A Method to estimate Grape Phenolic Maturity based on Color Features

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Abstract. The phenolic ripeness of the grape is one of the most important parameters to determine the optimal time for harvest. A recent line of studies proposes visual seed inspection by a trained expert to determine Phenolic Maturity. In this paper a innovative method to estimate the Grape Phenolic Maturity based in digital images is presented. Three classes of seed are defined (immature, mature and overmature) by the expert (enologist) involved in the research. A robust method of segmentation was proposed. The classification of seeds according to their degree of maturity was performed by a Artificial Neural Network. Descriptor used by the Neural Networks corresponds to a histogram of the occurrence of colors in a color scale. The method as a whole proved to be simple and effective in the classification of seeds. Therefore, it is possible to visualize the implementation of the method in real conditions due the high performance obtained.

Keywords: Seed images,Phenolic Maturity,Neural Networks.

1 Introduction

The time at which the grape is harvested is related to the quality of the resulting wine. In particular, the Enologist is the one who must determine by a quantitative or qualitative method, if the grape is on the point of being harvested. From a technical point of view the estimated time of harvesting is done by studying the degree of Phenolic maturity of the grapes. To determine the degree of Phenolic maturity, the objective methods are very common. These methods are clasically related to the measurement of indicators such as pH, acidity, soluble solids, among others chemical analysis [6]. These methods are generally very accurate but involve high expensive laboratory analysis.

Moreover, subjective methods are based on the experience of the Enologist. In these methods the Phenolic Maturity is obtained by inspecting the aroma, flavor and appearance of both the fruit and the juice. These types of analysis are called Organoleptic Analysis. Traditionally, the organoleptic analysis is performed on the fruit of the grape, or on the juice of the grape.

Among the subjective methods a recent line of research examines the seed of the fruit to estimate its level of maturity. In [10] a study of the relationship between the development of the seed and the berry of the Vitis vinifera L. cv Shiraz was proposed. For the study, seeds were removed from the grape to analyze its physical properties such as weight, color and moisture, in addition to its phenolic components. Within the study three phases of growth and development of the seed were identified. In addition, changes were studied in the phenolic composition of the seeds in relation to the different stages of development and maturity of the seeds and berries.

In [4] a study of the relationship between the appearance of the seed and its phenolic maturity in cv. Carmenere was proposed. The objective of this research was to develop a simple objective indicator of maturity of the berry based on the color of the seed, in addition to comparing the evolution of their shape and color with the phenolic maturity of the berry. It was determined that there is a high correlation $R^2 = 0.96$ between the total polyphenol index and changes in the color of the seed.

Although the methods of visual inspection of the seed are of great interest due to its simplicity and low cost, they are prone to certain problems. First, the visual determination of the color is very subjective, which leads to errors. Secondly, it is not possible to infer information on the entire premises with a handful of seeds, which forces the expert to analyze a large volume of seeds to obtain representative information about the entire property. Finally, to make a subjective analysis a highly trained expert is required, someone who is aware of recent progress in this field, an expert who is not always available [5].

Given the above problems, it is attractive to develop automatic techniques for visual inspection of the seed. Works on this line can be seen in [1] and [11], where by using image processing techniques and pattern recognition the phenolic maturity of grape seeds is estimated.

In line with previous work, this research addresses the problem of estimating phenolic maturity by inspecting images of the seed. The estimation of the phenolic maturity as a problem of supervised classification is formulated and the methodology of pattern recognition is applied. Three classes of maturity in which the grapes are found are defined. These classes correspond to immature, mature and overmature class. These classes have been defined with the help of an human expert allowing define useful information to make decision of when is the optimal point of the grape harvest. After this, based on a set of seeds per class a color scale is created in the CIELAB model using a Support Vector Regression (SVR). This scale ranges from a green color, corresponding to the immature state of the seed, to a brown color, corresponding to the state of maturity. The scale is divided equidistantly and a count of the number of pixels of the seed that belong to each section of the scale is made. To determine the sector to which a pixel belongs, the Euclidean distance between said pixel and all the pixels from the scale is calculated, considering that the CIELAB model is a uniform color space. The descriptor used for the training of neural networks corresponds to the number of pixels per section. The pattern classification is performed by a

Multi-Layer Perceptron (MLP), which corresponds to a universal approximator of functions. The training of the MLP is done by Bayesian Regularization algorithm [3], which provides objective criteria to find the number of neurons in the hidden layer of the network, avoiding the overfitting of the model.

