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3D Monitoring of Woody Crops Using a Medium-Sized Field Inspection Vehicle

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Abstract. In this work, a crop inspection system is presented. A mobile platform, based on a commercial electric vehicle, is equipped with different on-board sensors to inspection annual crops (maize, cereal, etc.) and multi-annual crops (orchards, vineyards, etc.). The use of a low-cost RGB-D sensor, the Microsoft Kinect v2 sensor, for the inspection of woody crops is tested. A method to generate automatic 3D reconstructions of large areas, such as a complete crop row, from the information directly supplied by the RGB-D sensor is shown as well as a procedure to correct the drift that appears in the reconstruction of crop rows. All these methods were tested and validated in real fields at different times throughout 2016. The development presented in this paper is a promising technology to achieve better crop management, which will increase crop yield.

Keywords: 3D woody crop reconstruction · Low cost RGB-D sensor · Crop inspection platform

1 Introduction

Agriculture is the primarily land use in the European Union, covering 40% of the total land area [1]. A common desire of all farmers is to know their crop yields, since accurate yield predictions help they improve crop quality and reduce operational costs by making better crop management decisions. Yield estimation is usually based on the knowledge of the crop, historical data, meteorological conditions and manual samplings performed by operators. Manual sampling is a time-consuming, labour-intensive, and inaccurate process, since the number of samples is often too small to capture the magnitude of variations in yield in each crop block. Thus, it is extremely important to find an automated and efficient alternative that can accurately capture the spatial and temporal variations of a crop. Vehicles equipped with on-board sensing equipment are a promising choice among the various means of collecting well-structured information. The use of medium-sized platforms for full crop inspecting is a suitable choice to minimise soil compaction. This makes possible to perform more than one sampling throughout the year because of the minimal impact on the crop.

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On the other hand, 3D reconstruction of woody crops using non-destructive methods is a valuable technique for decision-making processes. The use of sensors for the characterisation of crops leads to a better understanding of the processes involved in tree development throughout the life cycle. With information obtained from a 3D reconstruction of the crop, important parameters such as growth status, height, shape, biomass, need for nutrients, health status, etc. can be estimated. The use of the information extracted from the 3D reconstructions can improve the decisions made related to crop management and contribute to creating new protocols to improve the profitability and health of the plants.

Currently, the Microsoft Kinect v2 RGB-D sensor, based on ToF (time-of-flight) technology, is a very effective device among 3D vision systems thanks to its low cost and good performance. Kinect v2 sensors have been used for the characterisation of plants in agriculture. In [2], the authors compared two low-cost 3D systems, including the Kinect v2 sensor, with an expensive high-precision laser scanner and concluded that low cost systems could replace the more expensive scanner in several plant phenotyping scenarios. The use of the Kinect v2 sensor is proposed in [3] to determine the volume of weeds in maize crops and to define their treatment period. The results suggest that this sensor can be a high precision device in estimating the volume of weeds and determining the state of the crop. In [4] a Kinect v2 sensor was used to estimate the volume of onions, showing that the calculated volume was directly related to the estimation with measurements from the sensor.

Although 3D reconstruction is a research line with numerous and important works in computer vision, the emergence of a type of cameras with good performance and low cost in last years, like above-mentioned Microsoft Kinect and Asus Xtion sensors, which provide information of distance to the objects closest to the scene, have opened up new possibilities in 3D reconstruction. Several of the recent researches have been focused on acquiring 3D scene reconstruction using the depth images supplied by these new sensors. Thus, different techniques that employ distinct types of accelerated data structures using graphic hardware to combine consecutive depth images with a certain degree of overlap have been developed. Each technique has its own advantages and disadvantages in terms of speed, scale and quality of the reconstruction.

Some methods use a voxel structure (a voxel represents a value on a regular grid in 3D space) to store the 3D sensor information [5–7]. A well-known example is the method described in [6], which generates high quality 3D reconstructions [8] and was adopted by KinectFusion [9, 10], the 3D reconstruction method included by Microsoft in its software development kit, Kinect for Windows Software Development Kit 2.0 [11]. However, the method presents an important constraint; it restricts the reconstruction to volumes up to 8 m^3. This justifies the emergence of variants on the method that allow reconstructions of larger volumes using voxel structures [12–14]. Other strategies proposed the use of hierarchical data structures that subdivide space effectively, but these strategies do not parallelise efficiently given added computational complexity [15, 16].

