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Towards Automated Yield Estimation in Viticulture

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Abstract

Forecasting the grape yield of vineyards is of critical importance in the wine industry, as it allows grape growers to more accurately and confidently invests in capital equipment, negotiate pricing, schedule labour and develop marketing strategies. Currently, industry standard forecasts are generated by manual sampling of bunch weights, grape size, grape numbers and seasonal predictions which takes significant time and effort and thus can sample a very small proportion of the vines. The first step in automating this procedure is to accurately estimate the weight of fruit on the vine and thus this paper presents a survey of the automated image processing methods which have been applied to this problem. Using manually harvested bunches photographed in a laboratory environment, the contribution of various bunch parameters to the weight of a bunch was examined to provide a baseline for the accuracy of weight calculation methods. Then, several recent colour classification methods were compared using images of grapes *in vivo*. The results showed that a linear regression approach to bunch weight estimation using berry number, bunch perimeter, bunch area and estimated bunch volume was accurate to within 5.3%. Results from *in vivo* colour classification showed a weight prediction accuracy of 4.5% on a much smaller dataset, demonstrating the promise of this approach in achieving grape grower yield estimation targets.

1 Introduction

Various yield-forecasting approaches are applied in modern agriculture for optimising market management. Doing so enables farmers to better monitor crop growth and provides a better overview of and increased control over the crop supply chain. Generally, these approaches are divided into two groups based on execution period; one uses historical records, for example, the rainfall, temperature, duration of sunshine, airborne pollen [Cristofolini and Gottardini, 2000] and crop yields in 5-20 years, and another uses a single growth cycle of the crop, analysing data such as remotely sensed images as well as sampling the fruit [Wulfsohn *et al.*, 2012] in one growth period.

Through their historical records, agriculture experts spend a great deal of time and energy to keep a record of variables such as environmental changes and corresponding annual crop yields. Much existing literature describes the production-forecasting model based on long-term records for the purpose of predicting yields.

For grape production, the relationship between weather and fruitfulness was investigated by Baldwin [1964] based on 18-year records for the sultana vine. Two variables assessed in this study are the hours of bright sunshine and the sum of daily maximum temperatures. The regression equation obtained in this paper indicated that yield could be forecasted but there was no evidence to suggest that other independent variables did not affect the accuracy of this model.

A 12-year cross validation study of yield-correlation masking was presented by Kastens and his colleagues [2005] for yield estimation in a major U.S. grape growing region. However, the author of this paper indicated that the data less than 11 years may not be enough to develop a reliable crop yield model.

Airborne pollen concentration data (for 5 years) was investigated for establishing a forecasting model for grape production by Cristofolini and Gottardini [2000]. Although this paper showed that there is a strong correlation between pollen concentration and grape production, this model is yet to be rigorous verified.

The obvious disadvantage of yield-forecasting from historical records in all of these approaches is the amount of time required and the relatively inaccurate results. Additionally, these approaches do not provide a direct and validated trend for crop yield estimation, and need further data to be collected for assessment purposes.

With the assistance of AVHRR (Advanced Very High Resolution Radiometer), remotely sensed images have been utilised for crop yield prediction, and this method has become mainstream in terms of regulating farming activities and maintaining a sustainable environment. A significant amount of research effort has been focused on generating fine resolution data from coarse resolution and then training a prediction model for grape, olive, corn and wheat yield [Bastiaanssen and Ali, 2003; Doraiswamy *et al.*, 2005; Bégué *et al.*, 2010]. The information abstracted from remotely sensed images is transferred to NDVI (Normalized Difference Vegetation Index) for exploring the correlation between NDVI and crop yield [Kastens *et al.*, 2005; Weissteiner and Kühbauch, 2005; Cunha *et al.*, 2010]. As well as recording environmental changes, most of these studies depend on long-term image capture. These studies just offer the spatial variation of crop yield for arranging harvest and they are more inclined to assessing the canopy of the crops, rather than the fruit themselves.

Given this, there is a high level of demand within the wine industry for the ability to forecast the final yield of grapevines from producers and consumers, who are both motivated by substantial economic benefits. Early forecasts of grape yield can significantly enhance the accuracy of managing labour, storage, delivery, purchases of related materials and so on. Most forecasting approaches mentioned in previous paragraph can be performed on grape yield but none of them are capable of providing a direct, efficient and valid forecasting model.

