Journal of Zhejiang University-SCIENCE B (Biomedicine & Biotechnology)
ISSN 1673-1581 (Print); ISSN 1862-1783 (Online)
www.zju.edu.cn/jzus; www.springerlink.com
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Sensory quality evaluation for appearance of needle-shaped green tea based on computer vision and nonlinear tools*

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http://dx.doi.org/10.1631/jzus.B1600423

Tea is one of the three greatest beverages in the world. In China, green tea has the largest consumption, and needle-shaped green tea, such as Maofeng tea and Sparrow Tongue tea, accounts for more than 40% of green tea (Zhu *et al*., 2017). The appearance of green tea is one of the important indexes during the evaluation of green tea quality. Especially in market transactions, the price of tea is usually determined by its appearance (Zhou *et al*., 2012). Human sensory evaluation is usually conducted by experts, and is also easily affected by various factors such as light, experience, psychological and visual factors. In the meantime, people may distinguish the slight differences between similar colors or textures, but the specific levels of the tea are hard to determine (Chen *et al*., 2008). As human description of color and texture is qualitative, it is hard to evaluate the sensory quality accurately, in a standard manner, and objectively. Color is an important visual property of a computer image (Xie *et al*., 2014; Khulal *et al*., 2016); texture is a visual performance of image grayscale and color changing with spatial positions, which can be used to describe the roughness and directivity of the surface of an object (Sanaeifar *et al*., 2016). There are already researchers who have used computer visual image technologies to identify the varieties, levels, and origins of tea (Chen *et al*., 2008; Xie *et al*., 2014; Zhu *et al*., 2017). Most of their research targets are crush, tear, and curl (CTC) red (green) broken tea, curly green tea (Bilochun tea), and flat-typed green tea (West Lake Dragon-well green tea) as the information sources. However, the target of the above research is to establish a qualitative evaluation method on tea quality (Fu *et al*., 2013). There is little literature on the sensory evaluation of the appearance quality of needle-shaped green tea, especially research on a quantitative evaluation model (Zhou *et al*., 2012; Zhu *et al*., 2017).

Therefore, we applied a computer vision system to obtain the visible light image of tea's appearance, extracted the color and texture characteristics, and associated the extracted characteristic variables with experts' sensory scores. Then, with the combination of linear method and nonlinear tools, we established a sensory quality evaluation method for the appearance of needle-shaped green tea, and revealed the quantitative relation between image feature vectors and human senses. This study provided a theoretical reference and conducted exploration in the evaluation method and technical means on the appearance quality of tea. It has direct significance for the accurate evaluation of quality in tea transactions.

In the study, in total 140 needle-shaped green tea samples were collected, which comprised 40 first-level, 77 second-level, and 23 third-level tea samples. The tea samples were evaluated by three sensory experts from the China Tea Science Society and Department of Tea Science of Zhejiang University (Hangzhou, China). The experts evaluated the appearance quality of the tea samples through the

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* Project supported by the National Natural Science Foundation of China (No. 31271875), the Natural Science Foundation of Zhejiang Province (No. Y16C160009), and the Key Research Projects of Zhejiang (No. 2515C02001), China
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sensory evaluation method (GB/T 23776-2009) in the code review form, which includes color, cleanliness, and uniformity (AQSIQ and SAC, 2009). The average score of their evaluation was taken as the final evaluation score. According to the appearance sensory scores divided by the Kennard-Stone method (Mir-Marqués *et al.*, 2016), 95 samples were used as the calibration set and the remaining 45 samples were used as the prediction set.

First, a computer vision system was designed. The system consists of image sensor, sample cell, even light source, and a graphical user interface (GUI) software processing system, and realizes the image collection and data analysis as per the technical approach shown in Fig. 1. The sensor uses the single lens reflex (SLR) camera (Canon EOS 60D 18MP, Japan); the GUI software processing system (software copyright No. 2013SR122183) uses MATLAB 2014b (The Mathworks, Natick, MA, USA) for compiling, which will automatically extract the image color and texture characteristics.

