A Camera/Ultrasonic Sensors Based Trunk Localization System of Semi-Structured Orchards

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Abstract—Semi-structured orchard environment has the characteristics of high complexity and strong uncertainty, which brings many challenges to the localization and navigation of agricultural automation equipment with limited sensors. This paper introduces a tree trunk localization system in a semi-structured orchard using camera/ultrasonic sensors fusion. In our method, the location of each tree trunk, which is relative to the robot, is obtained through the trunk tracking camera/ultrasonic detection system on the robot. And the location and direction of the robot are obtained through wheel odometer and IMU, respectively, rather than the traditional high-precision RTK-GPS. In order to reduce the error caused by odometer and IMU, several control points are introduced to revise the tree trunks’ location, of which positions are determinate. Experiments suggest that in a simulated environment and a real orchard, which both have a row-column spacing of 4.3m×3.4m, the tree trunk localization error of our approach is within 0.3m.

Index Terms—Semi-structured Orchard, Trunk Localization, Multi-sensor Fusion, Control Points

I. INTRODUCTION

In orchard precision agriculture, the automation equipment or robots need to finely manage each fruit tree, which brings great demands on the localization of each tree in the environment. In some open agricultural applications, such as large crop fields, it is effective to use high-precision real-time kinematic (RTK) GPS sensors to achieve positioning and navigation for robots [1], [2]. However, high-precision RTK-GPS is usually expensive. Thus it is not conducive to promote and popularize the agricultural automation robotic equipment for farmers in many regions around the world [3]. Additionally, in the environments like orchards, it is found that the GPS signal is easily obstructed and interfered with by the branches and leaves of fruit trees [4], making it challenging to meet the actual needs of localization and navigation. Using alternative approaches or sensors fusion to complete the orchard trunk localization has gradually attracted increasingly attention in this context.

In current researches, unmanned ground vehicle (UGV) is the most popular form of agricultural robots. Considering the complexity of the agricultural environment, many researchers adopt a multi-sensor fusion method to realize the navigation of the ground mobile robot. These solutions usually use the approach of RTK-GPS plus other sensors. For instance, Kurashiki et al. [5], [6] constructed the orchard tree trunk map by using RTK-GPS and Lidar. In this work, the location of trunks relative to the robot and the location of the ground robot was obtained from Lidar and RTK-GPS, respectively. Francisco et al. [7] used a stereo camera and GPS to create a global grid map in a vineyard. Their research realized the positioning and navigation of the robot by associating real-time positioning information with the grid map. In the research of Blackmore et al. [8], RTK-GPS, Lidar, and IMU were used to correct the position and pose of the robot to control the robot walking along the centerline of the road.

There is no denying the fact that RTK-GPS is a useful tool for localization and navigation. However, in the environment with dense trees, the RTK-GPS signal is easily blocked by the canopy and branches, which reduces the availability of agricultural robots. Under these circumstances, researchers are looking for other approaches to avoid the reliance on RTK-GPS. Velasquez et al. [9] proposed a farmland navigation system based on Lidar to avoid over-reliance on GPS signals. Though this method is reliable, Lidar is easily affected by crops of different heights, bringing specific errors to the system. Pieter M. Blok et al. [10] validated the performance of two localization algorithms that used a 2D Lidar for in-row robot navigation in orchards, which are particle filter (PF) with a laser beam model, and Kalman filter (KF) with the line-detection algorithm. The CASC research group from Carnegie Mellon University [11], [12] set up reflective tapes that were easily detected by Lidar at both ends of the tree row so that the robot could extract the endpoint features accurately when it reached the end of the row. In their research, the RTK-GPS was only used to obtain the global position of trees of both ends of each tree row. The point cloud feature of trees was obtained from Lidar, and the location and pose of the robot were estimated from the point-line feature gained from the extended Kalman filter (EKF) and odometer.

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Besides, some researchers have proposed alternative ways. One of the concerned methods is Lidar plus other sensors. For example, Cheein et al. [13] used machine vision to extract the olive tree trunk’s HOG features, then identified the trunk based on a support vector machine (SVM). After that, the distance from each trunk to the robot was measured by a Lidar. Shalal et al. [14], [15] used Lidar to find each trunk’s possible position and then extracted the edge and color features of the suspected trunk area in the image. The localization accuracy was improved by the EKF algorithm. Subramanian et al. [16], [17] used machine vision to extract the navigation baseline in the middle of the road through color clustering in a citrus orchard. The location of the plants on both sides was detected by a Lidar. After fusing machine vision, Lidar, and IMU data by fuzzy EKF algorithm, the robot could localize and navigate itself in the orchard.

