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Research Paper

Vision-based extraction of spatial information in grape clusters for harvesting robots

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Grapes are likely to have collisions and be damaged by manipulations when harvesting grape clusters. To conduct an undamaged robotic harvesting, this paper focuses mainly on locating the spatial coordinates of the cutting points on a peduncle of grape clusters for the end-effector and determining the bounding volume of the grape clusters for the motion planner of the manipulator. A method for acquiring spatial information from grape clusters is presented based on binocular stereo vision. This method includes four steps: (1) calibrating the binocular cameras and rectifying the images, (2) detecting the cutting points on the peduncle and the centres of the grape berries, (3) extracting three-dimensional spatial coordinates of the points detected in step 2, and (4) calculating the bounding volume of the grape clusters. A total of 300 images were captured in the vineyard and were tested to validate the method for the cutting point detection, and the success rate was approximately 87%. The accuracy of the localisation of the cutting points was determined under outdoor conditions, and the accuracy in the Z and X directions was 12 mm and 9 mm, respectively. The acquired bounding volume of the grape cluster was compared with manual measurements, and errors in the height and maximum diameter were less than 17 mm and 19 mm, respectively. The elapsed time of the whole algorithm was less than 0.7 s. The demonstrated performance of this developed method indicated that it could be used on harvesting robots.

1. Introduction

Grape harvesting is a time-consuming and labour-intensive procedure, and labour shortages and high labour costs are drastically becoming more serious along with the ageing population in China (Xiang, Jiang, & Ying, 2014). Thus, it is urgently needed to develop a robot for harvesting grapes in the vineyard. In the process of robotic harvesting, to complete an automatic harvest with undamaged grapes, the end-effector of the harvesting robot should avoid collisions with

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Nomenclature

Symbols

i	serial number of the detected lines
n	serial number of stereo image pairs
N	number of grape cluster samples
S_{GC}	pixel set of the grape cluster
x,y	pixel coordinates in the image
x_c, y_c	barycentre coordinates
x_t, y_t	pixel coordinates of the top point of the grape contour
x_0, y_0	centre coordinates of the berry
(x_{i1}, y_{i1}), (x_{i2}, y_{i2})	pixel coordinates of the detected line end
x_l, y_l	pixel coordinate of S_{GC} in the left image
X_w, Y_w, Z_w	three-dimensional coordinates under world coordinates
x_j, y_j, z_j	spatial coordinates of the front surface centre of the berries
$f(x,y)$	pixel values of (x, y) in the binary image
$L_i(x,y)$	equation of the detected line i
r	radius of the regression circle
θ	angle whose value range was from 0 to 360°
r_t	real radius of the berry
A	two-dimensional accumulator
B	baseline distance between the left and right camera
f	focal length
d	disparity between the left and right camera
L_{max}	maximum Euclidean distance between the left and right points of the grape contour
l_j	distance between the jth berry and the centre axis of the grape cluster
d_{jk}	distance between any two berries' centres, j and k
D_n	actual distance between the cutting point and the reference point in the x direction
$x(CP)_n$	x coordinate value of the cutting point acquired by the stereo-vision system
$x(RP)_n$	x coordinate value of the reference point on the calibration board
$z(CP)_n$	z coordinate value of the cutting point acquired by the stereo-vision system
$z(GT)_n$	depth value of the cutting point acquired by the ground-truth measurement device

Abbreviations

NCC	normalised cross correlation
ROI	region of interest
Roi_L	length of peduncle ROI
Roi_H	height of peduncle ROI

the grape clusters and other obstacles when it moves toward a target (Bac, Hemming, & van Henten, 2014). To plan a collision-free path, the location and bounding volume of the grape clusters must be sent to the motion planner. The grape character such as softness, irregular shape and contour make grasping the fruit directly not feasible, and thus, grasping and cutting the peduncle of the grape is an effective method for harvesting. Therefore, localisation of the cutting points on the peduncle and estimation of the bounding volume of the grape clusters have become essential functions of the harvesting robots.

In recent decades, many researchers have taken great interest in fruit-harvesting robots and have performed some studies on it, such as cucumber harvesting (Van Henten et al., 2003), strawberry harvesting (Hayashi et al., 2010; Kondo, Monta, & Hisaeda, 2001), tomato harvesting (Monta et al., 1998), apple harvesting (Si, Liu, & Feng, 2015; Zhao, Lv, Ji, Zhang, & Chen, 2011), aubergine harvesting (Hayashi, Ganno, Kurosaki, Arima, & Monta, 2003), litchi (Wang, Zou, Tang, Luo, & Feng, 2016) and de-leafing cucumber harvesting (Van Henten et al., 2006). However, most of these studies did not achieve commercialisation successfully because of certain factors, such as low success rates, low work efficiency, high costs, fruit damage and difficulty of detection in unstable illumination (Hayashi et al., 2010). To overcome these problems, the recognition and localisation of fruits via sensor equipment and image algorithms were widely studied by researchers from all over the world.

In the study of sensors, Jimenez, Ceres, and Pons (2000) adopted a laser-based computer vision system for fruit detection. This system was based on an infrared laser rangefinder sensor that provided range and reflectance images and was designed to detect spherical objects in unstructured environments. Additionally, Kondo, Shibano, and Mohri (1994) proposed a grape identification method early by using its spectral properties. Mehta and Burks (2014) utilised an inexpensive perspective transformation-based range estimation method that positioned 3D fruits in citrus harvesting based on a monocular camera-in-hand. To recognise clustered tomatoes, Xiang et al. (2014) used a binocular stereo vision to realise the recognition of the clustered tomatoes.

In addition, Berenstein, Ben, Shapiro, and Edan (2010) utilised the difference in the edge distribution between the grape clusters and the foliage to detect grape clusters for an autonomous selective vineyard sprayer. The bunches of grapes were detected in a natural environment based on their colour images (Reis, Morais, & Peres, 2012). The number of grape berries was counted by detecting specular spherical reflection peaks in RGB images obtained at night by artificial illumination (Font, Pallejà, Tresanchez, Teixidó, & Martinez, 2014). The grapes were recognised and localised by extracting the external rectangle of the grape contours for a grape bagging robot (Yang et al., 2013). Kai, Lining, and Zhe (2013) proposed an improved “super green” colour feature model (2G-R-B) to achieve target recognition and positioning of the grape for the bagging robot.

In the detection of fruit peduncles and obstacles, Cubero et al. (2014) presented a pedicel detection method that was implemented by detecting the connecting points of the contours between the peduncle and the fruit, which was suitable for grape berries but not grape clusters. To provide the harvesting robot with an obstacle location, Bac et al. (2014) used a support wire as a visual cue to locate the stem of a sweet-pepper. Van Henten et al. (2006) detected the peduncle of a leaf for a de-leafing cucumber harvesting robot based on two