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Hyperspectral analysis of storage rot disease in apple

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Abstract

Storage rot is a major cause of yield loss in apple production. The infection of lenticels with Gloeosporium spp. takes place in the orchard. At this stage, there are no visible symptoms. During storage, when the fruit continues to ripen, symptoms appear as brown spots. The aim of this study was to examine whether an early detection of an infection with Gloeosporium spp. is possible using hyperspectral image analysis. Using this technology, infected apples could be sorted out before storage, reducing the risk of infecting further apples during storage, as well as costs and energy consumption due to the timely removal of infected apples before the storage cycle. Images of apples of the variety Pinova were taken at the beginning and at the end of the storage period in a controlled laboratory setup. The second measurement was used to develop a classification of late symptoms. Subsequently, areas on the initial measurement, where symptoms will manifest, were annotated for the purpose of early detection via artificial intelligence based algorithms. First results are presented and upcoming challenges regarding the detection and classification are discussed.

Keywords: apple, storage rot disease, hyperspectral imaging

Introduction

The infection of apples with *Gloeosporium* spp. takes place in the orchard, when conidia are washed into lenticels (Edney, 1974). As there are no visible symptoms on the apple when put into storage after harvest, current detection of storage rot is based on manual inspection at a late state of storage when symptoms are visible to the bare eye. This method requires experienced personnel, is time consuming and subjective. In contrast to a visual inspection, hyperspectral image classification of late symptoms is a time-saving and objective approach and has been shown to be an effective means of detecting plant pathogen infection before visible symptoms appear (Thomas *et al.*, 2018). An early detection of storage rot before the storage would further enable savings in storage capacity.

Within this study the potential of hyperspectral image classification through machine learning methods for the early detection of storage rot disease was investigated through precision measurements at laboratory scale of apple before and after storage.

Material and Methods

Apples of the variety Pinova were used in this study. Hyperspectral images were acquired at the beginning and at the end of the storage period, using a hyperspectral camera (micro HSI 410 SHARK, Corning Inc., New York, USA) under laboratory conditions. The experimental setup consists of the camera and a lighting system which includes four quartz-wolfram-halogen lamps (Malvern Panalytical Ltd., Malvern, UK) with 70 W and 15 V. The camera operates as a pushbroom system, therefore camera and lighting system are integrated to a linear axle, so these two components can move over the sample placed beneath. The sensor setup is connected to a laptop for sensor operation and data acquisition. Two series of measurements with 80 apples were obtained. Before the first measurement, each apple was provided with adhesive markers on the upper and lower side

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to identify the identical locations on both measuring dates. After the first measurement, each apple was individually packed in a fruit net with numbering and stored in cold storage until the second measurement. Data were evaluated with the software fluxtrainer (LuxFlux GmbH, Reutlingen, Germany), where different artificial intelligence-based algorithms can be combined for processing the data.

The first step for analyzing the data was to perform a smoothing of the data (Savitzky-Golay-Smoothing) and a background masking through thresholding which is used to exclude background spectra so only relevant spectra are used for further processing. Then, k-means clustering was applied. An unsupervised approach which searches for clusters within the data was chosen to get an overview of the data. For classification of late symptoms, a cropped image which contains six apples was used for data annotation. As a next step, different supervised classification algorithms were tested for their performance, whereas a distance based classifier using the mahalanobis distance method has verified as favored method.

For early detection, images of the first and second measurement were placed on top of each other so the areas where symptoms will manifest could be annotated in the initial images. Then, the spectral signatures of lenticels which are located within the annotated area were compared.

Results

At the time of the first measurement, none of the apples showed symptoms. At the point of the second measurement 44 out of 160 apples developed storage rot symptoms. The performance of the distance classifier was tested by using the remaining apples with classification parameters based on the annotated training data. In figure 1, on the right side, the classification result of late symptoms can be seen represented via a false color image. The color code of groups is as follows: green – healthy tissue, brown – symptomatic tissue, olive green – lignified tissue, yellow – label. For comparison, there is the pseudo-RGB image on the left side of the figure. With this classification method all symptomatic apples could be detected. However, 8 healthy apples out of 160 were denoted as symptomatic, which results in an overall accuracy of 95% for the classification “healthy“ or “symptomatic“ apples. It is notable that even if the respective apple is assigned to the correct group “healthy” or “symptomatic” not all pixels have been assigned correctly, as can be seen in apple number 1 on the stem and in apples number 3 and 6 around the symptom (Fig. 1).

