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Wavelength Selection for Surface Defects Detection on Tomatoes by Means of a Hyperspectral Imaging System

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Abstract. It is a challenge to detect surface defects on tomatoes in an automatic sorting line. Since in comparison with bruises, the other surface defects, such as the blossom-end rot, sunscald, mold and cracks are not so difficult to recognize for a vision system, the efforts are described for recognizing the bruises on tomatoes in this paper. Only areas that are perceived as soft spots are considered as bruises. Due to the subtle color contrast, it is not an easy job for a conventional machine vision system to distinguish the bruised tissues from the sound ones. Therefore, an attempt was made for bruise detection on tomatoes by using a hyperspectral imaging setup in the wavelength region between 400 and 1000 nm. The chemometrics tools were used to extract the effective wavebands for surface defects detection and for identifying the stem-end. The orientation of the tomatoes in the field of view of the camera may affect the final classification accuracy. The research is a basis for automatic detection of surface defects on tomatoes using multiple spectral imaging.

Keywords. ***:*** Hyperspectral imaging; Tomato; Bruise; Geneteic Algorithm, Correlelogram; PLSDA

Introduction

Automatic fruit sorting can improve the quality of packed products, avoiding inconsistent manual evaluation and reduce dependency on available manpower. In recent years, a considerable amount of research work has been published with respect to non-destructive techniques to assess the quality of fruits and vegetables. Currently, there is a special interest in spectroscopy and machine vision applications. Machine vision is a useful tool for external features measurement, e.g., size, shape, color, and defects. Many reports can be found for detection of surface defects on apples using machine vision techniques, but not yet so many for tomatoes, especially not for the surface defects detection on tomatoes, i.e., bruises. Laykin *et al*. (1999) reported a 80% correct classification of bruised fruit (severe damaged) based on RGB image analysis. Research using thermography had only moderately satisfying results (Beverly et al, 1987).

The subtle color contrast between sound and bruised tissue is the major obstacle for employing a conventional machine vision system on a tomato sorting line, which means that there is a need to explore a wider wavelength range including both of the visible and NIR region. For this, a hyperspectral imaging setup is a good approach. The hyperspectral imaging system is built to integrate spectral and spatial (imaging) information of the samples. In the food quality assessment, the hyperspectral imaging technique has been studied for inspection of poultry carcasses (Chao *et al.*, 2001, 2002), defects detection or quality determination on apples and tomatoes (Kim *et al.*, 2002; Kavdir *et al.*, 2002; Polder et al., 2002; Xing et al., 2005a, b). This approach fits into the quest for a systematic method that relates high resolution spectral data to robust and simple imaging solutions. However, at present it is impractical to implement the hyperspectral imaging technique in an online system, because of the long image acquisition and analysis time. Therefore, multispectral imaging (using only a few wavebands) is preferred. Up to now, the research carried on tomato sorting technology focuses more on the color and shape grading, or the identification of stem-ends on tomatoes (Laykin et al., 2002; polder et al., 2002). However, the surface defects detection, especially the subtle defects such as bruises, has not yet been broadly reported. Another problem interesting to us is the orientation of the tomato in the field view of the optical system. The tomato fruits do not have a regular spherical shape like apples. Moreover, a tomato has locule tissue and cross-wall tissue, which have different structure. The bruised region can have different response in terms of the shape and discolorations. When light hits on different tissue, the scattering behavior of light is different, which should have effects on the images. All these lead to a more complicated situation than working with other fruits like apples.

The objective of the present study is focused on determination of the optimal wavebands for enhancing the contrast between damaged and intact tissues based on the analysis of the hyperspectral imaging data. Furthermore, the suitable wavebands for identifying the stem and the influence of the orientation of the fruits on the image quality were investigated.

Material and methods

Sample preparation

The tomatoes were purchased from a local supermarket in Leuven (Belgium). The original production place is Spain. The fruits were separated into damaged and intact group manually by visual inspection and touch. These fruits were stored at room temperature (18°C) after arriving in the lab until being measured.

