Identification of fruit and branch in natural scenes for citrus harvesting robot using machine vision and support vector machine

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Abstract: With the decrease of agricultural labor and the increase of production cost, the researches on citrus harvesting robot (CHR) have received more and more attention in recent years. For the success of robotic harvesting and the safety of robot, the identification of mature citrus fruit and obstacle is the priority of robotic harvesting. In this work, a machine vision system, which consisted of a color CCD camera and a computer, was developed to achieve these tasks. Images of citrus trees were captured under sunny and cloudy conditions. Due to varying degrees of lightness and position randomness of fruits and branches, red, green, and blue values of objects in these images are changed dramatically. The traditional threshold segmentation is not efficient to solve these problems. Multi-class support vector machine (SVM), which succeeds by morphological operation, was used to simultaneously segment the fruits and branches in this study. The recognition rate of citrus fruit was 92.4%, and the branch of which diameter was more than 5 pixels, could be recognized. The results showed that the algorithm could be used to detect the fruits and branches for CHR.

Keywords: citrus, machine vision, citrus harvesting robot (CHR), branch, identification, multi-class support vector machine (SVM)

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1 Introduction

As one of the favorite fruits, citrus is widely cultivated throughout the world. High quality of citrus is required for fresh fruit market. However, manual selectively harvesting is a time-consuming, laborious, and inefficient operation. Nevertheless, labor cost is becoming higher and higher. According to agricultural economists' reports, harvesting cost of citrus accounts for 35% to 45% of total production costs in Australia[1], 40% in USA[2], and 50% in Spain[3]. In order to reduce labor cost, large-scale mechanical harvesting has been attempted. But the harvested fruits were satisfactory only for fruit juice industry. The fruits could not meet the requirements of fresh market because of severe damage to the fruits[1,3]. Therefore, developing harvesting robots with selectivity and proper handling is desired for reducing the cost of production and satisfying the requirements of fresh market for citrus harvesting.

In unstructured natural scenes, the citrus fruits are

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randomly distributed in the tree, some on surface of the canopy, some inside the canopy, and some occluded by branches, leaves, or other fruits. The branches are the potential danger for possible collision between the branches and the robot, and the collision will bring damage to the latter. In order to pick mature fruits behind obstacles (i.e. branches and braces) in the canopy, the end-effector must be safely guided to the destination position without collision[4-7]. So, spatial location of mature fruit and obstacle are necessary. Identification of mature citrus fruit and obstacle is the priority of robotic harvesting.

Computer vision is the common and intuitive method for object identification. In 1968, computer vision was first proposed to detect citrus by Schertz and Brown[8]. Over the past four decades, researchers have applied many different computer vision techniques for fruit identification. Researches on the detection of different fruits and vegetables such as apple[9-11], cherry fruit[12], cucumber[4-5,13-14], citrus[7,15-20], tomato[21-22], and strawberry[23], etc. have been reported. Early developments included the use of monochrome cameras fitted with color filters to detect the fruits. A global thresholding approach was used to segment objects from the background[9]. With the advancement of sensor and computer technology in recent years, researchers have started to use color cameras. In scenes where significant color contrast exists between the fruit and canopy, the fruit could be segmented from the background. Color images were used for distinguishing the citrus fruit by setting a threshold in the hue value[24]. Grasso and Recce used RGB thresholding to segment an image[25], while Cai et al. used Otsu method to segment citrus from 2R-G-B image[26].

In order to ensure the safety of manipulator, identification and location of obstacles is essential. Up to now, there have been very few researches focusing on obstacle identification for harvesting robot. Cai et al. used dual-threshold to extract images of branches. However, its robustness was not strong enough for natural scene changes[15].

Different from structured scenes of industrial robots, agricultural harvesting robots work in highly unstructured natural outdoor scenes, which are complex and changeable. As shown by previous researchers, variable illumination is a major issue in machine vision applications in natural daylight conditions[19]. The amount of sunlight available is dependent on cloud cover and the incident solar angle on the scene[10,22]. This can cause significant differences on how the harvesting scene appears. The fruits and branches inside the canopy receive a different amount of illumination compared with the fruits on the canopy surface[26-28]. Furthermore, due to direct sunlight, occlusion and backlight, the different parts of an object receive different amounts of illumination. The image processing algorithm should be robust enough to deal with these kind of light variation. The inability to overcome scene change is very crucial for the success and safety of robotic picking.

This work focused on the image processing method for identification of citrus fruit and branch in natural scene image of orchard for citrus harvesting robot. The special objectives of this work were 1) to develop a method for segmenting the fruit and branch in citrus orchard image; 2) to explore the feasibility of identifying simultaneously fruit and branch using multi-class support vector machine; and 3) to investigate the robustness of the objects identification for varying lighting conditions.

