An automatic trunk-detection system for intensive olive harvesting with trunk shaker.

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Abstract

Trunk shakers are widely used for olive harvesting, being the main detachment system for fruit harvesting. In recent decades, the components of trunk shakers have evolved at mechanical, hydraulic and control levels. However, machine accuracy depends on the operator, whose expertise is a key factor for issues such as trunk debarking caused by grabbing systems, shaking parameters, or on-foot operator safety. The objective of this work was to develop an automatic harvesting system to reduce operator influence on the process. Thus, an automatic system for trunk detection via infrared sensor was implemented on a trunk shaker head hitched to a tractor. An algorithm and a visualisation interface for trunk shaker guidance were developed. The automatic system was tested under laboratory and field conditions to assess the influence of some variables on trunk detection. The evaluated variables were colour, material, diameter, and target location within the sensor field of vision. The success rate of the automatic system was 91% for trunk grabbing. In the field phase, the efficacy of the automatic system was compared to an operator performing the tasks manually, obtaining times of 16.05 ± 2.8 s tree^{-1} and 21.54 ± 5.29 s tree^{-1} respectively, and a percentage of success in trunk grabbing of 93%. Work capacity increased by 25% compared to the manual system. The developed system reduced operator influence on trunk shaker gripping success, reducing the influence of the human factor on the harvesting process.

Keywords: Vibration; Driver assistance system; Trunk grabbing; Trunk gripping; Effective field capacity; Debarking.

1. INTRODUCTION

Due to the increasing costs of labour, operational efficiency is currently a key factor for agricultural machinery (Kester, Griepentrog, Hörner, & Tuncer, 2013). In addition, some agricultural tasks suffer from a lack of trained workers (Bechar & Vigneault, 2016) along with a need to increase productivity, which could be achieved using automation and robotics (Xia, Wang, Chung, & Lee, 2015). There is a slow but steady implementation of robotics in the agricultural sector in general (Xue, Zhang, & Grift, 2012), but its use in olive groves has to date been scarce for various reasons, among which are the difficulty of obtaining standardised orchard categories that adapt the crop to the machine, or tailoring the machine to the crop. (Gil-Ribes, Blanco-Roldán, & Castro-García, 2010). Experimental progress is being made which could open the doors to the application of robotics in the short to mid-term in the sector, and automation is increasingly widespread for many agricultural applications; however, despite many on-going developments at the experimental stage, there has been little in-field automation in olive orchards.

The automation of processes within harvesting is an ongoing development for woody crops such as citrus (Li, Lee, & Hsu, 2011) and vegetable crops such as the sweet pepper (Bac et al, 2016) or greenhouse cucumbers, (Van-Henten et al, 2002). Automatic collection systems based on artificial vision face the difficulty of locating objects that are poorly defined by their position, shape, size and colour (Bac, Henten, Hemming, & Edan, 2014). The cost of a robotic system is usually too high when compared to the wages of a labourer with a temporary contract (Longo & Muscato, 2013), despite the fact that the last 20 years have seen excellent results in autonomous collection systems that have reduced costs, mitigated staff shortages and compensated for the existence of low-skilled workers (Kapach, Barnea, Mairon, Edan, & Ben-Shahar, 2012) in seasonal tasks. Bringing automation to agriculture would introduce high technology to the sector and, in the near future, the application of sensors initially developed for other spheres will be a first step for deploying robotic systems in harvesting.

Introducing new technologies to olive harvesting is a strategic need for the modernization and sustainability of the sector, which could be enhanced using robotics or automated devices. In most cases, olive orchards suffer from a lack of profitability and the need to improve orchard management in several process areas. The harvesting of oil olives represents approximately 40% of the cost of the crop (AEMO, 2012) and is a key factor for orchard profitability. Furthermore, as olive costs are highly conditioned by orchard category, management and topography there is no harvesting method suitable for all orchard types. However, increased mechanization, particularly of the harvesting operation, is necessary as it would bring major improvements to the sector’s competitiveness and to the quality of the oil.

