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A method to estimate Grape Phenolic Maturity based on seed images

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ABSTRACT

The timing of the grape harvest has a strong impact on wine quality. A recent line of studies proposes visual seed inspection by a trained expert to determine Phenolic Maturity. In this paper a method is presented to estimate Grape Phenolic Maturity based on seed images. The acquired images present problems such as shadows, highlights and low contrast. Two classes of seed are defined (mature and immature) by the expert (enologist) involved in the research. The method consists of three stages: segmentation, feature extraction and classification. Segmentation was performed by a hybrid method combining supervised and unsupervised learning, feature extraction by the Sequential Forward Selection algorithm, and classification by a Simple Perceptron. The results for each stage are presented. 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.

1. Introduction

Wine is a highly valued drink due to its natural origin and it has proven antioxidant benefits. In wine-producing countries, improvements in the production process have a strong economic impact. One of the relevant factors to obtain quality wines is to correctly determine the harvest timing for the grapes.

Traditionally, Phenolic Maturity estimation is done by a human expert (enologist) through organoleptic inspection of samples, or by laboratory chemical analysis. A recent approach to determine the Phenolic Maturity involves visual inspection of the seed. A pioneering work in this field is found in Ristic and Iland (2005) where a high correlation between visual seed appearance indicators (color, texture and shape) and the state of Phenolic Maturity of the grapes is reported. In a recent paper (Fredes et al., 2010), the evolution of wine astringency is studied, a color scale of the seed is developed, and the colors associated with minimal astringency are established.

Visual inspection of the seed has the advantage of being simple to perform, and does not require equipment. However, visual inspection requires a highly trained expert, and it is inherently subjective and imprecise, since color perception varies from one person to another. Furthermore, for the study to be representative, a large number of analyses must be performed, which is not feasible in real conditions.

The images involved in this work are those acquired in Fredes et al. (2010). These images have various problems, such as shadows, highlights and low contrast between pixels of the seed and the shadow.

Shadows are caused by light direction in image acquisition. Shadows produce serious problems in the segmentation, analysis and tracking of objects. Studies that describe and classify the great variety of techniques for the treatment of shadows can be found in Al-Najdawi et al. (2012) and Sanin et al. (2012). Shadows are divided into cast shadows and self shadows (Xu et al., 2006a); the cast shadows are external to the object, while self shadows are on the object itself. It is noted that the shadows present in the images of this work correspond to the cast shadows type.

To detect cast shadows, there is an established line of research based on color models that are invariant to illumination (hereinafter invariant model or simply "invariant"). These models are called "invariant" because the color configuration obtained from them remains approximately the same in the presence of changes in image capture conditions (changes in the viewing angle of the object, in the orientation of the surface, and in lighting conditions). A representative work in this area is Salvador et al. (2001), in which invariant models are used to detect and classify shadows in a static image, and edge detection is used to segment regions with shadow. A method to eliminate shadows based on representing the color image using a gray-scale invariant model is proposed in Finlayson et al. (2006). In this model, the edge of the shadow is defined as the pixels which are present in the edges of the original image but which are not present in the invariant. The problem with this

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method is that to generate the invariant, it is necessary to identify the angle of projection of the shadow, which can be very difficult. A technique that combines two invariant models is proposed in Xu et al. (2006b), the first based on a normalization of the RGB model, and the second based on the model proposed in Finlayson et al. (2006). The HSI color model and the *c1c2c3* model are combined in Sun and Li (2010) to obtain a more robust shadow detection. These methods based on the invariant are of great interest because they are relatively simple to implement. However, in complex images (such as grape seed) the invariant models do not produce good segmentation results, since they are based on the detection of edges, which are difficult to determine in processed images, even for the human eye.

To address both problems of visual inspection and poor image quality, this paper considers the visual inspection of the seed as a problem of pattern recognition in digital color images. First, a segmentation method robust to common image problems (shadows, highlights and low contrast) is developed. A hybrid method for detecting shadows is proposed, which combines neural networks of supervised learning with invariant color models. Second, two classes of maturity are defined, immature and mature. A large set of color, texture and shape features are computed and the relevance of these descriptors is studied, using the Sequential Forward Selection algorithm according to the methodology proposed in Mery and Soto (2008). The cited study allows to find a representative and reduced set of descriptors to separate the patterns into the categories defined for the problem. Finally, due to the high performance of the identified descriptors, classification is performed by means of a Simple Perceptron, which allows to distinguish classes of linearly separable data. Overall, the ability to sort seeds as mature and immature provides the enologist with objective information in order to make a better decision about the timing of the harvest.