2 Materials and methods

2.1 Image acquisition

The citrus trees tested in this study were planted in Jiangxinzhou, Zhenjiang City, Jiangsu Province of China. This fruit is primarily sold in fresh market. Therefore, selective harvesting is the best way to maximize market value of the fruit. Color images of scene (including citrus fruit, obstacle, leaves and background) were captured using a color CCD camera (LU075C, Lumenera Corporation, Canada) with 640 by 480 pixels, which is controlled by a desktop computer (Pentium Ⅳ CPU 3.0 GHz, memory: 1.5 G). The trees were randomly selected from the citrus orchard, and the scene images were taken under natural daylight light condition in harvesting period (November of 2008). Both sunny and cloudy conditions were considered. The scene images are shown in Figure 1.

In this work, the images were captured and processed by the software developed, which was implemented on Visual C++ 2008 (Microsoft Co., Redmond, USA), LuCam SDK V4.2 (Lumenera Corporation, Ottawa, Canada), and MVTec Halcon 9.0 (MVTec Software GmbH, München, Germany) software platform. The main control computer had Windows XP (Microsoft Co., Redmond, USA) operating system.

a b

Figure 1 Original images obtained in (a) sunny and (b) cloudy conditions

2.2 Image processing

From Figure 1, the scene images were composed of fruits, leaves, branches, grass and sky, etc. Segmentation is the separation of the interest objects from the background which is the first step for object recognition. Through analyzing the component images and fused images in some color spaces, simple threshold method, which was described in previous reports[9,10,16], could not effectively and self-adaptive segment the fruits, branches and other obstacles from the background under many natural light conditions.

Because the citrus, branch, leaf, and others are composed of different chemical constituents, they have different corresponding properties for light. In 2D color images, the fruits, branches and leaves etc. have different gray values in three color component images (RGB: red, green and blue). By analyzing the color images obtained under different conditions, it could be found that different parts of the same fruit, branch, or leaf have different gray values in the component images, because of their varying positions, posture and diversification of the light. It is difficult to separate the fruits and branches using conventional threshold method in the complex natural scenes[16,18,26].

As the features, R, G, and B values of every pixel were used to classify the pixels into citrus, branches, leaves and other background(such as sky, grassland, etc.). The images could be segmented using multi-class support vector machine (SVM). The segmented images were then processed to remove noise using the area threshold method and fill holes.

2.3 Multi-class SVM

SVM is based on statistical learning theory (SLT) as proposed by Vapnik and Chervonenkis[29]. The main idea of SVM is to separate the classes with a hyperplane surface so as to maximize the margin among them. Following structural risk minimization (SRM) principle, SVM can effectively overcome over-fitting and under-fitting problems and has greater generalization ability[29-30].

SVM classifier deals with two-category classification problems. Given a training sample set $D=\{x_i, y_i\}_{i=1}^{l}$ where $y_i=\{-1,+1\}$, $x_i \in R^n$ and l is the number of samples, SVM is developed for finding the optimal classification plane $x \cdot w_0 + b_0 = 0$ in the case of linear separability. The aim of SVM classifier is to maximize the margin between two categories besides distinguishing them. Under the case of linear separability, the classification problem can be described as:

$$\begin{aligned} &\min && \Phi(w)=\frac{1}{2}(w\cdot w) \\ &\text{s.t.} && y_i[(w\cdot x_i)+b]\geq 1, \quad i=1,\ldots,n \end{aligned} \tag{1}$$

whose dual problem is:

$$\begin{aligned} &\max && W(\alpha)=\sum_{i=1}^{l}\alpha_i-\frac{1}{2}\sum_{i,j=1}^{l}\alpha_i\alpha_j y_i y_j (x_i\cdot x_j) \\ &\text{s.t.} && \begin{cases} 0\leq \alpha_i, i=1,2,\cdots,l \\ \sum_{i=1}^{l} y_i\alpha_i=0 \end{cases} \end{aligned} \tag{2}$$

If α^* is a solution of Equation (2), then $w=\sum_{i=1}^{n}\alpha_i^* y_i x_i$. Choose an $\alpha_i \neq 0$, and the corresponding solution b is computed from the equation $\alpha_i(y_i(w\cdot x_i+b)-1)=0$. Then the category of an unknown sample x can be decided through $\mathrm{sgn}[w\cdot x+b]$.