As a result, yield-forecasting methods abstracted from the current growth cycle are widely exploited. Improved image processing technology provides a promising and efficient measurement of the amount of grapes before or at harvest [Dunn and Martin, 2004]. In this paper the relationship between fruit weight and the ratio of fruit pixels to total image pixels in 16 images was investigated. The images used in this study were taken from 1m$*$1m portions of Cabernet Sauvignon grapevine canopies close to harvest. Even though these images were captured manually in ideal conditions (a white screen background, well-exposed fruit and vertical shoot positioning), the results of this experiment indicated 85% of the variation in yield combinations, which does not meet the requirement of 95% from vineyard specifications. These results do however indicate that automatic yield forecasting based on image processing of grapevine canopies is technically feasible.

Recently there has been an increase in literature analysing the application of colour-based image processing techniques to detect the presence of grapes in images. Separation in the RGB and HSV colour spaces, as well as intensity [Bjurström and Svensson, 2002] was implemented for assessment of grape vigour. The work by [Reis *et al.*, 2012] is similar to [Bjurström and Svensson, 2002], except that it only considered the RGB colour space with further morphological dilation applied to detect the grape bunches at night. R. Chamelat [2006] proposed a new method that combines Zernike moments for shape detection, colour information for recognition rate, and support vector machines for learning. By this new method the accuracy and the rate of grape recognition are improved compared with previous work from others.

However, all these works are heavily dependent upon the assumption that the grape pixels are sufficiently distinct from the rest of environment. Finding the closest Mahalanobis distance [Diago *et al.*, 2012] was applied to classify pixels which belong to grapes, wood, young leaves or old leaves. This method is more successful than [Bjurström and Svensson, 2002] and [Reis *et al.*, 2012], and is capable of correctly identifying the various classes that were labelled in the image, including grapes, branches, trees, grass, and poles. It should be noted that the success of this approach is reliant on good selection of the labelled points, and that repeated labelling and classification is necessary to identify elements of the images that need to have their own class. Farias *et al.* presented an image acquisition and processing framework for grape and leaf detection based on a six-step methodology [Farias *et al.*, 2012]. The performance of this method is more successful than that of [Diago *et al.*, 2012] since this method accounts for effects of illumination and automatically clusters the training data.

It should be noted that within this existing research, there has been a heavy focus on quantifying the classification ability of a variety of methods, but rarely do the authors of the studies attempt to determine how successful these methods are in actually predicting and forecasting the yields of the vines.

Other work has focused on more geometrically-based approaches. In terms of automatically calculating the berry size and counting the number of berries in a non-destructive way, Rabatel and Guizard [2007] presented an elliptical contour model to determine the shape of each berry from its visible edges.

Another automatic berry number and berry size detection approach was proposed by Nuske *et al.* [2011]. The radial symmetry transform of Loy and Zelinsky [2003] was used for recognizing the potential centres of grape berries, which were classified based on a descriptor that takes into account a variety of colour information. This approach is no longer limited to colour contrast as in [Dunn and Martin, 2004], but the estimation of weight still has an error of 9.8%, which is in excess of the winemakers target of 5% error. In the following year, Nuske

Figure 1: A sample image from KH-V dataset

and his research team extended this detection approach to model and calibrate visual yield estimation in vineyards [Nuske *et al.*, 2012]. The potential correlation between berry number and weight was studied in both papers. The relationship between the berry size and cluster volume was investigated but it did not show particularly promising predictive ability.

Although a national approach to grape estimation instruction [Martin and Dunn, 2001] was created in Australia, very few grape farmers follow these instructions rigorously, since all of the sampling work is performed manually, which is labour-intensive and time-consuming. This inevitably results in high labour costs, but also means that inaccuracy in forecasting yield will be caused by subjective judgment on the part of the workers. Thus, improving the accuracy of yield forecasting while decreasing the labour required would have significant economic benefits to the winemakers responsible for a large amount of litres of wine Australia produces each year.

Given the preceding survey of image processing methods in viticulture, and in order to investigate their feasibility, this paper examines the contribution of various visual bunch parameters towards estimating the weight of the bunch. Visual bunch parameters for a large number of images of harvested grapes in laboratory conditions have then been manually calculated and analysed to provide a baseline with which automated image processing methods can be compared. Finally several recent colour automated classification methods were compared using images of grapes *in vivo*.

Subsequent sections proceed as follows: Section 2 presents an evaluation of the performance of various metrics on manually labelled data sets in predicting the weights of grape bunches, and Section 3 evaluates the performance of an automatic classifier using images captured from on-vine grapes. Section 4 concludes by relating these results to the expectations of winemakers and discusses directions for future research.

