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## **A Camera and Laser System for Automatic Vine Balance Assessment**

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**Abstract.** *Canopy performance, the balance of crop weight and canopy volume, is a key indicator of value in viticultural production. Timely and dense measurement offer the potential to inform management practices and deliver significant improvement in production efficiency. Traditional measurement practices are labor intensive and provide sparse data that may not reflect vineyard variability. We propose and demonstrate a combination of visual and laser sensing mounted on vineyard machinery that provides dense maps of canopy performance indicators. Current industry practice for measuring grape crop weight involves manually counting clusters on a vine with destructive sampling to find the average weight of a single cluster. This paper presents an alternative utilizing vision and laser sensing. We demonstrate use of machine vision to automatically estimate the weight of the crop growing on a vine. Validation of the algorithm was performed by comparing weight estimates generated by the system to ground truth measurements collected by hand. Machine mounted laser scanners provide direct measurement of canopy shape and volume. Validation of the canopy volume measurement is provided by correlation with manually collected dormant vine pruning weight. Attaching these laser and camera sensors to vineyard machinery will allow crop weight and canopy volume measurements to be collected on a large scale quickly and economically. Experiments performed at vineyards growing Traminette and Riesling wine grapes and Concord juice grapes show that we were able to determine both crop weight and canopy volume to within 10% of their actual values.*

**Keywords.** *Crop Estimation, Canopy Estimation, Machine Vision, Laser Sensing*

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## Introduction

If a vineyard manager effectively balances the size of crop and the size of the canopy, they can enhance the economic viability of a vineyard. To effectively manipulate the vine, the vineyard manager needs information about the current state of the vines with precision and accuracy. The current industry practice for estimating the crop and canopy size is labor intensive, expensive, inaccurate, spatially sparse, destructive and riddled with subjective inputs. Typically, the process for yield prediction is for workers to sample a certain percentage of the vineyard and extrapolate these measurements to the entire vineyard. The weight of the clusters is constantly increasing until harvest, so the vineyard manager must guess at what percentage of the final weight is the current measurement – a subjective input which leads to inaccurate predictions. The manual sampling practice scales poorly to large commercial vineyards and the industry is searching for an alternative. The process for estimating the size of the vine canopy from dormant pruning weight is equally labor intensive and inaccurate.



Figure 1: Example camera image of Gerwurztraminer wine grapes captured at véraison. Automatically detecting the grape crop within imagery such as this is difficult because of issues caused by the lighting and shadows, and the lack of contrast to the leaf background.

Here we report results of an approach to automatically detect and count grapes to forecast yield and also estimate the canopy size with precision and accuracy. Our approach extends the work presented in Nuske (2011). Conventional visible light cameras are driven through a vineyard to image the vines and detect the crop for yield prediction. Similarly, laser range scanners are used to measure the canopy size.

There are a few different existing industry practices for estimating the canopy size ranges from approximate measures via the winter cane pruning weight or the shaded area on vineyard floor at noon, to the most precise measure that is extremely tedious and destructive, where all the leaves of a vines canopy are stripped and measured individually. We present an alternative measure, the canopy volume taken from a 3D scan generated by a laser range scanner mounted to a vehicle traversing the vineyard.

The main challenge in generating a meaningful canopy volume measure is through dealing with the variability in the sampling density of the scanner. We show how to resolve this issue by using an appropriate representation for the 3D scans, a 3D occupancy grid, and present an algorithm that analyses the occupancy grid to generate a measure of canopy volume. We compare our automatic measure against the winter pruning weight for 1500 individual vines and find the measures with r-squared correlation of 0.65.

Traditional manual crop estimates look to sample the average number of grape clusters per-vine, the average number of grape berries per-cluster and average berry weight. Our approach is to estimate the total number of berries, essentially combining clusters per-vine and berries per cluster in the one measurement. Clusters per vine and berries per cluster account for 60% and 30% of variation in yield per vine respectively, therefore 90% of the variation in yield is accounted with accurate berry counts. Furthermore, the number of berries per-vine is a good measure to obtain because it is fixed from fruit-set all the way until harvest, unlike cluster weight for which a multiplier must be guessed and applied.

The challenges in visually detecting grape berries is their varying appearance under different lighting, the lack of color contrast to the background, which is often similarly colored to the grapes, and also occlusions causing not all grapes to be visible. An example of the difficulties of visually detecting grape crop can be seen in Fig. 1. The few existing methods for detecting crop in vineyards have been restricted to the laboratory (Federici, et al. 2009) or have relied on color contrast (Dunn and Martin 2004) and are therefore not applicable for detecting crop over a similarly colored background of leaves. Lack of color contrast is an important issue that occurs in the white-grape varieties and all the grape varieties prior to véraison (the onset of color development). We specifically address the issues of lighting and lack of color contrast, by using shape and texture cues for detection.

The issue of occlusion means it is not possible to detect and count all berries on a vine. However, our detection of grape berries is precise, ensuring that there are very few false positives. The result of precise detection is that our berry count is a reliable measurement of yield, despite the fact that our algorithm only counts a percentage of all the grape berries on a vine. We calibrate our berry count measurement to harvest yield from a set of vines, and apply this calibration to other vines not included in the calibration set, pointing to the fact that percentage of berries not detected is relatively constant from vine to vine.

