Estimation of Fruit Locations in Orchard Tree Canopies Using Radio Signal Ranging and Trilateration

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ABSTRACT.

The development of novel robotic harvesters could benefit significantly from a model-based design approach, in which harvesting performance metrics--such as fruit reachability and average pick-and-place cycle--are calculated via simulation, and are used to guide mechanical design. The actual spatial distributions of fruits on orchard trees are necessary for such an approach. Reported methods for measuring the locations of all fruits require several minutes per fruit, and, consequently, have been used only for very small numbers of trees. The novel method presented utilizes high-frequency radio signals and trilateration to measure the locations of all fruits in canopies, at speeds that are significantly higher than those of existing methods. More specifically, a fruit picker wears gloves on which an antenna has been attached. A mobile trailer carries four radio beacons that measure and log their distances from the antenna on each glove, every time a fruit is grasped to be picked. The coordinates of each glove are computed with respect to a coordinate frame attached to the trailer,

and the fruit position is approximated by these coordinates. Data from an RTK-GPS and an inclinometer on the trailer are used to compute georeferenced fruit coordinates. Data were collected for 32,193 fruits in eight California pear and cling peach orchards. The measurement rate varied from approximately 8 to 12 fruits per minute, with an average of 10.8, which is a magnitude faster than existing reported methods. In open space, the root mean square error between the estimated and true distance (DRMS) in the system's measurement volume was measured to be 10.3 cm. The error's 90th percentile (R90) was 13.1 cm. In the periphery of and inside canopies, these errors were calculated via Monte Carlo simulation to be equal to 15.7 cm and 24.9 cm respectively. The horizontal accuracies (across and along the row), and the vertical accuracy were 9.6 cm, 4.3 cm and 5.7 cm respectively. The corresponding worst-case relative accuracies were 2.7%, 1.6%, and 3.4%, and were calculated by dividing each accuracy component by the distance between the fruits that were as far away as possible from each other along the corresponding axis. Finally, fruit position statistics, such as fruit elevation and horizontal distance from the row centers were computed and reported for a set of pear trees. Such data can be very useful for growers and for model-based design of harvesting machinery.

Keywords: Mechanization; specialty crops; orchards; fruit localization.

1. INTRODUCTION

In this paper, a novel method is presented that utilizes Ultra-Wide-Band (UWB) radio signals and trilateration to measure the locations of *all* fruits in tree canopies, at speeds that are significantly higher than those of existing methods. The motivation behind this work is that fruit distributions, together with digitized branch geometries, will be used as inputs to software design tools that predict harvesting performance metrics and guide the design of novel robotic harvesters, thus enabling a model-based design approach. Together with purchase price, fruit reachability and harvesting throughput performance metrics have been shown to constitute the most important factors in deciding the economic feasibility of a robotic harvester (Harrell, 1987). Of course, a robotic harvester's actual

performance in the orchard will depend on the complex interrelationships among orchard layout, tree canopy structure, spatial fruit distribution, harvester kinematics and dynamics, fruit detection and localization, and actuator control. For this reason, performance is evaluated using physical prototypes in orchards during the short harvesting season. This fact renders the iterative process of designing, building, testing and modifying fruit-harvester expensive and slow.

The development of novel robotic harvesters could benefit significantly from a model-based design approach, in which harvesting performance metrics are estimated by simulating the parts of the harvesting operation that are essential and meaningful for design purposes. A major goal of model-based design would be to guide toward a *mechanical* design that *maximizes* performance in terms of fruit kinematic reachability and average pick-and-place cycle for trees of certain architectures. This goal can be achieved by assuming perfect perception and control. In other words, predicting harvesting performance for mechanical design should incorporate the constraints imposed by the tree geometries and fruit positions, but not the constraints that may arise due to poor fruit visibility, under-powered actuation, or non optimal control. The use of model-based approaches for robotic harvester design and optimization has been very limited. Edan et al., (1991) modeled a specific robot arm type and measured fruit locations on a few small trees, in order to calculate optimal picking sequences for the robot, and to study the effect of link masses on maximum throughput. Sivaraman and Burks (2006; 2007) used canopy volume estimates to perform robot manipulator kinematic design, with maximum fruit reachability as a design criterion. Van Henten et al., (2009) used workspace and manipulator specifications stemming from cucumber harvesting operations to optimize the kinematic structure, and link parameters of a three-link robot arm.

This paper focuses on the measurement of spatial distributions of all fruits on trees. Branches certainly affect fruit accessibility and harvester throughput (and, consequently, optimal mechanical design); therefore, their geometries would need to be incorporated, too. Measuring the locations of *all* fruits on trees can be a very time-consuming and expensive process. The first documented attempt to

74 mapfruit spatial distributions on trees was by Schertz and Brown (1966), who adopted a cylindrical
75 coordinate system and measured the coordinates of citrus fruits. More specifically, the longitudinal
76 axis of the coordinate system was oriented vertically and collinearly with the trunk of the tree. The
77 height of each fruit was measured by lowering a plumb bob on a calibrated tape. The point of
78 intersection of the plumb bob with a polar coordinate board at ground level gave both the angular and
79 the radial positions of each fruit. This approach was very time-consuming, and required onetotwo
80 days to map all the fruits on a single tree, depending on yield and tree size. Measurement accuracy
81 could not be assessed, but it obviously depended on user skill, because branches might also cause the
82 tape to deflect and deviate from a straight vertical line. Other researchers, such as Juste and Lee and
83 Rosa, have also used this simple approach (Juste, et al., 1988; Lee and Rosa, 2006).

84 Smith et al., (1992) used a theodolite to record the three-dimensional coordinates of kiwi fruits on
85 vines and sample the geometric structure of the vines themselves. The accuracy of the readings was
86 reported to be within millimeters of the position of each point. This method was limited, in that it
87 required unobstructed Line-of-Sight (LOS) between each fruit and the theodolite. This, however, is
88 impractical for trees with dense canopies and fruits hanging deep inside them. Also, fruit position
89 measurement was slow: each fruit required approximately 60 s, resulting in an effective rate of one
90 vine per one-to-two days, depending on yield and vine size. Smith and Curtis (1996) used a three-
91 dimensional position tracking system (PolhemusFastTrak™) to digitize tree structure and measure
92 fruit locations. This system used a low frequency magnetic field emitted by a transmitter to measure
93 the 3-D coordinates of the tip of a stylus; coordinates were relative to a coordinate system defined by
94 the transmitter. The RMS static accuracy of the system in the absence of metal objects is
95 approximately 1 cm, within 1 m from the transmitter. The system's operational radius was limited to
96 approximately 1.5 m; digitizing large trees was made possible by re-locating the transmitter to various
97 positions, while keeping at least three points from the previous position within range. As a result, an
98 appropriate coordinate transformation matrix can be computed. Data collection without moving the

transmitter was reported to take place at approximately 10 points per minute. However, digitizing 1300-1500 points on a larger kiwi vine with this system required 10-12 hours.

