2015 International Conference on Intelligent Environments

Towards Smart Farming and Sustainable Agriculture with Drones

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***Abstract*—The use of drones in agriculture is becoming more and more popular. The paper presents a novel approach to distinguish between different field's plowing techniques by means of an RGB-D sensor. The presented system can be easily integrated in commercially available Unmanned Aerial Vehicles (UAVs). In order to successfully classify the plowing techniques, two different measurement algorithms have been developed. Experimental tests show that the proposed methodology is able to provide a good classification of the field's plowing depths.**

I. Introduction

The continuous growth of the world population together with the lowering of resources at disposal pose the problem of smart usage of resources. This is very important especially in the field of food production and soil exploitation. The common methods used in agriculture to analyze and assess the correct production and usage of resources employs optical and multispectral techniques applied to photos captured from satellites. These techniques allow to assess the health state of farmings; for instance the light absorption from the leafs displays the presence of chlorophyll. This is a critical and important phase since the results of these phase will affect the decisions of interventions on the feeding of the soils, the protection from insects/fungi or if other countermeasures should be taken. The more frequently this kind of analysis is done, the more responsive and thus accurate the countermeasure will result. On the other hand this activity is time consuming if held by hand and satellite-time dependent if done by this kind of technology.

In the last years, there is a growing interest in the use of autonomous techniques for inspecting the health state of farming. Robotics jumped into this field providing interesting and effective solutions to several phases like harvesting or the plowing [1]. Compared with the satellite technology, the use of drones in agriculture and in smart farming is very effective due to the fact that unmanned aerial vehicles (UAV) can give farmers a bird's eye view of their fields still remaining close to the terrain and so providing more precise evaluations.

In particular, the use of drones does allow the opportunity to get an overall survey of the area and make a better use of farmer time, rather than just making him/her walk out blindly into a field that could be taller than his/her head, hoping that he/she stumble across any of the problem areas that might be in the field.

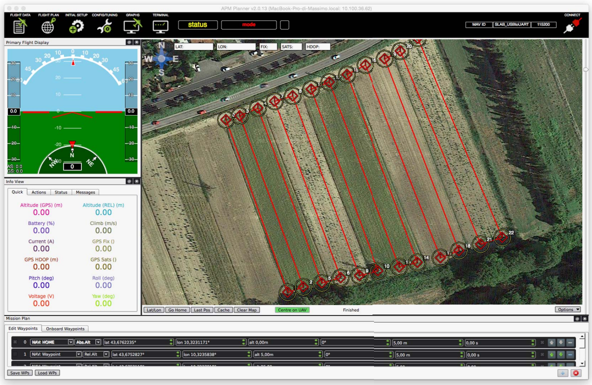

Fig. 1. Pre-programmed navigation trajectory for the soil assessment in the APM Planner open-source software.

Recently, to protect the natural ecosystem of farming fields, the Italian Tuscany region has given subsidies for the lavoration of small fields, giving prizes to farmers which will reduce the fields plowing depth by changing their plowing techniques. This direction looks promising and will be taken over probably by other regions and countries in the next future. To be able to assess directly the effective usage of the soils, satellite images could not be sufficient or should be validated at least from a closer inspection method. For this purpose, our work aims at developing a system capable of analyzing the soil condition with a rapid flight. The idea is to approach a correlation between radar (or satellite) acquired parameters and soil roughness values obtained from RGB-D cameras or laser scanners.

The paper is divided as follows: next section will introduces a brief description of the state of the art solutions. Section III will give a general overview of the system architecture. In section IV the data acquisition method is presented and analyzed in section V. Section VI shows the results of the data analysis procedure and finally section VII reports the paper statement together with conclusions and future development of the project.

II. State of the Art

Optical satellite images require specific time slots to be acquired and usually are quite expensive; for this reason a

978-1-4673-6654-0/15 $31.00 © 2015 IEEE
DOI 10.1109/IE.2015.29

radar image solution is more suitable. Radar images allow to distinguish between a tilled and not tilled soil [2] but the ability to classify different types of tillage is yet not proven. It is instead impossible to retrieve such information (terrain roughness) from high resolution satellite images. In the COSMO-SkyMed project [3] 3/5 meters resolution radar images in X bandwidth have been achieved with special spotlight stripmap images at the resolution of 1m requiring several acquisition phases. Usually this kind of system requires big parcels of terrain to be effective and cannot distinguish small cultivated fields.

