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A Study of Fruit Reachability in Orchard Trees by Linear-Only Motion

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Abstract: Robotic fruit harvesters typically utilize multiple-degree-of-freedom arms, often kinematically redundant. The hypothesis is that as branches constrain fruit reachability, redundancy is necessary to navigate through branches and reach fruits inside the canopy. Modern commercial orchards increasingly adopt trees of SNAP architectures (Simple, Narrow, Accessible, and Productive). This paper presents a simulation study on linear fruit reachability (LFR) on high-density, trellised pear trees; linear only motion was used to reach the fruits. Results based on digitized geometric tree models and fruit locations showed that 91.1% of the fruits were reachable after three "harvesting passes" with proper approach angles.

Keywords: Agriculture, trees, computer simulation, robotics, automation.

1. INTRODUCTION

In fresh market fruit production, harvesting is one of the most labor-intensive operations incurring high cost, and often dependence on a large seasonal semi-skilled immigrant workforce, which is becoming less available (Taylor et al., 2012). Mechanical mass harvesting systems (i.e., shake-and-catch) cause excessive damage and cannot target harvestable fruits. Therefore, their adoption has been restricted mainly to fruits harvested for juice or processing. Selective harvesting (i.e., robotic) technologies for fresh market fruits have also not been developed to the point where they can be used commercially. Robust, accurate and efficient fruit detection and localization poses a significant technical challenge. Two major obstacles for adoption, which are not exclusively related to perception, are very low fruit picking efficiency and throughput. These two harvesting performance metrics have been identified as the most important variables (along with purchase price) that define harvest cost (Harrell, 1987). Based on reported results from an extensive literature review, Bac et al., (2016) calculated an average fruit picking cycle equal to 33 s per fruit, and an average harvest success rate equal to 66% for robot prototypes developed so far. Although these numbers are averages over radically different crops, ranging from eggplants to citrus, and very diverse robot designs, it is indicative of the problem. Per comparison, a tree fruit or strawberry picker can pick at ten times this rate.

In general, the performance of robotic harvesting systems depends on the interrelationships among orchard layouts, tree canopy structures and spatial fruit distributions with harvester mechanics (and fruit transport logistics, at an orchard scale). For tree fruit harvesting, low performance is, to a large extent, the combined result of several factors. Fruit visibility is of course a very important one, but even if perception were perfect, performance would still be limited by fruit accessibility, and by complex, time-consuming motion planning (e.g., Schuetz et al., 2014) and control algorithms (e.g., Mehta & Burks, 2014). Such algorithms are needed because robotic fruit harvester prototypes typically utilize manipulators with many degrees of freedom. The hypothesis is that, as branches constrain fruit reachability, high kinematic dexterity is necessary to navigate through branches and reach fruits inside the canopy (e.g., van Henten et al., 2010). This is true for many crops. In fruit orchards, however, growers are increasingly adopting high-density SNAP (Simple, Narrow, Accessible, and Productive) tree architectures (Karkee & Zhang, 2012). Such orchards feature narrow almost two-dimensional canopies (e.g., tall and super spindle apple orchards) that create "fruiting walls", which are easier to harvest manually, either with ladders or with orchard platforms (Gallardo & Brady, 2015).

This paper presents a simulation study that estimates fruit reachability on trellised SNAP-type Bartlett pear trees using linear only motion (e.g., linear, telescopic arms). Spherical and cylindrical-type robots have been developed and tested by researchers in the past (Harrell, Adsit, Slaughter, 1985; Grand d'Esnon et al., 1987). Their use in traditional orchard architectures could not achieve picking efficiency and throughput that could justify commercialization. The goal of this work is to define linear fruit reachability metrics and to use geometric models of orchard trees and the locations of all their fruits to investigate how fruit reachability changes as a function of a linear arm's approach direction, and as several directions are used in a sequential fashion. The approach direction is defined by the combination of azimuth and elevation approach angles. A range of approach directions is explored for each pass, in order to find the best one(s). Our long-term vision is that such information can be used for the design of robotic harvesters that feature simpler (cheaper, faster) arms, albeit a large number of them. Also, such studies

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could potentially guide canopy shaping and fruit thinning strategies, thus leading to approaches that treat the trees and robots as a system that needs to be co-designed and co-optimized.

