Available online at www.sciencedirect.com
SCIENCE DIRECT®
Postharvest Biology and Technology 30 (2003) 249–258
Postharvest Biology and Technology
www.elsevier.com/locate/postharvbio

Effects of bruise type on discrimination of bruised and non-bruised 'Golden Delicious' apples by VIS/NIR spectroscopy

Juan Xing [a,*], Sandra Landahl [a], Jeroen Lammertyn [b], Els Vrindts [a], Josse De Baerdemaeker [a]

[a] *Laboratory of Agricultural Machinery and Processing, Catholic University of Leuven, Kasteelpark Arenberg 30, B-3001 Leuven, Belgium*

[b] *Laboratory of Postharvest Technology, Catholic University of Leuven, Willem de Croylaan 42, B-3001 Leuven, Belgium*

Received 3 September 2002; accepted 11 June 2003

Abstract

Visual (VIS) and near-infrared (NIR) spectroscopy was applied to discriminate bruises and non-bruised healthy spots on 'Golden Delicious' apples. Two types of bruises were examined; those created by controlled impact and those by compression. Reflectance spectra of apples were measured in the range from 400 to 1700 nm. The data were analysed with canonical discriminant analysis (CDA). The squared canonical correlation (CR^2) was 0.74 for discriminating impact bruises and non-bruised tissue, and a CR^2 of 0.68 was obtained for distinguishing compression bruises and sound tissue. Based on the linear discriminant functions, built with canonical components, the misclassification errors for non-bruised apples were mainly due to the presence of compression bruises. The classification accuracy was improved by taking the type of bruises into account in the model.

Keywords: Canonical discriminant analysis; Impact; Compression; Bruise; Apple; VIS/NIR spectroscopy

1. Introduction

Bruising is one of the most important and prevalent surface defects in apples (*Malus domestica* Borkh.). Apple bruising is a frequent cause of value loss in marketed and processed apples (Shewfelt and Prussia, 1993). The agitation and bouncing inherent in the transport of apples can cause bruising. Since the customer's buying behaviour is mostly determined by the visual appearance of the fruit, it is useful to be able to discriminate and sort the bruised apples from the healthy ones before sale.

There are two main types of bruises often encountered in apples: impact bruises and compression bruises. Impact bruises are formed when apples impact hard surfaces or other apples. Brown et al. (1993) state this type of bruise is most abundant in practice. The compression bruises are caused by a static or quasi-static force, in contrast with a dynamic force that forms impact

* Corresponding author. Tel.: +32-16-32-14-70; fax: +32-16-32-85-90.
E-mail address: juan.xing@agr.kuleuven.ac.be (J. Xing).

0925-5214/03/$ - see front matter © 2003 Elsevier B.V. All rights reserved.
doi:10.1016/S0925-5214(03)00117-0

bruises. Impact bruises are normally more severe than compression bruises and affect the appearance of the fruit. An impact bruise develops from skin to a shear region in the parenchyma tissue, while a compression bruise has a thin layer of damaged tissue under the skin. Because of this bruise geometry, compression bruises are very difficult to detect after 1 day (Upchurch et al., 1994). Furthermore, there is more free juice in the impact bruises (Holt and Schoorl, 1984).

During the last decade spectrophotometric surface defect detection has offered an alternative or complementary method to machine vision in food research (Zwiggelaar et al., 1996; Kim et al., 2001). Geoola et al. (1994) proposed diffuse reflectance spectroscopy in the wavelength range from 750 to 800 nm to classify bruised and non-bruised 'Golden Delicious' apples. Aneshansley et al. (1997) examined bruises that were 24 h old with an imaging system, using 58 wavebands in the 460–1030 nm region. They observed that all wavebands above 850 nm performed well for bruise detection on 'Golden Delicious' apples. Spectrophotometry in the visual/near-infrared (VIS/NIR) range is a suitable technique to detect disorders in fruit, because it is a non-destructive and fast method, so that large numbers of fruit can be evaluated without losses caused by the test.

The general objective of the research was to study the spectral detection techniques, to improve the bruise detection. Until now, the influence of different types of bruises has not been studied in depth. The type of bruise determines the degree of damage and the visual appearance, and may also influence the accuracy of classification. Therefore, the purpose of this paper was to evaluate the effect of the bruise type on the discrimination of bruised and non-bruised areas on 'Golden Delicious' apples using spectrophotometry in the VIS/NIR range.