Edan et al., (1991) measured fruit locations on twenty orange trees using a robotic manipulator on a mobile platform as digitizer. The data were collected manually, by placing the arm tip at each fruit on the tree, and storing the readings of each joint encoder at this position on a computer. Furthermore, the exact location of each fruit was calculated via the robot's forward kinematics. Accuracy and data collection rate were not reported. Relocating the robot tip – and possibly the platform – to reach each new fruit position should have required non-trivial effort, resulting in low collection rates. Also, larger trees would require a large robot, while branches could interfere with the robot links, thus rendering the task very difficult.

In contrast to manual methods, vision-based approaches use multiple cameras and points of view to detect and triangulate fruits from images. Takahashi et al. (2002) used stereovision to measure the range of apple fruits. The camera's position and Euler angles could be combined with the range to compute 3D fruit location. The range estimation errors were reported to be $\pm 5\%$ (average of -1.3% and standard deviation of 3.5%) at a distance range of 1.7m to 5.2m for non-overlapping fruits. Fruit localization has also been performed in yield estimation systems, such as the one developed by Wang et al., (2013), in order to avoid double counting of fruits in sequences of images. The authors do not report the position accuracy of the system, although they mention that fruits closer to 5 cm are counted as a single fruit. Here, it is important to note that their goal was yield mapping and not fruit localization. The major problem with vision-based approaches is that many fruits – especially those deeper into the canopy - are occluded by other fruits, leaves, or branches, and are not visible from the camera's viewpoints. For this reason, they cannot be localized.

In this paper, a novel method is presented, which utilizes Ultra-Wide-Band (UWB) high-frequency radio signals and trilateration to measure the locations of *all* fruits in tree canopies, while the fruits are being picked. UWB uses short pulse radio frequency waveforms over a large bandwidth (GHz) to

124 measure precisely the time-of-flight of a signal between a transmitter and a receiver. Trilateration
125 combines the measured ranges into an estimated position. UWB radios have been proposed for
126 localization in work environments associated with construction(Cheng, 2011) and mining (Chehri et
127 al., 2009).To the authors' best knowledge, the use ofUWB technology for localizing points close to, or
128 inside, tree canopies has not been reported in the literature. Results from data collection in several
129 orchards with different tree architectures are presented. These results establish that an average
130 throughput of the system is approximately 10.8 fruits per minute, which is at least one order of
131 magnitude faster than existing reported methods.

132 Another contribution of this work is the investigation of the effects of foliage on trilateration
133 accuracy. It is known that the water contained in vegetation attenuates radio signals, and that signal
134 reflection on the ground, as well as scattering at tree branches introduce multipath effects (Vougioukas
135 et al., 2013) that reduce UWB ranging accuracy. A novel trilateration error assessment method is also
136 presented, which uses the statistical distributions of range errors to estimate the trilateration error
137 inside foliage. The method is validated by means of experimental results, which are used to
138 characterize the accuracy of the measuring system. Finally, as an example of using the fruit position
139 data, some spatial statistics that could be relevant to machine design are calculated and presented.

140 **2. MATERIALS AND METHODS**

141 In this section, the hardware used in the experiments is presented,a description of the fruit position
142 measurement method is offered,and mathematical procedures for the estimation of positions and
143 position errorsare described in detail.

144 **2.1. HARDWARE**

145 The radio ranging transmitting and receiving units (RTRUs) used in this research are the PulsON
146 400 Ranging and Communications Modules (P400 RCM) (Time Domain, Inc, Huntsville, AL, USA).
147 The P400 RCM is an Ultra Wideband (UWB) radio transceiver that measures the distance between
148 the center-points A and B of two P400 RCM antennas (Figure 1). The units measure this distance

based on time-of-arrival (TOA) estimation of the direct path (DP) between points A and B.

Figure 1. A pair of UWB radios: Unit A measures the distance (red dotted line) between center points of antennas A and B.

The units operate in the band of 3.1GHz to 5.3 GHz, with a center frequency at 4.3 GHz. In a static scenario (when units are not moving) with an unobstructed LOS, the specifications for the range measurement precision (standard deviation) is 2.3 cm (0.9”), and for accuracy (bias) is 2.1 cm (0.83”). The units were configured to use seven pulses per data symbol (PII=7), which resulted in a maximum LOS range of 125 m (410 ft), and a measurement period of 20ms.

A mobile trailer (Figure 2) carried four identical RTRUs and their corresponding antennas on top of tall aluminum poles(Figure 3); the trailer RTRUs are also referred to as *trailer beacons*. The antenna coordinates with respect to the trailer’s coordinate frame are shown in Figure 2. The poles carrying the beacons were placed as far apart as possible on the trailer, under the constraint that they should not interfere with tree branches extending out into the orchard rows. The reasoning behind this choice is that the bigger the distance between beacons along an axis is, the better the localization accuracy along this axis will be(Manolakis, 1996). For the same reason, one beacon was placed much lower than the others.

Figure 2. CAD model of the trailer used to carry the four radio beacons.

Figure 3. A radio beacon placed at the top of a pole on the trailer. Poles are made of T-slotted aluminum extrusion rails.

The Trimble AgGPS 542 GNSS/RTK GPS System was used to record in real-time the geo-referenced location of the trailer with centimeter-level accuracy. The Ag542 Rover GPS on the trailer (Figure 4) received corrections from the Ag 542 Mobile Base Station GPS, using 900Mhz radio-modems integrated in the receivers.

Figure 4. RTK GPS receiver and modem antenna on the trailer provide accurate positioning for the trailer beacons.

A wireless attitude and heading sensor by YEI Technology, Inc. (Portsmouth, OH, USA) was used to measure the trailer's roll, pitch, and heading angles. The sensor has $\pm 1^\circ$ orientation accuracy for dynamic conditions, and repeatability better than 0.008° . The sensor outputs filtered absolute orientation angles in Euler format (pitch/roll/yaw). The computed order of rotation for the Euler angles is XZY. Therefore, the total Euler rotation matrix, R is composed of three rotation matrices, multiplied as $R = R_y R_z R_x$. The three angles are reported by each sensor as ψ, θ, ϕ , where pitch (ψ) is rotation about the X-axis (looking towards X; clockwise is positive), heading (θ) is about the Y-axis (looking towards Y; clockwise is positive), and roll (ϕ) is about the Z-axis (looking towards Z: clockwise is positive). Using GPS and angles, the 3D positions of the trailer beacons could be computed with respect to the world frame; Universal Transverse Mercator (UTM) coordinates were used for the projected coordinates.

The CST/berger 305R Electronic Reflector-less Total Station was used to locate the true positions (ground truth) of the trailer and glove beacon antennas in all experiments. The device uses a laser beam to locate a target surface and to report its angular position and coordinate position with respect to its own frame. The device has 5-second angle accuracy at a sighting distance of 100 m, which is equivalent to an accuracy of 2.5 mm in distance measurement. In all experiments, the operating range of the system was confined to 10m, which translates into an accuracy of 0.2 mm.

