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Identification of Soybean Foliar Diseases Using Unmanned Aerial Vehicle Images

Everton Castelão Tetila, Bruno Brandoli Machado, Nícolas Alessandro de Souza Belete, David Augusto Guimarães, and Hemerson Pistori

***Abstract*— Soybean has been the main Brazilian agricultural commodity, contributing substantially to the country's trade balance. However, foliar diseases are the key factor that can undermine the soy production, usually caused by fungi, bacteria, viruses, and nematodes. This letter proposes a computer vision system to track soybean foliar diseases in the field using images captured by the low-cost unmanned aerial vehicle model DJI Phantom 3. The proposed system is based on the segmentation method Simple Linear Iterative Clustering to detect plant leaves in the images and on visual attributes to describe the features of foliar physical properties, such as color, gradient, texture, and shape. Our methodology evaluated the performance of six classifiers for different heights, including 1, 2, 4, 8, and 16 m. Experimental results showed that color and texture attributes lead to higher classification rates, achieving the precision of 98.34% for heights between 1 and 2 m, with a decay of 2% at each meter. Results indicate that our approach can support experts and farmers to monitor diseases in soybean fields.**

***Index Terms*— Aerial images, precision crop protection, soybean foliar diseases, unmanned aerial vehicle (UAV)-based remote sensing.**

I. Introduction

SOYBEAN (Glycine max) has been the main Brazilian agricultural commodity, with an important economic contribution in the Brazilian trade balance. Despite the satisfactory numbers, many diseases—caused by fungi, bacteria, viruses, and nematodes—have considerably attacked soybean crops in different states. Early diagnosis of diseases is quite important to the pesticide management in the crop and, consequently, can reduce the environmental impact of agrochemicals and economic losses.

Pest control usually consists of taking decisions based on the level of infestation and on the development stage of the soybean plant. However, such an information can be obtained with regular inspections by sampling different regions of the field, and the inspection is performed visually from the ground [1]. Furthermore, the high cost of chemicals associated with low ecological impact actions lead to better practices of precision agriculture. Thus, the use of unmanned aerial vehicles (UAVs) in crop fields has been considered an important tool to identify patches of diseases, allowing experts and farmers to take better decisions.

In this letter, we have proposed a computer vision system to identify automatically foliar soybean diseases from aerial images captured by a low-cost and well-known UAV model in the market, named DJI Phantom 3. We have first considered an image segmentation step to detect the plant leaves in the images taken in the flight inspection. We describe the leaves using visual features, including color, gradient, texture, and shape. Our methodology evaluates six well-known classifiers from the literature, for five different heights. The proposed approach was tested using a data set with 3624 images divided into three classes: target spot, powdery mildew, and with no disease. The best performance on foliar disease identification was using heights between 1 and 2 m, once the plant image resolution changes to higher flights. Experimental results compared our results with local descriptors using the UAV images.

This letter is organized as follows. Section II presents a review of the literature. The proposed approach to identify soybean foliar diseases is described in Section III. Section IV describes the materials and methods adopted in this research. Section V describes the experimental results, followed by a brief discussion. Finally, conclusions and future works are given in Section VI.

II. Related Works

The application of UAV-based remote sensing has increased the opportunities in precision crop protection, including the detection, monitoring, and identification of weeds and plant diseases. Computer vision and machine learning methods have played a major role for automatic measurement and classification of the remote images. In the literature, there exist several reviews comparing different imaging sensors [2] and machine learning algorithms [3], [4] in order to identify plant diseases in different crops. However, a few of them addresses the use of images collected from UAVs for the identification of soybean diseases. In this context, using single scanned images, Pires *et al.* [5] proposed a method to identify soybean foliar diseases based on local descriptors and bag-of-visual words. Reference [6] reported a method for soybean leaf detection based on salient regions and k-means clustering. Reference [7] proposed a method for detecting brown spot and frog eye,

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two common soybean foliar diseases, by using shape features and k-nearest neighbors (k-NN) classification; images were taken with smartphones.

Recent studies on crop protection, using images obtained from UAV-based remote sensing and machine learning algorithms, were proposed to identify diseases in citrus [8] and detect weeds in wheat [9] and also in maize [10]. Similarly, Torres-Sánchez *et al.* [11] proposed a method based on UAV-images for the identification of weed plants, and [12] presented a machine learning strategy for weed monitoring. Bajwa *et al.* [13] used a remote sensing with visible and near-infrared imaging to detect two soybean diseases, including cyst nematode and sudden death syndrome. Yuan *et al.* [14] recently used UAVs to measure the soybean leaf area index.

