Object Detection under Natural Illumination Conditions using Superpixels and Local Binary Pattern Feature

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Abstract. This paper proposes a novel object detection method under natural illumination conditions in which a set of features, texture features and Local Binary Pattern (LBP) features, are extracted from the images acquired by a colour camera. The goal of this study is to develop a robust and fast algorithm to detect immature green citrus fruit in individual trees from colour images acquired under natural outdoor conditions. Colour and shape features are used to remove the complex background as much as possible. Since leaves share much more similarities with green citrus fruit in colour and to some extent in the shape, texture features are used for citrus detection. Statistical features, Tamura features and LBP features are used to build the KNN classifier. Experimental results show that the proposed approach provides fairly good object detection performance and confirms an efficient way for outdoor green citrus detection.

1. Introduction

Object detection, which is a task for searching and localizing a target in a particular scene, can be considered as a challenging problem in computer vision. This fact has stimulated the research in this field and as a result several algorithms have been proposed during the last several years [1][2][3]. The detection of object can be extended using robotics for fruit like apple, grape, citrus, etc. from the corresponding trees or plants using the computer vision and image processing techniques and it will be not only time saving, but liberating the human labour. The precise recognition of the fruit in field is the precondition of yield production and fruit picking for harvesting robots. Recognition and detection of green immature citrus fruit ahead of the harvesting time in groves under natural illumination conditions provide a promising benefit for growers to plan application of nutrients during the fruit maturing stages. This also allows citrus growers to plan in advance so they can determine how much labour is needed during the harvesting period and well allocate labour depending on the yield prediction.

Studies about recognizing fruit under the complex environment have been conducted. The present study, as a first step of developing such a system for orchard yield estimation, focused on the developing of a colour imaging system for automatically estimating the number of fruit on a tree. Ji and Zhao [4] developed a real-time machine vision system using a CCD camera to recognize apple fruit and guide a harvesting robot for fruit picking. Rakun and Stajnko [5] combined object’s colour, texture feature and 3D shape properties in building a computer vision-based model for detecting green apples in the orchard to estimate the number, diameter and yield of green apple fruit. Patel and Jain [6] developed an algorithm based on multiple improved features to locate the fruit on trees. The algorithm was designed using RGB images for calculating different weights for multiple features, like intensity, colour, edge and orientation in the testing images. The successful rate of extracting fruit region from
the background was more than 95%. Kurtulmus and Lee [7] developed a machine vision based algorithm, using colour images, to detect and count immature peach fruit in natural canopies environment.

This study developed a robust and fast algorithm to detect and count immature green citrus fruit in individual trees from colour images acquired under natural outdoor conditions. Based on the author’s previous work[8], the adaptive RB chromatic map was used to remove non-citrus pixels. Superpixels[9] were studied and used to separate citrus and non-citrus regions. In order to further eliminate false positives, the last stage, which was based on texture features analysis, was implemented and a final result was decided based on the colour, shape and texture information. The objective of this research was to explore an efficient way to detect green citrus fruit in the outdoor varying illumination conditions with highest recognition rate and lowest false positives and less missing fruit.

2. Materials and methods

2.1 Image acquisition

Green citrus images were captured and saved in the true colour space RGB in the daytime with various uneven illumination conditions from an experimental citrus grove at the University of Florida, Gainesville, Florida, USA in October 2010. The image resolution was 3648×2736 pixels using a typical digital camera (PowerShot SD880IS, Canon USA Inc., Lake Success, NY, USA) from citrus trees at the green stage of the immature citrus fruit. A total of 80 citrus fruit images were obtained, among those, 30 images were randomly selected for a training set and the rest of 50 images were used for testing. In order to make the fruit recognition system much more efficient, images were resized to 912×684 pixels. MATLAB 2015b (The MathWorks, Inc., Natick, MA, USA) is the programming language for post processing in this study.

2.2 Image pre-processing and initial background removal

The most commonly used and simplest way to segment an image is based on colour feature. It is essential to choose an appropriate colour space in colour image segmentation. Unfortunately, complex background, especially fruit and leaves, are not easily differentiated because these portions share a similarity in colour and they may be affected by the uneven illumination conditions. The adaptive RB chromatic aberration map[8] was used to reduce the impact of uneven illumination due to the effects of light.

