Automated Measurement of Berry Size in Images ⋆

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Abstract: Knowledge on berry size in grape vineyards can be a great asset for growers to help manage their crop whether for yield assessment or grape quality control. Having the ability to size berries of an entire field would allow growers to effectively monitor their vineyards at various stages of the growing season. Manual methods for determining berry size distribution of an entire field can be time consuming and rely on small sample sets which can lead to inaccuracies. This paper introduces an automated imaging system that measures diameter of grapes for every vine in an entire vineyard and generates a comprehensive map showing berry size variability which until now has not been available to growers. Believed to be the first example of mapping berry size across commercial vineyard blocks, this system uses computer vision techniques to locate and size the berries identifying submillimeter berry diameter differences. Maps of variability in berry size are shown to correlate with canopy size and yield. Diameter estimations are found to measure within 6% of manual measurements and a strong correlation is seen between estimated berry sizes and actual berry weights with $r^2 = 0.96$.

Keywords: computer vision, agriculture, stereo vision, image segmentation, image processing

1. INTRODUCTION

The ability to quantify grapevine traits can provide valuable knowledge for growers, allowing them to take better control of their fields, and to more effectively meet demands of the viticulture industry. One such characteristic is berry size which can be important for growers to posses during the growing season, not only for monitoring grape quality and composition, but also determining the current state of vineyard growth. The influence of berry size on wine quality has been a topic of great discussion as to whether smaller berries and yield can affect wine quality (Matthews and Nuzzo 2007; Barbagallo et al 2011). Whether berry size directly affects wine quality or rather the viticultural practices on vines is the main influencer, data on berry size can allow growers to apply the necessary techniques to craft the right balance between final yield and berry composition. Prior to veraison, rapid berry growth is characterized by cell division and cell enlargement (Dokoozlian 2000); water stress on vines during this time has been shown to stall berry growth (Keller et al 2006) and early water deficit from flowering to veraison can result in an irreversible decrease in cell volume (Ojeda et al 2001). The result in berry size due to these changes, whether intentional or not, indicate that monitoring berry growth can be important during this stage of development.

Data on berry size can be a tool to measure variability in the field. Identifying these variabilities can enable precision management in order to increase uniformity and distribute resources and labor in areas that need closer monitoring.

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Fig. 1. Vehicle mounted imaging system(top) and sample images of estimated grape diameters for Cabernet Sauvignon(bottom-left) and Petite Syrah(bottom-right)

One example can be seen in canopy management; as growers seek to better control the quality and quantity of their crop, canopy management practices becomes an essential factor in reaching their target outcome. A novel

irrigation practice proposed by Sanchez et al. (2014) introduces variable rate irrigiation(VRI) to compensate for soil variations within a vineyard in order to optimize for fruit yield, control canopy development variability, and conserve water usage. VRI resulted in an overall decrease in spatial variability in a 4.05-ha rectangular area as viewed by canopy sensor data. Having a vineyard map of berry size variations can be one way to verify whether canopy management practices are producing the desired outcome on the fruits.

Ideally a mechanism would be needed to monitor an entire field and get frequent measurements of grape sizes during the growing season. The developed methods in this paper provide a non-destructive approach for finding the diameter of grapes in metric units using computer vision techniques. Two different algorithms are used to measure the diameter of grapes; one for grapes that reflect a shiny bright center and the other for matte grapes. This is due to the observation that when light is shined on different grape varieties the light reflectance is varied. Fig. 1 shows an example where Petite Syrah grapes reflect a shiny center whereas Cabernet Sauvignon are more matte; the imaging system is automated to choose the algorithms accordingly. These two grape types were chosen as they provide good texture variety and are also two popular wine grapes. The algorithms are applied in a vineyard using a stereo imaging system that can be mounted onto a tractor/UTV, constantly taking images while driving through each row in the field. A sample of the images are used to manually find the diameter of grapes as ground truth data to validate the diameter estimation algorithms. Furthermore, the algorithms are applied in a controlled setting to size clusters of grapes cut from several vines in order to compare against yield measurements.