We deployed our method in a vineyard and conducted an experiment in which manual per-vine harvest weights were collected and used as ground truth to evaluate our automated yield measurements. The size of the experiment is significant, including roughly 450m of vines, including two different grape varieties, where the total harvest weight of the vines totaled over 2000kg. Our method calculates yield within 9.8% of ground truth.

### **Related Work**

The quality of the vineyard harvest is known to be a function of crop load (canopy size to crop size ratio) and is optimized when vines are not heavily over or under cropped (Reynolds and Vanden Heuvel 2009). Crop load is a measure of vine balance often expressed as crop yield per dormant pruning weight unit or as leaf area per fruit weight units with optimum values between five and ten or 1.1 to 1.4 m<sup>2</sup> per kg fruit, Naor et al. (2002), Kliewer and Dokoozlian (2005). Unfortunately, pruning weight ratios can only be measured once a year and leaf areas are time consuming and expensive to assess, especially if the exposed leaf area is to be discriminated from the total (Lakso 2009). No attempts have been made to characterize crop load in vineyards with ground-based or remote sensing methods.

### **Related Canopy Size Measurement Work**

Methods to characterize grapevine canopies have been developed for individual vines and are not readily applicable to whole vineyards. A formula to calculate exposed leaf area based on average external geometric canopy shape was developed by Smart and Robinson (1991). The same authors also adapted Point Quadrat Analysis (PQA) for use in vineyards at mid-season to measure many canopy attributes. PQA has been used to characterize different trellis systems (Gladstone and Dokoozlian 2003) and has been enhanced with canopy light measurements (Meyers and Vanden Heuvel 2008), however both PQA methods are time consuming and the values would be difficult to be spatially mapped to align with vineyard variability for use in precision viticulture.

New technologies are being developed to automate the collection of data that can be used for canopy assessment. Multiple researchers have deployed wireless sensor networks to collect meso-scale environmental data in vineyards (Beckwith et al. 2004, Burrell et al. 2004) and in more general horticultural settings (Benson et al. 2009, Lea-Cox et al. 2008, Panchard et al. 2008, Baggio 2005, Goense et al. 2005), however none of this work has sought to directly use the collected data to determine canopy performance. Laser range scanners (LiDAR) have been used to successfully estimate canopy shape and leaf area index in forestry (Van der Zande et al. 2009, Lefsky and McHale 2008) while combinations of lasers with ultrasonic sensing (Tumbo et al. 2002) and stereo cameras (Swanson et al. 2009) have been used to estimate canopy volume and automated crop management decision making in citrus (Campoy et al. 2010).

### **Related Crop Size Measurement Work**

Current practices to forecast yield are inaccurate because of sampling approaches that tend to adjust towards historical yields and include subjective inputs (Clingeffer et al. 2001). The calculation of final

cluster weight from weights at véraison use fixed multipliers from historic measurements (Wolpert and Vilas 1992). Unfortunately, multipliers are biased towards healthier vines thus discriminating against missing or weak vines and multipliers for cluster weights vary widely by vineyard, season and variety.

Sensor-based yield estimation in vineyards has been attempted with trellis tension monitors, multispectral sensors, terahertz-wave imaging and visible-light image processing. A dynamic yield estimation system based on trellis tension monitors has been demonstrated (Blom and Tarara 2009) but it requires permanent infrastructure to be installed. Information obtained from multispectral images has been used to forecast yields with good results but is limited to vineyards with uniformity requirements (Martinez-Casasnovas and Bordes 2005). A proof of concept study by Federici et al. (2009) has shown that terahertz imaging can detect the curved surfaces of grapes and also has the potential to detect these through occluding thin canopy. The challenge for this approach is to achieve fast scan rates to be able to deploy the scanner on a mobile platform.

Dunn and Martin (2004) demonstrated small-scale yield estimation based on simple image color discrimination. This approach was attempted on Shiraz post-véraison (i.e. after color development, very close to harvest) in short row segments. The method would not be applicable for the majority of real world examples where the fruit appears over a background of similarly-colored leaves, as is the case in white grape varieties and in all varieties before véraison. More complex crop detection based on computer vision methods using color pixel classification or shape analysis has been attempted on various fruit types – Jimenez et al. (2000) provides a summary of fruit detection work, Singh et al. (2010) present a method for detecting and classifying fruit in apple orchards and Swanson et al. (2010) use the shading on the curved surfaces of oranges as a cue for detection.

### ***Canopy Size Measurement***

The interaction of location, cultural practices, vine spacing and training system determines canopy architecture and density and hence canopy microclimate and performance. This significantly impacts fruit maturation, composition and date of harvest (Dokoozlian and Kliewer 1995; Bergqvist et al. 2001; Spayd et al. 2002). Measuring the canopy size during the growing season can give the vineyard manager information they need to make necessary manipulations to their vines to optimize their crop.

We use laser range scanners mounted to utility vehicles to scan the canopy of the vines, generate a registered 3D model, convert the model into an occupancy map representation and extract a measure of the canopy size.

