A medium size field inspection vehicle

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Abstract: The society and EU legislation drive actions to achieve sustainable use of pesticides by reducing their risk and impact on human health and the environment. The concept of Integrated Pest Management (IPM) integrates as key element, the monitoring or continuous inspection of crops to ensure early detection thereof. Thus, new methods for crop assessment using robotic systems could help in this task. A novel approach using a mobile robotic platform has been designed and developed. The platform allows to perform an inspection on two types of scenarios: annual crops (maize, cereal, etc) and multiannual crops (orchards, vineyards, etc). A system acting on the throttle, brake and steering of the vehicle to control both, the vehicle speed and the vehicle turning, has been proposed. The combination of this system and fuzzy control techniques allow the autonomous navigation and the control of the platform while field inspection. With the acquired information, our group (Artificial Perception Group - GPA) is working on detection, characterization and recognition of crop plants (vineyards, maize, winter cereals) and weeds by the generation of 2D and 3D maps of crops.

1 INTRODUCTION

Agriculture is the main use of land in the European Union (EU) covering 40% of the total land area (Eurostat, 2016). In 2012, more than 60% of this agricultural land was devoted to annual crops (cereal, maize…) while 6% was dedicated to multiannual crops (olive trees, vineyards, fruit trees…). Factors affecting crops (pathogens of plants, invertebrates and weeds) can significantly reduce agricultural production, reaching in some cases up to 40% overall reduction in crop yield (Oerke, 1994). It is estimated that the amount of crops eaten by insects would be enough to feed more than one billion people (Birch, 2011). This scenario may worsen with the establishment of exotic pests favored by climate change. Thus, the increasingly warm and humid climate of northern Europe will favor the development of new diseases, while drier and warmer conditions in southern Europe will increase insect pests. It is estimated that every 10 months a new agricultural pest enters in southern Europe moving north as conditions change (Reddy, 2015). Although the negative effects lead to difficult problems as the emergence of secondary pests and resistances, most farmers and producers in the EU depend on broad spectrum chemical pesticides. This fact has led the EU to pass a legislation banning an important number of synthetic chemical pesticides (Regulation (EC) No 1107/2009 and Directive 2009/128/EC of the European Parliament and of the Council). This new scenario drives actions to achieve sustainable use of pesticides by reducing their risk and impact on human health and the environment, promoting the concept of Integrated Pest Management (IPM) in which a key stage is the monitoring or continuous inspection of crops to ensure early pest detection. Whereas in small fields, operators can effectively perform this surveillance, in large areas, only sampling at certain selected points is a viable monitoring option. Therefore, the development of technologies that enables the autonomous and continuous inspection of crop fields is a pending task of great interest.

This paper describes a multisensory inspection system integrated in an on-ground autonomous platform. The aim of this research is to perform a preventive and predictive inspection of crops. The acquired heterogeneous information will be integrated to generate 2D and 3D maps of the crops. The vehicle will fully cover a field following a predefined route plan (Conesa-Muñoz, 2016). It will be able to perform one of the two implemented types of navigations: 1) Guided by information provided by the RTK-GPS receiver, which is an appropriate navigation for narrow row crops, such as cereal, as well as multiannual crops, such as vineyards, fruit trees, etc. 2) Guided on real-time by visual detection of some element of interest, such as crop rows; this navigation could be appropriate in cases where the vehicle can move between the crop row without stepping it, such as maize crops.

2 MATERIALS AND METHODS

2.1 Hardware

The inspection vehicle (Figure 1) is based on a heavy quadricycle-classed Urban 80 model (Twizy, Renault). It features a 13 kW (17 hp) electric motor and it can travel up to 80 km/h (50 mph) with an autonomy of around 80 km after a 3.5 hours charge from a standard electrical supply. It is an ultra-compact vehicle, with a length of 2.32 metres, 1.19 metres width and 1.46 metres height. Thanks to its electric motor, the vehicle can move at speeds below 3 km/h with low vibrations, which is a great advantage for high-quality information acquisition.

