Acta Technica 62 No. 2B/2017, 455–464

Automatic color grading model of foie gras based on machine vision

Pang Bin[1], Liu Tai-lian[2]

Abstract. To make up a disadvantage of traditional manual grading method, an automatic color grading model of foie gras was proposed based on machine vision and statistic recognition. Foie gras sample images from four different color grades were collected by a color CCD camera. After preprocessing and segmentation of the images, 12 color features were extracted from the foie gras area. To reduce color feature dimension, principal component analysis(PCA) was utilized. Afterwards, a multiple linear regression (MLR) model and a canonical discriminate analysis (CDA) model were set up respectively to predict color grade. The MLR model achieved the accuracy of 92 % and the CDA model of 100 %, showing that the machine vision combined with statistic recognition can provide an effective way for predicting foie gras color grades automatically.

Key words. Foie gras, color grading, machine vision.

1. Introduction

Currently, foie gras grading in China is carried out manually based on the quality indices such as weight, color, resilience and defects. Nevertheless, manual grading method relies on sensory experience of human grader, which usually lead to incompatible grading judgment. Besides, this method is costly and time-consuming for modern foie gras industry. It is evident that use of such method can not quantify the color index of foie gras. Therefore, utilization of new method such as machine vision and statistic recognition can be a substituted solution for automatic color grading of foie gras.

The machine vision technology has been considered as an objective and consistent way to estimate the quality of food product [1]. Many related studies using machine vision technology for color grading [2, 3], shape measurement [4-7] and defect detecting[8, 9] have been reported. However, although there are many studies

[1] College of Food Science and Engineering, Qingdao Agricultural University, Qingdao, Shandong, 266109, China

[2] College of Science and Information, Qingdao Agricultural University, Qingdao, Shandong, 266109, China

for meat products by using machine vision to predict color attributes, foie gras color grading by machine vision has seldom been studied. Chen et al. proposed an automatic method combined with machine vision and support vector machine(SVM) to determine color score of beef fat. Results showed that the machine vision combined with SVM discrimination method can predict color scores of beef fat effectively. Sun et al.analyzed fresh beef lean color image features for predicting beef color scores. It was reported that the machine vision combined with SVM classifier can achieve the best performance percentage of 94.7%. Jia et al. applied a locally liner embedding (LLE) method to reduce the dimensions of pork color feature. The results showed pork color grading accuracy can be improved combined with LLE manifold learning method and SVM.

In this project, a color automatically grading method based on computer vision system was established to predict foie gras color grades. The aim of this study was to:

1) Segment foie gras sample from background using imaging processing.

2) Extract color features from RGB and $L*a*b*$ color spaces.

3) Estimate correlations between color grades and color features.

4) Reduce dimension of color features using PCA.

5) establish and test two different regression models for predicting foie gras color grades.

2. Materials and methods

2.1. Sample preparation

A total of 75 Greylag Landaise geese at age of 150 days were selected to overfeeding in the same condition. The duration of the preliminary experiment was 7 days and the duration of the formal experiment was 30 days. Then 75 geese were slaughtered and livers were classified manually by color according to Chinese foie gras standard. The 75 foie gras samples were divided into four color grades. As shown in Fig. 1, 14 pieces of grade one (G1) samples were marked with level 1, 15 pieces of grade one (G2) samples were marked with level 2, 30 pieces of grade one(G3) samples were marked with level 3, 16 pieces of grade one (G4) samples were marked with level 4.

2.2. Machine vision system

The machine vision system (Fig. 2) for collecting sample images consisted of a color CCD camera(Dimage Z1, Minolta Co.Ltd., Japan) with the maximum resolution 2048 by 1536 pixels, two adjustable LED lamps (YX-BL25040, Yongxin Ltd., China) with 400 Lux and a computer system (2.4 GHz Intel Core Duo CPU with 2 GB RAM).