One of the problems with all 3D reconstruction methods is that they estimate the position and orientation of the sensor with the information from its images, i.e. there may be slight variations among the position and orientation calculated and the actual values obtained by the sensor. This happens primarily with similar scenes, such as crops, where the same structure is repeated over and over again, appearing as analogous information (canopies full of similar leaves to analogous distances from the sensor). These slight variations in position and orientation calculated may give rise to a drift that causes deformations in 3D reconstruction, with it being more pronounced with the greater size of the reconstruction.

The overall objective of this work is shown a method to generate automatic 3D reconstructions of large areas, such as a complete crop row, from the information directly supplied by the Microsoft Kinect v2 sensor on-board an inspection vehicle. Additionally the paper presents a procedure developed to correct the drift that appears in the 3D reconstructions of long rows.

2 Materials and Methods

2.1 Field Platform

The field platform (Fig. 1) is based on a Renault Twizy Urban 80 model, which has a 13 kW electric motor and is able to travel up to 80 kmh-1. The vehicle has an autonomy of approximately 80 km. The field platform is an ultra-compact vehicle, with a length of 2.32 m, width of 1.19 m, height of 1.46 m and unladen weight of 450 kg. The electric motor of the vehicle allows vibration free speeds below 3 kmh-1, which is convenient for high-quality information acquisition.

Fig. 1. Electric inspection platform

An aluminium support structure has been integrated for easy placement of sensors. Two devices were integrated, adapting their positions to the crop features of each sampling. The first one is a Microsoft Kinect v2 RGB-D sensor, which at 30 fps, supplies RGB images with a resolution of 1920 × 1080 pixels together with depth information with a resolution of 512 × 424 pixels. Depth data is obtained by using ToF technology. The depth measurement range of the sensor is 0.5–4.5 m, but outdoors the maximum range is smaller. Thus, studies carried out outdoors with sunny daytime illumination show that the sensor supplies valid depth measurements up to 1.9 m. The distance increases until reaching 2.8 m with the diffuse illumination of an overcast day [17].

The other on-board sensor is a Canon EOS 7D reflex camera, which, at 2 fps, supplies high-quality RGB images with a resolution of 2592×1728 pixels. Both sensors were connected to the on-board computer, which has an Intel Core i7-4771@3.5 GHz processor, 16 GB of RAM, and an NVIDIA GeForce GTX 660 graphic card. Furthermore, the inspection vehicle is equipped with an R220 Hemisphere RTK-GPS receiver, which provides location data at 20 Hz sample rate with an error below 2 cm.

To get an idea of what a journey of 80 km (range of vehicle) involves in inspection, we analysed how many hectares would be covered in the case of a woody crop inspected with RGB-D sensors. If the woody crop is a vineyard, space between crop rows are usually 2 m wide. If two RGB-D sensors are placed on both sides of the vehicle to take images of each row while the vehicle advances along the lane, it would cover a total of 16 ha with its 80 km of range, if the movements in crop headers, to change lane, are not taken into account. As the average size of a vineyard in Spain is 1.8 ha [18], in the best-case scenario, this platform on a single charge could inspect around 9 vineyards. In the case of carrying a single RGB-D sensor, the vehicle would be able to cover 8 ha, since would have to cover the same lane twice; therefore, it could inspect more than 4 vineyards of 1.8 ha under a single charge. The covered area could be somewhat reduced, considering the consumption of equipment connected to the battery of the vehicle and movements made in the crop headers.

The inspection plan to be followed by the platform is generated by a path planner [19], which can be formulized as the well-known Capacitated Vehicle Routing Problem, as stated in [20]. Basically, the problem consists of determining the best inspection route that provides complete coverage of the field considering features such as field shape, crop row direction, the type of crop and some characteristics of the platform, such as the turning radii or the number of sensors on-board. Therefore, the planner determines the order for performing the lane analysis in such a manner that an established optimisation criterion gets minimal.

While this mobile platform is prepared to inspection annual crops (maize, cereal, etc.) and multi-annual crops (orchards, vineyards, etc.) with its on-board sensors, the present work is focused on the inspection of woody crops with the information supplied by the RGB-D sensor.

2.2 3D Reconstruction

After studying different 3D reconstruction methods [12–14, 16], the algorithm described in [14] was selected for the 3D reconstruction of woody crops. This method provides good results in large area reconstruction (fundamental in this application) from the information directly supplied by the Microsoft Kinect sensor.

