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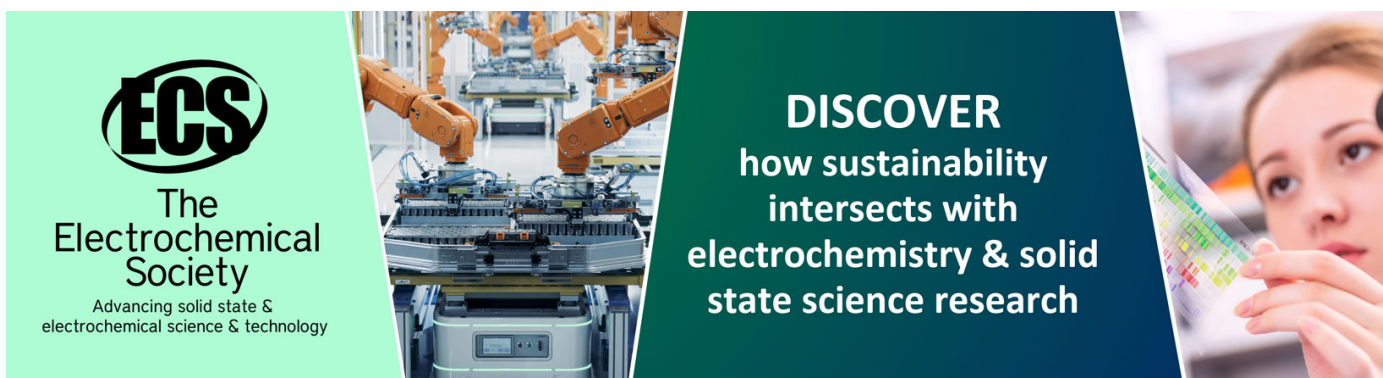
Development of an aerial counting system in oil palm plantations

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Development of an aerial counting system in oil palm plantations

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Abstract. This paper proposes the development of a counting aerial system capable of capturing, process and analyzing images of an oil palm plantation to register the number of cultivated palms. It begins with a study of the available UAV technologies to define the most appropriate model according to the project needs. As result, a DJI Phantom 2 Vision+ is used to capture pictures that are processed by a photogrammetry software to create orthomosaics from the areas of interest, which are handled by the developed software to calculate the number of palms contained in them. The implemented algorithm uses a sliding window technique in image pyramids to generate candidate windows, an LBP descriptor to model the texture of the picture, a logistic regression model to classify the windows and a non-maximum suppression algorithm to refine the decision. The system was tested in different images than the ones used for training and for establishing the set point. As result, the system showed a 95.34% detection rate with a 97.83% precision in mature palms and a 79.26% detection rate with a 97.53% precision in young palms giving an F1 score of 0.97 for mature palms and 0.87 for the small ones. The results are satisfactory getting the census and high-quality images from which is possible to get more information from the area of interest. All this, achieved through a low-cost system capable of work even in cloudy conditions.

1. Introduction

Colombia is the largest producer of palm oil in America and fourth in the world; thus the oil palm cultivation is a significant economic activity. These plantations cover vast areas affected by natural phenomena as plagues, diseases, storms and streaks of lightning [1]. These cause that the number of palms changes quickly and every plant represents money, time, and services. So, it needs to perform a census that can frequently be updated with high precision, so that provides as much as possible information about the content of the plantation allowing the farmers to have more control of the required work and the physical and economic resources of the company.

For a long time, this process has been done with workers going through the entire growing counting the number of palms and writing this information with pencil and paper. This technique takes too much time and so is not performed often, besides it is subject to human error. Currently, some companies have turned to modern technologies such as satellites and radars to get aerial views of the plantations and new information for the monitoring [2][3][4]. But, the typical cloud from the tropical weather where the oil



palm grows makes the task even more challenging, and the access to these resources has a high price. In the agricultural industry, the UAVs have been used to spread chemicals in the cultivations [5], and the obtained images have been used to perform remote monitoring of the products [6] and to create topographic maps with information about the ground conditions [2].

