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Review

A review on the main challenges in automatic plant disease identification based on visible range images

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The problem associated with automatic plant disease identification using visible range images has received considerable attention in the last two decades, however the techniques proposed so far are usually limited in their scope and dependent on ideal capture conditions in order to work properly. This apparent lack of significant advancements may be partially explained by some difficult challenges posed by the subject: presence of complex backgrounds that cannot be easily separated from the region of interest (usually leaf and stem), boundaries of the symptoms often are not well defined, uncontrolled capture conditions may present characteristics that make the image analysis more difficult, certain diseases produce symptoms with a wide range of characteristics, the symptoms produced by different diseases may be very similar, and they may be present simultaneously. This paper provides an analysis of each one of those challenges, emphasizing both the problems that they may cause and how they may have potentially affected the techniques proposed in the past. Some possible solutions capable of overcoming at least some of those challenges are proposed.

1. Introduction

Plant disease identification is one of the most basic and important activities in agriculture. In most cases, identification is performed manually, either visually or by microscopy. The problem with visual assessment is that, being a subjective task, it is prone to psychological and cognitive phenomena that may lead to bias, optical illusions and, ultimately, to error. On the other hand, laboratorial analyses such as molecular, immunological or pathogen culturing-based approaches are often time consuming, failing to provide answers in a timely manner. In this context, it is compelling to develop automatic methods capable of identifying diseases in a rapid and reliable way. The vast majority of automatic methods proposed so far rely on digital images, which allows the use of very fast techniques. However, intrinsic and extrinsic factors mean these methods remain too error prone, which was the motivation for the current review.

Most of the methods described in the literature are based on digital images of symptoms in the visible and near-infrared bands (Barbedo, 2013), with those bands being considered in isolation or represented in multi and hyperspectral images. Although multi and hyperspectral images can potentially

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Nomenclature

IR	Infrared
LED	Light Emitting Diode
VR	Visible Range

carry more information than normal photographs, they are usually captured by expensive and bulky sensors, while conventional cameras are ubiquitous and present in many consumer-level electronics stores. This has resulted in developing systems based on the visible range, which also leads to a more focused discussion. More information on multi and hyperspectral imaging applied to plant pathology can be found in Sankaran, Mishra, Ehsani, and Davis (2010) and Bock, Poole, Parker, and Gottwald (2010).

Some of the methods exploring visible range images focus on detecting a single disease of interest amidst other diseases, healthy tissue, nutritional problems and pests (Barbedo, Tibola, & Fernandes, 2015; Oberti et al., 2014; Polder, van der Heijden, van Doorn, & Baltissen, 2014; Pourreza, Lee, Ehsani, Schueller, & Raveh, 2015, Pourreza, Lee, Etxeberria, & Banerjee, 2015; Zhang, Yuan, Pu, Loraamm, Yang, & Wang, 2014; Zhou, Kaneko, Tanaka, Kayamori, & Shimizu, 2014), while others try to detect and discriminate different diseases. Although progress has been made regarding the disease classification problem, the vast majority of the methods are only capable of discriminating among a small number of diseases (Phadikar, Sil, & Das, 2013; Pydipati, Burks, & Lee, 2006; Sanyal & Patel, 2008). In general, this is too limited for real-world applications, because the number of pathogens that can simultaneously infect a plant and cause disease symptoms is usually higher. Also, nutritional deficiencies (Pagola et al., 2009; Romualdo et al., 2014; Wiwart, Fordonski, Zuk-Golaszewska, & Suchowilska, 2009) and pests (Clément, Verfaille, Lormel, & Jaloux, 2015; Koumpouros et al., 2004; Škaloudová, Křivan, & Zemek, 2006) may produce symptoms that mimic very closely the characteristics of some diseases. To make matters even more complicated, there are some challenges that affect virtually all studies devoted to the automation of the disease diagnosis process and that have not yet been properly investigated. The objective of this review was to identify some of the most important of those challenges, to explore in depth their causes and their impact on the performance of the techniques proposed so far, and to propose some possible avenues to be explored in order to mitigate or eliminate their adverse effects. The challenges selected as the most impactful were the following:

- The background often contains elements that can make it very difficult to correctly segment the region of interest where the symptoms are manifest.
- Capture conditions are difficult to control, which may cause the images to present characteristics that are difficult to predict and make the disease identification more challenging.
- Most symptoms do not have well defined boundaries, rather gradually fading into normal tissue, making it difficult to clearly define which are the healthy and diseased regions.
- A given disease may possess very different characteristics depending on its stage of development, and sometimes on where it is located on the plant.
- Symptoms produced by different diseases may be present simultaneously, manifesting either physically separated or combined into a "hybrid" symptom that may be difficult to identify.
- Symptoms produced by different diseases may be visually similar, which forces the methods to rely on very tenuous differences to discriminate among them.

The first two challenges can be viewed as extrinsic factors, while the remaining four are intrinsic to the problem.

It is important to highlight that, although the focus is on the identification of plant diseases, the challenges discussed here are also relevant for disease severity measurement, with some references on the matter also being included. In fact, the only major difference is that accurately outlining the symptoms is not necessarily critical for disease identification, while it is paramount for severity measurement. All other challenges cited above have roughly the same importance for both issues, especially considering that the disease identification may be a necessary intermediate step for the severity measurement, particularly when multiple diseases are expected to coexist.

Because of space limitations, technical details about the methods, including the software used, were omitted, but a comprehensive discussion on the matter can be found in Barbedo (2013). The discussions presented were based on research reported primarily for leaf symptoms (by far the most explored), however they are, for the most part, valid for other plant parts, including stem, fruit and flowers.

2. Extrinsic factors

2.1. *Image background*

Leaf segmentation is the first step of most image-based tools for leaf analysis. If some kind of panel (preferably white or blue) is placed behind the leaf, this task can usually be performed automatically without much problem. On the other hand, if the background contains plants, leaves, soil and other elements, the segmentation may be a challenge.

Segmenting the leaf is particularly difficult when the background has a significant amount of green elements, for example as in Fig. 1. The segmentation of leaves from busy backgrounds is a problem that has received some attention: Zhang and Meng (2011) directly separated the lesions from leaf and background using a two-step hierarchical matching procedure; Alenyà, Dellen, Foix, and Torras (2013) used depth information for localizing the leaves and extracting them from the rest of the image; while Wang, He, Han, Ouyang, and Li (2013) used the so-called marker controlled watershed segmentation, which is based on the selection of certain local minima from the image's gradient as control markers, for separating leaves from the rest of the image.

Fig. 1 – Example of busy background.

Other researchers chose to tackle the problem under more controlled conditions, in which the images of plants placed in pots are captured in the laboratory. In this case, usually only the pot and compost are to be removed from the image. The solutions used in this case range from traditional vegetation indices (Sena, Pinto, Queiroz, & Viana, 2003) to probabilistic frameworks (Huang, 2007).

The vast majority of studies either remove the background manually (Cui, Zhang, Li, Zhao, & Hartman, 2009, 2010; Kruse et al., 2014), or isolate the leaf from other elements prior to image capture. The latter may be achieved in a number of different ways, such as using a panel behind the leaf (Moya, Barralesa, & Apablaza, 2005), or detaching the leaves and placing them in Petri dishes (Škaloudová et al., 2006; Olmstead, Lang, & Grove, 2001; Peressotti, Duchêne, Merdinoglu, & Mestre, 2011), using scanners (Berner & Paxson, 2003; Boissard, Martin, & Moisan, 2008; Romualdo et al. 2014), containers (Pydipati et al., 2006; Wijekoon, Goodwin, & Hsiang, 2008), boards (Wiwart et al., 2009), closed boxes (De Coninck et al., 2011; Xu, Zhang, Shah, Ye, & Mao, 2011) and devices specially designed for image capture (Boese, Clinton, Dennis, Golden, & Kim, 2008; Clément et al., 2015; Martin & Rybicki, 1998; Tucker & Chakraborty, 1997).