The method extends the algorithm proposed by [6] to reconstruct large surfaces using the fusion of different overlapped depth images, storing information only on the voxels closest to the observed object. All other voxels are not allocated in the memory. In this way, the need to have a complete regular voxel grid stored in the memory is eliminated, given the computational advantages that this involves. To exploit this aspect, the implemented procedure uses a hash table to store the voxels.

Given a new input depth image and known camera position, the ray casting technique [21] is used to project a ray from the camera focus for each pixel of the input depth image in order to determine the voxels in the 3D world that cross each lightning. In this way, the voxels related to the depth information are determined.

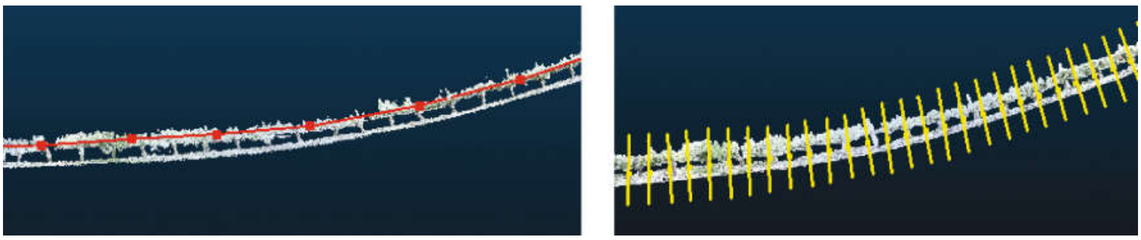
Once the surface of the scene has been extracted using the ray casting technique, this information is used to estimate the position and orientation of the camera (6 degrees of freedom) when a new input image arrives. For this, a variant of the ICP (Iterative Closest Point) algorithm [22] is used.

To dump the information of the voxels to a triangular mesh that represents the 3D reconstruction of the scene, the Marching Cubes algorithm [23] is used. The 3D reconstruction obtained represents a woody row, but it does not appear to be as straight as the original due to the drift effect (Fig. 2).

Fig. 2. 3D reconstruction of a woody row with presence of drift

A method is developed to correct this drift using minimal scene information, such as the location of the starting and ending points of the row as well as the fact that trees are planted in straight lines (sowing with precision seeder).

First, the algorithm divides the whole mesh into smaller meshes with the same number of vertices. It then calculates the centroid for each of these meshes using the position coordinates of its vertices (Fig. 3a). Note that although each mesh contains the same number of vertices, it does not represent the same length of the woody row because the vertices distribution in the whole mesh is not uniform. The number of pieces of smaller meshes may be estimated from the row total length. Next, the line that joins all the centroids (model line) is built and used to divide the initial mesh into same-length sections separated by planes perpendicular to the line in each separating point (Fig. 3b).



(a) (b)

Fig. 3. (a) Model line by using centroids. Note that centroids are not equidistant (b) Crop row divided into sections. Note that all sections have the same length.

Since the model line goes over the crop line, the vector that indicates the direction of the crop in each section can be calculated using the starting and ending segment points of the model line where the section is contained. Ideally, the direction of this vector should coincide with the direction of the actual crop row. However, this does not happen due to the drift that appears in the 3D reconstruction. To solve this and correct the drift, each section must be corrected so that it is rotated to align the vector that indicates the model line in that section with the actual direction of the crop. The rotational formula of Rodrigues [24] is used to calculate the rotation matrix applied to each section.

Once the drift of each section has been corrected, the sections are aligned, thus correcting the drift produced during 3D reconstruction.

3 Results

Several tests were conducted in 2016 in the vineyards owned by Codorniu S.A. (Raimat, Lleida, Spain). The inspection platform moving at 3 km/h was used to collect the information. The sensor Kinect v2 was mounted at approximately 1.4 m in height with a 10º pitch angle, oriented to the crop rows, and approximately 1 m from the crop row (Fig. 4).

Fig. 4. Sampling in vineyards owned by Codorniu S.A. (Raimat, Lleida, Spain) in May 2016

From each row inspected, the starting and ending geographical positions of the row, supplied by the RTK-GPS receiver from the vehicle, were stored.

