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IDENTIFICAÇÃO DE ELEMENTOS ESPECÍFICOS DAS FOLHAS DO ALGODOEIRO EM IMAGENS COM FUNDOS COMPLEXOS

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Resumo: O uso de técnicas de processamento digital de imagens e visão computacional na análise foliar frequentemente depende de uma separação prévia das folhas das plantas do restante da cena. Essa segmentação pode ser um problema de difícil solução se as condições não são estritamente controladas, sendo particularmente desafiadores os casos em que várias folhas, muitas vezes sobrepostas, estão presentes na cena. Nesses casos, qualquer informação capaz de ajudar na localização das folhas é de grande utilidade. Nesse contexto, este artigo apresenta um método para identificar o nó principal e a nervura principal de folhas do algodoeiro, o que fornece informações valiosas sobre a posição e orientação dessas folhas. A única restrição à qual o método está sujeito é que a folha de interesse esteja localizada numa posição central na imagem.

Palavras-chave: nervuras, folhas do algodoeiro, imagens digitais, segmentação.

IDENTIFICATION OF SPECIFIC ELEMENTS OF COTTON LEAVES IN IMAGES WITH COMPLEX BACKGROUNDS

Abstract: The use of digital image processing techniques and computer vision in leaf analysis often relies on a previous separation of the plant leaves from the rest of the scene. Such a segmentation can be a difficult problem if the conditions are not strictly controlled, with the cases in which several possibly overlaid leaves are present being particularly challenging. In those cases, any information capable of aiding the process of leaf localization is very useful. In this context, this paper presents a method for identification of the main node and main vein of cotton leaves, providing valuable information about position and orientation of the leaves. The only restriction to which the method is subject is that the leaf of interest be located in a central position in the image.

Keywords: venations, cotton leaves, digital images, segmentation.

1. Introduction

Digital image processing (DIP) has been increasingly applied to problems found in agriculture, and most tools of this kind focus on the leaves, which are usually the most prominent part of the plants. Among the main applications that use DIP for leaf analysis, one can cite disease detection and diagnosis, nutrient deficiency detection, venation detection, among others.

In those applications, usually the first step is to isolate the leaf from the rest of the scene. If the leaf image is captured under controlled conditions, which normally means removing the leaf from the host plant, this task is relatively simple (HENRIES, 2011; VALLIAMMAL e GEETHALAKSHIMI, 2012).

Some proposals try to solve the leaf segmentation problem using images captured in the field, that is, with little or no control over environmental factors. This is a difficult problem, especially if there are other similar leaves in the scene, which is often the case. Because of that, those methods require that certain conditions be met in order to work properly (MANH et al., 2001; CAMARGO NETO et al., 2006; WANG et al, 2008). A comparative analysis of 14 segmentation techniques applied to leaves contained in images with complicated backgrounds is presented by GRAND-BROCHIER et al. (2013).

Even if the conditions required by those methods are met, the results are still far from ideal. This proposal aims to overcome some of those limitations by identifying the position of the main node (where leaf and petiole meet) and of the main leaf vein. Such information may serve as a starting point for other techniques, which would thus have data beyond that obtained directly from the image to perform the segmentation.

The method for node and vein identification proposed here is entirely based on color information, morphological operations and heuristic rules, thus being easy to implement and relatively light in computational terms. The only condition for the method to work properly is that the targeted leaf must occupy a central position in the image. The tests were performed using cotton leaves, but the extension of the technique to other cultures is possible.

2. Materials and Methods

The images used to train and test the algorithm were captured in the field using two different cameras: the first a consumer-level compact digital camera (Panasonic DMC-LZ10, 10 MPixels), and the second a cell phone camera (Sony Xperia ZQ, 12 MPixels). Four images (two from each camera) were used in the training, and 50 (25 from each camera) in the tests. The captured images have different characteristics in terms of illumination, leaf color, lesions and disease symptoms. All images have a main leaf, with the background containing other leaves and soil.

In its first step, the algorithm performs two color transformations, one from the RGB to L*a*b*, and the other from RGB to CMYK. Only a few channels of these new color channels are used: channel *a* from the L*a*b* space, and channels *C* and *M* from the CMYK color space, which are successful in visually highlighting both petioles and veins. Fig. 1 shows an example of a cotton leaf image used in this work, as well as the images in grayscale of each color channel considered.

In the sequence, channel *a* is thresholded, in such a way all pixels with values above 240 are made white, and all the others are made black. This procedure usually isolates all central nodes, but also some background areas with similar characteristics.