For linear non-separable case, a loose variable $\xi \geq 0$ and a mapping $\phi(x)$ are introduced to get a nonlinear support vector machine. Then the former problem can be described as:

$$\begin{aligned} \min \quad & \Phi(x) = \frac{1}{2}\|w\|^2 + c\left[\sum_{i=1}^{l}\xi_i\right] \\ \text{s.t.} \quad & y_i((w \cdot \Phi(x_i)) + b) \ge 1, \quad i = 1,\dots,n \end{aligned} \tag{3}$$

where, C is a penalty factor. Its dual problem is:

$$\begin{aligned} \max \quad & W(\alpha) = \sum_{i=1}^{l}\alpha_i - \frac{1}{2}\sum_{i,j=1}^{l}\alpha_i\alpha_j y_i y_j K(x_i \cdot x_j) \\ \text{s.t.} \quad & \begin{cases} 0 \le \alpha_i \le C, i = 1,2,\cdots,l \\ \sum_{i=1}^{l} y_i\alpha_i = 0 \end{cases} \end{aligned} \tag{4}$$

where, $K(x_i, y_i)$ is a kernel function satisfying the Mercer condition. There are several classical kernel functions, such as linear kernel, radical basis function (RBF) kernel, polynomial kernel, and sigmoid kernel.

SVM was originally developed for two-class discrimination. It can be extended to solve multi-class discrimination problem by combining a number of two-category classifiers in a certain manner to form a multi-class classifier. The one-against-rest method and the one-against-one method are commonly used multi-class classifiers.

1) One-against-rest SVM: N binary SVM classifiers are constructed, one classifier for each class. All of the samples are considered when training each SVM. Here the i-classifier is trained on the whole training data set in order to classify the members of class i against the rest. In the classification phase, the classifier with the maximal output defines the estimated class of input sample. Therefore, the training process for all the N classifiers consumes long time. Besides, the great quantitative discrepancy between the negative and the positive samples in the classification problem with many classes would degrade the classification performance. Another severe shortcoming of this method is that there are unclassified samples.

2) One-against-one SVM: For each possible pair of N classes, a binary SVM classifier is constructed, the total number of classifiers is $N(N-1)/2$. All classifiers are combined through a majority voting scheme to estimate the final class of input sample. Compared with the one-against-rest method, the classification accuracy is improved.

In this study, the one-against-one SVM strategy was adopted, and RBF kernel function was used to segment the boundaries of fruit, branch, leaf and background. The mathematical representation of RBF kernel is described as follows:

$$K(x_i, x_j) = \exp(-\gamma \| x_i - x_j \|^2) \tag{5}$$

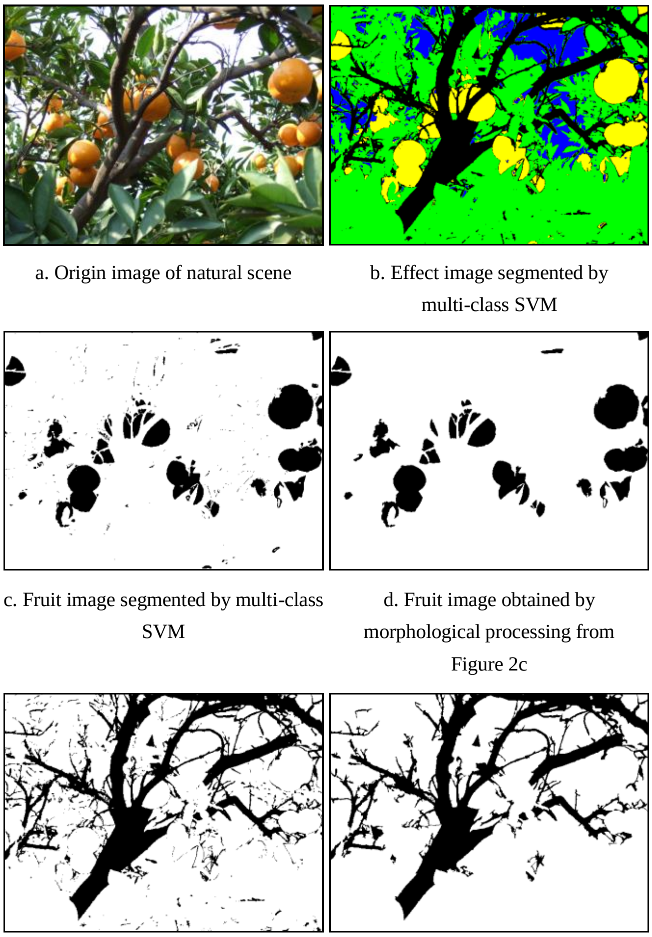
where, γ is kernel parameter. In these test experiments, the best parameters of the training experiments were selected: C = 100, and γ = 0.25 for RBF SVM classification.

3 Results and discussion

The image obtained from orchard in natural scenes mainly includes four kinds of tissues, i.e., fruit, branch, leaf, and background (such as sky, grassland, etc.). Among the four classes, the fruit and the branch were the objects that must be segmented. Each pixel has a gray value in each component image of the color image. The representative regions of citrus, branch, leaf, and background can be extracted from the color image. The representative regions were used as training sets of the four kinds of tissues for multi-class SVM classifier. To obtain better results, selection of representative regions is critical. In this study, the regions were selected manually from the fruit area, the branch area, the leaf area, and the background area respectively. For each class of the top three classes (citrus, branch, and leaf), three regions (50 pixels) were selected from the direct sunlight region, the occluded region, and backlight region of their tissues respectively. For the background, three same size regions were selected from the sky, the grassland, and the ground.

