Available online at www.sciencedirect.com

ScienceDirect

journal homepage: www.elsevier.com/locate/issn/15375110

Research Paper

Detection of passion fruits and maturity classification using Red-Green-Blue Depth images

Shuqin Tu [a], Yueju Xue [b,c,*], Chan Zheng [a], Yu Qi [a], Hua Wan [a], Liang Mao [b]

[a] College of Mathematics and Informatics, South China Agricultural University, Guangzhou 510642, China
[b] College of Electronic Engineering, South China Agricultural University, Guangzhou 510642, China
[c] Guangdong Engineering Research Center for Datamation of Modern Pig Production, Guangzhou 510642, China

ARTICLE INFO

Article history:
Received 12 October 2017
Received in revised form
27 August 2018
Accepted 4 September 2018

Keywords:
Fruit detection and maturity identification
DSIFT
Locality-constrained linear coding
Faster R-CNN

A machine vision algorithm was developed to detect passion fruits and identify maturity of the detected fruits using natural outdoor RGB-D images. As different passion fruits on the same branch can be in different maturity stages, detection and maturity classification on a complex background are very important for yield mapping and development of intelligent mobile fruit-picking robots. In this study, a Kinect sensor was used for data acquisition, and maturity stages of the fruits were divided into five categories: young (Y), near-young (NY), near-mature (NM), mature (M) and after-mature (AM). The algorithm involved two stages. First, by colour and depth images, passion fruits were detected using faster region-based convolutional neural networks (Faster R-CNN), and colour-based detection was integrated with depth-based detection for improving detection performance. Second, for each detected fruit region, the dense scale invariant features transform (DSIFT) algorithm combined with locality-constrained linear coding (LLC) was used to extract and represent the features of fruit maturity from R, G, and B channels, respectively. In addition, the RGB-DSIFT-LLC features were input into a linear support vector machine (SVM) classifier for identifying the maturity of fruits. By conducting an experimental study on a special dataset, we verified that the proposed method achieves 92.71% detection accuracy and 91.52% maturity classification accuracy.

1. Introduction

Passion fruit contains a variety of functional active compounds, which have high nutritional and medicinal value (Lewis et al., 2013). With expansion of passion fruit planting areas in South China, significant economic benefits can be obtained. Passion fruits on the same branch of a tree do not usually ripen at the same time during harvesting season. Labour expense of handpicked passion fruit for fresh markets is increasing owing to a severe shortage of available farm workers. Efficient harvesting labour assignment in large passion fruit fields could significantly reduce the associated cost. In addition, yield estimation before fruit ripening would be valuable for efficient labour deployment. Furthermore, yield estimation prior to harvest helps growers to proactively detect problems. It is also useful for making decisions pertaining to irrigation, pest control, and weed control. Thus, there is an increasing demand for automatic detection of fruits and

* Corresponding author.
E-mail address: xueyueju@163.com (Y. Xue).
https://doi.org/10.1016/j.biosystemseng.2018.09.004

Nomenclature

Acronyms

AM	After-mature
BoF	Bag-of-features
CE	Circle Estimation
CHT	Circle Hough Transform
DSIFT	Dense Scale-invariant Feature Transform
HOD	Histogram of Oriented Depths
HOG	Histogram of Oriented Gradients
LLC	Locality-constrained linear coding
NY	Near-young
NM	Near-mature
PCA	Principal Component Analysis
RG	Red-Green
RGB	Red-Green-Blue
RGB-D	Red-Green-Blue Depth
R-CNN	Region-based Convolutional Neural Networks
ScSPM	Sparse code Spatial Pyramid Matching
SVM	Support Vector Machine
VQ	Vector Quantisation
VGG	Visual Geometry Group

Parameters/Variables

b	Perpendicular distance from optimal hyper plane to the origin
B	Visual codebook
C	Codes set for X
d_i	Locality adaptor that gives measures the similarity between the X and B
f	Function estimates the label of test vector
p	Resulting probability of RGB-D
p_D	Resulting probability of detecting depth images
p_{RGB}	Resulting probability of detecting RGB images
t_i	SVM input
w	Normal vector of the hyper plane
X	Local descriptors set of an image
Y_i	SVM output label to be assigned as either positive (+1) or negative (−1)
α_i	Nonzero coefficients as obtained with the quadratic programming
λ	Constant value
λ_1	Scalars controlling the relative contribution of the sparsity and locality constraints
σ	Adjusting the weight decay speed for d_i

accurate and efficient recognition of their maturity, given passion fruit tree canopy images.