2.2. FRUIT POSITION MEASUREMENT METHOD

The fruit position measurements were made during manual harvesting with bags and ladders. In each orchard, a number of trees along a row were tagged, and each tree was given a unique identification (ID) code. In the orchard row, the trailer was placed next to the tree(s) to be picked, having the tree row at its right side. A picture of the trailer positioning relative to a tree-row from actual experiments is shown in Figure 5.

Figure 5. Photo of the trailer between tree-rows; it was taken during system deployment in an orchard.

The length of the system's intended measurement volume along the row (Y axis) was 4.5 m, its width (X axis, into the canopy) was 2.4 m, and its height (Z axis) was 4.5 m. The system's measurement volume was intended to cover the left half of the volume of each measured orchard tree; the right half volume is picked with the trailer placed in the right-adjacent row. The reason behind this choice is that fruit picking was also limited to half the tree volume, on the side of the row that the trailer was positioned, in order to reduce the amount of foliage and the resulting signal attenuation, scattering and diffraction between the glove antenna and the beacon antennas.

A picker was instructed to pick all the fruits from the left halves of the tagged trees inside the trailer's measurement volume. After finishing, the trailer was moved forward to the next unpicked trees in the +Y direction. The picker carried one small Radio Ranging Transmitter and Receiver Unit (RTRU) on

215 her/his belt (Figure 6), and wore gloves with an antenna attached on each glove (Figure 7). This
216 RTRU is referred to as the *mobile beacon*. The antennas on both hands were connected via cables to
217 the RTRU on the belt (two antennas per RTRU). The pickerwasinstructed to pick only one fruit at a
218 time,without displacing the branch of the fruit, in order not to change its original location. Also, the
219 picker was instructed to grasp the fruit in a manner that the antenna would face the trailer beacons,
220 i.e., the vector normal to the picker's palm would face toward the negative X-axis.

222
223 Figure 6. Ranging transmitter - receiver unit (RTRU) attached with Velcro on a belt worn by the picker.

225
226 Figure 7. The mobile beacon antenna was placed in a protective enclosure (flexible PVC tube) that was attached to the
227 picker's glove.

228
229 Every time the picker grasped a fruit in order to detach it from a tree, a human observer standing
230 close to the pickerregistered the event by pushing a button on a wireless Xbox™ controller. A simple

231 “protocol” was established to ensure the synchronization of the fruit-grasp event and the recording of
232 the four mobile-to-trailer beacon antenna ranges. First, the picker was instructed to shout “Aye” upon
233 fruit grasping. Secondly, the observer verified visually that the picker was grasping the fruit, pushed
234 the button to initiate the recording of the ranges, waited to feel the controller vibrate upon completion
235 of range recording (400 ms for four ranges – see next paragraph), and then shouted “OK”. Last, the
236 picker detached the fruit upon hearing “OK” from the observer. The protocol was used consistently;
237 however, it is possible that, on some occasions, the picker’s hand was not still, or in full contact with
238 the fruit during the 400 ms interval of range recording. In such cases, the respective estimated fruit
239 positions would contain errors that are difficult to model. Given the visual check by the observer and
240 the short time duration of range recording, such errors are expected to be infrequent and minor; for
241 this reason, they may not impact substantially the overall accuracy of the system.

242 Custom-written data collection software polled all sensors, and logged their readings together with
243 the ID of the tree being harvested, the ID of the hand used (1 for left / 2 for right), and a unique
244 timestamp for the fruit-grasp event. The GPS polling rate was kept low, at 1Hz, because the trailer
245 was static while the worker picked fruits. The attitude sensor was polled at 10 Hz. Each beacon was
246 polled every 20 ms. Each recorded range was calculated as the median value of five consecutive range
247 measurements, in order to reject outliers. Hence, a new filtered range update was available for each
248 beacon, approximately every 100 ms. One laptop was used for all data collection, and, therefore, all
249 events were time-stamped using the same real-time clock.

250 After all fruit had been collected, the 3D georeferenced coordinates of each picked fruit
251 were approximated by the coordinates of the antenna on the hand of the picker, when the hand grasped
252 the fruits. These coordinates were estimated via *trilateration*-- a procedure that uses the measured
253 ranges to compute an estimated position.

254

2.3. TRILATERATION OF THE MOBILE BEACON ANTENNA

Let the coordinates of the j th trailer beacon with respect to the world frame be (bx_j, by_j, bz_j) . Their calculation is derived in the Appendix. Each time a fruit is grasped by the worker, the timestamp of the “fruit-grasp” event is recorded together with a left or right hand flag, and an identification number for the tree that the fruit is picked from. Let $\mathbf{p}_i = [x_i, y_i, z_i]$ be the real coordinates of the glove antenna with respect to the world frame (measured with the Total Station), and d_{ij} be the true (geometrical) distance between the j th trailer beacon and $\mathbf{p}_i$:

$$d_{ij} = \left((x_i - bx_j)^2 + (y_i - by_j)^2 + (z_i - bz_j)^2 \right)^{1/2} \quad (1)$$

Due to multipath or intense signal attenuation conditions, the estimation of TOA (and subsequently of range) of the direct path between beacon j and point $\mathbf{p}_i$ will typically contain a random error. If this error is ε_{ij} , then the measured range r_{ij} is:

$$r_{ij} = d_{ij} + \varepsilon_{ij} \quad (2)$$

Trilateration is used to estimate the glove antenna coordinates $\mathbf{p}_i^t = [x_i^t, y_i^t, z_i^t]$ based on the four measured distances r_{ij} . In the presence of range errors, trilateration using least-squares optimization results in the optimal position estimation (Navidi et al., 1998):

$$(x_i^t, y_i^t, z_i^t) = \arg \min_{x_i, y_i, z_i} \sum_{j=1}^4 (r_{ij} - d_{ij})^2 \quad (3)$$

The position coordinates of each picked fruit are approximated by the coordinates (x_i^t, y_i^t, z_i^t) of the glove antenna on the surface of the fruit. All calculations were performed using Matlab R2013a (MathWorks, Natick, MA, USA); equation (3) was solved using the *fminsearch()* Matlab optimization function.

