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Multi-feature fusion tree trunk detection and orchard mobile robot localization using camera/ultrasonic sensors

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ABSTRACT

In a semi-structured orange orchard, multi-tree trunk detection is an effective method for mobile robot localization. However, because of the complex background of the natural orchard environment, dwarf orange tree trunks are easy to misrecognize. In this paper, we present a novel tree trunk detection method based on multiple cameras and ultrasonic sensors integration technology. These devices are integrated into a single organic mechanical structure that can rotate to detect the surrounding orchard environment such that they can reduce the non-detection zone. Multi-feature fusion will be used in this study. First, histograms of oriented gradient (HOG) and support vector machine (SVM) are used to train an initial tree trunk classifier. Next, the gray scale histogram features of the tree trunk and non-trunk images are extracted to optimize the classifier. Finally, the Roberts cross edge detector is used to extract the trunk's gradient histogram features, which will improve the recognition accuracy of the classifier. The orange tree trunk recognition experiments exhibited a recall rate and accuracy of 92.14% and 95.49%, respectively. On this basis, ultrasonic sensors are used to get the location data of the trunks and a moving average filter is used to reduce the error of mobile robot localization. The experiment showed that the average localization error was approximately 62 mm (2.5%), and the robot moved stably and precisely along the road of the semi-structured orange orchard.

1. Introduction

Orange tree cultivation is widespread throughout the world and can bring huge economic value to farmers (Zapata-Sierra and Agugliaro, 2017). The management of orange orchards is an important part of orange production, such as irrigation, spraying, harvesting and so on. The development of precision agriculture provides a new way for orchard operation. Especially, the use of orchard agricultural robot technology can assist farmers with orchard irrigation, as well as in regular and quantitative spraying (Gonzalez-De-Soto et al., 2016; Oberti et al., 2016). Consequently, it can improve resources utilization, reduce resources waste, and help to avoid environmental pollution without excessive use of pesticides, fertilizers, and other resources. The use of orchard agricultural robots plays an important role in improving the quality of orange and green fruit production and, as a result, it can improve fruit profit and famers' income.

Therefore, the orchard agricultural robot localization and navigation, which are based on environmental perception and cognition, have become more and more important. The orchard is a typical semi-structured outdoor natural environment and the fruit trees are planted in nominally straight and parallel rows and the distances between the rows are almost equal, which is suitable for the mobile robots' self-localization and navigation. However, the orchard environment is just "semi-structured", meaning that there is a large error in tree planting position. Otherwise, the different shapes of the tree trunks will also make it difficult to detect them correctly and obtain the localization information.

In current research mobile robot self-localization technologies, the simultaneous localization and mapping (SLAM) Dissanayake et al. (2002) is a prerequisite, and if the localized location map is built by the surrounding environmental information, the position accuracy would be higher than the position accuracy obtained through traditional GPS position. In the semi-structured orchard environment, the position of trees could be used as landmarks for SLAM, and then used to provide information on the localization and navigation path for robot autonomous mobility (Asmar et al., 2006). In the studies of Zhou and Chen (2015) and Lepej and Rakun (2016), the trees are detected only by 2D laser scanner and the localization of trees is used to correct the inertial navigation error and construct the local navigation map of apple orchard or vineyard. However, the methods mentioned above work well in the orchard when non-trunk objects do not exist and the tree trunks are not covered by the drooping branches and leave.

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A single sensor, such as laser scanner, can only detect the objects around the mobile robot; however, it cannot discriminate tree trunks from non-tree objects. In the semi-structure orchard environment, the non-tree objects, such as farm tools, tree supports and farmers often appear randomly in the places between two rows of trees. That will cause the laser scanner to collect a significant amount of wrong detection data, which can make the simultaneous localization and mapping (SLAM) less reliable and even lead to the failure of the robot navigation in an orchard. To optimize the detection method, a multi-sensor combination is used to detect the tree trunks. Early work was implemented in Shalal et al. (2013), in which the camera was used to recognize simulated tree trunks based on RGB color and edge features, and the laser scanner was used to acquire the accurate real-time localization information of the tree trunks. In the subsequent research (Shalal et al., 2015a,b), the method was used in a real orchard environment, where the tree trunks were not covered by tree branches and leaves, to construct a local navigation map. To optimize the recognition performance, the HOG features of the tree trunks were extracted in the study of Cheein et al. (2011), and the features were used to train an SVM classifier for recognizing tree trunks. Meanwhile, the distance between the mobile robot and tree trunk was measured by a laser scanner for a position and navigation system. The algorithm could remove most of the non-tree objects, however it was easy to recognize cylindrical objects such as tree supports. Garcia-Alegre et al. (2011) and Ali et al. (2008) proposed some methods to segment the image into tree trunks and background objects separately with a cluster algorithm based on color and texture features, and the laser sensor was used for the mobile robot localization.