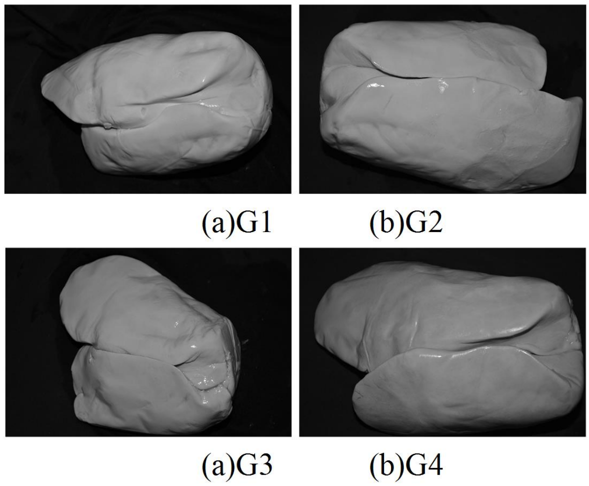

Fig. 1. Typical foie gras samples of different color grades

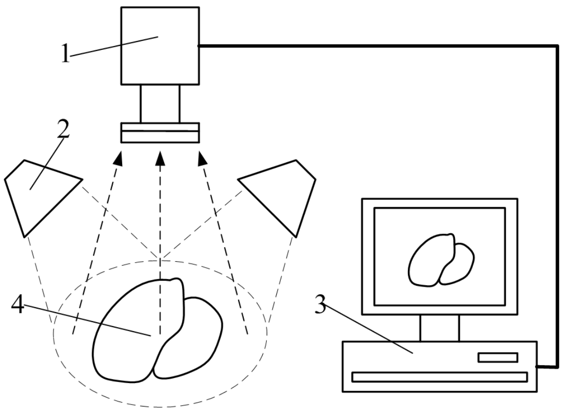

Fig. 2. Machine vision system: 1–CCD camera, 2–LED lamp, 3–computer system, 4–foie gras

2.3. Image processing and color feature extraction

Once images were collected, image processing and color feature extraction were performed using Matlab software. To remove the background, the Otsu's method was used to select the segmentation threshold value automatically. Each sample image was preprocessed to remove the background in the way and all of resulting images were subjected to extraction of color features. As resulting images were represented in RGB color space, a transformation from RGB to Lab was required. Then the mean (μ) and standard deviation (σ) were calculated in RGB and $L*a*b*$ color spaces.

2.4. Data analysis

Twelve color features(μR, μG, μB, μL, μa, μb, σR, σG, σB, σL, σa, σb) were evaluated using statistical software (SPSS 20.0). The 12 color features were reduced by principal component analysis in order to find the comprehensive features to explain foie gras color. The comprehensive features were pooled into the MLR and CDA model to quantify foie gras color grades.

3. Results and discussion

3.1. Color features extraction

As described in Section 2.3, twelve color features that characterized foie gras color were extracted from the sample images. Table 1 lists the descriptive statistics (means, standard deviations) of foie gras color features with different color score. As shown in Table 1, 12 color features (μR, μG, μB, μL, μa, μb, σR, σG, σB, σL, σa, σb) were replaced by $X_1 - X_{12}$ respectively. The standard deviation of the color features fluctuated less significantly than the mean, suggesting that the standard deviation is not a critical index.

Table 1. Descriptive statistics of foie gras color features

CF	G1	G1	G2	G2	G3	G3	G4	G4
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
X_1	145.60	6.21	135.91	3.65	137.25	2.53	123.40	3.60
X_2	132.37	3.58	122.51	3.99	118.23	3.63	104.69	5.04
X_3	118.93	2.56	105.66	3.38	101.49	3.01	97.60	5.04
X_4	142.42	6.19	134.55	2.91	130.34	3.42	118.25	2.64
X_5	131.29	0.72	130.87	0.37	134.81	0.77	134.00	1.03
X_6	136.14	1.38	138.84	1.26	139.99	1.59	134.99	1.65
X_7	6.53E-02	2.66E-03	5.22E-02	3.10E-03	5.53E-02	2.36E-03	4.53E-02	1.90E-03
X_8	6.57E-02	2.21E-03	5.02E-02	2.15E-03	5.06E-02	2.36E-03	4.46E-02	2.75E-03
X_9	5.90E-02	2.83E-03	4.43E-02	3.03E-03	4.17E-02	2.72E-03	4.12E-02	2.60E-03
X_{10}	6.77E-02	1.80E-03	5.22E-02	1.97E-03	5.29E-02	3.18E-03	4.70E-02	2.59E-03
X_{11}	4.03E-03	2.57E-04	2.16E-03	2.64E-04	2.93E-03	7.02E-04	3.92E-03	3.21E-04
X_{12}	5.08E-03	2.94E-04	5.34E-03	1.87E-04	6.85E-03	2.55E-04	4.31E-03	2.82E-04

Note: CF = Color features.

3.2. PCA of color features

Twelve principal components (PC1–PC12) were calculated from the 12 color features extracted from 75 sample images. The variance contribution rates of each principal component are shown in Table 2.