Figure 5 shows examples of the information provided by Kinect v2 sensor in the vineyard in the tests conducted in May 2016. Figure 5a shows the RGB information of the scene. Figure 5b shows a false colour representation of the depth information (distance of objects in the scene), where near objects appear in red and further ones in blue, and the rest of the intermediate objects are shown in various shades of orange, yellow and green, depending on their distance from the sensor. From the depth images, it can be seen that the sensor range of operation meets the inspection requirements of the vineyard rows because objects of no interest are ignored, such as those close and the distant areas that usually contain other vineyard rows.

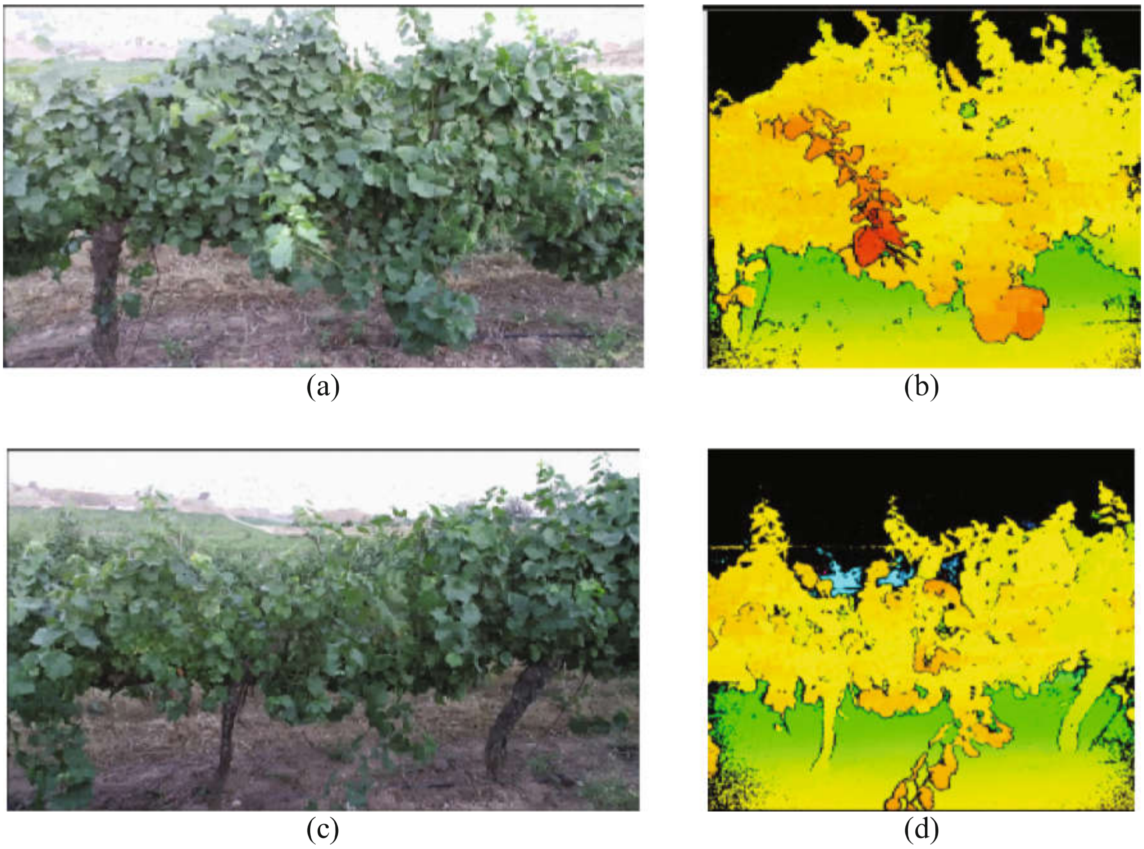


Fig. 5. (a) and (c) RGB images supplied by Kinect v2 sensor; (b) and (d) Depth images supplied by the sensor at the same time as (a) and (c)

With the information supplied by the Kinect v2 sensor and stored in the vehicle's on-board computer, the 3D reconstruction of the sampled rows of vines was performed. For that, a desktop computer with an Intel Core i7-6900K@3.2 GHz processor, 64 GB of RAM, and an NVIDIA GeForce GTX Titan X graphics card was used. Figure 6 shows an example of one of the 3D reconstructions generated, and Fig. 7, shows the 3D mesh structure obtained in one of these reconstructions.