### **Sensing Hardware**

Our sensing approach is to use two SICK LMS laser range scanners, that each generate a 2D scan pattern at 0.5 degree increments over a 180 degree field of view. We mount both scanners sideways generating a vertical pattern; one low on the vehicle at a height of 0.5m and one mounted high at a height of 1.6m as shown in Fig. 2. The high and low mount points increase the visibility of the canopy that otherwise with one scanner might have been restricted by occlusions. Each laser scanner generates 75 scans per second, which as we move through the vineyard we register into a 3D scan of the canopy. The registration is performed using a Trimble GPS/INS unit that gives the full 6 degree-of-freedom pose of the vehicle. Calibrating the relative position and orientation of the scanner with respect to the GPS/INS unit enables the laser range points to be projected into world coordinates.

The projection of the scan points into the world frame generates a dense 3D point cloud of the canopy as shown in Fig. 3. The 3D point cloud as a representation, whilst being high resolution, has two separate problems. First, it is an incredibly fine-grained representation, which obviously is a benefit, but its sheer size is difficult to store and process computationally. Second is that the variability of the velocity of the vehicle driving up the rows and the distance of the vehicle from the canopy will cause unwanted variability in the density of the 3D points. If nothing is done to account for this variability, it will translate into disturbances in the extracted measurements

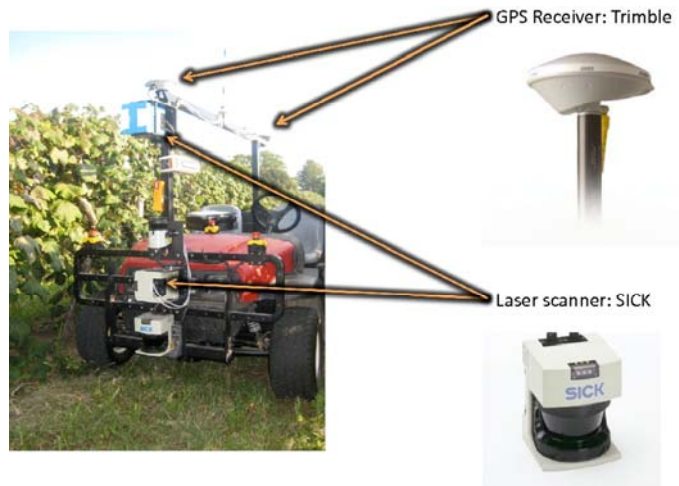


Figure 2: Image illustrating the vehicle and sensors used for canopy size measurements. of canopy size.

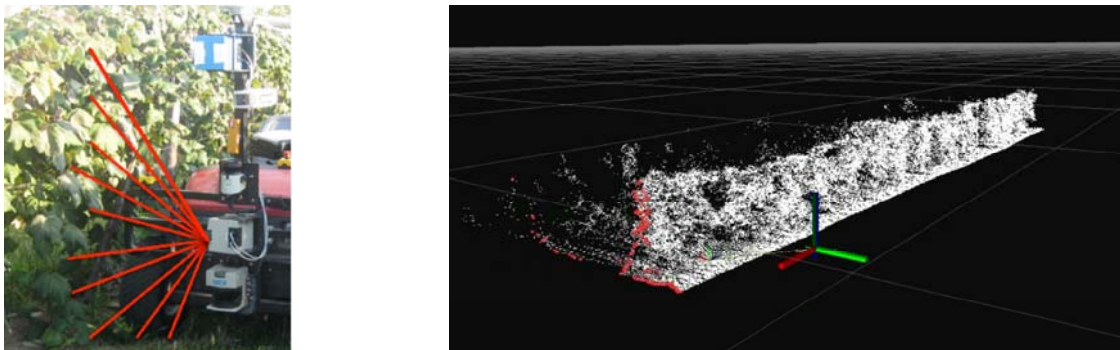


Figure 3: Canopy scanning. Sideways mounted laser scanner generates a 2D line of range measurements (left). Integrating measurements over time as the vehicle moves gives a dense 3D scan of the vine canopy (right).

### 3D Occupancy Grid

To alleviate the density variability issues and to increase the compactness of the 3D representation we translate the 3D point cloud into a 3D occupancy grid. The grid is a discrete representation of the world in which each cell (voxel) represents a location in the world with a defined volume. Each grid cell is defined as either occupied or un-occupied, based upon whether one or more laser range measurements were recorded there. We use 50mm cubes as the size of each cell which gives a good balance providing enough fine detail to measure canopy size, whilst being much more efficient than a raw point cloud. The grid size is on the order of the combined errors due do laser resolution and global position registration.

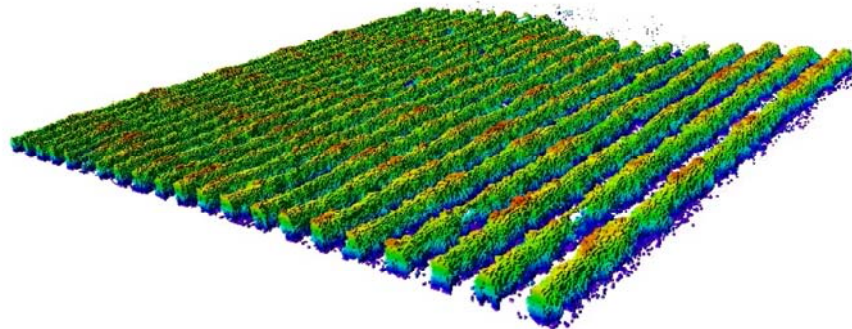


Figure 4: Example of occupancy grid for a 2 acre vine canopy block generated by laser scanners. Grid is colored according to height, ranging from blue at the vineyard floor to red at the highest point of the vines.