It is worth mentioning that if the constraint of using only visible light is relaxed, better background segmentation may be achieved, provided that such a background does not include leaves similar to the one selected for analysis. This was explored by Polder et al. (2014), who employed all channels of a multispectral camera for separating tulip plants from the background.

There are possible solutions to segmentation issues that have not yet been explored. One possible strategy for isolating the objects of interest is creating a measurement for the sharpness of their main features, since those objects will tend to be focused more sharply than the rest of the image, as can be clearly seen in Fig. 1. Also, if the images are captured manually, the objects of interest will tend to be located in the centre of the image, which is information that can be used to narrow the objects of interest (this approach will not be reliable if the capture is performed automatically by a machine). Finally, improvements in edge detection procedures may provide more powerful tools for improved delimitation of all elements present in the image, which would greatly benefit all types of segmentation. A good example of recent advancement on this subject can be found in Dollár and Zitnick, 2014.

2.2. *Image capture conditions*

Several factors may influence the characteristics of the images, making it more difficult for an automatic algorithm to perform a meaningful analysis. Ideally, all images should be captured under the same conditions. In practice, this can only be achieved in a controlled environment, such as a laboratory. However, a software for automatic identification of diseases is more useful if it can be used in the field, where conditions may be partially controlled, if at all. Thus, a more realistic approach is to study the impact of the main factors affecting segmentation, and subsequently design methods to deal with them.

Illumination concerns are especially important in the field, where aspects such as time of day, position of the sun with respect to the leaf, and overcast conditions, can greatly affect image characteristics. Variation in illumination is unavoidable. Varying capture conditions were mentioned as a major problem in the context of citrus canker severity measurement (Bock, Cook, Parker, & Gottwald, 2009), analysis of *Zostera marina* leaf injuries (Boese et al., 2008), and identification of citrus diseases (Pydipati et al., 2006). Some effort has been made toward the development of illumination invariant methods (Guo, Rage, & Ninomiya, 2013; Ye, Cao, Yu, & Bai, 2015), but their success has been modest so far. In any case, some serious illumination problems can be avoided or minimized, as discussed below.

One of the most difficult illumination issues to deal with is specular lighting, which is a high intensity reflection that occurs at certain angles of view. This phenomenon can be minimized by altering the angle of capture and/or the position of the leaf, although some degree of reflection will almost always occur. Another problem that can be minimized, or even avoided, is the simultaneous presence of shadow and direct illumination. In fact, a shadow should be cast over the leaf during the capture whenever possible. Zhou et al. (2014, 2015) reported shadows and specular reflections as primary sources of error when monitoring the presence *Cercospora* leaf spot on sugar beet leaves. This happened because the captures were automated, making it more difficult to prevent illumination problems. An example of an image containing both specular and light/shadow effects is shown in Fig. 2.

It is important to note that, even under the controlled environment of laboratories, there will be illumination variations that can cause problems for segmentation. Peressotti et al. (2011) observed that more tightly controlled illumination conditions would probably improve the results obtained for computer-aided quantification of grapevine downy mildew sporulation. Although the variation is nearly impossible to be eliminated completely, there have been some attempts to reduce them to a minimum, such as the method proposed by Clément et al. (2015), which employs a carefully designed set of illuminants for conditions as uniform as possible, and the one proposed by Pourreza, Lee, and Ehsani (2015) and Pourreza, Lee, and Etxeberria (2015), which uses a

Fig. 2 – Example of a leaf image with specular reflections and several light/shadow transitions.

customized LED-based illumination system and a set of polarization filters for detecting Huanglongbing in citrus leaves.