Meanwhile, the image processing and the machine learning applies in the assessment of the ripeness stage of fruits such as tomatoes [7], avocados [8] and the fruit of the oil palms [9]. A new use for this technology has been recently proposed: to identify plants that present specific colors which are characteristic of some diseases in the oil palms [10] and despite, this has been tested in domestic plants, its performance has never been verified in real oil palm plantations.

This paper presents the development of a system that uses a UAV to fly over the plantation and to get images that are processed with a photogrammetry software to create orthomosaics of the interest zones and then obtains an automatic census of the palms using a detection and counting software. Its general structure is described in figure 1 as a block diagram.

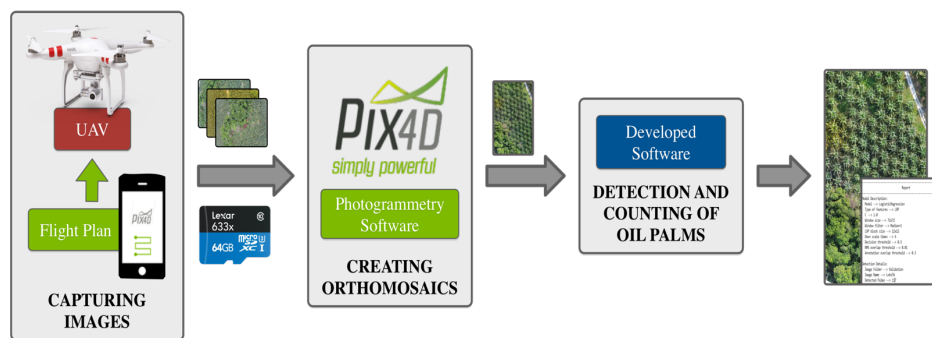


Figure 1. Block diagram of the general structure of the system.

2. Capturing images

Data is obtained using a UAV DJI Phantom 2 Vision+ controlled by a mobile app installed on a device with an iOS operating system where is possible to set the area of the plantation that will be covered by the UAV and the points where photos must be captured.

2.1. Factors influencing the selection process of the UAV

To define an adequate UAV model, a comparative analysis is performed between some models available in the market considering the most important aspects according to the project needs such as the capacity of integration with a photographic camera, cost, camera type, flight time, compatibility with photogrammetry tools and autonomous flight. Besides, it is important to considerate that oil palm plantations are distributed by lots that usually are only accessible through a dirt road that subdivides them, and when the palms are mature the ramifications stick out over the road limiting space. So the vertical takeoff UAVs such as helicopters and multi-rotors are an adequate solution and so the selection process is restricted only to this type of aircraft.

2.2. Comparison of some available models

The preceding factors were considered in three UAV references available in the Universidad Pontificia Bolivariana (Bucaramanga) to determine if any of them fulfilled the project needs: AR.Drone (Parrot), AR.Drone 2.0 (Parrot) and Phantom 1 (DJI) equipped with a GoProHERO3 camera. The AR.Drone model was rejected because it was not capable of taking photos or implementing a GPS system[11]. Some tests were performed with the other two models to compare their behavior, and it concluded that the AR.Drone 2.0 did not have the required stability to carry out long flights in an open field, meanwhile the Phantom 1, despite not having this problem, did not offer the possibility to execute autonomous flights.

2.3. Model selection

The Phantom 2 Vision+ (DJI) was an adequate UAV for the task because it integrated all the advantages of the analyzed models. This UAV allows realizing long and stable autonomous flights to get high-quality images since it implements an electronic gimbal mount for the camera with stabilization in the three axes.

3. Creating orthomosaics

Figure 2 shows a group of photos acquired by the UAV in an area of the plantation. It shows the perspective distortion problem generated by the camera on-board the UAV due to its wide-angle lens which offers a wide visual field but causes distortions in the image. This is the reason why the palms are recognizable in the central zone of the photo, but as it reaches the borders, the perspective distortion increases making harder to differentiate between palms.