2. Materials and methods

2.1. Fruit material

From a local supermarket, 168 'Golden Delicious' apples were purchased in June 2000 (108 apples) and April 2001 (60 apples). The origin was France. In addition, 200 'Golden Delicious' apples were harvested from the Centre for Fruit Cultivation in Rillaar (Belgium) in September 2001.

2.2. Compression bruising and impact bruising

As described by other researchers (Upchurch et al., 1994; Zwiggelaar et al., 1996; Blahovec et al., 1997) compression bruises were created with a Universal Testing Machine (UTS-5T™, UTS Test system GmbH & Co. KG, Ulm). From the 168 purchased apples, 78 were compressed between two flat steel plates. The moving plate went downwards with a speed of 10 mm min^{-1} to a displacement of approximately 5 mm to reach the bioyield point in the force–deformation curve. The upper steel plate exerted compression force at the top of an apple and the lower plate bruised the bottom of the apple at the same time. Each surface was dusted with flour to mark the exact compression area on the apple.

A pendulum set up described by Van Zeebroeck et al. (in press) was used to induce impact bruises. The impact energy was about 0.05 J. Multiple impacts due to rebounds were prevented. Two impact bruises were induced on opposite sides of each apple (90 of the 168 purchased apples and 200 apples from the Centre for Fruit Cultivation).

2.3. Optical data acquisition

Reflectance spectral measurements were carried out with Zeiss MCS 501 and Zeiss MCS 511 instruments (Carl Zeiss Jena GmbH, Jena, Germany) in the wavelength range of 400–1000 nm and 900–1700 nm, respectively. The intersection was selected at 980 nm.

A schematic of the spectral reflectance measurement system is shown in Fig. 1a. The light source was a 20 W halogen lamp. A fibre holder (shown in Fig. 1b) was used to fix the fibres that carried the light to the sample and the reflected light from the sample to the detectors. The angle between the light source and detector fibre head was 45°. The fibre holder and sample were in contact while measuring. The size of the opening of the fibre holder was chosen so that only a marked spot, not

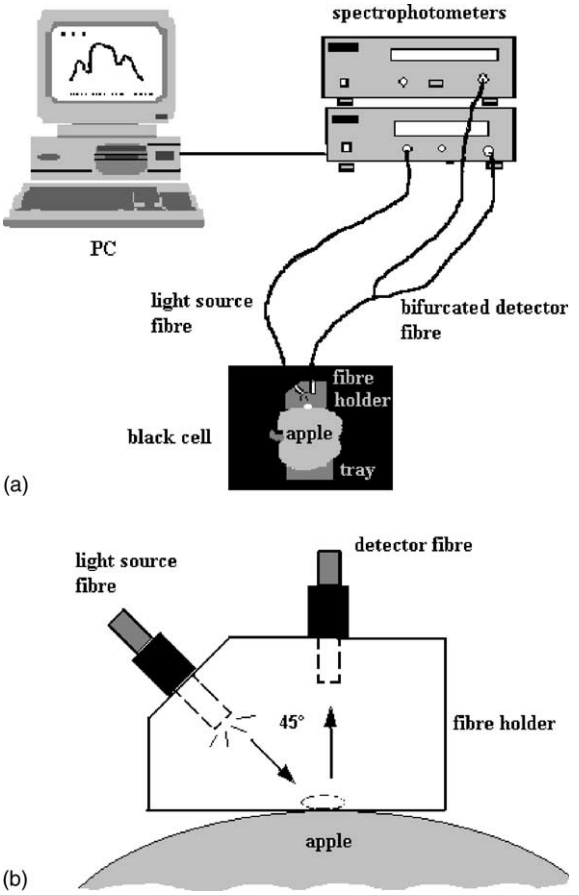

Fig. 1. Diagram of the spectral reflectance measurement system (a) and enlarged drawing of the fibre holder (b).

the surrounding tissue, was measured. A dark correction was performed by turning off the light source and covering the head of the fibre with an opaque cap. The calibrated reflectance was calculated as the percentage of the reflection of a standard reference material (spectralon, of 99% reflectance, Labsphere Inc.). The reference calibration and dark correction were repeated every half an hour to remove the temperature influence on the equipment.