Intensive olive orchards are usually planted with rectangular spacing, which is adapted to mechanical harvesting (Rallo et al, 2013) and other mechanised operations. Planting density is between 180 to 800 trees per hectare. This orchard category covers 2 174 076 ha worldwide (COI, 2015) and represents approximately 21.8% of the total surface area for olive tree culture. Intensive orchards have been developed in new areas with high water availability and better soil-climatic conditions (Fernandez-Escobar et al, 2013). Although this type of intensive orchard is prepared for mechanical harvesting with trunk shakers, the harvesting system employed has a low level of automation. The structure of an intensive olive orchard (with one trunk, trained trees that are clear of low branches and have a crotch height of 0.8 to 1 m) makes it possible to develop an automatic system for trunk grabbing using trunk shakers. It has been established that the main response of the olive to forced vibration differs depending on tree architecture (Castro-García, Blanco-Roldán, Gil-Ribes, & Agüera-Vega, 2008), vibration parameters that facilitate acceleration transmission to the fruit (Jimenez-Jimenez et al, 2015), and locating production in the middle and upper part of the crown (Castillo-Ruiz et al, 2015). Although the peduncle is a distinctly different structure from the branch in which it is inserted (Torregrosa, Albert, Aleixos, Ortiz, & Blasco, 2014), it is possible to reach high fruit detachment efficiencies in autonomous systems of vibration collection, which may be facilitated through annual moderate or heavy pruning (Tombesi, Boco, Pilli, & Farinelli, 2000).

Mechanical harvesting in intensive olive orchards is mainly carried out using trunk shakers along with hand-held shaking combs or manual poles, and gathering the detached fruit on nets extended under the tree canopy or on previously prepared soil (Gil-Ribes, López-Giménez, Blanco-Roldán, & Castro, 2008). To improve the competitiveness of the olive sector, it is advisable to replace manual labour with mechanical harvesting (Fergurson, 2010). In recent years, attempts to tackle this problem have seen the development of intensive olive harvesting systems such as canopy shakers, which directly apply vibration to fruit-bearing branches (Sola-Guirado et al, 2014). Although a large part of operations are mechanised in intensive olive orchards, very few operations are automated in olive cropping, and those that are mainly consist of olive harvesting with trunk shakers. A vital step towards the automation needed in olive cropping would be to make advances in the design of an intelligent robot with human-like perceptual abilities (De-An, Jidong, Wei, Ying, & Yu, 2011).

In Spain, trunk shakers are widely used for harvesting several woody crops. Trunk shakers can be tractor-hitched or self-propelled with three (most common due to higher manoeuvrability) or four wheels. The total number of vibrators sold in Spain in 2015 was 325 units (ROMA, 2015), of which 86.15% were tractor-hitched compared to 13.85% self-propelled, and 86.67% of the total sold were tricycle type. To make immediate improvements in this area it is necessary to develop a vibrator coupled to a tractor and automate the tasks of detection, approximation and trunk gripping, in addition to refining the vibration and collection systems, all of which would improve the machine's working capacity.

The objective of this paper is to develop an automatic system for a trunk shaker in order to compare manual and automatic modes in terms of time required for trunk detection, shaker head approach and trunk grabbing. In order to do this, we developed a control logic, implemented in software and hardware systems, which was tested to build an automation system for a tractor adapted to trunk shaker operations.

2. MATERIAL AND METHODS

The trunk shaker prototype that was tested consisted of a mechanical-hydraulic part hitched to the tractor and another electronic part that formed the automation system (Figure 1) composed of hardware and software. The trunk shaker was designed to work in intensive olive orchards.