The use of computer vision techniques from drones will allow to water or spray only where necessary applying a selective spraying in sections of the field that need the treatmens. From captured images it is also possible to analyze the watering level within plants, to plan crops with precision and possibly automate tractors.

With the help of hyper-spectral measures it is possible to evaluate the hydraulic stress of sites classifying them based on the stress level [4], assess the chlorophyll content [5], verify ozone damage on leaves [6] and differentiate plant species based on leaves properties.

III. System overview

The sensing technology presented in this paper is meant to be used as part of a robotic assessment system composed of an aerial vehicle, an RGB-D sensor and a software interface responsible for the navigation phase and the post-processing of the acquired data.

Many different avionics could be used to achieve the terrain assessment. In particular, in the literature and in the market domain, many aerial system producers propose both fixed and rotatory wings alternatives. As an example the senseFly company proposes an advanced drone called eBee [7] with autopilot capabilities that can handle take-off, flight, and landing autonomously. The eBee is also packed with a high-resolution camera that might be useful for 3D maps with 5-10 cm accuracy.

The proposed system employs a commercial low-cost RGB-D camera, an Asus Xtion Pro, for the visual analysis of the soil and thus it can be employed both in a fixed-wing drone or in a rotatory wings like a multi-rotor system. The choice of using a commercial sensor has the advantages of being relatively cost effective compared to a prototype solution, it doesn't require dedicated acquiring electronic components and can be embedded in a large number of aerial vehicles.

Localization, navigation and mapping has been a very active area of research lately and many works can be found in literature on this topic [8] [9]. Without the need to employ state of the art techniques, for the navigation goals of our system it is necessary to employ the classic sensor fusion technique involving GPS integration with Inertial Navigation Systems (INS). In fact these two sensing modalities are extremely complimentary: the GPS module provides a slow-update positional information with bounded error, while the INS system provides unbounded integration error, but with a fast update rate. Combining the two, it is possible to achieve high-fidelity localization estimation.

For the purposes of our goal, this technology is sufficient and the use of a standard Extended Kalman Filter solution [10] for the navigation problem is advised.

Several software solutions are freely available for download over the Internet for the automatic navigation control of drones equipped with a GPS module. As an example of that in Fig. 1 the trajectory performed with a Parrot Ar.drone 2.0 GPS edition in order to completely scan a parcel of terrain is shown.

In order to collect topological data for the surface analysis of the different fields, a point cloud [11] representation of the three-dimensional structure of the field has been created.

The AUV should be distance controlled with respect to the terrain; to do so a simple PID controller [12] can be implemented using, as sensing technology, a camera (video-based) or an ultrasound/infrared distance measurement sensor. If due to environmental conditions the distance from the terrain changes, the acquired point cloud should be scaled accordingly. In such case, the point cloud is firstly used to obtain a mesh and then scaled with respect to the acquisition distance (relative distance between the RGB-D camera and the terrain) to make the dimentions consistent among the different samples. A second step would be to sample the mesh with an equally spaced grid.

IV. Data Acquisition

RGB and depth data has been acquired using an Asus Xtion Pro sensor on three different consequent parcels of a common field which have been plowed with different depths: the first parcel was unplowed, Figure 2 (a), the second parcel had a 25 cm plow, Figure 2 (b), while the third parcel had a 50 cm plow, Figure 2 (c). A short RGB-D video has been captured for each field storing the rgb and depth data. The distance of the Xtion from the terrain didn't change during the acquisition phase.

Afterwards, using the data of each stream, a point cloud stream has been created using PCL, *Point Cloud Library*, and three representing clouds for each field have been extracted. This has been done to avoid sparse point clouds containing a lot of obscure regions, given that the Asus Xtion Pro camera is very sensible to sun light. To avoid this problem also a big sun screen has been used to avoid direct lighting.

V. Data analysis

During the acquisition phase, the camera was not facing the terrain in a perpendicular way, resulting in a point cloud in which the height variations ware not clearly identifiable. For the purpose of obtaining a height field it is necessary to rotate the point cloud accordingly. In this analysis this operation has been carried out by applying Principal Component Analysis (PCA) over the points in the point cloud: when applied over 3D points the PCA corresponds to finding the rotation in which the resulting axis, called principal axis, have maximum variance. In this case it is correct that the resulting x and y axes correspond to some axis parallel to the terrain while the z axis is perpendicular. The choice of x and y is clearly influential for this application.