2.4. ERROR METRICS

Let the 3D distance error between the trilaterated position $\mathbf{p}_i^t$ and the true position of the glove antenna at point $\mathbf{p}_i$ be:

$$e_i = \left((x_i^t - x_i)^2 + (y_i^t - y_i)^2 + (z_i^t - z_i)^2 \right)^{1/2} \quad (4)$$

Let the distance error parallel to the orchard tree rows (y-axis) be e_{yi} , the error perpendicular to the tree rows be e_{xi} , and the error along the vertical axis be e_{zi} ; these errors are defined as:

$$e_{xi} = x_i^t - x_i, \quad e_{yi} = y_i^t - y_i, \quad e_{zi} = z_i^t - z_i \quad (5)$$

Given a set of N measurements, the system's accuracy was characterized using a number of metrics. The first accuracy metric is the Distance Root Mean Square error (DRMS):

$$DRMS = \sqrt{\frac{1}{N} \sum_{i=1}^N e_i^2} \quad (6)$$

The advantage of this metric is that it is a radial error; in other words, it is invariant to the rotation of the axes used to describe the error. However, in an orchard setting, it is important to distinguish between errors along the tree row axis, and errors perpendicular to it. Therefore, three additional metrics are computed--mainly, the average absolute errors in the x , y and z directions:

$$ABSE_x = \frac{1}{N} \sum_{i=1}^N |e_{xi}|, \quad ABSE_y = \frac{1}{N} \sum_{i=1}^N |e_{yi}|, \quad ABSE_z = \frac{1}{N} \sum_{i=1}^N |e_{zi}| \quad (7)$$

Two disadvantages of the above metrics are that isolated large outlier errors have a large effect on them, and that the metrics are not tied to a specific probability level. Therefore, the 90th percentile or R90 error metric is also computed based on the 3D distance error, e . This metric is equal to the radius of a sphere centered at the true position, containing the position estimate with a 90% probability.

2.5. TRILATERATION ERROR ASSESSMENT METHOD

The trilateration error at each antenna location $\mathbf{p}_i$ inside the measurement volume depends on: a) the relative geometrical arrangement of the mobile antenna and the fixed beacon antennas, i.e., $\mathbf{p}_i$ and ${}^{WF}\mathbf{b}_j, j=1,2,3,4$; and b) the range errors ε_{ij} . Antenna placement causes the Dilution of Precision (DOP) effect: when position is computed via trilateration, the range errors are amplified by a factor that depends on the relative arrangement of the antennas (Manolakis, 1996), which, in our case, varies

301 over the measurement volume. In open space with unobstructed LOS range, radio signal path loss is
302 not spatially uniform, and is typically larger close to the ground, because of wave reflection and
303 resulting signal fading and multipath echoes (Saidi, et al., 2011; Sangodoyin et al., 2016). These
304 factors can increase UWB range errors (Sahinoglu, et al., 2008). In the presence of foliage, signal
305 attenuation is typically higher and varies with distance, even at relatively shorter ranges (Vougioukas
306 et al., 2013). Hence, when foliage is present in the LOS, range errors are expected to be higher. Main
307 reasons include: increased signal attenuation from the water in the vegetation, increased multipath due
308 to signal diffraction and scattering on leaves, branches and fruits, and lower light speed through leaves
309 and branches (light speed is used to convert TOA to range).

310 For the reasons described above, the trilateration error is expected to vary over the
311 measurement volume. In open space, it is possible to measure directly the trilateration error at points on
312 a sampling grid that covers the measurement volume using a surveying instrument (Total Station).
313 The trilateration error at any position can then be estimated by interpolating the errors from its
314 neighboring grid points. However, surveying instruments require unobstructed LOS to the position
315 being measured. Therefore, measuring the trilateration error on a sampling grid inside tree canopies is
316 practically impossible, mainly because of foliage that blocks LOS. Furthermore, experimentally
317 measured open-space trilateration errors cannot be used as “reasonable” estimates of trilateration
318 errors for locations inside canopies, because the corresponding range errors exhibit different
319 behaviors.

320 This challenge is addressed by introducing a trilateration error assessment method
321 that utilizes Monte Carlo simulation to estimate trilateration errors based on measured range error
322 statistics. Essentially, range errors from experimentally derived range error distributions propagate via
323 the trilateration equation (3) to calculate trilateration errors over a grid of points in the measurement
324 volume. Error propagation via Monte Carlo simulation is a well-established technique in metrology
325 (JCGM 101:2008) that has been used extensively in various domains (e.g., Cox et al., 2002). The steps

326 of the proposed method are given below.

327

328 **Sampling Step:** Generate K sets H_k ($k = 1, \dots, K$) of points, each containing M points. These sets create
329 a sampling distribution of points $\mathbf{p}_i$ that sample adequately the measurement volume;

330 **Range Error Characterization Step:** Estimate experimentally the probability distribution $P_k(\varepsilon)$ of
331 range errors ε_{ij} from all beacons to all points $\mathbf{p}_i \in H_k$;

332 **Simulation Step:** For each set H_k and for each point $\mathbf{p}_i \in H_k$:

- 333 1. Calculate the true beacon-to-point distances d_{ij} using Eq. (1);
- 334 2. Generate a large number N of range errors ε_{ijn} using $P_k(\varepsilon)$;
- 335 3. For each sample ε_{ijn} :
- 336 4. Add ε_{ijn} to true distances d_{ij} to produce noisy ranges r_{ijn} using Eq. (2);
- 337 5. Calculate the n th trilaterated position $\mathbf{p}_{in}^t$ using Eq. (3);
- 338 6. Calculate the n th trilateration errors e_{in} , e_{xin} , e_{yin} , e_{zin} , using Equations (4) and (5);
- 339 7. Calculate trilateration error metrics for sets H_k , and the entire measurement volume.

340

341 The application of this method to the fruit-position measuring system was validated in open space,
342 where direct trilateration error measurements were available. Then, the probability distribution $P_k(\varepsilon)$
343 of range errors in foliage were estimated (Sampling and Range Error Characterization Steps), and the
344 Simulation Step of the above method was executed to predict trilateration errors for sets H_k , and the
345 entire measurement volume in foliage. The experimental design of the measurement campaigns and
346 the results will be presented in the following sections.

347

348 3. EXPERIMENTAL DESIGN

349 3.1. SAMPLING OF MEASUREMENT VOLUME

350

It has been observed that trilateration error – in particular, the elevation component – is larger at points closer to the ground (Saidiet al., 2011). Main reasons include wave ground reflections, and resulting signal fading and multipath echoes. Therefore, five ($K = 5$) sets H_k of points were defined that correspond to five planes at increasing heights equal to 0.91 ($k = 1$), 1.83 ($k = 2$), 2.74 ($k = 3$), 3.66 ($k = 4$) and 4.57 m ($k = 5$). These correspond to approximately 3, 6, 9, 12 and 15 ft. These planes are shown in Figure 8.

Figure 8: The system's measurement volume was sampled at five horizontal planes H_k of increasing heights.

Each plane contained $M = 24$ points arranged in a uniform grid of size approximately equal to $0.6 \text{ m} \times 0.9 \text{ m}$ ($2 \times 3 \text{ ft.}$). A total of $K \times M = 120$ points were used to sample the measurement volume. As an example, the points on the grid in H_1 are shown as star symbols in Figure 9.

Figure 9: Illustration of measurement points forming a uniform grid on plane H_1 of the measurement volume.