Hyperspectral imaging system

The hyperspectral imaging system (*Fig. 1*) consists of four components: a sample transportation plate, two 150 W halogen lamps, an ImSpector V10 spectrograph (Spectral Imaging Ltd, Oulu, Finland) coupled with a standard C-mount zoom lens (Cosmicar H6Z810), and a 10 bits Hitachi KP-F120 monochrome camera. The prism-grating-prism (PGP) construction inside of the ImSpector spectrograph disperses the incoming line of light into the spectral and spatial matrices and then projects them onto the charge-coupled-device (CCD) of the camera. The optics, spectrograph and the camera, has a sensitivity from 400 to 1000 nm. Each time, the reflectance of one line on the sample can be recorded. The transportation plate moves the sample passing through the field view of the optical system. After finishing scanning of the entire sample, a data cube can be obtained: two spatial dimensions and one spectral dimension. This laboratory-based system was operated in a dark cell to minimize interference from ambient light. The resolution of the image acquisition system was 800 by 1040 pixels.

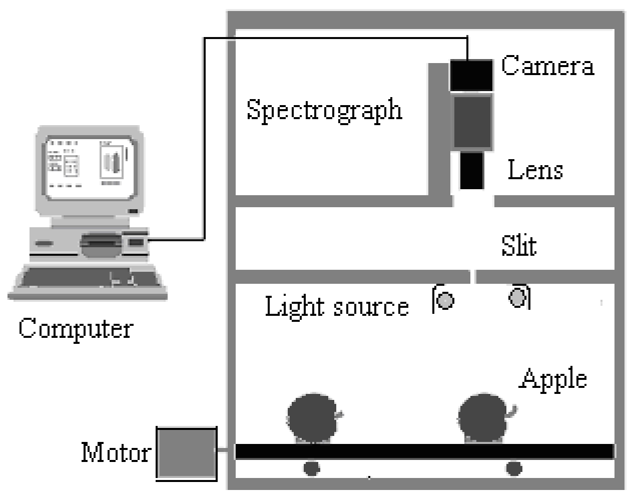


Figure 1 Schematic of hyperspectral imaging system

Data processing and analysis

The image capture and automatic thresholding program was developed in Labview (National Instrument Corporation, Austin, USA). The image processing program was developed in Matlab (The MathWorks Inc., Natick, USA).

Data reduction and smoothing

Before doing further data processing, the background of the image was removed by the simple thresholding method. Normally, the surface of a tomato is quite smooth and shinning, which causes the saturation in the image. The saturated area cannot provide useful information; therefore, such areas are also eliminated from the images by setting the values of the pixels in such region to 0.

For the data smoothing and reduction, the spatial-spectral data from each scan was averaged by 10 neighbouring pixels in the spectral dimension and average of 5 pixels in spatial dimension. It results in a 73 spectral channels with approximately 7 nm increments per pixel. To avoid low signal-noise ratio, only the wavelength range from 500 to 950 nm was used in this analysis.

Wavelength calibration and reflectance calibration

The comparison of the respective spectrum of a TLP 32W/33 type TL-lamp obtained from a spectrophotometer and hyperspectral imaging setup gives the wavelength calibration equation as:

$$\lambda_p = 6.306\,p + 331.63$$

where: λ_p is the wavelength at pixel p in nm.

For the reflectance calibration, a standard reference of 99% reflectance (Spectralon, Labsphere Inc.) was used for reflectance calibration. The dark current was measured by turning off all light sources and covering the lens with a black cap. The reflectance (R) was calibrated with the following equation:

$$R = \frac{R_{im} - R_{dark}}{R_{ref} - R_{dark}}$$

where: R_{im} is the intensity of an image; R_{ref} is the intensity of the standard reference spectralon 99%; and R_{dark} is the intensity of the dark image.

Variable selection methods

In the hyperspectral imaging system, it is time consuming to acquire the spectral and spatial information of the entire sample. It is not practical to implement it online as such. However, by means of analysis the hyperspectral imaging data, it is possible to select a few effective and suitable wavebands for building a multiple spectral imaging system to meet the speed requirement of a sorting line.