After the PCA rotation the point-cloud has been then transformed into a uniformly sampled height field by means

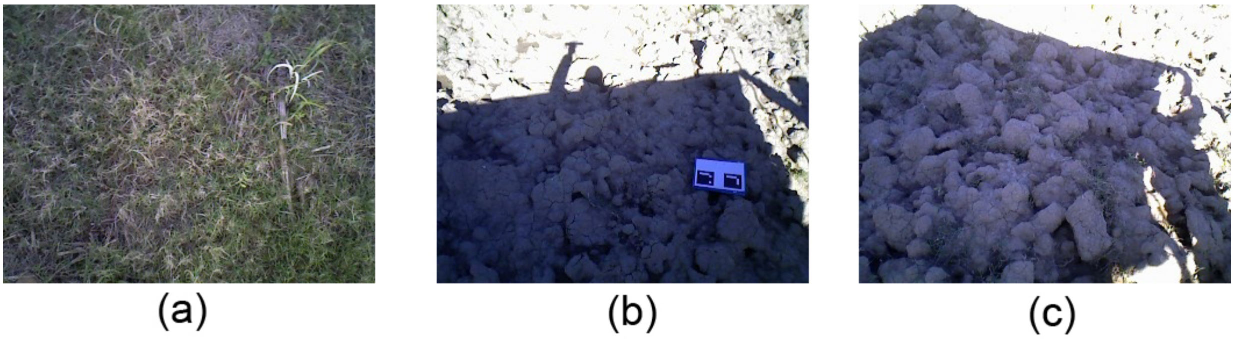

Fig. 2. Images of the 3 field's parcels used in the analysis. (a) Unplowded parcel (b) 25cm plow depth (c) 50cm plow depth

of Delaunay triangulation. The resulting height-field for the three plowing depths is shown for one sample in Figure 3, 4, 5. The result of the pre-processing is a height-field over which two different measures have been used for plowed state discrimination.

To obtain two discriminating parameters a two dimensional *Fast Fourier Transform* (FFT) has been applied to the Z axis and then the power spectral density (PSD) has been computed for each sample as shown for example in Figure 6, 7, 8 from which two values have been extracted:

- The maximum of each fft of each sample has been extracted and the mean value has been calculated obtaining the results shown in Table I
- The mean power of each fft has been calculated and then the mean value for each field has been extracted and reported in Tabel II