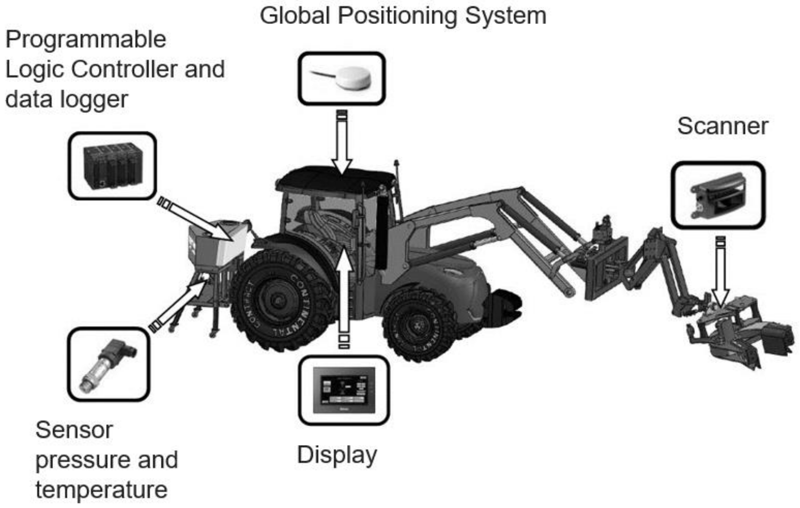

Figure 1. Prototype main systems and their location respect to the tractor.

2.1. Mechanical-hydraulic part

The trunk shaker approach system employed to conduct these experiments was composed of a pantographic arm, which could move the trunk shaker head on the three coordinated axes. The trunk shaker prototype is orbital with a scissor type gripper (Tecniagri Agricola and Forestal SL, model Orbit 450), attached to the front of a tractor (John Deere, 6420, Moline, IL., USA).

2.2. Automation system

To gather real-time information about the trunk shaker working parameters, the prototype was equipped with sensors to measure the pressure and temperature of the oil in the hydraulic system. The sensors issued alerts for the operator, warning about risks such as excess temperature. The prototype was equipped with a data logger with Secure Digital (SD) storage connected to the PLC via an RS-232 port to register working parameters from the sensors.

An infrared (IR) light emitting diode (LED) scanner (Pepperl-fuchs, OMD8000-R2100-R2-2V15, Germany) with an RS-232 port communication and a measurement range of 0.2 to 8 m was used for trunk detection. This system performed continuous measurement in two dimensions (2D) (Barawid, Mizushima, Ishii, & Noguchi, 2007). The scanner had eleven Light Emitting Diodes (LEDs) that detected objects in an opening cone of 88º with an amplitude of 0.55 m to 4 m and a sampling frequency of 50 Hz. The measuring range of the LED scanner was 0.2 to 8 m depending on the reflectivity of the material to be measured, although measurements nearer than 1 m were unstable.

The reflection of a laser beam varies depending on the colour and the structure of the surface upon which it reflects. To assess how the scanner detected the trunk, a white material was initially tested at a distance between 0.10 and 1.70 m and an angle from -21.5º to +21.5º, to experimentally determine the scanner’s field of vision since these measurements are the range of approach for the trunk shaker to grab the trunk. The process of automatic trunk detection was then repeated using a piece of olive tree trunk with the same scanner surface of action, and the same detection surface was obtained. So, although refection variance exists between different surfaces and colours, it did not affect our experiments.

The distance to the object measurement obtained by each LED is the hypotenuse of a right triangle, and the perpendicular distance was obtained by conversion of the measurements captured by the scanner using trigonometric relationship, except for the central LED.

Finally, the automation system included a parking alert for the tractor that indicated when to start automatic mode, in order to assist the driver in choosing the best vehicle position to optimise the grabbing process. To do this, the automation system looked for a trunk to grab, and once a trunk was detected, the parking alert came on. Finally, in order to give a fully adjustable system, the vibration pattern, acceleration and frequency could be also programmed before starting automatic mode.

2.3. Control logic

The working area of the trunk shaker was divided into two main areas, with an additional four distances defined at the edges of the areas (Figure 2). The four distances were defined as:

- Optimal grab distance (OGD) at 0.1 m from the scanner, which was the distance at which the grabbing and shaking process started.
- Search threshold distance (STD) at 0.35 m from the scanner, which was the smallest distance to look for the trunk.
- Speed threshold distance (SpTD) at 1 m from the scanner, the separation of Area 1 from Area 2.
- Grab threshold distance (GTD) at 1.7 m from the scanner, the distance from which the trunk shaker could not grab the trunk.