2 Manual correlation of properties with weight on *ex vivo* grapes

Before attempting to perform automatic prediction of bunch weights, a variety of metrics have been tested on manually labelled data in ideal conditions in order to determine which methods have the best performance, prior to automating them.

A number of experiments have been conducted on images of *ex vivo* grape bunches in order to determine which yield the best results. The grape variety used was Shiraz, and bunches were collected just prior to harvest. A sample image from this data set is shown in Figure 1.

Given the 2-dimensional nature of the images collected, it is difficult to infer the weight of bunches of grapes, so a variety of metrics have been proposed and tested:

- Volume—calculated by taking cylindrical sections along the length of the grape bunches.
- Pixel area—calculated as the total number of visible grape pixels.
- Perimeter—calculated as the length of the border of pixels that have been labelled as grapes.
- Berry number—the number of visible grape berries.
- Berry size—calculated as the average radius of individual berries within bunches.

Manual colour classification and morphological methods have been applied on 16 images, with each image containing 18 bunches of grapes (288 bunches in total). 16 images were divided into 2 groups which are labelled as KH-V (Figure 1) and WV-H. The group of KH-V is used for filtering the ideal parameter set to segment the bunch from the background. The ideal parameter set is

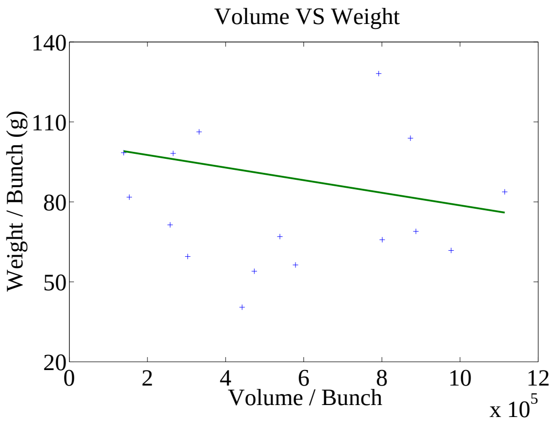

Figure 3: The relationship between of the volume of bunch and the weight of bunch

applied to process the images from the group of WV-H, for each of which the number of visible grape pixels has been calculated. From this the correlation coefficient has been calculated to be 0.88 (Figure 2), which is higher than 0.85 in Dunn's work [2004]. In addition to this, the average error between the predicted and actual weights using K-fold cross-validation (with K = 18) has been calculated to be 3%.

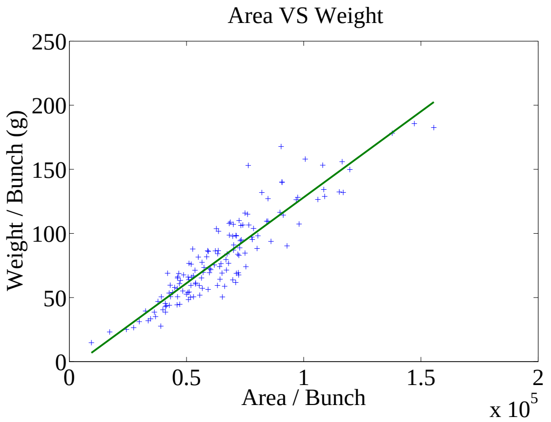

Figure 2: The relationship between pixel counts belonging to each bunch and the weight of each bunch for WV dataset

In order to mine more information for determining the correlation of bunch volume, bunch area, bunch perimeter and berry number with the bunch weights, 18 bunches in a single image of KH-V have been investigated. The correlations between each of these metrics and the weights of the grape bunches are illustrated in the following figures (Figure 3 – Figure 6).

The individual correlations between bunch weight and four metrics are relatively poor, as demonstrated by their correlation coefficients of 0.157, 0.681, 0.078 and 0.278 and as shown in Figure 3 – Figure 6. Again, K-fold cross validation has been applied for calculating the discrepancies in the weight predictions, with average errors of 15.76%, 7.07%, 17.59% and 13.83% respectively.

