African Journal of Agricultural Research Vol. 7(7), pp. 1142-1149, 19 February, 2012
Available online at http://www.academicjournals.org/AJAR
DOI: 10.5897/AJAR11.1264
ISSN 1991-637X ©2012 Academic Journals

Full Length Research Paper

Application of color features for the rapid determination of internal qualities of grapes (*Vitis labrusca*)

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Accepted 25 January, 2012

The aim of this study was to evaluate the feasibility of using color features for the rapid determination of internal qualities expressed as soluble solids content (SSC) and pH in grapes (*Vitis labrusca*). A total of 120 color features were obtained from the mean and standard deviation of pixel intensity within the interested area at each color channel of RGB, HIS, NTSC, YCbCr, and HSV color spaces. Least-squares support vector machines (LS-SVM) models were established based on different combinations of the extracted color features. The maximum correlation-coefficient method was used to select the optimal color features. These established models obtained the root mean square error for prediction (RMSEP) of 0.0611 and 0.737 for pH and SSC prediction respectively, which were better than the results of using visible-near infrared spectroscopy. It is concluded that the color features can be used for the rapid and non-invasive measurement of pH and SSC within grapes.

Key words: Color feature, grapes (*Vitis labrusca*), soluble solid content (SSC), pH, computer vision.

INTRODUCTION

The *Vitis labrusca* is a species of grapevines belong the *Vitis* genus of *Vitaceae* family. Grapes fruits need to meet certain quality grade requirements before they are shipped to the marketplace. The pH and soluble solids content (SSC) are two important internal quality attributes of grapes in determining maturity and harvest time, and in assessing and grading post-harvest quality. Nowadays, destructive techniques are commonly used for the quantitative measurement of pH and SSC of fruits. These destructive ways are only suited in the inspection of a small percent of samples from the entire lot. Because there is always inherent biological variability among each fruit, the destructive sampling ways cannot assure all the fruit samples to meet the higher quality standards which are important in the today's intense competitive global markets. Therefore, a rapid, reliable, and non-destructive approach for the measurement of pH and SSC is in strong need to ensure the quality of grapes.

Recently, many researchers have attempted to develop non-invasive or non-destructive techniques to assess the composition and quality of agricultural and food products (Du and Sun, 2004). Spectroscopy is widely used in recent years for the quality evaluation of agricultural and food products (Wu et al., 2008, 2009a, b, 2010, 2011). Cao et al. (2010) used visible and near infrared (NIR) spectroscopy for SSC and pH prediction and varieties discrimination of grapes. Zude et al. (2006) used NIR

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Abbreviations: E, Mean absolute relative error; **FS_{RGB}**, feature set contained all mean and standard deviation of the pixel's intensity values of RGB color channels in object region; **FS_{HSI},** feature set contained all mean and standard deviation of the pixel's intensity values of HSI color channels in object region; **FS_{NISC},** feature set contained all mean and standard deviation of the pixel's intensity values of NTSC color channels in object region; **FS_{YCbCr},** feature set contained all mean and standard deviation of the pixel's intensity values of YCbCr color channels in object region; **FS_{HSV},** feature set contained all mean and standard deviation of the pixel's intensity values of HSV color channels in object region; **LS-SVM,** least-squares support vector machines; **PCR,** principal component regression; **PCs,** principal components; **RBF,** radial basis function; **RMSEC**, root mean square error of calibration **RMSECV,** root mean square error of cross-validation; **RMSEP,** root mean square error for prediction; **SSC,** soluble solids content.

spectroscopy for SSC prediction of apple. However, common spectroscopy systems only have spectral information. They cannot provide the spatial information which is regularly required for and is critical in food inspection.