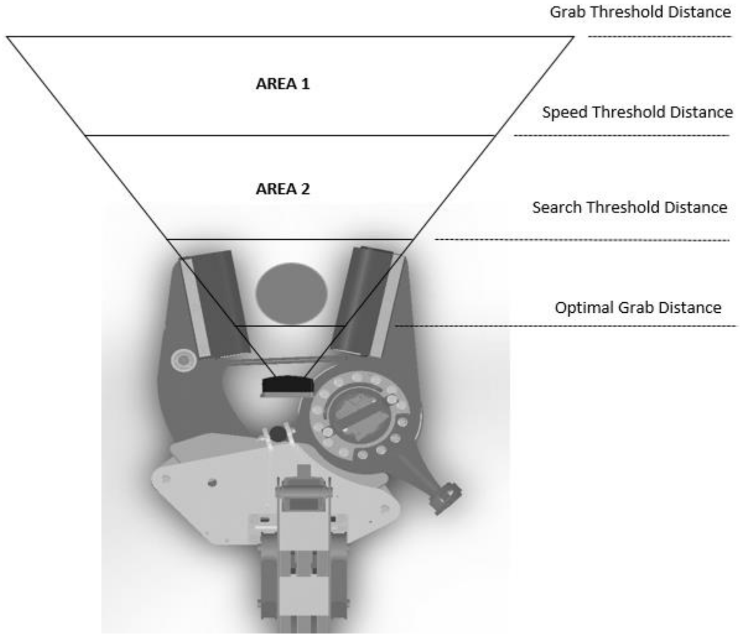

Figure 2. Work areas for trunk shaker automatic mode depending on trunk distance to the scanner.

A control algorithm was implemented to position the clamping jaws at both sides of the trunk. The distance between the trunk shaker and the trunk was divided in two areas depending on the relative position of the trunk to the scanner attached to the shaker head:

- Area 1: When the trunk was located in this area, the prototype was given a higher movement speed than when in Area 2 and the scanner’s real time measurements were stable. In this area, lateral movements of the shaker head enabled it to centre the jaws for trunk grabbing, which was controlled using measurements obtained by the scanner’s central LED.
- Area 2: When the trunk was located in this zone, shaker head lateral movement for trunk grabbing was performed at a lower speed to increase accuracy. Accurate movements were required to introduce the trunk between the clamping jaws without touching and to avoid trunk debarking. The automated system identified the group of LEDs that impacted on the trunk and, using this information, the shaker head attempted to position the clamping jaws so that the trunk was centred between them

When the “Start” command was executed, the clamping jaws opened and the automatic system looked for a tree trunk. The nearest LED or minimum distance LED (MDL) was identified to determine the next direction of trunk shaker movement. If the trunk was outside the scanner’s field of vision, the automated process would not start and the trunk grabbing process failed.

Once the minimum distance to the trunk had been checked, the shaker head moved into position in front of the trunk, according to the LED selected as the centre on the display (LED 6). For this, if the MDL is greater than the central LED (CL) the pantograph turns to the left and if the MDL is smaller, it pivots to the right. When both coincide (CL = MDL) the pantograph stops and advances to the input in Area 2. If the scanner detects that the vibrator has become decentred during the advance, a new centring process begins.

When the shaker head approached the trunk, it entered Area 2. In this area, the automatic system attempted to increase trunk detection accuracy. To this effect, the LEDs that intercepted the trunk were identified, taking into account their location, to decide the shaker head’s next movement. Finally, when optimal grab distance was reached, the clamping jaws closed. At this point, the trunk shaker automatically started a previously determined vibration sequence. When this sequence ended, the clamping jaws opened and the shaker head returned to the nearest position to the tractor, ending the automatic process.

2.4. Laboratory tests

To evaluate and classify the behaviour of the automatic system, we tested it on a previously cut trunk in a laboratory. A confusion matrix was used (Bac, Hemming, & Van Henten, 2013), taking two dichotomous variables (true-false, positive-negative) to identify each attempt at gripping the trunk. Possible results were:

- True positive (VP): The sensor detected the trunk and the trunk was grabbed properly.
- True negative 1 (TN1): The sensor detected the trunk but the time spent grabbing exceeded 60 s so the automatic process ended.
- True negative 2 (TN2): The sensor detected the trunk but the operator had to stop the grip due to poor execution of the automated system.
- False (F): the sensor did not detect the trunk.

The control logic was tested for two trunk diameter ranges: trunk diameter less than 0.2 m and trunk between 0.2 and 0.3 m. In addition, different positions of the trunk in relation to the trunk shaker were also tested. Trunk position was classified taking into account the trunk distance to the scanner. Trunk angle to the forward-moving axis was also considered in order to study the automatic system’s capabilities related to distances and angles (Video 1) (Figure 3).

