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Grape berry calibration by computer vision using elliptical model fitting

G. Rabatel, C. Guizard

Cemagref, 361 rue J-F Breton, BP 5095, 34196 Montpellier Cedex 5, France
gilles.rabatel@montpellier.cemagref.fr

Abstract

In the context of vineyard and wine process management, producers are looking for novel tools to estimate the growth stage and potential quality of vine grapes. Several studies show the importance of the berry size as a growing and quality indicator. This paper proposes an image processing method to estimate the berry size of vine grapes by image acquisition in the field. The goal is to recover the profile of each visible berry in the grape, including partially occluded ones. In the present approach, an elliptical contour model is used to recover the complete shape of each berry from its visible edges. This method combines a primary edge detection and cleaning process based on a watershed algorithm, and a direct least square ellipse fitting algorithm.

Keywords : vineyard, berry size, image processing, deformable templates

Introduction

Grape growers have to take into account the growing stage when scheduling treatment, irrigation or harvest operations. For instance, the farmer can pilot the growing by removing a part of the harvest, in particular during thinning process; this operation improves the harvest global quality. In the same way, the choice of the wine-making process depends on the expected quality of the product.

For these reasons, the prediction of the expected yield and quality of grapes at a former stage by in-field observation is an important requirement from grape growers. First scientific analyses on production estimation feasibility began in the 1950s (Wurgler et al, 1955). Studies on the relation between the bunch weight and quality appear later (Booyesen et al, 1978). Serrano et al (2002) showed the existence of a correlation between the bunch ripening volume and its weight to the vintage by carrying out large scale tests.

Several studies also demonstrate the importance of the berry size as a growing and quality indicator (Roby et al, 2004). The berry size can be correlated to water deficit. In red wine production, a small size is also an indicator of a better ratio grape-pomace /juice. Berry size heterogeneity also indicates a non-homogeneous maturation. All these data can help to produce better wine.

Berry size measurement is presently done by means of calipers. This method is mainly used in technical centers for experimentation purposes, and requires a manual separation of the berries. In this context, a method based on image analysis would be very helpful, especially if it is able to work directly on entire vine grapes.

Considering these various requirements in terms of grape volume and berry size estimation, an experimental tool, named REV¹, has been developed by Cemagref in 2005, in collaboration with the French Vine Technical Institute² and a cooperative of vine growers³. With this tool, numerical images of individual grapes in the field can easily be acquired, with correct control of target distance and light conditions. Its first objective was a non-destructive estimation of the bunch weight at an early stage, by using computer vision to estimate the grape volume from its visible area (Serrano et al, 2005). However, more detailed information such as berry color and size are also available, if appropriate image processing algorithms could be developed.

In the present paper, the feasibility of berry size measurement on such individual grape images is considered. In this approach, a first assumption is that an analysis limited to the visible berries in front of the camera is sufficient to provide valuable agronomic information. The challenge is then to recover the exact profile of as many berries as possible, including those that are partially occluded.

The segmentation of partially occluded biological objects in images usually requires deformable templates, in order to model the expected complete shape of objects (Manh et al, 2001). In the present case, an elliptical contour model is used, as being well adapted to berry profiles. This model is fitted using discrete edges resulting from a previous image preprocessing. Best model fittings are then selected using a quality criterion.

The paper is organised as following: first, the grape image acquisition tool is presented. Then the proposed image processing algorithm for berry size recovery is described, as well as the primary results obtained on a typical grape image. Finally, main issues and ways of improvement to achieve an operational system are discussed.

Image acquisition tool (REV)

The REV tool has been designed to acquire photographic images of isolated vine grapes in a way that is suitable for further image processing. Built around a digital camera with a 28 mm focal length, it includes the following features:

- an acquisition procedure using a flash synchronised with a high shutter speed (1/2000 s), in order to minimise the influence of ambient light.
- An orange colour "V" shape background. The orange colour has been chosen to facilitate the grape/background color segmentation, while the "V" shape keeps the bunch well centred.
- A rigid support to facilitate the apparatus handling and to guarantee a constant distance between the lens and the grape support as well as a constant camera view angle.

¹ REV : « Rendement Estimé par le Volume » (Yield estimation by volume)

² ITV: Institut Technique du Vin . Vinnopôle – BP 22. 81310 PEYROLE - FRANCE

³ Vine growers of Rabastens: 33 road of Albi 81800 RABASTENS - FRANCE

This tool is illustrated in figure 1.

