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Detection of citrus fruit and tree trunks in natural environments using a multi-elliptical boundary model

Tian-Hu Liu[a,*], Reza Ehsani[b], Arash Toudeshki[b], Xiang-Jun Zou[a], Hong-Jun Wang[a]

[a] College of Engineering, South China Agricultural University, 483 Wushan Road, Guangzhou, Guangdong 510642, China
[b] School of Engineering, University of California, Merced, CA 95343, USA

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ABSTRACT

Intelligent detection is a key technology in precision agriculture. As items of different color cluster in different non-overlapping elliptical regions, this study proposed a method for constructing a multi-elliptical boundary model in Cr-Cb co-ordinates to detect citrus fruit and tree trunks in natural light environments. Here, the detected citrus variety was spring sweet tangerine, and the parameters of the elliptical boundary models for detecting these fruit and tree trunks solved by color-space transformation and ellipse fitting. A series of image detection experiments were performed to evaluate the method's performance. The experimental results showed that the correct and false positive percentages in fruit identification from images were 90.8 and 11.2%, respectively. The number of correctly detected images in distinguishing tree trunks from background was 44 of 50 images.

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1. Introduction

A key technology in precision agriculture is intelligent detection, which is used in target location and robot navigation. Identifying farmed objects in natural environments is important for the proper functioning of intelligent agricultural robots. Currently, machine vision detection is a topic in agricultural engineering, with various studies having been conducted to detect fruit, branches and trunks of fruit trees using machine vision. For example, a computer vision-based method has been used in Tabb [1] to reconstruct three-dimensional (3-D) fruit trees. Under the assumption that tree trunks are relatively narrow, vertical shapes, Lu and Rasmussen [2] have proposed a contrast-based method for tree detection and shape estimation from ground-plane perspective images. Shao et al. [3] have presented a method for recognizing tree trunks based on Hough transformations in CIE L*a*b* color space (International Commission on Illumination). Shao et al. [4] have used a backpropagation neural network in recognizing trunks from an image. Juman et al. [5] have achieved detection rates of 44.0, 59.2, 92.25 and 91.7% using support vector machines (SVM), neural network, Viola and Jones and their Viola and Jones+ pre-processing methods for detecting palm tree trunks on static images. Yıldız [6] has achieved an 88% detection rate in trunk identification from the heterogeneous dataset by grouping vertical edges into potential tree trunks.

Many studies have used machine vision techniques for fruit identification. Stajnko et al. [7] have estimated the number and diameter of apple fruit in an orchard during the growing season using thermal imaging. Zhang and Zhou [8] have studied a three-layer BP neural network method for segmenting strawberry images. Miao et al. [9] have presented a watershed algorithm based on Zernike-moment edge detection to extract grape fruit contour features. An improved R-G image recognition method has been proposed by Zhao et al. [10] to recognize apples at night, which did not account for sheltered and adhesive apples, but the identification rate in 60 images acquired at night reached 83.7%. Many studies have reported citrus fruit detection in images. Hue and saturation thresholds have been applied by Annamalai and Lee [11] to detect citrus fruit in images. Xu et al. [12] and Zhang et al. [13] have identified citrus fruit in the tree canopy based on color-image processing. Hannan et al. [14] have produced an algorithm using a red chromaticity coefficient to identify oranges and achieved a 90% detection accuracy with a 4% false-positive rate. Wang et al. [15] have presented an image processing method for identifying citrus fruit of different maturities in complex natural scenes, with an accuracy rate of 92%. Okamoto and Lee [16] have developed a hyperspectral image processing method to detect green citrus fruit in individual trees. Lu and Nong [17] have detected citrus fruit within the tree canopy under natural illumination conditions, by analyzing the salient edges of

* Corresponding author.
E-mail address: liuparalake@scau.edu.cn (T.-H. Liu).

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chromatic aberration maps of R and B channels in the RGB color model. Kane and Lee [18] have used a monochromatic near-infrared camera equipped with interchangeable optical band pass filters to capture citrus fruit images and apply indices and morphological image processing techniques in segmenting the images, they achieved an average correct pixel identification of 84.5%. Cubero et al. [19] have reviewed recent works that use color and non-standard computer vision systems for the automated inspection of citrus. Kurtulmus et al. [20] have used color, circular Gabor texture analysis, and a novel 'eigenfruit' approach for green citrus detection, and successfully detected 75.3% of the actual fruit in the images. Zhao et al. [21] have detected immature green citrus based on color feature and sum of absolute transformed difference (SATD) using color images in the citrus grove, and achieved more than 83% recognition accuracy.