2.4. Sample preparation

For the apples purchased from the supermarket, due to time restriction, the spectral measurements were finished within 3 days after bruise induction. To maintain the bruise level consistency during the testing period, the apples were stored in a cool room at 2 °C and 85% relative humidity while not being measured. Three hours before the measurements the apples were kept at room temperature to equilibrate.

Four spots (two controlled bruised and two non-bruised) were marked and measured for each apple. The non-bruised areas were determined at positions where no bruises were detected by manual inspection. All together 670 spectra were registered from these 168 purchased apples, from the four controlled spots on each apple (two observations were removed as outliers).

Similarly, 800 spectra were collected from the 200 apples picked from the Centre for Fruit Cultivation in Rillaar (Belgium). Since the optical measurements were performed locally on the apples, each measurement was used as an independent observation in the analysis.

2.5. Pre-processing methods

Before discriminant analysis, the spectra were pre-processed to decrease the influence of noise. The pre-processing procedures were performed with a statistical program for multivariate calibration called 'The Unscrambler® 6.11' (CAMO ASA, Trondheim, Norway). After smoothing and reducing the number of variables by the averaging method, a 10 nm spectral resolution was obtained. Afterwards, a first derivative was calculated with the technique developed by Norris (1983). Three neighbouring points were selected for this calculation.

2.6. Canonical discriminant analysis (CDA)

The bruised and intact surfaces are expected to be different in VIS/NIR reflectance spectra. To study this hypothesis, a CDA was performed.

In SAS/STAT® User's Guide (SAS Institute Inc., 1990), CDA is described as a dimensional-reduction technique related to principal component analysis and canonical correlation. Given a class variable and several quantitative variables, CDA derives canonical components (linear combination of the quantitative variables) that sum-

marise between-class variation in much the same way that principal components summarise total variation. The first canonical component has the maximal multiple correlations with the class variable. The second canonical component is uncorrelated with the first one and corresponds to the second highest possible multiple correlations with the class variable, etc.

The number of canonical components, which have statistically significant meaning, is defined as the minimum of k and $(c - 1)$, where k is the number of original variables and c is the number of levels of the class variable.

In this case, two class variables were defined to group observations in the discriminant analyses, 'property' and 'type'. Class variable 'property' has two levels indicating 'Bruise' and 'Non-bruise'. The 'Bruise' group includes compression and impact bruises. Class variable 'type' has three levels indicating 'Compression bruise', 'Impact bruise' and 'Non-bruise'. The original variables in this study are the wavelengths ranging from 409 to 1639 nm pre-processed as described above. As a consequence, only one or two canonical component(s) would be retained in the discriminant analysis.

The canonical function is defined as:

$$\mathrm{CANm}_i = \sum_{j=1}^{k} \beta_{mj} X_{ij}$$

where CANm_i refers to the mth canonical components for the ith measurement. X_{ij} is the first derivative of reflectance value for the ith measurement at the jth variable (wavelength). β_{mj} is the coefficient of the mth canonical component for the jth original variable.

The coefficients or the weights for each original variable were exported and afterwards they were applied to a new measurement to perform the same transformation. In the canonical space, the new observation was classified depending on Mahalanobis distance to the group means.

The squared canonical correlation (CR^2) and Wilk's lambda (λ) were used to assess the discriminant function(s). The value of CR^2 gives the amount of variation among the groups that is explained by the discriminating variable(s). It can be considered as the equivalent of R^2 (coefficient of determination) in regression analysis for canonical analysis (Sharma, 1996). The Wilk's λ value, ranging from 0 to 1 gives an idea about the structure of the data. The closer the value is to 1, the more overlap there is among different groups.

CDA was carried out with SAS® V8.2 (SAS Institute Inc.).

3. Results and discussion

3.1. Visual inspection

A small number of apples were cut into two parts through the bruised spots after optical measurements. Then the maximum depth of the bruise on the vertical section was measured. The average depth was about 5 mm for the impact bruises and 4 mm for compression bruises. Generally, for the compression bruises the flesh discoloration (brown) was discontinuous, whereas the impact bruise coloration was more homogeneous. Most of the impact bruised areas turned brown within 30 min after impacting. However, for the compression bruises the softening was more significant than browning.

