Tree centric localisation in almond orchards

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Abstract
Robotics and intelligent sensing systems can provide useful information to improve yield and quality in specialty crop production. A key requirement for tree-crop applications is the ability to associate sensed data to the individual trees in an orchard. A mobile ground robot with a scanning lidar (laser range sensor) is used to build a three dimensional (3D) model of an orchard and algorithms are derived to automatically detect and segment each tree. The height profile of each canopy is used to match the tree to a previously obtained database, to determine the location of the robot in the orchard, and to associate newly obtained agronomic data to the existing database. Experiments were conducted over 16 months in a 2.3 ha section of an almond orchard in Mildura, Victoria. An average tree segmentation accuracy of 99.1% was obtained, and the localisation accuracy was 98.2% for data obtained one full year apart. The method is sufficiently accurate to provide a feasible mechanism for localisation and data management in orchard environments.

Keywords: robotics, sensing, precision-agriculture, intelligent information systems

INTRODUCTION
To meet growing food demands, intelligent information systems have an increasing role, providing farmers with high resolution, timely, composite soil and crop pictures, from which sustainable production can be optimised. The use of mobile air and ground robots equipped with sensors is an emerging technology for this purpose.

Mobile, ground-based, intelligent information systems involve three steps: 1) traverse the farm acquiring raw sensory data (e.g., from cameras, lidar, soil conductivity), 2) use algorithms and software to convert raw data to usable information (e.g., estimate yield, detect weeds, pests or diseased crops) and 3) present the information in a form that is easy for growers or agronomists to interpret, such as maps.

Geolocation is therefore a core enabling component. This is commonly provided by the Global Positioning System (GPS), however, in many environments such as orchards, GPS is unreliable due to satellite occlusion. This paper presents an orchard localisation and mapping technique that does not rely upon GPS. Instead, height profiles of the trees are measured and used to form sequences like a ‘digital barcode’, to identify the specific rows and trees. Other sources of data (e.g., soil, crop, etc.) can then be measured, stored, compared across seasons and presented by association to the unique row and tree identifier.

Existing general purpose approaches to 3D segmentation such as (Douillard et al., 2011) are not appropriate in this application, due to the overlapping geometry of the tree canopies. We adopt an orchard specific approach, extending from work on lidar-based tree counting (Wellington et al., 2012). In previous work (Jagbrant et al., 2015), we extended from this to additionally identify and match trees to a database, and in this paper, results are extended to cover a full growing season (Underwood et al., 2015).

MATERIALS AND METHODS
A general purpose ground vehicle robot “Shrimp” was used to acquire data, see Figure 1. It is a four-wheel skid-steer, mobile robot equipped with a combination of sensors; the side facing SICK-LMS291 lidar was used to scan one side of a tree in passing. The robot was driven in both directions (to scan both tree sides) along each of ten rows of an almond orchard in Mildura, Victoria, covering an area of 2.3 ha. Data were gathered over a period of...
16 months, including the early fruit-set period in October 2012, followed by flowering, fruit-set and pre-harvest in 2013/2014. Each raw dataset comprised a 3D point-cloud model of the orchard.

Figure 1. "Shrimp" ground vehicle robot, equipped with sensors including lidars, cameras and soil sensors.

The algorithms and software developed for this application perform three distinct operations. Firstly, a Hidden Semi-Markov Model (HSMM) is used to separate individual trees from the 3D model of the whole orchard, using a similar approach to (Wellington et al., 2012), with minor modifications to explicitly accommodate smaller re-planted trees. Secondly, each tree is characterised by geometric properties such as height, volume and height profile (a signature based on the canopy profile). Finally, a Hidden Markov Model (HMM) is used to match trees by comparing these characteristics in sequence. The trees were labelled by hand to enable quantification of the performance of the software.
RESULTS AND DISCUSSION

The accuracy of the algorithm is measured by comparing the output of the software to the hand-labelled ground-truth. It is calculated as the number of correctly segmented or matched trees, divided by the total number of trees in the data.

Segmentation accuracy

The accuracy of the first segmentation step was quantified, prior to performing the characterisation and matching steps, because segmentation errors can cause subsequent matching errors. The performance is tabulated for all datasets in Table 1. Accuracy varied between 95.8 to 100.0%, with an average of 99.1%.