As shown in Table 2, the eigenvalues of first 3 principal components (PC1, PC2, PC3) with cumulative variance contribution rate of 86.24 % are greater than 1. Thus, the first 3 principal components (PCs) were chosen to replace the original 12 color features. Fig. 3 showed the data point distribution of the first 3 PCs. As shown in Fig. 3, the data point regions of different color grade were plotted into 4 regions clearly and had no overlap. The distribution of G3 data point region was relatively scattered. The distribution of G1, G2, G4 data point regions were relatively centralized.

Table 2. Variance contribution rate of each principal component

Principal component	Eigenvalue	Variance cntribution rate (%)	Cumulative variance contribution rate (%)
PC1	6.36	53.02	53.02
PC2	2.70	22.43	75.45
PC3	1.30	10.79	86.24
PC4	0.58	4.81	91.04
PC5	0.29	2.45	93.49
PC6	0.21	1.74	95.23
PC7	0.16	1.32	96.55
PC8	0.11	0.94	97.48
PC9	0.10	0.84	98.32
PC10	0.08	0.62	98.95
PC11	0.07	0.59	99.54
PC12	0.06	0.46	100.00

3.3. MLR model of color grade

On the premise of guaranteeing sample proportion with 2:1 in different color grade, 50 samples were drew randomly in all 75 samples as the calibration set and the rest samples were drew as the validation set. Then the first 3 PCs were calculated from calibration set and MLR model was set up. The model could be expressed as equation (1), where Y is the predict grade.

$$Y = -0.39\mathrm{PC1} + 0.01\mathrm{PC2} + 0.19\mathrm{PC3} + 2.63\,. \tag{1}$$

Figure 4 shows the calibration results of MLR model with $R^2 = 0.912$ (R^2 being the determinate coefficient of MLR model) and standard deviation of calibration set is 0.307.

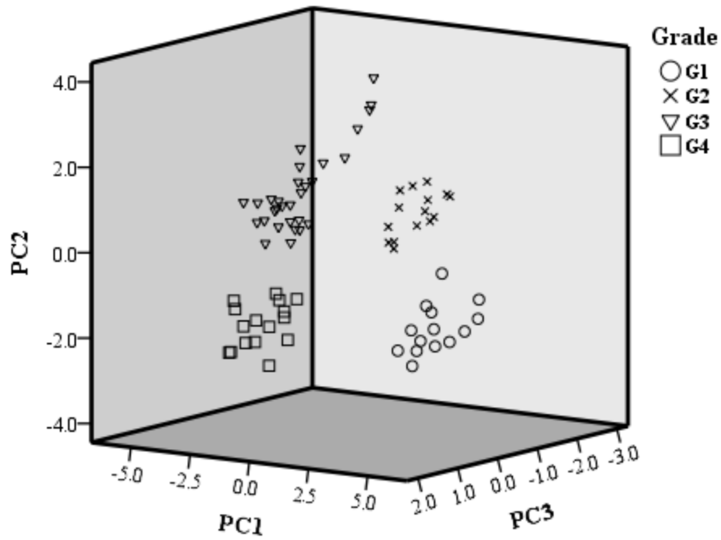

Fig. 3. Foie gras color score plot of the first 3 PCs

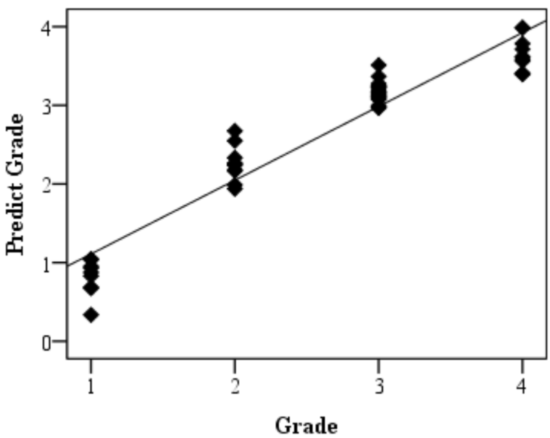

Fig. 4. Calibration results of MLR model

Figure 5 shows the validation results of MLR model with $R^2 = 0.935$ and standard deviation of validation set is 0.271. Similar predict results in two set indicated that the MLR model of color grade has some stability.

Foie gras color grade was calculated using MLR model in calibration set and validation set. The calculated results were rounded to express the estimated color grade using MLR model. Table 3 and Table 4 show the estimated results in calibration set and validation set, respectively.