An orthomosaics allows getting, from a succession of pictures, an image as the presented in figure three which covers vast extensions and permit to observe all the elements under the same orthogonal projection without perspective distortion. For this, it is necessary to use photogrammetry tools [12] as the mobile app Pix4Dmapper Capture utilized to program a flight path as a grid that guarantees that all the photos are taken at the same height and with a constant overlap percentage. Later, these photos were processed in a computer with the software Pix4Dmapper to create the corresponding orthomosaics.



Figure 2. Photos from wide-angle lens with the perspective distortion problem.



Figure 3. Orthomosaic with constant orthogonal projection for all the elements.

4. Detection and counting software

4.1. Training of the logistic regression model

To detect the palms, the system implements a supervised machine learning [13][14][15] model that requires an image database labeled with the corresponding categories. First, a person selects the positive (palms) and negative (backgrounds) samples in the four orthomosaics used for training using an interface developed in Python. As result, a database with 450 positives samples and 2500 negatives samples are obtained getting a total of 2950 samples as the ones presented in figure 4. Every sample has the size of a window of 72x72 pixels in which is possible to frame the center of a grown palm without including all its branches. Each one is described using the Uniform-LBP operator (Local Binary Pattern) so that each pixel gets a value according to the texture patron that surround it. To make the model more robust, the window is divided into several overlapping blocks, so the U-LBP blocks are set with a size of 12x12 pixels with an overlap of 6 pixels between them, obtaining a total of 121 LBP blocks for a 72x72 window. Each U-LBP [16] block is represented by its histogram, which has 59 possible patrons, and the entire window is characterized by the sequence of these histograms. Thus, the characteristics vector of a window has 7139 values.