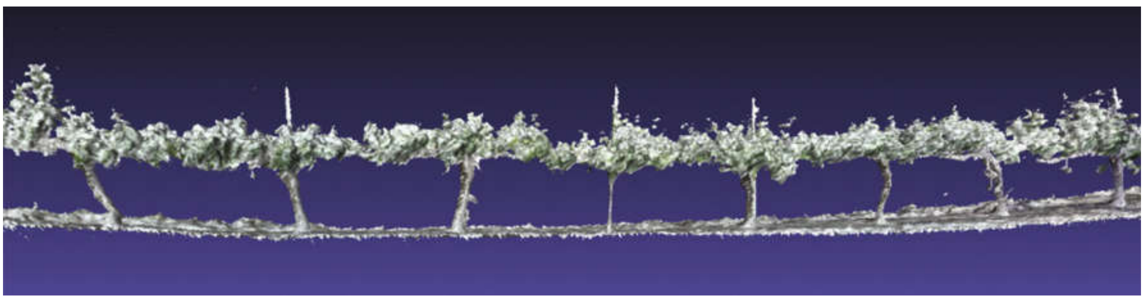


Fig. 6. 3D reconstruction of a row of vines

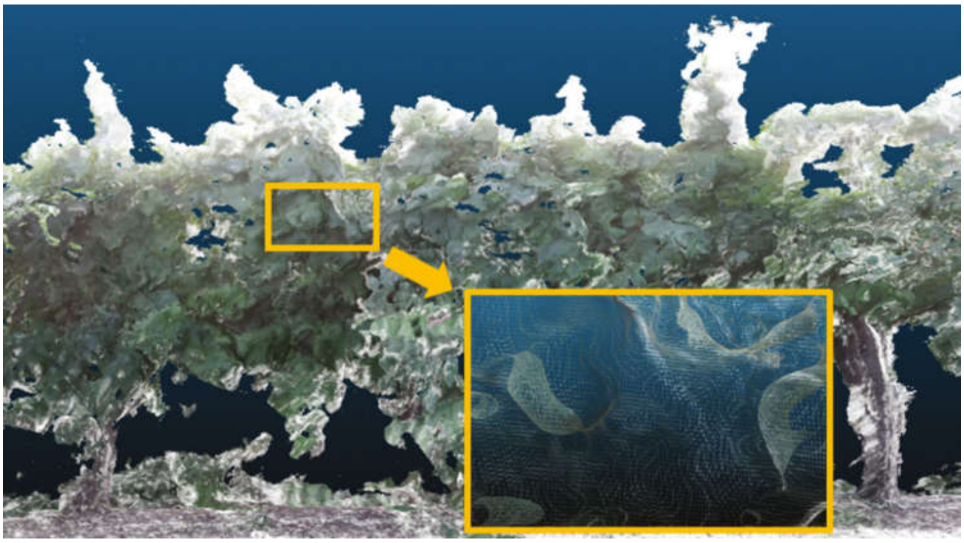


Fig. 7. Detail of a 3D reconstruction of a vine that shows the mesh obtained from a point cloud

As discussed before, when performing 3D reconstructions of long crop rows, a drift may appear that causes deformation in the reconstruction. Figure 8 shows the deformation that appears in the reconstruction of one of the sampled vineyard rows of 85 m length.