In the field environment once all images are collected and processed, a map of berry diameters is generated for the entire vineyard. The amount of processed data for generating the maps is significant and comprehensive, comprising of several 100,000 images for more than 10,000 vines in order to most accurately reflect the observed vineyard in its entirety. As a result, regions of diameter variability achieved from these maps are then shown to correlate with the same regions of canopy size and yield.

2. RELATED WORK

Numerous approaches for measuring berry size have focused on pulling off berries from clusters, using image processing to segment individual grapes, and finding their diameters. Tardaguila et al. (2012) sampled 100 berries showing strong correlation between berry size and weight with r^2=0.96 and 0.97. Kicherer et al. (2013) introduced BAT(Berry Analysis Tool) which uses a DSLR camera to take images of individual grapes laid down on a perforated metal plate. It can accurately measure berry diameters with r^2=0.96 to actual hand measurements, giving an overestimation of only 0.3 mm in a laboratory setting.

More recent work by Liu et al. (2013) attempted to predict weight of entire grape bunches using numerous metrics such as volume, pixel area, perimeter, berry number, and berry size. Visible pixel(bunch area) resulted in the most accurate predictor of bunch yield with a 7.07% error in a controlled setting. Other works by Diago et al. (2014) accurately predict weight of a cluster(up to 95%) in a controlled lighting environment by taking multiple images of the cluster at different viewpoints. Roscher et al. (2014) present a five step framework for detecting and sizing berries; pixel measurements are converted to metric units using a known structure but they recognize that a stereo camera system can help to further automate this process.

In this paper berries are detected and sized for entire vineyards without destemming or destructive sampling. The algorithms are optimized for field conditions, being invariant of distance from camera to berries and outdoor lighting. And finally the stereo camera system is automated, taking as input numerous images and presenting the compiled data to growers in a way that is meaningful in order to help with precision management.

3. APPROACH

3.1 Vehicle Mounted Machine Vision System

The imaging system used to detect and size grapes is a sideways-facing stereo camera mounted onto a vehicle and driven through each row of a vineyard. The two Point Grey 9.1 megapixel cameras have a baseline separation of 90mm and global shutter in order to capture still images as the vehicle is moving. Traveling at 5 feet per second the cameras and a high intensity xenon flash are triggered at 5Hz to take images; the GPS coordinates at each trigger is also recorded automatically by the system. Once all images are collected, the algorithms for estimating grape diameters are automated to step through each image and size the berries. This setup can be seen in fig. 1 and a sample field image with estimated grape diameters in fig. 2. Only the median diameter in each image is used for generating the final berry size variability map; this eliminates any outliers that may have occurred during the grape detection or sizing process.

Fig. 2. Cabernet Sauvignon field image with marked berry circumferences using estimated diameters

3.2 Berry Detection And Diameter Estimation

The berry detection algorithm used is from the three step process described in Nuske et al. (2014) where image keypoints are first detected for potential berry locations, followed by classification of keypoints into *berry* or *not-berry*, and finally grouping of neighboring berries together.

To find the metric diameter of grapes in images first an image patch is created of each detected grape in order to

Algorithm 1 Angular Invariant Maximal Detector

```
Input
c : grape coordinate in image
r_max : maximum radius
output
best_diameter : final estimated diameter

procedure ANGULAR INV MAXIMAL DETECTOR
    for sector = 1 → n_sectors do
        reset radius_increase
        grow sector = true
        while grow sector do
            for scan_line = 1 → scan_lines_per_sector do
                new_point=scan_line_loc+radius_increase
                if new_point intensity > (scan_line_loc
                intensity · threshold) then
                    continue to next scan line
                end if
                if new_point intensity > (grape center
                intensity · threshold) then
                    continue to next scan line
                end if
                all_scan_lines(scan_line)=radius_increase
            end for
            if no increase in majority of scan lines then
                grow_sector = false
            end if
            radius_increase += 1
        end while
    end for
    best_diameter = mode(all_scan_lines < r_max )·2
end procedure
```