Within tremendous amount of spatial resolution, image techniques has also been used for the automatic inspection of agricultural and food products. Mendoza et al. (2011) used hyperspectral scattering data for prediction of apple fruit firmness and soluble solids content. Qing et al. (2007) predicted soluble solid content and firmness in apple fruit by means of laser light back-scattering image analysis. Martinsen and Schaare (1998) measured soluble solids distribution in kiwifruit using near-infrared imaging spectroscopy. Other applications for the quality evaluation of fruits using image detection techniques include multi- or hyper-spectral imaging techniques which have near infrared bands (Singh and Delwiche, 1994; Steinmetz et al., 1999; Lu, 2004), ultra-sound (Hassen et al., 2001; Fortin et al., 2003; Moeller and Christian, 1998; Hulsegge and Merkus, 1997), X-ray technology, magnetic resonance imaging (Evans et al., 2002; Troutman et al., 2001; Nott et al., 1999), and computed tomography imaging (Barcelon et al., 1999; Brecht et al., 1991; Romvari et al., 2002). These imaging techniques can not only provide the spectral information but also the special information. The information of objectives can be obtained non-destructively by imaging techniques comparing to those destructive detection methods. However the instruments of these methods are expensive.

Color is an important information for the consumers to percept the fruit qualities. Prior to purchase, the level of acceptability is determined by the color of fruits. Due to the lack of available resources for adequate technologies, the consumers always like to associate the color of fruits with their internal qualities (Brosnan and Sun, 2004). Therefore the color information of fruits is important to evaluate the qualities of fruits. In image analysis for food products, colour has proven successful for objective measurement of many types of food products with applications ranging from fruit, grain, meat to vegetable (Brosnan and Sun, 2004).

RGB is one of the most widely used color spaces to obtain the color information of samples. RGB color space is an influential attribute and powerful descriptor in which red, green, and blue light are added together in various ways to reproduce a broad array of colors. RGB color space is easy obtained by a low cost digital camera. In the field of fruit inspection based on RGB imaging system, Choi et al. (1995) estimated the tomato maturity on the basis of color image analysis. Morimoto et al. (2000) used digital images to quantitatively measure the shape of tomato fruits. However, most papers focused on shape and size detection, like orange (Ruiz et al., 1996), and pear (Ying et al., 2003). There are few papers about the application of RGB images in the field of the internal quality inspection of fruits, because of its limited spectral measurement range detecting internal attributes (Du and Sun, 2004). To overcome the above limitation, other color spaces and ratios of different channel of RGB space which contain more information might be helpful for the quantitative measurement of internal quality within fruits.

Besides RGB color space, there are other color spaces such as: HIS, HSV, NTSC, and YCbCr. HSI color space is very important and attractive color space for image processing applications, because it represents color's similarly how the human eye senses colors. HSI color space represents every color with three components: hue (H), saturation (S), intensity (I) (Singh et al., 2003). NTSC, named for the National Television System Committee (Miller and Delwiche, 1989), contains the NTSC luminance (Y) and chrominance (I and Q) color components, which is the analog television system. YCbCr is a family of color spaces used as a part of the color image pipeline in video and digital photography systems (Singh et al., 2003). Y is the luminance component, Cb and Cr are the blue-difference and red-difference chrominance components. The HSV color space describes color based on three properties: Hue, Saturation and Value (Pavlova et al., 1996). These color spaces contain more color information than RGB color space and might be helpful in the field of the quality inspection of fruits.

Different channels of color space contain different attribution which would be useful for mining color information related to quality of grapes. Ratios of different channel of RGB space were widely used color feature in imaging process technique. For instance, Normalized Difference Vegetation Index (NDVI) is widely used to analyze remote sensing measurements and assess whether the target being observed contains live green vegetation or not. Therefore different ratios between color channels within color spaces (that is, RGB, HSV, HIS, YCbCr, and NTSC) space were used for the assessment of SSC and pH of grapes.

The objective of this study was to determine the SSC and pH of grapes (*Vitis labrusca*) according to the color information extracted from five color spaces, namely RGB, HSV, HIS, NTSC and YCbCr. Data mining algorithms were used for the extraction of color features. The efficiency of these color features will be evaluated on the basis of the maximum correlation-coefficient method to find the most appropriate features for the quality evaluation of grapes.

