Plant Disease Diagnosis Based on Image Processing, Appropriate for Mobile Phone Implementation

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Abstract. A steady plant monitoring is necessary to control the spread of a disease but its cost may be high and as a result, the producers often skip critical preventive procedures to keep the production cost low. Although, official disease recognition is a responsibility of professional agriculturists, low cost observation and computational assisted diagnosis can effectively help in the recognition of a plant disease in its early stages. The most important symptoms of a disease such as lesions in the leaves, fruits, stems, etc, are visible. The features (color, area, number of spots) of these lesions can form significant decision criteria supplemented by other more expensive molecular analyses and tests that can follow. An image processing technique capable of recognizing the plant lesion features is described in this paper. The low complexity of this technique can allow its implementation on mobile phones. The achieved accuracy is higher than 90% according to the experimental results.

Keywords: plant disease, lesions, image processing, agricultural production.

1 Introduction

Plant diseases can increase the cost of agricultural production and may extend to total economic disaster of a producer if not cured appropriately at early stages. The producers need to monitor their crops and detect the first symptoms in order to prevent the spread of a plant disease, with low cost and save the major part of the production. Hiring professional agriculturists may not be affordable especially in remote isolated geographic regions. Machine vision can offer an alternative solution in plant monitoring and such an approach may anyway be controlled by a professional to offer his services with lower cost. Of course, there are several additional tests that have to be performed in order to confirm a specific disease but image processing can give a first clue on what really happens at the field.

Before focusing on the existing image processing techniques, the features of molecular tests are reviewed (Sankaran et al, 2010). Molecular test sensitivity depends on the minimum amount of microorganism that can be detected. For example, bacteria detection can range from 10 to 10^6 colony forming units per mL (Lopez et al, 2003). A popular molecular diagnosis method is the ELISA that is

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based on the use of a microbial protein associated with the plant disease. This protein is injected into an animal that produces antibodies that are extracted and used for antigen detection with fluorescence dyes and enzymes. PCR is another popular technique based on DNA analysis (Shaad and Frederick, 2002). Molecular tests require expensive equipment and samples may need to be transported to the premises where the tests can be performed, although portable low cost equipment has been recently presented capable of performing tests like PCR (Spathis et al, 2014).

The spectroscopic and imaging are non-destructive low cost techniques that can be used for plant disease diagnosis based on its symptoms. Spectroscopic techniques can also identify water stress levels and nutrient deficiency, measure the fruit quality after the harvest, etc. Spectroscopic techniques include fluorescence or multispectral imaging (Chaerle et al., 2007), infrared spectroscopy (Purcell et al, 2009), etc.

Reviews of image processing techniques in visual light for plant disease detection can be found in (Barbedo, 2013), (Camargo and Smith, 2009) and (Kulkarni and Patil, 2012). In (Kulkarni and Patil, 2012) an image segmentation takes place in the CIE L*a*b color scale, then a Gabor filter is used to generate the input of a neural network that achieves a disease recognition with a 91% accuracy. Other classification techniques take into consideration the shape, the texture, fractal dimensions, lacunarity, dispersion, grey levels, grey histogram discrimination and the Fourier descriptor.

Most of the image processing and spectroscopic techniques require the analysis to be performed by specialized equipment and software packages. In this paper, we focus on a low complexity image processing technique that can be implemented and installed on a mobile phone. The image processing technique described here, is developed in the framework of a plant disease recognition system that is under development. This system operates in multiple levels ranging from a single standalone mobile phone, to a mobile phone communicating with a cloud or database and cooperating with the portable DNA analysis equipment for complementary PCR-like tests (Spathis et al, 2014).

Although the color features are also important in the process of plant disease recognition we focus on three parameters of the lesions that can appear at the leaves, the stem, or the fruit of a plant: (a) the number of spots, (b) their area and (c) their gray level. The measurement of these three features can give a first indication on the condition of the plant. The proposed system called henceforth Spot Recognition System (SRS) can be easily extended to generate the Red-Green-Blue (RGB) features of the spots or their CIE L*a*b color scale as will be described in the following sections although this feature is not experimentally tested in the present work.

Having installed the software implementation of the described image processing technique on a mobile phone, the producer would be able to take pictures of plant parts with lesions, immediately analyze the photos and take any further action needed to confirm the potential disease and apply the recommended therapy.

