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Title: Developing a Methodology for Better Fruit Value for an Apple Orchard - Year 2/2

Submitted to: State Horticultural Association of Pennsylvania

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Proposed Project

5/1/2021 - 4/30/2022

Total Project Request: \$13,277

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1. Title

Developing a Methodology for Better Fruit Value for an Apple Orchard – Year 2/2

2. Personnel

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3. Duration of Project: One year (May 1, 2021 – April 30, 2022)

4. Justification

Problem: Accurate measurement of fruit count and size have important implications for predicting orchard profitability (Marini, 2001, 2017). Quantifying the distribution of apple size and weight can help growers estimate profits and take actions early in the season to obtain desired fruit size distributions. In recent years, computer vision systems and deep learning algorithms have made it possible to detect fruit accurately. However, these recent works were not focused on apple size or the effect of occlusion on the instance segmentation of the fruit for sizing. Another challenge is to generate actionable information beyond the acquisition of a large amount of data. In many agricultural applications, it has become easier to collect various forms of real-world data from cameras and devices (e.g., images of fruit on canopy). Using deep learning, it is easier and faster to store, process, and analyze quantifiable information (e.g., fruit detection). However, combining qualitative and quantitative data and translating it to contextual information for growers and agricultural robotics (e.g., which fruit should be removed during the green fruit thinning process) remains challenging.

Summary of previous work: Last year, we proposed to develop a methodology to obtain early season estimates of fruit count and size. The objectives were: (1) Improve technical challenges in an existing computer vision system to accurately estimate fruit size and weight, and (2) Develop a sampling strategy to better represent an entire tree for the size and weight distribution of crops. A method for sizing apples in images was developed using deep convolutional neural networks to select the best apples for sizing. The hardware used for data acquisition was a field-deployable stereo vision system with high-resolution cameras and active lighting (Figure 1). We developed an LED strobing mechanism and integrated it with a



Figure 1. An image acquisition prototype using a wagon as a sensing platform. The wagon was equipped with a stereo vision camera to capture images of an entire canopy in 3D up to 14 ft.

machine vision system for overcoming lighting variability and motion blur to provide precise segmentation of object boundaries in images and estimate fruit sizes more accurately. Also, the stereo camera pair allows for retrieving depth information on each apple and therefore accurate conversion from pixel coordinates to a metric coordinate system. Instead of attempting to find the diameter of apples for sizing, the Mask R-CNN model was used to find the metric surface area of each fruit on trees during the growing season (Figure 2, Mirbod et al., 2020). The accuracy of the apple sizing method was evaluated on ground truth data: comparison of the apple surface area with apple diameters using an EFM device. The correlation analysis was performed on 30 trees with two trees excluded. One tree had minimal harvest and heavy occlusion and had only one apple candidate. The second exclusion was an outlier observed from the harvest weight data. For the ground truth data on apple diameters, ten apples were sampled from each tree and their diameters measured using the EFM device. The mean of the ten measurements then represented the average fruit diameter per tree. The comparison results for June 16, July 17, and September 20 datasets are shown in Figure 3. The mean average errors were 1.8, 2.2, and 2.8 mm with a standard deviation of 1.3, 1.4, and 2.2 mm for June 16, July 17, and September 20 datasets, respectively.



Figure 2. Sample images from mask generation output of selective apples used for sizing. Surface area calculations were done on apples with the orange mask while apples with red dots were not included in the surface area calculations.

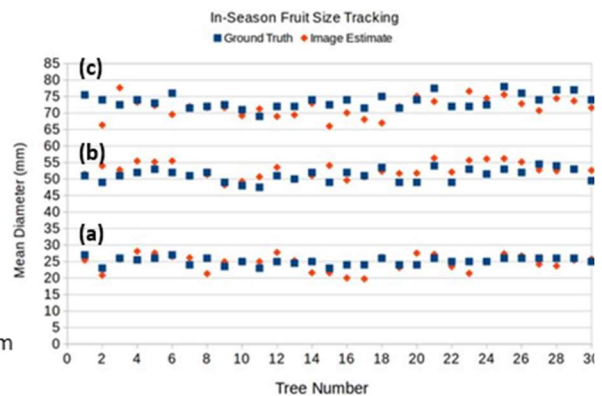
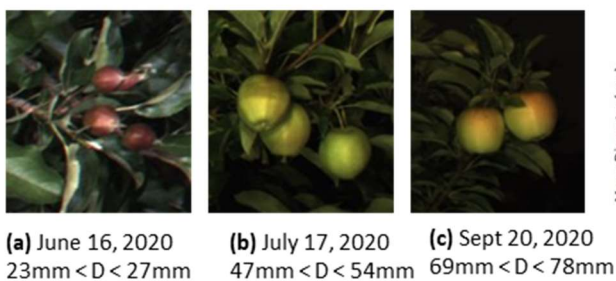