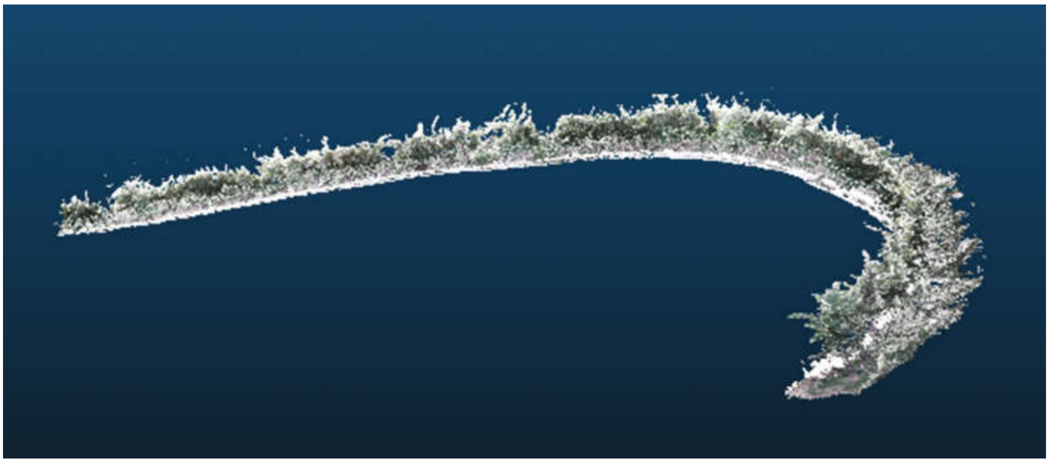


Fig. 8. 3D reconstruction of a row of vines with significant presence of drift

Using the method described above, it is possible to correct the drift obtained during the reconstruction of the rows. The vineyard row of Fig. 8 is divided in sections of 5 m, and, during the process, the rotation angle of each section, to use in the Rodrigues' rotation formula to correct the drift, is calculated. Table 1 shows the calculated rotation angles.

Table 1. Calculated rotation angles applied to each section to correct it.

Section	Angle (°)
1	0.96
2	6.34
3	4.95
4	11.50
5	5.59
6	6.67
7	5.31
8	5.75
9	5.66
10	4.31
11	5.60
12	4.15
13	5.15
14	6.65
15	8.06
16	6.88
17	3.11

After the drift correction process finishes, the corrected reconstruction of the row displayed in Fig. 9 is obtained.

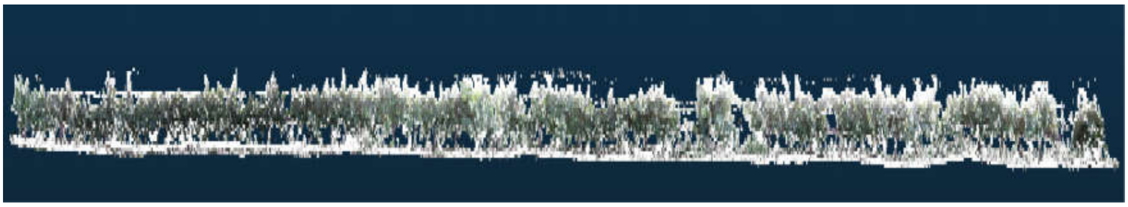


Fig. 9. 3D reconstruction of the row of vines of the Fig. 8 with the drift corrected

The average generation time of a 3D reconstruction with the corrected drift for a 50 m vineyard row using the computer described above is approximately 15 min. The average number of vertices in a reconstruction of a 50 m row is around 8 million.

Figure 10 shows four vineyard rows reconstructions belonging to a plot of ecological vineyard with a presence of highly developed vegetation cover sampled in July 2016, in a false colour scale representation according to its height from the ground, and the path followed by the vehicle to acquire data (red).

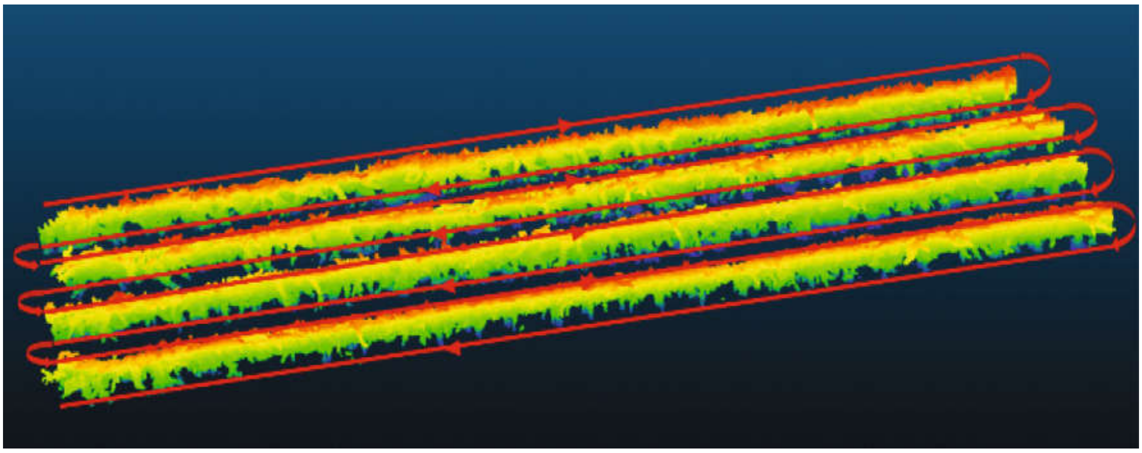


Fig. 10. Four vineyard rows reconstructions in a false colour scale representation according to its height from the ground, and path followed by the vehicle to acquire data (red)

Furthermore, the 3D reconstruction method with the drift correction was tested in a plot of pear trees. Due to the size of the plot, two passes had to be made: one to sample the top of the trees and the other one for their bottom, joining the reconstructions of both passes together later. A 3D reconstruction of a row of pear trees with the drift corrected can be seen in Fig. 11. Figure 12 shows a part of this row at a greater magnification.