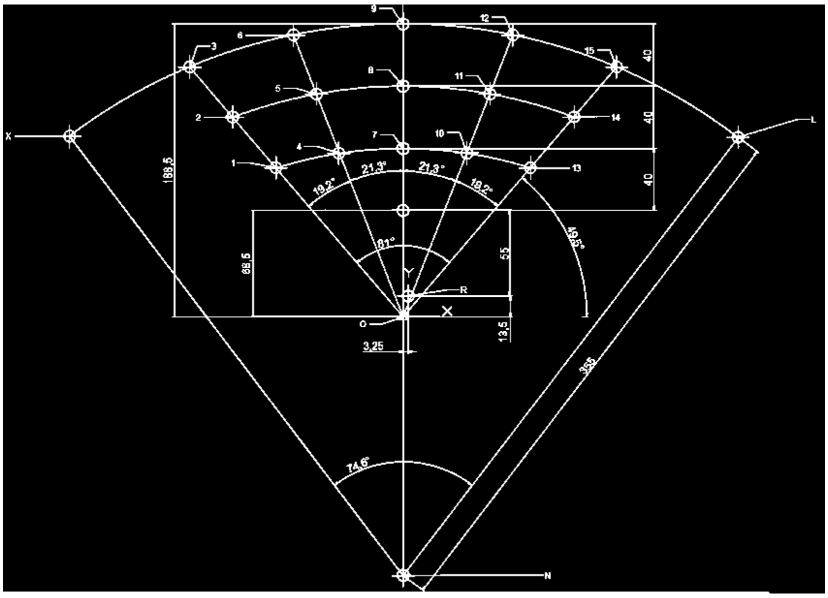

Figure 3. Geometrical location for grabbing positions in laboratory tests

2.5. In-field tests

After completing the tests and calibrations of the control logic in the laboratory, in-field tests were performed to compare the efficiency of the automatic system with manual mode of the trunk shaker. The olive harvesting process was divided into six steps: shaker head positioning, trunk grabbing, vibration, clamping jaws opening, shaker head movement away from the trunk, and tractor displacement.

In order to evaluate trunk detection efficiency, software was developed to record the time spent in the work cycle and to classify each grabbing process. The trunk shaker with automation system was tested in an intensive olive orchard with 4 x 5 m spacing (500 trees ha^{-1}) located in Córdoba, Spain. The trees were one trunk, trained with a crotch over 0.8 m and vase shaped in order to leave an adequate line of vision for the automatic system (Figure 4). To determine canopy geometry, canopy dimensions were measured using a surveying rod. Measurements were taken in two perpendicular directions for tree height, minimum skirt height and canopy width at 1.5 m above the ground.

Canopy volume was calculated assuming the profile of the crown as an ellipsoid, as proposed by (Muñoz-Cobo & Humanes-Guillén, 2006), and modified according to Equation 1. Skirt height was included in the original formula.

$$\text{Canopy volume } (\mathrm{m}^3) = \frac{1}{6}\pi\, \mathrm{D}_1\,(\mathrm{m})\, \mathrm{D}_2\,(\mathrm{m})\, \frac{1}{2}\,(\mathrm{Ht}_n - \mathrm{Hs}_n)\,(\mathrm{m}) \qquad \text{(Eq. 1)}$$

Where: D_1 and D_2 are crown diameters, Ht is tree height and Hs is skirt height.