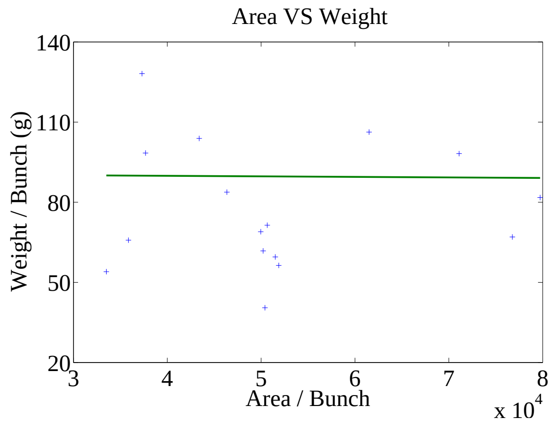

Figure 4: The relationship between of the area of bunch and the weight of bunch

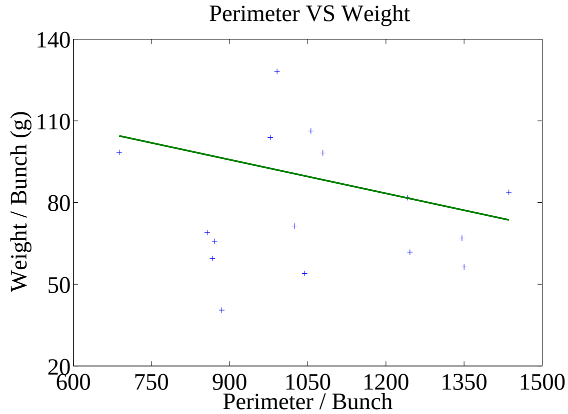

Figure 5: The relationship between of the perimeter of each bunch and the weight of each bunch

From this, it is clear that the method that most accurately predicts the yields of the grape bunches yield of the grape bunches is the number of visible pixels (bunch area) with an error of 7.07%. This result is better than the 9.8% error in [Nuske *et al.*, 2011], but it should be noted that all these images are captured in ideal conditions, with white background and the grapes ex vivo. Interestingly, the other metrics such as perimeter, berry number, and volume have performed quite poorly.

Additionally the relationship between the berry size of each bunch and bunch weight was assessed, but there is little to no correlation between these two variables, as demonstrated in Figure 7. So the related berry numbers were multiplied with the average berry size of each bunch, shown in Figure 8. The correlation coefficient in this case is 0.7, which is slightly better than the result from Figure 6, but still not enough for precise yield prediction.

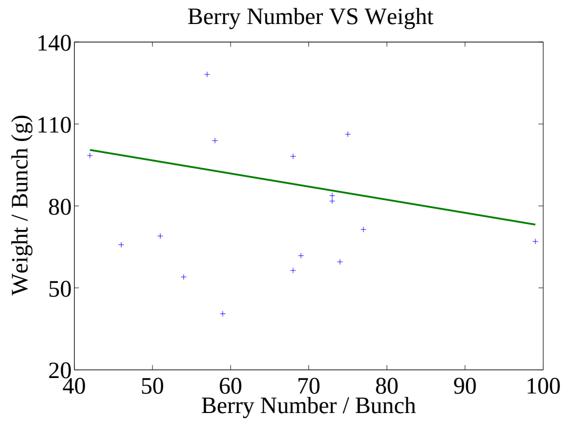

Figure 6: The relationship between of the berry number of each bunch and the weight of each bunch

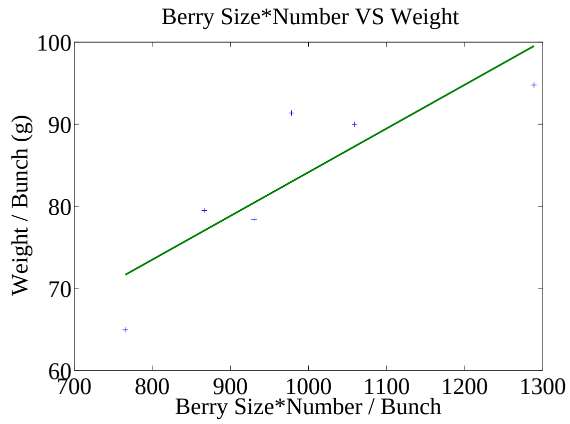

Figure 8: The relationship between the berry size multiplied by the berry number of each bunch and the weight of each bunch

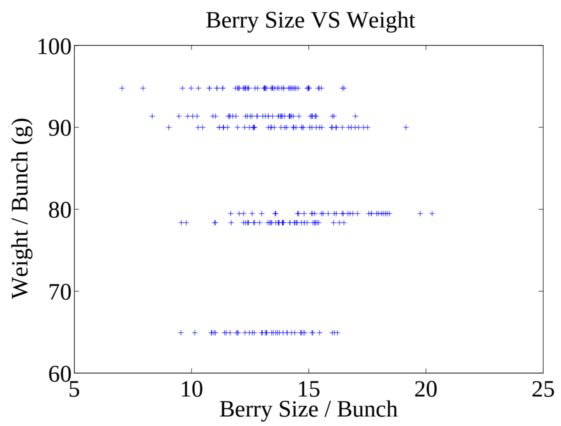

Figure 7: The relationship between of the berry size of each bunch and the weight of each bunch

Given the relatively ordinary performance of the individual metrics in isolation, multi-dimensional analysis has been investigated as a means of improving the results.

