Abstract
Multispectral imaging with 19 wavelengths in the range of 405–970 nm has been evaluated for nondestructive determination of firmness, total soluble solids (TSS) content and ripeness stage in strawberry fruit. Several analysis approaches, including partial least squares (PLS), support vector machine (SVM) and back propagation neural network (BPNN), were applied to develop theoretical models for predicting the firmness and TSS of intact strawberry fruit. Compared with PLS and SVM, BPNN considerably improved the performance of multispectral imaging for predicting firmness and total soluble solids content with the correlation coefficient (r) of 0.94 and 0.83, SEP of 0.375 and 0.573, and bias of 0.035 and 0.056, respectively. Subsequently, the ability of multispectral imaging technology to classify fruit based on ripeness stage was tested using SVM and principal component analysis-back propagation neural network (PCA-BPNN) models. The higher classification accuracy of 100% was achieved using SVM model. Moreover, the results of all these models demonstrated that the VIS parts of the spectra were the main contributor to the determination of firmness, TSS content estimation and classification of ripeness stage in strawberry fruit. These results suggest that multispectral imaging, together with suitable analysis model, is a promising technology for rapid estimation of quality attributes and classification of ripeness stage in strawberry fruit.

Introduction
Strawberry fruit (Fragaria × ananassa Duch.) is an economically important fruit which is more popularly consumed fresh, as well as used for garnishing cakes and pastries, flavored for juices and milk products, and processed into jams and other products. Therefore, together with the recent attention for food quality and safety, technologies for estimating the fresh quality of strawberry fruit are being sought [1]. At present, fruit are sorted manually or automatically on the basis of their external quality features. However, internal quality attributes such as firmness, sweetness, acidity and flavor are very important in the quality evaluation industries. In addition, since the strawberry is a non-climacteric fruit, in order to achieve good quality, it is essential to harvest at the optimum stage of ripening [2]. Currently, many objective criteria for judging maturity of strawberry have been used, for example, firmness, total soluble solids, titratable acidity, and determination of total anthocyanins. However, standard methods for these quality measurements are mostly destructive, slow, and prone to operational error. In order to overcome these disadvantages, nondestructive methods, especially those based on optical properties, are urgently required.

Near infrared spectroscopy (NIRS) is a nondestructive technique and highly suited to the measurement of quality attributes in fresh fruits and vegetables. It is a chemical-free, rapid measuring method with limited sample preparation, and enables the simultaneous determination of several attributes [3,4]. Recently, many published studies address the application of NIRS technology to determine firmness, soluble solids content, titratable acidity, pH and soluble sugar components in strawberry fruit [4–7]. However, NIR spectrometers only detect a small portion of the fruit; therefore, the spectra are sometimes not representative for the whole fruit.

Hyperspectral imaging is an emerging nondestructive technology that integrates conventional imaging and spectroscopy to attain both spatial and spectral information from an object simultaneously [8,9]. In strawberry fruit, Nagata et al. [1] had developed prediction models for firmness and soluble solids content using hyperspectral imaging in the visible range (450–650 nm). Similarly, Tallada et al. [10] conducted a hyperspectral imaging investigation for firmness in strawberry fruit using NIR hyperspectral imaging. Recently, ElMasry et al. [11] determined moisture content, total soluble solids content and pH in strawberry fruit using hyperspectral imaging in the visible and near-infrared region. However, the rich information in hyperspectral imaging...
results in difficulties in data processing, which makes it hard for industrial online applications. To overcome this problem, a simplified version called multispectral imaging (MSI) is available. This technology has recently been applied as a powerful process analytical tool for rapid, nondestructive inspection of internal and external attributes in various fruits and vegetables [12–20]. However, to our knowledge, there is no published data on the multispectral imaging for determination of quality attributes and ripeness stage in strawberry fruit. Furthermore, all of above predictions of quality attributes in strawberry fruit based on spectral imaging technique have been made using PLS analysis or MLR analysis. New regression methods such as support vector machine (SVM) and back propagation neural network (BPNN) appear promising in that they enable the non-linearity of data to be modeled using local or specific equations which could improve prediction models. Therefore, the main objective of this study was to assess the application of multispectral imaging for predicting the major quality attributes and ripeness stage in strawberry fruit, and comparing the performance of prediction models obtained using PLS, SVM and BPNN.