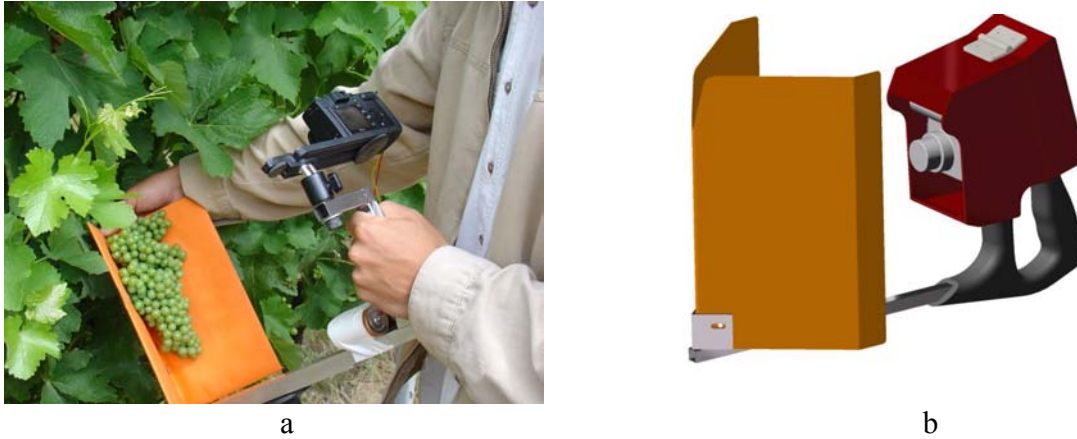


Figure 1. REV image acquisition tool
a) REV first prototype b) synthetic image of the final tool

Berry size recovering algorithm

A grape image consists of a set of berries with nearly identical colour properties, so that the available information for berry separation mainly rely on their contours. Thanks to the smooth 3D shape of the berries, these contours are accessible as luminance discontinuities in the image. Let us consider a typical vine grape luminance image and the corresponding gradient image (Figure 2).

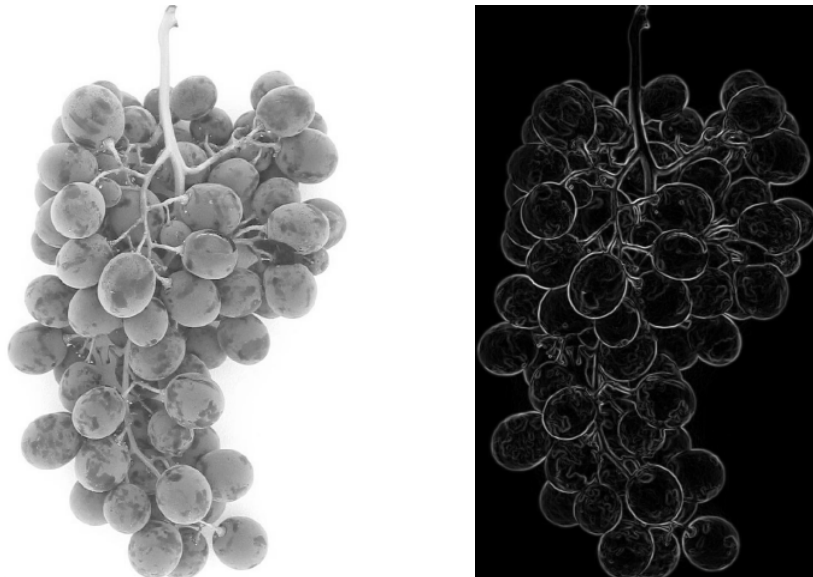


Figure 2. Grape image
a) Luminance image. b) Image of the gradient modulus

Figure 2.b shows that most of the berry contours correspond to high gradient values. However, other luminance transitions are due to surface heterogeneities on berries themselves. For this reason, whatever will be the process involved to recover the berry profiles from image edges, a primary selection among these edges has to be made. These two steps will now be considered successively.

Primary edge detection and selection

Starting from a gradient image such as in Figure 2.b, image edges are usually obtained using a thresholding operation. However, in the present case, we have chosen to use a watershed algorithm (Vincent & Soille,1991), which has the advantage of directly giving edges of one pixel width, and a result that is much less dependent on the threshold value⁴.