The rest of the paper is organized as follows: Section 2 provides a description of the segmentation method employed . Section 3 presents the descriptor employed. Section 4 presents the details of the classifier employed to determine the maturity of the grapes. Experiments and results are provided in Section 5. Finally, Section 5 presents the conclusions.

2 Seed Segmentation Method

The first step in the classification of the seeds consisted on obtaining a correct segmentation of all seeds in the images. Overall, in the acquired images it is easy to differentiate the seeds from the background; however they do present certain defects. In the case of the images used in this work two major flaws exist: shadows and highlights. The $c_1c_2c_3$ invariant model used in [12] was adopted for this work, due to its good performance with shadows and highlights. The expression of the model is as follows:

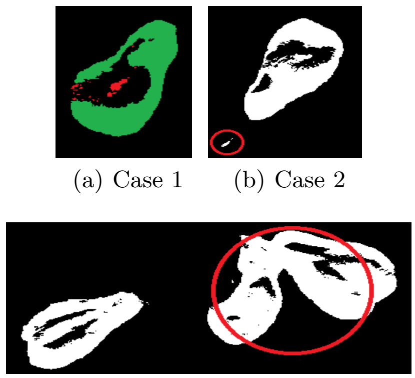
$$c_{1i,j} = arctan\frac{R_{i,j}}{max(G_{i,j}, B_{i,j})} \tag{1}$$

$$c_{2i,j} = arctan\frac{G_{i,j}}{max(R_{i,j}, B_{i,j})} \tag{2}$$

$$c_{3i,j} = arctan\frac{B_{i,j}}{max(G_{i,j}, R_{i,j})} \tag{3}$$

where $R_{i,j}$, $G_{i,j}$ y $B_{i,j}$ represents a pixel in the red, green and blue components from the image I.

Automatic segmentation of the channel c_3 is performed by the known method of Otsu [9]. The c_3 channel has been chosen due to the good results obtained in the proposed work on [2]. To properly compute the descriptors for the seeds is necessary to analyze each of them individually. Since the image used for the estimation of the maturity contains hundreds of seeds, isolation is required for each of them. This is done by calculating the connected components with connectivity 8 on the binary image resulting from the segmentation. This algorithm allows to identify and label the objects present within the image. The labeling of objects allows to estimate its area by determining the number of pixels that conforms it. Thus it is possible to observe a new problem: the segmentation identifies numerous objects with areas too small or large to correspond to individual seeds. Through a visual inspection of these objects is possible to distinguish three particular cases of errors. Figure 1 shows examples of the 3 cases identified where some objects are incorrectly recognized as individual seeds. Figure 1(a) shows the case 1, where the internal parts of the seed (red color) are improperly identified as non-seed (green color) objects. Figure 1(b) shows the case 2, where an object is detected even when there is no seed present. Finally, Figure 1(c) shows the case 3, where two seeds that are in contact with one another are identified as a single object.

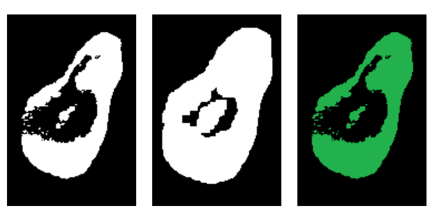


(a) Case 1 (b) Case 2

(c) Case 3

Fig. 1. Objects misidentified as single seeds.

To solve the problem presented in case 1 (Figure 1(a)), it is necessary to allocate the misidentified objects (red color) to the seed object to which they belong (green color). For this it is necessary to determine the sets of objects to be grouped together because they form part of the same seed. The proposed solution makes use image dilation. After the image dilation, the objects are recognized as being part of the same one. Figure 2 illustrates the described process. Figure 2(a) shows the original binary image, Figure 2(b) corresponds to the dilated binary image, and Figure 2(b) shows the grouping of all identified objects in the original image belonging to the same object in the dilated image.



