Automatic Image-Based Detection and Recognition of Plant Diseases – A Critical View

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ABSTRACT

This paper presents a critical analysis of the current state and future perspectives for the use of digital images applied to plant pathology. The differences between the processes of automatic detection and recognition of diseases in plants are presented, with emphasis on the respective current challenges and difficulties. Some of the limitations intrinsic to the use of digital images for detection and recognition of diseases are discussed. Because some of those limitations are mostly inevitable, they may require the use of ancillary data, which may not always be obtained automatically. As a result, depending on the application, the development of completely automatic diagnosis methods may be unfeasible. Thus, the main objective of this paper is to show that one of the main causes for the low relevance attributed to most algorithms proposed so far is the lack of knowledge by the researchers, especially regarding the real difficulties involved in the diagnosis process. The text concludes showing that significant advancements in this area will only be achieved through careful experimental delineation, realistic objectives, and construction of an image database capable of suitably represent all variations expected to occur within the scope of the algorithm to be developed.

KEYWORDS: Disease diagnosis, Image processing, Plant pathology.

RESUMO

Este artigo apresenta uma análise crítica da situação atual e das perspectivas futuras do uso de imagens digitais aplicadas à fitopatologia. São apresentadas as diferenças entre os processos de detecção e reconhecimento automático de doenças em plantas, com destaque para os respectivos desafios e dificuldades enfrentados na atualidade. Em seguida, são discutidas algumas das limitações intrínsecas ao uso de imagens digitais para detecção e reconhecimento de doenças. Tais limitações, por serem em sua maior parte inevitáveis, podem demandar o uso de dados auxiliares, os quais nem sempre podem ser obtidos automaticamente. Como resultado, dependendo do tipo de aplicação, o desenvolvimento de métodos de diagnóstico totalmente automáticos pode ser inviável. Com isso, chega-se ao principal objetivo deste artigo, que é mostrar que uma das principais causas para a pouca relevância atribuída à maioria dos algoritmos propostos até o presente é a falta de conhecimento por parte dos pesquisadores, especialmente a respeito das reais dificuldades envolvidas no processo de diagnóstico. Conclui-se mostrando que avanços significativos na área só poderão ser alcançados através de cuidadoso delineamento experimental, estabelecimento de objetivos realistas, e construção de bases de imagens capazes de representar adequadamente todas as variações esperadas dentro do escopo do algoritmo a ser desenvolvido.

PALAVRAS-CHAVE: Diagnóstico de doenças, Processamento de imagens, Fitopatologia.

INTRODUCTION

Plant diseases cause significant economic, social and environmental losses. Timely diagnosis is thus very important, so corrective and preventive measures can be quickly implemented. The detection and identification of diseases are mostly performed visually and without a systematic strategy. In this context, the detection and recognition of diseases using digital images can greatly contribute to improve the response to plant pathologies.

At this point, it is important to make a distinction between the detection and recognition (or identification) tasks. The former aims at detecting a specific disease of interest, usually with potential to cause significant damage, while the latter aims at detecting symptoms and determine their origins. The detection task can be seen as a recognition task in which there are only two classes, the disease of interest and everything else (other diseases, healthy tissue, etc.). Thus, although both tasks are challenging, the recognition issue is usually more difficult, especially if the aim is to identify every type of disorder that can affect a given plant.

Among the imaging techniques that can be used for plant disease analysis, the most common are the fluorescence (BAURIEGEL; GIEBEL; HERPPICH, 2010; BELIN et al., 2013), multispectral and hyperspectral (BARBEDO; TIBOLA; FERNANDES, 2015; OBERTI et al., 2014), and conventional photographs (BARBEDO; KOENIGKAN; SANTOS, 2016; POURREZA et al., 2015). The difficulties related to the use of digital images in plant pathology applications were thoroughly explored in Barbedo (2016). The challenges mentioned in that work will serve as reference for many of the issues discussed throughout this text, especially regarding conventional photographs in the visible spectrum.