MATERIALS AND METHODS

Sample preparation and reference method

In this study, there were 180 samples of grapes (*Vitis labrusca*) obtained by harvesting from three vineyards in Haining, Zhejiang Province, China. The grape cultivar was Dazhiwang. The stalks of grapes were removed right before the collection of RGB images. x was used to collect the RGB images of grapes (Du and Sun, 2004). The camera had an Interline Transfer Super68 HAD CCD of 1/3 inches with a horizontal resolution of 540 lines. The efficiency pixel

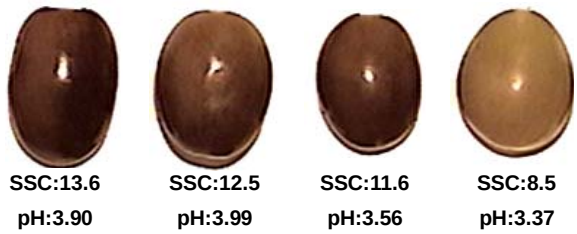

Figure 1. Pictures of grapes (*Vitis labrusca*).

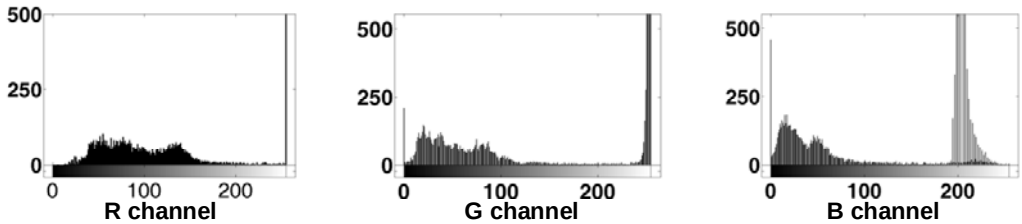

Figure 2. Histogram of 3-channel RGB image of grapes (*Vitis labrusca*).

is 752(H) ×582(V) and the scanning mode is 635 rows with 25 frames per second. The camera lens was vertical down. For each grape, its final image contains both two opposite side surface by combining the images of two sides together. The RGB image of grapes (*Vitis labrusca*) is shown in Figure 1.

After the image collection, grapes were peeled and made into juice. The reference pH was measured using a pH meter (Model: PHS-4CT, Shanghai Dapu Instrument Co. Ltd., Shanghai, China) with measuring range of 0~14, resolution ratio of 0.001 and output voltage range of -1999.9~1999.9 mV. The reference SSC values were measured by an Abbebenchtop Refractometer (Model: WAY-2S, Shanghai Precision and Scientific Instrument Co. Ltd., Shanghai, China). The ◦Brix (%) range is 0-95% with temperature correction and the refractive index75 accuracy is ±0.0002.

Color feature extraction

The histograms of each color channel of RGB are shown in Figure 2. The background was almost a white area with pixel value of 255 in the R channel. Therefore, the interest region could be separated from background well based on R channel. The mask to separate the sample and the background area was obtained based on R channel (Delon et al., 2005). Then the objective extraction was processed based on the mask on three channels respectively. Finally, by calculating the mean and standard deviation value of the pixel grey value of the objective areas in these three channels, six RGB image color features were obtained.

There were nine color channels [R/G, R/B, B/G, G/R, B/R, G/B, (R-G)/(R+G), (R-B)/(R+B), and (G-B)/(B+G)] obtained based on the calculation of the ratio and normalized operations between R, G, and B channels (Townshend and Justice, 1986). Then a total of 18 color features were obtained from the mean and standard deviation of the pixel's intensity values at each of nine color channels in object region. Finally, 24 color features were obtained based on RGB color space.

Furthermore, the images of HIS (Singh et al., 2003), NTSC (Miller and Delwiche, 1989), YCbCr (Singh et al., 2003), and HSV (Pavlova et al., 1996) were calculated from RGB image and 24 color features were extracted from each of these color spaces (that is, HSI, NTSC, YCbCr, and HSV) as what was done for the RGB color space. Finally, a total of 120 color features (24 color features ×5 color spaces) were obtained.

Calibration algorithms

Principal component regression (PCR) is a standard method among the multivariate calibration methods available for prediction using numerous correlated variables. PCR is used for relating the variations in a response variable (Y-variable) to the variations of several predictions (X-variables), with explanatory or predictive purpose. PCR is a two-step algorithm. First, a PCR is carried out on the X-variables. The principal components (PCs) are then used as predictions in a Multiple Linear Regression. The advantage with respect to MLR is that, the X-variables (PCs) are uncorrelated and that the noise is filtered (Nicolai et al., 2007).