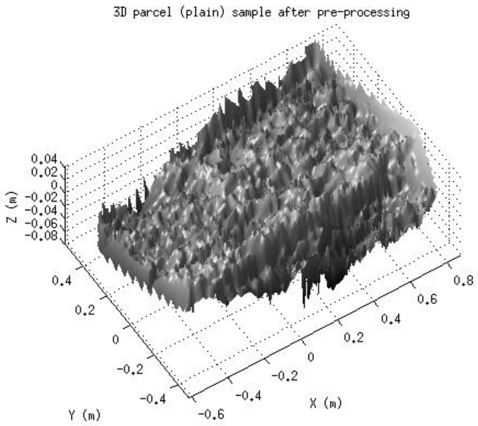

Fig. 3. Unplowded field mesh after the pre-processing step

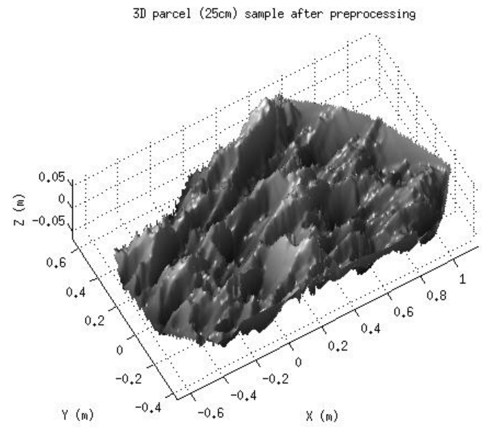

Fig. 4. 25cm deep plow mesh after the pre-processing step

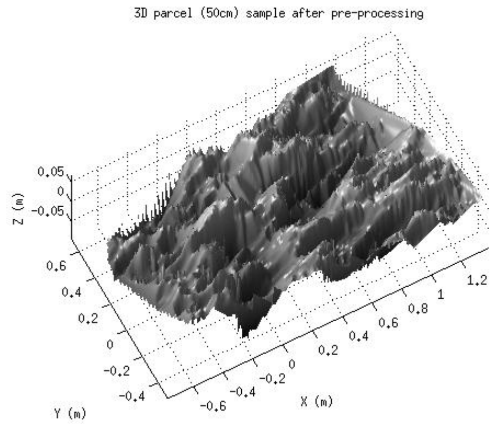

Fig. 5. 50cm deep plow mesh after the pre-processing step

VI. Data Evaluation

The first and second extracted measure show that there is the possibility two distinguish between the three fields; the calculated values have three different ranges, having the lowest values for the plain field, high values for the 25cm field and intermediate values for for the 50cm field.

VII. Conclusions and Future Work

The presented work describes a vision-based technique for the analysis of soil characteristics. In particular the method has been employed in the plowing type discrimination and

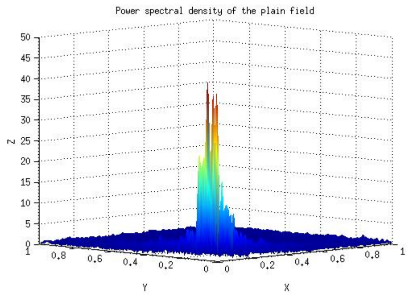

Fig. 6. Unplowed field fft power spectral density

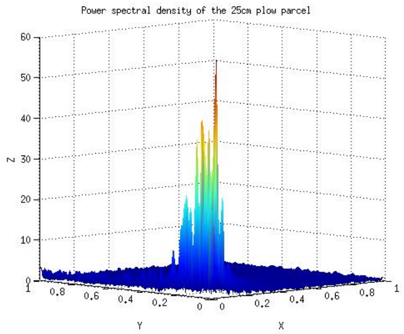

Fig. 7. 25cm deep plow fft power spectral density

Plow depth	Mean	Variance
plain	11.00	8.00
25cm	47.28	28.45
50cm	21.75	9.45

TABLE I. VALUES OBTAINED USING THE FIRST ANALYSIS METHOD FOR THE DIFFERENT PARCELS.

Plow depth	Mean	Variance
plain	$1,23 \times 10^4$	$2,50 \times 10^3$
25cm	$2,53 \times 10^4$	$3,94 \times 10^3$
50cm	$2,05 \times 10^4$	$4,56 \times 10^3$

TABLE II. VALUES OBTAINED USING THE SECOND ANALYSIS METHOD FOR THE DIFFERENT PARCELS.

the solution has been tested on field. The experimental results prove the feasibility of the proposed approach as terrain classifier. The software is able to discriminate among three different plowing depths which are in this case plane, 25cm, 50cm.

Future work will focus on the installation of the sensing component on a UAV and in the substitution of the actual Xtion Pro sensor with the new Kinect v2.0 that allows a greater resolution and does not present interference with daily light emissions. This could bring also the possibility of having the UAV flighing at a higher distance from the field and scanning a bigger areas in the same time w.r.t. the Xtion Pro sensor. The main disadvantage of the kinect v2.0 relies in the fact that it needs more space to be installed on an UAV system, an increased payload capability, and the need of an external

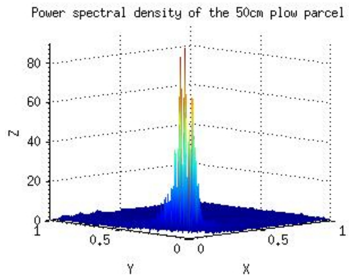

Fig. 8. 50cm deep plow fft power spectral density

power supply given that it is not USB powered.

Another improvement will be to embed on the UAV the whole computing system (vision + navigation + data analysis) using a mobile GPU. The re-orientation technique based on PCA has a $O(m \times n^2)$ cost, with m number of point, n fixed as 3, meaning that the algorithm is linear in the points, and it can be easily parallelized on GPU, while Delaunay triangulation has a complexity of $O(nlogn)$. In addition the re-orientation can be integrated by sensor fusion with the inertial unit of the UAV.

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