A System Embedded in Small Unmanned Aerial Vehicle for Vigor Analysis of Vegetation

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Abstract. *This work presents a system embedded in a fixed-wing unmanned aerial vehicle that analyzes images and recognizes deformities in plantations in real time, saving their respective geographical location. With this system, a second flight of a lower altitude may be executed over specific points selected on the first flight, obtained a more approximated view, or even applying some fertilizer. A sugar cane plantation in the Northeast of Brazil was used as a case study. As validation, the general architecture of the system is presented, including layout of the electronics, image capture system and computational application developed for vigor analysis of the plants.*

1. Introduction

There is concern about food generation on the planet [Mousazadeh 2013]. It is estimated that by 2050 the production of groceries should be on average 70% higher than the one produced currently [Vasudevan et al. 2016]. With limited natural resources, providing these foods becomes a challenge that requires efficiency in agriculture [Lee et al. 2010].

A solution is the adoption of intelligent computational systems that assist producers to monitor the health of planting, harvesting, irrigation, among other tasks. These systems detect the problem prematurely and automatically, optimizing the harvesting gains. Computer vision systems have been developed with the purpose of solving problems that involve several areas, such as: pattern recognition [Shet et al. 2011], remote monitoring [Stokkeland et al. 2015], navigation [Morris and Barnard 2008], etc.

This technology is being widely used in precision agriculture [Maldonado and Barbosa 2016] [Story et al. 2010] in order to detect planting failures, weeds, pests, climatic problems and nutrient insufficiency, which are increasing productivity [Gée et al. 2008] [Tellaeche et al. 2008]. Significant data can be extracted from images captured in plantations and from these data decisions such as fertilizer application or irrigation can be taken to improve quantity and quality in the harvest.

Allied to computer systems, robotics has also been used in agricultural areas. Unmanned Aerial Vehicles (UAV) are assisting in monitoring plantations, [Colomina and Molina 2014], these vehicles automate tasks that typically require many hours of work [Yu et al. 2013]. Computer vision and UAVs work cooperatively in an efficient manner to solve problems that can totally harm the crop. But there are obstacles such as cost and complexity, which prevent the adoption of such systems in larger scale [Zhang and Li 2014]. These systems cost around US$125,000 [eBee 2017], making it almost impossible to apply to medium and small farms.

Based on the this problem, this study has the objective to develop a solution to automatically detect anomalies in sugarcane plantations, such as weeds, water scarcity, nutritional insufficiency, etc. This detection is done through the analysis of aerial images captured by a low-cost UAV during the fligth. This work presents two main contributions: i) a low cost fixed wing UAV with an embedded computing system, and ii) a software for real-time anomaly detection with geo-localization in plantations. A sugarcane plantation in Northeast Brazil has been used as a case study.

The work is organized as follows. Section II present background concepts important to the development of this work. Section III presents some related work. Section IV presents technologies and methods adopted in this research. Section V presents the case study. The results are presented in Section VI, followed by future works and references.

2. Background

2.1. UAVs in Precision Agriculture

An Unmanned Aerial Vehicle (UAV) is an aircraft that does not require a crew to fly. This technology is designed for different purposes, from recreational to dangerous situations in hostile or inappropriate situations for humans [Pajares 2015]. Most UAVs can be remotely piloted and are based on two navigation technologies: Global Navigation Satellite Systems (GNSS) (eg. GPS) and Inertial Navigation Systems (INS) [Valavanis and Vachtsevanos 2014].

There are many variations of models currently manufactured. In simple terms they can be divided into two groups: fixed wing, used in this study (see Figure 1), and multirotors that can be tricopters, quadricopters, hexacopters, etc [Colomina and Molina 2014]. This project adopted the use of a wing-type fixed wing because it is an economical model and higher power efficiency. Since the focus here is on monitoring sugarcane plantations with a low-cost solution, a light model was built (even carrying multiple sensors) with capability for long flight time.