Nine color indexes, including red channel mean (R), green channel mean (G), blue channel mean (B), hue mean (H), vision mean (V), saturation mean (S), lightness component mean (L^*), a component mean (a^*), and b component (b^*), were obtained by transforming the color models between red-green-blue (RGB), hue-saturation-value (HSV), and white-black, green-red, and blue-yellow (Lab). Based on the statistical attributes of a gray histogram, six texture characteristics as mean grey (m), standard deviation (δ), smoothness (r), third moment (μ), uniformity (U), and entropy (e) were calculated (Xie *et al.*, 2014; Sanaeifar *et al.*, 2016), and in total 15 image characteristic variables (color and texture) were obtained.

Partial least squares (PLS) method and extreme learning machine (ELM) method (Tian and Mao, 2010; Huang *et al.*, 2012) were used respectively to conduct linear and nonlinear quantitative modeling (Yu *et al.*, 2016). The performance parameters (PCs, number of principal components; R_c, correlation coefficient of calibration; R_p, correlation coefficient of prediction; RMSEC, root mean square error of calibration; RMSEP, root mean square error of prediction; Bias, bias ratio; SEP, standard error of prediction; CV, coefficient of variation; RPD, residual predictive deviation value of prediction) from the literature were used for reference for the evaluation indexes of the model performances (Huang *et al.*, 2014). Generally, the smaller the RMSEP, SEP, CV, and Bias, the higher the R_c, R_p, RPD, and the accuracy and generalization of the model will be (Chia *et al.*, 2012; Luo *et al.*, 2014). All the data were processed under MATLAB 2014b.

Table 1 shows the results of image feature and sensory score for different levels of quality of needle-shaped green tea. The correlation analysis on the appearance evaluation and vision characteristic variables of the test samples showed that: except for the values of R, G, V, L^*, and U, all the image characteristic parameters are significantly correlated with the appearance scores, and exhibited the highest correlation coefficient at b^* value (0.740). The analysis indicated that the green tea has the highest appearance sensory score when the color is yellow-green or tender green rather than green, yellow, or dark. This is also in accordance with the sensory evaluation standard of green tea.

As a single-hidden layer feedforward neural network (SLFN) algorithm, the ELM has a better learning

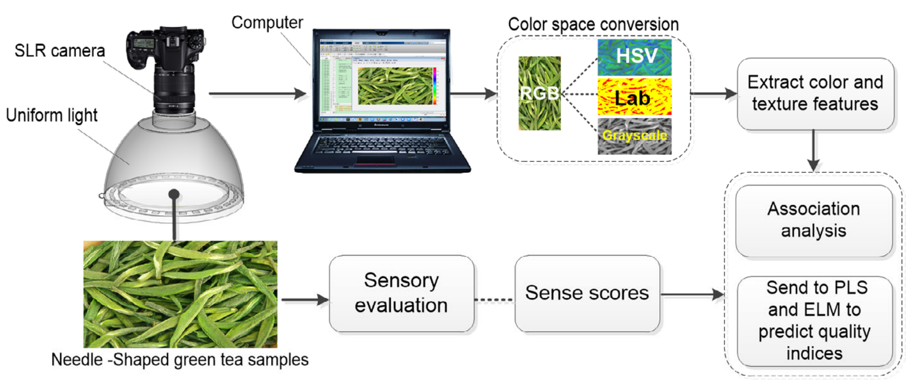

Fig. 1 Flowchart of the algorithm employed for color measurement
SLR: single lens reflex; PLS: partial least squares; ELM: extreme learning machine; RGB: red-green-blue; HSV: blue-saturation-value; Lab: white-black, green-red, and blue-yellow

Table 1 Results of image feature and sensory score for different levels of quality of needle-shaped green tea