Materials and Methods

Sample Preparation

Unripe (white color) and ripe (orange-red color) strawberry fruit (Fragaria × ananassa Duch.) were harvested manually from local commercial greenhouse in Hefei City, China in March 2013. The study was carried out on private land and the owner of the land gave permission to conduct the study on this site. Furthermore, the field studies did not involve endangered or protected species. Two hundred and ten fruit (including seventy unripe fruit and one hundred and forty ripe fruit) with uniform shape and size and free from any abnormal features such as defects, diseases, and contaminations were selected, and transported for a short distance to the laboratory. Unripe and seventy ripe fruit were then acquired multispectral images immediately. In order to generate overripe (dark red color) fruit, seventy ripe fruit were kept in room temperature for 2 days. All green calyxes were completely removed from the tested fruit.

A penetration test was performed on the skin of whole fruit using a TA.XT2i texture analyzer (Stable Micro Systems, Guildford, UK) with a 6 mm diameter cylindrical probe. Samples were penetrated to a depth of 7 mm. The speed of the probe was 1.0 mm/s during the pretest as well as during penetration. From the force versus time curves, firmness was defined as the maximum force in newtons (N). Each fruit was measured at two perpendicular sides. Total soluble solids content of strawberry fruit was measured at room temperature using a hand held refractometer (WYT-32; QuanzhouOptical Co. Ltd, Quanzhou, China). A drop of clear juice was placed on an absolutely dry and clean refractometer prism, and a reading was taken directly. The total soluble solids content was expressed as a percentage on the Brix scale. Each fruit was measured in triplicate and both of these measurements were performed immediately after multispectral imaging measurements.

Multispectral Imaging System

The data acquisition was done using VideometerLab equipment (Videometer A/S, Horsholm, Denmark) which
acquires multispectral images at 19 different wavelengths from the visual (VIS) region to the lower wavelengths of the NIR region and the detailed information of the measured wavelength were 405, 435, 450, 470, 505, 525, 570, 590, 630, 645, 660, 700, 780, 850, 870, 890, 910, 940 and 970 nm. The majority of the wavelengths are in the visual region. Fig. 1 shows the principal setup of the system. The acquisition system records surface reflections with a standard monochrome charge coupled device chip, nested in a Point Grey Scorpion camera. The object of interest is placed inside an integrating sphere with a matte white coating to ensure that the light is scattered evenly with a uniform, diffuse light at illumination. At the rim of the sphere light emitting diodes (LEDs) are positioned in the pattern of side by side distributing the LEDs at the specific wavelength uniformly around the entire rim. The LEDs are strobing successively, resulting in an image for each LED of dimensionality 1280×960. The system is first calibrated radiometrically using both a diffuse white and dark target followed by a light setup based on the type of object to be recorded. The system is geometrically calibrated with a geometric target to ensure pixel correspondence for all spectral bands [21–23]. Each multispectral image consists of 19 separate images, which are recorded at 19 different wavelengths. Segmenting images into distinct regions is an important preprocessing step in image analysis. Image segmentation was performed using the VideometerLab software version 2.12.23. To remove the image background, all items except the strawberry fruit were removed by a Canonical Discriminant Analysis (CDA) [24] and segmented using a simple threshold. The decomposed result with desired features highlighted was then segmented easily using an adaptive thresholding technique known as Otsu adaptive thresholding method [25]. The images of strawberry fruit samples without the background could be transformed to spectra based on a mean calculation. Thus each image contributed with a single spectrum for the model calibration.

Data Analysis

Spectral analysis for predicting quality attributes. To develop a model between the extracted spectra and reference quality attributes (firmness and total soluble solids content), partial least square (PLS), support vector machine (SVM) and back propagation neural network (BPNN) were applied to build the model of prediction. PLS is a linear regression method for multivariate calibration. It has been widely applied in fruits and vegetables analysis and obtained favorable results. Leave-one-out cross-validation was used to evaluate the quality and to prevent over-fitting of calibration models. The optimal number of latent factors was determined at the lowest value of predicted residual error sum of squares. Latent factors can eliminate noises and random errors in the original data and account as much as possible for the variability of the original variables. The theory of PLS has been presented extensively in [26].