Fig. 2 shows the average of the Norris' first derivatives of the spectra for each group. From this plot, it can be observed that there is less difference between healthy and compression bruised spots than between the healthy and impact bruises.

3.2. Canonical discriminant analysis

To compare the discriminating power of the different wavelength ranges, CDA was performed in VIS (409–700 nm), in NIR (700–1639 nm) and in the full spectral range (409–1639 nm) after preprocessing as described above. The CR^2 and λ values (data not shown) show that better discriminant results can be obtained in the full range than only in NIR or VIS. Therefore, the full VIS/NIR range was used in further analysis.

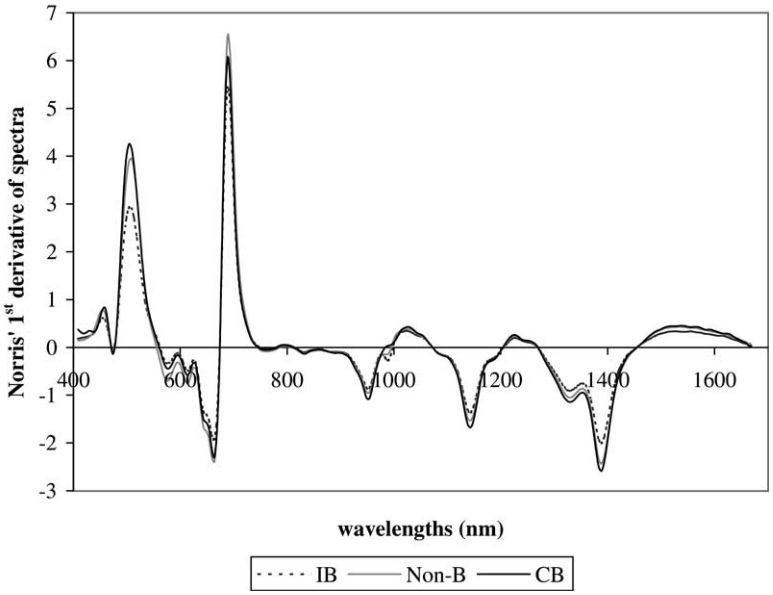

Fig. 2. Average plot of the first derivative of spectra for each group. IB: the average of 180 observations from 'Impact bruise' group; Non-B: the average of 336 observations from 'Non-bruise' group; CB: the average of 154 observations from 'Compression bruise' group.

3.2.1. Comparison of CDA results by taking bruise type into account or not

The scatter plot of the 670 observations, which is obtained from the 168 purchased apples, represented in two canonical dimensions is shown in Fig. 3a. The class variable 'type' is used to group the observations. Three clusters are clearly defined in the plot, corresponding to the groups 'Compression bruise', 'Impact bruise' and 'Non-bruise'.

Considering the centroid positions of each group (marked with black circle), the first canonical component (Can1) was good for discriminating the impact bruised spots from the compression bruised and non-bruised spots. In addition the second canonical component (Can2) was suited to separate the compression bruised and non-bruised spots.

The clear separation of the impact bruises and compression bruise could be a result of different factors. Firstly, it could be assumed that the apple groups used for bruising have different characteristics stemming from different production or postharvest treatment, and therefore are discriminated by their optical properties. However, in the group of 'Non-bruise', which includes measurements of all the apples, no clusters were detected, so the apple groups should have no significant influence on bruise type discrimination. Secondly, the clear discrimination between the bruise types might be due to the different ways of bruising. The bruising was done in controlled ways as described above. However, since the techniques are very different (static/dynamic) the resulting damage level (e.g. force, energy) of the tissue is not exactly the same.