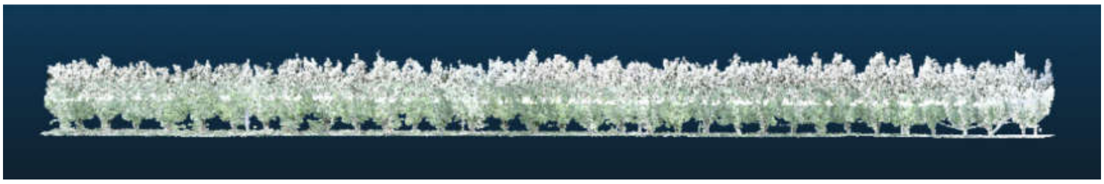


Fig. 11. 3D reconstruction of a row of pear trees

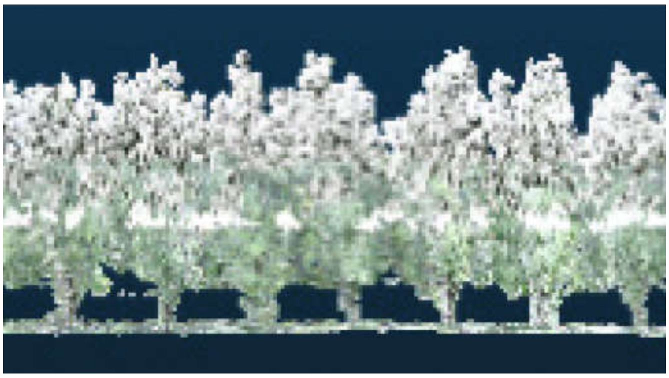


Fig. 12. 3D reconstruction of a part of a pear trees row

4 Conclusions

This paper describes a crop inspection system. The mobile platform, based on a commercial electric vehicle, is equipped with different on-board sensors to scan annual crops (maize, cereal, etc.) and multi-annual crops (orchards, vineyards, etc.).

The use of a low-cost RGB-D sensor has been tested and validated outdoors under uncontrolled lighting conditions. This sensor has been used for the inspection of woody crops, enabling 3D reconstruction of these scenarios from the RGB image and the depth information supplied by the sensor.

Different methods have been studied to perform automatic 3D reconstructions, since it is fundamental to generate the reconstruction of large areas, such as a complete crop row. Finally, the algorithm implemented provides good results in the reconstruction of large areas from the information directly supplied by the RGB-D sensor.

A method to correct the drift that appears in the reconstruction of crop rows has been developed and tested in actual fields. This method uses the Rodrigues' rotation formula and a minimal scene information, such as the location of the starting and ending points of the row, and requires that crops are planted in straight lines.

The work presented in this paper shows a promising technology that can achieve better crop management.

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References

1. Eurostat. http://ec.europa.eu/eurostat/web/agri-environmental-indicators/overview. Last accessed 6 July 2017
2. Paulus, S., Behmann, J., Mahlein, A.-K., Plümer, L., Kuhlmann, H.: Low-cost 3D systems: suitable tools for plant phenotyping. Sensors **14**(2), 3001–3018 (2014)
3. Andújar, D., Dorado, J., Fernández-Quintanilla, C., Ribeiro, A.: An approach to the use of depth cameras for weed volume estimation. Sensors **16**(7), 972 (2016)
4. Wang, W., Li, C.: Size estimation of sweet onions using consumer-grade RGB-depth sensor. J. Food Eng. **142**, 153–162 (2014)
5. Hilton, A., Stoddart, A., Illingworth, J., Windeatt, T.: Reliable surface reconstruction from multiple range images. In: Proceedings of 4th European Conference on Computer Vision, United Kingdom, pp. 117–126. Springer (1996)
6. Curless, B., Levoy, M.: A volumetric method for building complex models from range images. In: Proceedings of the 23rd Annual Conference on Computer Graphics and Interactive Techniques, United States, pp. 303–312. ACM (1996)