In order to eliminate some spurious objects created by the thresholding, some rules are applied. The object will be discarded if: it has more than NP/14000 pixels, where NP is the total number of pixels in the image; it has less than NP/140000; its centroid is less than NP/280000 pixels from the image borders; its eccentricity is larger than 0.95. Eccentricity is calculated in two steps: first, the object is approximated by an ellipsis, and then the ratio of the distance between the foci of the ellipsis and the length of the main axis is calculated, revealing the eccentricity.

Since spurious objects may still remain, an additional rule is applied: a band of 30 pixels around each object is defined, and if the mean value of those pixels in channel *M* is larger than 60, the object is discarded, an action that eliminates most remaining spurious objects.

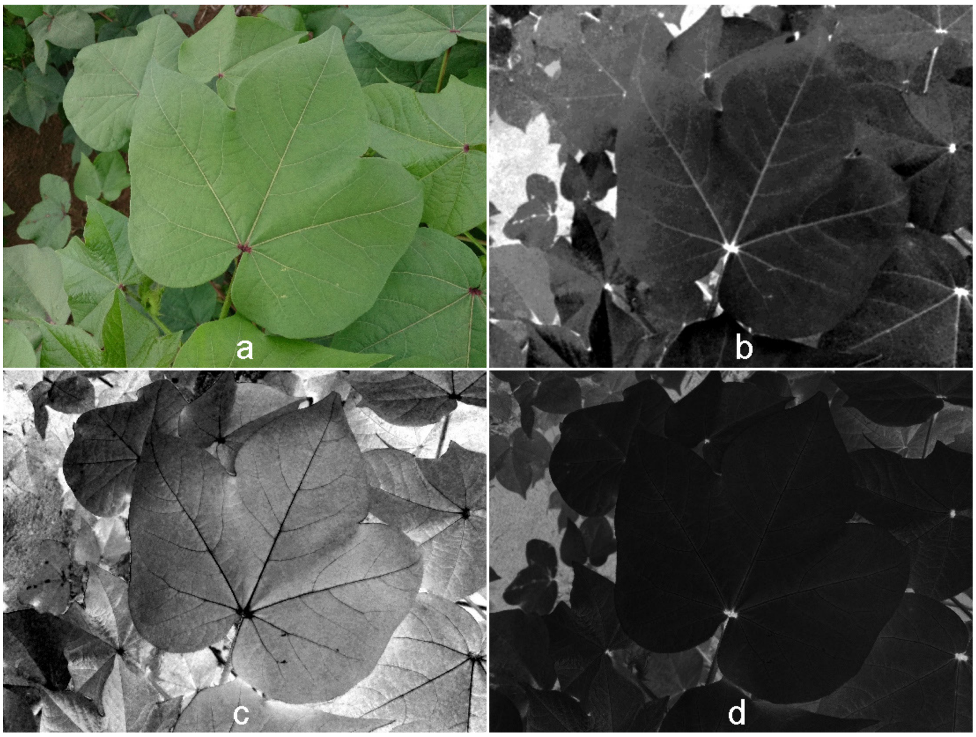

Figure 1. a) Example of cotton leaf image. b) Grayscale representation of the *a* channel. c) Grayscale representation of the *C* channel. d) Grayscale representation of the *M* channel.

The next step determines all potential nodes. Although at the end only the node and veins of the main leaf are to be isolated, at this point all detected objects are considered.

The next procedure is based on the fact that the veins are relatively straight, thus being possible to approximate them by line segments, at least for a limited extension. Thus, having as center the centroid of each object, a line of NP/280000 pixels, aligned with the abscissa of the image, was traced. Then, the mean and variance of the pixels located on this line were calculated, using channel *C*. The line was then successively rotated anticlockwise by an angle of 0.127º, being the mean and variance calculated at each step. When the line reaches the initial position, a series of mean and variance values has been generated. It was observed that the mean value normally drops in the vein positions, however they may also drop in other dark regions. On the other hand, the variance also tends to drop in the vein positions, but the same does not happen for other regions. Having those observations in mind, the following rules were applied:

- All local minima of the series of mean values are located. For each of those minima, the two largest local maxima are located, one considering 150 points (in the mean series) to the left, and other considering 150 points to the right. If the value of the local minimum is at least 20 units lesser than both local maxima, it is considered that position has a potential to be a vein.
- The value of the variance in the position of the potential vein is taken, as well as the values of two local maxima associated, in a procedure identical to that described in the previous item. If the value of the variance in the potential position is at least 700 units lesser than both local maxima, the position is considered as being indeed of a vein, otherwise it is discarded.

