Feasibility Study of In-Field Phenotypic Trait Extraction for Robotic Soft-Fruit Operations

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***Abstract*—There are many agricultural applications that would benefit from robotic monitoring of soft-fruit, examples include harvesting and yield forecasting. Autonomous mobile robotic platforms enable digitisation of horticultural processes in-field reducing labour demand and increasing efficiency through continuous operation. It is critical for vision-based fruit detection methods to estimate traits such as size, mass and volume for quality assessment, maturity estimation and yield forecasting. Estimating these traits from a camera mounted on a mobile robot is a non-destructive/invasive approach to gathering qualitative fruit data in-field. We investigate the feasibility of using vision-based modalities for precise, cheap, and real time computation of phenotypic traits: mass and volume of strawberries from planar RGB slices and optionally point data. Our best method achieves a marginal error of 3.00cm^3 for volume estimation. The planar RGB slices can be computed manually or by using common object detection methods such as Mask R-CNN.**

***Index Terms*—phenotyping, mobile robots, computer vision**

I. Introduction

Fruit detection is an area fast gaining interest in the horticultural industry. The environmental challenges posed by the fast growing population and climate concerns are spurring new innovative approaches to fruit detection, harvesting and yield estimation using computer vision e.g [1]–[3]. Phenotypic information such as volume shown in 1 about the fruit is important for all of these approaches. For harvesting it allows to automatically grade and harvest specific berry classifications, and for yield more specific estimates such as detection of waste strawberries or estimating a total yield volume can be computed. Phenotypic information is critical for any form of quality assessment.

Our method aims to estimate mass and volume of soft-fruit from robotic platforms in-field. We present a feasibility study in lab conditions for estimating these traits from images based on the intuition that most soft-fruits are ellipsoidal in nature and symmetrical around their major-axis. Meaning the methods presented are applicable to most of the soft-fruit family. Geometrically the major axis is the longer axis of an ellipse passing through its foci or centre of gravity in the case of our planar segment; minor axis is the shorter axis directly perpendicular to the major.

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(a) Actual Volume = 35.00cm^3 (b) Predicted Volume = 34.53cm^3

Fig. 1: Strawberry volume prediction, RGB image (1a), computed reconstruction surface of RGB segment (1b)

II. Data and Methods

In order to evaluate our methods, we required mass and volumetric data of soft-fruit. We chose to evaluate strawberries as they are readily available and have one of the most challenging shapes in the soft-fruit family compared to blackberries, blueberries etc. their surface is not as ellipsoidal and has a more teardrop profile. We collected 20 samples of class 1 ripe strawberries. To capture the data necessary, we used a 2cm^3 precision volumetric beaker, a 5g accurate scale, a 0.01mm accurate digital caliper and an Intel Realsense D415 computer vision camera to capture RGB images and depth information, pictured in Figure 2. Each strawberry was measured in three dimensions manually through its minor, major and cross sections which are the widest, tallest and deepest lengths of the berry respectively. Then it was weighed and placed in the volumetric breaker, a control rod of a known volume was used to fully submerge the berry to get more accurate readings. Finally, the berry was placed at a set distance away from the downwards facing camera, flat on a table to simulate the conditions met in field and the RGB and depth information was captured and logged.

A. Volume Estimation

A segment (planar RGB slice) is a binary mask detailing all of the pixels that belong to an object in an image. We use

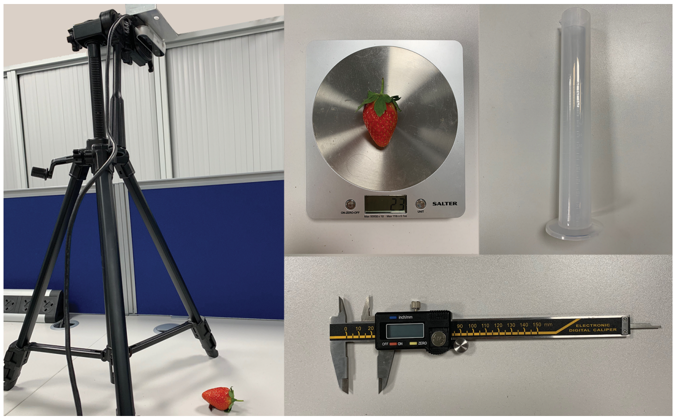

Fig. 2: Equipment used for data collection.

these segments to estimate the volume of the strawberries. The computational resources required to process these segments are very low and are a typical output of modern object detectors in this field, meaning this approach is easily integrated with existing work with negligible overhead. We present the results in Figure 3.