Another factor that influences the image is the angle of capture. Ideally, the leaf should be perfectly perpendicular to the central axis of the sensor during the capture, because slanted angles may cause some parts of the leaf to be out of focus. Pourreza, Lee, and Ehsani (2015) and Pourreza, Lee, and Etxeberria (2015) experienced difficulties with capturing analysable images when they tried to apply their system to detecting Huanglongbing in leaves attached to a tree, as the leaves presented a range of orientation. Boese et al. (2008) observed that curled and wrinkled leaves may also cause localized loss of focus, a fact that motivated Clément et al. (2015) to develop an experimental suction table for mechanically flattening the leaves.

Interestingly, a counterpoint to the perpendicular angle of capture being considered ideal was given by Oberti et al. (2014). They analysed different angles of capture for detecting powdery mildew in grapevine leaves, coming to the conclusion that angles between 40° and 60° are the most appropriate. They state "the reason for this may likely be related to the fact that at initial stages the filamentous structures of the mycelium start to grow vertically from hosting tissue, and hence their impact on leaf reflectance can be largely emphasized by observing by an angle the back-scattered light from these structures". It should be stated that those results were obtained using multispectral images, so it is not clear if they can be extended to images captured exclusively in the visible range.

The equipment used in image capture may also impact the characteristics of the images. Although image resolution is an important factor, most devices nowadays offer resolutions that should be enough for detecting even small lesions and spores. Optical quality and image compression, on the other hand, play much more important roles. High-end DSLR (digital single-lens reflex) cameras will always provide better optical performance than a mobile phone camera. Fortunately, the technology has evolved to a point where even low-end mobile phones have cameras that, under well illuminated conditions, can provide images of reasonable quality. However, very small symptoms will be flawlessly outlined only in images with very sharp features, which may require an equipment with superior optical quality and capable of a higher resolution.

With respect to image processing and storage, the greater the compression, the more information is lost. This may not affect much the analysis of large lesions, but may cause small symptoms to become highly distorted and, depending on the compression factor, nearly undetectable. Thus, image compression should be kept to a minimum, or even completely avoided, especially in the case of small symptoms. More information on this matter can be found in Steddom, McMullen, Schatz, and Rush (2005).

3. Intrinsic factors

3.1. *Symptom segmentation*

As commented before, most symptoms do not have well defined edges. Instead, they gradually fade into healthy tissue (Fig. 3). As a result, there is no unambiguous segmentation. If manual, visual delineation cannot clearly determine the boundary, it will leave any machine-based delineation open to subjective question too. The main advantage of using the latter might be consistency among images, but even this is questionable as image/symptom variability is another problem superimposed on symptoms with poorly defined edges. This may affect the accuracy of thresholding and other procedures, even if some kind of adaptive scheme is adopted (Barbedo, 2014; Camargo & Smith, 2009).

The problem of subjectively delimiting diseased areas was first addressed by Olmstead et al. (2001), and subsequently by Moya et al. (2005), who stated that some kind of external standard or reference should be created in order to properly validate methods for disease detection and identification.

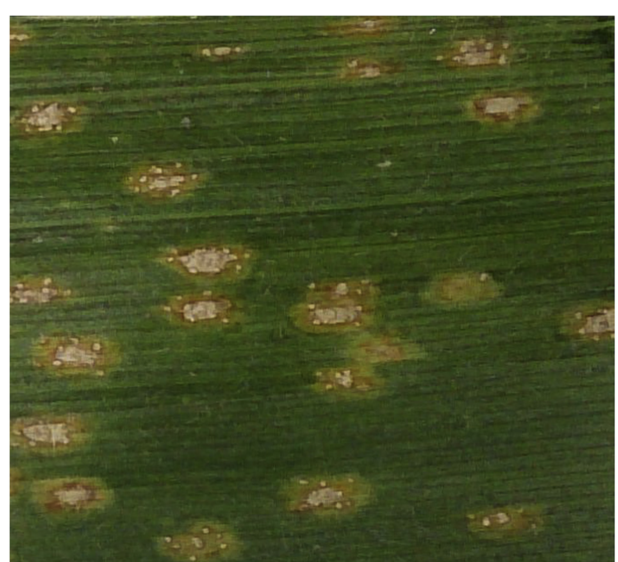

Fig. 3 – Example of symptoms with no clear edges.