Support vector machine (SVM) proposed by Cortes and Vapnik [27] is a learning algorithm used for classification and regression tasks. It has been effectively used to perform multivariate function estimation, non-linear classification, or non-linear regression. SVM model is a representation of the calibration sample set as

Table 1. Range, mean and standard deviation (SD) for the parameters studied in calibration (N_{Calibration} = 162) and validation (N_{Validation} = 48) sets.

| Parameter | Set       | Range    | Mean    | SD     |
|-----------|-----------|----------|---------|--------|
| Firmness  | Calibration | 0.86–7.48 | 2.65    | 1.60   |
|           | Validation | 0.89–6.37 | 2.28    | 1.31   |
| TSS (°Bx) | Calibration | 5.0–11.4  | 7.89    | 1.29   |
|           | Validation | 6.3–10.6  | 7.79    | 0.93   |

Figure 2. Average reflectance from the multispectral images of unripe, ripe and overripe strawberry fruit. Vertical bars represent standard deviations from seventy measurements.

doi:10.1371/journal.pone.0087818.g002
vectors in space mapped so that the samples from the separate categories are divided by a clear gap that is as wide as possible. New samples from cross-validation or a test set are then mapped into that same space. Based on which side of the gap between classes they fall, they are predicted to belong to one category or another. SVM show high performance in practical applications.
when solving sophisticated classification problems. In SVM regression, the prediction errors are penalized linearly with the exception of a deviation below a certain value, ε, according to Vapnik’s ε-insensitive loss function. It is possible to use kernel functions, or kernels, that enable non-linear regression in a very efficient way. The values of ε and the parameter C (regularization parameter) have to be defined by the user; both are problem- and data-dependent. Cross-validation by leave-one-out procedure was performed during the validation step in order to define the optimum number of parameters that should be kept in the model and to detect any outliers. Compared with other methods, SVM does not require a large number of training samples for model development and is not affected by the presence of outlier [28]. The theory of SVM has been described extensively in Sun et al. [29] and Devos et al. [30]. But the major drawbacks of SVM are determined by the least prediction error. The theory of BPNN has been described in detail in Dubey et al. [32].

A total of 210 fruit were included in the analysis; 162 fruit including 54 unripe samples, 54 ripe samples and 54 overripe samples were used as a calibration set for developing models, and 48 fruit including 16 unripe samples, 16 ripe samples and 16 overripe samples were used for model validation to verify the prediction power of the calibration models. Models were calibrated using leave-one-out cross-validation (LOOCV). The quality of the calibration model was evaluated by the standard error of calibration (SEC), standard error of prediction (SEP) and the correlation coefficient (r) between the predicted and measured value of the attribute. A good model should have a high correlation coefficient (r), and a low SEC and SEP with little difference between them. These criteria are defined as follows:

\[
\text{SEC} = \sqrt{\frac{1}{I_C - 1} \sum_{i=1}^{I_C} (y_i - \tilde{y}_i)^2}
\]  

(1)

\[
\text{SEP} = \sqrt{\frac{1}{I_P - 1} \sum_{i=1}^{I_P} (y_i - \tilde{y}_i - \text{bias})^2}
\]  

(2)

\[
\text{bias} = \frac{1}{I_P} \sum_{i=1}^{I_P} (\tilde{y}_i - y_i)
\]  

(3)

Where, \( \tilde{y}_i \) is the predicted value of an attribute in fruit number \( i \); \( y_i \) is the measured value of an attribute in fruit number \( i \); \( I_C \) is the number of fruit (spectra) in the calibration set; and \( I_P \) is the number of fruit (spectra) in the validation set.

**Spectral analysis for classifying ripeness stage.** SVM and principal component analysis-back propagation neural network (PCA-BPNN) were applied to classify fruit ripeness stage. For the PCA-BPNN model, PCA was performed firstly to extract information from the whole spectral regions, and the few principal components were used to be the BPNN input layer. A total of 210 fruit were included in the analysis. Of these, 150 fruit including 50 unripe samples, 50 ripe samples and 50 overripe samples were used for the development of the classification models, and 60 fruit including 20 unripe samples, 20 ripe samples and 20 overripe samples were used for model validation to verify the prediction power of the calibration models.

**Statistical Analysis**

All image analyses and statistics were carried out using Matlab 2009 (The Mathworks Inc., Natick, MA, USA) and Origin 8.5.

