BIOSYSTEMS ENGINEERING 147 (2016) 104–116

Available online at www.sciencedirect.com

ScienceDirect

journal homepage: www.elsevier.com/locate/issn/15375110

Research Paper

Identifying multiple plant diseases using digital image processing

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ARTICLE INFO

Article history:
Received 23 September 2015
Received in revised form
3 March 2016
Accepted 28 March 2016
Published online 29 April 2016

Keywords:
Automatic disease recognition
Visible symptoms
Colour transformations

The gap between the current capabilities of image-based methods for automatic plant disease identification and the real-world needs is still wide. Although advances have been made on the subject, most methods are still not robust enough to deal with a wide variety of diseases and plant species. This paper proposes a method for disease identification, based on colour transformations, colour histograms and a pairwise-based classification system. Its performance was tested using a large database containing images of symptoms belonging to 82 different biotic and abiotic stresses, affecting the leaves of 12 different plant species. The wide variety of images used in the tests made it possible to carry out an in-depth investigation about the main advantages and limitations of the proposed algorithm. A comparison with other algorithms is also presented, and some possible solutions for the main challenges that still prevent this kind of tool to be adopted in practice.

1. Introduction

The timely diagnosis of plant diseases is as important as it is challenging. Although human sight and cognition are remarkably powerful in identifying and interpreting patterns, the visual assessment of plant diseases, being a subjective task, is subject to psychological and cognitive phenomena that may lead to bias, optical illusions and, ultimately, to error. Ambiguities may be resolved by laboratorial analysis, however this is a process that is often time consuming and expensive. Additionally, many producers around the world do not have access to technical advice from rural extension, making their crops especially vulnerable to yield losses and further problems caused by plant diseases.

Considerable effort has been made in the search for methods to improve the reliability and speed of the process, which inevitably involves some kind of automation. Most of the methods proposed so far try to explore imaging technologies to achieve this goal (Barbedo, 2013). Among the most used imaging techniques are the fluorescence (Bauriegel, Giebel, & Herppich, 2010; Belin, Rousseau, Boureau, & Caffier, 2013; Kuckenberg, Tartachnyk, & Noga, 2009; Lins, Belasque, & Marcassa, 2009; Rodríguez-Moreno et al., 2008), multispectral and hyperspectral (Barbedo, Tibola, & Fernandes, 2015; Mahlein, Steiner, Hillnhütter, Dehne, & Oerke, 2012; Oberti et al., 2014; Polder, van der Heijden, van Doorn, & Baltissen, 2014; Zhang e al., 2014), and conventional photographs in the visible range (Barbedo, 2014; Clément, Verfaille, Lormel, & Jaloux, 2015; Kruse et al., 2014;

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http://dx.doi.org/10.1016/j.biosystemseng.2016.03.012

Nomenclature

c	Number of disease classes
CD	Correlation differences
CMYK	Cyan–Magenta–Yellow-Key colour space
D	Set of all diseases
HSV	Hue-Saturation-Value colour space
L*a*b	Colour space with L^* representing lightness and a^* and b^* representing colour-opponent dimensions
L_d	Likelihood that the symptoms were produced by disease d
M	Final segmentation mask
M_1, M_2, M_3, M_4	Basic binary segmentation masks
M_a, M_b	Intermediate binary segmentation masks
MPixels	Millions of pixels
r_1, r_2	Deviation of each pixel from a purely green hue towards red and blue
RGB	Red–Green–Blue colour space
ROI	Region of interest
v_1, v_2	Correlation difference vectors.
$X_{c,d}$	Cross-correlation between intensity and reference histograms, considering channel c and disease d
ε	Arbitrarily small value that aims at avoiding divisions by zero

Phadikar, Sil, & Das, 2013; Pourreza, Lee, Etxeberria, & Banerjee, 2015; Zhou, Kaneko, Tanaka, Kayamori, & Shimizu, 2015). The latter one is the least expensive and most accessible technology, as the prices of digital cameras continue to drop, and most mobile devices include cameras that provide images with acceptable quality.

Thus, it is no surprise that methods for automatic plant disease diagnosis based on visible range digital images have received special attention. However, although there have been advances, those are mostly limited to cases in which the conditions, both in terms of disease manifestation and image capture, are tightly controlled. As a result, there is a lack of methods that can be used under the real, uncontrolled conditions found in the field. The reasons for this are discussed in depth in Barbedo (2016).

This paper presents a new digital image-based method for automatic disease identification. This method, which is based on colour transformations, intensity histograms and a pairwise-based classification system, was designed specifically to operate under uncontrolled conditions and to deal with a large number of diseases. Additionally, new diseases can be included without changing the component of the system that has already been trained, making the process straightforward. This method was tested with a large, unconstrained set of leaf images containing symptoms belonging to 74 diseases, 4 pests and 4 abiotic disorders, affecting 12 different plant species. The images containing symptoms that were not produced by diseases were included because those are also important sources of diagnosis confusion, making the database more comprehensive. The images were captured under a wide variety of conditions regarding lighting, angle of capture, stage of development of the disease and leaf maturity. No constraint was enforced during the captures, and no image was removed from the dataset, no matter how far from ideal was the capture conditions. As a result, the method was stressed to its limits, revealing a wealth of information about the challenge of disease identification when several diseases are considered. This allowed an in-depth analysis of the challenges that are expected to be faced in practice, as discussed here and, in more detail, in Barbedo (2016).

2. Material and methods

2.1. Image dataset

As mentioned before, the database used in this work contains images of 82 different disorders distributed over 12 plant species: Common Bean (*Phaseolus vulgaris* L.), Cassava (*Manihot esculenta*), Citrus (*Citrus* sp.), Coconut Tree (*Cocos nucifera*), Coffee (*Coffea* sp.), Corn (*Zea mays*), Cotton (*Gossypium hirsutum*), Grapevines (*Vitis* sp.), Passion Fruit (*Passiflora edulis*), Soybean (*Glycine max*), Sugarcane (*Saccharum* spp.) and Wheat (*Triticum aestivum*). The images were captured using a variety of digital cameras and mobile devices, with resolutions ranging from 1 to 24 MPixels. About 15% of the images were captured under controlled conditions, either by transporting the detached leaves to laboratories, or by placing the leaves inside closed dark boxes with an opening for lighting and image capture. The remainder 85% of the images were captured under real conditions, with the leaves attached to the host plant, at several experimental fields of the Brazilian Agricultural Research Corporation (Embrapa). For these, no constraint regarding resolution, field of view or capture conditions was enforced during the image capture. This decision aimed at producing an image database closely reproducing conditions and situations that the proposed method will have to deal if used in practice by producers with little or no knowledge about imaging techniques. All images were stored in the 8-bit RGB format. Table 1 shows how the database is distributed in terms of plant species and disorders.

2.2. Image analysis procedure

Figure 1 shows the general structure of the proposed algorithm for the analysis of the symptoms. As it can be seen, the algorithm was divided into three main blocks, basic processing, training (performed only once) and core. Each box will be detailed in the following.

The implementation of the algorithm included a graphical interface to guide the user through the process. Figure 2 shows the interface, with an image of southern corn leaf blight symptoms as example.

2.2.1. Basic processing

The first task was the segmentation of the leaf containing the symptoms in order to remove the background. If the leaf is isolated from the background by some kind of screen, the task is trivial, however this was not the case for many of the images used in this work. As a result, the Guided Active Contour