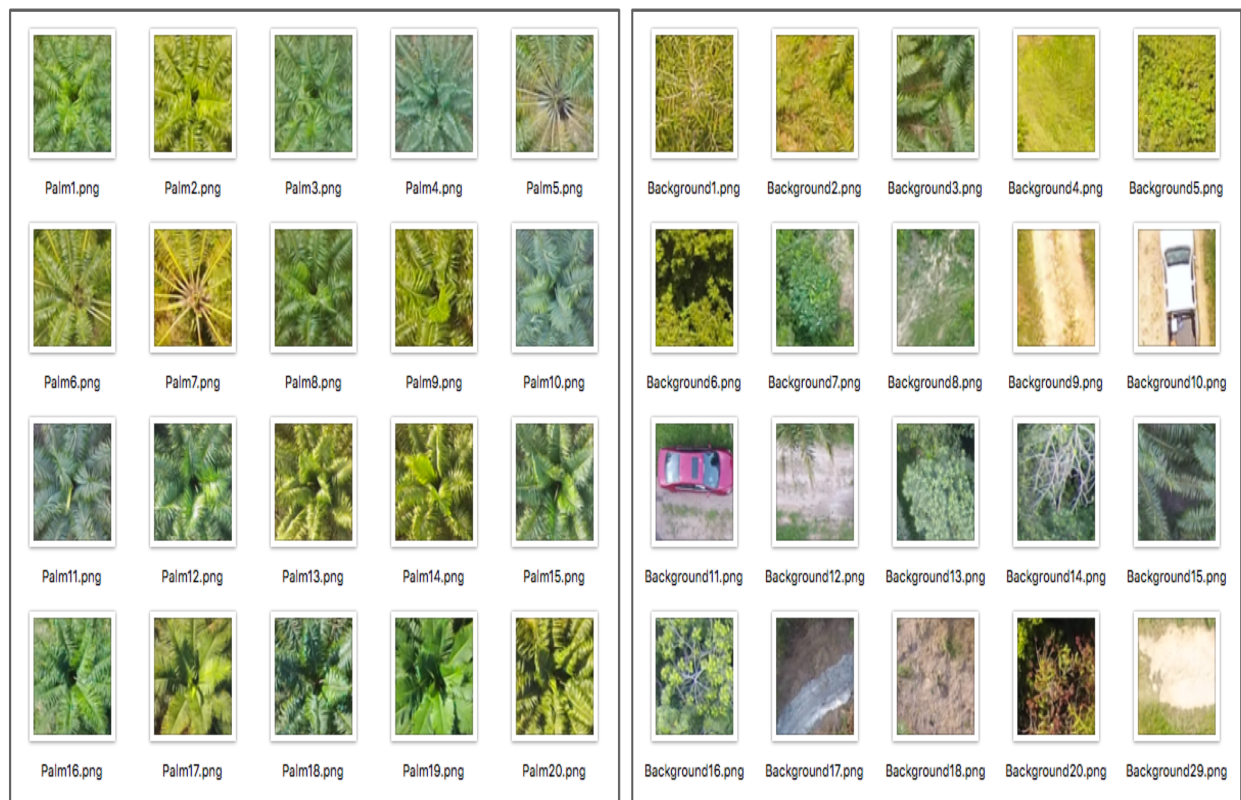


Figure 4. Examples of positive and negative samples from training database.

These samples are organized to train a logistic regression model [17] which gets a score of 1.0 when evaluates all the training samples, which means that is capable of classifying all the samples used for its training.

4.2. Software for detection and counting of oil palms

The block diagram in figure 5 presents the process to detect and count palms in an orthomosaic.

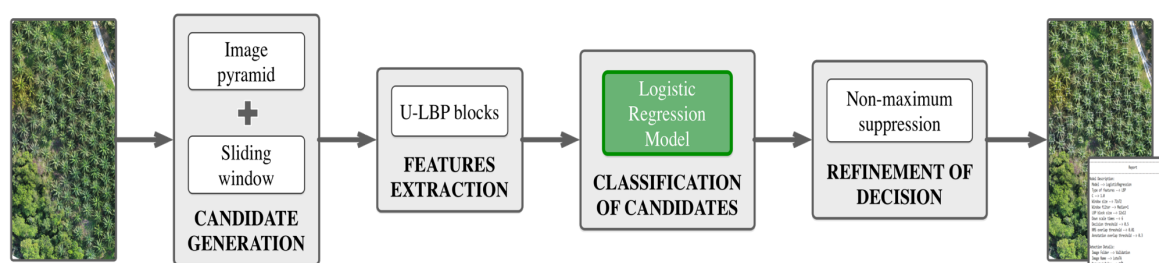


Figure 5. Block diagram of the software to detect and count palms.

First, the software converts the image to grayscale and identifies all the possible 72x72 windows where a palm can be located. Then, a Gaussian pyramid [16] is implemented to identify palms of different sizes in the various levels of the pyramid. But, only the first six levels of the pyramid are considered due to the limitation in the size that a palm can occupy in the image. Each level is scored with a sliding window, and each candidate window goes through the same U-LBP characteristics extraction process that the

training windows and thus feature vector with 7139 values describes the texture of the candidate window and allows the model to understand the type of contained object.

The model gives a score for every analyzed window indicating the probability to contain a palm. When this score exceeds the established decision threshold (0.5), the window qualifies as palm. But, one palm can be detected by several boxes that obtained enough score to surpass the threshold and hence the decision is refined with the non-maximum suppression technique [18]. The length of the vector with the last detection boxes indicates the number of detected palms, which is presented in a report. Besides, the bounding boxes are drawn in the images as well as the scores given by the model.

5. Evaluation

The performance of the system is evaluated in new orthomosaics, different to the ones used to train and adjust the system: one with mature palms and one with small plants.

5.1. Evaluation metrics

A per-image evaluation technique is used. It requires knowing the correct location of the palms in the image, which is made by a human expert manual selection. Then, the detection software is run for the first orthomosaic without including the NMS algorithm, so all the possible detections are considered. The NMS is applied changing the threshold from -2 to 2 with 0.02 steps and the detections for every threshold are saved.

For each operation point, the detections are compared against the coordinates annotated for the human expert and an overlap of 30% or more indicates a correct detection. This allows calculating the False Positives per Image (FPPI) vs. Miss Rate, and Recall vs. Precision curves. Every point in this plots describes the performance of the system for a particular threshold (operation point). Besides, An F1 score is computed, which considers the detection rate and the precision.