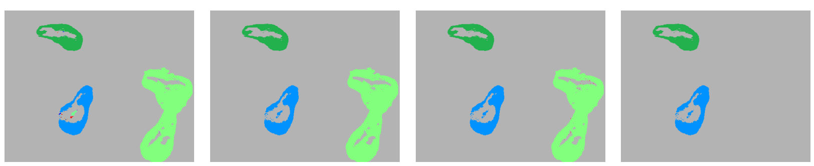
(a) Original (b) Dilation (c) Solution

Fig. 2. Process solution to the problem of object detection, case 1.

For cases 2 and 3 (Figure 1), it is necessary to filter out those objects that have a too small and large area respectively. To establish what is meant by a small or large area, using a Gaussian mixture model [8] with 3 components and unsupervised clustering is used. Previously it has been determined that there are 3 types of objects identified: individual seeds, small objects and large objects. For this reason three components are used in the mixture model. The unsupervised clustering allows to identify which are the objects that belong to each of the three categories.

Through the area average is possible to determine which category corresponds to each type of object. The component with the lowest average area corresponds to small objects (Component 1), the component with the highest average area is equivalent to large objects (Component 3) and the component equivalent to the median average area corresponds to the individual seeds (component 2).

Figure 3 shows the different steps in the seed identification process. Figure 3(a) shows the identification of objects in a section of the original image. It is possible to observe that the interior of the seed is not associated with it and objects with several seeds are considered as a single object. Figure 3(b) shows the solution to this problem (case 1), associating correctly the center of the seed as a single object. Figure 3(c) shows the resulting image filtering objects with smaller areas (case 2). Finally Figure 3(d) shows the filtering of seeds that are in contact with one another (case 3).



(a) Initial Obj. (b) Case 1 (c) Case 2 (d) Case 3

Fig. 3. Complete process solution to the problem of object detection.

It is noteworthy that the amount of eliminated objects with the mentioned filtering is less than 10% of the seeds, so that removing this set of objects does not influence the result of the classification. In this way a proper identification of the seeds within the image was done. With a correct segmentation is possible to extract the information needed to the seed classification according to their degree of maturity.

3 Descriptor Based on Color Histogram

In the previous section the results obtained from preprocessed stage corresponding to the segmentation of each image was presented. After this stage, the determination of the most representative descriptor for each class. The Maturity classes chosen corresponds to those suggested by the expert, which are: Immature, Mature and overmature. Figure 4 shows examples of seeds for each of the classes of maturity. Figure 4(a) corresponds to the immature class, Figure 4(b) corresponds to mature class and finally figure 4(c) to overmature class.

(a) Inmature (b) Mature (c) Overmature

Fig. 4. Images of the classes of interest: (a) immature class, (b) mature class, and (c) overmature class.

3.1 Color scale based on SVR

As shown in [4] the color scale is generated manually, which is very prone to human error. Therefore an automatic color scale based on regression support machines was devised, which are built based on all the acquired samples. For each sample acquired the representative color of a certain seed was estimated, where the method used was proposed in [7]. After obtaining the representative for each seed color, it was necessary to devise a way to build a continuous scale, for which a regression was performed based on the colors obtained.

The representative color is computed for each seed in the existing image. This value corresponds to a color in the LAB model, which generate a set of points in $\mathbf{R}^3$. A data set of the form $\mathbf{x} = (x_1, x_2, x_3)$ is obtained. These values correspond to the L,A and B channels, respectively.

The method used to perform regression is based on support machines for regression, which allows to generate continuous outputs based on the input data, where similarly to the case of the classification [13] a margin is built into the space of the target y.

Moreover, the SVR traditional model has an output y that corresponds to a real value, which limits us if we look based on a single color to estimate the other two with a single model. Following this it is proposed to generate two models, which based on a color channel estimated the other 2. Therefore, the proposed model is defined as follows

$$L_E(B) = \sum_{i=1}^{m} (\alpha_i^* - \alpha_i) k(B_i, B) + b \tag{4}$$

and

$$A_E(B) = \sum_{i=1}^{m} (\alpha_i^* - \alpha_i) k(B_i, B) + b \tag{5}$$

where k is the kernel function, α and b are parameters defined in the support vector machines, B corresponds to the values of channel B, L_E and A_E are the estimates values for channels L and A respectively.