UAVs are applied in Precision Agriculture for the monitoring of a previously delimited territory [Coelho et al. 2004]. The technologies used in this monitoring are GPS (Global Positioning System), Geographic Information Systems (GIS), and other sensors [Abdullahi et al. 2015]. In this way, the use of UAVs in Precision Agriculture presents several advantages over traditional systems such as images from satellites or manned flights. As an example, the following advantages can be mentioned: high SPATIAL resolution images and capture in real time, monitoring of crops, identification of pests and crop failures, cost reduction (when compared to manned flights), etc. In addition, images captured by UAVs do not present problems with the overlap of clouds when compared

with images provided by satellite [Vega et al. 2015]. However, it is still considered a difficult to control system, requiring specialized operators, including processing and interpretation of the images [Zhang and Li 2014].

2.2. Normalized Difference Vegetation Index

One of the techniques used in precision agriculture is the analysis of aerial images through indexes, such as Soil-Adjusted Vegetation Index (SAVI), Leaf area index (LAI), Simple Ratio Index (SRI), Normalized Difference Vegetation Index (NDVI) [Coutinho et al. 2016]. The NDVI plays an important role in vegetation monitoring, and has been used to analyze dry seasons to estimate vegetation cover, to predict crop yields [Huang et al. 2014], and productivity control of sugarcane straw [Daniel G. Duft 2013]. In addition, it derives the other indexes previously cited [Liu 2017].

The NDVI takes into account the absorbed and reflected energy (Near Infrared - NIR) during the process of photosynthesis [Liu 2017]. The values obtained by the calculation of the NDVI are concentrated between [-1,1] and are used to quantify the vigor of the vegetation. Thus, the higher the NDVI value, the more vigorous will be the plant [Guerrero et al. 2016]. The formula for calculating this index [José et al. 2014] is described in Equation 1. The NDVI is calculated for each pixel of the image, where VLI (visible Light Index) represents the visible spectrum of light absorbed at the time of photosynthesis and the NIR the near infrared intensity at that pixel.

$$NDVI = \frac{(NIR - VLI)}{(NIR + VLI)} \tag{1}$$

3. Related work

Several works use Unmanned Aerial Vehicles to support precision agriculture. Most of them use expensive equipments. Even systems such as those presented in [Ghazal et al. 2015] [Velasquez et al. 2016] require high cost equipment. The first one uses a multi-rotor and a custom Gopro Black for capturing videos that are later used for Building of mosaics. The second work uses a customized webcam for image capture, but does not describe the amount spent in the construction of the multi-rotor, enumerating only the values of the sensors used. Both solutions use the NDVI only to quantify planting vigor.

Some works use ready-made systems classified as low cost [Calderón et al. 2013] [Zhao et al. 2016], however the capture devices are duplicates. In the first two cameras, RGB and NGB, are used to capture images, while in the second two fixed wing UAVs are employed with the justification of greater area coverage. Both calculate the NDVI for early detection of deformities. The works [Zheng et al. 2016] and [Bendig et al. 2015] establish relationship between the NDVI and the growth of plants and nitrogen concentration, respectively. Both use low cost multirotors for image capture and IR camera. However the processing is not performed in real time.

Other work presents some low-cost systems and explains that even with so many existing models it is still a complex thing to handle [Gago et al. 2015]. Other works are being developed aiming of making this technology available to all types of end users [Romero-Trigueros et al. 2017] [Chaves and La Scalea 2015]. However, they are based

on high-cost system, making it impossible to benefit small and medium-sized agricultural producers. The two studies, especially the second one, present a sequence of steps for the processing of the images very similar to the one proposed in the present work, including the NDVI to quantify exposed soil, biomass and plant structure. But unlike what is being proposed here, license-protected software is used and image processing is not done in real time.

The results of the presented related work demonstrate that it is possible to correlate the NDVI with several aspects of the vegetation. Being a simple way to obtain significant data in the recognition of weeds, water scarcity, nutritional insufficiency, etc. However, none of these researches presents an automated image analysis that facilitates the understanding by the farmers. The related works also do not present a solution that geo-locate the regions with deficiencies as we propose to do.

This work presents a system that analyzes images and recognizes deformities in real time, saving their respective geographical locations. With this approach, a second flight of a lower altitude may be executed over specific points acquired on the first flight, obtained a more approximated view, or even applying some fertilizer.

4. Development

The system was developed in two parts: a fixed-wing UAV and an application for image analysis. The monitored area is 60 hectares. The altitude of the flights was 120 meters, with an area per pixel (GSD - Ground Sample Distance) of 4cm.