**Results and Discussions**

**Reflectance Spectral Analysis**

Fig. 2 shows the average relative reflectance spectra in a range of 403–970 nm of strawberry fruit sampled at three ripeness stages. In despite of ripeness stage, the reflectance curves of strawberry fruit were rather smooth across the entire spectral region. Anthocyanins and chlorophyll which represent the color characteristics in the strawberry fruit have previously been identified at around 520 and 680 nm wavelength, respectively [33,34]. ElMasry et al. [11] reported that NIR absorption at around 840 and 960 nm were related to sugars and water content.

### Table 2. Performance of PLS, SVM and BPNN models for predicting firmness and TSS.

| Parameter     | Method | Spectra | SEC  | r     | SEP  | r     |
|---------------|--------|---------|------|-------|------|-------|
| Firmness(N)   | PLS    | VIS     | 0.518| 0.91  | 0.451| 0.93  |
|               |        | NIR     | 0.859| 0.81  | 0.943| 0.67  |
|               |        | Whole   | 0.504| 0.91  | 0.421| 0.94  |
|               | SVM    | VIS     | 0.149| 0.94  | 0.674| 0.76  |
|               |        | NIR     | 1.523| 0.78  | 0.794| 0.72  |
|               |        | Whole   | 0.112| 0.94  | 0.532| 0.78  |
|               | BPNN   | VIS     | 0.599| 0.90  | 0.436| 0.93  |
|               |        | NIR     | 0.677| 0.87  | 0.713| 0.87  |
|               |        | Whole   | 0.424| 0.93  | 0.375| 0.94  |
| TSS (°Brix)   | PLS    | VIS     | 0.776| 0.64  | 0.638| 0.73  |
|               |        | NIR     | 0.783| 0.55  | 0.795| 0.67  |
|               |        | Whole   | 0.713| 0.81  | 0.575| 0.76  |
|               | SVM    | VIS     | 0.756| 0.67  | 0.784| 0.60  |
|               |        | NIR     | 2.780| 0.48  | 0.855| 0.42  |
|               |        | Whole   | 0.361| 0.92  | 0.775| 0.62  |
|               | BPNN   | VIS     | 0.721| 0.59  | 0.656| 0.78  |
|               |        | NIR     | 0.753| 0.58  | 0.705| 0.74  |
|               |        | Whole   | 0.506| 0.76  | 0.573| 0.83  |

doi:10.1371/journal.pone.0087818.t002
respectively. In the present study, the chlorophyll absorption band at 660 nm was almost absent in ripe and overripe fruit due to the chlorophyll degradation in this fruit. Meanwhile, the relative reflectance at anthocyanin absorption band (at 525 nm) was much lower in ripe and overripe fruit than those in unripe fruit, indicating that the anthocyanin content in the ripe and overripe fruit are much higher. The results were similar to those reported by ElMasry et al. [11], who showed that the anthocyanins in the ripe and overripe fruit were higher than unripe fruit. Previous research identified that the main contributors to total soluble solids content were sugars and the sugar content accounted for 57% to 82% of total soluble solids content [5]. The relative reflectance at sugars absorption band (at 850 nm) was much lower in overripe fruit than those in unripe and ripe fruit, which may be attribute to the higher total soluble solids content in overripe fruit ($8.63^\circ$Bx) than those in unripe and ripe fruit ($7.03$ and $7.79^\circ$Bx, respectively).

**Quality Attributes Prediction**

Table 1 shows values for range, mean and standard deviation for firmness and TSS predicted using the calibration and validation sets ($N_{\text{Calibration}} = 162$ samples; $N_{\text{Validation}} = 48$ samples). Structured selection using only spectral information treatment algorithms proved adequate, since the calibration and validation sets displayed similar values for mean, range and standard deviation for all the parameters studied. The prediction performance of PLS, SVM and BPNN models for predicting firmness and TSS content of strawberry fruit are shown in Fig. 3 and Table 2. The performance of these models was evaluated by correlation coefficient ($r$), SEC and SEP. The number of latent factors for PLS model of firmness and TSS was determined as five through comparison of the value of predicted residual error sum of squares (PRESS). Regarding SVM model, optimization of the meta-parameters $C$ (regularization parameter) and $G$ (RBF kernel parameter) is the key step in SVM as their combined values.
determine the boundary complexity and the prediction performance. In order to obtain good prediction performance, some parameters in SVM have to be chosen carefully. The best $C$ and $G$ were found to be 11.31 and 0.06 for firmness prediction, and 2 and 0.06 for TSS content prediction, respectively. For BPNN model, the optimal parameters in modeling process were set as follows after the adjustments of parameters. The number of hidden nodes, the goal error and iteration times were set as 20, $1 \times 10^{-8}$ and 1,000, respectively.