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

2. Hybrid method of object segmentation robust to shadows

The focus of this section is to describe in detail the hybrid method of segmentation robust to shadows. This method combines an unsupervised approach based on invariant color models and a supervised approach based on neural networks.

2.1. Determining relevant features for classification

A first approach to separate the seed from its shadow was the study of color characteristics. For this purpose, samples of pixels were taken both from seed and shadow in different images. The values of these pixels were transformed to various color models (RGB, HSV, YIQ, YCbCr, XYZ, CMYK, Lab, Luv, among others), including the invariant models *l1l2l3* and *c1c2c3* proposed in Gevers (1999). To determine the channels that allow greater distance between seed and shadow, the Sequential Forward Selection algorithm (SFS) was used (Jain et al., 1999). This algorithm provides a ranking of the features according to their contribution to the separation of the classes (in this case, seed and shadow). The highest-ranked features were the invariant model channels; however, the performance function obtained by the SFS algorithm yielded a value near zero. Fig. 1 shows that the SFS algorithm selected three color channels; adding a fourth channel did not significantly increase the classification performance. The channels selected by the SFS were *S* (from the HSV model), *l1* and *c3*. It is observed that

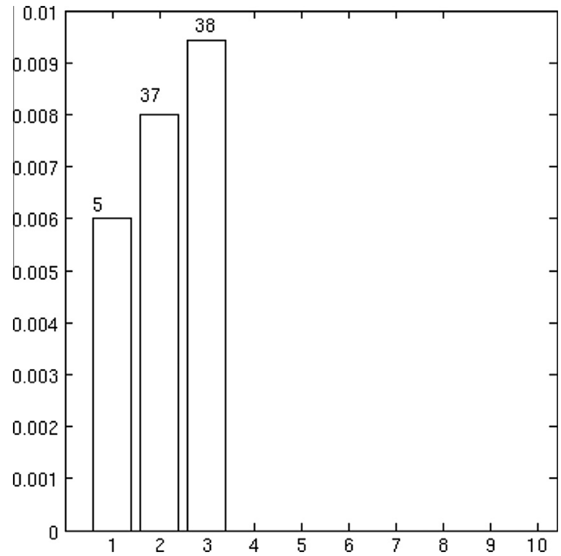

Fig. 1. Color channel selection using SFS algorithm.

the performance function provides a very small value, close to 1%. This shows that color characteristics are insufficient to separate the seed from the shadow.

Therefore, the use of texture features is considered to separate the classes, adopting the Haralick (Haralick, 1979) descriptors for this task. It is noted that these descriptors were chosen over other texture features, such as LBP and Gabor, due to the better performance of the Haralick descriptors in the analysis performed by SFS.

After the selection of descriptors, the extraction of features was performed as follows: 500 samples of seeds and 500 samples of shadows were taken from different images. Each sample corresponds to a window of 41×41 pixels. Fig. 2 shows the samples from one seed image. Thus, the training data set corresponds to a matrix of 1000 rows and 28 columns, where each column is a texture feature. For each sample, Haralick descriptors where computed. Initially, 28 texture descriptors were computed, and application of the SFS algorithm established that nine features yielded a good separation of the classes.

2.2. Segmentation using a neural classifier

A multilayer perceptron (MLP) was considered as classifier because this architecture corresponds to a universal function estimator, and it also allows to group patterns which are not linearly separable. For training, the Bayesian Regularization method was adopted (Forensee and Hagan, 1997). The advantage of this method is that it provides a criterion for determining the number of neurons in the hidden layer, based on the effective parameters of the network. Briefly, the procedure for determining the number of neurons of the hidden layer is as follows: gradually increase the number of neurons of the hidden layer until the effective parameters of the network stabilize.

The neural classifier has 9 inputs (one for each texture descriptor) and 1 output to differentiate between the two classes (seed and non-seed). To segment the seed by means of the neural network, a grid with cells of 41×41 pixels is set in the image. For each cell, the 9 selected Haralick texture descriptors are computed, which are then assigned as inputs to the neural network. The segmentation process is shown in Fig. 3. Fig. 3(a) presents an example of a seed image (Fredes et al., 2010), in which very little difference is observed between the edge of the seed and the shadow. Fig. 3(b) shows a cell on the original image, illustrating that the size of the