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Research paper

Detection of cherry tree branches with full foliage in planar architecture for automated sweet-cherry harvesting

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Fresh market sweet cherry harvesting is a labour-intensive operation that accounts for more than 50% of annual production costs. To minimise labour requirements for sweet cherry harvesting, mechanized harvesting technologies are being developed. These technologies utilise manually-placed limb actuators that apply vibrational energy to affect fruit release. Machine vision-based automated harvesting system have potential to further reduce harvest labour through improving efficiency by eliminating manual handling, positioning and operation of the harvester and/or harvesting mechanism. A machine-vision system was developed to segment and detect cherry tree branches with full foliage, when only intermittent segments of branches were visible. Firstly, an image segmentation method was developed to identify visible segments of the branches. Bayesian classifier was used to classify image pixels into four classes – branch, cherry, leaf and background. The algorithm achieved 89.6% accuracy in identifying branch pixels. The length and orientation of branch segments were then analysed to link individual sections of the same branch together and to represent the branches with an equation. Linear and logarithmic model equations were fitted to the branch segments and the equation with minimum residual was selected as the best-fit model representing the corresponding branch. Branches detected with this algorithm were compared with manual counting. The method achieved a branch detection accuracy of 89.2% in a set of 141 test images acquired during full-foliage canopy. This study shows the potential of using a machine vision system for automating shake-and-catch cherry harvesting systems.

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Nomenclature

USDA	United States Department of Agriculture
UFO	Upright Fruiting Offshoots
RDA	Rapid Displacement Actuator
3D	3-Dimensional
2D	2-Dimensional
WSU	Washington State University
mm	Millimetres
LED	Light Emitting Diode
HFOV	Horizontal Field of View
RGB	Red–Green–Blue
CIELAB	1976 CIE L*a*b*
x	Feature vector
wi	Class definition
P(wi)	Prior probability of class wi
pdf	Probability density function
p(x|wi)	Class conditional distribution of x given that it belongs to class wi
p(wi|x)	Posterior probability of wi given the evidence x
p(x)	Probability of x
di(x)	Decision function to decide class given the value of x
Ci	Covariance matrix
mi	Mean vector
|Ci|	Determinant of covariance matrix
ln	Natural logarithm
px	Pixels
Y	Pixel position in rows
X	Pixel position in columns
m	Slope
C	Intercept

1. Introduction

Washington State produced more than 264,000 tonnes of sweet cherry in 2012, which was 62% of total production of United States (USDA, 2013). Currently, all of these fruit are harvested manually, which is a highly labour intensive operation. Labour for harvesting constitutes more than 50% of total production costs (Seavert, Freeborn, & Long, 2008) and about 71% of the total human labour required for sweet cherry production (Employment Security Dept., 2013). As labour-related issues are becoming challenging due to increasing cost and decreasing availability (Fennimore & Doohan, 2008; Gongal, Amatya, Karkee, Zhang, & Lewis, 2015; Hertz & Zahniser, 2013), the interest in developing mechanical harvesting solutions has increased.

In recent years, sweet cherry growers in Washington State have been adopting new orchard training systems that are more compatible to mechanical harvesting (Long, 2010; Peterson & Wolford, 2001) than traditional systems. The upright fruiting offshoots (UFO) canopy architecture is a modern, planar training system that consists of trees with a permanent horizontal limb from which multiple vertical limbs are grown (Whiting, 2009). The UFO system may be trained to a vertical or Y-trellised architecture which provides a compact fruiting wall. Such a system is amenable to mechanical or automated harvesting aided by a machine vision system for fruit and branch detection. Investigations on mechanical harvesting have shown the potential to improve harvest efficiency by adopting the UFO training system (Chen et al., 2012; Du, Chen, Zhang, Scharf, & Whiting, 2011). An economic study suggested that mechanically harvested cherry production systems will return more money to growers than the traditional system (Seavert & Whiting, 2011). The study was based on the results from a USDA mechanical harvester evaluated in early 2000's (Peterson & Wolford, 2001). The actuator of this harvester was manually controlled by a joystick to position and engage a rapid displacement actuator (RDA) on a limb.

Evaluations of the prototype mechanical harvester revealed the difficulty for the operator to position the actuator due to limited viewing angle from the operator's fixed seated position (Peterson, Whiting, & Wolford, 2003). A subsequent study on mechanical harvesting of sweet cherry reported a significant effect of orchard characteristics and operator performance on the harvest rate (Larbi & Karkee, 2014). In addition, multi-layer catching surfaces located very close to the canopy may be essential to improve collection rate and reduce fruit damage rate during mechanical harvesting. However, this type of collection mechanism will critically limit the visibility and ability of an operator to localize branches for shaking. To address these issues, there is a need to develop an automated harvester using a machine-vision-based system for detecting shaking point in tree branches, and positioning the end-effector.

Systems and methods for mechanised cherry harvesting have been widely studied (Du, Chen, Zhang, Scharf, & Whiting, 2012; Halderson, 1966; Larbi & Karkee, 2014; Norton et al., 1962; Peterson et al., 2003; Peterson & Wolford, 2001; Zhou, He, Zhang, & Karkee, 2014), yet only limited studies have investigated the potential for automating these harvesters. One study attempted to develop a cherry harvesting robot capable of picking individual cherries from tree canopies with the aid of 3D machine vision sensors (Tanigaki, Fujiura, Akase, & Imagawa, 2008). The 3D sensors were attached to a robotic manipulator, which was able to pick the cherries that were visible to the sensors from a given viewpoint. However, cherries could be located all around the tree trunk. To minimise undetected cherries due to occlusions, the arm has to be moved to different viewpoints (Tanigaki et al., 2008). Fruit detection accuracy is critical for obtaining high harvesting efficiency because sweet cherry is characterised by many small fruit. Automated mechanical shakers may be more practical than robotic harvesting for crops like sweet cherry. One advantage of mechanical shaking method is that not every fruit needs detection as long as concentrated areas of fruit in branches are detected. For automatically harvesting cherries using mechanical shakers, a machine vision system needs to be capable of detecting and localising fruit as well as branches.

Studies have been reported in the past for detecting tree branches or similar structures in images. Detection of road network from aerial or satellite images using 2D image processing has been one of such studies (Hu, Razdan, Femiani, Cui, & Wonka, 2007; Laptev et al., 2000; Trinder & Wang,