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GRAPE MATURITY ANALYSIS USING IMAGE PROCESSING

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ABSTRACT

A method for detecting automatically individual berries from a bunch sample of Cabernet grapes in vineyard based on a vision system using the Hough transform is presented in this paper. By applying a segmentation algorithm it is obtained a sub-image for each grape. A color space transformation from RGB to CIELAB or L* a* b* is applied to extract a* and b* color parameters. Then color information is contrasted against their sugar contents in degree Brix and pH; a correlation of both methods is presented. Berry size is also determined in this experiment and compared against a diameter measurement performed using a caliper.

1. INTRODUCTION

Many agriculture processes rely on decisions based on the appearance of the product. Applications for grading the fruit by its quality, size or ripeness are based on its appearance, as well as a decision on whether it is healthy or diseased. Humans are easily able to perform intensive tasks like harvesting using basically the visual sensory mechanism. This suggests that a system based on a visual sensor should be able to emulate the interpretation process of the human visual recognition system [1].

The use of machine vision systems to analyze images has many potential applications for automated agricultural tasks [1] and its use has increased during recent years. Researches in this area indicate the feasibility of using machine vision systems to improve product quality while freeing people from the traditional hand sorting of agricultural materials [2], which lead to significant economic and labor saving benefits [3]. A basic vision system is integrated by the following stages: image acquisition, pre-processing of image, segmentation, feature extraction, classification, inspection, and finally actuation, which is an interaction with the scene under study. Vision system developments in manufacturing can result in improvements in the reliability and the quality of the product as well as enabling technology for a new production process [4].

Wine industry is one of the most interested sectors on using vision systems to improve crop quality [5]. An increasing number of grape and wine producers are recognizing the advantages of understanding the inherent biophysical characteristics and performance of their vineyards for improved viticultural management and decision-making [6].

Winemakers commonly have a goal for grape ripeness that they would like to achieve for the wine they will produce.
Such a goal can vary, even within the same grape variety, depending on the type or style of desired wine [7]. For ripening characterization, physicochemical analysis like sugar content, acid and pH analysis are carried out [8], being sugar content one of the most important factors [9]. Fig. 1 shows a generalized graphical representation of grape berry compositional changes during development and ripening.

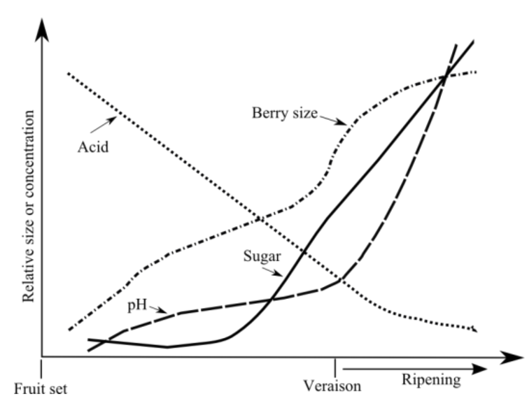

Fig. 1. Grape berry development and ripening

Sugar content of grapes is commonly monitored by periodically measuring soluble solids content of ripening berries with a refractometer. It operates by

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measuring the light refracted trough grape juice on a prism. Sugar level is generally expressed in degree Brix which represents grams of sugar per 100 grams of juice; thicker juice shows a higher degree Brix on the scale.

The key for a good estimation of fruit maturity is to collect a sample that is truly representative of the entire harvested unit (i.e., block of one variety). This requires a systematic sampling strategy that collects a large enough sample, in random fashion, to objectively represent the entire crop that will be harvested and processed [7]. Samples may be taken as individual berries or whole clusters. The fruit is crushed without breaking the seeds but taking care of crushing thoroughly each berry; then the collected juice is measured using a refractometer.
This work shows an automatic complementary method to measure grape maturity and size using image processing, giving the average, maximum and minimum values for a* and b* color parameters.

2. IMAGE PROCESSING

Image processing is the main component of a vision system. Different processing techniques can be applied to a fruit image in order to extract basic features that characterize it: intensity, color, shape and texture [10]. In this work the Hough Transform, which is an image processing technique to identify specific shapes in an image was used. This method intends to convert pixels in (x, y) coordinates to a different space where shapes can be identified. This concept can be applied to detect circles, ellipses, among other geometric shapes [11] [12]. Due to the small size of wine grape, it can be represented with a circular shape, which in terms of geometry is an specific case of an ellipse. Hough transform for circles have been used to find out individual berries in grape clusters for yield estimation in vineyards [13]. However, to our knowledge it has not been used for extracting color information.