When a reference is not used, the number of false negatives or false positives found in the fading regions of symptoms is inflated, as observed by Oberti et al. (2014) for powdery mildew on grapevine leaves, and by Kruse et al. (2014) for injuries on lettuce leaves.

It is worth noting that changing the edges of the segmented regions may have a big impact on the features extracted to describe those regions. This was the case of the method proposed by Bock, Parker, Cook, and Gottwald (2008), who observed differences in the detection accuracy when the delimitation of citrus canker lesions was manually varied.

Some proposals group the pixels into a number of clusters instead of simply dividing the regions into healthy and diseased (e.g. Boese et al., 2008). If the clustering is performed properly, one cluster will correspond to the most acute parts of the lesion, while the transition regions will be represented by one or more clusters, depending on their characteristics. The problem with this approach is that the labelling of the clusters is almost always manual, in a process that is thus highly subjective.

There are not many solutions to the problem of symptom segmentation, because the inconsistencies are intrinsic to the process. However, some groups have investigated the possibility of adopting alternative approaches which avoid segmentation altogether. One of those alternatives was investigated by Cui, Zhang, Li, Hartman, and Zhao (2010), who used the centroid of the leaf colour distribution in the polar coordinate system for extracting information about the leaf's health. Also, some techniques allow the problem to be formulated directly as an image categorization task, in which context deep convolutional neural networks have played an important role (Lin, RoyChowdhury, & Maji, 2015; Zhang, Donahue, Girshick, & Darrell, 2014; Zhang et al., 2015).

Ultimately, the accuracy of symptom segmentation will always have to be judged according to the context in which it is carried out. In many cases, mild inconsistencies in the segmentation will have little impact on the final results, while in other instances tighter control will be critical. In other words, this problem is highly application-dependent, and its various underlying aspects need to be analysed and addressed as such.

3.2. *Symptom variations*

A common assumption associated with specific disease identification is that the symptoms will always have the same characteristics. Indeed, many disease symptoms are characteristic and readily identified by an expert. However, there is invariably some variation in the colour, shape and size of symptoms. This creates problems for image-based diagnostics using the visible spectrum to delineate ‘healthy’ or ‘diseased’ pixels. Many factors may modify symptom characteristics. In some cases, the symptoms are the result of the interaction between disease, plant and environment, and changes in any of those elements may alter the symptom, as discussed below.

Disease: different stages of development may produce quite different symptoms. Bock et al. (2008) observed that the symptoms produced by the citrus canker in grapefruit leaves change as the infection progresses, making its detection and identification a complex task. The same problem was pointed out by Zhang and Meng (2011), who used a hierarchical classification scheme, combined with a set of features, to reliably identify the canker lesions. Additionally, some diseases produce symptoms that are highly heterogeneous and that possess a highly variable distribution, making them difficult to characterize. This was observed by Camargo and Smith (2009) when dealing with symptoms caused by black leaf streak disease in banana leaves, and by Moya et al. (2005) when assessing the severity of powdery mildew on squash leaves. Finally, different diseases may be present simultaneously, and the combination of symptoms may be quite different from the individual ones (see Section 6).