5.2. Results

The results from the per-image evaluation [18] in the orthomosaic with mature palms are presented in the figures 6 and 7. For the chosen operation point (threshold = 0.5) which minimizes the miss rate and the FPPI, and maximizes the recall and precision, the system achieves a detection rate of 95.34% with a miss rate of 4.66% indicating that is capable of identifying most of the relevant results. The precision of 97.83% shows that the system presents more relevant results than irrelevant, so there are more true detections than false positives, which have an average of 5 FPPI. Considering that each orthomosaic includes between 150 to 250 palms, among 7 to 12 palms are not identified by the system, but the average of FPPI counteracts this value. Finally, for this case, the system obtains an F1 score of 0.97.

When the per-image evaluation is implemented in the orthomosaic with small young palms, the performance graphics presented in figures 8 and 9 are obtained. The chosen operation point (threshold = -1.5) for this situation must be smaller than the previous section. The system achieves a detection rate of 79.26% with a miss rate of 20.74% decreasing the performance when the palms are small. The high precision of 97.53% shows that despite all the desired plants are considered, the detected are mostly true detections. Finally, for this type of palms, the system gets an F1 score of 0.87.

6. Conclusions

The high-quality aerial views obtained in the orthomosaics using the photogrammetry tools from Pix4Dmapper solved the perspective distortion problem. Moreover, it was possible to prove that the UAVs are a successful tool to monitor plantations hence they allow obtaining useful information cheaper than the satellites and without the cloud problems. Besides, they prevent the worker to go through the entire plantation facilitating the work conditions and updating the information with more frequency.

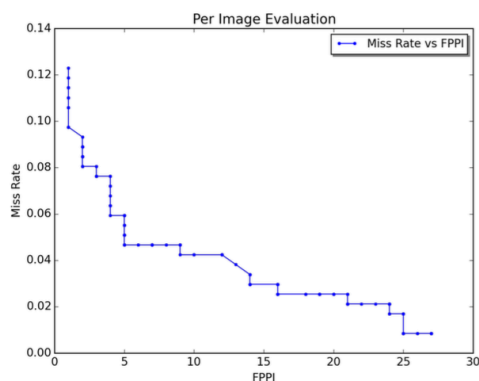


Figure 6. FPPI vs Miss Rate in mature palms

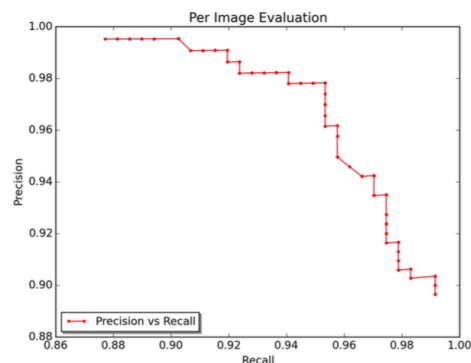


Figure 7. Recall vs Precision in mature palms

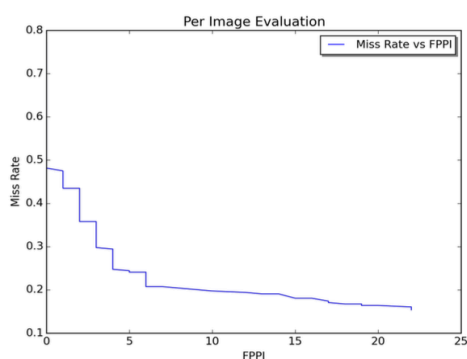


Figure 8. FPPI vs Miss Rate in young palms

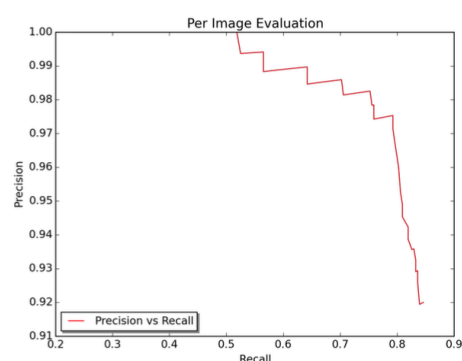


Figure 9. Recall vs Precision in young palms

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