Furthermore, the vehicle is equipped with a support structure. This element allows the positioning of cameras as required. Two cameras are placed on the structure for data adquisition: 1) An RGB-D sensor (Kinect v2, Microsoft), which uses ToF (time-of-flight) technology to generate depth information at 512×424 pixels resolution and RGB images of 1920×1080 pixels at a rate of 30 frames per second. 2) A reflex camera (EOS 7D, Canon) able to provide around two high-quality colour images (2592×1728 pixels) per second. Both cameras were connected to an on-board computer that includes an Intel Core i7-4771@3.5GHz processor, 16 GB of RAM, and a NVIDIA GeForce GTX 660 graphic card. The inspection vehicle is completed with a RTK-GPS receiver (R220, Hemisphere), which provides 20 locations per second with an error below 2 cm.

2.2 Software

Autonomous navigation of the vehicle needs to control the speed and the vehicle turn, which implies acting on throttle, brake and steering system. The Figure 2 illustrates the developed control architecture.

The on-board computer is responsible for decision making processes, sending the commands to the vehicle when working in remote control mode, or autonomously based on RTK-GPS receiver information or on-board sensors information.

When turning the direction of the vehicle is required, the on-board computer sends the necessary commands to a motor controller. Then, the motor combined to the steering of the vehicle acts, turning the steering wheels as required.

Figure 1 : Electric inspection platform.

Speed variations are commanded by the on-board computer. It sends commands to an Arduino board which generates signals to the internal motor controller of Renault Twizy, simulating that the throttle pedal has been pressed. Thus, an extra mechanical actuator is saved.

A braking actuator system is also controlled. The on-board computer commands the Arduino board to generate a signal, which starts a servomotor acting on the brake pedal. Unlike the throttle pedal, braking pedal on Renault Twizy is mechanical, not digital, so it requires an actuator element to press the brake pedal.

The on-board computer takes the decisions to control the vehicle by using fuzzy control techniques. There are many approaches to address the automated vehicle control. The conventional control methods produce reasonable results at the expense of the high computational and design costs to obtain the mathematical model of the vehicle (Rossetter, 2002; Sheikholeslam, 1992). Wheeled mobile robots are characterised by nonlinear dynamics and they are affected by an important number of disturbances, such as turning and static friction or variations in the amount of cargo. Alternatively, human behaviour regarding speed and steering control can be approached using artificial intelligence techniques. The techniques that provide a better approximation to human reasoning and give a more intuitive control structure are often based on fuzzy logic (Zadeh, 1965; Sugeno, 1999). Indeed, some authors have proposed solutions that are based in fuzzy logic for autonomous navigation (Fraichard, 2001; Naranjo, 2007; Kodagoda, 2002; Bengochea-Guevara, 2016), demonstrating their robustness. In (Fraichard, 2001), fuzzy control is employed on a car to perform trajectory tracking and obstacle avoidance in actual outdoor and partially known environments. In (Naranjo, 2007), fuzzy controllers are implemented on car to conduct experiments on actual roads within a private circuit. Their results showed that fuzzy controllers perfectly mimic human driving behaviour while driving and route tracking, as well as complex, multiple-vehicle manoeuvres, such as adaptive cruise control or overtaking. In (Kodagoda, 2002), authors developed and implemented fuzzy controllers for the steering and speed control of an autonomous guided vehicle. Their results indicate that the proposed controllers are insensitive to parametric uncertainty and load fluctuations and outperformed conventional proportional-integral-derivative (PID) controllers, particularly in tracking accuracy, steady-state error, control chatter and robustness. For the proposed inspection vehicle, the fuzzy controllers to achieve remote controlled navigation, and lately autonomous navigation, are being developed taking into account previous work of the group (Bengochea-Guevara, 2016; Bengochea-Guevara, 2014), where the development of a small autonomous vehicle for crop