3.2 Features Extraction

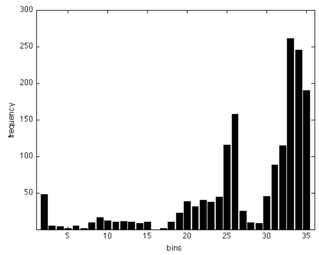
After the generation of the color scale, we proceed to the features extraction. The descriptor of each seed used in this works corresponds to a histogram generated based on the color scale. After creating the color scale with N points, the steps to generate the descriptor of each seed corresponds in the first instance, on dividing the scale in M equidistant sections, compute the Euclidean distance of each pixel in the seed with each N points on the scale, counting in the M sections the amount of pixels that are closer to them, noting the section that contains the shortest distance to the seed pixel.

Fig. 5. Color Scale generated with $N = 1035$ points.

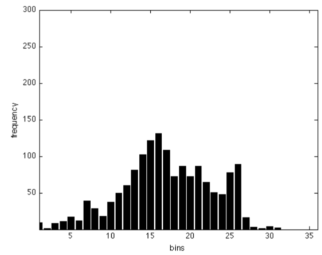
In the presented case has been chosen to generate a scale with $N = 1035$ points from the model obtained above. Figure 5 shows a representation of the generated scale. It is possible to notice that the start of the scale corresponds to the color of the seeds in their immature state, while that in mature class a brown color is obtained. Thereafter, this scale has been divided into $M = 35$ equidistant sections. After, the descriptor of each seed is obtained by calculating the distance of each one of the pixels to the N points of the scale. Figure 6 shows the histograms obtained by counting the sections containing the closest pixels to the seed. Figure 6(a) shows the histogram obtained for a seed corresponding to the immature class, Figure 6(b) shows the histogram obtained for a seed of mature class and Figure 6(c) shows a histogram of an overmature seed . Each of these histograms can be used as the descriptor used for subsequent training and classification of each of the seeds.

3.3 Training and Classification

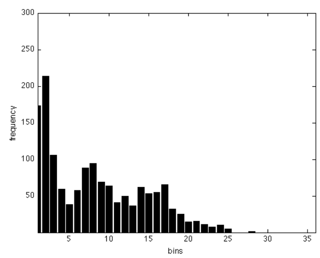
The architecture of the designed classifier for this problem comprises 3 neural networks, one for each class. The training set considers 140 seed images by class, and the test set corresponds to the 60 images of seeds kinds.



(a) Immature



(b) Mature



(c) Overmature

Fig. 6. Seed Histograms with $m = 35$ sections.

To determine the number of neurons in each hidden layer the algorithm of Bayesian regularization was used [3]. This algorithm allows to determine the number of effective parameters (EP) used by the neural network. Thus, it is possible to start with a low number of neurons in the hidden layer, observe the amount of EP used and gradually increase the number of neurons until that amount is stabilized. This stabilization indicates that a greater number of neurons is not necessary, since their additional parameters will not be used. For tests on three neural networks between 2 and 15 neurons in the hidden layer were considered, performing 1000 tests per case. Due to the desire of simplifying the networks it is expected to select a low number of neurons in the hidden layer that is able to achieve an appropriate amount of EP.

After the determination of the number of neurons in the hidden layer, the training of each of the networks was done. The training set corresponds to 140 seeds per class. Each network was trained 25000 times to obtain networks that perform suitable classification with the training set. To classify a sample, this is processed by the 3 already trained neural networks. It is posible determine the class to which it belongs by observing the network that produces the nearest to 1 output.

4 Results

The percentages of success for the proposed classifier are 95.52% for a training set with 140 seeds per class, and 93.33% for the test set of 60 seeds per class. As expected, the success rate for the training set is higher than for the test set, but still the result is quite high considering the difficulty of the problem.

If is desired to establish an individual performance per network is necessary to establish a threshold for the activation of each of them, since the network whose output is closest to 1 is not chosen in this case. Considering this, table 1 shows the percentages of success per network using a threshold of 0.2. This means that the network will be activated if the output X is in the range $0.8 <= x <= 1.2$.