Many techniques are available for choosing the most informative variables (wavebands) from the spectral data, i.e., Correlelogram, PLSDA and Genetic algorithms.

A ***correlelogram*** is a plot of the correlation coefficients between the predictor variables and the dependent (response) variable. In this paper it was used for spectral analysis. The predictor variables are wavelengths and the response variable is a binary treatment class (*i.e.*, bruised *vs*. sound). It displays the contribution of each wavelength to the treatment effect. Through selecting the most correlated wavebands to the treatment effect, it is possible to reduce the dimension of the wavelength space.

Partial Least Square Discriminant Analysis (PLSDA) is a multivariate inverse least squares discrimination method used to classify samples. In particular, the objective with PLSDA is to find models that allow the maximum separation among classes of objects. A dummy variable can be constructed, representing the sample properties (*e.g.*, sound = 1, bruised = 0) and then used as

Y-variable. The prediction from a PLSDA model is a value of nominally zero or one. A value closer to zero indicates the new sample is not in the modeled class; a value of one indicates a sample is in the modeled class. In practice a threshold between zero and one is determined above which a sample is in the class and below which a sample is not in the class. The loadings plot of the PLS latent variables gives the weights of each wavelength to the discrimination.

Genetic algorithm variable selection is a technique that helps identify a subset of the measured variables that are, for a given problem, the most useful for a precise and accurate regression model.

Many regression problems benefit from the multivariate advantages of more precise predictions and outlier detection, like PLS. In some cases, however, some variables may be difficult to measure (expensive variables) and others may contain noise or interfering signal, which may actually deteriorate the accuracy and/or precision of a regression model (noisy variables). In these cases, it can be advantageous to discard some variables. However, the choice of what variables to discard is not clear.

Genetic algorithms (GA) provide a straightforward method based on a "survival of the fittest" approach to modeling data. Given an X-block of predictor data and a Y-block of values to be predicted, one can choose a random subset of variables from X and, through the use of cross-validation and any of the regression methods, i.e., PLS, determine the root-mean-square error of cross validation (RMSECV) obtained when using only that subset of variables in a regression model. Genetic algorithms use this approach iteratively to locate the variable subset (or subsets), which gives the lowest RMSECV.