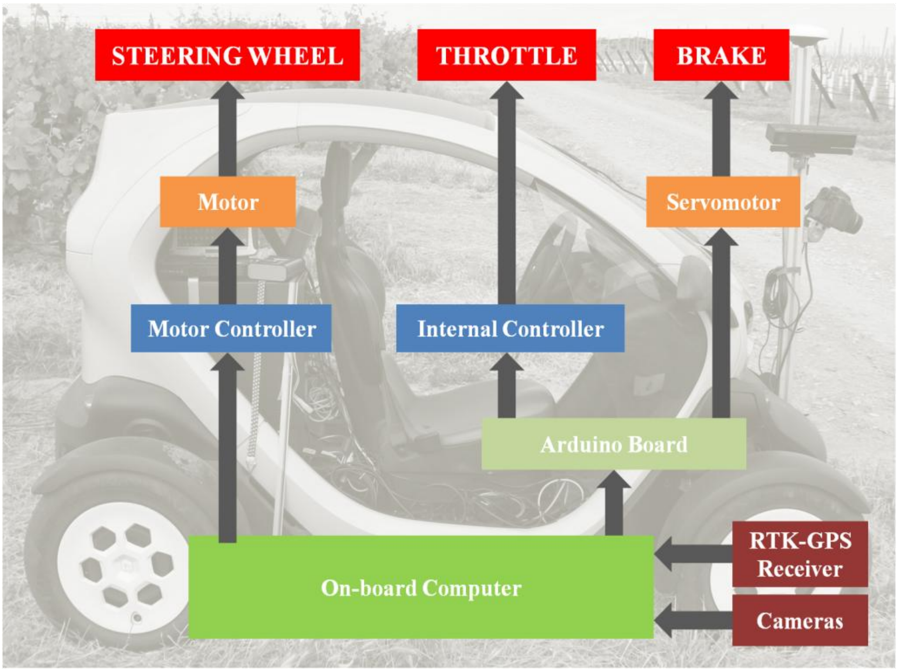

Figure 2 : System proposed.

inspection using fuzzy control was presented.

Regarding 3D scene reconstruction, the fusion of different overlapped depth images is accomplished by a method based on the algorithm described in (Niessner, 2013). The algorithm was selected due to its good results for the 3D reconstruction of large areas from the information directly provided by the Kinect sensor. Others 3D reconstruction methods (Chen, 2013; Niessner, 2013; Steinbrucker, 2013; Whelan, 2012) including the Microsoft software (Newcombe, 2011), which encloses an important constraint in the agricultural context since it only manages volumes up 8 cubic meters, were considered.

The 3D reconstruction method estimates the position and orientation of the camera that best aligns the current image with the intermediate model. Furthermore, a variant of the Iterative Closest Point (ICP) algorithm (Chen, 1992) has been integrated to improve the quality of the reconstructed model by reducing the drift in the reconstruction. Thus, new depth information is fused to the current model using a weighted moving average while the RGB information is also updated using an exponential moving average. Furthermore, during sampling time, the position of the Kinect sensor was continuously recorded from the signal provided by the GPS-RTK receiver. Lately during the reconstruction phase, these locations are used to improve the accuracy of the 3D map. The developed method uses a process of reconstruction in sections which harmonized the position of the points in the cloud with the GPS positions taken during the sampling.

Once the point cloud is obtained, a mesh can be built using the Marching Cubes algorithm (Lorensen, 1987).

Finally, weed detection and crop estimation (Ribeiro, 2005; Burgos-Artizzu, 2011) is performed with 2D maps automatically generated from the images provided by the Canon camera along with the RTK-GPS location data.

3 RESULTS AND DISCUSSION

First tests were conducted on February 2016 in the vineyards owned by Codorniu S.A. (Raimat, Lleida) and in a wheat cereal field (Muller, Lleida).

Figure 3 shows an example of information provided by Kinect v2 sensor in the vineyard. The sensor was stood at approximately 1.4 m height and around 1 m of distance from the crop row. Figure 3a shows the RGB information of the scene while Figure 3b shows a colour representation of the depth information (distance of objects in the scene), where near objects appear in red and further ones in blue, while the rest of intermediate objects are shown up in various shades of orange, yellow and green depending on their distance to the sensor.

(a)

(b)

Figure 3: (a) Color image and (b) depth image taken by Kinect v2 sensor.