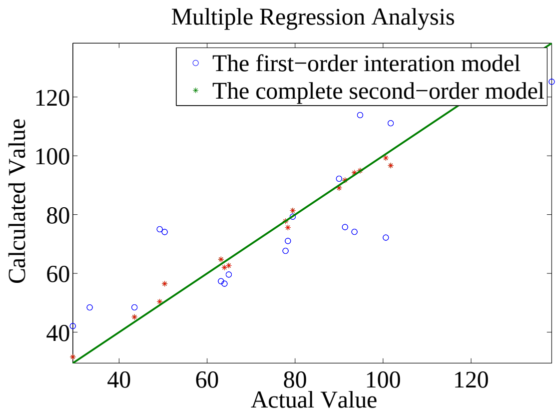

Figure 9: The multiple regression analysis of 16 bunches by combining bunch volume, bunch area, bunch perimeter and berry number

By combining the metrics of volume, bunch area, bunch perimeter and berry number, two correlation coefficients calculated by multiple regression analysis were obtained: one is 0.7 from the first-order interaction model while another is 0.99 from the complete second-order model, as illustrated in Figure 9. The error percentages of weight prediction were 5.31% (first-order) and 24.86% (second-order) by K-fold Cross Validation (K=18). This indicates that the complete second-order model is overfitting so a first order model is recommended. The results from the first-order prediction are close to the limit required by grape growers, suggesting vision processing is feasible at least in ideal conditions.

3 Automated image processing

3.1 Image processing tools to detect image properties

Given the strong performance from pixel based prediction, the remainder of this paper is focused on experiments to determine the performance of methods of automatically detecting and classifying pixels in images of grapes, concluding with an evaluation of the predictive ability of these methods.

Another area of research that has been focused on pixel-level classification is skin detection and classification [Jones and Rehg, 1999; Phung *et al.*, 2005]. One of the most successful approaches in this area has been the use of colour histograms, which we now present in more detail. This has been demonstrated to be successful in particularly challenging environments where there are significant similarities between the objects that are intended to be classified and the surrounding environment.

These colour histograms are 3-dimensional, with one dimension per colour channel, and are constructed in the following manner: pixels that have been manually labelled as being either grape or non-grape are accumulated within two separate histograms. These histograms will contain the number of occurrences of each pixel combination in both the grape and non-grape sets.

Following this, the histograms are converted into a discrete probability distribution in the following manner:

$$\begin{aligned} P(r,g,b|grape) &= \frac{Nr,g,b|grape}{Ngrape} \\ P(r,g,b|\neg grape) &= \frac{Nr,g,b|\neg grape}{N\neg grape} \end{aligned} \tag{1}$$

At this stage, we have the conditional probability of a given pixel being a grape as well as the conditional probability of it not being a grape. Using this information, we can implement a Bayesian classifier for grape pixels based on a likelihood threshold, as was done in [Jones and Rehg, 1999; Phung *et al.*, 2005], where a pixel is classified as being a grape if:

$$\frac{P(r,g,b|grape)}{P(r,g,b|\neg grape)} > \alpha \tag{2}$$

Here α is a threshold that can be used to vary the true positive and false positive rates of the classifier.

This histogram inherently gives the classifier the ability to be able to classify pixels down to the size of the bins used in the histogram, which means that this approach does not face the difficulties of the aforementioned alternatives in terms of relying on the ability to correctly segment the classification space into grapes and non-grapes.

3.2 Prediction of weight using automatic classification using *in-vivo* dataset

In order to experimentally verify the performance of the classifier, images taken from the aforementioned data set used in [Dunn and Martin, 2004] have been manually labelled for the purposes of training and validating the performance of the colour histograms in predicting the yields of the grapevines.

The images below illustrate an example of the classification that results from using the optimal combination of parameters for both colour histograms (to be discussed shortly), colour thresholding in the RGB colour space, and a combination of fuzzy-clustering and SVM [Farias *et al.*, 2012]. Here, pixels that have been classified as grapes are indicated in red, with the manually labelled grapes shown in black.