	Training Set		Test Set	
Network	N seeds	Hit Rate (%)	N seeds	Hit rate (%)
Inmature	140	100	60	98
Mature	140	98	60	90
Overmature	140	98	60	87

Table 1. Success rates per class.

5 Conclusions

In this paper an original method for the estimation of grape maturity based on pattern recongnition techniques has been proposed.

The identification of the seeds within the image is performed by a segmentation process, which includes the automatic filtering of the objects that do not correspond to individual seeds. This is, small objects and groups of seeds that are in contact with other seeds. Also a solution using an invariant color model for the shadows and highlight problem is presented.

For the classification of seeds according to their degree of maturity the MLPs were used. To obtain the descriptors to be used by the MLPs, first is necessary the creation of a color scale based on the representative color of several seeds, which represents its different stages of maturity through time. The creation of this color scale allows calculating and representing each of the seeds through a histogram, which at the same time is used as the descriptor that allows the classification. Subsequently the number of neurons in the hidden layer of the MLP is determined, using Bayesian Regularization and multiple training of a MLP using a small set of samples. Once the number of neurons has been determined, numeroues trainings are performed, achieving the creation of a robust classifier for a test set of considerable size.

The proposed robust to overfitting classifier allows to obtain acceptable success rates for the problem. In general, it can be concluded that the methodology presented provides relevant information to objectively estimate the time to harvest.

Acknowledgment

This work has been fully funded by IDeA FONDEF CA12i10236: "Estimation of Phenolic Maturity based Grape Seed Image". Marco Mora, Claudio Fredes, Sergio Hernandez. National Commission for Scientific and Technological Research (CONICYT), Government of Chile.

References

1. Avila, F., Mora, M., Fredes, C.: A method to estimate grape phenolic maturity based on seed images. Computers and Electronics in Agriculture 101, 76 – 83 (2014)
2. Avila, F., Mora, M., Fredes, C., Gonzalez, P.: Shadow detection in complex images using neural networks: Application to wine grape seed segmentation. In: Adaptive and Natural Computing Algorithms, Lecture Notes in Computer Science, vol. 7824, pp. 495–503. Springer Berlin Heidelberg (2013)
3. Dan Foresee, F., Hagan, M.T.: Gauss-Newton Approximation to Bayesian Learning. In: IEEE International Conference on Neural Networks. vol. 3, pp. 1930–1935 (1997)
4. Fredes, C., Von Bennewitz, E., Holzapfel, E., Saavedra, F.: Relation between Seed Appearance and Phenolic Maturity: A Case Study Using Grapes cv. Carmenere. Chilean Journal of Agricultural Research 70, 381 – 389 (09 2010)
5. Gawel, R., Godden, P.W.: Evaluation of the consistency of wine quality assessments from expert wine tasters. Australian journal of grape and wine research 14(1), 1–8 (2008)
6. Gil, G.F., Pszczólkowski, P.: Viticultura: fundamentos para optimizar producción y calidad. Santiago: Universidad Católica de Chile (2007)
7. Hanbury, A., Serra, J.: Mathematical morphology in the cielab space. Image Analysis & Stereology 21 (2011)
8. Moon, T.: The expectation-maximization algorithm. Signal Processing Magazine, IEEE 13, 47–60 (1996)
9. Otsu, N.: A threshold selection method from gray-level histograms. Automatica 11(285-296), 23–27 (1975)
10. Ristic, R., Iland, P.G.: Relationships Between Seed and Berry Development of Vitis Vinifera L. cv Shiraz: Developmental Changes in Seed Morphology and Phenolic Composition. Australian Journal of Grape and Wine Research 11(1), 43–58 (2005)
11. Rodríguez, F., Ferrer, R., Lourdes, M., Rivas, C., Escribano, M., Heredia, F.: Preliminary Study to Determine the Phenolic Maturity Stage of Grape Seeds by Computer Vision. Analytica Chimica Acta 732(0), 78 – 82 (2012)
12. Salvador, E., Cavallaro, A., Ebrahimi, T.: Cast shadow segmentation using invariant color features. Computer Vision and Image Understanding 95, 238 – 259 (2004)
13. Scholkopf, B., Smola, A.J.: Learning with Kernels: Support Vector Machines, Regularization, Optimization, and Beyond. MIT Press, Cambridge, MA, USA (2001)