In conclusion, most of the tree trunk detection methods are based on multi-sensor fusion, such as the laser scanner and camera. However, in the current research, the robustness of the tree trunk detection algorithms is not satisfactory, and it works well only in the orchard environment without non-trunk objects and when the trunks are not covered by drooping branches and leaves, like the methods presented in papers (Shalal et al., 2013, 2015a; Cheein et al., 2011). Although some researchers have used machine vision for tree trunk recognition, they did not carry out an in-depth study of the trunk recognition in the semi-structured orchard environment, where the unpredictable non-trunk objects always appear randomly between two rows of trees. In addition, more redundant non-trunk data are acquired by the laser scanner such that it becomes difficult to match the correct trunk data with the trunk of the image recognition. Therefore, it is still a challenge to recognize and locate accurately the tree trunks in the semi-structured orchard environment.

This paper studies the orange orchard as shown in Fig. 1. The tree trunks of the dwarf orange tree are short and they are covered easily by drooping branches and leaves. The tree trunks and leaves are intertwined, such that the mobile robot finds it difficult to recognize the orange tree trunks. Additionally, more redundant non-trunk data is acquired by the laser scanner, as a result the accurate data is easily submerged in the interference data.

This paper presents a novel orchard tree trunk detection and mobile robot localization method. The multi-feature fusion which, being based on the color, texture and contour, will be used to recognize orange tree trunk. In order to reduce redundant and useless detection information, the ultrasonic sensor will take place of the laser scanner to measure the distance between the mobile robot and the tree trunk, and the measurement data will be acquired only when the trunks are recognized accurately. In addition, the tree trunk detection mechanism can be rotated to perform multi-angle detection, such that the more comprehensive orange image information could be obtained for the tree trunk detection algorithm. On this basis, the tree trunks are used as landmarks for the mobile robot localization.

This paper is organized as follows. Section 2 describes the orange orchard layout and the mobile robot platform architecture. Section 3 explains the proposed method for orange tree trunk detection based on multi-feature. Section 4 shows the experiment of the mobile platform self-localization. Finally, the conclusion is presented in Section 5.

2. Orange orchard environment and robot equipment

2.1. Semi-structured orange orchard environments

The orange orchard for our study is shown in Fig. 1 and it is a typical semi-structured outdoor environment. The distance between the tree rows is approximately 5 m, while the trees are planted at intervals of approximately 3.5 m in each row. In this orchard, 200 mm–250 mm of each tree trunk is exposed above ground level. However, there are large planting errors in the rows and columns of orange trees. Orange trees growth are not the same throughout the year, particularly during the harvest season when the fruit weighs the branches down and the tree trunks are covered with leaves.

In orchard environment, the semi-structured roads are still rough and bumpy in some places. When the robot moves in the orchard, the detection range may deviate from the preset detection area easily, and the fixed installation of the tree trunk detection mechanism makes it difficult to obtain consistent images and detect tree trunk accurately.

2.2. Mobile robot platform architecture

As shown in Fig. 2, the mobile robot platform moves in the middle of the two rows of orange trees. The length and width of the platform are 1.2 m and 0.7 m, respectively, and the 4 cameras/ultrasonic sensors detection mechanisms are installed on the four corners of the platform. The No. 1 and No. 2 detection mechanisms are used to detect the two trees in front, and the No. 3 and No. 4 detect the two trees that are at the rear side of the mobile robot platform. The camera/ultrasonic mechanical structure can rotate horizontally, such that the mobile robot platform can obtain orange images from different visual angles, and reduce the non-detection zone. Furthermore, the mechanical structures rotate to follow the tree trunks and acquire the trees' location information in real time. The horizontal angle range of the camera is 60 degrees and the image resolution is 640×480. Therefore, the width of the visual orchard scene is $w = 2.6$ m when the distance between the

Fig. 1. Semi-structured orange orchard environment.