Figure 3. Size and weight estimation during growing season. (a) Correlation result from June 16 dataset, and (B) Correlation result from July 17 dataset, (C) Correlation result from September 20 dataset

What this project will address and benefits to agricultural communities: This year, we will continue improving the existing computer vision system for size and weight estimation of early-season apples in canopies. Also, we will develop a decision support tool for green fruit thinning

using AI and new data science technologies. Being able to estimate early-season fruit count and adjust final fruit number per tree or branch can be very useful for growers, to allow them to take actions to maximize net returns per acre. Among the SHAP's research topic priorities, this project contributes to (1) Horticulture: (i) Crop Load Management of New Varieties, (ii) Integration of New Technology for Improved Farm Efficiency and Decision Making, and (2) Ag Engineering: (i) Sensor Technologies, and (ii) Use of New Technology to Improve Data Collection for Decision Making.

5. Objectives

The **primary goal** of this year's project is to **develop a crop management decision support tool in order to obtain early season estimates of fruit count and size and adjust the final fruit number per tree for optimal packout and yield of an apple tree**. The objectives are below.

Objective 1. Improving an existing computer vision system for accurate estimation of early-season fruit size and weight, and

Objective 2. Collecting preliminary data for developing AI-based decision support tool for green fruit thinning.

6. Procedures

For both objectives we will use a total of 80, 4-year-old Golden Delicious/M.9 trees at the Russell E. Larson Agricultural Research Center at Rock Springs. The reason we chose these trees is that they are relatively small and uniform in shape.

Objective 1. Improving technical challenges in an existing computer vision system

In Objective 1, we will examine various methods to identify axes of fruit hanging from branches for better size estimation using computer vision and image processing techniques. Also, we will develop a more precise deep learning model to reduce errors compared to 2020 results. In the 2020 season, the results were calculated including all detected apples in a canopy image resulting in a low R^2 value (0.23) between estimated diameter and actual size. For preliminary testing, we manually selected only fully exposed apples to be included in diameter estimation and found that

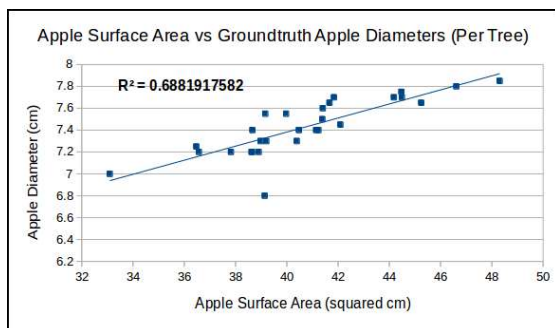


Figure 4. Correlation between apple fruit size using surface area calculation and ground truth apple diameters.

R^2 values were improved significantly (Figure 4). In the 2021 season, we will train a deep convolutional neural network to automatically select good candidates for apple sizing for better diameter and weight estimation. We expect to have an improved R^2 value for size estimation. Additionally, we will develop a method for fruit registration in virtual 3D space to reconstruct apple trees, canopies, and individual fruits. Each fruit and trunk will be assigned with (x, y, z) coordinate in 3D space. The accurate position information prevents

double counting of fruit in overlapping images and reidentify fruit if it becomes fully visible in order to take size measurement.