## Registration to Individual Vines

The next step to extracting canopy size measurements is to register the 3D representation to specific rows and specific vines in the vineyard. We do this by manually tagging a time when the vehicle just starts to enter a row to scan the vines, and also tag the time as it leaves the row. The time-stamps are synchronized against the GPS device that gives the start and end locations of each row that was scanned. The vines are equally spaced in most vineyards and therefore, by breaking up the 3D representation from the start to the end according to the vine spacing we know which part of the 3D occupancy grid belongs to which vine.

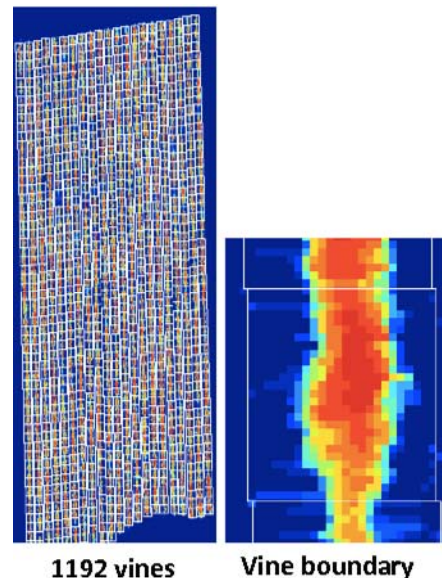


Figure 5: Using information extracted from the GPS enables registration of the 3D-occupancy grid to specific rows and vines in the vineyard. Vines are planted in straight rows at 6 feet spacings and registration can be performed automatically, once the start and end location of the vines are known.

## Canopy Size

The final stage is to analyze the 3D occupancy grid for a given vine and generate a size measure. There are different options here for measurement of canopy size and ultimately a grower may want multiple different measures. There are three obvious measures of canopy size that are known to be useful in evaluating a vine's performance. These include the exposed leaf area, the shaded leaf area and the combination of the two being the total leaf area. The exposed leaf area is a measure of the leaves, which positively contribute to the vines health, the shaded area being the measure of leaves that do not photosynthesize any light and essentially act as a sink, draining nutrients from the vine without positively contributing the vine. These two measures are the ultimate desire to have a lucid measure of canopy performance.

In reality these two measures are difficult to obtain at any meaningful scale. The only true method that presently exists to obtain accurate measurements of both shaded and exposed leaf area is to mark the exposed leaves with spray paint, destructively remove all the leaves from the vine, sorting into exposed (those with paint) and shaded (those with no paint), and measure their area either manually by laying them out side by side or by using a machine which takes leaves as input on a conveyor belt and sums up their area.

The existing measurements that we can use as a groundtruth on a suitable scale are approximations of total leaf area. Total leaf area is a common measure of the vine size and vigor. The traditional measure used for decades is the winter pruning weight and a more recent approach is the percent shaded area on vineyard floor at solar noon.

Our approach to measuring the vine size is taking the volume of the occupied cells in the 3D occupancy grid for a given vine. We assert that this measure is a valid approximation of total leaf area as our scanners, mounted sideways on the vehicle will see both the exposed leaves and also many shaded

leaves as many scan points penetrate between the gaps of the exposed leaves. Our approximation of total leaf area – the volume of occupied cells in our 3D grid – we validate against the winter pruning weight that is an established approximation of the total leaf area. We present details on this validation later in the results section.

### **Crop Size Measurement**

We deploy a sideways-facing camera and lighting on a small vineyard utility vehicle to detect the grape berries and predict the harvest yield – the crop size. For our experiments we use a Canon SX200IS, mounted facing sideways at the same height of the fruit zone, capturing images of the crop. The camera is set in continuous capture mode, recording images at 3264 x 2448 resolution, at approximately 0.8Hz. We mount halogen lamps facing sideways, illuminating the field of view of the camera to improve the lighting of the fruit-zone, which is often in the dark shadows of the canopy. The camera vehicle is driven along the rows in the vineyard capturing images at approximately 0.5m/s. The images capture the vines and are processed with our algorithm to detect and count the crop. In traditional vineyard yield estimation the crop components that are measured to derive a final estimate are:

1. Number of clusters per vine (60% of the yield variation)
2. Number of berries per cluster (30% of the yield variation)
3. Berry size (10% of the yield variation)

These three components combine to describe all the variation in harvest yield. Current practice is to take samples of each of these components to compute an average and compute the final yield. We take an approach to estimate the first two of these items together in one measurement – that of the number of berries per vine. The reason being that it is difficult, especially late in the season, to delineate the boundaries of clusters within images. However, it is possible to count the total number of berries seen, hence combining the two components – number of clusters per vine and berries per cluster – into one measurement: berries per vine. An interesting observation can be drawn that humans are better at counting clusters per vine and weighing individual clusters, whereas conversely it seems robotic sensing struggles to accurately count mature grape clusters. Instead it is easier to use robotic sensing to count the number of berries on vine, a measure that would not be possible for a human to directly produce.