7. Wheeler, M.D., Sato, Y., Ikeuchi, K.: Consensus surfaces for modeling 3D objects from multiple range images. In: Proceedings of Sixth International Conference on Computer Vision, India, pp. 917–924. IEEE (1998)
8. Zhou, Q.-Y., Koltun, V.: Dense scene reconstruction with points of interest. ACM Trans. Graph. **32**(4), 112 (2013)
9. Newcombe, R.A., Izadi, S., Hilliges, O., Molyneaux, D., Kim, D., Davison, A.J., Kohi, P., Shotton, J., Hodges, S., Fitzgibbon, A.: KinectFusion: real-time dense surface mapping and tracking. In: Proceedings of 10th IEEE International Symposium on Mixed and Augmented Reality, ISMAR, Switzerland, pp. 127–136. IEEE (2011)
10. Izadi, S., Newcombe, R.A., Kim, D., Hilliges, O., Molyneaux, D., Hodges, S., Kohli, P., Shotton, J., Davison, A.J., Fitzgibbon, A.: Kinectfusion: real-time dynamic 3d surface reconstruction and interaction. In: Proceedings of the Annual Conference on Computer Graphics and Interactive Techniques, SIGGRAPH, Canada, p. 23. ACM (2011)
11. Microsoft Kinect for Windows Software Development Kit 2.0. https://developer.microsoft.com/es-es/windows/kinect/develop. Last accessed 6 July 2017
12. Steinbrucker, F., Kerl, C., Cremers, D.: Large-scale multi-resolution surface reconstruction from RGB-D sequences. In: Proceedings of the IEEE International Conference on Computer Vision, Australia, pp. 3264–3271. IEEE (2013)
13. Whelan, T., Kaess, M., Fallon, M., Johannsson, H., Leonard, J., McDonald, J.: Kintinuous: spatially extended kinectfusion. In: Proceedings of Workshop RGB-D, Advanced Reasoning with Depth Cameras, Australia, pp. 573–580 (2012)
14. Nießner, M., Zollhöfer, M., Izadi, S., Stamminger, M.: Real-time 3D reconstruction at scale using voxel hashing. ACM Trans. Graph. **32**(6), 169 (2013)
15. Zeng, M., Zhao, F., Zheng, J., Liu, X.: Octree-based fusion for realtime 3D reconstruction. Graph. Models **75**(3), 126–136 (2013)
16. Chen, J., Bautembach, D., Izadi, S.: Scalable real-time volumetric surface reconstruction. ACM Trans. Graph. **32**(4), 113 (2013)
17. Fankhauser, P., Bloesch, M., Rodriguez, D., Kaestner, R., Hutter, M., Siegwart, R.: Kinect v2 for mobile robot navigation: evaluation and modeling. In: Proceedings of 2015 International Conference on Advanced Robotics (ICAR), Turkey, pp. 388–394. IEEE (2015)
18. Ministerio de Agricultura, Pesca y Alimentación. http://www.mapama.gob.es/es/estadistica/temas/estadisticas-agrarias/memofinalvinedo_tcm7-443391.pdf. Last accessed 6 July 2017
19. Conesa-Munoz, J., Bengochea-Guevara, J.M., Andujar, D., Ribeiro, A.: Efficient distribution of a fleet of heterogeneous vehicles in agriculture: a practical approach to multi-path planning. In: Proceedings of the 2015 IEEE International Conference on Autonomous Robot Systems and Competitions (ICARSC), Portugal, pp. 56–61. IEEE (2015)
20. Bochtis, D.D., Sørensen, C.G.: The vehicle routing problem in field logistics part I. Biosyst. Eng. **104**(4), 447–457 (2009)
21. Roth, S.D.: Ray casting for modeling solids. Comput. Graph. Image Process. **18**(2), 109–144 (1982)
22. Chen, Y., Medioni, G.: Object modelling by registration of multiple range images. Image Vis. Comput. **10**(3), 145–155 (1992)
23. Lorensen, W.E., Cline, H.E.: Marching cubes: A high resolution 3D surface construction algorithm. In: Proceedings of the 14th Annual Conference on Computer Graphics and Interactive Techniques, SIGGRAPH, United States, pp. 163–169. ACM (1987)
24. Rodrigues, O.: Des lois géométriques qui régissent les déplacements d'un système solide dans l'espace: et de la variation des cordonnées provenant de ces déplacements considérés indépendamment des causes qui peuvent les produire. J. Math. Pures Appliquées **5**, 380–440 (1840)