III. Proposed Approach

In this section, we introduce a computer vision approach to identify soybean foliar diseases via UAV-images. The proposed approach adopts the Simple Linear Iterative Clustering (SLIC) superpixels algorithm, proposed by Achanta *et al.* [15], in order to detect the plant leaves in the images. The SLIC algorithm was chosen because it is faster with linear complexity, more memory efficient than methods based on superpixels, and it yields the state-of-the-art adherence to image boundaries, which outperforms existing methods when used for image segmentation.

The method SLIC employs the k-means algorithm for the generation of regions, called superpixels. The parameter k of the algorithm refers to the number of superpixels in the image and it allows to control the shape and size of the superpixels. Here, we adjust the parameter k to better segment the soybean plant leaves.

The superpixel SLIC algorithm groups pixel according to the color of the pixels using the CIELAB components, L, a, and b, as well as the x- and y-coordinates of the pixels. An input image is segmented into rectangular regions by defining the number k of superpixels, with approximately (N/k) pixels, where N is the number of pixels of the image. Each region composes an initial superpixel of dimensions $S \times S$, where $S = [(N/k)]^{1/2}$. The centers of superpixel clusters $C_k = [l_k, a_k, b_k, x_k, y_k]$ with $k = [1, k]$ are chosen, spaced on a regular grid to form clusters of approximate size S^2. The centers are moved to the lowest gradient value over a 3×3 pixel neighborhood, avoiding centroid allocation in edge regions or having noisy pixels. Instead of using a simple Euclidean norm in the 5-D space, a distance measure D_s is defined as follows:

$$d_{\text{lab}} = \sqrt{(l_k - l_i)^2 + (a_k - a_i)^2 + (b_k - b_i)^2} \tag{1}$$

$$d_{xy} = \sqrt{(x_k - x_i)^2 + (y_k - y_i)^2} \tag{2}$$

$$D_s = d_{\text{lab}} + \frac{m}{s} * d_{xy} \tag{3}$$

where D_s is the sum of the distance d_{lab} [see (1)] and the distance d_{xy} [see (2)], normalized by the interval S. The parameter m corresponds to the superpixel compactness control; the greater the value is, the more compact the clustering is in terms of spatial proximity. Each pixel of the image is associated with the closest centroid, and after all the pixels are associated with a centroid, a new center is calculated with the $Labxy$ vector of all superpixels belonging to the group. At the end of the process, some pixels may be connected to a group incorrectly, so the algorithm reinforces connectivity in the last step by assigning the pixels alone to the largest neighboring groups [15].

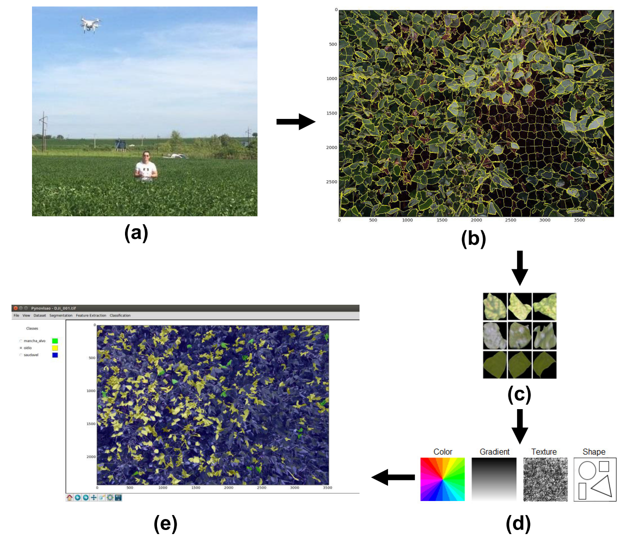

Fig. 1. Proposed computer vision system to identify soybean foliar diseases with UAV-images. (a) Image acquisition. (b) SLIC segmentation. (c) Image data set. (d) Feature extraction. (e) Image disease classification.

A schematic of the proposed system is shown in Fig. 1. It illustrates the methodology that consists of five steps: (a) image acquisition; (b) SLIC segmentation; (c) image data set; (d) feature extraction; and (e) leaf disease classification. Initially, the flight inspection was conducted with the UAV in the field to capture images of soybean crop fields at different heights (see step (a) in Fig. 1). These images were segmented by using the SLIC *superpixels* method (see step (b) in Fig. 1). Each superpixel segment has been visually classified into a specific class: target spot, powdery mildew, or healthy leaf samples.