4.1. General System Architecture

A low cost UAV was developed for this project. Aerodynamics, weight, materials center of gravity were some of the important requirements. The appropriate choice of these items reflects the results obtained in the image capture and the long flight time, for example. The choice of a fixed-wing UAV was due to flight stability, providing satisfactory conditions for high-quality photos. It has been observed through empirical tests that this model allows a greater energy autonomy, ideal for flights with long distances. To reduce costs the UAV was built with polystyrene. Figure 1 presents the structural organization of the main components used in the UAV built for this project.

For automatic flight control and UAV stability, the Ardupilot Mega (APM) Mini was used as flight controller, which is the small size version of the Mega APM. Ardupilot is a platform for air and land model control, based on the Arduino platform [ArduPilot.org 2015]. It is based on open-source software and hardware with the ability to execute autonomous flights. With this tool it is possible to create a solution with control and flight management that uses sensors for stabilization, positioning, navigation and radio communication with ground communication. Therefore it offers an expandable, configurable, modular and low-cost system.

The Mission Planner [ArduPilot.org 2016] was used as the ground station to determine the flight mission. This application is part of the Ardupilot project and was developed to cooperate with APM. It is responsible for programming all the coordinates that the UAV must visit during the flight, as well as monitoring its conditions (current, voltage, position, etc.).
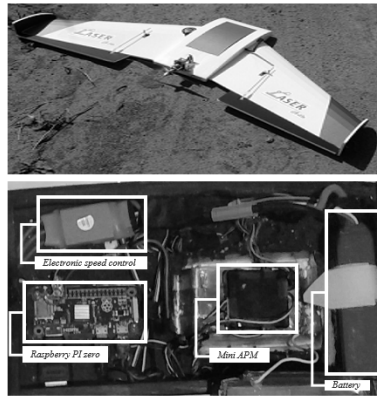
Figure 1. Fixed-Wing UAV (upper part of figure) and main electronics installed in UAV (lower part of figure).

Another important component in the proposed system is the Raspberry PI Zero, which consists of 512MB of RAM and 1GHz and single core CPU. This board is extremely low cost (only 5 dollars), even though, has multiple functionality because acting like a mini computer. A PiNoiR digital camera with 5-megapixel maximum image resolution with a CMOS image sensor was docked on Raspberry. This camera has a NGB filter (NIR, green and blue). In low cost applications it is common to use sensors with this feature [Vinícius Andrei Cerbaro 2015] [Zhao et al. 2016]. Raspberry performs capture, processing and detection on images, and classifies the areas of interest and georeference each of them. The geographic coordinates are provided by the GPS connected to the APM.

For the mosaic composition, it was used the Image Composite Editor (ICE) [ICE 2015] tool. It is a free software created by Microsoft Research Computational Photography Group for joint images. With that application a set of surface images can be used to form a high resolution mosaic, or even a video can serve as a basis for the construction of the mosaic. This application was choosed due to its simplicity of use and efficiency.

4.2. Application

The software application developed for this project is responsible for capturing and georeferencing the images, calculating the NDVI, classifying the vigor of sugarcane and creating a record of flight data. It creates a log file where all information about the flight as well as the coordinates of each photo are stored. Figure 2 demonstrates the general architecture of the developed system.

The Raspberry PI reads latitude to longitude from the GPS module. It then captures the image and calculates the NDVI. The calculation results in an array of dots between -1 and 1 (with the same image size). Then, the areas with low vigor is located. These processes are performed for each captured image. At the end of the trajectory a log file is generated with the coordinates of the regions with possible anomalies. It is worth noting that the algorithm is able to return the points with healthy plants or even exposed soil, by simply delimiting a specific threshold. The NDVI calculation is applied to each image using the NIR and blue bands. Figure 3 presents a diagram that outlines the algo-
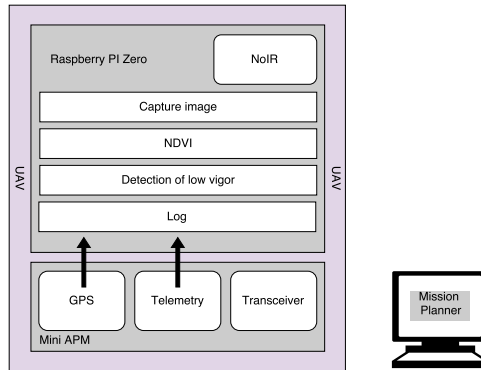
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Figure 2. General architecture.