Objective 2. Collecting preliminary data for developing AI-based decision support tool for green fruit thinning

Removing excessive blossoms or young fruit in early season is an essential task to have an optimal leaf to fruit ratio. Growers need to use their best judgment over a series of decision-making process such as the timing of thinning, thinning method or concentration (chemical or hand), optimal final fruit count per tree, and selecting fruits for removal based on fruit size and spacing for hand thinning. This decision-making process often involves contextual information from the field by combining qualitative and quantitative data which growers can learn from years of experience. In artificial intelligence, machine learning models and rule-based systems are widely used to make inferences from data objectively to improve decisions. Each of these methods has a different approach to making inferences from data. In a rule-based system, a deterministic approach is used and typically a human is involved to decide a set of stepwise requirements. With this approach, experts teach the machine how to thin the tree in the same way as humans decide what to remove. Consequently, the rule-based approach requires skilled experts such as experienced growers, or horticulturists to encode each thinning rule in artificial intelligence with the help of a computer programmer. On the other hand, machine learning systems utilize a probabilistic approach rather than a deterministic approach. This approach is based on learning data by analyzing the training set to produce its own classifiers without being explicitly programmed about the rules. In recent years, a machine learning approach is generally preferred when good training data sets are available and rules are not clear. While a machine learning approach is considered revolutionary, it lacks transparency (it is often called a black box system) and a large amount of ‘good’ training data is required for the system to learn. For some applications, it is important to have a transparent AI system for operational reasons. For those cases, the deterministic approach can be a good option. In this objective, we will investigate both machine learning and rule-based system approach to create a decision support tool for fruit thinning. This year, we will focus on collecting data to be used for training machine learning algorithms and interpreting contextual information on human operation for fruit thinning into the machine or numerical languages.

Expected outcomes: A machine vision system with an accurate three-dimensional sizing and counting capability will be developed. The collected data and developed AI algorithms during the 2021 season will be used as a preliminary study for larger federal grant application regarding artificial intelligence (USDA NIFA Food and Agriculture Cyberinformatics Tools).

7. Budget (Total of \$13,277)

Salaries/Wages (\$6,930)

- Summer salaries for a graduate student (Grade 12, 0.5 FTE, \$6,930) for 2021 Summer Semester is requested. A student will work on sensing fabrication, field experiment as well as data analysis.

Fringe Benefits (\$549)

Fringe benefits are computed using the fixed rates of 34.88% applicable to Category I Salaries, 12.35% applicable to Category II Graduate Assistants, 7.94% applicable to Category III Salaries and Wages, 0.31% applicable to Category IV Student Wages, and 23.88% for Category V, Postdoctoral Scholars and Fellows, for fiscal year 2021 (July 1, 2020, through June 30, 2021). If this proposal is funded, the rates quoted above shall, at the time of funding, be subject to adjustment for any period subsequent to June 30, 2021, if superseding Government approved rates have been established. Fringe benefit rates are negotiated and approved by the Office of Naval Research, Penn State's cognizant federal agency.

Materials and Lab Equipment (\$5,498)

Budget for two cameras (\$4,598 = 2*\$2,299, [link](#)) and camera lenses (\$800) and mount (\$100) to upgrade the existing computer vision system for obtaining higher resolution images are requested.

Additional Fees (\$300)

Land use fee (\$300/acre * 1 acre) for using Rock Springs Horticulture Farm is requested.

Indirect Costs (\$0)

F&A rates are negotiated and approved by the Office of Naval Research, Penn State's cognizant federal agency. Penn State's current provisional on-campus rate for research is 60.50% of MTDC from July 1, 2020, through June 30, 2021. New awards and new competitive segments with an effective date of July 1, 2021, or later shall be subject to adjustment when superseding Government approved rates are established. Per 2 CFR 200 (Appendix III, Section C.7), the actual F&A rates used will be fixed at the time of the initial award for the duration of the competitive segment. Per sponsor guidelines, indirect costs are not included in this proposal budget.

References

- Marini, R.P. and R. Trout. (1984). Sampling procedures for minimizing variation in peach fruit quality. *J. Amer. Soc. Hort. Science*. 109:361-364.
- Marini, R. P. (2001). Estimating mean fruit weight and mean fruit value for apple trees: comparison of two sampling methods with the true mean. *Journal of the American Society for Horticultural Science*, 126(4), 503-510.
- Marini, R. P. (2017). Fruit Harvest - Estimating Apple Yield and Fruit Size. Penn State Extension. Available at: <https://extension.psu.edu/fruit-harvest-estimating-apple-yield-and-fruit-size>. Accessed by Dec 30, 2019.
- Mirbod, O., Choi, D., Heinemann, P., & Marini, R. (2020). Towards image-based measurement of accurate apple size and yield using stereo vision cameras. 2020 ASABE Annual International Meeting, Paper No. 2001115, July 12- 15, 2020. (pp. 1-6).