A hypothesis might also be formulated based on the state of the plasma membrane and the viscoelastic property of apples. The plasma membrane is partially permeable in living cells, allowing water to pass through relatively freely, but restricting the movement of sugars and many ions and salts. Bruising can only take place when the membrane is ruptured. After that, oxygen from the air is available, allowing enzymatic reactions and the browning of tissue. Holt and Schoorl (1984) have shown that in a slow compression bruise test, there are as many bands of burst cells as cell-bursting episodes recorded on the force–deformation curve. Between the bands, the tissue appeared largely undamaged. In this experiment this might

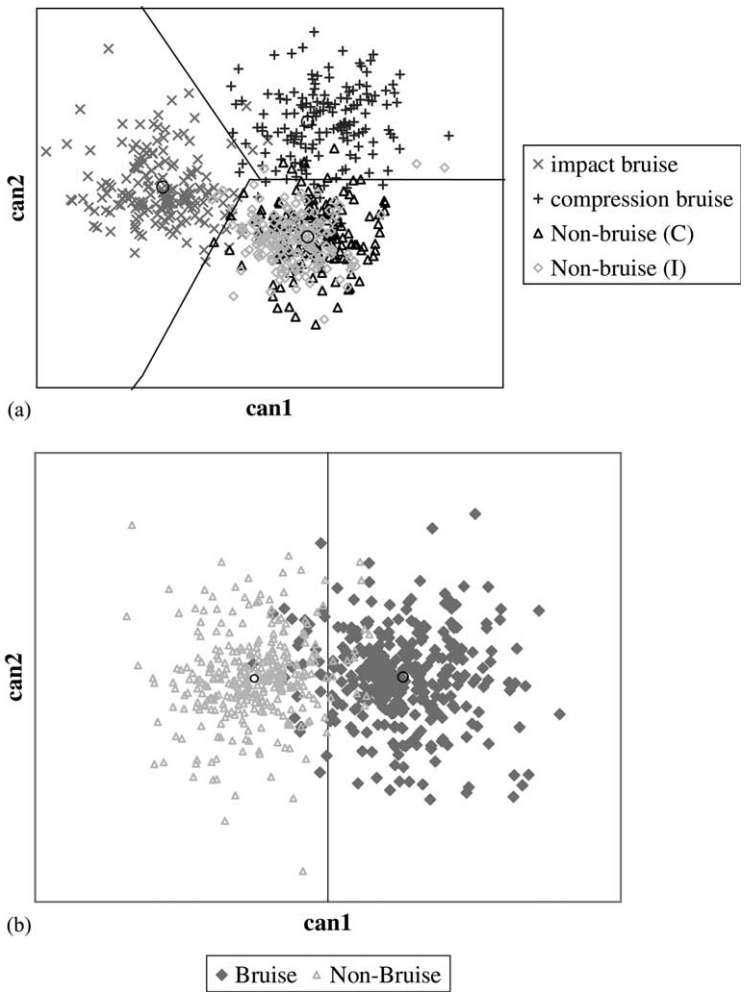

Fig. 3. Scatter plot of Norris' first derivative spectral data in the canonical space. (a) Grouping with class variable 'type'; 'Non-bruise' (I): healthy observations on impacted apples; 'Non-bruise' (C): healthy observations on compressed apples. (b) Grouping with class variable 'property'. The centroids of each group are marked with a black circle.

be represented by the above described discontinuous coloration of the bruise. In the impact test, a few cell-bursting bands were distinguished, and generally the whole region was damaged. During compression less rupture of the plasma membrane will occur than during impacting. As a consequence, less brown discoloration reactions take place in the plate-contact area of the apple within some time after compression. In Mohsenin (1986, pp. 553–560), it is also indicated that many commodities, including apples, show different kinds of damage under quasi-static loading than under impact loading, and the differences have been reasonably interpreted based on viscoelasticity.

Fig. 3a shows that misclassification mainly occurs on the edge along the classification lines with the most overlap between compression bruise and non-bruise. However, as this can be noticed in Fig. 3b, which is the scatter plot of canonical scores for the spectra by using the class variable 'property' to group the observations, the misclassification can occur at a place far from the classification line. Without considering the types

Table 1
Classification results (in percentages) obtained with and without considering bruise type based on the canonical component(s)

Actual class group	Number of observations	Classified as			
		'Bruise'	'Non-bruise'	'Impact bruise'	'Compression bruise'
(a) Without considering the bruise type[a]					
Non-bruise	336	2.98	97.02		
Bruise	334	88.02	11.98		
(b) Considering the bruise type[b]					
Non-bruise	336		97.02	0.89	2.09
Impact bruise	180		6.11	92.22	1.67
Compression bruise	154		8.44	1.30	90.26
(c) For the dataset only including impact bruised and non-bruised observations[c]					
Non-bruise	336	1.19	98.81		
Impact bruise	180	95.00	5.00		