Data preparation

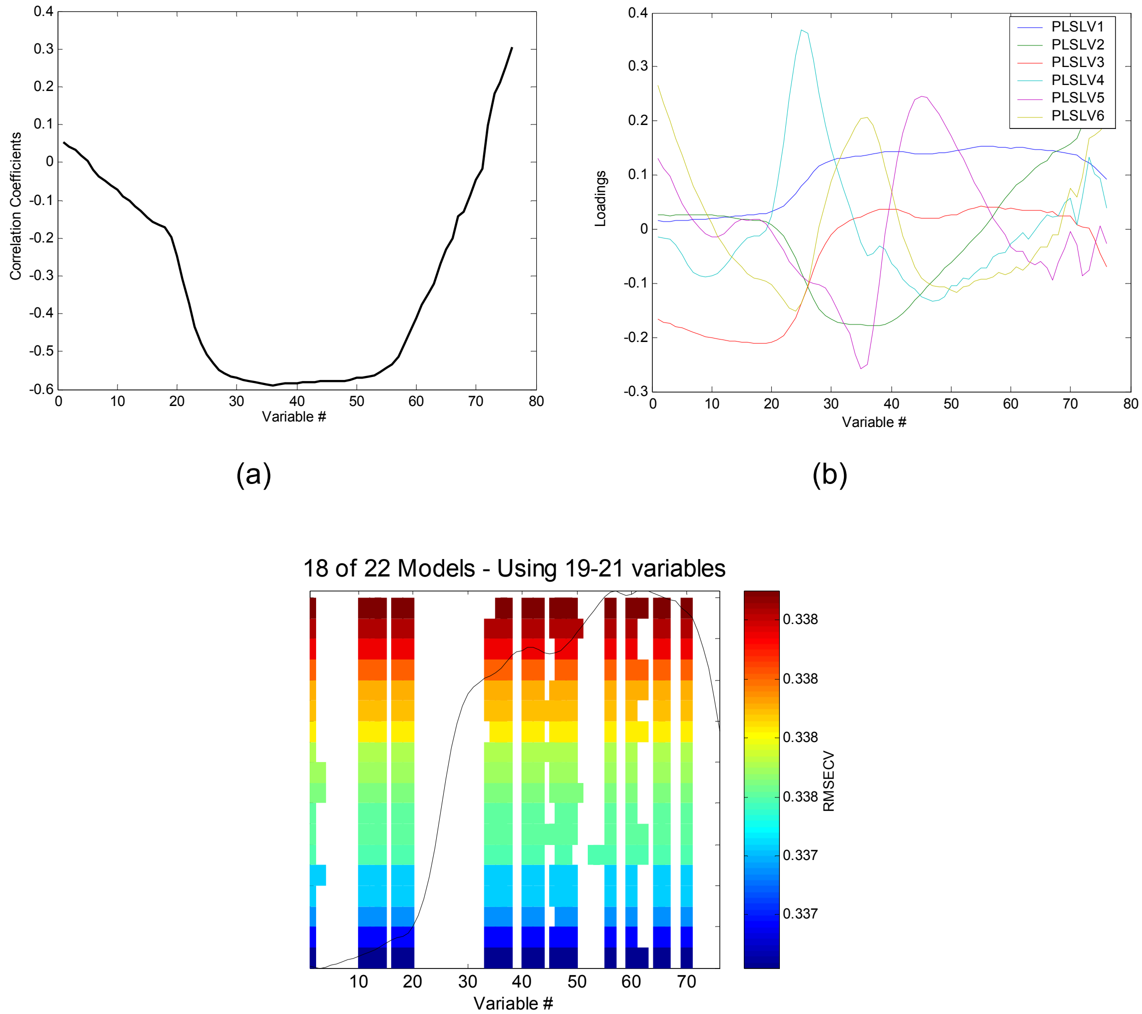
In total 58 tomatoes were used for imaging in this experiment. Thirty of them were intact and 28 with bruises. Since most of the bruised regions were not observable by visual inspection, an ‘indication image’ was recorded after finishing the normal image acquisition for a bruised tomato. In the ‘indication image’, the bruised region was marked with white paper to indicate the positions. Afterwards, it was used to segment the bruised regions from the hyperspectral images for collecting the spectra for the calibration dataset. For the dummy variable Y, a ‘1’ was assigned to the pixel in the sound tissue and ‘0’ for the pixel in the bruised region.

Results and discussion

Suitable wavebands selection

The correlelogram, PLSDA and Genetic algorithm techniques were applied on the spectral data, respectively. The results are demonstrated in Fig. 2. As can be seen, these three techniques all suggested that the variable between #30 and #50 (corresponding to the wavelengths between 640 and 750 nm) contributed more to the discrimination of two groups than the other wavebands. More specifically, according to the loadings plot of the PLSDA, the wavelengths at around 600, 675 and 735 nm were more pronounced. In the genetic algorithm results, the variables selected by the 18 models are quite consistent. The variables between #20 and #30 (corresponding to the wavelengths between 570 and 640 nm) can be discarded. This wavelength region is for the yellow and orange color, which have little contribution for discriminanting the bruised and sound tomato tissue. Surprisingly, the wavelengths between 515 and 570 nm (variables between #10 and 20) are also preferred by the genetic algorithm technology. This waveband is in the green color region, which is little reflected by the red fruit.

The correlelogram indicates that this region has low correlation with the presence or absence of bruises (r = -0.1). In the PLDA loadings plot, this wavelength region has relative high weights for the third latent variable (PLSLV3). The reliability of this region for bruise detection on red tomatoes should be further investigated. At this moment, only the wavelength region between 640 and 750 nm were determined as the suitable wavebands for detecting bruises on red tomatoes.