Automated computer vision systems are commonly used for detecting and identifying the maturity stages of various fruits, such as apples, citruses, and blueberries. The detection accuracy for citruses and apples was reported to be between 70.0 and 92.0%. A recognition algorithm for apple detection was proposed based on the colour differences, such as red minus blue (RB), and green minus red (GR) (Zhou, Damerow, Sun, & Blanke, 2012). The coefficients of determination (R^2) for the apples detected by the fruit counting algorithm and an actual harvested yield ranged from 0.57 for young fruits to 0.70 for ripening ones. Ji et al. (2012) reported that the highest accuracy (92.0%) for identifying red apples was obtained using a colour camera and the support vector machine (SVM) for image classification. Image segmentation for fruit identification has also been investigated using texture, colour, and geometric properties. The fusion of blob analysis and the circular Hough transform (CHT) method were developed for detection of apples when the fruits in canopy images are occluded by leaves, branches, and other fruits (Gongal, Amatya, Karkee, Zhang, & Lewis, 2015). This algorithm was tested on 60 images of apple trees and yielded a 90% apple identification accuracy. For detection of citruses, a new 'eigenfruit' approach (Kurtulmus, Lee, & Vardar, 2011) was developed for detection of immature green citrus fruits from colour images acquired under natural outdoor conditions, and reported a detection accuracy of 75%. Bansal, Lee, and Satish (2013) used the fast Fourier transform leakage values for detecting immature green citruses and obtained an accuracy of 82%. For detection of blueberries, Li, Lee, and Wang (2014) developed the colour component analysis-based detection (CCAD) method for identifying blueberries in different growth stages using natural outdoor colour images, and used the forward feature selection algorithm (FFSA) method to separate all berries in four maturity stages using three classifiers, which yielded a high accuracy of 90%. The accuracy of fruit detection and maturity estimation was shown to be affected by uncertain and variable lighting conditions in the field environment, as well as by complex canopy structures (Karkee & Zhang, 2012).

Detection of green fruits is an especially difficult task, owing to the following issues: (1) the colours of green fruits and leaves in the same image are often very similar; (2) most of the existing detection algorithms are sensitive to various lighting conditions and occlusion of fruits. Various types of sensor systems and image processing methods have been studied for improving detection accuracy of green fruits. An automated yield monitoring system was developed (Chang, Zaman, Farooque, Schumann, & Percival, 2012), consisting of two colour cameras and a real time kinematic-GPS receiver. Yang, Lee, and Gader (2014) explored the feasibility of hyperspectral imaging for classifying the growth stages of blueberries and achieved a nearly 88% classification accuracy. A stereovision camera was used for localisation of fruits in global coordinates, to identify repeated counting of apples owing to multiple imaging (Wang, Nuske, Bergerman, & Singh, 2013). A stereovision camera addresses issues by using a single camera-based system which is relatively complex and whose classification accuracy is low, particularly for outdoor environments where stereo matching is problematic. A laser range finder (Bulanon & Kataoka, 2010) has demonstrated better location accuracy compared with other currently used sensors. However, this system is comparatively bulky, slow, and costly. Nissimov, Goldberger, and Alchanatis (2015) presented an approach for obstacle detection in a greenhouse environment using the Kinect 3D sensor, and developed an obstacle detection system based on the information about depth, colour, and texture, to achieve obstacle detection robustness. Because the Kinect sensor utilises the time-of-flight principle, which is similar to the working principle of three-dimensional photonic mixer device (3D PMD) cameras,