The procedure of potential vein identification is performed for all objects remaining after the node selection. However, the objective here is to identify the node and central vein of the main leaf of the scene. Thus, the following rules are applied:

- The node with the largest number of veins associated (*N*) is identified. Nodes that have less than *N*-1 veins associated are immediately discarded.
- For the remaining nodes, the mean value of the pixels located in the lines that characterize all veins associated to each node is calculated using the *C* channel. The node that has the lowest mean value is chosen as the main node.

Once the main node is determined, the only task remaining is to identify, among all veins associated to that node, which one defines the center axis of the leaf (thus defining its orientation). Only the two veins with lower mean pixel values are assumed to be a potential candidate. Next, the angle of the line connecting the centroid of the node to the center of the image is calculated with respect to the abscissa axis. The following rules are applied:

- If the mean values for the two potential veins have a difference lesser than 10 between them, the one that has the smallest angle with respect to the line that connects the node centroid to the center of the image is taken as the main vein.
- If such a difference is larger than 10, the angle between them is larger than 135º, and the angle between the vein with larger mean and the line connecting the centroid to the center of the image is lesser than 90º, the vein with lower mean value is actually considered as being part of the petiole, and the second vein is taken as the main one. If at least one of those conditions is not met, the vein with lower mean is taken as the main one. The algorithm ends at this point, since both the main node and the central vein have been determined.

3. Results and Discussion

Two factors were analyzed in the tests: a) accuracy in the identification of the main node, which reveals if the algorithm identified the correct leaf, and b) accuracy in the identification of the vein, which indicates if the leaf orientation was correctly determined. Table 1 shows the general results obtained by the method with respect to the node identification.

Table 1. General results in the identification of the main node.

	Actual node	Node another leaf	Lesion	Soil
Occurrence	96%	0%	4%	0%

As can be seen, the correct node was identified in 96% of the cases. The algorithm works properly under most conditions, but may fail when the leaf is severely affected by lesions.

Table 2 shows the results in the identification of the main vein. The results reported in this table assume that the main node was correctly identified.

Table 2. General results in the identification of the main vein.

	Actual Vein	Secondary Vein	Other
Occurrence	96%	2%	2%

As can be seen, the results are similar as those obtained for the nodes. Under certain illumination conditions, secondary veins may appear with more prominence in the *C* channel used in this kind of detection, which may lead to error. Severe lesions may also cause error, since they cause deformities that not only change the characteristics expected for the veins, but also assume tonal characteristics that may cause the algorithm to fail. However, those cases are rare.

The results show that the method succeeds in identifying prominent leaf structures in busy images. However, some factors may interfere with the performance of the method:

- Lesions with tonal characteristics close to those found in nodes and veins may be challenging. The algorithm is relatively robust to this situation; however, if the lesions cover more than 20% of the leaf, the algorithm tends to fail.
- Lesions may distort the leaves to the point that its geometry is no longer recognizable, making it difficult to identify structures, particularly the veins.
- Tests have revealed that the algorithm is very robust to different lighting conditions. However, when both shade and sunlight coexist in the same leaf, there is potential for misidentifications, so this situation must be avoided, if possible.

- Extreme angles of capture may cause rules based on the geometry of the structures to fail. Therefore, the capture must be as orthogonal to the leaf's surface as possible.
- As can be seen in Table II, errors happened for only two of the 50 images used in the tests. Both images were captured using the cell phone camera, however it they are more likely caused by the lighting conditions of the image than by the type of sensor. The influence of the sensor on the accuracy of the method is a topic to be further studied in the future.

Only cotton leaves were used in the experiments. It is likely that the extension of the vein identification procedure to other species will be straightforward. On the other hand, the extension of the node identification may depend on adaptations specific to the species under consideration.

4. Conclusions

This paper presented a method to identify the position of the central node and the orientation of the main vein in cotton leaves. The proposed method has the potential to benefit leaf segmentation methods, which are still limited by constraints when dealing with images taken under uncontrolled conditions. The method is entirely based on rules applied to different color channels, and also on well known morphological operations. The only constraint is that the main leaf be at a central position in the image. Tests demonstrated the effectiveness of the method, and that only a few factors can cause the method to fail. Future work will be dedicated to extend the method to other plant species, test it with some leaf segmentation techniques, and to investigate the influence of different sensors on its accuracy.

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