3.2 RANGE ERROR MEASUREMENT IN OPEN SPACE

In open space, it is possible to measure range errors at all points of the sampling grid. Four RTRUs on the trailer frame acted as known-position fixed beacons. A five-meter-long T-slotted aluminum extrusion rail was used as a mobile pole, and was placed at the x-y ground coordinates of each ‘column’ of sampling points. At each position of the pole (M in total), an RTRU that acted as a mobile beacon was placed on the pole, and raised to each of the K different heights defined by the planes. The coordinates of all beacon antennas were measured using the Total Station. Fixed-to-mobile beacon antenna distances were to be measured at all grid points. For each grid point $\mathbf{p}_i$ in the workspace one thousand ($N = 1,000$) r_{ijn} range measurements were to be recorded by each of the four fixed beacons. The true distances d_{ij} between each of the fixed beacons and mobile beacon antennas were to be computed using the measured coordinates. The errors ϵ_{ijn} between the true distances and the measured ranges were to be used to estimate a non parametric model (frequency histogram) of the range error probability distribution $P_k(\epsilon)$ at each individual height.

3.3 RANGE ERROR MEASUREMENT IN FOLIAGE

Depending on the position of fruit in the canopy, a percentage of the LOS between a trailer beacon and the glove beacon will contain vegetation (leaves, branches, and fruits). This percentage may vary

303 from 0% for fruits in the periphery of the canopy, to 100% for cases when the entire tree's half-
 304 volume is between the glove and a trailer antenna, and when branches extend out to that trailer beacon
 305 antenna. The actual frequency with which each ratio is encountered depends on factors such as tree
 306 type, training system, pruning, and inter-row distance in the orchard. To estimate the range errors in
 307 the presence of foliage, equal numbers of range measurements were recorded for three percentages of
 308 vegetation coverage at approximately 35%, 70% and 100%, at different heights. The true locations
 409 were measured with the Total Station. At each height, the errors from the three vegetation ratios were
 410 used to estimate the corresponding range error histograms. The tree used was a Bartlett pear tree
 411 (*Pyrus communis* 'Williams pear') of the open-vase architecture.

408 For each vegetation percentile data set, a beacon antenna (referred to as “fixed”) was placed and
 409 held fixed at two different locations (No.1 and No.2 in Figure 10), each time at five different heights
 410 (0.91, 1.83, 2.74, 3.66 and 4.5 m). For each combination of location and height of the fixed
 411 antenna, a “mobile” beacon antenna was moved to nine different locations on the other side of the tree,
 412 as shown in Figure 10, at a height of 2.32 m from the ground. This height is the same as the trailer's
 413 three beacons. Hence, 18 experiments were conducted for each height of the fixed beacon, and a total
 414 of 90 measurement sets were taken.

Figure 10: Spatial arrangement of mobile and fixed beacon antennas for evaluating range errors when vegetation is present

404 in the direct radio transmission path between them.

405

406 4. EXPERIMENTAL RESULTS AND DISCUSSION

407 All transmitter beacons were calibrated before the experiment to compensate for antenna cable
408 length delays. The calibration was performed according to the manufacturer's suggested procedure.

409 4.1 RANGE ERROR STATISTICS IN OPEN SPACE

410 The range error histograms that approximate distributions $P_k(\varepsilon)$ were computed for five different
411 heights ($k = 1, 2, \dots, 5$), from 70,626 measurements at each height. Two-sample Kolmogorov-Smirnov
412 tests were used for each possible pair of distributions $P_m(\varepsilon)$, $P_n(\varepsilon)$, with $m, n \in \{1, 2, \dots, 5\}$ and verified
413 at the 5% significance level that error data at different heights came from different distributions. The
414 histograms for the lowest plane ($P_1(\varepsilon)$) and highest plane ($P_5(\varepsilon)$) are shown in Figure 11.

415

416
417 **Figure 11: Open-space range error histograms at two heights: $P_1(\varepsilon)$ at 0.9 m (left) and $P_5(\varepsilon)$ at 4.5 m (right).**

418

419 Error metrics of the distributions are given in Table 1 for each height and for the entire
420 measurement volume (last column). Although all beacons had been calibrated before the experiments,
421 the range error distributions were slightly biased. In theory, bias for UWB ranging systems should
422 always be positive, because it results from delayed signal arrivals due to wave reflections. A possible
423 reason for negative range errors and bias is electromagnetic field saturation. When the antennas are

too close together, the returning signal may enter a trailer RTRU directly through its antenna connector, instead of entering from the antenna and propagating through the antenna cable.

Table 1. Range error metrics in open space when LOS is unobstructed; they were calculated from experimentally derived error distributions $P_k(\varepsilon)$ at five different heights (units in cm).

	$P_1(\varepsilon)$	$P_2(\varepsilon)$	$P_3(\varepsilon)$	$P_4(\varepsilon)$	$P_5(\varepsilon)$	ALL
Mean	3.83	1.70	2.81	2.04	-0.13	2.05
Std. dev.	4.22	3.89	3.90	2.98	2.57	3.80
Mean absolute	4.56	3.23	3.62	2.81	1.88	3.22
Root Mean Square (RMS)	5.7	4.24	4.81	3.61	2.58	4.32
R90	9.2	6.88	8.37	5.98	3.86	7.48

The general trend was for range errors to decrease as height increased. At 2.7 m ($k = 3$), the error seems to deviate from the trend. However, at a later point, it was noticed that a horizontal aluminum tube that provided structural support to the beacon poles was close to that height. Therefore, it is possible that it interfered in the signal propagation. This “anomaly” manifested itself in the trilateration error, too (see Figure 15 later).

4.2 RANGE ERROR STATISTICS IN FOLIAGE

The error measurements were taken in a pear orchard at the UC Davis campus. Visual inspection indicated that the foliage density was typical of commercial orchard pear trees, similar to the ones visited for our data collection (described later). Unfortunately, these trees had been hedged, and their height did not exceed 4 m. Therefore, the range error histograms that approximate distributions $P_k(\varepsilon)$ were computed for four – instead of five - different heights ($k = 1, 2, \dots, 4$). A total of 18,000 measurements were taken at each height. Two-sample Kolmogorov-Smirnov tests were used for each possible pair of distributions $P_m(\varepsilon)$, $P_n(\varepsilon)$, with $m, n \in \{1, 2, 3, 4\}$, and verified at the 5% significance

level that error data at different heights came from different distributions. The histograms for the lowest plane ($P_1(\varepsilon)$) and highest plane ($P_4(\varepsilon)$) are shown in Figure 12.

Figure 12: Range error histograms in foliage at two heights: $P_1(\varepsilon)$ at 0.9 m (left) and $P_4(\varepsilon)$ at 3.6 m (right).

In Table 2, error metrics of the distributions are given both for each height and for the entire measurement volume (last column).

Table 2.Range error metrics when LOS contains vegetation; they were calculated from experimentally derived error distributions $P_k(\varepsilon)$ at four different heights(units in cm).