2.3 Object segmentation using superpixels

The object segmentation aims to generate a pixel-level segmentation of the input image. In this paper, we apply the local structure of the image to produce its representation, which is different with the pixel grid. We consider small regions, namely, “superpixels”, which is taken from the conservative over-segmentation. Superpixels, as its name implies, it refers to divide the image from pixel-level to district-level. It can be regarded as an abstraction of basic information. For example, when an image was segmented into superpixels, many regions of different sizes would be created. Effective information, such as colour histogram, texture information, can be extracted from these regions.

Recently, superpixels are increasingly used in the computer vision applications. However, the constitution of a good superpixel algorithm is not clear. A new superpixel algorithm, simple linear iterative clustering (SLIC)[10], was proposed to generate superpixels efficiently. This algorithm adheres to boundaries better than previous methods[11][12], and executes faster and consumes less memory. Moreover, it is scalable to extend to superpixel generation.

Fruits randomly distribute along branches and even grow in clusters. In order to count the number of citrus fruit more accuracy, jointed regions need to be separated. Compared with superpixel segmentation, watershed segmentation, a morphological based method, which depends mostly on the estimation of image gradients, was also applied to segment fruit region from background. However, it
should be noticed that the watershed segmentation always resulted in over-segmentation. Some schemes [13][14] employ $H$–minima transform with the watershed segmentation to partially solve the over-segmentation problem. Compared with $H$-minima, superpixels can avoid the over-segmentation and provides good object segmentation.

Shape based methods such as the circular Hough transform (CHT)[15] on image segmentation has some issues from the application. The interference of background, leaves, or curvature from the other non-fruit features would be misinterpreted. The shape analysis could be integrated with an advanced technique of the acquisition of as many potential green citrus fruit as possible. Most citrus had approximately circular shape, so the CHT was used to initially detect green citrus. The exact radius of citrus was unknown due to the variety of citrus growth conditions. However, the minimum and maximum radii were found from the training set, to be approximately 30 pixels to 100 pixels. According to this radius range, a CHT was performed to determine the potential green citrus fruit in images.

2.4 Feature extraction and build a classifier

Texture can therefore be used to differentiate between these two regions of interest, citrus and leaves. Two types of small patches with 20×20 pixels from both citrus and non-citrus areas were randomly chosen from the training set.

Tamura textures, coarseness, contrast, directionality, linelikeness, regularity, and roughness, were key features to define texture of a surface[16]. Coarseness relates to distance of notable spatial variations of grey levels, contrast measures how grey levels vary in the image, and directionality calculates the edge direction. The first three features were chosen to be used in this study.

Local Binary Pattern (LBP) is a simple yet very efficient texture operator which was first introduced by Ojala et al.[17]. The LBP operator was originally designed for texture description, testing the relation between pixel and its neighbours. It has been widely used in various applications, such as texture classification, image retrieval etc. Original LBP operator set the pixel value in the central element within 3×3 windows to be as the threshold. Then labelling the pixels was conducted by comparing each pixel with the threshold. The position of pixels was marked as 1 if it is greater than the threshold, i.e., the value of the central element; otherwise it was labelled as 0. The LBP values of central elements, an 8-bit binary number which was called an LBP code, and its corresponding decimal number substituted the central element. The image was divided into rectangular regions, and calculated the histogram of the LBP code of each region. Finally, the histogram of each region was concatenated into one that represents the whole image.

The LBP histogram of a particular cell was computed using the decimal form LBP code. Finally, the histograms obtained from different cells were concatenated into one feature vector for the input image. In this way, information on different levels of locality was preserved: the LBP code of a pixel contained pattern information on the pixel level, the histogram of the frequency of each LBP code in a cell contained information on the regional level and the regional histograms were concatenated to build a global description on the image level. The resulting LBP of a given pixel at $(x_c, y_c)$ can be expressed in decimal form as following:

$$LBP_{C,R}(x_c, y_c) = \sum_{n=0}^{n-1} s(i_n - i_c)2^n$$

where $i_c$ and $i_n$ are gray-level values of the central pixel and $n$ surrounding pixels in the circle neighborhood with radius $R$.