Our approach does not attempt to measure berry weight. However, we account for 90% of the harvest yield variation with berries per vine (Clingeffer 2001). Furthermore, instead of taking a small sample and extrapolating, we aim to estimate non-destructively the specific yield at high resolution across the entire vineyard. Hence, we will not introduce sampling errors into the process. Our algorithm to detect the berries in imagery has three distinct stages:

1. Detecting potential berry locations with a radial symmetry transform
2. Identifying the potential locations that have similar appearance to grape berries
3. Group neighboring berries into clusters

#### **Detecting Potential Berry Locations with a Radial Symmetry Transform**

The first step of our algorithm is to find points with a high level of radial symmetry as these points are potential centers for grape berries, see Fig. 6. To find these points, we use the radial symmetry transform (Loy and Zelinsky 2003). The algorithm is robust to the issues of lighting and low color contrast, which cause problems for the existing crop detection techniques that rely on simple color discrimination (Jimenez et al. 2000, Dunn and Martin 2004). The approach detects the centers of berries of all colors, even those that are similarly colored to the background leaves.

The radial symmetry transform requires us to know the radii of the berries as seen in the image ahead of time. The berry radii (in pixels) are dependent on the focal length of the camera, actual berry size and the distance from the camera. The focal length is kept fixed in our tests and the vehicle maintains a relatively constant distance from the vines. There is still variation in the radius the berries appear in the image from differing berry sizes and also some variation in location within the vine. We account for this variation by searching for radially symmetric points over a range of possible radii,  $N$ . Individual radii are denoted as  $n$ .

The transform first computes the locally normalized gradient  $\mathbf{g}$  with magnitude and orientation information at each image pixel. In a Hough Transform like setup, each edge pixel  $\mathbf{p}$ , with a gradient value above a threshold  $T$  votes for possible points of radial symmetry  $\mathbf{p}_s(\mathbf{p})$  given by:

$$\mathbf{p}_s(\mathbf{p}) = \mathbf{p} \pm n \frac{\mathbf{g}(\mathbf{p})}{\|\mathbf{g}(\mathbf{p})\|}. \quad (1)$$

For each radius  $n$ , these votes from the edge pixels are counted in a vote image  $F_n$ , which is then smoothed out with  $A_n$ , a 2D Gaussian filter, to produce  $S_n$ , the radial filter response at radius  $n$ . These filter responses at different radii are then combined to form the overall radial filter response  $S$  which is given by.

$$S_n = F_n * A_n \quad (2)$$

$$S = \max_n S_n \quad (3)$$

We compute local maxima in the response image  $S$  with a non-maximal suppression, and threshold to find the potential centers. We choose the threshold to ensure as many berry centers are detected as possible at the expense of admitting many false positives. We use the following stages in the algorithm to filter out the false positives.

### Classifying Interest Points Appearing Similar to Berries

The next stage in our algorithm is to classify the detected points that appear most like grapes, see Fig. 6(b). We first take a patch in the image around each detected center. The patch size has a radius defined by the previous radial symmetry detector step. We then compute features from that image patch. The features we use are a combination of color and texture filters, which combine to form a 34 dimensional feature vector. We use the three RGB channels, the three L\*a\*b color channels and Gabor filters with 4 scales and 6 orientations. The features are not chosen specifically for the grape detection task – we use generic low-level image features.

We take a small number of training samples from our datasets, by selecting a random subset of images and manually define in the images which regions have grape berries. We compute our features in these regions that correspond to the positive examples of the appearance of berries. For negative examples we compute features at radially symmetric interest points outside of our defined crop areas.

Given an input image we take each radially symmetric interest point, compute the feature vector, and apply the k-Nearest Neighbors algorithm. The k-Nearest Neighbors algorithm computes the distance in feature space to every point in the training set and determines whether the nearest neighbors are positive berry examples or negative. If the  $k$  closest positive examples are closer than the  $k$  closest negative examples, that interest point is classified as a berry. We use a value of three for  $k$ , which empirically seems to function appropriately.

### Group Neighboring Berries into Clusters

After classification of the interest points, a small number of false positives still remain. Most of the remaining false positive detections are isolated while grape berries naturally occur in clusters so we apply contextual constraints that dictate that there should be a minimum number of berries in a cluster. We cycle through each classified berry, computing the distance to every other berry, and remove berries that do not have at least 5 other berries within their immediate neighborhood, which we define as a radius of 150 pixels. The process results in the clustered berries shown in Fig. 6(c).





(a) Detect Berry Locations with Radial Symmetry Transform



(b) Identify Locations with Similar Appearance to Grape Berries



(c) Group Neighborhoods of Berries into Clusters

Figure 6: Example images showing the functioning of our visual berry detection algorithm on a Gewurztraminer vine. Input image is seen in Fig 1. (a) potential berry locations in the image that have been detected as having radial symmetry. (b) points marked blue have been classified as having appearance similar to a berry. (c) berries that neighbor other classified berries are clustered together.

## Results

### Datasets

The results generated in this paper are from three different grape varieties – Concord, Gewurztraminer, Traminette and Riesling. Canopy size experiments were only on Concord due to ground truth availability.

For validation of our canopy size measurements, a two-acre, high-wire (6") cordon trained Concord vineyard was used to represent a sprawling canopy system. During the winter of 2009/10, vines were manually pruned and dormant cane pruning weights collected on 1,250 vines. Between 50-70 days after

bloom (full canopy development), vehicle-mounted laser scanners were used to collect canopy data that were further processed and compared to vine size information.