Figure 10 shows that the colour histogram classifier (b) performs very well in terms of detecting bunches of grapes present in the image, as it successfully detects almost all of the grape pixels, whilst maintaining a small number of false positives in a challenging environment where there are similar coloured objects such

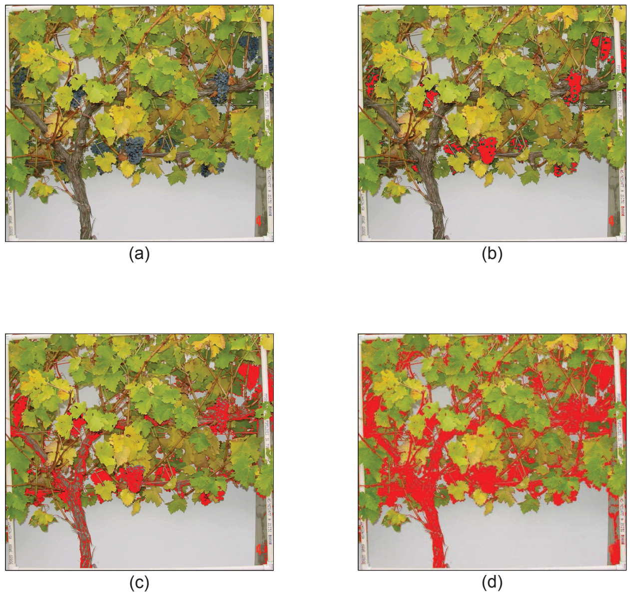

Figure 10: (a) Original image of in-vivo grapes. (b) Results of classification using colour histogram. (c) Results of classification using RGB thresholding. (d) Results of classification using fuzzy clustering and SVM.

as branches and posts. We observe relatively poor performance when using a threshold-based approach (c) or fuzzy clustering method (d), noting that although many of the grapes have been correctly identified, there is a significantly large amount of false positives, particularly on the branches. This is due to the fact that the branches are of a relatively similar colour to the grapes, particularly when compared with other objects in the image.

There are two important variables that dictate the performance of the colour histograms; the colour space used, and the number of bins in the histogram. The colour spaces that have been tested experimentally are RGB, HSV, and YCrCb. The histogram bin sizes that have been tested are 16, 32, 64, 128, and 256.

Figure 11 illustrates the ROC curves for these colour spaces as the size of the histogram bins vary, as well as the best responses from within each colour space.

These results support the observational evidence presented in the Figure 11. With the optimal combination of parameters, a true positive rate of 95% is achieved, with a false positive rate of only 2%. This is in contrast with the other two methods tested; RGB thresholding yields a true positive rate of 87%, with a false positive rate of 5%, whilst fuzzy clustering and SVM results in a true positive rate of 97%, but a false positive rate of 16%.

From this, we can see that a relatively small number of bins has the best response, and that the HSV and YCrCb colour spaces have the best results. This is similar to the results from [Jones and Rehg, 1999], where an increase in bin size improved performance, but different to [Phung

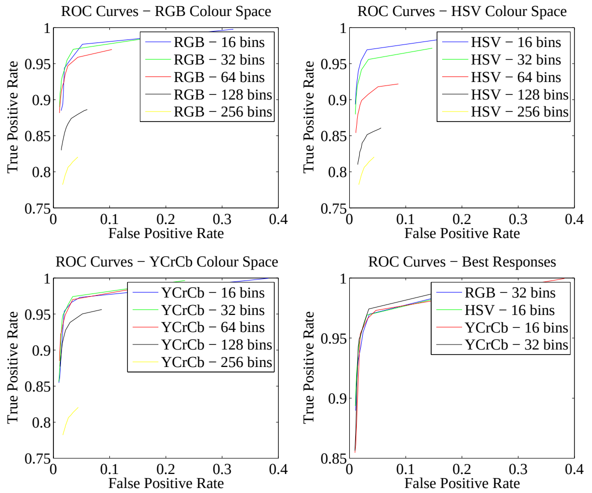

Figure 11: Effect of colour space and bin size on pixel classification accuracy

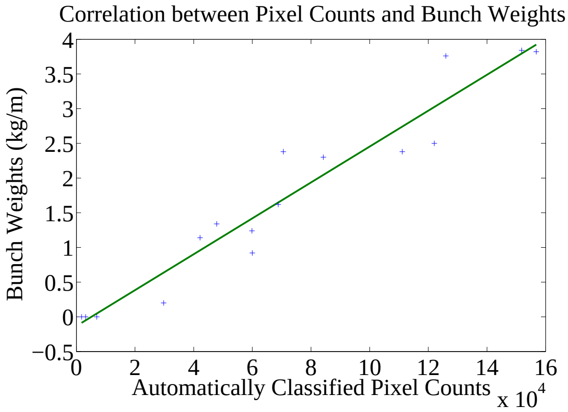

Figure 12: Correlation between pixel counts and bunch weights

et al., 2005], where optimal performance was achieved with the smallest bin size. [Phung *et al.*, 2005] suggests that this is possibly due to the fact that the training sets used in this work and in [Jones and Rehg, 1999] are comparatively small, resulting in poor results for a large number of bins due to the fact that much of the colour space has not been well represented.