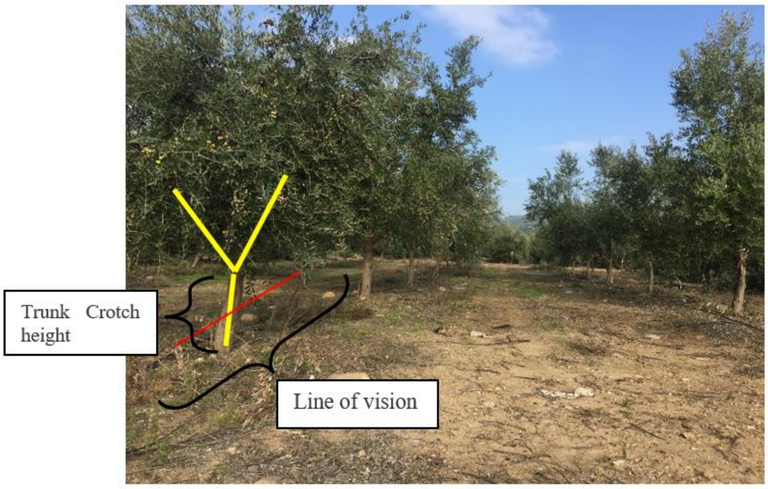

Figure 4. Trunk and tree training requirements for automatic mode

3. RESULTS

3.1. Laboratory tests

We measured the percentage of success at different positions on the trunk within the trunk shaker's work area (Figure 5) in a laboratory test, and achieved a success rate of 91%. However, when the trunk was located at angles more acute than 21.3° compared to the forward-moving axis, and when distances were greater than 1.35 m from the scanner, the success rate increased as far as 96.7 %.

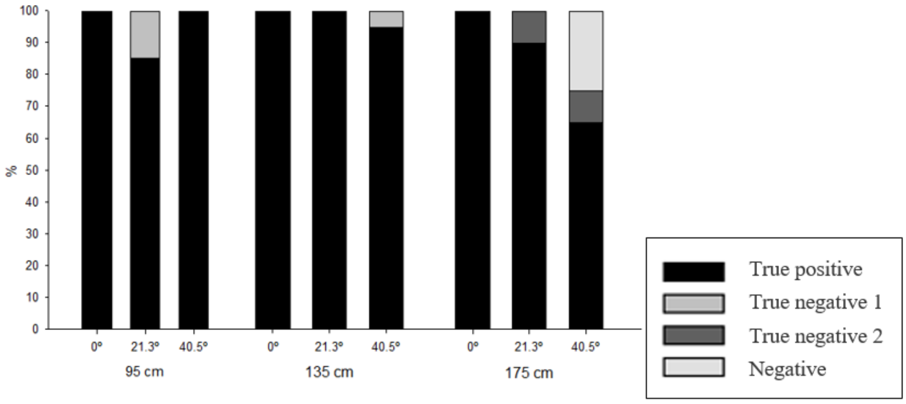

Figure 5. Results for laboratory tests depending on trunk distance to the scanner and angle between trunk and moving forward direction.

Time to trunk grabbing is a key factor for trunk shaker effective field capacity. For this reason the time to tree grabbing is limited to 20 s. This time limitation is justified because the system should improve on the effective field capacity of manual systems (Figure 6). The average time taken to perform a successful grip was 7.8 ± 2.9 s (mean ± standard deviation).

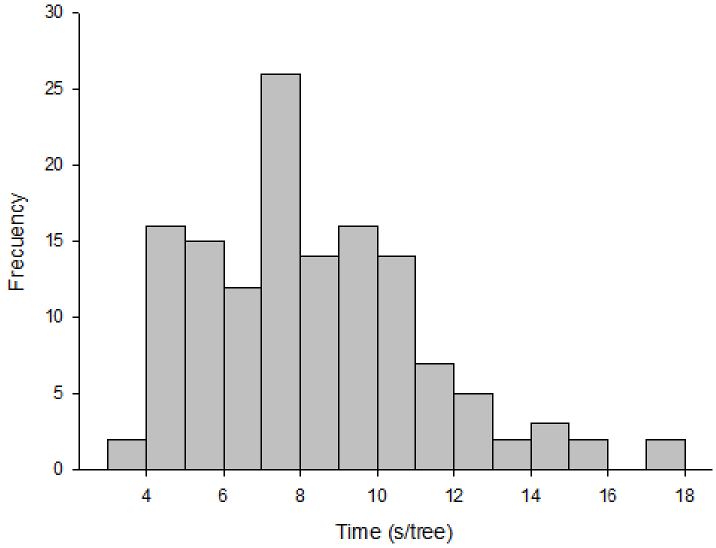

Figure 6. Grabbing Geometrical location for grabbing positions in laboratory tests time distribution for all laboratory tests

The control logic of the automatic system should improve the effective field capacity for the harvesting process using a trunk shaker. The three factors that could affect automatic system performance are: the angle between the trunk and the forward-moving axis, the distance between the grabbing point and the scanner, and trunk diameter. The influence of trunk diameter on the time taken to perform trunk grabbing showed no significant differences ($\rho<0.05$) (Results not shown); therefore, trunk size did not affect the time in which the trunk was grabbed. On the other hand, we studied the angle between the trunk and the forward-moving axis, and the distance to the trunk as variables that influenced trunk grabbing time. Significant differences were found for both variables ($\rho<0.05$) showing that, as expected, lower angles and closer distances were more favourable for trunk grabbing time (Figure 7).

