Available online at www.sciencedirect.com

ScienceDirect

IFAC-PapersOnLine 49-16 (2016) 105–109

# Automated Detection of *Mycosphaerella Melonis* Infected Cucumber Fruits

**Danijela Vukadinovic, PhD*. Gerrit Polder, PhD**. Gert –Jan Swinkels ***.**

**Wageningen University and Research Centre , Wageningen, the Netherlands*
*(e-mail: danijela.vukadinovic@wur.nl).*
*** Wageningen University and Research Centre , Wageningen, the Netherlands*
*(e-mail: gerrit.polder@wur.nl).*
**** Wageningen University and Research Centre , Wageningen, the Netherlands*
*(e-mail: gert-jan.swinkels@wur.nl)*

**Abstract:** In this paper we present a novel method for automated detection of *Mycosphaerella melonis* infected cucumber fruits. The two-step method consists of machine learning approach using: shape based features extracted from cucumber color images and light transmission spectra based features. The automated detection rate was compared to the manual detection rate of the human workers. Our automated method reached the 95% detection accuracy, which is comparable to the manual detection accuracy of 96%.



*Keywords:* Fruit disease detection, Machine learning, Computer vision, Sorting machines, Automation.

## 1. INTRODUCTION

*Mycosphaerella melonis* is one of the two main pathogens that cause two most destructive diseases to cucurbits crops, namely *Fusarium* wilt and gummy stem blight (Zhang, *et al.* 2005). Because few effective, economical, and environmentally safe management options are available for these diseases, they are a yield-limiting factor in cucurbit family (cucumber, squash, melon, pumpkin, vegetable marrows, bitter melon and zucchini) plant production worldwide. A major reason for this is the inability to accurately detect the presence and identity of the two fungal pathogens, especially in plant tissues and soil. Under favourable climatic conditions, *Mycosphaerella melonis* can infect all parts, except roots, of the cucumber plant at all stages of plant development (Fig. 1).

Fig. 1. Severe cases of *Mycosphaerella melonis* infection symptoms on the cucumber leaf (left), stem (middle) and fruits (right). Image source: http://www.shouragroup.com/v_cucumber_e.htm .

Infection at fruit development often leads to internal fruit rot that may go unnoticed at harvest. This raises concern among growers because the inevitable post-harvest fruit decay at the grocer creates a poor image for the distributor (packing house) and grower. Additionally, the infected cucumbers are not saleable and could infect the healthy fruits. The disease is especially not easy to manage in the greenhouses due to the humid climate conditions (*Olsen et al.*) that are favourable for the disease development and spread and because there is a constant occurrence of fresh wounds from pruning and harvesting that serve as new infection sites. During sorting, the contaminated cucumbers are difficult to recognize, even by experienced personnel who is trained to separate these as good as possible (Fig 2). Due to manual sorting on *Mycosphaerella melonis*, the processing speed must be reduced. Therefore, automation of this process would be highly desirable**.** For these reasons, we focus on the detection of the *Mycosphaerella melonis* in the infected fruits after harvesting.

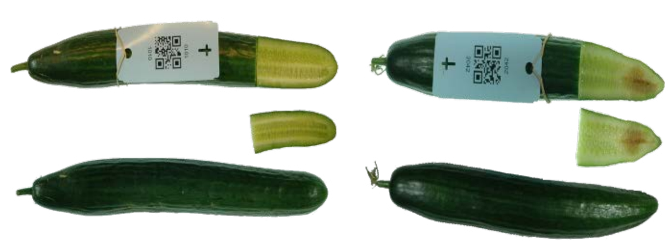

Fig. 2. Examples of the cucumber fruits used in our study: *Mycosphaerella melonis* healthy (left) and infected (right) cucumber fruits.