After segmenting the image with the superpixel method SLIC, leaf segments belonging to a certain class were visually analyzed by an agronomist in order to construct an image data set for training and testing of the system (see step (c) of Fig. 1). In this case, the agronomist was responsible for assessing the representativeness of samples for statistical analysis. Subsequently, images were described as features based on color, gradient, texture, and shape (see step (d) of Fig. 1). At each height, leaf image samples were used in the classification of soybean foliar diseases (see step (e) of Fig. 1). The final step shows a test image assessed by our computer vision system. The result of the percentage of classification is shown in the screenshot of our tool.

IV. Materials and Methods

A. Experimental Design

For the experiments, we conducted several tests to find the highest foliar disease classification according to specific heights of the UAV, including 1, 2, 4, 8, and 16 m. To this end, images were captured from an experimental

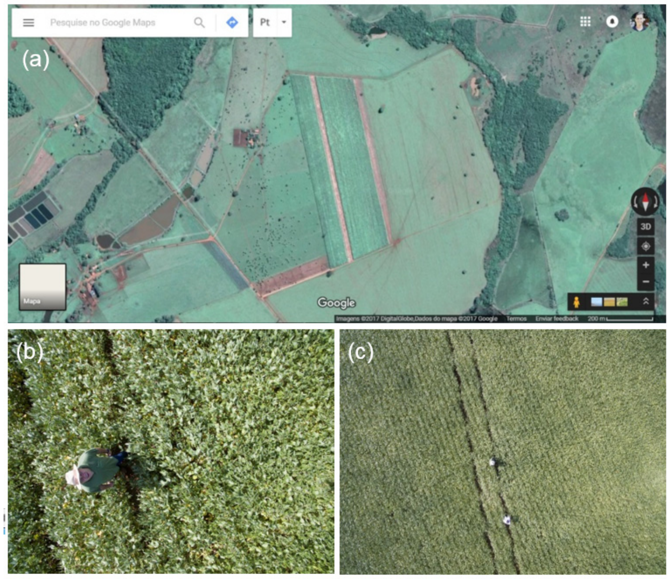

Fig. 2. (a) Experimental area used for planting soybean crop from top view (image created with Google Earth). (b) and (c) Image samples obtained by the UAV with heights of 4 and 16 m, respectively.

soybean field, as shown in Fig. 2(a). We collected images in different days and with different weather conditions. A total amount of 300 aerial images were taken in the crop year September 2016–February 2017. In order to identify the plant diseases in the images, each image was segmented by using the superpixel-based method, according to the parameter k that better adjusts the detection of the leaves in the plant. The value of k was set to divide the plant images into k leaf segments. Accordingly, the parameter k was defined by the boundary adherence of the algorithm SLIC. Each image has a dimension of 4000×3000 pixels, totalizing 12 000 000 pixels. A soybean individual leaf at a height of 1 m has about 12 000 pixels. Thus, the segmentation parameter k was set to 1000 regions; dividing 12 000 000 pixels by 1000 regions, we got 12 000 pixels for each leaf. The same idea was considered to double the height, i.e., if we have a height of 2 m, the number k of regions was 2000, and so on. After image SLIC segmentation, 3624 images of superpixels were generated, that is, leaf images divided into three classes of the soybean diseases: target spot, powdery mildew, and leaves with no disease.

With the support of an agronomist, each image was annotated in order to construct the image data set and the machine learning model. Images were captured in the digital negative (DNG) format, with different heights using the DJI Phantom 3 Professional, equipped with a Sony EXMOR sensor of 1/2, 3-in and 12.3-megapixel resolutions. In Table I, we obtained the ground sample distance (GSD) with a real focal length of 3.57 mm for different flight altitudes, showing the area with its respective GSD. The images were captured in the crop fields, using a 90° angle of the camera in relation to the ground. Thus, it was possible to calculate how many pixels has one leaf in the images taken under different heights.

B. Feature Extraction and Classification

There exist several visual attributes that describe physical properties of images, which rely mainly on color, gradient, texture, and shape. Color attributes focus on physical properties of object surfaces as it reflects different wavelength values. Texture attributes focus on describing images as repetitive patterns that can vary according to the size, which produces different tactile sensations associated with roughness, coarseness, and regularity. Shape describes images according to the contour of the objects, while gradient features are based on the derivatives in different directions of the image. In our image classification system, we have used as features the following methods.

1) Color: color statistics [16].
2) Gradient: histogram of oriented gradients [17].
3) Texture: gray-level cooccurrence matrix [18] and local binary patterns [19].
4) Shape: Hu's moment and central moments [20].