**Firmness Prediction**

Compared with PLS and SVM models, BPNN model had the best prediction performance in firmness predicting based on the whole spectra with correlation coefficient ($r$) of 0.93 and 0.94 for calibration and prediction sets, respectively. The SEP and bias in prediction set were 0.375 and 0.035, respectively (Table 2). Although the correlation coefficient in PLS model was similar to that in BPNN model, the SEC and SEP were higher than those in BPNN model indicating that the BPNN model can achieve slightly better prediction accuracy than the PLS model. The results in Table 2 also showed that the prediction models were mostly based on the VIS parts of the spectra and if the NIR parts of the spectra were included the models were slightly improved. Similar findings are reported by Nagata et al. [1], who observed SEP of 0.364 and correlation coefficient ($r$) of 0.784 for the firmness prediction in technically ripe strawberry using hyperspectral imaging in the visible range. Similarly, Tallada et al. [10] conducted a NIR hyperspectral imaging investigation for firmness estimation in strawberry fruit and found that the three-wavelength model had correlation coefficient ($r$) of 0.786 and SEP of 0.350 MPa in 50% to full-ripe group. Furthermore, notice that there was a markedly high variability of firmness values for unripe strawberry fruit and less with the ripe and overripe fruit. As the strawberry fruit mature, aside from increasingly becoming soft, the firmness approaches to a relatively uniform common value.

**Total Soluble Solids Content Prediction**

For TSS content prediction, the best prediction performance was also obtained using BPNN model with the correlation coefficient ($r$) of 0.76 and 0.83 for calibration and prediction sets, respectively. The SEP and bias in prediction set were 0.573 and 0.056, respectively (Table 2). Similar to firmness prediction, the VIS parts of the spectra were more important than NIR parts of the spectra and the best models for TSS prediction were attained using the combined VIS and NIR spectra. Our results are consistent with the findings of ElMasry et al. [11], who found correlation coefficient ($r$) of 0.80, SEC of 0.233 and SEP of 0.184 for the prediction of TSS in strawberry fruit using hyperspectral imaging. However, Nagata et al. [1] showed that the TSS calibration models require individual maturity level analysis for more reliable predictions in strawberry using hyperspectral imaging. Therefore, in the present study, an improvement was observed for firmness and TSS prediction in strawberry fruit with the use of multispectral imaging technique and BPNN model compared with previous reports [1,10,11]. The improvement was observed for TSS prediction is probably attributed to the analysis approach and the large number of training samples for model development.

**Classification of Fruit Ripeness Stage**

Although PCA itself cannot be used as a classification tool, this behavior may indicate the data trend in visualizing dimension spaces. For visualizing the data trends and the discriminating efficiency of the multispectral imaging preprocess, a scatter plot of samples using the first three principal components (PCs) issued from PCA of the data matrix was obtained which are showed in Fig. 4. As can be seen, there is a neat separation of the three ripeness stages of strawberry fruit in the three-dimensional PCA space with the whole wavelengths data. In addition, Fig. 4 also shows the separation was clearer when using the VIS parts of the spectra than that of using the NIR parts of the spectra and if the NIR parts of the spectra were included the separation was slightly improved.

For PCA-BPNN model, the number of hidden nodes, the goal error and iteration times were set as 20, $1 \times 10^{-8}$ and 1,000, respectively. Table 3 shows the classification results of three ripeness stages of strawberry fruit in the prediction set using SVM and PCA-BPNN models, respectively. The results showed that the classification accuracy of BPNN model was achieved 93.33%.

For SVM model, the best $C$ and $G$ were found to be 0.25 and 2, respectively. The results showed that high classification accuracy of 100% was achieved using SVM model, which was higher than that of using PCA-BPNN model (Table 3). The classification accuracy was much higher than that of ElMasry’s study (89.61%) [11]. This increased accuracy is very important for classification of fruit ripeness stage in practical applications. Furthermore, compared to hyperspectral imaging system [11], the multispectral imaging system can shorten the image acquisition and processing time, enabling real-time automated quality monitoring systems.

