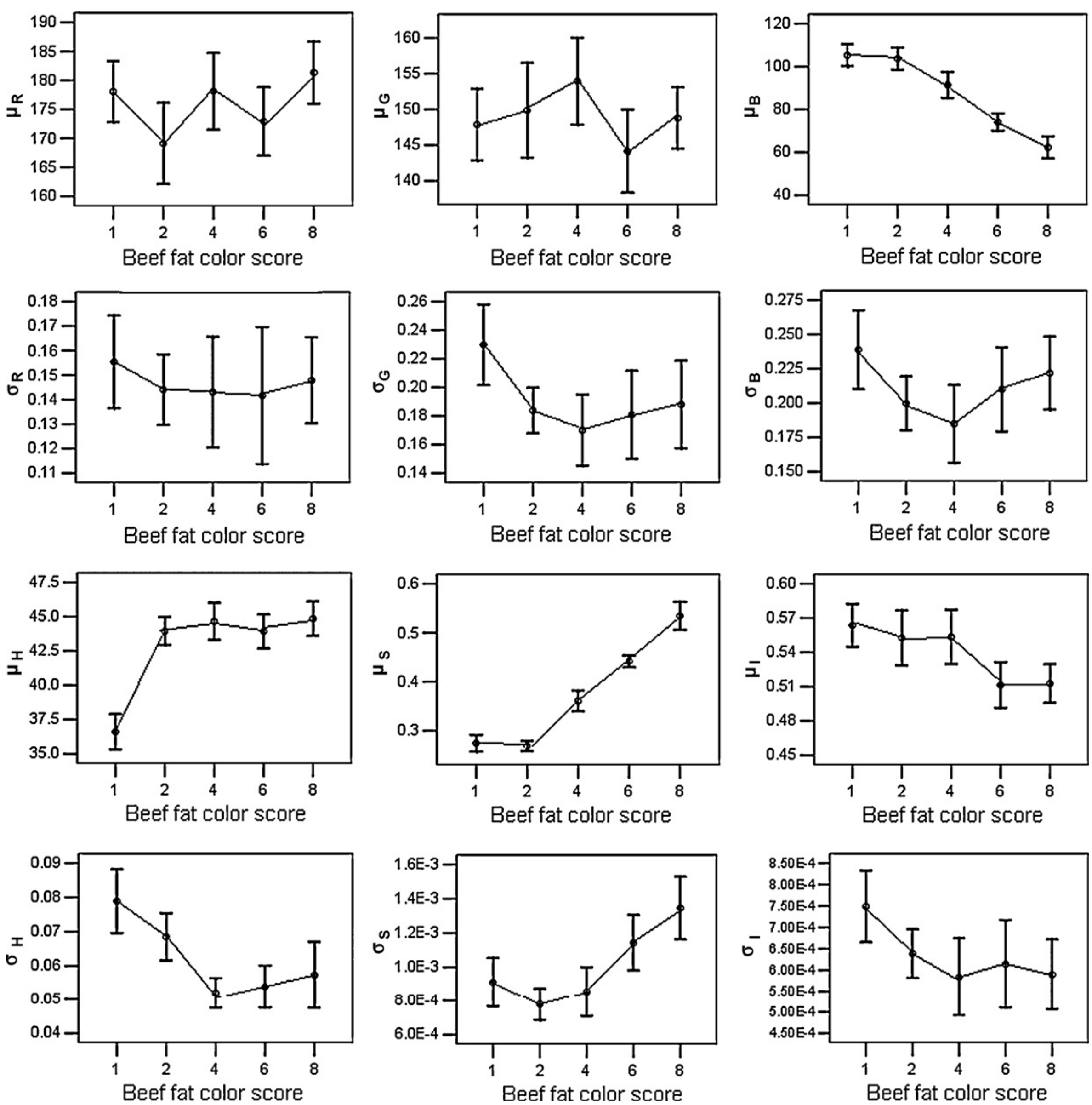

Fig. 5. Relationship between color features and scores of beef fat.

tures had less narrow variations. This revealed that the standard deviations were less important indicators of beef fat color than color component means. The reason could be that most fresh beef is relatively uniform in fat color. Additionally, data were plotted with 95% confidence interval and 12 of color feature values were plotted against color scores, respectively (Fig. 5). Fig. 5 shows that there were complex relationships between sensory scores and color features. It could be difficult to develop a simple model, for example, a linear model to predict fat scores based on these color features.

3.2. Prediction of fat color scores by SVM-based classifier

The training set was used to train the multiclass SVM classifiers to look for the optimal combination of σ and C. Table 2 presented predicting results given by the multiclass SVM classifiers with various combinations of σ and C. It could be seen that the combination of $\sigma = 5$ and $C = 100$ resulted in the highest correct classification rate of 97.4%. Thus, we selected $\sigma = 5$ and $C = 100$ to construct the optimum SVM classifier for predicting beef fat color score.

The optimum SVM classifier was validated using the independent test set to evaluate its performance. Out of the 38 samples, 37 samples were correctively classified by the proposed classifier. The performance percentage (refers to the ratio of correctly classified samples to the total samples) was 97.4%. The results showed that these extracted and computed color features contained useful information to discriminate color scores of beef fat. Pooling these features in a comprehensive analysis could construct a perform-well SVM classifier which was capable of predicting the color scores of fat color with a satisfactory accuracy.