Although the use of Lidar plus other sensors can get rid of the dependence on GPS, this type of method still has shortcomings. Firstly, the point cloud data obtained by Lidar is susceptible to interference from non-trunk objects in the orchard, such as supporting rods, drooping branches, and leaves. The low signal-to-noise ratio of the Lidar data makes it challenging to represent the trunk information precisely. Secondly, high-precision Lidar is still an expensive sensor, which makes the agriculture robot difficult to become commercial [3]. In contrast, machine vision has the advantages of a large amount of information, high signal-to-noise ratio, and low-cost.

Consequently, many researchers used machine vision in the field of environmental perception and navigation of agricultural robots. For instance, Vieira et al. [18] proposed a vision-based method to detect and segment tree trunks from unstructured environments. Ahmadi et al. [19] proposed a navigation framework for row crop fields only using on-board cameras, which utilized the conventional crop row structure existing in the field without the need to perform explicit positioning or maintain a map of the field. Adrien et al. [4] proposed a vision-based inspection system for orchard trunks, which mainly used four stereo cameras to detect the environment around the robot and extract tree trunk information. Apart from the researches above, the vision-based approach supplemented by some conventional sensors with less data redundancy (such as ultrasonic sensors, IMU, etc.) has become another way to the localization and navigation in semi-structured orchard. In the research of Chen et al. [20], the detection of tree trunks in the image was realized by an SVM. And the location of the trunk relative to the robot was measured by the ultrasonic sensors with step motors. However, this research only succeeded in controlling the robot walking between two rows of trees, which did not complete localization of the tree trunks.

In the environment of large semi-structured orchards, fruit trees are planted in rows, and the distance between fruit trees is basically unchanged. Therefore, compared with the work in a completely unknown environment, semi-structured environment can bring certain convenience. However, the uncertainty of this environment also makes it challenging for trunk localization to reach high accuracy. Besides, the accuracy of trunk localization in a large area has limitations due to the cumulative error, which needs to be reduced.

This paper proposes an approach for obtaining each tree’s location in a semi-structured orchard using camera/ultrasonic system. Moreover, in order to reduce the error resulting from the odometer and IMU, this paper introduces control points to modify the trees’ location. The main contribution of this paper is a practical trunk localization method using multi-sensors fusion. Additionally, the introduction of control points is proved to be useful to reduce the error caused by the odometer. According to the experiment, the accuracy of this method basically reaches the accuracy of the researches using expensive high-precision sensors, such as RTK-GPS, and Lidar.

II. PROPOSED METHOD

The principle of this method is shown in Fig.1. The trunks are recognized through a camera. Then the camera/ultrasonic system is guided by the visual information to align the center of trunks. Since the centers of the camera and the ultrasonic sensors are overlapping, the ultrasonic sensors will aim at the trunks as soon as the camera does so. After that, the distance between the camera/ultrasonic system and the trunk is measured. And the angle of the system is obtained through an encoder. In addition, the location and direction of the robot are measured through the odometer and inertial measurement unit (IMU), respectively. The proposed localization approach for each tree is based on the sensors information mentioned above. The schematic diagram of this method is shown in Fig.2.

This section is arranged as follows: Sect.II.A-C gives the principle of trunk localization, while Sect.II.D shows the principle of control points to reduce the localization error.
Fig. 3. The camera/ultrasonic detection system.

A. Measuring trunks’ location relative to the robot

The detection of the trunks’ location relative to the robot mainly depends on the camera/ultrasonic detection system, as shown in Fig. 3. It is used to detect the environment on both sides of the robot. The key point of this system is to align the ultrasonic sensor with the centerline of the tree trunk. Since the camera and the ultrasonic sensor are in the same coordinate system, they are able to aim at the trunk simultaneously. The identification target of the camera is trunk, while the rest of the environmental information is noise.

Fig. 3 shows the principle of the developed system, which consists of the perception unit and the tracking unit. Firstly, the image captured from the camera is processed to identify the trunk. The details were shown in the previous work of our research group [20]. After that, the angle that the perception unit needs to rotate is calculated through the number of pixels between the centerline of the image and the identified trunk in the image. The tracking unit then makes the perception unit rotate a particular angle so that the center lines of the image and the trunk overlap. Finally, the distance between the trunk and the detection system is measured by the ultrasonic sensor after recording the tracking unit’s angle through the encoder. And the location of the trunk relative to the robot is obtained.