**Conclusion**

In this paper a multispectral imaging system and different analysis approaches were investigated to examine the possibility of using multispectral imaging to assess the quality attributes and ripeness stage in strawberry fruit. Compared with PLS and SVM models, BPNN model for the firmness ($r=0.94$, SEP = 0.375 and bias = 0.035) and TSS content ($r=0.83$, SEP = 0.573 and bias = 0.056) demonstrated good prediction performance. High classification accuracy of 100% for correctly identifying ripeness stage of strawberry fruit was achieved using SVM model, which was higher than that of using PCA-BPNN model. Moreover, all these models were mostly based on the VIS parts of the spectra and if the NIR parts of the spectra were included the models were slightly improved. In conclusion, the present study has shown that multispectral imaging is a promising nondestructive method for rapid analysis of the quality attributes and ripeness stage of strawberry fruit.

**Acknowledgments**

We thank H Zhang and G Zhao for thoughtful comments on the project.

**Author Contributions**

Conceived and designed the experiments: LZ CL. Performed the experiments: CL FM. Analyzed the data: WL. Contributed reagents/materials/analysis tools: JY XL. Wrote the paper: CL LZ. Proofreading and consulting expertise: WC JY.

**References**

1. Nagata M, Tallada JG, Kobayashi T, Cui Y, Gejima Y (2004) Predicting maturity quality parameters of strawberries using hyperspectral imaging. ASAE/CSAE annual international meeting, Ottawa, Ontario, Canada, Paper No.043033.

2. Sturm K, Koron D, Stampar F (2003) The composition of fruit of different strawberry varieties depending on maturity stage. Food Chemistry 83: 417–422.
3. Nicolai BM, Beullens K, Bobelyn K, Peirs A, Saey W, et al. (2007) Nondestructive measurement of fruit and vegetable quality by means of NIR spectroscopy: A review. Postharvest Biology and Technology 46: 99–118.

4. Sánchez MT, De la Haba MJ, Bentíez-López M, Fernández-Navales J, Garrido-Varo A, et al. (2012) Non-destructive characterization and quality control of intact strawberries based on NIR spectral data. Journal of Food Engineering 110: 102–108.

5. Ito H (2002) Potential of near infrared spectroscopy for nondestructive estimation of Brix in strawberries. Acta Horticulturae 587: 751–754.

6. Shao Y, He Y (2008) Nondestructive measurement of acidity of strawberry using Vis/NIR spectroscopy. International Journal of Food Properties 11: 102–111.

7. Nishizawa T, Mori Y, Fukushima S, Natouga M, Maruyama Y (2009) Non-destructive analysis of soluble sugar components in strawberry fruits using near-infrared spectroscopy. Nippon Shokuhin Kagaku Kaishi 56: 229–235.

8. Gowen AA, O’Donnell CP, Cullen PJ, Downey G, Frias JM (2007) Hyperspectral imaging – an emerging process analytical tool for food quality and safety control. Trends in Food Science & Technology 18: 590–596.

9. Feng YZ, Sun DW (2012) Application of hyperspectral imaging in food safety inspection and control: a review. Critical Reviews in Food Science and Nutrition 52: 1039–1058.

10. Tallada JG, Nagata M, Kobayashi T (2006) Non-destructive estimation of firmness of strawberries (Fragaria x ananassa Duch.) using NIR hyperspectral imaging. Environment Control in Biology 44: 245–255.

11. ElMasry G, Wang N, ElSayed A, Ngadi M (2007) Hyperspectral imaging for nondestructive determination of some quality attributes for strawberry. Journal of Food Engineering 81: 98–107.

12. Kim MS, Lefcourt AM, Chao K, Chen YR, Kim I, et al. (2002) Multispectral detection of fecal contamination on apples based on hyperspectral imagery: Part I. Application of visible and near-infrared reflectance imaging. Transactions of the ASAE 45: 2027–2037.

13. Lu R (2004) Multispectral imaging for predicting firmness and soluble solids content of apple fruit. Postharvest Biology and Technology 31: 147–157.

14. Peng Y, Lu R (2006) Improving apple fruit firmness predictions by effective correction of multispectral scattering images. Postharvest Biology and Technology 41: 266–274.