The adoption of image-based tools in plant pathology applications has been slow. This is due to the technical limitations that still permeate all of those tools, which, in turn, are due to both technical difficulties and unrealistic or incomplete knowledge about the problem. While Barbedo (2016) focused on the technical aspects, this paper gives more emphasis to the flaws in design, validation and perception that lead to the development of methods of limited usefulness. It also discusses some ways to avoid this kind of problem, offering a perspective on possible solutions to be explored in the future.

CURRENT PROBLEMS, THEIR REASONS AND POSSIBLE SOLUTIONS

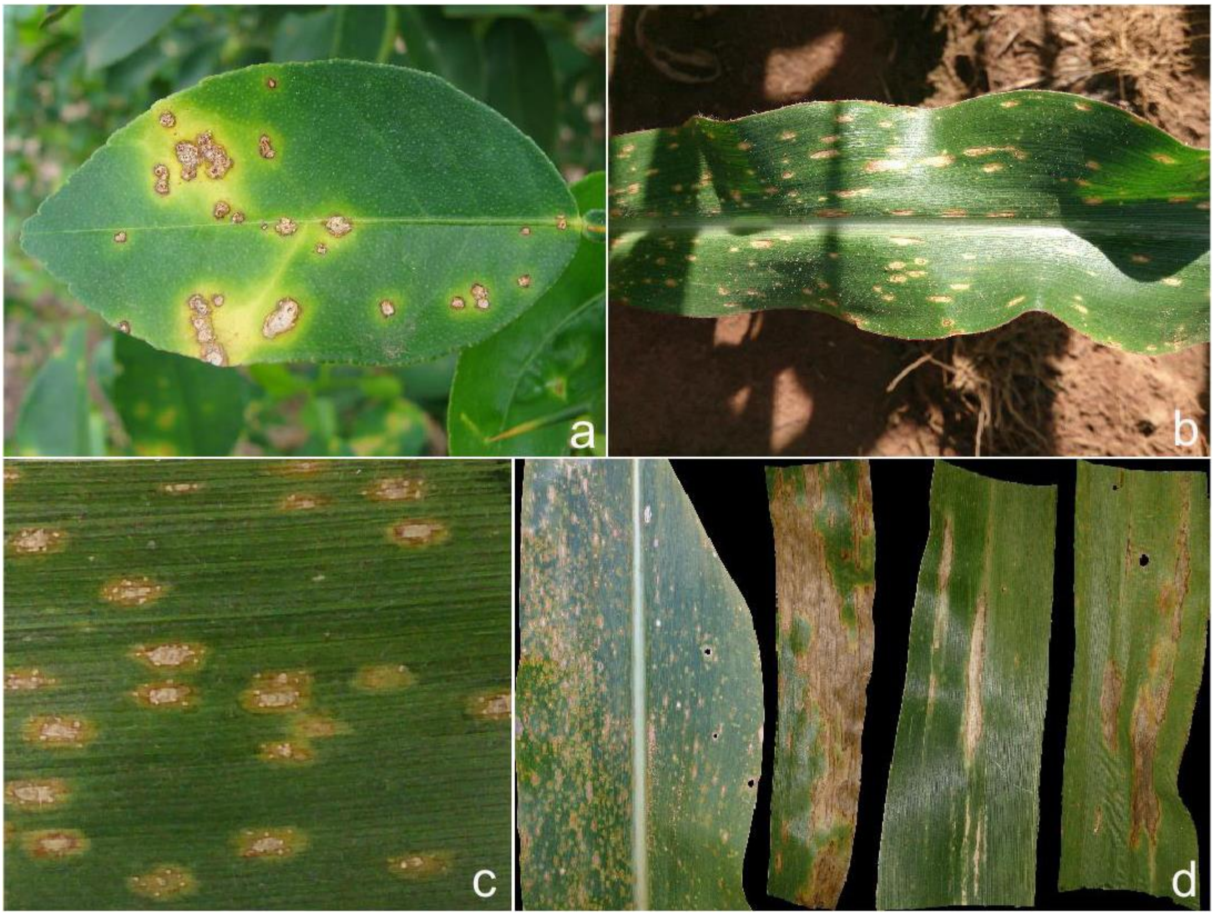
Most problems are common to both the detection and recognition issues. However, as these also have some specific issues, this section is divided into three subsections, one general and two dedicated to the specific issues.