In figure 2, the annotated areas in the first measurement can be seen on the right side. The orange colored circle is the area, where the symptom is located later. Every lenticel located within this area was annotated to an own group. The lenticels are marked by the blue circles. The red marked lenticel which in the center of the symptomatic area is suspected to have been infected and from which the symptom has spread. The spectral signatures of the individual lenticels are shown in figure 2, on the left side. It can be observed that, the higher the lenticel is placed on the apple, the higher the reflectance level is.

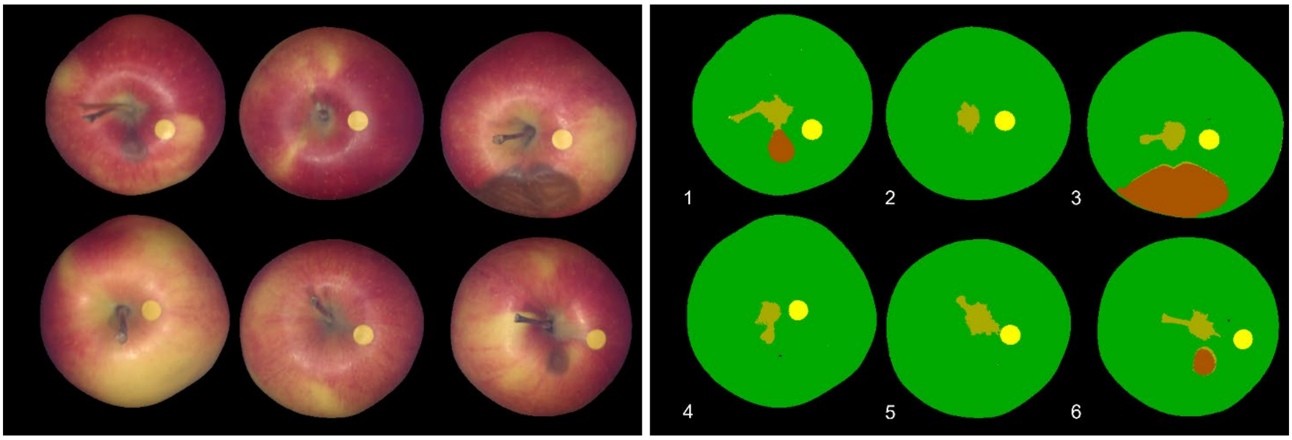

Figure 1: Hyperspectral images of apples after storage. Pseudo-RGB (left) and false color representation of the classification result (right). Green – healthy tissue; brown – symptomatic tissue; olive green – lignified tissue; yellow – label.