15. Xing J, Jancso G, De Baerdemaeker J (2006) Stem-end/calyx identification on apples using contour analysis in multispectral images. Biosystems Engineering 96: 231–237.

16. Peng Y, Lu R (2007) Prediction of apple fruit firmness and soluble solids content using characteristics of multispectral scattering images. Journal of Food Engineering 82: 142–152.

17. Lloë L, Barreiro P, Ruiz-Altisent M, Herrero A (2009) Multispectral images of peach related to firmness and maturity at harvest. Journal of Food Engineering 93: 229–235.

18. Lunadei L, Diezma B, Lleo L, Ruiz-Garcia L, Cantalapiedra S, et al. (2012) Monitoring of fresh-cut spinach leaves through a multispectral vision system. Postharvest Biology and Technology 63: 74–84.

19. Lunadei L, Galleguillos P, Diezma B, Lleo L, Ruiz-Garcia L (2011) A multispectral vision system to evaluate enzymatic browning in fresh-cut apple slices. Postharvest Biology and Technology 60: 225–234.

20. Løkke MM, Sætre HD, Skov T, Edelebros M (2013) Color and textural quality of packaged wild rocket measured by multispectral imaging. Postharvest Biology and Technology 75: 86–95.

21. Gomez DD, Clemmensen LH, Erbsell BK, Carstensen JM (2007) Precise acquisition and unsupervised segmentation of multi-spectral images. Computer Vision and Image Understanding 106: 183–193.

22. Dissing BS, Nielsen ME, Erbsell BK, Frosh S (2011) Multispectral imaging for determination of astaxanthin concentration in salmonids. PLoS ONE 6: e19032.

23. Dissing BS, Papadopoulos OS, Tasson C, Erbsell BK, Carstensen JM, et al. (2012) Using Multispectral Imaging for Spoilage Detection of Pork Meat. Food and Bioprocess Technology, 10.1007/s11947-012-0886-6.

24. Cruzastillo JG, Ganeshanandam S, Mackay BR, Lawes GS, Lawoko CRO, et al. (1994) Applications of canonical discriminant-analysis in horticultural research. HortScience 29: 1115–1119.

25. Otsu N (1979) A threshold selection method from gray-level histograms. IEEE Transactions on Systems, Man, and Cybernetics 9: 62–66.

26. Lorente D, Aleixos N, Gómez-Sancho J, Cubero S, García-Navarrete OL, et al. (2012) Recent advances and applications of hyperspectral imaging for fruit and vegetable quality assessment. Food and Bioprocess Technology 5: 1121–1142.

27. Cortes C, Vapnik V (1995) Support vector machine. Machine Learning 20: 273–297.

28. Burges C (1998) A tutorial on support vector machines for pattern recognition. Data Mining and Knowledge Discovery 2: 121–167.

29. Sun X, Chen RJ, Maddock-Cartin KR, Anderson VL, Lepper AN, et al. (2012) Predicting beef tenderness using color and multispectral image texture features. Meat Science 92: 386–393.

30. Devos O, Ruckebusch C, Durand A, Duponchel L, Huvenne JP (2009) Support vector machines (SVM) in near infrared (NIR) spectroscopy: Focus on parameters optimization and model interpretation. Chromometrics and Intelligent Laboratory Systems 96: 27–33.

31. Lawrence S, Giles GI, Tsoi AC (1997) Lessons in neural network training: Overfitting may be harder than expected. In Proceedings of the fourteenth national conference on artificial intelligence. AAAI-97 (pp. 540–545). Mento Park, CA: AAAI Press.

32. Dubey BP, Bhagwat SG, Shouche SP, Sainis JK (2006) Potential of artificial neural networks in varietal identification using morphometry of wheat grains. Biosystems Engineering 95: 61–67.

33. Abbott JA, Lu R, Upchurch BL, Stosrhine RL (1997) Technologies for nondestructive quality evaluation of fruits and vegetables. In Horticultural reviews – Technologies for nondestructive quality evaluation of fruits and vegetables (Vol. 20, 1–120). John Wiley & Sons, Inc. ISBN 0-471-18906-5.

34. Serram NP, Lee R, Scheuller HS, Heber D (2006) Identification of phenolic compounds in strawberries by liquid chromatography electrospray ionization mass spectroscopy. Food Chemistry 97: 1–11.