The three evaluated methods are ellipsoidal, surface area integration and disc summation. The ellipsoidal method computes the volume as $\frac{4}{3}\pi m_i m_a d$ where m_i is the minor axis, m_a is the major and d is the cross section length. These volume measurements are computed from both the ground truth (GT) data and measurements extracted from the depth map. The method we deem surface area integration uses the fundamental relationship in calculus that states the integral of a function f over an interval can be calculated by finding an anti-derivative F of f. For an ellipsoid the volume is the integral of the surface area with respect to the radius.

$$f(c, r) = \frac{r}{m_i}\left(\frac{\sum_{k=0}^{n}(c_{xk}, c_{yk})}{n} - c\right) + c \tag{1}$$

$$V = 2\int_0^r 2a(f(c, r))\mathrm{d}x \tag{2}$$

In Equation (2) we show the integral for computing the volume V of an irregular segment, by taking the product of $\mathrm{d}x$, the height of each slice and the contour c. We scale each slice by each slice radius r in function $f(c, r)$ (1) and calculate its area $a(f(c, r))$. The function $a(x)$ is the shoelace algorithm for finding area of simple polygon (no intersection or holes) expressed as Cartesian coordinates of a segment. We use the integral range $[0, r]$ and multiply the result by 2 to only consider positive contour values.

$$v_i = \sum_{j=1}^{n} c_{ij} \qquad v = \left(\pi\frac{v_i^2}{4}d_y\right)_{i=1}^{n} \qquad V = \sum_{k=0}^{n} v_k \tag{3}$$

Finally, the disc method shown in Equation (3) estimates the volume of the segment by treating each of its rows of size d_y as a cylinder. The segment is split into sizes of d_y for each the volume is calculated as $\pi r^2 d_y$. This method should be more robust than the integration step in cases when the orientation estimate error is large. Since each row is treated independently, a more complete surface not dependant on axial symmetry can be reconstructed, whereas with integration the entire contour is used with a singular estimate of the cross length.

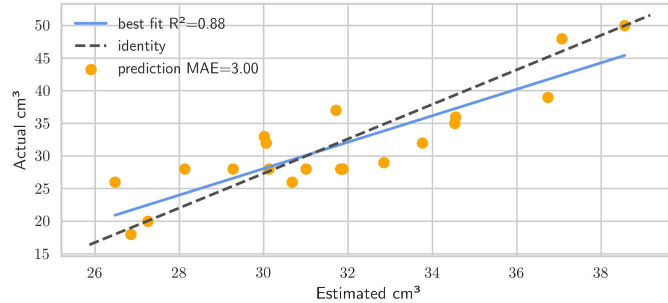

Fig. 3: Volume estimates using surface area integration.

$$c'_x = \frac{z_{max}}{f_x}(c_x - p_x) \qquad c'_y = \frac{z_{max}}{f_y}(c_y - p_y) \tag{4}$$

The presented methods approximate the volume in pixels (px^2). To calculate the volume in centimetres (cm^2), we simply deproject the contour c by the camera intrinsic parameters focal length f_x, f_y, principal point p_x, p_y and an estimated distance z_{max} from the camera obtained from the max value bounded by the segment. For the disc method the z_{max} value is equal to the local max at each row rather than the entire segment. The deprojection step is shown in Equation (4) and is applied prior to volume estimation.

B. Mass Estimation

We model the relationship of mass and volume as the least squares regression fit to our data, and estimate the mass from predicted volume fit.

III. Results and Conclusions

We have presented a non-invasive/destructive, inexpensive method for volume and mass estimation in-field designed for use on a robotic platform. Our results for volumetric and mass estimation of the chosen soft-fruit are presented in Table I. It's evident that this method is appropriate for calculating the volume from only two dimensional data (segments) since the median absolute error is only 3.00cm^3 for the best method, which is only 1.00cm^3 above the maximum precision of the volumetric measurements. The relatively poor results for mass estimation were due to the low precision of the equipment.

	Ellipsiod GT	*Ellipsiod Depth*	*Integration*	*Disc*
Volume	3.28cm^3	3.94cm^3	**3.00cm^3**	3.22cm^3
Mass	10.19g	11.90g	9.96g	**9.85g**

TABLE I: Median Absolute Error of volume and mass estimation methods, bold indicates the best method.

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