Plant: the literature presents three main plant-related factors that may influence the characteristics of the symptoms. The first, the plant's genotype, was shown to affect the visual estimation of sunflower blight (Tucker & Chakraborty, 1997) and downy mildew on grapevine leaves (Peressotti et al., 2011). The second, healthy tissue colour variation (and consequent contrast alterations), was reported to be an important source of error in the analysis of *Z. marina* leaf injuries (Boese et al., 2008), quantification of foliar discolouration (Clément et al., 2015), and detection of injuries in lettuce leaves (Kruse et al., 2014). The third, leaf age, was identified as an important factor by Zhang and Meng (2011), who reported that citrus canker symptoms are strongly influenced by age, and by Zhou, Kaneko, Tanaka, Kayamori, and Shimizu (2015), who pointed out that older sugar beet leaves tend to present more severe symptoms of *Cercospora* leaf spot.

Environment: factors like humidity, exposure to sunlight, temperature, wind, and other meteorological phenomena may also alter the symptoms. In this context, Zhou et al. (2014) remarked that weather conditions caused the morphological characteristics of sugar beet leaves to change considerably, making the detection of *Cercospora* leaf spot more challenging. A more specific problem was faced by Polder et al. (2014), who reported that the presence of rain or droplets severely hampered the effectiveness of the system they used for disease severity estimation.

Some diseases are more prone to symptom variations than others. Figure 4 shows an example of the variation found in symptoms of Southern corn leaf blight. A possible solution to this problem is to capture images that cover the

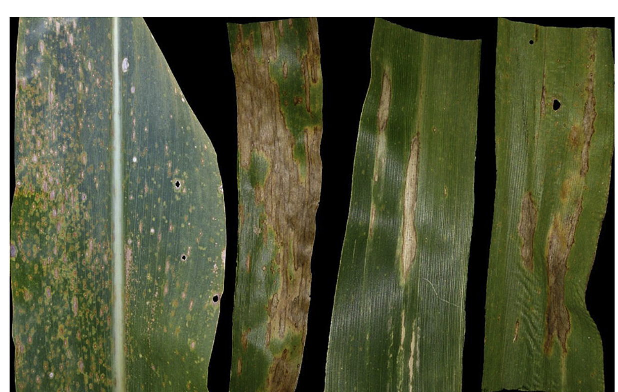

Fig. 4 – Variation in symptoms of Southern corn leaf blight.

entire range of variation, so the algorithm being developed can be properly trained. This is a very complex and time consuming task, because not only does it depend on the right opportunity, but it is nearly impossible to know when the whole range of variation has been captured. Continuously adding new image samples to the database, gradually expanding it to a truly comprehensive set, may reduce the impact of this problem.

3.3. Multiple simultaneous disorders

Many algorithms assume that only one disease is present in each image. However, other diseases, as well as other kinds of disorders such as nutritional deficiencies and pests, may manifest simultaneously. This is exemplified in Fig. 5, where two diseases are present on the same leaf. This is quite common because, as a plant immune system is weakened by an infection, other disorders can more easily move in. Ahmad, Reid, Paulsen, and Sinclair (1999) and Bock et al. (2009) have both observed the simultaneous presence of symptoms caused by different diseases, remarking that this could result in identification problems and that further advance would be necessary in order to tackle this situation.

When symptoms of different disorders manifest simultaneously, but are physically separated, one possible solution would be to analyse each individual diseased area (spot, lesion, spore, etc.) separately, assigning a different label to each one of them. This was the approach adopted by Zhang and Meng (2011), who used an hierarchical classifier for discriminating canker lesions from other types of symptoms. This approach is not always applicable though, especially in the case of diseases that produce very small lesions or powder-like symptoms, because they either carry too little information to be treated individually, or they cannot be resolved at all.

If the symptoms cohabit the same space, the resulting symptoms may depart dramatically from the characteristics expected for the original diseases. Again, the solution would be to train the algorithm to recognize such cases, which would demand suitable images showing the possible variations for such a combination. However, if generating comprehensive databases for isolated symptoms of individual diseases is a daunting task by itself, trying to create a database containing combinations of symptoms is nearly impossible, not only because they are much rarer, but also because they are challenging to identify visually. Thus, a solution for this problem is not expected in the near future.