General Issues

Barbedo (2016) identified several challenges that prevent the development of suitable solutions that hold for a wide range of situations (some examples can be found in Figure 1). Those factors should be carefully considered when evaluating any new algorithm, but the majority of studies ignore most or all of them. As a consequence, those algorithms are never validated under realistic conditions. This largely explains why most of those algorithms never find practical applications. A discussion about the consequences of ignoring those factors is presented next.

The background often contains elements that make it very difficult to correctly segment the region of interest where the symptoms are manifesting (BARBEDO, 2016), as seen in Figure 1a. In order to avoid problems associated with this fact, many studies either remove the parts containing the symptoms and image them in a controlled environment with a neutral background (HUANG, 2007), or remove the background manually before applying the algorithm (KRUSE et al., 2014). While the latter prevents the method from being fully automatic, the problem with the former is that it is often not practical to remove parts of the plants, neither to access controlled environments, even if using portable devices (DE CONINCK et al., 2011). A potentially viable solution would be using a panel behind the leaf (MOYA; BARRALESA; APABLAZA, 2005). However, it is not always easy to keep the panel steady and capture the image at the same time. More importantly, the potential client for the tool will usually detect the symptoms during normal everyday activities, and it would be unlikely that this person would carry the panel at all times. The ideal solution for the problem would be the automatic removal of the background. This has been tried by some authors (ALENYÀ et al., 2013), but this is a very difficult problem by itself that still needs further research.

Figure 1 – a) Example of busy background. b) Example of illumination variation. c) Example of symptoms with unclear edges. d) Variation in symptoms of a corn disease.



Capture conditions in the field can vary greatly, making disease identification very challenging. Again, many authors solve this problem simply by capturing the images under controlled conditions (CLÉMENT et al., 2015). This may be unpractical in real world applications, especially considering that many crop fields are located in remote areas. There are many factor that influence capture conditions: illumination variations (Figure 1b), specular reflections, angle of capture, optical quality of the equipment, image compression, etc. All those factors are relevant in the field, thus if a method fails to take them all into consideration, the probability of failure increases.

Recognition Issues

Most methods involve some kind of segmentation prior to the identification of the disease. Defining the region to be segmented is not a well-defined task, because most symptoms do not have a clear boundary. Instead, they gradually fade into healthy tissue (Figure 1c). As a result, small changes in the parameters of the segmentation procedure (e.g. pixel value threshold) may result in widely diverse segmentations, as more or less of the transition region is considered. In cases like these, there is no ground-truth to be pursued, and the segmentation may be considered correct as long as it includes the whole core of the symptom and does not include healthy tissue. An undesirable consequence of this fact is that the amount of the transition region remaining after the segmentation will vary from image to image, and this may have a great impact on the classification accuracy, especially if it employs features based on color and texture. This is true even when an adaptive approach is used (BARBEDO, 2014). Few methods take this issue into consideration, and even fewer propose a solution for this difficult problem. The most promising approach seems to be avoiding segmentation altogether by formulating the problem directly as an image categorization task, in which context deep convolutional neural networks have played an important role (BARBEDO, 2016; ZHANG et al., 2014).

Intraclass variations are very prominent for most plant diseases (Figure 1d). Those variations may be caused by factors such as plant genotype, variations on healthy tissue color, leaf age, humidity, exposure to sunlight, temperature, wind, etc. (BARBEDO, 2016). However, most techniques proposed in the literature are validated using very small image databases that do not properly cover the variety of symptoms that can be found for each disease. As a result, those techniques tend to fail when used under more realistic conditions. This fact highlights the need for the construction of more comprehensive databases, which is not a trivial task given the difficulties involved (BARBEDO, 2016).

Interclass similarities are also an important factor. Detecting the differences between classes is the primary objective of any disease classification method, so every technique in the literature considers this one way or another. However, since those studies often fail to consider the entire range of symptom variations, two diseases that appear very dissimilar under this limited setup may have relevant similarities when the variety of symptoms is better represented. The consequences and respective solutions for this problem are the same discussed for the intraclass variations.