Moreover, the 3D reconstruction (Figure 4) maintains the proportions. Thus, important values can be estimated, such as height or foliar volume, to determine structural parameters of the vineyard. This information is crucial for managing and early detection of crop problems. Several methods for value extraction are being tuned based on previous experience of the group (Andújar&Dorado, 2016; Andújar&Ribeiro, 2016; Andújar&Rosell-Polo, 2016).

The Canon camera was located in the front of the vehicle focused to the ground to capture vegetation cover information. Some examples of the taken images are illustrated in Figure 5. In the left column, the first two images correspond to vineyard cover while the latter is the cereal crop cover. The right

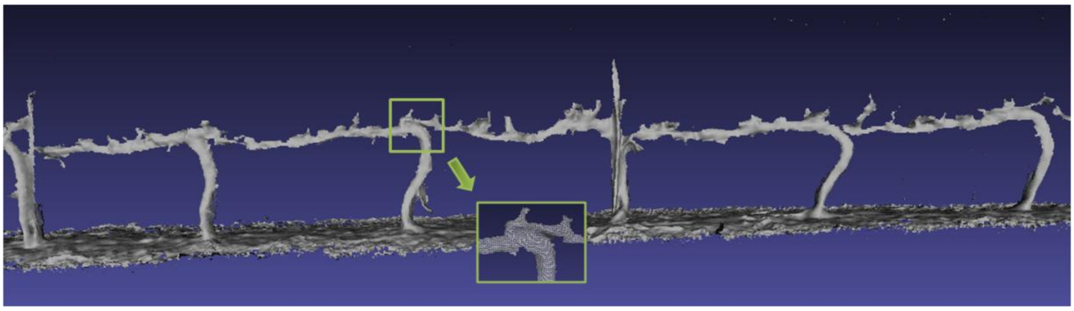

Figure 4: 3D reconstruction of a row of vines. In the square, a detail of a 3D reconstruction of a vine which can be seen the mesh obtained from a point cloud.

column show the result of applying a color index based segmentation (Burgos-Artizzu, 2010; Burgos-Artizzu, 2011; Burgos-Artizzu, 2009; Guijarro, 2011; Ribeiro, 2011; Ribeiro, 2005; Sainz-Costa, 2011) to isolate the green areas. In the case of the vineyard, green areas correspond to weeds that must be detected. In the case of the cereal crop, green segmented zones are jointly formed by the crop and weeds, so a subsequently stage will be needed to discriminate weed from crop (Ribeiro, 2005; Burgos-Artizzu, 2011).

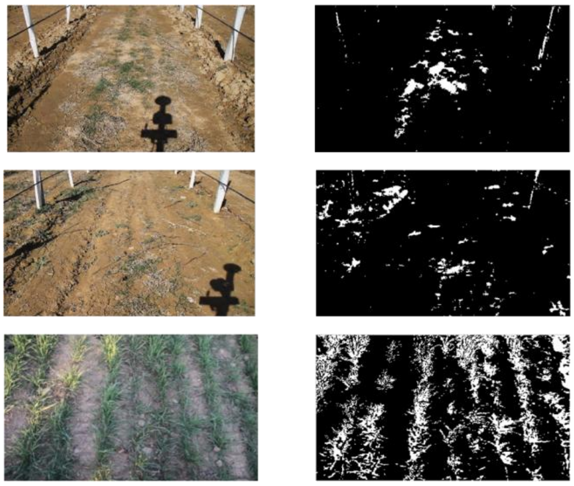

Figure 5: In the left column, images taken by the Canon camera of cereal field. In the right column, results of the segmentation of those images.

4 CONCLUSIONS

This paper presents some preliminary results of the crop inspection technology that is being set-up. Specifically, a mobile inspection platform based on an electric vehicle, capable of scanning in two types of scenarios: annual crops (maize, cereal, etc.) and multi-annual crops (orchards, vineyards, etc.). It has been proven the correct vehicle operation, including on-board sensors, as well as the reconstruction software performance by sampling actual crop fields and generating 2D/3D maps of the sampled crops. The technology presented in this paper is particularly important to actually implement a crop management consistent with the precepts of a Integrated Pest Management system.

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