In this paper we apply the proposed technique to tangerine tree leaves with lesions and measure the accuracy in the spot feature recognition. Such measurements could have been used to discriminate between sooty mold (fungal growth), citrus canker, scab, etc that can have affected a citrus tree. Experimental results show that the measurement of the number of spots, their gray level and area can be achieved with higher than 90% accuracy. The proposed technique is a low complexity algorithm that does not rely on expensive or complicated image processing tools and thus can be easily implemented in Java or C to create an appropriate mobile phone application. The results of the proposed image processing technique can be used for example by a neural network or by a more deterministic rule-based decision system.

The plant disease recognition framework where the proposed image processing technique has been developed is described in Section 2. The implementation details of the SRS are given in Section 3 and experimental results are presented in Section 4.

2 Plant disease recognition framework

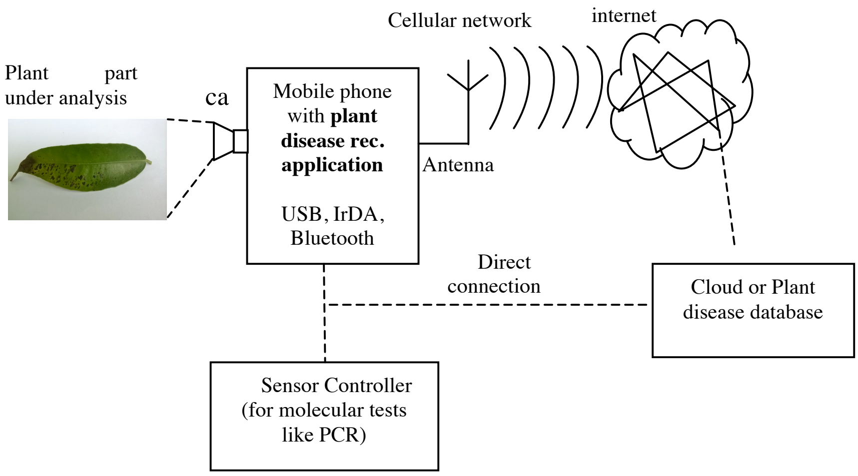


Fig. 1. The plant disease recognition framework under development.

The plant disease recognition framework under development is shown in Fig. 1. Its basic functionality operates on a single mobile phone equipped with a color camera with reasonable resolution. The mobile phone should be capable of connecting to the internet if a more detailed disease database or cloud has to be accessed. This may be required if the number of plants/diseases that can be examined is too high and the recognition rules, patterns and other data cannot be stored locally on the phone. Moreover, the storage of the pictures taken by the phone and the analysis results to the remote cloud or database can make easier their access by professional agriculturists.

The producer can use his phone with the installed plant disease recognition application when he wants to check the condition of the plants in his crops. He can take pictures of plant parts with lesions (e.g., leaves, stem, fruit) and run the plant disease recognition application on the pictures taken. The SRS of the plant disease recognition application extracts the lesion features like number of spots, grey level, area and these results are used by the decision module of the application that will extract a conclusion on the condition of the plant. As already mentioned the decision module can be a neural network. If a more advanced decision module has to be used operating on a diversity of disease recognition rules and data, the output of the SRS can be simply sent through GPRS or the internet to an external database or cloud. If the phone is moved close to the computer where this external cloud or database is installed then, the SRS results can be transferred through a different communication method like Bluetooth, WiFi, IrDA, etc. The plant disease recognition application may also need additional information that can be retrieved from the telephone itself like for example temperature and moisture conditions (e.g., these can be retrieved by the internet after the localization of the user geographical position). Additional statistical information can be given by the user through a questionnaire shown to him by the application.

In a more advanced setup, the mobile phone can cooperate with a DNA analysis module like the biosensor readout circuit described in (Spathis et al, 2014) that has been developed for the Corallia/LabOnChip project. The communication with this module can be performed in a wired or wireless manner (USB, WiFi, Bluetooth, etc).