Fig. 5 – Coffee leaf containing symptoms of rust and *Cercospora* leaf spot.

3.4. Different disorders with similar symptoms

One of the main challenges faced by methods of automated plant disease diagnosis is the similarity of the symptoms among different disorders, which include diseases, nutritional deficiencies, pests, phytotoxicity, excessive cold or heat, and varied mechanical damage. The range of possible disorders is wide, making it very challenging to identify the origins of a given symptom with certainty, especially if only the visible spectrum is used. In some cases, the use of other spectral bands like infrared may provide enough information to distinguish between those disorders (Aleixos, Blasco, Navarrón, & Moltó, 2002; Belin, Rousseau, Boureau, & Caffier, 2013; Cui et al., 2010; Dammera, Möller, Rodemann, & Heppner, 2011; Oberti et al. 2014). However, this may increase the costs associated with image capture, and most mobile telecommunication devices are not capable of capturing images in those additional bands, which again may prevent many potential users from adopting the technology. Also, it is important to note that some ambiguities cannot be resolved even when using several spectral bands.

A comprehensive study on this topic is yet to be performed due to the lack of image databases. In fact, most studies to date have chosen to discriminate only diseases with relatively dissimilar symptoms, because even those cases still pose significant challenges given the current ability of the technology. Some authors, however, reported that certain disorders had similarities substantial enough to cause issues in differentiation. Ahmad et al. (1999) observed multiple instances in which symptoms caused by *Alternaria* sp., *Phomopsis* sp., *Fusarium* sp. and mosaic potyvirus in soybean seeds were so similar their algorithm could not differentiate them. Wiwart et al. (2009) reported significant similarities in the visible characteristics of different nutritional deficiencies, and that those similarities vary according to the plant species.

The difficulty experienced in segmenting and separating disease symptoms varies considerably and is affected by the techniques used. As a result, it is often difficult to evaluate the performance of different methods, because the error rates are related both to the issues of the symptoms being analysed and to flaws in the techniques used in the study. Thus, it is very important that the experimental methods and techniques be thoroughly described, especially regarding the database used in the tests. This problem could be minimized if more image databases were made available for academic purposes, as this would allow different methods to be tested under the same conditions (i.e., using the same images).

4. Other challenges

There are some other challenges that affect automatic disease identification that cannot be categorized together with those already discussed. The first is real-time operation. Although all proposed methods are expected to operate under certain time constraints, only a few applications actually require real-time operation. Since the computational power available continues to grow, meeting real-time requirements would be expected to be easier with time. However, the resolution of the images also increases, thus demanding more computational resources. Also, portable devices and low cost computers such as Raspberry Pi (Raspberry Pi Foundation, Cambridgeshire, UK), have limited resources. Thus, depending on the intended application, reducing computational complexity and memory requirements may be a major concern. Using efficient programming languages, structuring the code to avoid unnecessary stress on computational resources, and reducing the image resolution during the processing are among the most common solutions adopted for reducing computational requirements.

Another problem that is very common arises from differences between the distributions of the training data used to learn the model and the data on which the model is to be applied, a situation that is commonly called covariate shift (Sugiyama, Nakajima, Kashima, Bünau, & Kawanabe, 2007). This is very relevant in the context of automatic identification of plant diseases, because the characteristics of the symptoms may vary with the geographic position, falling into the same problems described in Section 3.2. There is an entire area, the so-called "domain adaptation", dedicated to mitigating this problem (Ben-David et al., 2010). This includes techniques such as domain adaptation support vector machines (Bruzzone & Marconcini, 2010), Bayesian divergence prior (Li & Bilmes, 2007), PAC-Bayesian analysis (Germain, Laviolette, Habrard, & Morvant, 2015), transfer component analysis (Pan, Tsang, Kwok, & Yang, 2011), among others (see Jiang (2008) and Margolis (2011)).