The Gerwurztraminer dataset was collected just before véraison, before color development, and the berries were green in color, see Fig. 1. The Gerwurztraminer dataset was collected from a commercial vineyard and therefore we did not have access to the harvest crop weights. Only 5 vines were included in the dataset and we used it purely for developing the berry detection algorithm.

The Riesling and Traminette datasets were collected from an approximately one acre plot of these *Vitis vinifera* varieties. The Riesling cultivar is a 'White Riesling' *Vitis vinifera* and the Traminette is an intraspecific hybrid. We used four rows of Traminette vines and four rows of Riesling varieties, 224 vines in total. The Traminette were at 8ft spacing and Riesling were at 6ft spacing, which totaled 450m of vines.

The vines in this acre plot were vertically shoot positioned and basal leaf removal was performed in the cluster zone, a practice performed by vineyard owners to expose the fruit to the sun to change the flavor characteristics of the grapes. The basal leaf removal also makes yield estimation feasible towards the end of the growing season because the occluding canopy is removed from the fruit-zone. On the Traminette vines the basal leaf removal was performed just on the East facing side of the row and on both sides of the Riesling vines. Our tests captured images from the East side of the rows. Despite not all of the crop being visible from the one side, we calibrate our measurements from a portion of the harvest data, which takes into account the percentage of the grapes that were not visible.

The Traminette and Riesling vines are white grape varieties, the images of the crop were collected post-véraison, and even at this late stage the fruit still had similar coloring to the background of leaves. Similarly colored clusters and leaves are challenging and demonstrate the ability of our shape and texture approach to detect the crop amongst the canopy.

### Canopy Size

Scanning laser data produced canopy volume information with a linear correlation of 0.65 with vine pruning weight. The laser and hand collected data and correlation is displayed in Figs. 7-9.

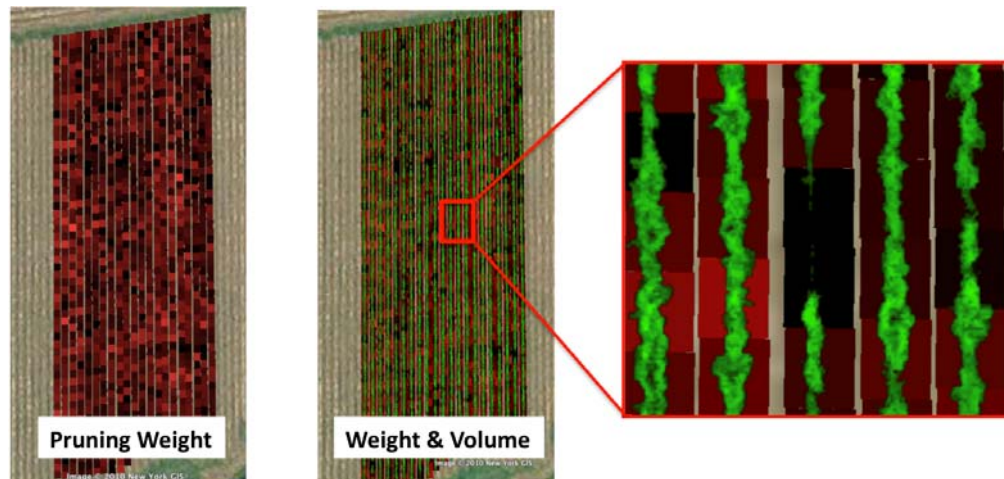


Figure 7: The winter pruning weights of the individual vines can be compared to the canopy scanning measurements. This top-down illustration gives a visual comparison between the two types of measurement. Left: The canopy pruning weight is visualized from black to red, where black is near zero weight and red is a large weight (which is around 5 pounds). Right: The canopy scan is rendered over the top as shades of green, where bright green represents high scan density in that vertical column in the occupancy grid and dark green is low-density. Inset: Zoom view of the comparison between scan and pruning weight. The gap in the scan clearly correlates with a near zero pruning weight, this is most likely the location of a dead vine.

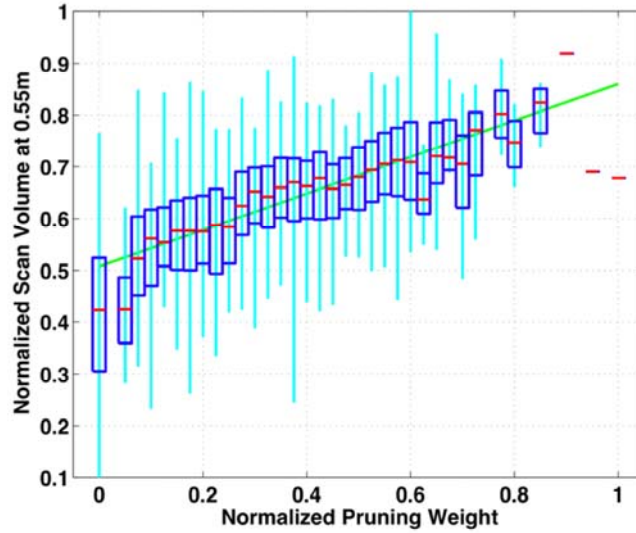


Figure 8: Correlation between vine canopy volume measured by the laser system and hand measured pruning weights. Data displays a strong relationship ( $r^2=0.65$ ), hence the ability to use laser volume as a yield predictor.

