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Research Paper

Immature citrus fruit detection based on local binary pattern feature and hierarchical contour analysis

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Detecting immature fruit in groves provides a promising benefit for growers to plan application of nutrients and estimate their yield and profit prior to harvesting. The goal of this study was to develop a robust algorithm to detect and count immature citrus fruit in images of the tree canopy. Images were all taken in low natural light conditions with a flashlight, and the green component of the colour images was used for further analysis. Local intensity maxima were detected and local binary pattern (LBP) features around them were extracted as an input of an ensemble classifier-RUSBoost. The positive predictions were considered as candidates and the hierarchical contour maps around them were extracted and fitted with Circular Hough Transform. The fitted circles were predicted as fruit targets if its radius were in a predetermined range.

The algorithm was evaluated with a test set of 25 images, achieved 80.4% true positive rate and 82.3% precision rate, and F-measure was 81.3%. The good performance of occlusion tolerance of the proposed method was mainly coming from the robust LBP texture descriptor and hierarchical contour analysis (HCA) which used the pattern of light intensity distribution on fruit surface. This study proposed an innovative method to detect green fruit in images of trees only by using texture and intensity distribution.

1. Introduction

Computer vision for agricultural robots, especially harvesting robots and providing yield estimation, is an exciting research domain for its extreme challenges and significant application prospects. Schertz and Brown (1968) first proposed the concept of automated citrus harvesting as an alternate to mechanical harvesting. Although much attention was given to this field during the last 30 years, no harvesting or yield estimation robot for citrus has ever reached commercial maturity.

In an attempt to exploit every possible type of information in the complex agricultural environment, computer vision algorithms for agricultural robots have tried to use a variety of visual cues and properties. The most common and important features are colour, texture, shape and their combination.

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Nomenclature

LBP	local binary pattern
HCA	hierarchical contour analysis
CHT	circular Hough transform
RGB	red–green–blue
$I(x, y)$	intensity value of a single pixel
$H(k)$	the kth bin of a histogram
RUSBoost	random under sampling boost
TPR	true positive rate
PCR	precision rate

Colour is one of the most important features used in machine vision system to distinguish fruit from leaves, branches and other background objects in the orchard environment. A number of researchers (Annamalai & Lee, 2003; Hannan & Burks, 2007; Harrell, Slaughter, & Adsit, 1989; Li, Wang, & Wang, 2010; Lü, Cai, Liu, Deng, & Zhang, 2014) have used colour-based segmentation in detecting fruit with distinct colours including tomatoes, red apples, peaches, mangoes, pineapples, and citrus. However, accuracy of fruit detection based on colour is affected by variation in fruit colour due to its maturity level, fruit variety, uncertain and varying background features and variable lighting conditions (Gongal, Amatya, Karkee, Zhang, & Lewis, 2015).

Geometric measures such as shape and size provide another set of distinct features of fruit such as citrus and apple. One global visual cue that could be less susceptible to illumination is the shape of the target, and although it is more computationally demanding to extract and analyse, shape is becoming increasingly more popular in harvesting robots (Kapach, Barnea, Mairon, Edan, & Ben-Shahar, 2012; Kong, Zhao, Zhang, Wang, & Zhang, 2010; Liu, Chen, & Qiao, 2011; Lu & Sang, 2015; Okamoto and Lee, 2009; Rakun, Stajnko, & Zazula, 2011; Yuan, Li, Feng, & Zhang, 2010; Zhang & Zhang, 2008). However, the main problem of shape is the occlusion of fruit by leaves, branches and other fruit.

Texture is another distinguishable feature that can be helpful in separating fruit from background. Fruits generally have smoother surfaces than background objects such as leaves and branches. Texture analysis is not affected by the colour on fruit surface so it can be used for the detection of fruit with similar colour to leaves and stems. Numerous studies have used texture analysis in fruit detection methods (Chaivivatrakul & Dailey, 2014; Kurtulmus, Lee & Vardar, 2011; Rakun et al., 2011; Zhao, Tow, & Katupitiya, 2005).

In harvesting robots, attempts to detect fruit using a single visual cue typically encounter problems due to illumination variations, spatial occlusions, and appearance variations, etc. Hence, fusing several cues together may provide increased performance altogether (Kapach et al., 2012). Researchers (Çakır, Kırcı, Güneş & Üstündağ, 2013; Li, Lee, & Wang, 2016; Linker, Cohen, & Naor, 2012; Lu & Sang, 2015; Payne, Walsh, Subedi, & Jarvis, 2013, 2014; Sengupta & Lee, 2014; Stajnko, Rakun, & Blanke, 2009; Zhao, Lee, & He, 2016) have integrated multiple features from two or more feature groups to improve the accuracy and robustness of fruit detection methods.

The intrinsic complexity of visual information processing in agricultural robots makes its success very limited even up to now, luckily it also makes agriculture as an important frontier of applied computer vision. As Kapach et al. (2012) pointed out, the challenges associated with machine vision in severely unconstrained environments like those encountered in agricultural settings are countless: objects of various colours, shapes, sizes, textures, and reflectance properties; highly unstructured scenes with large degree of uncertainty; ever-changing illumination and shadow conditions; severe occlusions. Some studies (Gongal et al., 2015; Lu & Sang, 2015) suggested that variable lighting conditions and occlusions were the major challenges limiting the fruit detection as well as localization accuracies in orchard environment. The variable lighting condition in the field will affect the colour and intensity of reflected light, moreover partial occlusion of fruit by leaves, branches, and other fruit will affect the geometric and texture features of fruit in images. In such scenario, it is reasonable to hope that one visual cue could compensate for the representational limitations or flaws of the others.

For overcoming the bad effect of variable natural lighting condition, several studies have investigated the use of night time imaging under artificial illumination (Linker & Kelman, 2015; Payne, Walsh, Subedi, & Jarvis, 2014). As pointed out by Font et al. (2014) and Linker et al. (2015), one useful feature of night time imaging is that in which convex surfaces exhibit a "bright spot" due to specular reflection (so-called specular highlights). Yamamoto, Guo, Yoshioka, and Ninomiya (2014) proposed a segmentation method for dividing multi-fruit blob into individual fruit by using the overexposed region on convex surface of tomato fruit caused by the camera flash. A similar observation and method were reported in Linker (2017). The whole image was segmented with a series of stepped thresholds and fitted by Circular Hough Transform.

In this paper, the specular reflection pattern on convex surfaces of citrus fruit was used under low light condition, such as in the morning and evening, although this pattern is more noticeable in night time images. The bright spots on fruit surface were detected firstly as local maxima, and classified with a RUSBoost classifier (Seiffert, Khoshgoftaar, Hulse, & Napolitano, 2010) by the local binary pattern features (LBP) for differentiating the spots on fruit surface from these on backgrounds. After classification, most true fruit were detected correctly but many spots on backgrounds were misclassified as fruit, so a new shape analysis method named as hierarchical contour analysis (HCA) was put forward in this study. The hierarchical contour maps around each local maximum were extracted and fitted with Circular Hough Transform, and the fitted circles were predicted as fruit targets if its radius were in a predetermined range. The hierarchical contour analysis proposed in this paper can utilise shape information effectively but do not need to extract and analyse the edge in an image, so it is efficient and robust under various illumination and occlusion in natural scene.

2. Materials and methods

2.1. Image acquisition and experimental platform

As mentioned in Introduction, when the light source is roughly aligned with the camera, each convex surface exhibits