3 The developed Spot Recognition System

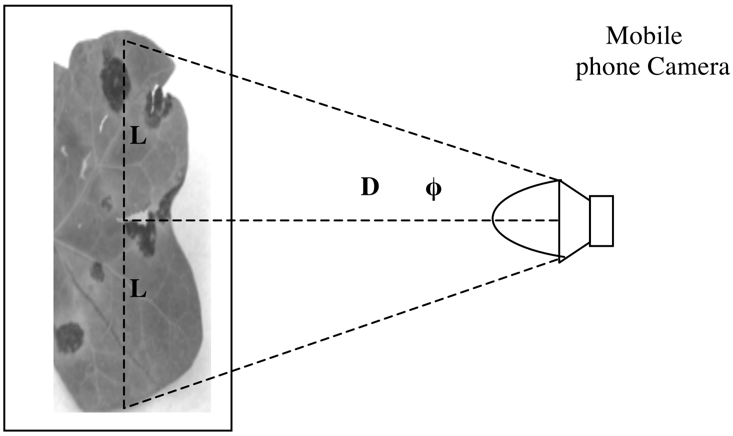


Fig. 2. Estimation of the leaf dimensions.

The Spot Recognition System (SRS) assumes that the picture of the plant part has been captured from as known distance *D* as shown in Fig. 2. The awareness of the distance *D* can be guaranteed if the user is ordered to take the picture from a roughly known distance e.g., related to his hand or to adjust the distance so that the plant part that will be captured fits the photograph. If the camera angle ϕ is also known then, the half leaf length is estimated by:

$$L=D\bullet\tan(\phi). \quad (1)$$

If the length L is known and it corresponds to P pixels then, the constant S can be used to estimate a distance from any other number of pixels:

$$S = \frac{L}{P} \tag{2}$$

For example, if two points in the horizontal axis, correspond to a real distance L' and the number of intermediate pixels is P' their distance L' is

$$L' = L\frac{P'}{P} \tag{3}$$

If the two points do not reside on the same axis, the same method can be used to estimate their distance and P' is the number of pixels between the two points in the diagonal line connecting them. In 2D, if the dimensions of the covered area are L_x, L_y in the x and y axis, corresponding to P_x and P_y pixels, then each pixel occupies an area A_p estimated as:

$$A_p = \frac{1}{S^2}\frac{L_x L_y}{P_x P_y} \tag{4}$$

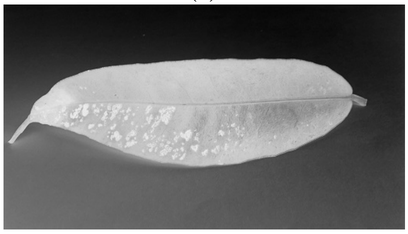
A spot of any shape consisting with P_i pixels will correspond to an area: $P_i \bullet A_p$.

The next issue is how the spots and their features (dimensions, position, color or grey level features) will be recognized using a simple algorithm. First of all, the plant part should be separated by its background. This can be performed by a segmentation procedure that nevertheless is based on complicated operations or a dedicated image processing libraries. A simple method used in this work is to assume that the background is much brighter than the plant color. This can be easily reassured if for example a leaf is captured with a white sheet of paper as its background. The user's hand can also be used as a background in most cases if the plant part has a darker color.

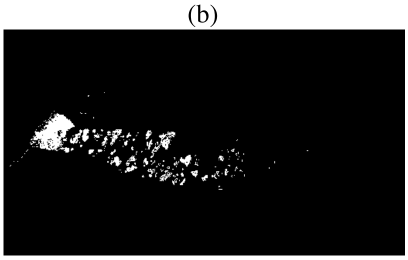
Although, the three color components of an image (Red, Green, Blue) can be easily handled to extract detailed image features we focus on a grey scale characterization of the image components and the spot number, coordinates, area and darkness are the outputs of the SRS. Thus, the captured image is initially converted into an inverted grey image and the original pixels with high brightness (below a threshold T_w in the inverted grey image) are ignored since they are assumed to belong to the background. An average grey level A_g is estimated by the rest of the pixels that are assumed to belong to the plant part. Then, the image matrix is scanned to locate the pixels i with a grey level G_i such as:

$$\left|G_i - A_g\right| > T_h \tag{5}$$

(a)



(b)



(c)

Fig. 3. Original photograph (a), in inverted grey level (b) and the visualization of BW1 with T_h=115 (c).