Least-squares support vector machines (LS-SVM) is an optimized algorithm based on the standard support vector machine (Suykens et al., 2002). Radial basis function (RBF) kernel was used. Grid-search technique was applied to choose the optimal parameter values which include regularization parameter gam (γ) and the RBF kernel function parameter sig^2 (σ^2). For each combination of γ and σ^2 parameters, the root mean square error of cross-validation (RMSECV) was calculated and the optimum parameters were selected when produced smaller RMSECV. The details of LS-SVM algorithm could be found in the literature (Wu et al., 2008).

Model evaluation standard

The models in this study employed these parameters for evaluation: mean absolute relative error (*E*), root mean square error of calibration (RMSEC) and root mean square error for prediction (RMSEP). Generally, an accurate and robust model is the one with lower *E* , *RMSEC* and RMSEP value.

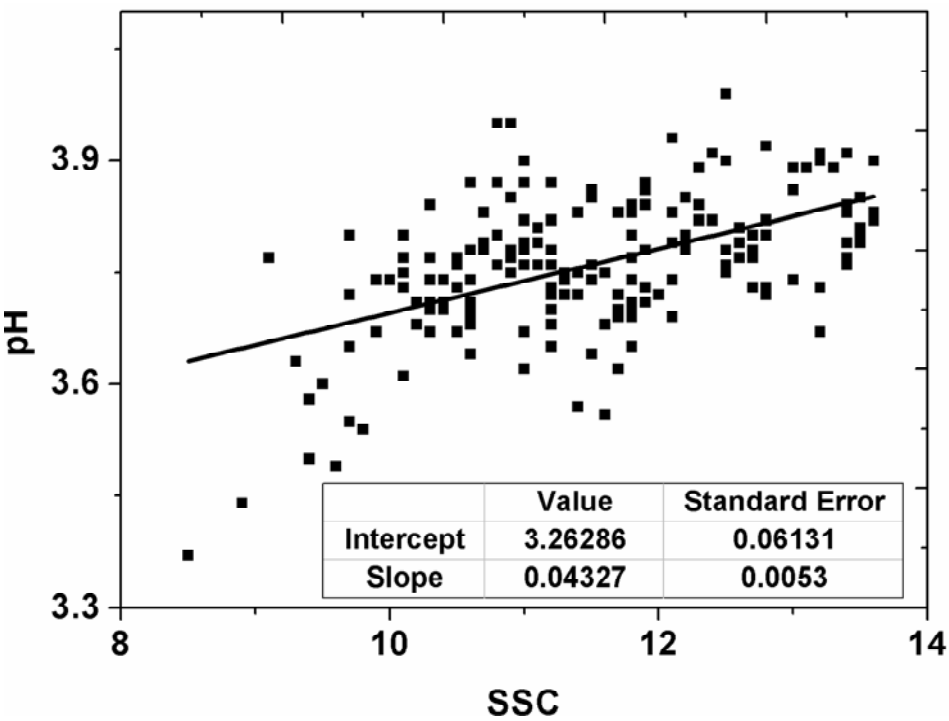

Figure 3. Correlation analysis between SSC and pH of grapes (*Vitis labrusca*).

Table 1. Results of SSC and pH analysis based on all features.

Parameter	Modeling method	Calibration		Prediction	
		E (%)	RMSEC	*E* (%)	RMSEP
pH	PCR	1.73	0.085	1.36	0.065
	LS-SVM	1.70	0.085	1.32	0.063
SSC	PCR	6.23	0.879	5.58	0.792
	LS-SVM	5.76	0.813	5.34	0.763

RESULTS AND DISCUSSION

Analysis of grape quality

The mean of SSC values of sample was 11.51°Brix with widely range which was from 8.50 to 13.60°Brix, while the mean of pH value was 3.76 with comparatively centralized range from 3.37 to 3.99. The standard deviation value of SSC and pH were 1.14 and 0.09, respectively. Correlation result between SSC and pH are shown in Figure 3. The correlation coefficient between SSC and pH was only 0.52. Therefore, it was necessary to establish the calibration models of SSC and pH, respectively.