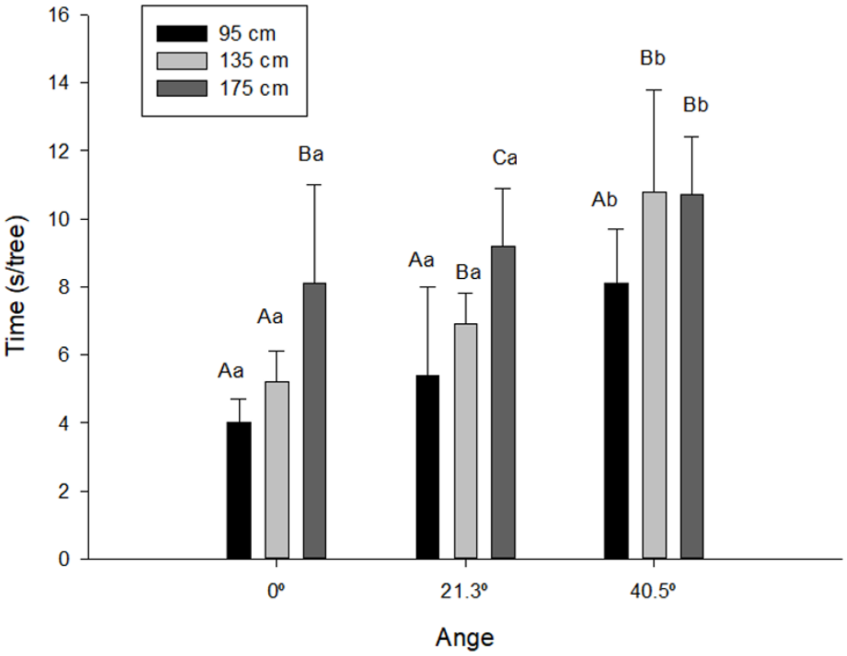

Figure 7. Influence of the distance and the angulation in the time used in the trunk griping. Different upper case letters indicate significant differences ($\rho<0.05$) for angles and the same

distance, and different lower case letter indicate significant different (ρ<0.05) for different distances at de same angle according to Tukey`s test.

3.2. Field tests

Firstly, in-field true cases were evaluated using the automatic system (Table 1). In-field true cases gave better results than laboratory tests. Thus, the automatic system showed a positive performance for in-field conditions, representing an interesting advance for commercial trunk shakers. In order to achieve this high success rate the tractor driver had to place the trunk shaker in the most appropriate position before starting the automatic sequence. This position needed to be as low as possible, and in a position around the trunk where there were no obstacles such as hanging fruit-bearing branches or scaffolds.

Table 1. Frequency and percentage of cases recorded during in-field tests.

	Cases (n)	**Porcentaje (%)**
True positive	39	92,9
True negative 1	1	2,3
True negative 2	2	4,8
False	0	0

The times required to perform the different tasks of the machine's work cycle were analysed for the automatic system and in manual mode. The times spent on trunk recognition in both modes were equal, 3 ± 2 s tree^{-1}. However, the whole cycle of trunk grabbing was shorter in automatic mode (16.05 ± 2.8 s) than in manual mode, which took 21.54 ± 5.29 s per work cycle (mean ± standard deviation). Automatic mode improved on manual mode, saving 27.3% of time, which contributed to significantly improving on the time taken for trunk grabbing and thus, on effective field capacity.