If the difference between the grey level of the pixel and the average is higher than the threshold T_h the specific pixel is assumed to belong to a spot (lesion) and a 0-1 matrix *BW1* (with the same dimensions as the original image) is constructed with 1's at the positions of pixels belonging to spots as shown in Fig. 3. The *BW1* is scanned again to group neighboring pixels belonging to the same spot. The resulting matrix *BW2* has an integer spot identity at the position of each pixel or 0 if the pixel does not belong to a spot. The *BW2* matrix is constructed using the following algorithm: a) the rows are scanned from left to right and neighboring pixels are assigned with the same identity, b) if the previous pixel on the left of the current one does not belong to a spot, the already visited neighboring pixels at the row above are checked and if one or more of these has been assigned to a spot identity, this identity is also used for the current pixel, c) the *BW2* matrix is scanned iteratively merging spot identities if neighboring spots are found with different identities until no change is detected. A filtering can also be applied discarding spots consisting of very few pixels (less than *MinArea*) because either they are noise or they are too small to be considered.

From the matrix *BW2* all of the desired features can be easily available: a) the maximum spot identity is the number of spots, b) area covered by the spots is estimated using the sum of the pixels belonging to spots (see equation (4)), an interesting parameter is the fraction of the plant part that is occupied by spots, c) the average grey level of each spot, d) the coordinates of each spot and its dimensions.

More advanced information can also be extracted if the coordinates of each spot are used to visit the original colored image and extract the texture of a spot, information like CIE L*a*b (Kulkarni and Patil, 2012), etc.

4 Experimental Evaluation

In this section the SRS method described in the previous section is applied to the pictures of Fig. 3a and Fig. 4a. These images show tangerine leaves with dark spots that may indicate for example the fungus Capnodium oleae or CTV among other diseases. The number of spots and the area they occupy on the leaf are significant inputs for the decision module of the mobile disease recognition application described in Section 2. The SRS output for the photographs of Fig. 3 and 4 are listed in Table 1. The grey level is not displayed since it cannot be compared to a reference grey level. The best results were retrieved when setting T_h equal to 115. The parameter *MinArea* of Table 1 that is set to 4 represents the least number of pixels required to take into consideration a spot.

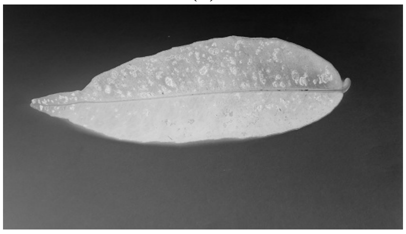
Table 1. SRS Measurement Result (MinArea=4, T_h=115).

Photo	Spots	Area	Spot Error	Area Error
Fig. 3	68	2.1%	-5.88%	+8%
Fig. 4	65	1%	-10%	-16%

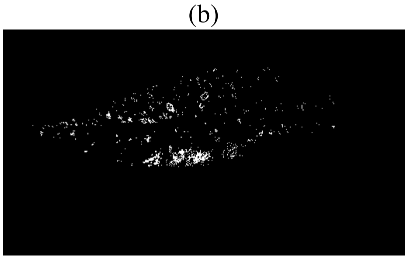
The negative sign in the errors of Table 1 indicates that the estimated number of spots or area is smaller than the real ones. The errors concerning the number of spots and the estimated area are inversely proportional. This means that when changing the parameters T_h and *MinArea* to improve one error the other gets worse. Using the image of Fig. 4 and setting *MinArea=2*, the number of spots recognized is higher since smaller spots will also be taken into consideration. If T_h is also increased (e.g., set to 120), then spots with higher contrast are used and those with lower contrast compared to the leaf background are ignored. Consequently, the parameters T_h and *MinArea* balance somehow each other. Setting T_h to a very high or a low value may significantly reduce or increase the estimated spot area respectively. Using MinArea=2 and T_h=120 with Fig. 4 leads to the detection of 87 spots (error +20%) but the estimated spot area is only 0.2%. The conducted experiments show that the values 2 and 115 selected for the parameters *MinArea* and T_h respectively lead to the highest estimation accuracy.

Although the spot recognition method has been applied in two indicative leave images, a predictable accuracy can be obtained in other plant case studies if the spot density and brightness is similar.

(a)



(b)



(c)

Fig. 4. Original photograph (a), in inverted grey level (b) and the visualization of BW1 with T_h=115 (c).

5 Conclusions

An image processing technique that can be easily implemented on smart phones, capable of recognizing plant lesion features has been presented. The preliminary measurement results in the recognition of the number of spots and their area on plant leaves showed accuracy higher than 90%.

In future work the color features of the recognized spots will also be taken into consideration for safer plant disease diagnosis and the presented algorithm will be implemented on smart phones and tested under outdoor conditions.

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