The vast majority of studies ignore the fact that multiple diseases may manifest simultaneously, with a few exceptions (ZHANG; MENG, 2011). This is a very damaging limitation, not only because this kind of situation is very common, but also because the interaction between diseases may produce symptoms with diverse characteristics. On the other hand, this is arguably the most difficult limitation to be overcome. As discussed before, it is quite difficult to build image databases encompassing the whole range of symptoms for the diseases of interest, so the task becomes massive if all possible combinations of diseases are to be considered. Thus, a solution for this problem is not expected in the near future (BARBEDO, 2016).

Even if every precaution is taken and state of the art techniques are used, it may not be possible to resolve all ambiguities and reach a reliable diagnosis. Some authors try to minimize this problem by applying fuzzy logic (XU et al., 2011). However, even this kind of approach cannot deal with all uncertainties, which means that some kind of ancillary data, such as geographic distribution of diseases, historical reports, etc., may be necessary. Ultimately, in some cases laboratorial analysis may be the only way to obtain a reliable diagnosis.

Detection Issues

Detection algorithms are usually intended to be used in the field with fixed sensors without supervision, which creates some specific problems that need addressing.

Many diseases, particularly those caused by fungi, have symptoms that manifest on the bottom of the leaves, making them very difficult to be detected by sensors mounted in fixed supports. A possible solution for this issue would be using small robotic rovers capable of going underneath plant canopies. There are some initiatives towards this goal, but much research has yet to be done before it becomes a viable solution.

The lack of sensor mobility may bring other problems. As plants grow, their canopy architecture changes, so the initial position of the sensor may no longer be appropriate. This may be minimized by placing the sensors farther away from the plants, thus covering a larger area. On the other hand, this procedure requires higher resolutions in order to discriminate finer details that may be important for disease detection. Again, mobile sensors seem to be the best solution given their adaptability to different situations.

Monitoring large areas is also challenging. Although there are some areas more likely to be the point of origin for infections, the first symptoms may occur anywhere in the property. In order to assure a timely response, it may be necessary to place a large number of sensors in strategic positions, which may be expensive and, more importantly, may demand a complex communications system for data transmission. Once again, mobile sensors may dramatically reduce the number of devices needed, as they can theoretically cover large extensions relatively quickly.

Although weather-resistant equipment and devices are common, extreme events may cause considerable damage. Thus, equipment placed in areas prone to such extreme weather events may have to include some extra protection, but even if this is the case, it is important to have replacements ready in case of damage.

DISCUSSION

Most technical issues discussed in the last section depend on the construction of more comprehensive databases to be suitably addressed. Some commercial tools, such as Plantix™ (plantix.net), are starting to break the barrier of database representativeness by developing networks of producers and agronomists to capture and label images of symptoms. However, even these more successful tools have a relatively limited scope regarding plant species and variety of diseases, so a lot more effort has to be spent for their expansion.

As mentioned before, the adoption of image-based tools applied to plant pathology has been slow. The technical difficulties discussed above play an important role, but are not the only reasons for this situation. With the expansion of the smartphone user base, and with most software tools being implemented in the form of applications, it would be reasonable to expect a sharp growth in the use of software tools aimed at agricultural applications. The adoption of this kind of technology by producers is slowed down by two opposite factors. First, many people are naturally skeptical about the ability of technology to replace, with advantages, the processes that have been executed manually for generations. In the opposite side of the spectrum, there are people that have unrealistic high expectations about the performance of those same tools. As a result, they deem the application unsuitable and unreliable, quickly abandoning its use. Thus, it is important to educate potential users about the advantages and limitations of those technologies, making it possible to their potential to be fully realized.

CONCLUSIONS

This paper presented a critical view about some of the main challenges and limitations that still affect the practical adoption of technologies related to the automation of plant pathology activities. It was argued that the main technological barriers can only be overcome, or at least minimized, by the expansion of the existing image databases for plant diseases and by advances in robotics (especially rovers). It was also discussed that unrealistic expectations, both negative and positive, are a major adverse factor in the adoption of low-cost automation technologies in agriculture. Despite those barriers, image-based technologies applied to agriculture are evolving faster than ever, which means that many of the technical difficulties should soon be overcome.

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