[a] Using high prior probability for non-bruised group, and using one canonical component.
[b] Using high prior probability for non-bruised group, and using two canonical components.
[c] Using equal prior probability for both groups, and using one canonical component.

of bruises, there is more overlap between the healthy and bruised groups. The total misclassification would be higher. The classification lines drawn in the figures are defined with equal prior probability, and can be shifted to meet some special requirements. For example, if a high classification accuracy for the 'Non-bruise' group is wanted, the classification line can be shifted more to the bruises group by using a high prior probability for the healthy observations during calibration.

To get numerical information about the CDA, a linear classification procedure was performed based on one or two canonical component(s) depending on the class variable used for grouping observations. The classification results are shown in Table 1. Cross-validation was used. By this method, CDA classifies each observation in the dataset using a discriminant function computed from the other observations in the dataset, excluding the observation being classified (SAS Institute Inc., 1990).

By using a high prior probability for the 'Non-bruise' group, the correct classification for the healthy group reaches a plateau of 97.02% for both the 'type' and 'property' class variables to group observations. Forty spectra (11.98% of 334 spectra) of bruised areas were classified as 'Non-bruise' when the type of bruises is not considered (see Table 1a). Only 24 bruises in total were misclassified from either 'Impact bruise' (11) or 'Compression bruise' (13) to 'Non-bruise' when the type was taken into account (shown as percentages in Table 1b). The total number of misclassified observations decreases when the type of bruise is taken into account while building a model.

Data in Table 1b also suggest that more misclassification between the 'Compression bruise' and the 'Non-bruise' groups occurred than be-

Table 2
CR^2 and λ of the canonical discriminant analysis in full range

	IB, CB and Non-B	IB–Non-B	CB–Non-B	Bruised–Non-bruised
Squared canonical correlation (CR^2)	Can1: 0.741, Can2: 0.681	Can1: 0.805	Can1: 0.823	Can1: 0.695
Wilk's lambda (λ)	Can1: 0.083, Can2: 0.319	Can1: 0.195	Can1: 0.177	Can1: 0.304

IB, CB and Non-B dataset includes all observations and using 'type' as the class variable; IB–Non-B dataset includes the observations from 'Impact bruise' and 'Non-bruise' groups; CB–Non-B dataset includes the observations from 'Compression bruise' and 'Non-bruise' group; Bruised–Non-bruised includes all observations but using 'property' as the class variable.

tween groups of 'Impact bruises' and 'Non-bruise'. If compression bruised spots are excluded from the analysis, the correct classification of non-bruised spectra in canonical dimension is improved to 98.8% (Table 1c).

3.2.2. Assessment criteria for CDA

The values of CR^2 and λ from different models are shown in Table 2. While using 'type' as the class variable to distinguish three groups, the CR^2 was 0.741 for Can1 and 0.681 for Can2. It indicates that the discrimination is more powerful along Can1 than Can2 (see description above). Visual inspection of Fig. 3a suggests that it is easier to separate impact bruises from the non-bruised group than to distinguish compression bruises from the healthy tissue. Similarly, the CR^2 were obtained between each 'Bruise' and the 'Non-bruise' groups. As listed in Table 2, those CR^2 values are apparently greater than those distinguishing three groups from each other at a time, which indicates that the discrimination is more able to separate two groups than three groups. The model using the class variable 'property' for group observations (without considering the 'Bruise' type) gives a CR^2 value of 0.695, which appears to be a low value compared to the other models.

The λ values for the data grouping by variable 'type', are 0.083 for Can1 and 0.319 for Can2 and indicates that there is much more overlapping on the second canonical axis and confirms the visual inspection from Fig. 3a.