Due to the complex nature of fruit images, no existing algorithm is totally effective for fruit identification from fruit images. This study examined a machine vision algorithm suitable for detecting citrus fruit and tree trunks. Fruit and tree trunk detection are both important for intelligent fruit-harvesting machines, such as intelligent canopy shaking machines [22] and fruit picking robots [23], in which tree trunk detection method is used in robot navigation and fruit detection method used for choosing target locations. The present study focused on an image segmentation algorithm, which was, to the authors' knowledge, the first study to date that has examined this strategy.

2. Materials and methods

2.1. Algorithm description

This image segmentation algorithm was similar to a single supervised-learning method, which was based on artificial classification and whose computational complexity was much simpler than algorithms based on machine and deep learning. This approach generalized well with relatively less training data and needed much less data storage. A mapping model that can distinguish multiple regions in an image, should be able to demonstrate some relationships between a series of sets $E_J = \{e_1, e_2, \ldots, e_m\}$ and a series of image regions$A_J = \{a_1, a_2, \ldots, a_m\}$ (Fig. 1). If an image can be described by a collection of several non-overlapping elliptical regions (Fig. 2), then there exists a function G that can map a region a_i of an image into a feature model $g = R^k$, with $g(a_i)$ reflecting some of the region's characteristics.

Y′CbCr color space separates color out into a luma signal (Y′) and two chroma components (Cb and Cr). Experiments here showed that, if RGB images were transformed into Y′CbCr images, the color projected in the Cr-Cb co-ordinates for a series of objects a_1, a_2, . . . , a_m were clustered in a series of non-overlapping elliptical regions e_1, e_2, . . . , e_m. Based on this feature, this study proposed a multi-elliptical boundary model for detecting citrus fruit and tree trunks. The method included two processes. The first process calculated the elliptical boundary regions in the Cr-Cb co-ordinates, which included four steps:

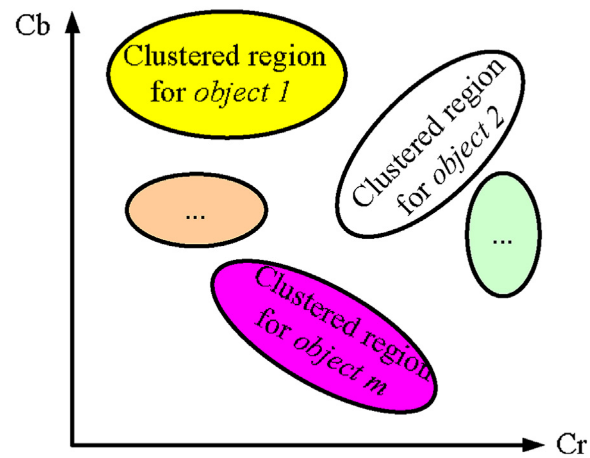

Fig. 2. Several elliptical regions that are not overlapping.

Step 1: Obtain template images for object 1, object 2, . . . , object m;

Step 2: Conversion of template images from RGB space to Y′CbCr space;

Step 3: Sampling skin areas for object 1, object 2, . . . , object m from template images; and

Step 4: Obtain color clustered regions e_1, e_2, . . . , e_m for object 1, object 2, . . . , object m in the Cr-Cb co-ordinates and construct multi-elliptical boundary model.

The second process captured images in the natural light illumination environment and used the multi-elliptical boundary model to detect fruit and tree trunks. This process had three steps:

Step 1: Capture RGB images;

Step 2: Conversion of captured images from RGB space to Y′CbCr space; and

Step 3: Segment object 1, object 2, . . . , object m from the captured images using the multi-elliptical boundary model. The flow chart of this method was shown in Fig. 3.

2.2. Image acquisition

The 300 images were acquired from a citrus grove (As shown in Fig. 4.) in Huizhou, Guangdong, China, in April 2017, using a consumer grade regular digital camera (Sony Cyber-shot DSC-H50), while the flash light was kept always off. The citrus variety was spring sweet tangerine. Those images were taken at 1 to 2 m of distance between the objects (fruit or tree trunks) and the camera between 10:00 am and 4:00 p.m. Those images were

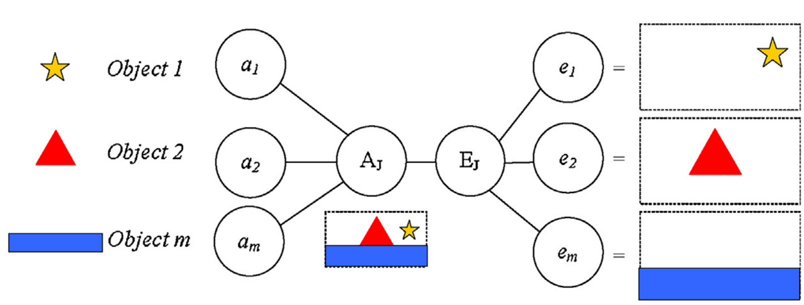

Fig. 1. Multi-object mapping and segmentation.

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