For image classification, machine learning algorithms use the described images to identify and classify according to visual patterns. Here, we have employed supervised learning models with training and test sets divided according to the tenfold cross validation. We compared well-known classifiers, including sequential minimal optimization (SMO) [21], Adaboost [22], decision trees using the J48 algorithm [23], (k-NN) [24], random forest [25], and naive Bayes [26], in order to statistically evaluate the potential of the proposal of soybean foliar recognition in the field assessing different heights.

TABLE I
GSD VALUES CALCULATED FOR DIFFERENT HEIGHTS OF PHANTOM 3

Flight Altitude (m)	**GSD** (mm)	**Image Width** (m)	**Image Height** (m)	**Area** (m^2)	**Pixels per Leaf**
1	0.43	1.72	1.29	2.24	12,000
2	0.86	3.45	2.59	8.96	6,000
4	1.72	6.91	5.18	35.84	3,000
8	3.45	13.82	10.37	143.37	1,500
16	6.91	27.65	20.73	573.50	750

V. EXPERIMENTAL RESULTS AND DISCUSSION

In this section, we describe experiments and results obtained by the proposed approach. In the classification task, we submitted to the machine learning models images captured in different heights. To evaluate the performance of the classifiers, correct classification rate (CCR) was used. For training and testing of the classifiers, stratified tenfold cross validation was used. In this scheme, images of the data set are partitioned into tenfolds ensuring that each fold has the same proportion of each class. Then, onefold is used for testing, while the remaining folds are used for training the SMO classifier. The process is repeated ten times using each fold exactly once for testing. Finally, the CCR is given by the mean of the ten rounds. For each algorithm tested, we also calculated the average performances for the CCR and F-measure metrics.

To verify if the algorithms tested differ statistically in relation to performance and height, we used the ANOVA hypothesis test in RStudio, with each block corresponding to one of the classes of the problem. The p-values found for each metric and the level of significance required were reported to discard the null hypothesis. Then, the data were analyzed from a descriptive statistical line in the boxplot diagram.

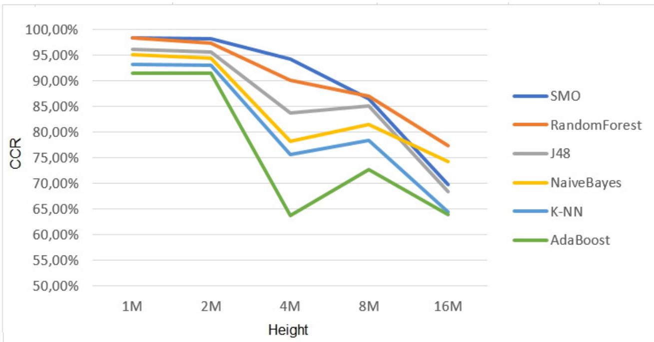

Fig. 3. CCR obtained at different heights using combined feature extractors based on color, gradient, and texture.

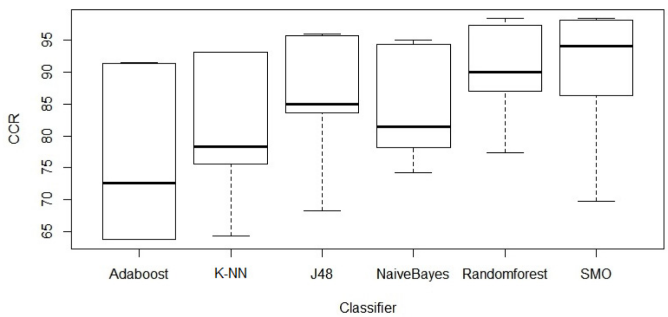

Fig. 4. Boxplot diagram comparing the performance among classifiers for the CCR metric.

A. Classifier and Height Evaluation

Fig. 3 shows the results obtained by six classifiers well-accepted in machine learning and artificial intelligence, as described in Section IV. The best performance of the CCR was obtained by the SMO classifier, followed by the random forest method.

Fig. 4 shows the performance of each classifier, with the median value highlighted in the boxplot diagram. The diagram also shows the range of performance variation obtained from each classifier. In the figure, the SMO classifier presented the best CCR, having a higher value for the median and dispersion of data in the best value range for CCR.

In Fig. 5, we can observe that the values of the medians and of the dispersions of data resulted in a better range of CCR between the heights of 1 and 2 m. These heights did not present significant variations in the realized experiments, having strong statistical evidence of similarity.

B. Feature Extraction Evaluation

Another goal of the experiments was to evaluate the individual performance of the attributes extracted for the recognition of soybean leaf diseases. For this purpose, the attributes based on color, gradient, texture, and shape were compared in terms of CCRs calculated by the classifiers at different heights, as shown in Fig. 6. The results of this experiment demonstrate that color is the most important attribute when compared with the gradient and shape attributes in the task of soybean leaf disease recognition.