	$P_1(\varepsilon)$	$P_2(\varepsilon)$	$P_3(\varepsilon)$	$P_4(\varepsilon)$	$P_5(\varepsilon)$	ALL
Mean ($\bar{\varepsilon}$)	5.16	4.52	6.34	6.39	-	5.60
Std. dev.	4.93	2.56	6.11	5.05	-	4.90
Mean absolute	5.28	4.63	6.96	6.63	-	5.88
Root Mean Square (RMS)	7.13	5.20	8.81	8.14	-	7.45
R90	10.74	8.17	12.98	14.90	-	12.19

A comparison of Tables 1 and 2 reveals that, on the whole, the presence of foliage increased the mean error (bias) by 173%, the standard deviation by 28.9%, the mean absolute error by 82.6%, the RMS by 72.5% and the R90 by 63%. In contrast to open space, the range error in the presence of

foliage increased as elevation increased. This could be attributed to the increased foliage density at the upper parts of the open-vase Bartlett pear tree that was used for testing. In general, lower limbs on such trees tend to lose vigor, and upper limbs tend to grow above lower ones and shade them out (Mitcham and Elkins, 2007). More data would be needed to support this hypothesis. The histograms of all range error measurements in open space and foliage are juxtaposed in Figure 13.

Figure 13: Range error histograms of all sampled points inside the system's measurement volume in open space (left) and with vegetation (right).

The presence of foliage has "shifted" the histogram to the right resulting in larger bias, and has also increased the standard deviation to 4.9 cm, compared to 3.8 cm in open space.

4.3 TRILATERATION ERRORS IN OPEN SPACE - VALIDATION

The open-space trilateration errors were measured, and their spatial distribution is shown in Figure 14.

Figure 14: Spatial distribution of measured trilateration DRMS error at five heights inside the system's measurement volume.

Metrics of the measured trilateration error at different heights and over the entire measurement volume (last row labeled “Overall”) are given in Table 3. The standard deviations reflect the precision of the measurements in the three axes.

Table 3. Open-space trilateration accuracy metrics calculated from measurements of uniformly sampled points at five different heights inside the system's measurement volume (units in cm).

	DRMS	ABSE _x ± std	ABSE _y ± std	ABSE _z ± std	R90
Height 1	12.9	7.2 ± 6.1	3.1 ± 2.3	6.3 ± 4.7	16.9
Height 2	11.6	5.2 ± 4.9	4.2 ± 2.9	6.0 ± 4.5	17.1
Height 3	9.8	3.4 ± 2.9	5.1 ± 3.4	4.9 ± 3.8	13.9
Height 4	8.9	4.0 ± 3.7	3.5 ± 2.1	4.5 ± 3.5	13.5
Height 5	7.7	4.3 ± 3.2	2.6 ± 2.1	3.6 ± 2.5	11.4
Overall	10.3	4.8 ± 4.5	3.7 ± 2.8	5.1 ± 4.0	15.1

The general trend was that trilateration errors decreased as height increased. This is in agreement with previous results for UWB-based trilateration close to the ground (Saidiet al., 2011). The effect

484 was more pronounced in the X and Z-axes, where the ABSE_x and ABSE_z errors at 4.5 m were
 485 approximately 60% of the corresponding values at 0.9 m. Also, the errors along the X and Z-axes
 486 were significantly larger than the Y-axis errors at all heights, except for 2.7 m (Height 3). The
 487 explanation for this lies in the geometrical configuration of the trailer beacons. It is known
 488 (Manolakis, 1996) that, the bigger the distance between beacons along an axis, the better the
 489 localization accuracy along this axis. The trailer beacons were farther apart in the Y-axis than in the X
 490 or Z-axes.

491 The Monte Carlo simulation was implemented in Matlab, and was executed using the open-space
 492 range error histograms that resulted from our measurements. The metrics of the simulated errors are
 493 reported in Table 4. For comparison purposes, the DRMS errors from measurements and Monte Carlo
 494 simulation are presented in Figure 15.

495 **Table 4.** Open-space trilateration accuracy metrics calculated via Monte-Carlo simulation at
 496 uniformly sampled points, at five different heights inside the system's measurement volume (units in
 497 cm).

	DRMS	ABSE _x ± std	ABSE _y ± std	ABSE _z ± std	R90
Height 1	13.7	9.4 ± 7.3	3.7 ± 2.9	4.0 ± 2.7	20.7
Height 2	11.7	8.3 ± 6.5	3.0 ± 2.4	2.5 ± 2.0	18.2
Height 3	11.7	8.1 ± 6.2	3.2 ± 2.5	3.2 ± 2.3	18.0
Height 4	8.7	6.0 ± 4.7	2.4 ± 1.9	2.4 ± 1.7	13.4
Height 5	6.9	4.8 ± 4.0	1.8 ± 1.5	1.4 ± 1.2	11.0
Overall	10.8	7.4 ± 6.1	2.8 ± 2.4	2.7 ± 2.2	16.9

498

Figure 15: Measured and simulated/predicted trilateration DRMS error at all sampled points in the measurement volume.

The graph shows that the simulator captured the general trend of decreasing trilateration errors with increasing height. From Tables 3 and 4, it can be deduced that, over the entire measurement volume, the simulator overestimated ABSE_x by 54.2%, underestimated ABSE_y by 24.3%, and underestimated ABSE_z by 47.1%. However, since non-directional range error statistics were used for the Monte-Carlo error assessment method, non-directional trilateration error metrics are better suited to evaluate it. These metrics were much better: DRMS was overestimated by only 4.9%, and R90 was overestimated by 11.9%. Therefore, the Monte-Carlo method can be used for trilateration error assessment.

4.4. TRILATERATION ERRORS IN TREE CANOPIES - SIMULATION

The range error distributions that were determined experimentally in foliage were used to execute the Monte Carlo simulation. 1,000 range error samples were generated for each point of the grid at each height. The error statistics of the simulated errors are reported in Table 5.

Table 5. Estimated trilateration accuracy metrics in the presence of vegetation calculated via Monte-Carlo simulation at uniformly sampled points, at five different heights inside the system's measurement volume (units in cm).

DRMS	ABSE _x ± std	ABSE _y ± std	ABSE _z ± std	R90
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Height 1	16.2	9.8 ± 9.8	4.0 ± 3.9	5.2 ± 3.4	27.8
Height 2	9.4	5.7 ± 4.4	2.9 ± 2.0	4.6 ± 1.8	13.5
Height 3	19.4	12.8 ± 10.3	5.3 ± 4.3	6.5 ± 4.1	30.1
Height 4	16.2	10.3 ± 8.1	4.8 ± 3.7	6.5 ± 3.5	24.4
Height 5	-	-	-	-	-
Overall	15.7	9.6 ± 8.8	4.3 ± 3.7	5.7 ± 3.4	24.9

519

520 In contrast to open space, the expected trilateration error did not seem to reduce as height increased.
521 This was to be expected, since the same was true for the range errors in foliage. As in open space, the
522 errors along the X and Z-axes were significantly larger than the Y-axis errors at all heights, because of
523 the trailer beacon configuration.