Note that another advantage of using a smaller number of bins is the reduction in memory requirements due to not having to store the larger histograms.

As discussed above, we are most interested in the correlation between the number of grape pixels detected in an image and the weights of the bunches of grapes present in that image. In this regard, the results of our preliminary analysis are very promising. When using the classifier discussed above, we obtained the results shown in Figure 12 for the correlation between the number of automatically classified pixels and the weights of the grape bunches.

Here we have demonstrated that the number of detected pixels using the proposed method of pixel classification is able to account for more than 93% of the variation in the weights of the grape bunches. This is up from 85% that was achieved in [Dunn and Martin, 2004] using the same data set. This improvement is due to the fact that the method used in [Dunn and Martin, 2004] is based on applying thresholds across the RGB colour space. It is interesting to note that the performance of the automatic classification is very slightly better than that of the manual classification, which is most likely due to the fact that the automatic classification has been conducted on a limited data set.

In order to further quantify the predictive power of the proposed approach, the average error between the predicted and actual weights has been calculated using leave-one-out cross-validation (ignoring images where there are only very small amounts of grapes due to excessive relative errors) to be 4.46%. This relates well to the winemakers target of 5% error and shows that there is indeed great potential for automatic grape classification that is capable of accurately predicting the yields of grapevines.

4 Conclusion

This preliminary analysis suggests that there is great potential for automatic image processing to be used to improve the accuracy of grape vine yield estimates over existing manual methods of forecasting, with consequent economic benefits.

The results showed that a linear regression approach to bunch weight estimation using berry number, bunch perimeter, bunch area and estimated bunch volume was accurate to within 5.3% in ideal conditions whereas by only using berry number the accuracy decreased to 7.1%. Results from in vivo colour classification showed a weight prediction accuracy of 4.5%, however this made use of a very limited dataset and further field tests are planned for the current growing season.

Robust pixel-classification methods have also been demonstrated to be more accurate than colour thresholding, as well as increasing the ability to estimate the weights of grape bunches. Currently only a limited number of image processing and pixel classification methodologies have been surveyed and this will be expanded in future work. The sensitivity of classification to variation in the colour space and bin size in different environmental conditions will also be investigated.

One of the critical factors that will dictate the long-term success of this research will be the ability of the methods proposed and tested to be implemented in a real-world system. All bunches analysed in this paper have been post-veraison and close to harvest when manual sampling is currently used for yield estimation. Going forward, it is planned that entire vineyards will be surveyed and images collected for use in the grape classification. Currently, only a very small percentage (<0.2%) of vines area very small percentage (<0.2%) of vines is sampled using manual methods. By using a much larger sample size, it is anticipated that much more accurate yield estimates will be possible.

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References

[Cristofolini and Gottardini, 2000] F. Cristofolini and E. Gottardini. Concentration of airborne pollen of Vitisvinifera L. and yield forecast: a case study at S.Michele all'Adige, Trento, Italy. *Aerobiologia*, 16:171–216, 2000.

[Wulfsohn *et al.*, 2012] D. Wulfsohn, F. Aravena Zamora, C. Potin Téllez, I. Zamora Lagos, and M. García-Fiñana. Multilevel systematic sampling to estimate total fruit number for yield forecasts. *Precision Agriculture*, 13:256–257, 2012.

[Baldwin, 1964] J. Baldwin. The relation between weather and fruitfulness of the sultana vine. *Australian Journal of Agricultural Research*, 15:920–928, 1964.

[Kastens *et al.*, 2005] J. H. Kastens, T. L. Kastens, D. L. A. Kastens, K. P. Price, E. A. Martinko, and R.-Y. Lee. Image masking for crop yield forecasting using AVHRR NDVI time series imagery. *Remote Sensing of Environment*, 99:341–356, 2005.