Five statistical features were extracted from the LBP matrix, i.e., mean, standard deviation, entropy, smoothness and angular 2nd moment. For classification, a non-parametric classifier, KNN, was built using statistical features, Tamura features and LBP features, to remove false positives which contained more non-citrus pixels.
3. Test Results and Discussions

3.1 Object segmentation based on superpixel and H-minima watershed segmentation

Superpixels with SLIC method were applied to the background removal image, which would be much more effectively compared with doing the same processing on the original colour image. It can be seen from Fig. 1 that image segmentation based on superpixels showed a better result than the improved watershed segmentation method. Fig. 1a is the original image, resized to 912x684 pixels. Fig. 1b is the initial background removal result utilizing the ARB map. While there are still several non-citrus pixels left after segmentation. This may be caused by the colour similarity between green citrus and leaves, and the uneven sunlight could be another reason. Fig. 2c shows the division result using superpixels. After simple linear iterative clustering, the red line, shown in and Fig. 2d, are boundaries of the object regions. Compared with H-minima watershed (Fig. 1f), superpixel segmentation (Fig. 1e) lower the possibility of over-segmentation as can be seen from the round fruit placed at the bottom of the image.

(a) The original colour image                         (b) Background removal using ARB map

(c) superpixel result masked on the color image             (d) Region boundary

(e) Segmentation result using superpixel     (f) Segmentation result using H-minima watershed

Fig. 1 Object segmentation from complex background

3.2 In-field citrus fruit detection

The proposed algorithm in this study was tested with the validation images. After background removal, it is still inevitable that there still several non-citrus pixels and regions remain. This may be
caused by the colour similarity between green citrus and leaves, and the uneven sunlight could be another reason. CHT was carried out after morphological processing, such as filling holes and removing small areas.

Initially results were obtained by running CHT on the validation images to detect as many green citrus fruit as possible. Then a maximal squared patch was taken from the inside of each circle. After dividing it into several 20×20 small patches, the KNN classifier was run to classify each of them, and majority of vote was taken to determine they were fruit or non-fruit.

A classifier was used to remove false positives and multiple circles were merged according to the distance between each centre. Fig.2 presented the final citrus detection result after false positive removal using aforementioned features, such as LBP features and Tamura features.

![Fig. 2 Final detection results after false positives removal](image)

To verify the applicability of the proposed object detection method based on colour and texture feature analysis, images with different illumination conditions were tested. In one regular illumination image, almost all fruit were detected except for a missing one which was overlapped a lot by leaves with less than a quarter area revealed from our viewing angle. In our algorithm, the fruit with less than a quarter can be seen would be ignored. In some complex illumination condition with strong sunlight and shadows appeared on fruit surface, several false positives were also kept for the algorithm treated those non-citrus regions as fruit because of the similarity of leaves and fruit and the complicated background. The results show that the detection results tested in the validation set, with a total of 167 green citrus. The performance of the algorithm was analyzed in terms of total number of fruit, missed fruit and false positives.

Among the validation images, the algorithm proposed in this study correctly recognized 139 green citrus fruit, which achieved above 83% recognition rate. Meanwhile there were still 28 missed fruit, which accounting for nearly 17%. Besides, the false positives rate was lower than the missed fruit rate, for about 15%. There are three main reasons for these errors in detecting green citrus fruit. Firstly, the complex of the growth environment resulted in citrus fruit overlapped by other objects, for instance, green leaves, branches, and even adjacent other citrus. The complicated grove situation made it hard to correctly recognize all the target objects. The other major reason was uneven illumination conditions. The varying illuminations have many impacts on the features of each category. Highly contrasted spots in the image would make it hard to extract different objects. The third reason was the colour similarity. Green citrus and green leaves share a much more similar colour features. Due to the above mentioned reasons, it was difficult to detect all green citrus in the grove, and some potential citrus was lost, while other regions not belonging to green citrus may be falsely detected as citrus.

4. Conclusion

A recognition algorithm was presented to count green citrus fruit on trees using colour images taken in the citrus grove. An adaptive RB chromatic aberration map was used due to the high contrast between green citrus and leaves. Superpixel and simple linear iterative clustering were applied for object segmentation, which revealed advantages in avoid over-segmentation under complex conditions. Then morphological processing was utilized prior to Circular Hough transform. A KNN classifier was built, using extracted features, to remove falsely detected regions. The final decision was made by
merging multiple circles. The developed algorithm in this study was able to yield number of the immature green citrus fruit in the canopy images. Further improvement is needed to speed up the recognition time, increase the recognition rate, and decrease false positives. Moreover, the algorithm should be more robust to accommodate the varying outdoor conditions, both illumination and growth environment.

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