B. Obtaining the location of trunks in the orchard environment

The odometer used in this paper consists of two encoders installed on both sides of the driving wheels of the crawler-type mobile platform. For each turn of the driving wheel, the encoder outputs 1024 pulses. Thus, without considering the track slippage, the relationship between the movement distance $\Delta S$ of the track and the detected pulse number $n$ is:

$$\Delta S = \frac{n}{1024} \times 2\pi \times (r_w + h_t)$$

(1)

where $r_w$ represents the radius of the driving wheel, and $h_t$ represents the thickness of the track. Then the distance traveled by the center of the mobile platform $\Delta S_c$ can be expressed as:

$$\Delta S_c = \frac{\Delta S_l + \Delta S_r}{2}$$

(2)

where $\Delta S_l$ and $\Delta S_r$ represent the moving distance of the left and right track, respectively. Fig. 4 shows the principle of obtaining trunk coordinates in the orchard coordinate system. In this paper, we consider the coordinate axis under the orchard coordinate system as $X_OO_0Y_O$. Since the computer control system is discrete in time, the movement process of the mobile platform can be discretized. Assume that the location and direction of the mobile platform at moment $t – 1$ and $t$ are $(x_{t-1}, y_{t-1}, \theta_{t-1})$ and $(x_t, y_t, \theta_t)$, respectively. The positive direction of the direction angle $\theta_t$ and $\theta_{t-1}$ is the Z-axis in the Cartesian coordinate system, and the zero position coincides with the $X_O$ axis in the orchard coordinate system. When the sampling period is relatively small, it can be approximately considered that the movement distance of the platform center $\Delta S_c$ is equal to the length of the platform center displacement $\Delta l$, and the platform direction angle $\theta_t$ is equal to the angle $\alpha$. Then the positional relationship between the mobile platform at moment $t$ and $t – 1$ can be described as:

$$\begin{bmatrix} x_t \\ y_t \end{bmatrix} = \begin{bmatrix} x_{t-1} \\ y_{t-1} \end{bmatrix} + \begin{bmatrix} \cos \theta_t \\ \sin \theta_t \end{bmatrix} \Delta S_c$$

(3)

When the position and direction of the mobile platform in the orchard are calibrated in advance, the position and direction of the robot in the orchard environment can be obtained.

So far, we have known the trajectory of the mobile platform in the orchard environment. On this basis, we need to know the location of the trunk relative to the mobile platform in order to calculate its location in the orchard coordinate system. As shown in Fig. 4, taking the left camera/ultrasonic detection system as an example, we can measure the distance $d$ between the detection system and the trunk, and the rotation angle $\varphi$ of the detection system in the coordinate system of the platform $X_RO_RY_R$. The trunk location $(x_t, y_t)$ in the platform coordinate system can be described as:

$$x_t = (d + r_t) \cos(\varphi)$$

(4)

$$y_t = (d + r_t) \sin(\varphi) + \Delta Y_R$$

(5)

where $\Delta Y_R$ represents the distance between the centers of the camera/ultrasonic system and the mobile platform. $r_t$ represents the radius of the trunk. Since the radii of each trunk in the same orchard are barely the same, we consider...
the radius as a constant. Then the trunk location \((x_{L}, y_{L})\) in the orchard coordinate \(X_{O}O_{O}Y_{O}\) can be expressed as:

\[
\begin{bmatrix}
  x_{L} \\
  y_{L} \\
\end{bmatrix} = \begin{bmatrix}
  \cos\theta_1 & -\sin\theta_1 \\
  \sin\theta_1 & \cos\theta_1 \\
\end{bmatrix} \begin{bmatrix}
  x_{1} \\
  y_{1} \\
\end{bmatrix} + \begin{bmatrix}
  x_{t} \\
  y_{t} \\
\end{bmatrix} \tag{6}
\]

C. Calculation of the estimated coordinates of trunks in the orchard trunk environment

Through the approaches mentioned above, we can get the trunk location in the orchard environment. However, affected by track slippage, obstructions, and road inequality, the same trunk’s measurement results will not overlap at one point. They will exist in the form of point clouds. As is shown in Fig.5 Left, the schematic point clouds will be approximately distributed around the center of the actual location of each trunk. Therefore, we can calculate the center point of each point cloud by the K-means clustering algorithm. The location of the center is the estimated location of each trunk in our method.