When circle is detected on a particular image using the Hough transform, center coordinates *(x,y)* and radius information is obtained, so a segmentation process can be applied to extract that portion of the image in order to be analyzed. In agriculture, one the most important parameters to classify fruits is their color and size [14]. Color can be expressed in different spaces and proper selection of the color space is critical, and the choice depends on conditions of the object under study as well as the information required.

CIELAB color space or L* a* b* is an approximately uniform color scale [15]. In a uniform color scale, the distance differences between points plotted in the color space correspond to visual differences between the colors plotted. CIELAB color space is represented by three components or coordinates: L* coordinate that corresponds to the lightness, and a* and b* coordinates which are related to red-green and yellow-blue chroma perceptions respectively [16], as is shown on Fig. 2, CIELAB can also be represented in terms of cylindrical coordinates. The cylindrical coordinate (Figure 2b) system provides predictors of chroma C^*_{ab} and hue h_{ab} (hue angle in degrees) where:

$$C^*_{ab} = \sqrt{a^{*2} + b^{*2}} \quad (1)$$

$$h_{ab} = tan^{-1}\left(\frac{b}{a}\right) \quad (2)$$

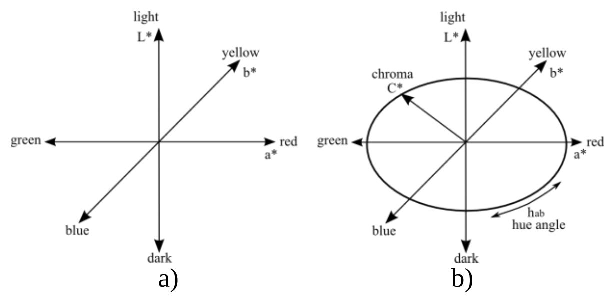

Fig. 2. (a) Cartesian CIELAB components representation. (b) Cylindrical CIELAB components representation.

CCD cameras produce images in RGB color space; this implies a space conversion from RGB to CIELAB to work with L*, a* and b* parameters [17].

In agriculture applications it is difficult to adapt existing hardware set-ups and image processing algorithms due to the fruit shape and color variability. The main objective of this research is to develop a vision system along with adequate image processing algorithms in order to extract the color information from individual grapes collected in vineyards as samples for maturity tests. As a result it is expected to provide more objective indicators of grape maturity to wine producers.

3. METHODOLOGY

Many grape berry sampling techniques have been tested [18]. The chosen method involved collecting three berries from each cluster of Cabernet grape;

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one berry came from the top of the cluster, one berry from the middle of the cluster and one berry from the tip of the cluster. Images from sampled berries of three different clusters were acquired using a high resolution USB CCD camera (DCU223) under light controlled conditions using the vision system set-up showed on Fig. 3.

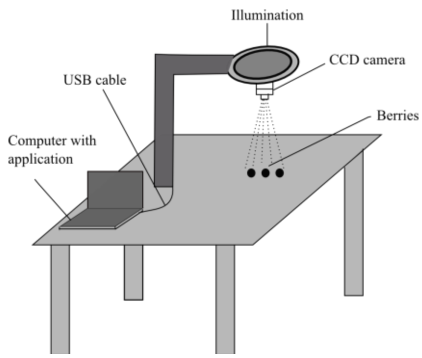


Fig. 3. Vision system Set-up used to acquire sample images

Acquired images were converted to gray scale and equalized using a contrast-limited adaptive histogram equalization (CLAHE), which enhances the contrast of grayscale images [19] [20]. A Hough transform was then applied in order to locate the grapes. Once the transform was completed, three vectors corresponding to (x,y) and radius parameters from berries were obtained; then, individual berries detected were segmented from background, saved in sub-images and then converted to CIELAB color space to be analyzed.
Fig. 4 shows a flow chart of steps performed for this analysis.

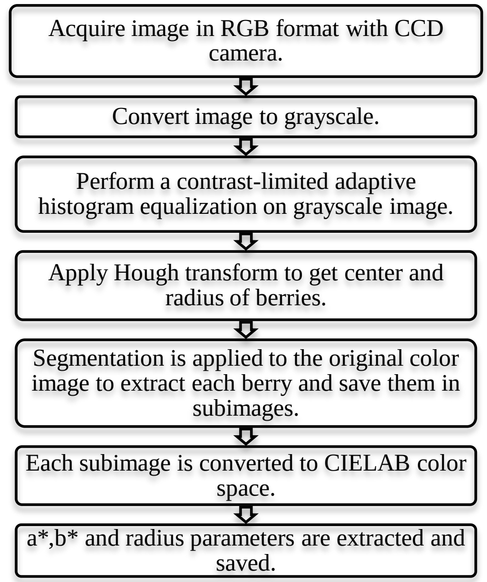
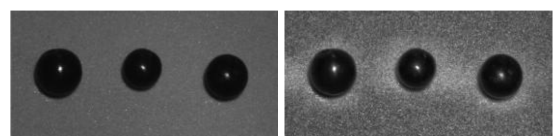


Fig. 4. Algorithm applied to grape images.