As shown in Table 3, two G2 samples were wrongly estimated to 3, one G3

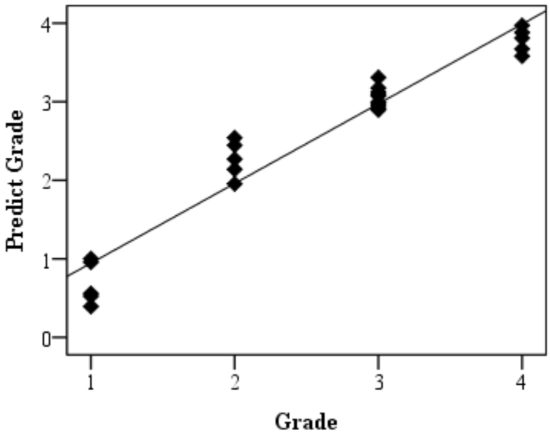

Fig. 5. Validation results of MLR model

sample was wrongly estimated to 4, two G4 samples were wrongly estimated to 3. The accuracy in calibration set was 90 %. As shown in Table 4, one G2 samples were wrongly estimated to 3 and the accuracy in validation set was 96 %. From the above, six samples of all 75 samples were wrongly estimated and total accuracy of MLR model was 92 %. Results showed that MLR model has high accuracy and stability. There were some error in MLR model, as adjacent color grade had similar color features which lead to wrong estimation.

Table 3. Estimated results in calibration set using MLR model

Grade	N	Estimated grade				Accuracy (%)
		1	2	3	4	
G1	9	9	0	0	0	100
G2	10	0	8	2	0	80
G3	20	0	0	19	1	95
G4	11	0	0	2	9	82
Total	50	9	8	23	10	90

Table 4. Estimated results in validation set using MLR model

Grade	N	Estimated grade				Accuracy (%)
		1	2	3	4	
G1	5	5	0	0	0	100
G2	5	0	4	1	0	80
G3	10	0	0	10	0	100
G4	5	0	0	0	5	100
Total	25	5	4	11	5	96

3.4. CDA model of color grade

Three canonical discriminate functions ($F1$, $F2$, $F3$) were calculated from the first 3 PCs in validation set using canonical discriminate analysis. The variance contribution rates of each function were shown in Table 5. As shown in Table 5, the eigenvalues of first 2 functions ($F1$, $F2$) with cumulative variance contribution rate of 97.18 % were chosen to replace the first 3 PCs. The transformation relation was CDA model of color grade which could be expressed as equation (2)

$$\begin{cases} F1 = -2.72\mathrm{PC1} + 1.33\mathrm{PC2} + 1.00\mathrm{PC3} - 0.23, \\ F2 = 0.50\mathrm{PC1} + 1.51\mathrm{PC2} + 1.18\mathrm{PC3} - 0.03. \end{cases} \tag{2}$$

Table 5. Variance contribution rate of each canonical discriminant function

Function	Eigenvalue	Variance cntribution rate (%)	Cumulative variance contribution rate (%)
$F1$	35.82	74.95	74.95
$F2$	10.64	22.23	97.18
$F3$	1.36	2.82	100.00

According to CDA model, data points of $F1$ and $F2$ in validation set are plotted in Fig. 6. As shown in Fig. 6, data points of different color grade are distributed around their mass center. The G1 mass center was (-11.29, 0.38), the G2 mass center was (-1.86, -1.16), the G3 mass center was (3.78, 3.16) and G4 mass center was (4.04, -5.00). Data points of different color grade around 4 mass centers have no overlap.

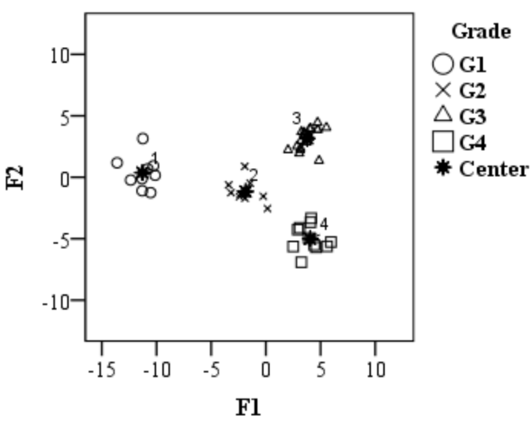

Fig. 6. Foie gras color score plot of $F1$ and $F2$ in validation set

To validate CDA model effect, data points ($F1$, $F2$) were classified according to minimum Euclidean distance from the mass centers. Table 6 shows the estimated results in validation set. As shown in Table 6, samples of 4 color grade were classified correctly and the accuracy of CDA model was 100 %. To further validate effectiveness of CDA model, data points of $F1$ and $F2$ in calibration set were plotted in Fig. 7. As shown in Fig. 7, the distribution is similar to Fig. 6. Table 7 shows the estimated results in calibration set. As shown in Table 7, samples of 4 color grades are classified correctly and the accuracy of CDA model is 100 %.