Establishment of all-feature model

The samples were divided randomly into calibration set of 120 samples and prediction set of 60 samples. A total of 120 features were used to determine the SSC and pH. The determination models of SSC and pH were established using obtained color features based on PCR and LS-SVM, respectively (Table 1). For pH analysis, *E* values of LS-SVM (1.70% for calibration model and 1.32% for prediction model) were lower than that of PCR model (1.73% for calibration model and 1.36% for prediction model). For SSC analysis, *E* values of LS-SVM model (5.76% for calibration model and 5.34% for prediction model) were lower than that of PCR model (6.23% for calibration model and 5.58% for prediction model). The RMSEC and RMSEP values of LS-SVM models were also lower than those of PCR models for both pH and SSC analysis. The result shows that LS-SVM was better than PCR for either pH or SSC determination. Therefore, LS-SVM was used in the further analysis.

Table 2. Results of SSC and pH analysis based on single color space.

Property	Feature set	Calibration		Prediction	
		E (%)	RMSEC	*E* (%)	RMSEP
pH	S_{rgb}	1.75	0.086	1.32	0.062
	S_{ntsc}	1.81	0.090	1.39	0.064
	S_{ycbcr}	1.79	0.089	1.34	0.061
	S_{hsv}	1.78	0.088	1.42	0.065
	S_{hsi}	1.69	0.083	1.36	0.063
SSC	S_{rgb}	6.27	0.859	5.33	0.778
	S_{ntsc}	5.70	0.814	5.41	0.802
	S_{ycbcr}	6.34	0.877	5.25	0.769
	S_{hsv}	6.15	0.852	5.23	0.763
	S_{hsi}	6.29	0.872	5.43	0.773

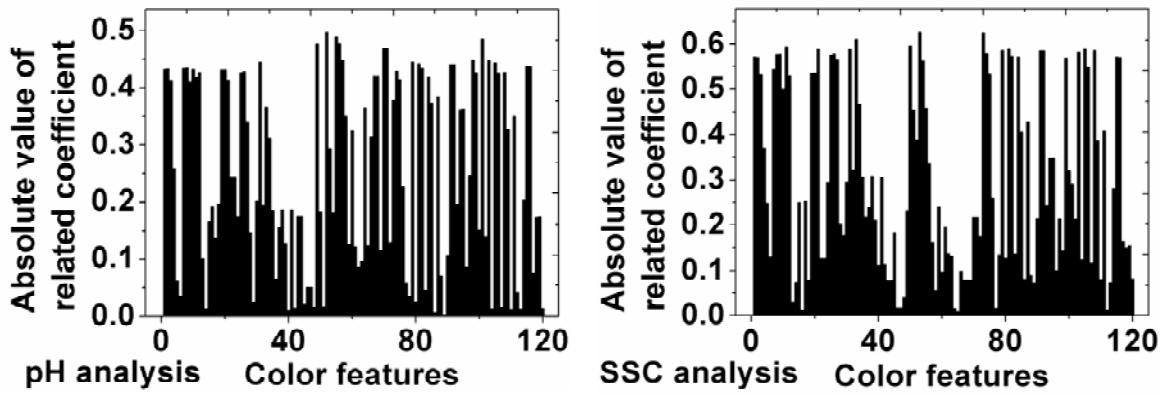

Figure 4. Absolute values of correlation coefficient between color features and SSC (or pH).