524 4.5. ESTIMATION OF FRUIT LOCATIONS IN ORCHARDS

525

526 Fruit positions were measured using the developed system in eight (8) commercial orchards in
527 California, in July and August 2014. The primary goal was to assess the system's fruit position
528 digitization rates in different orchards under typical harvesting operations. The digitization rates
529 depend on non-picking (non-productive) times, which are mainly the result of using ladders.
530 Therefore, trees were not randomized; instead, fruit positions from consecutive trees in a random row
531 of each orchard were digitized. A total of 32,193 fruit positions were measured from 66 trees: 24 cling-
532 peach trees (*Prunus persica*(L.) Batsch) and 42 pear trees (*Pyrus communis* 'Williams pear'). Tree
533 architectures were: Standard Open Vase (SOV); High-Density Open Vase (HDOV); Trellised (T);
534 High Density Trellised (HDT). Tree information and average fruit position digitization rates are
535 shown in Table 6.

536

537 **Table 6.** Fruit position measurement rates for several cling-peach and pear tree architectures.

538

Canopy	Number of	Number	Tree height (m)	Tree age	Digitizing rate
--------	-----------	--------	-----------------	----------	-----------------

architecture	trees	of fruits		(years)	(Fruits / minute)
SOV - Peach	4	5142	3.7	12	14.13
SOV - Peach	6	4010	4.1	22	11.2
SOV - Peach	4	5075	4.9	14	11.71
HDOV - Peach	10	3999	3.4	4	11.93
SOV – Pear	3	3694	4.3	33	9.09
SOV – Pear	4	3329	4.1	15	8.79
HDT – Pear	28	4329	2.7	9	11.48
T – Pear	7	2615	4.9	12	7.99

539

540 The fruit position digitizing rates include the time required by pickers to locate, reach, pick, place,
541 transport fruit to bins, and move ladders, as well as the time required by researchers to pull (manually)
542 the data acquisition trailer along the orchard rows. The digitizing rates for cling peach and pear trees
543 varied from 11 to 14, and from 8 to 11.5 fruits per minute, respectively. In particular, for SOV peach
544 trees, the digitizing rate was 12.3 fruits per minute based on 14,227 fruits collected from 14 trees (1.4
545 hours per tree), while for SOV pear trees it was 8.9 fruits per minute based on 7,023 fruits collected
546 from 7 trees (1.9 hours per tree). The main reason behind this difference is that SOV pear trees have a
547 more complex canopy structure than cling peach trees of the same architecture; therefore, pickers
548 needed more time to move ladders and position themselves on them. The digitization rate as a
549 function of total number of harvested fruits – regardless of fruit type and tree architecture – is shown
550 in Figure 16. There seems to exist a linear correlation between digitization rates and total number of
551 harvested fruits (Pearson's $r = 0.9$). If the same number of fruits were located sparsely on large trees
552 rather than closer together on small trees, the corresponding digitization rate would be expected to be
553 lower. To capture this, spatial density of harvested fruits (fruits/m³) was used as an independent
554 variable, and its relationship to harvesting rate is shown in Figure 17. Spatial density was calculated
555 by dividing the total number of harvested fruits over the volume occupied by all trees, including the
556 space between trees in the row. A linear correlation seems to exist between fruit spatial density and
557 digitization rate (Pearson's $r = 0.7$), which becomes much stronger (Pearson's $r = 0.9$) if the first data
558 point is ignored (at 3.7 fruits/m³, 11.48 fruits /min). This point corresponds to high-density pear trees

565 (HDT – Pear) with low height at 2.7 m, which require significantly less usage of ladders for
 566 harvesting. The correlation can be explained by the fact that when many fruits are harvested in smaller
 567 volume, picking (i.e. digitizing) time dominates over non-productive, i.e. non-picking time.

565 **Figure 16. System's fruit position measurement rate versus total number of harvested fruits.**

567 **Figure 17. System's fruit position measurement rate versus spatial density of harvested fruits (fruits/m³).**

569 Next, a fruit position 3D map from one field experiment in a pear orchard in Lakeport, CA is
 576 presented along with some spatial statistics. The Bartlett pear trees were approximately 5 m tall. The
 577 data were collected from seven trees along a row; an aerial view of the part of the orchard row is
 578 shown inFigure 18.

574

Figure 18: Satellite image of Bartlett pear orchard. Fruit positions were measured from the seven trees inside the yellow rectangle.

A map of the fruit locations in 3D is shown in Figure 19. The horizontal fruit coordinates are georeferenced in UTM, but, for the sake of readability, they are expressed in the figure with respect to the trailer's initial position. Furthermore, heights are with respect to the ground (0 m). Maps like these could be used by growers to assess how their flower and fruit thinning strategies affect fruit distribution, with the purpose of adjusting them accordingly.

Figure 19: 3D pear-fruit locations measured from seven trees in a row. Coordinates (m) are expressed with respect to the trailer's initial position and to the ground (0 m).

The yield of each tree can be seen in Figure 20. Although the trees were next to each other in the same row and had the same age, yield variability was significant: minimum and maximum yields were 301 and 429 respectively (42.6% difference). The mean was 373.6 fruits, while the standard deviation 43.4 fruits. Such information – if it becomes available for more trees – could be used by farmers to identify problems--such as water and nutrient availability--and manage the orchard more precisely.

Figure 20: Bar chart showing the total number of fruits (yield) on each tree.

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The height distribution of the pears for the seven trees in the row is shown in the normalized histogram in Figure 21. The mean value of this height is $E(h) = 2.6$ m, and the standard deviation, $\sigma = 1$ m.

Figure 21: Bar chart depicting the normalized histogram of fruit heights (z coordinates).

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The corresponding cumulative height histogram is given in Figure 22. It can be seen that these trees bear fruit from near the ground to their tops. Approximately 60% of the fruit is above 2.2 m; i.e., the average picker on the ground cannot reach it. Such information can be very useful for the design and fine-tuning of harvesting and harvest-aiding equipment, such as orchard platforms.

Figure 22: Bar chart depicting the cumulative histogram of fruit heights (z coordinates).

The normalized histogram of the fruit distances from the row-centers is shown in Figure 23. The mean value of this distance is $E(d) = 1.2$ m, and the standard deviation, $\sigma = 0.4$ m. These distances are useful to know, because they relate to the extension requirements toward the canopy for any type of fruit picking actuator (or human) carried by a mobile platform. Hence, they can be used to drive the design of such equipment.

Figure 23: Normalized histogram of fruit horizontal minimum distance from the left and right row centers.

5. CONCLUSIONS

A novel approach to fruit localization, which utilizes high-frequency radio signals and trilateration to measure the locations of fruits in trees while fruits are picked, was developed and tested. Overall, 32,193 fruit positions were recorded; such a large dataset has never been available thus far. The average

610 fruit localization rate was 10.8 fruits per minute. Such a rate is at least one order of magnitude faster
611 than existing reported methods. As a consequence, it renders the system practical for real-world use.
612 In open space, the RMS error between the estimated and true distance (DRMS) in the system's
613 measurement volume was measured to be 10.3 cm. The error's 90th percentile (R90) was 13.1 cm. The
614 corresponding errors for locations in tree canopies had to be estimated using Monte Carlo
615 simulation, and were calculated to be equal to 15.7 cm and 24.9 cm respectively. This accuracy is
616 about an order of magnitude worse than that of commercial magnetic field based digitizers, which can
617 work without LOS (unlike surveying instruments). However, the range of these systems is limited to 1
618 – 1.5 m, whereas the developed system can handle very large trees, up to 5m tall.