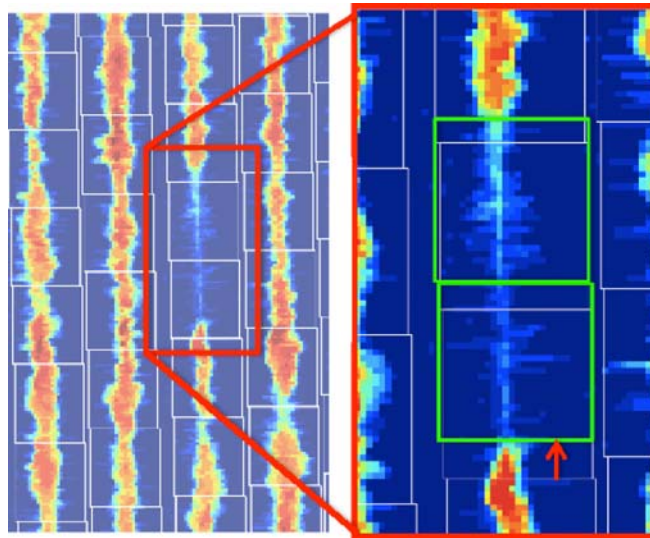


Figure 9: Example of using laser canopy volume measurement to detect missing vines.

### Berry Detection Performance

We first evaluate the performance of our berry detection algorithm, by selecting five images from each of the three different datasets; Gerwurztraminer, Traminette and Riesling. We processed the images with the berry detection algorithm and also manually counted detection statistics, presenting these results in Table 1. These show that our algorithm detects a minimal number of false berries. However, it is conservative, it does not detect a sizeable percentage of berries that are visible in the images and therefore has a high false negative count and therefore a moderate recall rate.

To gain an understanding of what part of the algorithm are most responsible for the false negatives detections we break-down the false negatives into the three stages of the algorithm; False detections that are not detected by the radial-symmetry detector, those that are misclassified, and those that are not clustered to neighboring berries. Table 2 presents the false negative breakdown by algorithm stage. The table shows that around 60% of all missed detections are caused by the radial symmetry transform, around 30% are classified as *non-berry* and only 10% of the false negatives are to be blamed on the clustering. We show in the following section that, even with these false negatives, we can still acquire accurate yield prediction because of the high precision rate. However, to further improve performance we

could look at modifying the radial symmetry transform to improve the number of berries it can detect without drastically increasing the false detections.

Table 1: Berry Detection Statistics. Berry count – The number of berries reported by the algorithm. True positives – The number of berries detected that were actual berries. False positives – The number of false berry detections. False positives – The number of berries visible in the image that were not detected. Recall – Percentage of visible berries detected. Precision – Percentage of detections that were berries.

Variety	Berry Count	True Positives	False Positives	False Negatives	Recall	Precision
Gerwurztraminer	1073	1055	18	354	74.9%	98.3%
Traminette	1116	1096	20	658	62.8%	98.2%
Riesling	784	762	22	657	53.7%	97.2%
Overall	2973	2913	60	1659	63.7%	98.0%

Table 2: Break-down of False Negatives

Variety	Not-detected	Mis-classified	Not-clustered
Gerwurztraminer	51.7%	31.9%	16.4%
Traminette	73.9%	16.0%	10.0%
Riesling	53.9%	40.2%	5.9%
Overall	61.1%	29.0%	9.7%

### Yield Estimation

For the yield estimation results, we compare our berry counts against actual harvest weights collected from the Traminette and the Riesling datasets. First, we register images together, and assign registered images to specific vines by defining the boundaries of the vines within the images, cropping-out overlapping content to avoid double counting. We conduct this process manually, but this could be performed automatically if we had in place a localization system, such as GPS and odometry system, which would be able to register data based on the fixed spacing of the vines. See Fig. 11. for examples of our automated berry counts being compared to the harvest data, the row and vine number, the harvest crop weight, and the detected berry count are displayed over the images. Cluster counts are also displayed, however our automated cluster counts were inaccurate because of the difficulties determining separate clusters – late in the season clusters tend to grow over each other. We focus on the berry counts in this work because they produce more accurate yield estimates.



Figure 11: Example showing berry detections for the Traminette (left) and Riesling (right) varieties used in the yield estimation experiment. Detected berries are highlighted by a red contour. The row and vine number, the harvest crop weight, the cluster counts and the berry count are displayed over the images.

Once registered to specific vines, we compare our automated berry counts with the harvest crop weights. Our automatically generated berry counts produced a linear relationship with actual harvest crop weights with correlation score  $r^2 = 0.74$ . Fig. 12 shows the data, correlation and the distribution of measurements.

We saw in Table 1 that our recall rate is not high and we also know that occlusions will cause further berries to not be counted by our algorithm. Despite these issues we still get good correlation to the

harvest weights. Reasons that our measurements achieve good correlation are first through the high precision of our detection algorithm which rarely counts false positives and also because the occlusion level and the percentage of visible berries that are missed has reasonable constancy across the vineyard. Further improvements to the detection algorithm and incorporating an estimate of any variations there may be due to occlusion will only improve the correlation score.

Finally, we evaluate the accuracy of our estimates in terms of predicting harvest weight. We fit a function to a part of our dataset that provides a mapping from berry count to harvest weight, and calibrates for the berries that are out of view and missed by the detection algorithm. We calibrate the function using two rows of data (either 48 vines for Traminette or 64 vines for Riesling), and apply the function to the other rows' berry counts.