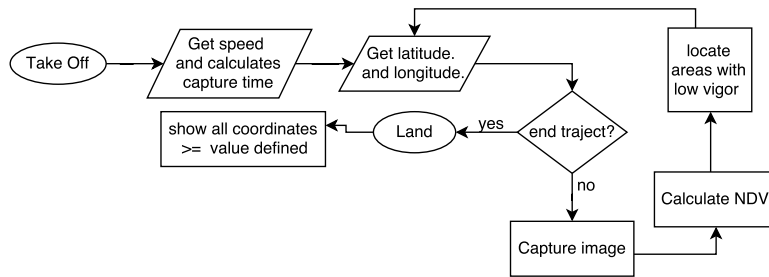rithm developed to execute during the flight. This algorithm is run by the Raspberry PI Zero.

Figure 3. Algorithm for capture and analysis of images embedded in Raspberry PI.

The images are captured at specific points in the trajectory. These points are calculated dynamically ensuring that the amount of images is sufficient to cover the monitored area. So avoiding wasted memory and processing. This calculation is based on the total analyzed area, focal length, image size, speed, and altitude.

Images are captured with 60% horizontal and vertical overlap. In this way a mosaic can be constructed at the end, so that one has a broad view of the area. The capture time of each image is based on the current speed of the airplane, this time guarantees the overlap of images. The equation for average speed and a triangle similarity are used to form Equations 2 and 3. The dimensions of the camera sensor, focal length and flight height were used as parameters in the capture time equation. The Figure 4 presents a simplistic diagram of the steps followed for the calculation.

$$\Delta t = \frac{\Delta s}{Vm} \quad (2)$$

$$Distance = \frac{sensorArea \times Altitude}{FocalLength} - (Overlap) \quad (3)$$

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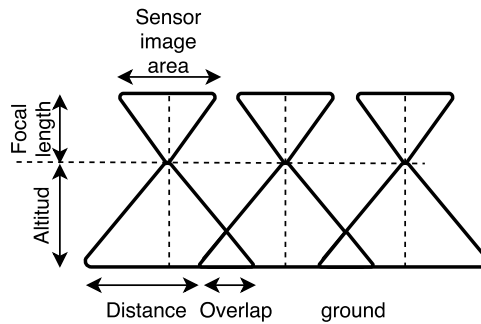
Figure 4. Basis for overlay calculation.

It was also developed, another application for the processing of the images with the intention of simplifying the understanding by the end user. The application generates a color map that marks each region according to the vegetation vigor. This application is executed after the flight.

5. Case study

The sugarcane area that was monitored is part of a plant located in Northeast Brazil. There were 3 flights in a period of 90 days, between April and June of 2017. All flights were conducted in the morning with an altitude of 120m.

Initially, a subgroup of images containing only sugarcane, without elements such as exposed soil, roads etc, was used as an estimate for the classification of healthy vegetation, seeking to establish the appropriate threshold for all plantation.

The threshold found was between [0.018; 0.035]. This delimitation was done with the objective of avoiding wrong classifications due to different spectral signatures present in the elements of nature. Figure 5 shows the monitored area with the flight plan.

Figure 5. Monitored area with the flight plan.

6. Results and discussion

The analysis of the results takes into account the time consumed by the system during the processing of the images, which consists of detecting regions with low vigor and weeds

using NDVI. Table 1 displays the processing time spent by the computing system. The data generated are total time, average and standard deviation. A total of 796 images were processed, which is the regular amount captured in a flight. The results demonstrated each image is processed in about 1.7 seconds, which is considered enough for the proposed application. Considering that the sensor area of the camera and the focal length are respectively 3.76x2.74 mm, 3.6 mm, and that at an altitude of 120 m the area covered in ground by the camera is 125x94 m, it was concluded that the maximum speed that the UAV could arrive, so that there was no loss of images, would be 26 m/s, or 90 km/h.