Further analyzing the data, we could find that all samples with scores of 2, 4, 6 and 8 could be correctly classified by the optimum SVM classifier. Whereas out of the eight samples with color scores 1, one sample was incorrectly assigned to score 2. The proposed classifier gave a correct classification rate of 87.5% for the samples with color score 1, implying that the present classifier would perform slightly worse on samples with scores of 1 than that with scores of 2, 4, 6 and 8. To improve classification accuracy of the SVM classifier, more representative samples are necessary.

4. Conclusions

Segmentation of subcutaneous fat from rib eye could be achieved by boundary tracking, thresholding and morphological operations image processing. The sensory color scores of beef fat are non-linear correlated with the color features extracted from the subcutaneous fat images. The optimum SVM classifier was obtained by searching for the best combinations of parameters controlling the performance of SVM. Applying the presented SVM classifier to estimating fat color scores resulted in a classification rate of 97.4%. Therefore, color score of beef fat can be predicted with a satisfactory accuracy by using machine vision and support vector machine techniques.

Acknowledgement

We acknowledge Ms. Bo.Lu for her help in preparing the manuscript and funding by the China Department of Agriculture (project 2006G35).

References

Burges, C.J.C., 1998. A tutorial on support vector machines for pattern recognition. Data Mining and Knowledge Discovery 2 (2), 1–47.
Chen, K., Qin, Ch., 2008. Segmentation of beef marbling based on vision threshold. Computers and Electronics in Agriculture 62 (2), 223–230.
Chen, Q.Sh., Zhao, J.W., Fang, C.H., Wang, D.M., 2007. Feasibility study on identification of green, black and oolong teas using near-reflectance spectroscopy based on support vector machine (SVM). Spectrochimica Acta Part A 66, 568–574.
Faucitano, L., Huff, P., Teuscher, F., Gariepy, C., Wegner, J., 2005. Application of computer image analysis to measure pork marbling characteristics. Meat Science 69, 537–543.
Gerrard, D.E., Gao, X., Tan, J., 1996. Beef marbling and color score determination by image processing. Journal of Food Science 61 (1), 145–148.
Herbrich, R., 2004. Learning Kernel Classifier. MIT Press, New York.
Jackman, P., Sun, D.W., Du, Ch.J., Allen, P., Downey, G., 2008. Prediction of beef eating quality from color, marbling and wavelet texture features. Meat Science 80 (4), 1273–1281.
Larraín, R.E., Schaefer, D.M., Reed, J.D., 2008. Use of digital images to estimate CIE color coordinates of beef. Food Research International 41, 380–385.
Lu, Q.Y., Chen, K.J., 2008. Design and research of lighting device for capturing system of beef image. Journal of Agricultural Mechanization Research 6, 78–81.
Lu, J., Tan, J., Shatadal, P., Gerrard, D.E., 2000. Evaluation of pork color by using computer vision. Meat Science 56 (1), 57–60.
Mancini, R.A., Hunt, M.C., 2005. Current research in meat color. Meat Science 71, 100–121.
O'Sullivana, M.G., Byrnea, D.V., Martensa, H., Gidskehauga, L.H., Andersenb, H.J., Martensa, M., 2003. Evaluation of pork color: prediction of visual sensory quality of meat from instrumental and computer vision methods of color analysis. Meat Science 65, 909–918.
Otsu, N., 1979. A threshold selection method from gray-level histogram. IEEE Transactions, SMC-15, 652–655.
Ringkob, T.P., 2001. Image analysis to quantify color deterioration on fresh retail beef. In: Proceedings of the 54th Reciprocal Meat Conference, 24–28 July, Indianapolis, Indiana.
Ringkob, T.P., 2002. Using image analysis to measure pork fat color. In: Proceedings of the 55th Reciprocal Meat Conference, 24–28 July 2001, Indianapolis, Indiana.
Ringkob, T.P., 2003. Comparing pork fat color from barley and corn fed pork using image analysis. In: 56th Reciprocal Meat Conference, 28–31 July 2003, Lansing, Michigan.
Shiranita, K., Miyajima, T., Takiyama, R., 1998. Determination of meat quality by texture analysis. Pattern Recognition Letters 19, 1319–1324.
Tan, J., 2004. Meat quality evaluation by computer vision. Journal of Food Engineering 61, 27–35.
Van Oeckel, M.J., Warnants, N., Boucque, Ch.V., 1999. Measurement and prediction of pork color. Meat Science 52, 347–354.
Wang, Y.Q., 2006. Research on Classification of Wood surface Color based on Computer Vision. Northeast Forestry University (in Chinese with English abstract).
Yang, S.H.Y., 2005. Image Processing Algorithm Design in VC++. Tsing University Press, Beijing.
Yoshikawa, F., Toraichi, K., Wada, K., Ostu, N., Nakai, H., Mitsumoto, M., Katagishi, K., 2000. On a grading system for beef marbling. Pattern Recognition Letters 21 (12), 1037–1050.