Parameter	Number of samples	Mean	Minimum	Maximum	Standard deviation	Variance
R	23[a]	0.441	0.362	0.484	0.034	0.0011
	76[b]	0.500	0.386	0.613	0.056	0.0031
	40[c]	0.490	0.411	0.645	0.073	0.0053
G	23[a]	0.411	0.339	0.447	0.030	0.0009
	76[b]	0.456	0.348	0.555	0.053	0.0028
	40[c]	0.448	0.373	0.615	0.071	0.0051
B	23[a]	0.293	0.242	0.332	0.022	0.0005
	76[b]	0.308	0.215	0.395	0.043	0.0018
	40[c]	0.301	0.236	0.480	0.067	0.0045
H	23[a]	48.925	47.350	51.079	1.019	1.0391
	76[b]		43.860	51.107	1.322	1.7470
	40[c]	47.855	45.463	50.303	1.056	1.1149
S	23[a]	0.233	0.197	0.276	0.022	0.0005
	76[b]	0.270	0.221	0.320	0.022	0.0005
	40[c]	0.277	0.173	0.318	0.036	0.0013
V	23[a]	0.382	0.314	0.416	0.028	0.0008
	76[b]	0.421	0.316	0.517	0.050	0.0025
	40[c]	0.413	0.341	0.580	0.070	0.0049
a^*	23[a]	−2.202	−2.723	−1.730	0.303	0.0918
	76[b]	−2.147	−3.141	−1.255	0.389	0.1517
	40[c]	−2.340	−2.980	−1.693	0.323	0.1042
b^*	23[a]	13.354	11.425	16.140	1.397	1.9510
	76[b]	15.936	13.669	18.338	1.074	1.1545
	40[c]	16.212	11.278	18.488	1.605	2.5753
L^*	23[a]	70.045	64.715	72.526	2.142	4.5888
	76[b]	73.065	65.473	79.323	3.448	11.8870
	40[c]	72.426	67.388	82.466	4.496	20.2108
m	23[a]	0.380	0.313	0.414	0.028	0.0008
	76[b]	0.420	0.315	0.516	0.050	0.0025
	40[c]	0.412	0.340	0.579	0.070	0.0049
δ	23[a]	0.045	0.037	0.054	0.006	0.0000
	76[b]	0.048	0.036	0.071	0.007	0.0001
	40[c]	0.052	0.040	0.082	0.010	0.0001
r	23[a]	2.057	1.333	2.892	0.499	0.2486
	76[b]	2.366	1.327	5.005	0.733	0.5372
	40[c]	2.784	1.602	6.637	1.180	1.3915
μ	23[a]	9.295	4.600	12.008	2.232	4.9799
	76[b]	6.847	3.306	10.297	1.478	2.1838
	40[c]	6.361	2.738	8.809	1.256	1.5782
U	23[a]	6.558	6.066	7.288	0.320	0.1025
	76[b]	6.122	5.267	8.464	0.562	0.3164
	40[c]	6.811	5.060	21.905	3.390	11.4905
e	23[a]	7.536	7.387	7.608	0.052	0.0028
	76[b]	7.638	7.506	7.743	0.044	0.0020
	40[c]	7.658	7.336	7.803	0.086	0.0075
Appearance score	23[a]	84.304	79.500	85.500	1.724	2.9713
	76[b]	87.967	86.000	89.500	1.008	1.0156
	40[c]	90.675	90.000	92.500	0.730	0.5327

[a] First-level quality tea; [b] Second-level quality tea; [c] Third-level quality tea

speed and generalization performance than classical quantitative analysis methods, such as PLS and back propagation artificial neuronal network (BP-ANN) (Tian and Mao, 2010). AdaBoost is an integration machine learning algorithm, which is often used with a plurality of weak learning algorithms to enhance ultimate performance. This paper takes ELM as the weak predictor to form the AdaBoost strong predictor and the principal component as the input item of the strong predictor to establish the Ada-ELM hybrid modeling method. It optimizes the parameters based on the RMSEC values of the model, with PCs equal to 6, and parameter Φ (the prediction error threshold value) equal to 0.061, the RMSEC of the model reaches the minimum (0.547), and the R_P, RMSEP, Bias, SEP, CV, and RPD of the prediction set are 0.892, 0.874, −0.148, 0.226, 0.018, and 2.014, respectively.

The performances of the PLS linear model and the nonlinear model (ELM and Ada-ELM) are compared in Table 2. As shown, the performance parameters of the nonlinear model prediction set are obviously better than those of the linear model. The Ada-ELM model has the best prediction performance. Small SEP and CV mean a small degree of sample deviation and discrete variation. In particular, the RPD value is greater than 2, which shows that the model has good prediction and can be used for quantitative analysis.