The one-against-one SVM strategy and RBF kernel function were used to discriminate the fruit, branch, leaf and background. Figures 2 and 3 showed the identification results of sunny and cloudy conditions respectively. Investigated from the figures, the impact of light varying was to some extent eliminated for the recognition results during the day.

There were 592 mature fruits visually counted from 87 images. The performance for citrus of this algorithm was 92.4% of correct recognition (547 fruits). The result was better than 87% reported by Bulanon D. M. et al.[16], 87.2% by Lü Q. et al.[19] for the fruit. As a supervised classification method, multi-class SVM improved the classification accuracy of the unknown-class pixels in the citrus tree images.



a. Origin image of natural scene

b. Effect image segmented by multi-class SVM

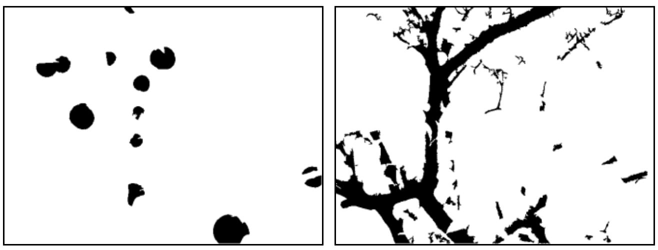
c. Fruit image segmented by multi-class SVM

d. Fruit image obtained by morphological processing from Figure 2c

e. Branch image segmented by multi-class SVM

f. Branch image obtained by morphological processing from Figure 2e

Figure 2 Segmentation results of fruit and branch in the image obtained under sunny condition



a b

Figure 3 Segmentation results of (a) citrus fruit and (b) branch from figure 1b using multi-class SVM

There were many factors which affected the recognition results. The segmented regions of some fruits might be too small and were removed by area threshold processing. The fruits far away from the camera, and incomplete segmentation of the images might be the reasons that resulted in failure in recognizing small visible regions. The main factors of incomplete segmentation of citrus were described as follow: Firstly, citrus local reflection was seriously. Due to the direct sunlight and citrus is a near-spherical object, it will cause quite strong reflections on some surfaces of citrus which result in great change of the R, G and B component values in these areas. Secondly, some fruits were not fully mature. Thirdly, some fruits were occluded by branches, leaves and other fruits. Lastly, citrus regions were split up to some small regions by branches and leaves in the images.

There was some error segmentation in branch recognition. If the diameters of branches were less than 5 pixels in images, they could not be effectively segmented. The workspace radius of CHR was set to 1.5 m. At points 1.5 m away from the camera, the actual diameter of the twig corresponding to the 5-pixel-diameter in image was about 5.9 mm. Its stiffness could not cause damage to the manipulator. If the distance between the twig and the camera was more than 1.5 m, the twig could not damage the robot because it was out of the workspace of CHR.

If the twig color is similar to leaf, it is difficult to be segmented. For the better flexibility and low lignifications of twig, its effect on the manipulator work is little. There were some branches occluded by fruits and leaves. It could not be segmented or might be removed by morphological processing for its small visible area. If the branch was behind the fruit, the collision probability between the manipulator and the branch was low when the robot was working. The branches after the leaves, if it could not be detected, would be a potential danger for the harvesting robot, which needs further study. Similarly, there were some non-branch that could be mis-classified as branch, such as seriously shading leaves, the nightside of leaves, and local profile of fruit nightside.

4 Conclusions

1) In order to guide the manipulator and end-effector to target position without collision between the harvesting robot and citrus tree, a machine vision system including a color CCD camera and master computer was developed

to identify the citrus fruit and branch.

2) The multi-class SVM segmentation technology was applied to the processing of citrus tree images in unstructured orchard scenes under sunny and cloudy conditions. The experimental results show that the success rate of citrus fruits was 92.4%, and the branch whose diameter was more than 5 pixels could be recognized.

3) In contrast to traditional recognition methods (i.e. threshold segmentation), objects segmentation using the multi-class SVM as a novel ideal has advantages in recognizing fruit and branch under the unstructured environment. And this method is robust enough to eliminate the impacts of complex background and various sunlight conditions. Thus, it is concluded that the multi-class SVM segmentation technology has a high potential for the development of computer vision system for identification of citrus fruit and branch.

4) Although there were the advantages of objects identification in natural scenes based on multi-class SVM, the effect on features extraction of the fruit and branch (such as center and radius of fruit, and radius, length and curvature of branch), and real-time response of the identification method have to be further investigated, analyzed and optimized in the next phase.

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