619 In relative terms, the worst-case position accuracy along each axis can be calculated by dividing the
620 corresponding error (ABSE_x, ABSE_y, or ABSE_z) by the distance between the fruits that are as far
621 away as possible from each other along the corresponding axis. Distances along x, y and z are 3.49 m,
622 2.7 m, 1.67 m, respectively. The relative fruit position accuracies in the x, y and z-axes were
623 calculated to be 2.7%, 1.6% and 3.4%, respectively. If such fruit position data are used as input for
624 fruit reachability and picking cycle simulations, the computed metrics will also contain uncertainty.
625 The effects of such fruit position uncertainties on the value of the computed metrics for design
626 purposes cannot be quantified at this point. However, two important facts should be considered. First,
627 since standard deviations are known, uncertainty in fruit positioning can be propagated via the
628 harvesting simulator, and translated into variance of harvesting metrics. Consequently, quantitative
629 estimates of the effects of fruit position uncertainty on harvesting metric uncertainty can be computed
630 and evaluated. Second, it is the *difference* in the calculated performance metrics between alternative
631 designs that drives the model-based design process, and not the values of the metrics themselves. This
632 implies that uncertainty/variance in a harvesting metric may not be important, as long as the expected
633 values of the metrics of two alternative designs are far apart from each other. Therefore, the relatively
634 small fruit position measurement uncertainties may constrain the resolution of the design space being

635 explored—in other words, the length increment of a robot arm link in a parametric optimization—but
636 they are not expected to undermine the validity of model-based design for robotic harvesters.

637

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707 **APPENDIX: GEO-REFERENCING OF THE TRAILER BEACON ANTENNAS**

708 Our goal is to calculate the instantaneous georeferenced 3D position of each j th beacon antenna
709 expressed in world frame coordinates (bx_j, by_j, bz_j) . The reason is that, given these four positions and

710 the four distances between the beacon antennas and a glove antenna, we can calculate the 3D position
 711 of the glove antenna using trilateration. Next, we show how to compute this.

712 First, the following reference frames need to be defined: world frame (WF); initial trailer frame
 713 (ITF) at the beginning of data collection; initial attitude sensor frame (YTF) at the beginning of data
 714 collection; instantaneous trailer frame (TF); instantaneous Rover GPS frame ($GPSF$); instantaneous
 715 attitude sensor frame (AF). Let us also define the following positions as homogeneous-coordinate
 716 vectors expressed with respect to the trailer frame: receive-transmit center points on the antennas of
 717 the trailer beacons, ${}^{TF}\mathbf{b}_j = [bx_j \ by_j \ bz_j \ 1]^T$, $j = 1, 2, 3, 4$; Rover GPS receiver origin,
 718 ${}^{TF}\mathbf{p}_{GPSF} = [\Delta x_{gps} \ \Delta y_{gps} \ \Delta z_{gps} \ 1]^T$; and the origin of attitude sensor: ${}^{TF}\mathbf{p}_{YF} = [\Delta x_{yei} \ \Delta y_{yei} \ \Delta z_{yei} \ 1]^T$. All the above
 719 positions were measured manually, after the beacons, GPS, and attitude sensor were rigidly placed on
 720 the trailer.

721 Let the homogeneous coordinates of the j th beacon antenna with respect to the world frame be
 722 ${}^{WF}\mathbf{b}_j = [bx_j \ by_j \ bz_j \ 1]^T$. The position of the origin of the trailer frame expressed in the Rover GPS
 723 frame is ${}^{GPSF}\mathbf{p}_{TF} = [-\Delta x_{gps} \ -\Delta y_{gps} \ -\Delta z_{gps} \ 1]^T$. Let us define a matrix I as,

$$724 \quad I = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{pmatrix} \quad (8)$$

725
 726 Then, the homogeneous (4 x 4) coordinate transformation matrix of the instantaneous Rover GPS
 727 frame $GPSF$ with respect to the instantaneous trailer frame TF is ${}^{TF}H_{GPSF} = [I \ {}^{TF}\mathbf{p}_{GPSF}]$, and the
 728 transformation matrix of TF with respect to $GPSF$ is ${}^{GPSF}H_{TF} = {}^{TF}H_{GPSF}^{-1} = [I \ {}^{GPSF}\mathbf{p}_{TF}]$. The instantaneous
 729 trailer position and orientation measurements are given next: the position of the trailer's Rover GPS is
 730 ${}^{WF}\mathbf{p}_{GPSF} = [x_{gps} \ y_{gps} \ z_{gps} \ 1]^T$; the rotation of the attitude sensor with respect to the initial attitude sensor
 731 frame (YTF) is:

$${}^{YTF}R_{TF} = \begin{bmatrix} c\theta c\varphi & s\psi s\theta - c\psi c\theta s\varphi & c\psi s\theta + c\theta s\psi s\varphi \\ s\varphi & c\psi c\varphi & -c\varphi s\psi \\ -c\varphi s\theta & c\theta s\psi + c\psi s\theta s\varphi & c\psi c\theta - s\psi s\theta s\varphi \end{bmatrix} \quad (9)$$

Since the GPS and attitude sensors are rigidly attached to the trailer, the following transformations are equal, i.e., ${}^{YTF}R_{AF} = {}^{YTF}R_{TF} = {}^{YTF}R_{GPSF}$. At each time instant, the rotation of the trailer with respect to the world frame can be computed as:

$${}^{WF}R_{TF} = {}^{WF}R_{ITF} {}^{ITF}R_{YTF} {}^{YTF}R_{AF} \quad (10)$$

The position of trailer frame expressed in the world frame as:

$${}^{WF}\mathbf{p}_{TF} = {}^{WF}H_{GPSF} {}^{GPSF}\mathbf{p}_{TF} = \begin{bmatrix} {}^{WF}R_{TF} & {}^{WF}\mathbf{p}_{GPSF} \\ 0 & 0 & 0 \end{bmatrix} {}^{GPSF}\mathbf{p}_{TF} \quad (11)$$

Now, at each time instant, the 3D georeferenced homogeneous position of each trailer beacon antenna expressed in the world frame (${}^{WF}\mathbf{b}_j = [bx_j \ by_j \ bz_j \ 1]^T$) can be computed using the following equation:

$${}^{WF}\mathbf{b}_j = {}^{WF}H_{TF} {}^{TF}\mathbf{b}_j = \begin{bmatrix} {}^{WF}R_{TF} & {}^{WF}\mathbf{p}_{TF} \\ 0 & 0 & 0 \end{bmatrix} {}^{TF}\mathbf{b}_j \quad (12)$$