2. MATERIALS AND METHODS

2.1 Trees and Fruit Positions Digitization and Modelling

A large-volume digitization system was developed that utilizes electromagnetic field for data acquisition (Sinoquet, 1997; Arikapudi et al., 2015)). A PowerTRAK 360TM digitizer (Polhemus, Colchester, VT, USA) was used to manually digitize points on tree surfaces with an RMS accuracy of 0.2 cm. The PowerTRAK 360TM sensor connects via cable to a G4 'Hub' module; this module transmits digitized data via Radio Frequency (RF) to an RF module connected to the computer via USB. A 'Source' module generates the electromagnetic field required to track the sensor. The precision and accuracy of the devices were calculated via experimentation; the sensor had precision and accuracy better than 1 cm when the tracking volume was about 1.5 m x 1.5 m x 1.5 m from the source. The digitizer was to be used for pear and cling-peach trees. The maximum volume of such trees in commercial orchards in California is 3 m x 4.5 m x 4.5 m. To digitize these trees at an accuracy and precision better than 1 cm, 18 sources are needed because each source can cover – with such accuracy - a volume of 1.5 m x 1.5 m x 1.5 m. The sources should be placed at appropriate locations to cover the entire volume of an individual tree. To achieve this, a frame was built for the digitization process so that the sources were moved within the frame in sequence to cover the whole tree volume. Six sources were used to speed up the digitization process of each side of a tree (volume of 1.5 m x 3 m x 4.5 m). Since the sensor used for data collection was based on the interaction of magnetic fields created by the G4 source and the field created by the Power Track 360TM the workspace should be free of metal to ensure the tracked volume had no interference. So, the frame that was built was made of wood and plastic to mitigate error in the collected data. The digitization process followed the following procedure for data acquisition.

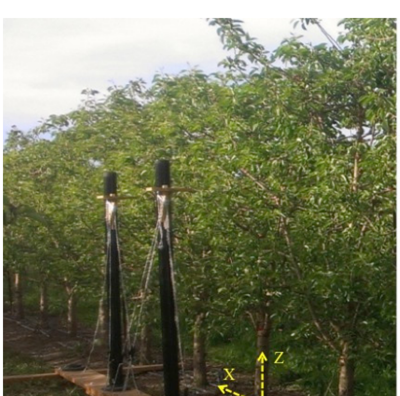

Fig. 1. A wooden frame carried six digitizer 'source' modules, in order to cover the volume of large trees.

Tree architecture was defined by its trunk, number of main branches, sub-branches, sub-sub-branches, and so on. Each of these branches was divided further into segments such that each segment was approximately straight. The architectural information of the tree was saved with each of the segment during data collection. Branches that were thin enough to be flexible (< 2.5 cm) were not digitized, as they do not present obstacles to the movement of robotic harvesters; hence, they do not limit reachability. After the entire tree was digitized, the surface of each segment was approximated with a conical frustum. An example of a reconstructed high-density, trellised Bartlett pear tree model with its fruits is shown in Fig. 2.

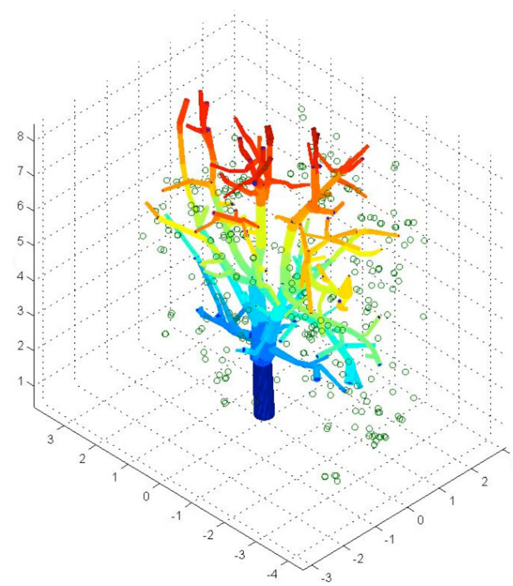

Fig. 2. Reconstructed pear tree geometric model; segments are represented as frustums.

2.2. Linear Fruit Reachability

Consider the coordinate system of Fig. 1, and a unit vector **d** defined by two angles: an azimuth/pitch angle, α, about the z-axis, and an elevation/zenith angle, θ, around the x axis. Elevation is -90^{o} along the –z axis and 90^{o} along the z axis. Azimuth ranges from -180 ^{o} to 180 ^{o} and it is defined as 0^{o} along the y axis; it increases clockwise.

Individual fruit reachability is defined as a Boolean variable that is zero if the fruit's geometric projection along the approach direction vector **d** results in collision with a branch; otherwise, it is one. This definition corresponds to linear motion, if an actuator were used to pick the fruits, so we refer to it as "linear reachability". Fruit-with-fruit collisions are not included in this definition of reachability, because in a real harvesting scenario a fruit occluding other fruits along **d** would be picked first, since it would be closer to the 'harvesting' side; therefore it would not present an obstacle.

Linear fruit reachability $LFR(\mathbf{d})$ is defined as the total number of linearly reachable fruits on a number of trees along a particular approach direction **d,** divided over the total number of trees.