As sensory evaluation is to use eyes to observe the color, evenness, strip thickness, purity, uniformity, and tenderness of the tea samples, integrate the vision information, and make a comprehensive evaluation through a complicated neural network system, the final sensory score has a certain nonlinear relationship with the color and the shape. The PLS method only treated the linear relationship between the variables and sensory score, which ignored the existence of the nonlinear relationship (Chen *et al.*, 2008; Fu *et al.*, 2013). However, ELM is a nonlinear artificial neural network modeling method, which has stronger adaptive and generalization ability (Tian and Mao, 2010). Hence, it has better prediction accuracy than the PLS model.

To make up for the shortage existing in the traditional sensory evaluation methods, and with the purpose of quantitatively and objectively evaluating the appearance quality of needle-shaped green tea, this paper collected the texture and color characteristics of different levels of tea samples, adopted a hybrid algorithm of AdaBoost algorithm and ELM neural network, and established a nonlinear Ada-ELM quantitative evaluation model. The results showed that the model can be used to evaluate the appearance quality of needle-shaped green tea, and the nonlinear modeling method can better represent the quantitative analytical relation between the image information and sensory scores.

This study provided an effective technical approach and idea for the development of sensory evaluation methods of tea. It is possible that transferring veteran tea makers' experience to a neural network to develop an expert decision support system or special purpose instrument, which would help achieve automatic control of needled-shaped green tea processing, and produce needled-shaped green tea with uniform quality and stable style. It is one of the most promising techniques for large-scale tea processing quality evaluation, which has become the main constraint in realizing automated and intelligent green tea processing technology. In addition, this has prospects of broad application in the tea trade as well as tea making and blending technology.

Compliance with ethics guidelines

Chun-wang DONG, Hong-kai ZHU, Jie-wen ZHAO, Yong-wen JIANG, Hai-bo YUAN, and Quan-sheng CHEN declare that they have no conflict of interest.

This article does not contain any studies with human or animal subjects performed by any of the authors.

Table 2 Results of different models for predicting sensory scoring of needle-shaped green tea

Method	PCs	Calibration set			Prediction set					
		R_c	RMSEC	Bias	R_p	RMSEP	Bias	SEP	CV	RPD
PLS	7	0.834	1.387	−0.003	0.777	1.215	−0.148	0.226	0.018	1.271
ELM	6	0.889	1.147	0.003	0.860	1.032	−0.326	0.246	0.019	1.625
Ada-ELM	6	0.973	0.576	−0.003	0.892	0.874	−0.148	0.226	0.018	2.014

PCs, used latent variables; R_c, correlation coefficient of calibration; R_p, correlation coefficient of prediction; RMSEC, root mean square error of calibration; RMSEP, root mean square error of prediction; Bias, bias ratio; SEP, standard error of prediction; CV, coefficient of variation; RPD, residual predictive deviation value of prediction

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中文概要

题　目：基于机器视觉和非线性的芽形绿茶外形感官品质评价

目　的：针对传统人工感官评价缺陷，建立客观、量化、有效和无损的芽形绿茶外形品质表征方法。

创新点：采用图像特征（色泽和纹理）和 AdaBoost 改进的 ELM（极限学习机）混合算法（Ada-ELM），明确了茶叶外形表象与人的感官感受间的非线性量化解析关系。

方　法：基于机器视觉和图像处理技术，提取不同品质茶样的纹理和色泽等图像特征（表 1），并与专家感官评分进行关联分析，筛选出 10 个极显著相关的特征变量（图 1）。进而采用偏最小二乘法（PLS）和 Ada-ELM，分别建立了针芽形绿茶外形感官品质的线性和非线性预测模型（表 2），并进行模型性能比较。

结　论：非线性模型能更好地表征图像信息与感官评分间的关联，且 AdaBoost 集成算法能进一步提升 ELM 模型的预测精度和泛化性。综合而言，采用计算机图像特征量化评价芽形绿茶的外形品质是可行的，为拓展茶叶感官评审方法和规模化、自动化加工中品质的专家决策技术，提供了一种新的技术途径和思路。

关键词：芽形绿茶；外形品质；图像特征；非线性建模；极限学习机（ELM）