In a real semi-structured orchard, mobile robots need to work along multiple tree rows. Consequently, the robot has to make a turn at the end of each tree row. Due to terrain constraints, the turning radius is usually small. Thus this may cause slippage. Additionally, there may be complex terrain such as slopes in the orchard, bringing errors to the odometer. Moreover, the error from the IMU should also be considered, for the reason that in many cases, the IMU is not that accurate when doing a U-turn at the end of each tree row. The mobile robot in this paper has two sets of camera/ultrasonic detection system installed symmetrically on both sides. Therefore, for the same row of trees, the detection system will measure them twice. We can use the same tree row data measured at different times to revise their coordinates to improve the localization accuracy.

As is shown in Fig.5 Right, inside the yellow box is the localization result of the robot moving between the first and the second row. The pink box shows the result between the second and the third row. The second row is not coincident due to the existence of sensors error. To reduce the error, we can process the trunk coordinates in the pink box by translation and rotation so that the blue tree row in the pink box coincides with that in the yellow box. In the orchard environment, suppose the coordinate sets of the trees in the second row in the yellow and pink boxes are \((x_{0}, y_{0})\) and \((x_{1}, y_{1})\), and the coordinates of the last fruit tree in the yellow and pink boxes are \((x_{a}, y_{a})\) and \((x_{b}, y_{b})\), respectively. Then \((x'_{1}, y'_{1})\) can be obtained by rotating \((x_{1}, y_{1})\) the angle \(\beta\) around the origin of the orchard coordinate system:

\[
\begin{bmatrix}
  x'_{1} \\
  y'_{1} \\
\end{bmatrix} = \begin{bmatrix}
  \cos\beta & -\sin\beta \\
  \sin\beta & \cos\beta \\
\end{bmatrix} \begin{bmatrix}
  x_{1} \\
  y_{1} \\
\end{bmatrix} \tag{7}
\]

where \(\beta\) represents the angle between the fitted line of the second row in the pink and yellow box. Every time the robot makes a U-turn, which could be measured by the IMU, the system will consider it as a symbol of the end of the tree row. After that, the fitted line of the tree row is calculated. According to the newest fitted line and the previous line, we are able to get \(\beta\). Then, perform a translation on \((x'_{1}, y'_{1})\) so that the rotated \((x'_{b}, y'_{b})\) and \((x_{a}, y_{a})\) are coincident. After that, the \((x''_{1}, y''_{1})\) after translation is shown as:

\[
\begin{bmatrix}
  x''_{1} \\
  y''_{1} \\
\end{bmatrix} = \begin{bmatrix}
  x'_{1} \\
  y'_{1} \\
\end{bmatrix} + \begin{bmatrix}
  -x'_{b} + x_{a} \\
  -y_{b} + y_{a} \\
\end{bmatrix} \tag{8}
\]

Since we only overlap the first tree by rotation and translation, other trunks of the second row do not necessarily overlap. Thus, we need to average the coordinates of these trunks. Consider the averaged trunk coordinates \((x_{c}, y_{c})\) as the estimated trunk coordinates in the orchard environment. \((x_{c}, y_{c})\) can be expressed as follows:

\[
\begin{bmatrix}
  x_{c} \\
  y_{c} \\
\end{bmatrix} = \frac{1}{2} \left( \begin{bmatrix}
  x_{0} \\
  y_{0} \\
\end{bmatrix} + \begin{bmatrix}
  x''_{1} \\
  y''_{1} \\
\end{bmatrix} \right) \tag{9}
\]

Based on Sect.II.A-C, the initial trunk location in the orchard environment could be obtained.
D. Revising the orchard trunk coordinates by control points

Although we have initially completed the orchard trunk localization through the approaches mentioned above, the odometer’s errors are still inevitable, especially in a large orchard. This section intends to revise the trunk coordinates by setting up specific control points, of which the coordinates are known before localization.

Control point is an essential concept in geomatics. It has absolute coordinates on a map. In geomatics engineering, it is often used in map stitching and merging [21]. The principle of revising the trunk coordinates using control points is shown in Fig.6. In the orchard coordinate system, we should firstly measure the precise coordinates of several tree trunks as control points information. Take the first and second row from the right in Fig.6 into consideration, the coordinate of the control point in the second row is \((x_{0\text{con}}, y_{0\text{con}})\). When the robot finds this control point, it record the coordinates of the control point \((x_{0\text{det}}, y_{0\text{det}})\). Since the odometer’s error is accumulated, we use the scaling transformation to the coordinates of the detected trunk \((x_{\text{det}}, y_{\text{det}})\) in the blue area. The transformation is completed when \((x_{0\text{det}}, y_{0\text{det}})\) coincides with \((x_{0\text{con}}, y_{0\text{con}})\). Their relationship is shown as follows:

\[
\begin{bmatrix}
  x'_{\text{det}} \\
  y'_{\text{det}}
\end{bmatrix} =
\begin{bmatrix}
  x_{0\text{con}} & 0 \\
  0 & y_{0\text{con}}
\end{bmatrix}
\begin{bmatrix}
  x_{\text{det}} \\
  y_{\text{det}}
\end{bmatrix}
\]