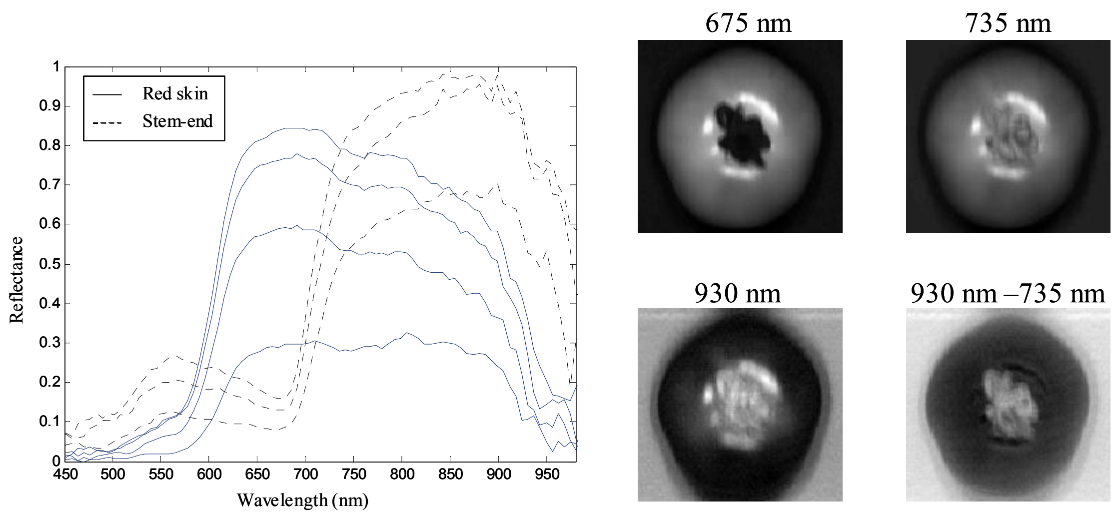
(a) (b)

(c)

Figure 2 Results of variable selection by using correlelogram (a); PLSDA (b) and genetic algorithm (c)

Detection of the stem-end

Fig. 3a shows the spectra of the pixels on the green stem-end and those on the red tomato surface, respectively. Several spectral features were observed for the purpose of separating the stem-end from the flesh with red skin. Apparently, the big contrast occurs at around 675 nm, which is the chlorophyll waveband. The chlorophyll in the stem-end has a strong absorption for the light of this wavelength leading to the much lower reflection comparing to the red skin. In the green wavelengths region, the reflection of the stem-end is also higher than that of the red skin; however, the contrast is not so distinct as that around 675 nm. Another noticeable feature is the slope change in the section between 735 and 930 nm. For example, the slope of the spectra of the flesh with red skin is negative and is positive for the spectra of the stem-end. Fig. 3b demonstrated the tomato images at some specific wavebands. There is a bruise near the stem-end in the demonstrated tomato image. The bruised region, as well as the stem-end, shows lower reflectance values in the visible wavelength region. However, as can be seen in the image at 930 nm, the stem-end has higher reflectance than the flesh of the tomato. In the differential image (930 nm – 735 nm), the stem-end is even clearer to be indicated differently from the flesh tissues with red skin. It may be considered a good feature for separating the stem-end from the true defects.