During the experiments, the speed reached by the UAV varied between 5 m/s and 19 m/s, due to unfavorable climatic conditions. In addition, the automatic control of the APM and some mechanical characteristics of the UAV, such as rotor power and propeller type, limit the speed of the UAV. The standard deviation demonstrates that the time spent by each image during processing was similar, this can be associated with terrain constancy.

Table 1. Processing time

Images	796
Full time	1398.47 sec.
Average	1.75 sec./image
Std. deviation	0.18 sec.

Figure 6 shows some images processed during the flight. From left to right are respectively a captured image, an image after processing of the NDVI and a histogram of the NDVI values. At the bottom of the captured images are their latitudes and longitudes. These images present some of the issues being monitored. Figure 6A presents an area with no apparent problems. Figure 6B presents an area with weeds that were detected by the NDVI (small white spots). Figure 6C shows low vigor, in addition to exposed soil within the plantation, with histogram presenting a different behavior due to these problems, with a range between -0.1 and 0.5.

Figure 7 represents the mosaic generated in order to give a more general view of all plantation. The processing of this mosaic is done after each flight by a PC. It use the images and the log file with the coordinates of each photo as input.

The regions marked in the mosaic of Figure 7 are the images presented in Figure 6. The light gray and black colors possibly represent low vigor and scarcity or excess of water or of nutrients. The white color represents different vegetation of sugar cane. In the lower part of Figure 7 are presented the histogram and an enlargement of the NDVI interval for better visualization.

7. Final considerations

This study presented a systems developed to be embedded in small UAVs for remote sensing of vegetation in real time. The results showed that it is possible to detect specific regions with low vigor in sugarcane plantation still during the flight. It is worth noting that the presented system is capable of accurately detect planting failures. In future works, a collection of leaves and soil will be done for laboratory analysis in order to compare these results with those presented by the NDVI. The application can also be adjusted to
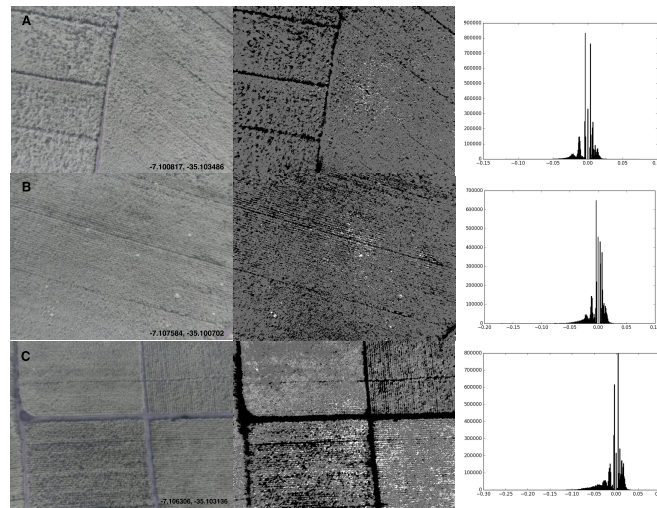
Figure 6. Some images processed (left), NVDI images (center) and histogram (right).
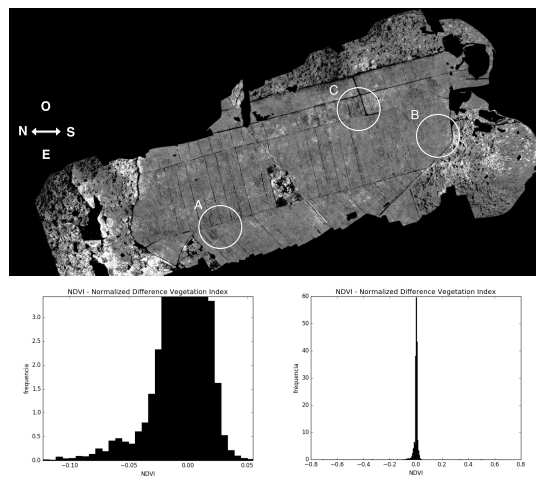

Figure 7. Mosaic (top) with its histogram (bottom-left) and the NDVI interval (bottom-right).

detect not only regions of low vigor, but other elements such as fire, flooding, animals, vegetation specie, etc. To do this, it is only necessary to know the range of each searched elements in NVDI scale.

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