[Bastiaanssen and Ali, 2003] W. G. M. Bastiaanssen and S. Ali. A new crop yield forecasting model based on satellite measurements applied across the Indus Basin, Pakistan. *Agriculture, Ecosystems & Environment*, 94:321–340, 2003.

[Doraiswamy *et al.*, 2005] P. C. Doraiswamy, T. R. Sinclair, S. Hollinger, B. Akhmedov, A. Stern, and J. Prueger. Application of MODIS derived parameters for regional crop yield assessment. *Remote Sensing of Environment* , 97:192–202, 2005.

[Bégué *et al.*, 2010] A. Bégué, V. Lebourgeois, E. Bappel, P. Todoroff, A. Pellegrino, F. Baillarin, *et al.*. Spatio-temporal variability of sugarcane fields and recommendations for yield forecast using NDVI. *International Journal of Remote Sensing*, 31:5391–5407, 2010.

[Weissteiner and Kühbauch, 2005] C. J. Weissteiner and W. Kühbauch. Regional Yield Forecasts of Malting Barley (Hordeum vulgare L.) by NOAA-AVHRR Remote Sensing Data and Ancillary Data. *Journal of Agronomy and Crop Science*, 191:308–320, 2005.

[Cunha *et al.*, 2010] M. Cunha, A. R. S. Maral, and L. Silva. Very early prediction of wine yield based on satellite data from Vegetation. *International Journal of Remote Sensing*, 31:3125–3142, 2010.

[Dunn and Martin, 2004] G. M. Dunn and S. R. Martin. Yield prediction from digital image analysis: A technique with potential for vineyard assessments prior to harvest. *Australian Journal of Grape and Wine Research*, 10:196–198.

[Bjurström and Svensson, 2002] H. Bjurström and J. Svensson. Assessment of Grapevine Vigour Using Image Processing. *Masters Thesis, Department of Electrical Engineering, Linköping University*, 2002.

[Reis *et al.*, 2012] M. J. C. S. Reis, R. Morais, E. Peres, C. Pereira, O. Contente, S. Soares, *et al.*. Automatic detection of bunches of grapes in natural environment from color images. *Journal of Applied Logic*, 10:285–290, 2012.

[Chamelat *et al.*, 2006] R. Chamelat, E. Rosso, A. Choksuriwong, C. Rosenberger, H. Laurent, and P. Bro. Grape Detection By Image Processing. *IECON 2006–32nd Annual Conference*, pages 3697–3702, 2006. IEEE Industrial Electronics.

[Diago *et al.*, 2012] M. P. Diago, C. Correa, B. Millán, P. Barreiro, C. Valero, and J. Tardaguila Grapevine Yield and Leaf Area Estimation Using Supervised Classification Methodology on RGB Images Taken under Field Conditions. *Sensors*, 12:16988–17006, 2012.

[Farias *et al.*, 2012] C. Correa Farias, C. Valero Ubierna, and P. Barreiro Elorza. Characterization of vineyard's canopy through fuzzy clustering and svm over color images. 2012.

[Rabatel and Guizard, 2007] G. Rabatel and C. Guizard. Grape berry calibration by computer vision using elliptical model fitting. *Presented at the 6th European Conference on Precision Agriculture*, Skiathos, Greece, 2007.

[Nuske *et al.*, 2011] S. Nuske, S. Achar, T. Bates, S. Narasimhan, and S. Singh. Yield estimation in vineyards by visual grape detection. *IEEE/RSJ International Conference*, pages 2352–2358. Intelligent Robots and Systems (IROS).

[Loy and Zelinsky, 2003] G. Loy and A. Zelinsky. Fast radial symmetry for detecting points of interest. *IEEE Transactions*, 25:959-973, 2003. Pattern Analysis and Machine Intelligence.

[Nuske *et al.*, 2012] S. Nuske, K. Gupta, S. Narasimhan, and S. Singh. Modeling and Calibrating Visual Yield Estimates in Vineyards. *Proceedings of International Conference on Field and Service Robotics*, 2012.

[Martin and Dunn, 2001] S. Martin and G. Dunn. Crop Development, Crop Estimation and Crop Control to Secure Quality and Production of Major Wine Grape Varieties: A National Approach. 2001.

[Jones and Rehg, 1999] M. J. Jones and J. H. Rehg. Statistical Color Models with Application to Skin Detection. *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 1999.

[Phung *et al.*, 2005] S. L. Phung, A. Bouzerdoum, and D.Chai. Skin Segmentation using Color Pixel Classification: Analysis and Comparison. *IEEE Transactions*, pages 148–154, 2005. Pattern Analysis and Machine Intelligence.