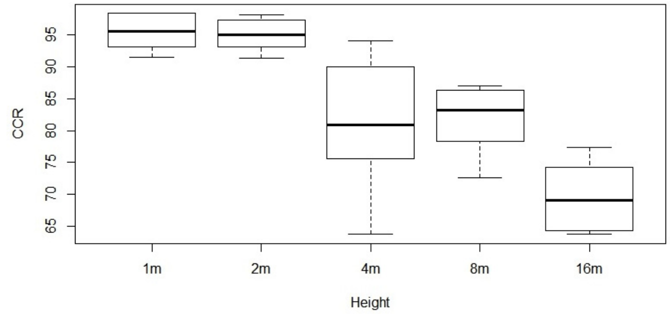

Fig. 5. Boxplot diagram comparing performance among classifiers to different heights.

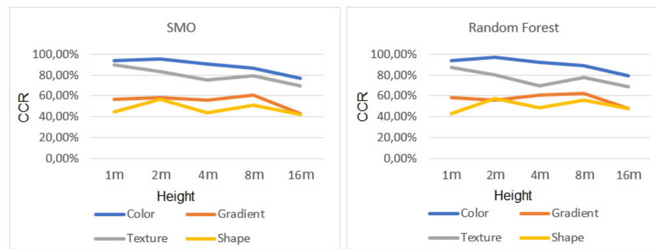

Fig. 6. CCRs obtained by classifiers at different heights using attribute extractors based on color, gradient, texture, and shape.

TABLE II

COMPARISON OF OUR APPROACH WITH LOCAL DESCRIPTORS FOR SOYBEAN LEAF DISEASE IDENTIFICATION UNDER TWO DIFFERENT HEIGHTS

Local Descriptor	SVM (%)			K-NN (%)	
	k	1m	2m	1m	2m
SURF	500	56.38	38.05	55.56	35.56
HOG	1,000	61.66	62.77	45.00	36.11
DSIFT	2,000	63.05	56.38	44.44	35.56
SIFT	3,500	46.94	34.44	39.17	34.44
PHOW	3,500	69.72	58.61	45.28	36.44
Our Approach	-	98.34	98.09	93.14	93.05

C. Comparison With Local Descriptors

In this experiment, we compared our approach with local descriptors used to identify soybean foliar diseases using a desktop scanner, proposed in [5]. To this end, we used the same implementation of the authors applied to the best altitudes, 1 and 2 m. We also used the best parameters k for each local descriptor tested in [5], in order to set the number of visual words used in the dictionary of the bag-of-visual words approach.

Table II shows the CCR for each local descriptor and two classifiers, SVM and k-NN. As can be seen, our approach overcame the local descriptor methods for all values of k. Our approach achieved the best result with the classifier SVM. The local descriptors methods PHOW, DSIFT, and HOG provided 69.72%, 63.05%, and 62.77% for 3500, 2000, and 1000 visual words, respectively. For sparse local descriptors, SIFT and SURF achieved 46.94% and 56.38% with images taken under the height of 1 m.

The SVM model exhibited the highest accuracy, using features based on color and texture. Local descriptors-based methods did not achieve the same accuracy as reported in [5] because of the distance between the camera and the leaf, if compared with any desktop scanner. Therefore, the SVM was the most suitable model for the classification of soybean diseases using images from the UAV Phantom 3, and the most appropriate height was 1 m.

VI. Conclusion and Future Work

In this letter, we have proposed a new approach based on the segmentation method SLIC to identify soybean foliar diseases using UAVs. We considered an image segmentation step in order to detect the plant leaves in the images taken with flights of a Phantom UAV model. Subsequently, we described the leaves using visual features, including color, gradient, texture, and shape. In the classification step of our approach, we compared six well-known classifiers in the literature. The experiments were able to support the hypothesis of our approach that closer heights between the UAV and the plant presented higher classification rates. The CCR confirmed that our approach achieved the precision of 98.34% in foliar disease identification using heights between 1 and 2 m, with a decay approximately of 2% at each meter, once the plant image resolution changes to higher heights. Experimental results also showed that color and texture attributes lead to higher classification rates. In addition, with the experiments, we were able to determinate the lower height limit of our approach. Although we can take photographs with different heights, when using different lenses, we recommend experts to consider heights higher than 1 m, because UAV rotor blades can shake considerably the plant leaves. As part of the future work, we intend to test convolutional neural networks, increasing the amount of diseases. We also consider evaluating our approach with higher resolution and multispectral cameras.

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