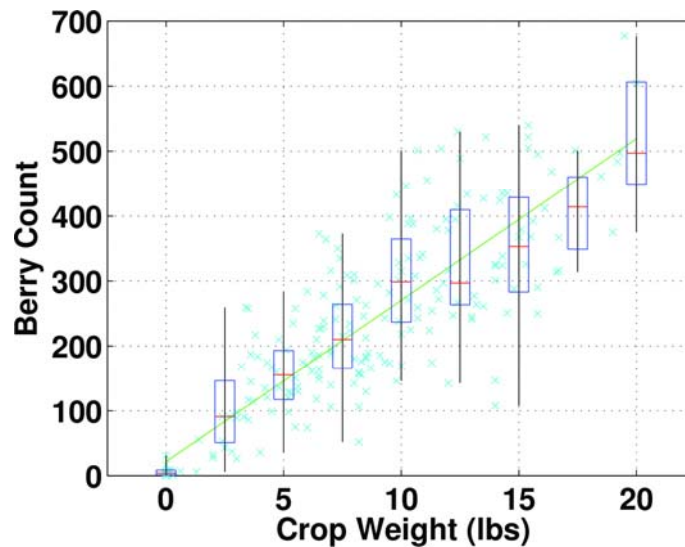


Figure 12: Correlation between our detected berry count and harvest crop weights gives a correlation score of  $r^2 = 0.74$ . The box-plot marks show the distribution within the measurements, the green line represents a linear fit and each of the blue data points represents the measurement of a vine, for a total of 224 vines. By comparison, the typical yield prediction approach would take a measurement at a small fraction of the vines and extrapolate, whereas we can measure every vine.

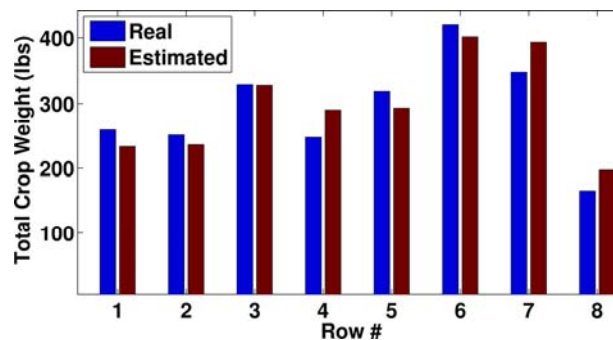


Figure 13: Graph showing our predictions of the harvest weight of rows in a vineyard. Rows 1 to 4 have 24 Traminette vines each. Rows 5 to 8 have 32 Riesling vines each. Predictions are generated from the functions mapping berry count to crop weight that were calibrated on data from other rows. Our yield estimates have a mean error of 9.8% of the weight of the row. Producing yield predictions at this accuracy at the resolution of single row surpasses the coarse sampling approaches currently used in vineyards.

Once we have functions calibrated from portions of our data we evaluate how accurate our berry counts are at predicting the total weight of other rows of vines for which we have not calibrated our measurements. Fig. 13 presents a graph of the predicted versus actual harvest weights for four rows of Traminette and four rows of Riesling vines. The average error of these results is at 9.8% of the eventual actual harvest weight. An estimate of harvest yield generated taken from measurements at every single

vine and achieving 9.8% accuracy for a row, already exceeds what is possible with current practices that are restricted to very coarse sampling across a vineyard.

## **Conclusion and Future Work**

We have demonstrated that laser sensing and computer vision can provide high-resolution automated canopy volume and crop yield estimates for vineyard management. For canopy volume we demonstrated laser based volume measurement that showed strong correlation with dormant pruning weight, the traditionally used manual indicator. For crop yield we combined traditional measurements of clusters per vine and berries per cluster, with a single estimate of berries per vine. The number of berries on a vine is known to account for 90% of the variation in harvest yield. We developed an algorithm to detect individual berries in camera images and evaluate in actual vineyard conditions. Unlike other image detection approaches, our approach is not reliant of color contrast, and can detect berries of all colors, even those that are similarly colored to the background of leaves.

We evaluated our approach on what we think is the largest automated crop imaging experiment demonstrated in a vineyard. On approximately 450m of vines we compute an automated estimate of the harvest yield using measurements taken from imagery and compare against the actual yield, meticulously measured by hand at harvest time. We compare our measurements to yield and show we can estimate the weight of a row of vines with 9.8% error.

Our results have significance on the future of vineyard operations through our ability to make yield, volume and efficiency predictions with high fidelity opening up the possibility of vineyard owners making precise adjustments to their vines, where previously they have been restricted to using cumbersome and inaccurate measurements.

There are a number of avenues of work to further improve our approach. For canopy volume a priority is reducing the use of high-end GPS/Inertial sensing. For yield, the first priority is to find ways to improve the recall rate of the current berry detection system. An extension would be to augment the berry counts with a method that measures berry size, which is known to account for the remaining 10% of the variation in final yield. In other ongoing work we hope to evaluate how much the function correlating visible berry counts to yield varies by variety, by trellis structure, by differing times of the growing season, and from year to year. We also will look to develop an approach to count grape clusters early in the season, even before berries have formed, to give vineyard managers information with maximum time before harvest to make the necessary adjustments to their vines.

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