Algorithm 2 Sum of Gradient Estimator

```
Input
r_min : minimum radius
r_max : maximum radius
c : grape coordinate in image
corr : grape center correction fraction
output
best_diameter : final estimated diameter

procedure SUM OF GRADIENT ESTIMATOR
P = grape_image_patch(c,r_max)
gx = sobel_gradient_x(P)
gy = sobel_gradient_y(P)
g_mag = √(gx² + gy²)
    for r = r_min → r_max do
        corr_pixels = r · corr
        for u = r - corr_pixels → r+corr_pixels do
            for v = r - corr_pixels → r+corr_pixels do
                score=0
                for α = -π → π do
                    x=r·cos(α)
                    y=r·sin(α)
                    score+=g_mag(u+x,v+y)
                end for
                if score > best_score then
                    best_score = score
                    best_diameter = 2·r
                end if
            end for
        end for
    end for
end procedure
```

localize the region of interest. In the field, distance from grapes to camera can vary causing some grapes to appear smaller and others larger, therefore it is important that the size of the patch is adjusted accordingly. This is valuable compared to using one patch size for all grapes as a large patch size for a grape far away can encompass multiple grapes and a patch too small can miss the circumference of a closer grape entirely. First the metric distance from each detected grape to the camera is determined by triangulating corresponding image points p_1, p_2. Using camera focal length(f) and camera baseline b the distance to each grape is then:

$$B_w = norm(X_G, Y_G, Z_G),\ where$$
$$Z_G = \frac{f \cdot b}{(p_1 - p_2)}, X_G = \frac{p_{1x} \cdot Z_G}{f}, Y_G = \frac{p_{1y} \cdot Z_G}{f} \tag{1}$$

B_w is the berry metric world coordinate relative to the camera and X_G, Y_G, Z_G are its X,Y,Z components. The length of the square patch in pixels for each grape then becomes:

$$L = \frac{D_{max} \cdot f}{B_w} \tag{2}$$

where D_{max} is an estimated maximum grape diameter in metric units to be used for the field.

Once the patch containing the grape is extracted, the light reflectance from grape's surface is measured by looking at a single row of pixel values in the patch which includes the detected berry coordinate and finding the mean intensity value of that row. If the center intensity value of the row deviates by more than 40% from the mean intensity then light distribution is considered more varied(shiny grapes), otherwise light intensity is equally distributed(matte grapes). The result from this step will lead to one of two berry sizing algorithm to be used for diameter estimation:

Algorithm 1. Angular invariant maximal detector(Pothen et al. 2016)
Algorithm 2. Sum of gradient estimator

In Algorithm 1 each detected berry is divided into 8 sectors; as the sectors grow in radius an intensity change threshold checks for berry boundary. The berry diameter is determined by looking at the mode of estimated radius for all sector. In Algorithm 2 a search is performed along a set of minimum and maximum radii. In each iteration a sum of gradient magnitude along the perimeter of the current radius is computed; the best radius is defined by the sum of gradient magnitude that is greater than the previous sum. The angular invariant maximal detector gave more accurate diameter sizing of Petite Syrah grapes whereas the other had better estimates for Cabernet Sauvignon.

Lastly the estimated diameter is converted to metric units; the camera's focal length(f), berry world coordinate(B_w), and pixel diameter of berry (D_p) relate to the metric length of the berry diameter (D_m) by:

$$D_m = \frac{D_p \cdot B_w}{f} \tag{3}$$

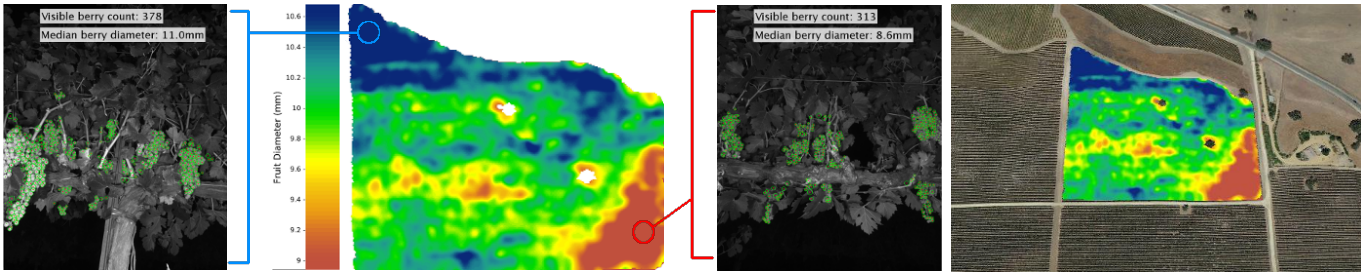

Fig. 3. A generated map of berry size for a Merlot field. Rightmost image is the vineyard superimposed on Google Earth. Left images show the field map plus sample detail images where map regions were clicked