Various studies have used different methods for the classification of plant diseases based on spectral data. For instance, Wu et al. (2008) used PCA-based back-propagation neural network (BPNN) model and PLS wavelength-based BPNN for detection of *Botrytis cinerea*-affected eggplant leaves under laboratory conditions. Prior to the visibility of


Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2016.10.020

symptoms the BPNN model predicted fungal infections with a maximum of 85% classification accuracy. Mahlein et. al. (2012) applied hyperspectral imaging to symptoms caused by different sugar beet diseases induced by different fungal pathogens in the laboratory. High detection accuracy was achieved when disease symptoms were externally visible. Silva et al. (2008) applied a neural network and principal component analysis to grayscale digital images to detect black sigatoka in banana plants (caused by the fungus *Mycosphaerella fijiensis*), however, the accuracy of the classification was not very high (51.67%). Pixia and Xiangdong (2013) used image processing and recognition technologies to study the disease of downy mildew, powdery mildew and anthracnose on cucumber leaves. The detection accuracy was very high: 96% for downy mildew and 100% for powdery mildew and anthracnose. However, the disease symptoms were visible externally and were clearly able to be identified by visual inspection. *Mycosphaerella melonis* shows no externally visible symptoms in infected cucumber fruits and therefore is a problem that is more difficult to solve by using conventional image processing techniques. To the best of our knowledge, an automated method on this topic has not been reported before.

The *Mycosphaerella melonis* infection always enters the fruit through the flower and therefore is always located at the tip of the cucumber fruit. The infection is externally invisible (Fig 2). Manual workers, trained to sort out the infected fruits, rely on the combination of the fruits tip hardness differences and barely visible difference in fruits tip shape between healthy and infected fruits (the infected fruits have a pointier tip). This manual method of detecting the infected fruits is highly unreliable and slow.

In this paper we present a novel method for automated detection of *Mycosphaerella melonis* infested cucumber fruits which aims at achieving both high speed and a high accuracy. The visual differences between the healthy and infected cucumbers are analysed using cucumber shape features. Similarly, the internal tissue changes in the infected cucumbers, i.e. less water content that causes firmness and internal browning, are detected using light transmission spectra analysis.

The method consists of three steps**.** First, the colour image based extraction of cucumber shape features and a cucumber classification that utilizes these features is performed. Subsequently, cucumber classification using transmission light spectra intensities as features is done. Finally, a combination of the two classifications resulted in the final infested cucumbers detection.

The remainder of the paper is organized as follows: in the section 2 the methodology used is described, followed by the experimental set up description in section 3 that includes data collection process and datasets characteristics. Results are presented in section 4, followed by a discussion in section 5 and conclusions in section 6.

## 2. METHODOLOGY

The first step of the method is a sample based linear classification that utilizes shape descriptors extracted from a colour image of a cucumber. The second step is a sample based linear classification that uses transmission light spectra intensities as features. In the last step, a combination of the results of the two classifications is used as the final resulting classification result.

### 2.1 Shape based features

The automated shape analysis method starts with individual cucumber segmentation, based on the excessive green transformation (Fig 3). The linear combination of the red, green and blue component of a RGB image:

$$I_{EG} = 2*I_G - I_R - I_B, \quad (1)$$

Results in the excessive green image $I_{EG}$. Here $I_G$, $I_R$ and $I_B$ denotes the green, red and blue component of the colour image respectively. The excessive green image is thresholded using an automatic threshold using the hysteresis (Canny, 1983) in order to segment a cucumber.

Fig. 3. Separate cucumber segmentation: RGB image (left), excessive green image (middle) and the final cucumber segmentation produced by the excessive green image thresholding (right).

Once the cucumber is segmented, we analyse only the tip of the cucumber where the infection is located. The length of the cucumber tip is experimentally chosen to be 20% of the cucumber length. This part of the cucumber is pointier for the *Mycosphaerella melonis* infected fruits. Therefore, the pointiness is described by the cucumber width distribution.

First, the cucumber length is normalized to 1000 pixels, then the first 200 cucumber widths starting from the top are extracted and finally, each of the widths represented one feature for the machine learning method (Fig 4). Widths are defined as distances between two cucumber borders along the lines orthogonal to the cucumber centreline. The centreline is determined by fitting an ellipse to the binary object (Haralick, *et. al.*)