(10)

where, \([x'_{\text{det}}, y'_{\text{det}}]\) represents the coordinates of trunks after transformation in the blue area.

By setting markers on the trunk, as is shown in Fig.6, the robot can recognize different control points through the camera. The advantage of this kind of marker is that the camera/ultrasonic detection system can be directly used to identify and locate the control points without adding new sensors. Additionally, it is low-cost and easy to maintain.

III. EXPERIMENTAL EVALUATION

This section mainly presents the validation experiments and results. Three experiments were conducted to validate the proposed method: the experiment of single-row trunk localization, three-row trunk localization, and the experiment of revising the raw localization results using control points. The first two experiments were completed in simulated orchard environment. And the third one was completed in a real orchard environment. The reason that the row spacing of trunks was set by 4.3m×3.4m is that it is the same as it in the real orchard environment of the third experiment. The ultrasonic sensor used in this system is KS109 from Dauxi Technologies Co., Ltd. And the IMU used in this paper is JY61. The first two experiments correspond to Sect.II.B and Sect.II.C, and the third experiment corresponds to Sect.II.D.

A. Single-row trunk localization

As shown in Fig.1, this experiment was set as an outdoor simulated orchard environment, and the trunks used in the experiments were made of pine bark, with a diameter of nearly 20cm. The row spacing of trunks were arranged in the form of length and width by 4.3m×3.4m. Before the experiment, the zero position of the IMU on the robot was calibrated.

Then the robot started from the middle of two tree rows, and the starting point was set as the origin of the orchard coordinate system. The robot automatically tracked the center line of the two rows of fruit trees using the method described in [20], and the real-time sensor data was recorded during the robot motion, including camera/ultrasonic detection results and the odometer information. Then the recorded data was processed according to the method described in Sect. II.B and C in a real-time stage. The speed of the robot was about 0.8m/s.

The trunk localization results of the experiment above is shown in the blue dashed boxes in the top and bottom of Fig.7 (the blue boxes in the two figures are the same set of data). It can be seen from the enlarged part in the bottom of Fig.7 that the coordinates of each tree trunk (the green dots in Fig.7) do not overlap, and the distance deviation of some points reaches about 1m. However, after using the K-means algorithm, the estimated trunk position is not much different from the actual trunk position, and the distance deviation is about 0.2m. The error is the difference between the calculated position and the actual position, and the error measurement is decomposed on the \(X_O, Y_O\) coordinate axis. Through calculation, the maximum error in the \(X_O\) direction between the localization result of the tree trunk in the blue dashed box and the actual position of the tree trunk is 0.14m, and the maximum error in the \(Y_O\) direction is 0.15m.

B. Three-row trunk localization

This experiment had the same experiment scene as experiment A. The difference was that this experiment adopted three rows of trunks. The distance between the third row and the second row of trunks was set as 3.6m. When the robot reached the end of the centerline between the first and second rows,
the robot was manually controlled to turn in a certain radius, and started to move along the centerline of the second and third rows of trees. The real-time sensor data was recorded during the robot motion. Then the recorded data was processed according to the method described in a real-time stage. The result is shown in the top of Fig.7. It could be seen from the red dashed box that due to crawler slippage and IMU errors during turning, the two localization results for the second row of trees do not overlap and the error is large. At this time, the odometer and IMU data need to be revised. The result of revising the data according to the method described in Sect. II.C is shown in the bottom of Fig.7. The result shows that the maximum error between the estimated position of the tree trunk and its actual position in the $X_O$ direction is 0.14m, and the maximum error in the $Y_O$ direction is 0.16m.