3.3. External validation

CDA results, based on cross-validation, show that the bruise type has influence on bruise detection. This method however, is not a truly unbiased estimation of the probabilities of correct classification. For this reason, an external validation was performed by collecting 800 more spectra from the apples picked in Rillaar into analysis. On those apples no compression bruises were induced, since most bruises in apples are reported to be caused by impact. They were mixed with the 670 spectra obtained from the purchased apples and then split into a calibration and a validation dataset randomly. The 350 samples assigned to the validation dataset included 150 non-bruised spots, 49 compression bruised spots and 151 impact bruised spots. The remaining spectra composed the calibration dataset.

Table 3
Classification results (in percentages) from different models for the validation dataset

Actual class group	Number of observations	Classified as	
		'Bruise'	'Non-bruise'
(a) One-step model and without taking the bruise type into account during calibration[a]			
Non-bruise	150	4.67	95.33
Impact bruise	151	91.39	8.61
Compression bruise	49	75.51	24.49
(b) One-step model and with taking the bruise type into account during calibration[b]			
Non-bruise	150	8	92
Impact bruise	151	94.04	5.96
Compression bruise	49	93.88	6.12
(c) Two-step model[c]			
Non-bruise	150	4.67	95.33
Impact bruise	151	93.38	6.62
Compression bruise	49	95.92	4.08

[a] Total bruise classification accuracy: 87.5%; total misclassification rate: 9.14%.
[b] Total bruise classification accuracy: 94%; total misclassification rate: 6.86%.
[c] Total bruise classification accuracy: 94%; total misclassification rate: 5.43%.

Based on the same calibration and validation dataset, three models were built and compared with respect to the classification result. Model A and Model B were similar with regard to the cross-validation analysis. They finish the classification in one step. However, Model A did not consider the bruise type and Model B did, while calibrating models. The classification results are shown in Table 3a and b. The details of impact and compression bruises are given in the table. The result that we are interested in is bruise/non-bruise identification, rather than bruise type. Therefore, a value of total bruise classification accuracy is given in Table 3. It is a percentage of the sum of the observations correctly classified as bruise from 'Impact bruise' and 'Compression bruise' groups among the total number of bruised observations.

Model C was made in two steps, because according to the CR^2 values, from the CDA results above, a better discrimination was achieved when only two groups of the observations were used for calibration instead of three. It might improve the classification result if the calibration dataset only includes two types of observations each step: one type of bruise and non-bruise per step.

The two steps are:

Step 1: Using a model calibrated with impact bruise and non-bruise data, if a new observation is classified into the 'Bruise' group in this step, this observation would be regarded as bruised. The remaining observations enter the next step for further classification.

Step 2: Using a model calibrated with compression bruise and non-bruise data, if an observation is classified into the 'Bruise' group in this step, it would be regarded as bruised. Otherwise, it is considered as healthy and classified into 'Non-bruise' group.

Again, the aim is bruise detection, rather than bruise type. Therefore, the final number of bruises is the sum of those areas recognised as bruised in these two steps. The classification results from this two-step model are shown in Table 3c. The details of each step are listed in Table 4.

It is obvious that Model A and Model B perform more poorly than the classification model based on two steps with respect to the total misclassification rate (given in Table 3a–c). The total misclassification rate is defined as the percentage of all misclassified samples, bruised and healthy, among the total validation samples. Model A has the largest error of about 10% in total samples, nearly two times that of Model C.

With Model A the correct classification for intact areas is the same (95.3%) as that from the two-step model; however, its bruise detection is worse. This is mainly due to the large error in classifying the compression bruises, of which only 75.5% are correctly classified as bruise. With Model B, the bruise detection performs as well as the two-step model (94%); however, more loss is found in the healthy group.

Table 4
Details of steps 1 and 2

Actual class group	Classified as 'Bruise'	Remained for step 2
Step 1		
Non-bruise (n[a] = 150)	3	147
Impact bruise (n = 151)	140	11
Compression bruise (n = 49)	21	28
Came from step 1	Classified as 'Bruise'	Classified as 'Non-bruise'
Step 2		
Non-bruise (n = 147)	4	143
Impact bruise (n = 11)	1	10
Compression bruise (n = 28)	26	2

[a] Number of observations.