4. RESULTS

The approach taken to validate the system consists of first comparing the algorithms' berry sizing results to manually sized berries in images. This was done by running the algorithms on a small sample of berries in a field image, then on the same image manually tracing the berries to get their diameters. Second the berry sizing algorithms were used for yield estimation. The setup involved a handheld Canon camera taking pictures of grape clusters that were laid out on a black cloth. This was done in order to eliminate any field variables such as leaves, branches, and trunk so that the focus could be on determining whether diameter variations in grapes can be picked up by the system and correlated to yield. Finally the berry sizing methods were applied to an entire vineyard and a map was generated showing berry diameter variations in different regions of the field. These submilllimeter regional differences that are visible on the map were then compared to a map of canopy size variations.

4.1 Verifiying Diameter Measurements

To directly verify the diameter measurements from the two algorithms 60 grapes were taken from an image in Cabernet Sauvignon and Petite Syrah fields. The angular invariant maximal detector was tested on the Petite Syrah image and sum of gradient estimator on the Cabernet Sauvignon image. Manual measurements were made by clicking on three points in the image on each grape's circumference to create a circle; the same grapes were then compared to the imaging system's estimates. Table 1 shows the error produced between manual measurements and the algorithms' measurements in pixels; fig. 4 shows the correlation between the manual and automated measurements on the 60 grapes in each image.

An indirect verification was also made while looking at yield estimation when a sample 19 vines from a Cabernet Sauvignon field were sized by the algorithms and weighed. The correlation between observed berry size in the vines and total weight was $r^2 = 0.96$ whereas just comparing the observed berry count and total weight gave a correlation of $r^2 = 0.76$ as seen in fig. 5. With a strong correlation to berry weight, this not only indicates the success in estimating berry size variability, but also the importance in measuring berry size for yield prediction. The strong correlation between weight and volume is similar to results found by Tardaguila et al. (2012) when area and weight of Grenache and Tempranillo grapes were compared.

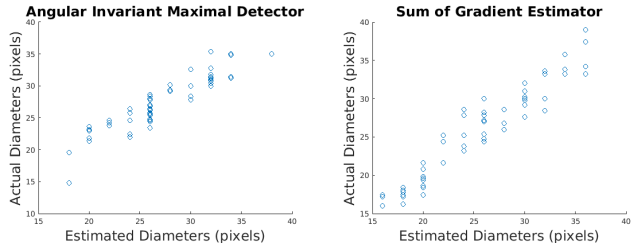

Fig. 4. Performance measurements for Angular Invariant Maximal Detector with $r^2 = 0.84$(left) and Sum of Gradient Estimator with $r^2 = 0.91$(right)

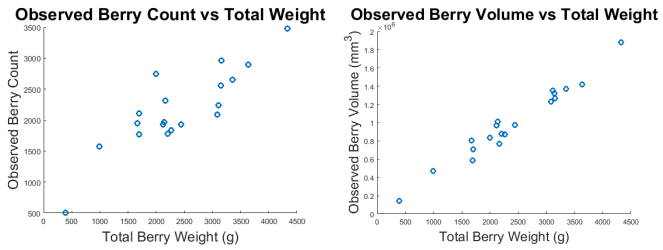

Fig. 5. Correlation between berry count vs weight (left) with r^2=0.76 and berry volume vs weight (right) with r^2=0.96.