4. DISCUSSION

Currently, trunk shakers are manually controlled by the tractor driver, who acts on all variables (Gil-Ribes, López-Giménez, Blanco-Roldán, & Castro, 2008). This factor may slow down the harvesting process for trunk shakers compared with new integral harvesters, mainly when trees are not properly trained as occurs in large-sized trees (Famiani et al, 2014) or in multi-trunk traditional trees (Muñoz-Cobo & Humanes-Guillén, 2006). New harvesting methods for olives based on straddle or side-by-side commercial harvesters usually present a higher effective field capacity and lower harvesting costs (Ravetti & Robb, 2010), which is why new harvesters are being developed for traditional olive orchards (Sola-Guirado et al, 2016). Furthermore, the new super-intensive olive orchards make it possible to deploy highly efficient harvesting systems which depend on the continuity of the crown (Rallo et al, 2013), making it necessary to limit vigour in these plantations (Tombesi & Farinelli, 2016) in order to perform mechanical harvesting.

There are large differences in effective field capacity of tractor-hitched trunk shakers without automatic systems (0.12 to 0.20 ha h^{-1}), self-propelled ones (0.25 to 0.30 ha h^{-1}) and straddle canopy shakers for super-intensive olive orchards, which could harvest up to 0.8 ha h^{-1} (Castillo-Ruiz, Pérez-Ruiz, Blanco-Roldán, Gil-Ribes, & Agüera, 2015; Fernández-Escobar et al, 2013). For this reason, tractor-hitched trunk shakers need to improve effective field capacity and thus reduce harvesting costs in order to increase their competitiveness compared with new harvesting systems or those under development. The introduction of automation systems is therefore necessary to increase effective field capacity (Amatya, Karkee, Gongal, Zhang, & Whiting, 2015), and reduce human error within the process. For instance, bark damage is a major issue during olive harvesting. This damage could be due to long vibration times (Blanco-Roldan, Gil-Ribes, Kouraba, & Castro-Garcia, 2009), trunk to shaker head displacements during the harvesting process (Leone, Romaniello, Tamborrino, Catalano, & Peri, 2015), clamp pressure that is too high (Ferguson, 2006), or human error during the clamping process. Therefore, further research should assess whether automation systems could reduce bark damage during olive harvesting with trunk shakers.

Tree training is a key factor to make optimised olive harvesting possible both for trunk shakers (Tombesi, 2013) and canopy shakers (Castillo-Ruiz et al, 2017). Automatic mode requires a well-trained trunk, with a crotch over 0.8 m above the soil, that is free from scaffolds, hanging fruit-bearing branches or other obstacles. For the correct operation of the trunk detection system, a pyramidal volume free of any obstacles from the scanner to the trunk is necessary to avoid interference with the light beams.

An automatic trunk detection system can improve issues such as debarking and work capacity, and may reduce human error by avoiding repetitive tasks. The use of a robotic system to control shaker head movement could also be included in trunk shaker-based olive harvesters, significantly reducing driver workload and simplifying the control panel of these machines. In that way it would be possible to avoid the human factor, which can lead to losses of time and fuel (Zheng, Liu, Wang, & Yang, 2012).

5. CONCLUSIONS

The automatic mode developed here showed highly reliable and efficient performance with a high ratio of success (true positive) cases in laboratory tests, findings which were slightly better for in-field tests. Results indicated the feasibility of automatic mode under real working conditions for intensive olive orchards. In addition, the time spent on trunk grabbing (trunk recognition, shaker head approach and grab) was 27.3 % lower for automatic mode than for manual mode. Under laboratory conditions, automatic mode presented a mean for the whole grabbing cycle (excluding closure of the jaw) of 7.8 ± 2.9 seconds in true positive cases, whereas in the field, this mode reached values of 3 ± 2 seconds in the most favourable positions. The alert, flow adjustment and vibration configuration systems worked properly, providing valuable support for the tractor driver in the decision-making process, and reducing the influence of the human factor on the harvesting process.

Further research is needed in order to assess the influence of automatic mode on tree debarking. Moreover, the driver assistance system should be improved and tested in long-term trials for in-field conditions. Both the parking alert to start automatic mode and shaker head speed should be adjusted to optimise the process in terms of effective field capacity, on-foot workers' safety and trunk debarking. Finally, the vibration pattern also needs studying so that farmers have clear information about the optimal variables for each tree structure and fruit stage.

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