With the two-step Model C, the classification results were 95.3% correct classification for the non-bruised and 94% for the controlled bruises. Among the correct classified controlled bruises, 93.48% of the impact bruises were classified correctly as bruise and a high 95.9% classification accuracy was achieved for the compression bruises. The higher classification accuracy for compression bruise may be explained by two factors. On the one hand, as shown in Table 2, the CR^2 value for discriminating only impact bruise and non-bruise is smaller than for distinguishing only compression bruise and non-bruise. On the other hand, the number of impact observations is much higher than that of compression bruise.

The comparison of these three models shows that taking the bruise type into account while calibrating could improve the total classification accuracy. In addition, the discriminant function built on two groups per step is more powerful than on three groups in one step.

4. Conclusions

Canonical discriminant analysis was used to discriminate between bruised and non-bruised

spots on 'Golden Delicious' apples. The Norris' first derivative of VIS/NIR reflectance spectra was used. The CDA results show that bruise type should be taken into account while building a classification model. More misclassification occurred between the groups of 'Non-bruise' and 'Compression bruise' than between the 'Impact bruise' and 'Non-bruise'.

The classification model composed of two steps can improve the classification performance. The good discrimination results are promising for detecting bruises on 'Golden Delicious' apples by using the VIS/NIR reflectance spectrophotometric method. However, in this research the reflectance spectra were measured locally rather than globally. The classification speed, in regard to the spectrum recording and data processing, is not quick enough to incorporate in grading machines. Further work is required to optimise and implement this technique. More fundamental research is also required to provide a physicochemical basis of the models.

Acknowledgements

The authors gratefully acknowledge the financial support of the Catholic University of Leuven.

References

Aneshansley, D.J., Throop, J.A., Upchurch, B.L., 1997. Reflectance spectra of surface defects on apples. In: Sensors for Nondestructive Testing: Measuring the Quality of Fresh Fruits and Vegetables. Northeast Regional Agricultural Engineering Service Publication No. 97, Ithaca, NY 14853, pp. 143–159.

Blahovec, J., Patoèka, K., Bareš, J., 1997. Low-level bruising of stored apples due to quasi-static loading up to constant compression strain. J. Text. Stud. 28, 87–99.

Brown, G.K., Schulte, N.L., Timm, E.J., Armstrong, P.R., Marshall, D.E., 1993. Reduce apple bruise damage. Tree Fruit Postharvest J. 4, 6–10.

Geoola, F., Geoola, F., Peiper, U.M., 1994. A spectrophotometric method for detecting surface bruises on "Golden Delicious" apples. J. Agric. Eng. Res. 58, 47–51.

Holt, J.E., Schoorl, D., 1984. Mechanical properties and texture of stored apples. J. Text. Stud. 15, 377–394.

Kim, M.S., Chen, Y.R., Mehl, P.M., 2001. Hyperspectral reflectance and fluorescence imaging system for food quality and safety. Trans. ASAE 44, 721–729.

Mohsenin, N.N., 1986. Physical Properties of Plant and Animal Materials. Gordon and Breach, London, pp. 553–560.

Norris, K.H., 1983. Extracting information from spectrophotometric curves: predicting chemical composition from visible and near-infrared spectra. In: Martins H., Russworm J. (Eds.), Food Research and Data Analysis, Applied Science Publishers, Barking, pp. 95–113.

SAS Institute Inc., 1990. SAS/STAT® User's Guide, Version 6, vol. 1, fourth ed. SAS Institute Inc., Cary, NC, pp. 387–399.

Sharma, S., 1996. Applied Multivariate Data Analysis. Wiley, New York.

Shewfelt, R.L., Prussia, S.E., 1993. Postharvest Handling: A Systems Approach. Academic Press, California.

Upchurch, B.L., Throop, J.A., Aneshansley, D.J., 1994. Influence of time, bruise-type, and severity on near-infrared reflectance from apple surfaces for automatic bruise detection. Trans. ASAE 37, 1571–1575.

Van Zeebroeck, M., Tijskens, E., Van Liedekerke, P., Deli, V., De Baerdemaeker, J., Ramon, H., 2003. Determination of dynamical behaviour of biological materials during impact using a pendulum device. J. Sound Vib., in press.

Zwiggelaar, R., Yang, Q.S., Garcis-Pardo, E., Bull, C.R., 1996. Use of spectral information and machine vision for bruise detection on peaches and apricots. J. Agric. Eng. Res. 63, 323–332.