4.2 Berry Sizing For Yield Measurement

In order to test the berry sizing algorithms for yield estimation a relation had to be found between weight of berries and size of berries. Two particular calibration parameters needed are the average density of a grape P and a visibility factor F representing the average percentage of grapes that are detected in an image relative to the actual total grape count. In a Cabernet Sauvignon field grape clusters were cut from a vine, their weights were measured, and laid down on a black background with their image taken by a handheld Canon camera. To find F, 150 berries were sampled from a vine cluster and were weighed at 79.5g; since the total weight of grapes in each vine is already known the relation between weight and number of detected berries was used to convert total weight of a vine to total number of berries on a vine. This process was repeated 19 times and the average percentage of detected berries to total berries was determined to be 37%. To find P the 150 grapes were assumed to be spherical; their berry diameters(D) were converted to berry volume(V) where $V = \frac{4}{3}\pi(\frac{D}{2})^3$. Knowing the total weight for these 150

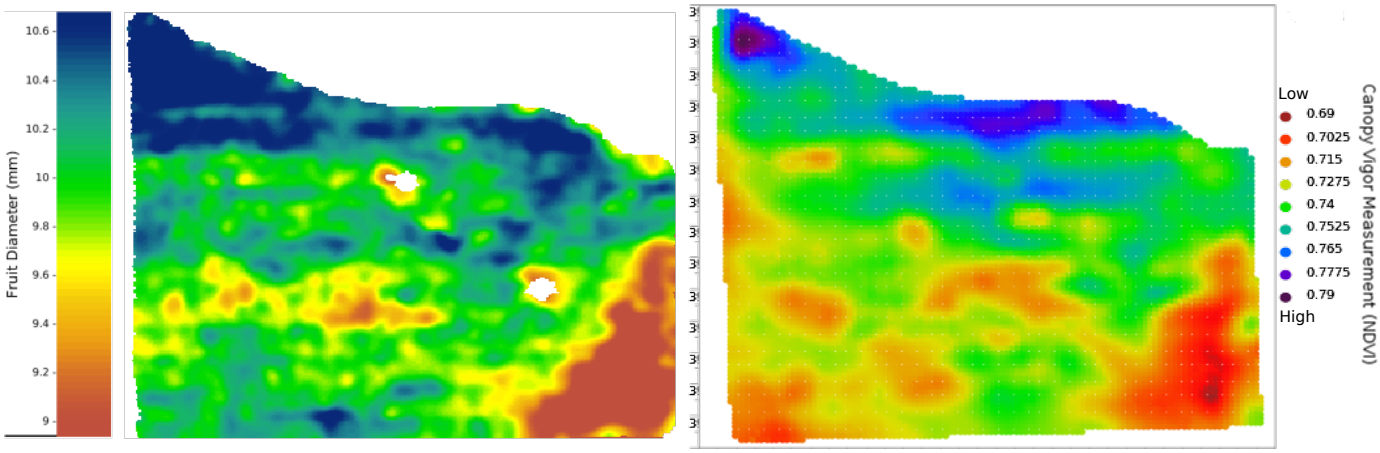

Fig. 6. Berry size distribution of a 15 acre Merlot vineyard imaged in June 2014(left) in comparison to canopy - NDVI(Normalized Difference Vegetation Index) measured in April 2014(right).

berries and their total volume, the average density factor for a berry was found to be $9.1 \cdot 10^{-4}(g/mm^3)$. Finally to get the estimated weight W for each vine the calculation then becomes:

$$\mathsf{W} = \frac{\sum DetectedBerries}{\mathsf{F}} \cdot median\{V\} \cdot \mathsf{P} \qquad (4)$$

where all detected berries are first converted to estimated total berries using the visibility factor. Next the estimated total berries are multiplied by the median grape volume found from the berry sizing algorithms followed by conversion from total volume to total weight using the density factor.

To estimate yield from berry sizing another set of 19 vines were cut from a Cabernet Sauvignon field adjacent to the field used to find the calibration parameters. The clusters for each vine were weighed, laid out on a black background, and imaged using the handheld Canon camera. QR tags were laid next to the clusters as a reference for converting diameters from pixel to metric units. The berry sizing algorithms were applied to the grape clusters and an estimated weight of each vine was found using (4); for the 19 new vines that were sampled the mean error for estimated vine weight vs actual vine weight was 6.3% with standard deviation of 4.4%.