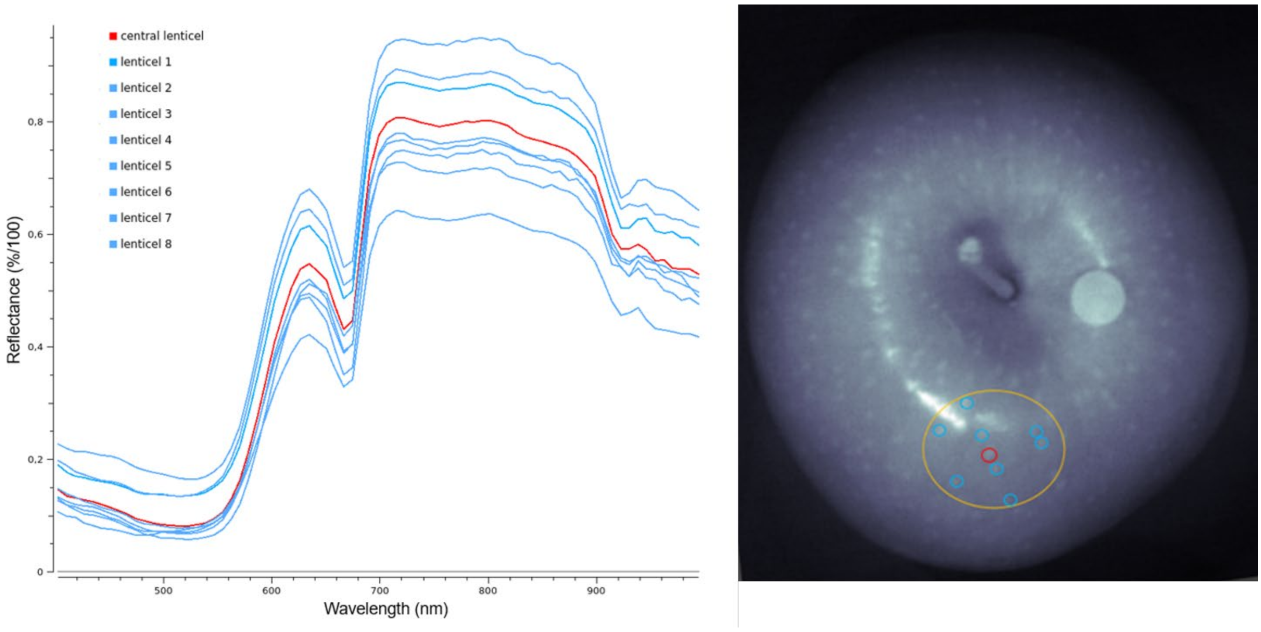

Figure 2: Pre-storage image of an apple that has been confirmed to show storage rot symptoms in the post-storage measurement. Spectral signatures of lenticels within symptomatic area (left) and false color representation of the apple showing the annotated areas of the respective lenticel spectral signatures (right).

Discussion

The architecture of the apple fruit causes suboptimal conditions for spectral analysis. Since it is a spherical object, there are differences in exposure intensity and light reflection properties. The planes which are located closer to the light source are more illuminated than those further below. In addition, the angle at which the light hits the surface influences the obtained reflectance (Shahrimie et al., 2016). Also, the skin color of the apples is not uniform and the distinction between the colors cannot be made clearly due to the color gradient. These circumstances cause a high variance of the data. Despite the given variance of the data, the symptomatic tissue of late stage symptoms can be well distinguished from healthy and lignified tissue. However, when it comes to transition areas between the different tissue types, the classification algorithm is not able to perform perfectly. This complication is caused by so called mixed pixels. The trade-off between spectral and spatial resolution results in pixels that contain spectral data from more than one area (Keshava & Mustard, 2002). Therefore, they cannot be clearly assigned to a respective group.

For early detection the spectral signatures of lenticels were investigated in the area, where a symptom has been shown to manifest in the post-storage measurement. As can be seen in the spectral signatures of the lenticels (Fig. 2), there are different reflectance levels of the individual lenticels. These differences in reflectance are caused by the position of the lenticels on the apple (Shahrimie et al., 2016). As explained before, the illumination depends on the distance and the inclination of the spot to the light source and to the camera. The red annotated lenticel, which is placed in the center of the symptomatic area also has a medium reflectance level compared to the remaining lenticels. Apart from the differences in the reflectance level, no clear differences in the spectral characteristics of the infected lenticels could be recognized in this study.

One reason, why no changes could be detected may be that mixed pixels play a role. The size of lenticels is around 2-3 mm, which does often lead to pixels with partial coverage of the lenticel and surrounding tissue. Additionally, when zooming into the image it becomes blurred and therefore challenging to annotate only the lenticel without possibly marking surrounding tissue as well.

The infection with *Gloeosporium* spp. leads to changes of the physiological properties of the apple fruit which can be clearly seen in spectral signatures of late stage symptoms. The changes of enzyme content which are given at the beginning of the infection could not be detected in these images (Schulz, 1978). Early detection would be desirable for agricultural applications to save energy costs and storage capacity, but automatic detection of late symptoms is a step forward to save time and manpower by eliminating the need for manual sorting and providing an objective damage assessment.

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