C. Revising the localization result via control points

In the real orchard environment, most of the robot’s working pavement is land. Thus the crawler robot would produce more slippage than the cement pavement during their movement. This would bring an increase in the result error of the odometer. In addition, there are systematic errors odometer itself. In a real orchard environment, these problems would cause decrease of the localization accuracy. In order to reduce the error caused by the odometer, control points were introduced to modify the orchard trunks’ coordinates. The validation experimental environment of this experiment is a real orchard (shown in Fig.8). Take the first tree in row 1 and 3 and the last fruit tree in row 2 as control points. The coordinates of the three points shown in Fig.8 were measured by a tapeline manually. Finally, stick three different identification marks on the trunk as the control points for the robot to recognize.

The top of Fig.9 is the result of the localization before modification with control points. It could be seen that the localization error gradually increases with the robot moving. The maximum error in the $X_O$ direction is 2.0m, and the maximum error in the $Y_O$ direction is 0.21m. This result has produced a large error with the actual situation. The result of using the control points to revise the localization result is shown in the bottom of Fig.9. After correction, the maximum error in the $X_O$ direction is 0.22m, and the maximum error in the $Y_O$ direction is 0.21m. The average error of the third experiment is shown in Table I. It can be seen that the use of control point information can effectively revise the trunks’ coordinates in the orchard.

![Fig. 8. The environment of the experiment using control points.](image)

![Fig. 9. The result of revising the trunks’ coordinates with control points.](image)

### IV. DISCUSSION

Overall, the proposed method could realize orchard trunk localization based on the camera/ultrasonic sensor system in the validation experiments. Moreover, the orchard trunk localization error in the experiment is $0.21\pm0.06$m, which is close to the results of some similar studies in the literature. For example, Kurashiki et al. [5], [6] adopted RTK-GPS and Lidar in positioning of orchards, and the error was $0.2$m. And the localization error in a similar work by Blackmore et al. [8] was $0.05$m. The olive grove mapping and positioning error using machine vision and Lidar was not more than $0.5$m by Cheein et al. [13]. The mapping and positioning method by Shalal et al. [14], [15] using vision and Lidar showed an error of $0.2$m. Based on the comparison above, this paper’s results suggest the potential usability of using low-cost sensors in trunk localization of orchards, which has an advantage of reducing the use of expensive sensors in agriculture robots, such as RTK-GPS and Lidar.

The method of using control points in this paper could achieve optimized localization result in the real trunk environment. However, only preliminary work has been achieved to apply control points to agricultural environments. There are several aspects to be improved in future work. For example, the coordinate acquisition of the control points in the orchard environment is crucial for a large area of semi-structured orchard environment. If the coordinate accuracy of the control points could not be guaranteed, the performance of the entire orchard trunk localization would decline. There are two possible solutions to this problem. For the first suggested solution, a high-precision GPS system could be used to measure and

| Error in $X_O$ | $0.15\pm0.07$ |
| Error in $Y_O$ | $0.16\pm0.05$ |
| Deviation      | $0.21\pm0.06$ |
record the precise position of each control point in the orchard coordinate. This solution only needs a high-precision GPS when setting control points, and the GPS does not need to be used in the subsequent localization. For another alternative solution, a long-distance laser ranging sensor could be used to measure the orchard’s length and width to determine the coordinates of the four corners of the orchard in the orchard coordinate system. Then measure the number of rows and columns of fruit trees in the orchard. By dividing the length and width by the number of rows and columns, the coordinates of the fruit trees at both ends of each row and column could be approximated. In an orchard environment where the row and column spacing is constant, these calculated coordinates could be approximately regarded as their precise coordinates and used as control points.

Furthermore, this paper presented a simple and effective method of arranging control points, that is to say, setting the control points on the trunk at the end of each fruit tree row. Future work could adjust the position and number of control points according to the actual needs of the orchard. The control points could also be set in other easily identifiable markers outside the trunk.

After completing the localization of trunks in the orchard, how to use the trunk information to navigate the orchard robot is also an important issue. The problem could be solved by setting a start point for the robot to determine its initial position. That is, the robot starts working in the same position every time. Then the system proposed in this paper could be introduced in operation for the orchard robot.

V. CONCLUSIONS

This paper proposes a tree trunk localization system in orchards based on camera/ultrasonic sensors, which is suitable for a semi-structured orchard environment where fruit trees are arranged in rows. The tree trunk localization is achieved through odometer, IMU, and visual/ultrasound information. The approach of using control points to improve the localization accuracy was also discussed. The usability of the proposed method was demonstrated through the verification experiment of a simulated environment and a real environment.

In future work, the proposed work is considered to be extended to a multi-robot system in orchards. Each robot in the system could use the control point information to splice and merge the established trunk information, which could improve the efficiency and automation in orchards.

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