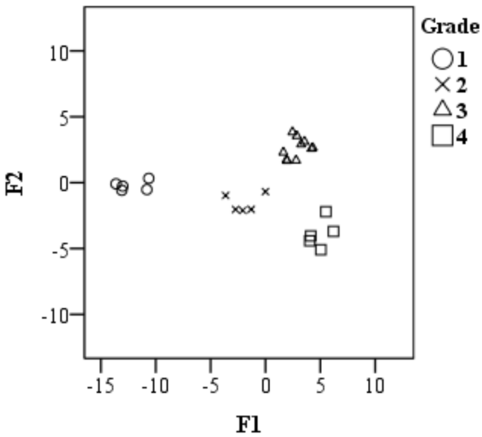

Fig. 7. Foie gras color score plot of $F1$ and $F2$ in calibration set

Table 6. Estimated results of foie gras color grade in validation set

Grade	N	Estimated grade				Accuracy (%)
		1	2	3	4	
G1	9	9	0	0	0	100
G2	10	0	10	0	0	100
G3	20	0	0	20	0	100
G4	11	0	0	0	11	100
Total	50	9	10	20	11	100

Table 7. Estimated results of foie gras color grade in calibration set

Grade	N	Estimated grade				Accuracy (%)
		1	2	3	4	
G1	5	5	0	0	0	100
G2	5	0	5	0	0	100
G3	10	0	0	10	0	100
G4	5	0	0	0	5	100
Total	25	5	5	10	5	100

4. Conclusion

In this paper, the automatic grading of foie gras color was studied by combining machine vision and statistic recognition. Conclusions were obtained:

(1) The MLR model of color grade had high accuracy and stability with total accuracy of 92 %. The model in validation set and calibration set had similar R2 and standard deviation.

(2) The accuracy of CDA model with accuracy of 100 % was higher than that of MLR model. The data points of 4 color grades in validation set and calibration set had similar distribution. Above all, on-line color grading system of foie gras could be developed using two models in order to replace manual grading in processing workshop. Furthermore, as sample number limited the accuracy and stability of the model, enlarged sample and repeated experiment were needed to make the color grading model more accurate and stable.

References

[1] B. Pang, X. Sun, C. W. Ye, K. J. Chen: *Grading of beef marbling based on image processing and support vector machine.* Computer Modelling and New Technologies *17* (2013), No. 3, 87–92.

[2] X. Sun, J. Young, J. H. Liu, L. Bachmeier, R. M. Somers, K. J. Chen, D. Newman: *Prediction of pork color attributes using computer vision system.* Meat Science *113* (2016), 62–64.

[3] Y. Zhang, W. Wang, H. Zhang, J. Zhang: *Meat sensory color grade: Mathematical simulation and its application in quality analysis of chilled pork.* Journal of Food Processing and Preservation *38* (2014), No. 4, 1957–1964.

[4] H. Chen, Q. Xia, T. Zuo: *Determination of shiitake mushroom grading based on machine vision.* Transactions of the Chinese Society for Agricultural Machinery *45* (2014), No. 1, 281–287.

[5] H. Li, H. Sun, M. Li: *Identification of cabbage ball shape based on machine vision.* Transactions of the Chinese Society for Agricultural Machinery *46* (2015), No. S1, 141–146.

[6] J. Wang, X. Cui, D. Xu, S. Zhao, H. Liu, S. Wang, J. Chen: *Plant image analysis machine vision system in greenhouse.* CCTA International Conference on Computer and Computing Technologies in Agriculture VIII, 16–19 September 2014, Beijing, China, Springer Nature, Book series (IFIPAICT) *452* (2014), No.662–690.

[7] B. Pang, X. Sun, X. Sun, K. Chen: *A fast beef marbling segmentation algorithm based on image resampling.* TELKOMNIKA Indonesian Journal of Electrical Engineering *12* (2014), No. 5, 3894–3901.

[8] B. Zhang, W. Huang, L. Gong, J. Li, C. Zhao, C. Liu, D. Huang: *Computer vision detection of defective apples using automatic lightness correction and weighted RVM classifier.* Journal of Food Engineering *146* (2015), 143–151.

[9] L. S. LeMasurier, J. F. Panozzo, C. K. Walker: *A digital image analysis method for assessment of lentil size traits.* Journal of Food Engineering *128* (2014), 72–78.

Received September 19, 2017