It should be noted that while applying the same density factor across different fields of Cabernet Sauvignon and getting a strong estimate to actual berry weight is a positive result, more experiments on this procedure still need to be performed on different grape type varieties and stages of maturity.

4.3 Map Generation of Berry Diameters in Field

As the imaging system is driven through each row of a vineyard GPS coordinates are recorded along with each acquired stereo image set. For a field of Merlot grapes a 15 acre vineyard was imaged in Paso Robles, CA. An estimated 15,000 vines were imaged generating 100,000 images for a total observed count of over 7 million grapes. Fig. 3 shows the resulting generated heat map of berry size for the vineyard; the map is also superimposed on a satellite image giving growers better indication of exactly where in the field the regions of berry size disparities are located. Users can click on the map to view individual images taken from the field, providing more detail of the number of detected berries and their average diameters at that particular location.

4.4 Correlation to Canopy Size

In addition to viewing regions of diameter variations, the berry sizing maps were compared to other measurements of interest such as canopy size. A map of canopy biomass of the Merlot field was generated using a Crop Circle sensor which provides data on the health–or vigor–of the vines. Taylor et al. (2013) show that when the sensor is directed at the canopy there is a strong correlation (r=0.75) between the sensor response at bloom and at late in the season. While the sensor's measurements at and after veraison is a good indicator of vine size, the authors suggest that the sensor's response at bloom can also be a good indicator of vine size for late in the season. In fig. 6 a map of canopy size taken in April 2014 is compared to the berry size map in June 2014. Vines with low vigor in the southeast corner of the field produced smaller berries whereas vines with more vigor in the northern region produced larger berries. It should be noted that this relationship between canopy and berry size may not always be present especially in overcropped vines.

5. DISCUSSION

The berry sizing algorithms tend to perform well for grapes before the onset of coloring. In one case, when Flame Seedless grapes were measured right before harvest, the algorithms had more difficulty in accurately sizing the berries. This may be due to the regions of dark and light coloring that appear on the grape's surface. Before veraison grape surfaces appear more uniform, Petite Syrah had a shiny center but the intensity distributed outward evenly. These characteristics make the overall grape texture still appear dominant compared to the surrounding background. With mature Flame Seedless grapes, as the algorithms are searching inside the grape the large regions of discontinuity can falsely serve as a potential background. More testing on other grape varieties before harvest will need to be done to verify this.

Method	Mean Error(%)	Stdev Error(%)	Est. Mean Diameter(px)	Est. Stdev Diameter(px)
Sum of Gradient	5.3	4.2	25.5	5.8
Angular Invariant Maximal	6.1	4.1	26.9	4.5

Table 1. Estimated Pixel Diameters vs. Manual Measurements

For yield estimation the correlation between berry weight and berry diameters and the results on estimating cluster weights showed that berry sizing can be a method to measure yield of a vine. As this was done in a controlled setting, challenges still remain in more accurately predicting the yield for entire vineyards as well as being able to perform large scale validation of the imaging system. For example, diameter estimation errors can occur when camera distance to vines increases significantly. As distance increases, the number of pixels representing a grape decreases which can lower precision when converting from pixels to millimeters. Also estimating the density of the berries is a further challenge since the density changes over time due to ripening and rain/irrigation events.

6. CONCLUSION AND FUTURE WORK

An imaging system was introduced for automating the measurement of berry diameters in a vineyard, capable of generating yield maps on commercial scale blocks. Methods were developed to size berries that were optimized for field conditions, taking into account distance of berries to the imaging system and algorithms were adapted to lighting conditions and berry texture. The approaches introduced in this paper were designed to work in a large-scale environment, capturing submillimeter berry growth variability in the field in order to allow growers to better manage their crop and increase uniformity. With numerous studies indicating strong correlation between berry size and berry weight, future experiments from this work hope to provide better yield estimation. The algorithms will need to adapt to texture variations during post-veraison development and the methods used for yield estimation need to be tested on more grape varieties and stages of maturity.

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