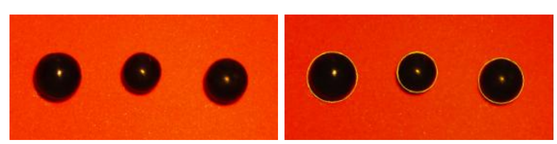
Fig. 5 shows the results of applying CLAHE equalization to the original grayscale image. As can be seen, obtained contrast between berries and background was improved.



a) b)

Fig. 5. Pre-processing of the image before applying the Hough Transform. (a) Original image in grayscale. (b) Results of applying CLAHE equalization.

After the Hough transform routine was finished, a drawing circle function was applied to the original color image in order to remark the circles (in yellow) as shown in Fig. 6.



a) b)

Fig. 6. Hough Transform. (a) Original image in RGB color space. (b) Results of the detected circles (remarked in yellow).

Using the information of center and radius corresponding to each berry, the segmentation process was applied to get their corresponding

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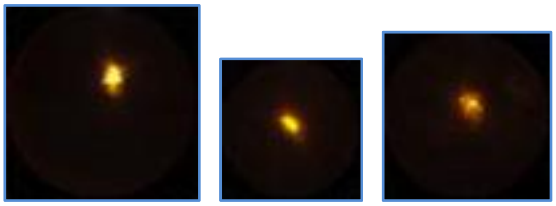
pixels and then saved on separate images as is shown in Fig. 7.



a) b) c)

Fig. 7. Sub-images depicting pixel information from each berry in RGB color space. (a) Berry 1 pixels. (b) Berry 2 pixels. (c) Berry 3 pixels.

RGB to CIELAB color space conversion was applied to the 3 pictures shown in Figure 3 to get a* and b* parameters, since the main interest of this article is to extract the color information, this procedure was implemented to three berries of three clusters. In order to correlate the color information with sugar content, a test was performed to the three clusters using a refractometer. Obtained values are presented along with a* and b* average parameters in

Cluster	Image processing measurements				Vineyard tests		
	a*	b*	$\sqrt{a^{*2}+b^{*2}}$	Berry size (mm)	°Brix	pH	Berry size (mm)
1	15.37	9.06	17.84	13.49	22.6	5.24	13.13
2	12.10	7.93	14.47	13.80	23.2	5.45	13.45
3	11.27	6.69	13.10	14.52	24.0	5.48	13.60

Fig. 8.

Cluster	Image processing measurements				Vineyard tests		
	a*	b*	$\sqrt{a^{*2}+b^{*2}}$	Berry size (mm)	°Brix	pH	Berry size (mm)
1	15.37	9.06	17.84	13.49	22.6	5.24	13.13
2	12.10	7.93	14.47	13.80	23.2	5.45	13.45
3	11.27	6.69	13.10	14.52	24.0	5.48	13.60

Fig. 8. Average color and size information of each cluster along with traditional vineyard test results.

4. CONCLUSIONS

Images of sampled berries from wine grapes were acquired, enhanced (using CLAHE equalization), segmented through Hough transform and individually saved in sub-images for color inspection.

Each berry image was converted to CIELAB color space, a* and b* parameters were extracted and compared against degree Brix (measured with a refractometer) as well as to their pH value. Data were analyzed yielding the same evolution. As we can see on

Cluster	Image processing measurements				Vineyard tests		
	a*	b*	$\sqrt{a^{*2}+b^{*2}}$	Berry size (mm)	°Brix	pH	Berry size (mm)
1	15.37	9.06	17.84	13.49	22.6	5.24	13.13
2	12.10	7.93	14.47	13.80	23.2	5.45	13.45
3	11.27	6.69	13.10	14.52	24.0	5.48	13.60

Fig. 8, grape cluster with higher degree Brix showed lower a* and b* color parameters which is a good indicator that the system provides promising values. Berry size was also determined, calculated sizes presented a maximum error of 7%, but this error is also obtained when is measured manually due to the grape is no completely spherical.

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