Model establishment on the basis of single color space

For single color space, 24 color features were obtained from the mean and standard deviation of the pixel's intensity values of 12 color channels in object region and were considered as one feature set of this color space. Thus, five feature sets were obtained from five color spaces, namely RGB (FS_{RGB}), HIS (FS_{HSI}), NTSC (FS_{NISC}), YCbCr (FS_{YCbCr}) and HSV (FS_{HSV}). Each feature set was used to determine pH and SSC based on LS-SVM, respectively. The results are shown in Table 2. The average *E* values of calibration and prediction were 1.76 and 1.37 for pH analysis, and 6.15 and 5.33 for SSC analysis, respectively. There was not much difference between the results of each color space. The best performance of pH prediction (*E* was 1.32%, and RMSEP was 0.062) was obtained when FS_{RGB} was considered. The FS_{HSV} obtained the best performance of SSC prediction (*E* was 5.23%, and RMSEP was 0.763). The overall results indicated that both pH and SSC can be well determined based on color features of any single color space. The RMSEP obtained in this study based on either all-feature (0.063 and 0.763) or color features of single color space (0.065 and 0.763) for pH and SSC prediction are lower than those of Cao et al. (2010)'s work, which were 0.1257 and 0.9252 for pH and SSC prediction respectively, using visible-near infrared spectroscopy. The results of this study show that extracted color features can be used as predictors for pH and SSC prediction in grapes.

Feature selection analysis for LS-SVM Model

In order to select the optimal features from all 120 features, maximum correlation coefficient method was adopted for the feature selection. The correlation coefficients between each feature and pH or SSC are shown in Figure 4. There were some useless features with lower correlation coefficients which should be eliminated. The high correlation coefficients for pH and SSC analysis were around 0.5 and 0.6, respectively.

For both pH and SSC analysis, sets of variables with

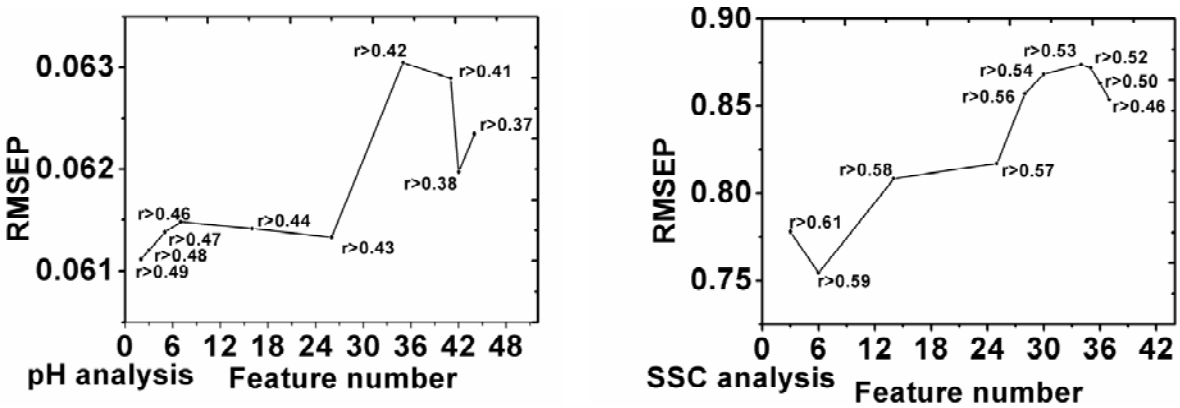

Figure 5. Results of LS-SVM models established by features selected based on different thresholds of absolute values of correlation coefficient.

different thresholds of correlation coefficient were obtained based on the maximum correlation-coefficient principle and the results are shown in Figure 5. For pH analysis, the best prediction model was obtained when the threshold of correlation coefficient was set as 0.49. Two features were selected, namely standard deviation of Y channel and mean of Y/Cb channel in YCbCr. RMSEP of the LS-SVM model was 0.0611, lower than the result with the REMSP value of 0.1267 obtained by Cao et al. (2010). The result was also better than the results of all features model (Table 1) or each color space model (Table 2). For SSC analysis, the best prediction model was obtained when the threshold of correlation coefficient was set as 0.59. Six features were selected, namely mean of G/B channel in RGB, mean of G/I channel in NTSC, mean and standard deviation of Cb channel in YCbCr, mean of V/S channel in HSV, and mean of H channel in HSV. RMSEP of the LS-SVM model was 0.754, lower than the REMSP value in Cao et al. (2010)'s work. The result was also better than the results of all features model (Table 1) or each color space model (Table 2).