<table>
<thead>
<tr>
<th>Date</th>
<th>Season</th>
<th>Correct</th>
<th>Incorrect</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2012-10-05</td>
<td>Fruit-set</td>
<td>580</td>
<td>1</td>
<td>99.8</td>
</tr>
<tr>
<td>2013-08-13</td>
<td>Flowering</td>
<td>1153</td>
<td>3</td>
<td>99.7</td>
</tr>
<tr>
<td>2013-08-14</td>
<td>Flowering</td>
<td>1210</td>
<td>4</td>
<td>99.7</td>
</tr>
<tr>
<td>2013-08-15</td>
<td>Flowering</td>
<td>1156</td>
<td>0</td>
<td>100.0</td>
</tr>
<tr>
<td>2013-08-16</td>
<td>Flowering</td>
<td>1156</td>
<td>0</td>
<td>100.0</td>
</tr>
<tr>
<td>2013-09-23</td>
<td>Fruit-set</td>
<td>1274</td>
<td>3</td>
<td>99.8</td>
</tr>
<tr>
<td>2014-02-10</td>
<td>Pre-harvest</td>
<td>1141</td>
<td>18</td>
<td>98.4</td>
</tr>
<tr>
<td>2014-02-11</td>
<td>Pre-harvest</td>
<td>1106</td>
<td>49</td>
<td>95.8</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>8776</td>
<td>79</td>
<td>99.1</td>
</tr>
</tbody>
</table>

The segmentation accuracy was nearly perfect, with a notable reduction in performance (95.8 and 98.4%) for data obtained immediately prior to harvest. At that point in the season, the foliage in the tree canopies is most voluminous, with adjacent canopies overlapping more significantly than at other times. These conditions presented the greatest challenge to the software. Segmentation errors also occurred when the software misidentified a person or vehicle adjacent to the last tree in a row, that was accidentally scanned upon exiting the row, which occurred at most once or twice per 2.3-ha scan.

Tree localisation accuracy

The accuracy of the tree matching process was quantified, after the initial step of segmentation. One dataset from Table 1 was used to provide the reference database and a second (always different) dataset was used to test the tree identification and matching. Permutations were chosen to evaluate results at different times of the season. To quantify the performance of the whole algorithm, segmentation errors from the previous step were left un-corrected. The results are shown for all tested permutations in Table 2.

<table>
<thead>
<tr>
<th>Map/Match</th>
<th>2012-10-05</th>
<th>2013-08-15</th>
<th>2013-09-23</th>
<th>2014-02-10</th>
</tr>
</thead>
<tbody>
<tr>
<td>2012-10-05</td>
<td>100 (116/116)(^1)</td>
<td>85.9 (397/462)</td>
<td>98.7 (457/463)</td>
<td>53.4 (246/461)</td>
</tr>
<tr>
<td>2013-08-15</td>
<td>71.8 (415/578)</td>
<td>100 (1156/1156)(^2)</td>
<td>98.4 (1141/1159)</td>
<td>84.7 (981/1158)</td>
</tr>
<tr>
<td>2013-09-23</td>
<td>97.8 (565/578)</td>
<td>98.9 (1143/1156)</td>
<td>99.2 (117/118)(^3)</td>
<td>91.3 (1057/1158)</td>
</tr>
<tr>
<td>2014-02-10</td>
<td>48.6 (281/578)</td>
<td>77.2 (893/1156)</td>
<td>77.0 (893/1159)</td>
<td>94.2 (1088/1155)(^2)</td>
</tr>
</tbody>
</table>

\(^1\)Multiple rows mapped and one test row localised. Data obtained on the same day, with one row scanned twice.
\(^2\)Multiple rows mapped and multiple test rows localised after scanning the following day.
\(^3\)Same-day.

The results along the diagonal of Table 2 show the performance when matching
against a database acquired on the same or previous day. This tests the matching ability when the trees do not physically change between scans. Perfect matching results (100%) were obtained during flowering, when there is minimal foliage and maximally separated canopies. During fruit-set, the performance was also high (99.2%), but decreases to 94.2% just before harvest. These errors are most likely caused by errors in the prior segmentation step, which occur at similar rates (see Table 1).

2. Same-year, different season.

The off-diagonal cells in Table 2 show the performance when a database is obtained at a significantly different time to the matching dataset. Under these conditions the physical nature of the trees can change (e.g., due to growth and seasonal changes, see Figure 2). Correspondingly the performance drops as low as 48.6% when comparing flowering to pre-harvest canopy geometries with the maximum available temporal separation of 16 months (both a different time of season and a different year). The difference between flowering and fruit-set was less pronounced during the same year and the performance was no worse than 98.4%.

3. Subsequent-year, same season.

Data obtained at the start of October 2012 and the end of September 2013 were used to test performance with one year separation, both at the time of fruit-set. This isolates changes in tree geometry due to growth, pruning and disease from the seasonal changes such as flowering and foliage development. The accuracy was 97.8%, indicating that the most significant cause of poor performance was due to the intra-seasonal changes (changes throughout one year) in tree canopy geometry.

CONCLUSIONS

The results show that the geometric profile of almond tree canopies can be used to identify individual trees in an orchard, when a sequence matching approach is used. Such a system can be used to locate a mobile sensing platform in an orchard, and to manage databases of sensed information on a per-tree basis, without relying upon GPS. The accuracy is highest when matching observations taken at the same time of season, while poorer performance was observed when attempting to match between seasons (e.g., flowering, fruit-set and pre-harvest). This could be managed by storing tree-appearance databases corresponding to each season, which is future work.
ACKNOWLEDGEMENTS

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Literature cited