5. Future prospects and possible solutions for the current limitations

The use of digital image processing in agriculture is quickly becoming ubiquitous, as emulating human visual capabilities is a fundamental step towards the automation of processes. Creating a computer vision system to perform disease diagnosis and severity measurement is one of the most challenging tasks currently underway. This paper was dedicated to identify and discuss some of the main challenges that still need to be overcome before a truly useful image-based diagnosis system becomes available.

One possible way to overcome some of the limitations that still affect this kind of technology is to place constraints to limit the capture condition variations. An undesirable side effect of this strategy is that the additional effort required to meet those constraints may dissuade many potential users from adopting the technology.

Even with very tight constraints, many challenges will still remain. Some of the main difficulties can potentially be mitigated with the use of more sophisticated techniques borrowed from the areas of computer vision and machine learning, such as Markov Random Fields (Li, 2009), Graph Theory (Bondy & Murty, 2008), Deep Learning (Deng and Yu, 2014), Mean Shift (Cheng, 1995), and Large Margin Nearest Neighbor (LMNN) classification (Weinberger, Blitzer, & Saul, 2009), among many others that have not yet been properly explored. LMNN, in particular, has the potential to minimize many of the problems caused by high intra-class variation (see Section 3.2) and low within-class variation (Section 3.4). The underutilization of tools and the relatively limited participation of the image processing and machine learning communities is probably not due to a lack of interest. The likely explanation is the lack of image databases comprehensive enough to allow the research. The few existing databases are either too limited or not accessible to the scientific community. Fortunately, some initiatives are already underway to remedy this situation, such as the database developed by Hughes and Salathe (2015), in which more than 50,000 images of healthy and diseased plants are being made available (https://www.plantvillage.org/).

Even with the use of more sophisticated techniques, there will still be many situations that cannot be dealt with by automatic methods based purely on computer vision and image processing techniques, as plant pathologists and agricultural engineers often have to resort to resources other than their own sight (e.g. laboratory analysis) in order to obtain a reliable diagnosis. Thus, a complete diagnosis system should include other modules capable of providing more information about the problem at hand. This will almost certainly result in loss of full automation, but the additional information may be necessary for a reliable diagnosis. A possible hybrid system would couple an automatic image-based module with an expert system, which is a computer system that emulates the decision-making ability of a human expert (Jackson, 1999). In this case, the automatic module would be responsible for narrowing down the set of possible diseases.

Computer-assisted plant disease diagnosis is a very challenging research field, with plenty of problems still to be solved. There is little doubt that the technology will continue to evolve more sophisticated tools, however there are so many factors involved, that it is unlikely that plant pathologists or other specialists in the plant sciences will be replaced. Instead, systems like those cited in this article will have the role of providing guidance for a quick first response, and as back up to those components of the system that can be automated. Those systems will also play an important role in monitoring vast areas in real time, releasing alerts as soon as a problem is detected. Finally, it is important to note that many farmers who have no access to plant science specialists can greatly benefit from automated, diagnostic image analysis technology, despite its imperfections.

6. Conclusions

Busy backgrounds, lack of clear borders around symptoms, variation in capture conditions, diseases producing varying symptoms, symptoms produced by different disorders manifesting simultaneously and different disorders producing similar symptoms are factors that still play an important role and have a significant impact on the effectiveness of the image analysis techniques proposed so far.

The use of digital image processing and computer vision in plant diagnosis is still new, which means there are still many alternatives to be explored with the potential to minimize at least some of the issues pointed out herein. Additionally, with the availability of greater computational power, strategies that were previously prohibitive may now be applied. Finally, advancements in imaging imply that images with superior quality can now be captured at low costs, and new improvements will certainly be developed. As a result, digital images will be a more trustworthy representation of the scene they depict, which will eventually allow the development of more accurate and powerful image analysis tools.

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