To further search the optimal color features, let $S=\{x_1,...x_6\}$ was denoted the set of six selected features in SSC analysis. $S_k^j\left(j=1,...,\frac{6!}{(6\text{-}k)!\ \ k!},k=1,...,6\right)$ is feature set which contained *k* features of *S*. Let $R_k=\min_j\left(R_k^j\right)$, where R_k^j is the RMSEP value of LS-SVM model based on feature set S_k^j. The results based on different feature sets are shown in Figure 6. The lowest RMSEP of 0.737 was obtained when two features were selected. They were mean of V/S channel in HSV color space and mean of Cb channel in YCbCr. The result based on these two features was better than that of six features (RMSEP was 0.754), but with less features. The results illustrated that mean of V/S channel in HSV color space and mean of *Cb* channel in YCbCr were the most important features for SSC analysis. Compared to the results of all-feature and the features of single color space, correlation coefficient method reduced immensely the model complexity without losing the prediction accuracy, which indicated that the correlation coefficient method has a good ability for color feature selection.

The results obtained in the study are better than those of Cao et al. (2010) (RESEP=0.9579) using visible-near infrared spectroscopy, showing that more information were extracted by using other color spaces and ratios of different channel of RGB space with data mining techniques, which are useful for the internal quality determination of grapes. The proposed RGB inspection system based on the extraction of color features and data mining techniques could also be used for assessing internal qualities of other fruits and other agro-food products. Moreover, RGB image acquisition devices have lower prices than those of near-infrared multi-spectral image devices which have been used in the detection of fruit quality. The rapid and non-destructive measurement of grape qualities could be achieved by installing the RGB image acquisition device on a conveyer belt during production with the minimum modifications of the existing industrial system.

CONCLUSION

In this study, a rapid, non-destructive and low-cost approach was proposed for the pH and SSC prediction of grapes (*Vitis labrusca*). The best prediction models were obtained with the RMSEP of 0.061 and 0.737 for pH and SSC analysis, respectively. The results indicated that color features were reliable and practicable for the pH and SSC prediction of grapes on the basis of the extraction of color features and data mining technique. Simple, low-cost and efficacious equipments for the quality inspection of grapes would be designed based on the selected color features for grapevine cultivation.

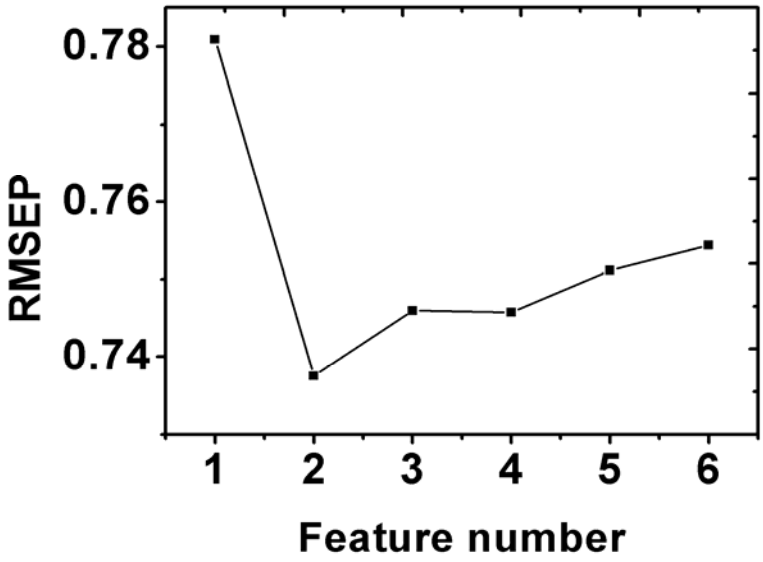

Figure 6. RMSEP of LS-SVM models based on the selected features.

ACKNOWLEDGMENTS

This study was supported by Natural Science Foundation of China (31071332), Zhejiang Provincial Natural Science Foundation of China (Z3090295), Important Zhejiang Provincial Science and Technology Specific Projects (2009C12002), National Special Public Sector Research of Agriculture (200903044), and National Agricultural Science and Technology Achievements Transformation Fund Programs (2009GB23600517).

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