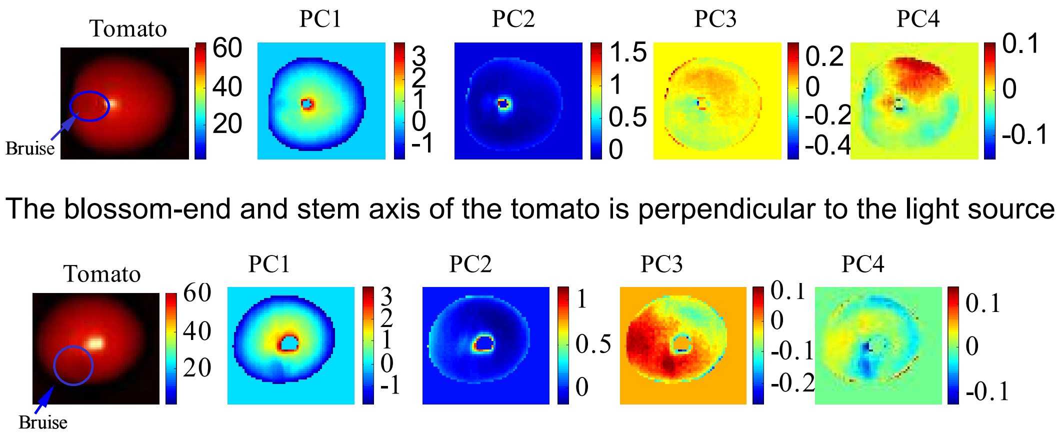


(a) (b)

Figure 3.Represntative spectra of the pixels on the stem-end and skin (a); demonstrate images of one tomato at different wavelengths for recognizing the stem-end

Influence of orientation of a fruit in the field of view of the camera

As described before, to identify the bruised tissue on a red tomato based on the discoloration is difficult. However, the physical alteration can be helpful in some cases, i.e., the shape deformation. The shape deformation on the bruises region normally appears as an indention, which results in a shadow in the reflectance image. Since the shape of a tomato is not a regular spherical, the damaged tissue can be a circular or elliptic area. Under the linear illumination, the contrast between the different shape of defects and of sound tissue might be enhanced to different degree. Therefore, the orientation of fruits in the field of view of the camera was assumed to have influence on the image quality.



The blossom-end and stem axis of the tomato is parallel to the light source

Figure 4 Pseudo RGB image of a tomato and its PCA scores images

Fig. 4 shows the pseudo-RGB color images of a tomato used in this study. There was an elongated bruised area as indicated in the figure on the tomato. From the variable selection procedure, the wavelength region between 640 and 750 nm was considered to be suitable for displaying the contrast between the sound and bruised tissue efficiently. In order to summarize the information in this wavelength region, Principal Components Analysis (PCA) was conducted. The first four PCA scores images are shown in Fig. 4. The images on the first row were obtained by moving the fruit with the blossom-end and stem axis perpendicular to the light source, which means that the light illuminated the sample along the dimension of the short axis of the defect. The first principal component scores image was believed to show the shape deformation (Xing et al., 2005b); however, the damaged region on this tomato was not displayed clearly in the PC1 scores image. This bruise cannot be identified from the following PCA scores images either. In the second row of Fig. 4, the images were obtained by moving the fruit with the blossom-end and stem axis parallel to the light source. Apparently, the bruised area is more obvious to be recognized from the PC1 scores image than previous one. The PC3 and PC4 scores images may be used to localize the bruise on the tomato. The orientation of fruits does not affect the image quality so much when the bruised region appears as a circular area (data not shown here).

Conclusions

The reflectance images of tomatoes were recorded using a hyperspectral imaging system for defining the efficient wavelength(s) for surface defects detection. Bruises were studied since they are more difficult to detect by a machine vision system compared to the other surface defects. Correlelogram, PLSDA and Genetic Algorithm were applied on the hyperspectral imaging data to determine the optimal wavelength(s) to enhance the contrast between the bruised and sound tissue. The results of the variable selection procedures indicated that the wavelength region between 640 and 750 nm were suitable for bruise detection on red tomatoes. Regarding to the identification of stem from the flesh with skin, the wavelength around 675 nm was considered as an appropriate choice. Moreover, the differential images between wavelength 930 nm and 735 nm could be helpful for separating the stem from the true defects.

Some efforts were made to investigate the influence of the fruit orientation on recognizing the bruises from the sound tissue as well. The results suggested that the illumination configuration should be taken into account while building a machine vision system. Different lighting could be good for highlighting certain defects present on the surface of tomato fruits.

More work is needed with respect to establishing a multispectral imaging system and developing an image processing algorithm to segment the damaged tissue from the healthy tissue on the tomato surface. The features of different maturity or color stages of tomato should also be investigated.

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