Figure 3.a gives the result of the watershed algorithm applied to a part of figure 2.b gradient image. Several steps are then applied to this watershed image to obtain a list of arcs:

- i) the entire watershed edges are analysed, looking for edge intersections, and stored as a tree structure of individual contour segments with recursive interconnections (Figure 3.b)
- ii) terminal segments in the tree structure with a length below a given threshold (10 pixels) are removed. The step i) is then applied again. This allows to eventually connect the remaining segments in larger ones. It results in a set of “cleaned” contours, as shown in figure 3.c
- iii) finally, each contour segment in the cleaned tree structure is decomposed to elementary arcs of constant curvature, that are stored in an arc list.

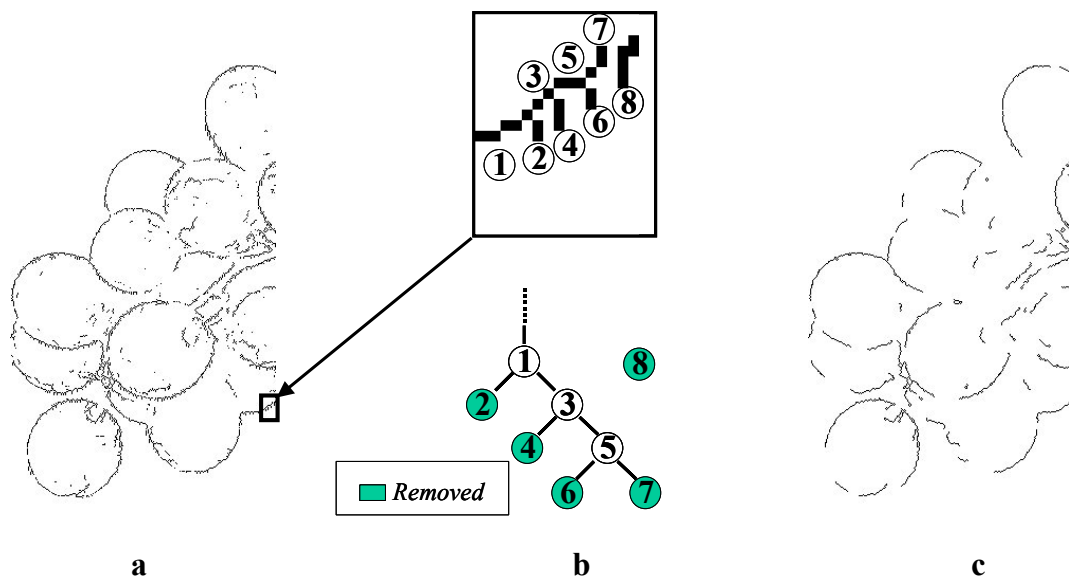


Figure 3. Watershed edge cleaning
a) Watershed initial result. b) Tree structure c) Cleaning process result

⁴ A threshold value is nevertheless required to remove very low level watershed crests.

Ellipse model fitting

We suppose in this part that we approximately know the centre position of a given berry. The challenge is thus, starting from this centre point, to fit an ellipse model to the berry edges around it.

Deformable templates can be considered as an extension of active contours or “snakes”, introduced by Kass et al (1988). In the present case, our ellipse model consists of 5 scalar parameters⁵, which have to be adjusted according to image data. Just as for snakes, deformable templates are usually fitted by using evolution “forces” that attract them to the image edges. Pressure (or “balloon”) forces can also be applied to make them evolve from a starting point (Cohen,1991).

In a primary stage of our study, we have tried to use such an evolution process, i.e. to make the ellipse model evolve from the center point, and then lock on high values in the gradient image. However, image edges due to berry surface heterogeneities introduce numerous erroneous model locking. A considerable improvement has then been obtained by using the list of arcs described above for model locking, for the following reason: for a given ellipse model instance, only “compatible” arcs can be selected, based on geometrical considerations (curvature value and relative orientation according to the ellipse). However, a lot of erroneous model locks were still observed.

Finally, the following procedure has been implemented: instead of applying evolution forces, we directly fit the ellipse model to a set of compatible contour arcs, using the least square algorithm proposed by FitzGibbon et al, (1999). The problem is here to define a pertinent set of contour arcs in each case. A combinatory procedure has been defined as following:

- i) for a given ellipse center, all contour segments in the arc list that are compatible with it (in terms of distance, curvature, orientation) are selected .
- ii) every possible subset of contour segments among the compatible contours found in i) are successively built. For instance, with 3 segments S1, S2, S3, 7 subsets will be built: {S1}, {S2}, {S3}, {S1 S2}, {S1 S3}, {S2 S3}, {S1 S2 S3}.
- iii) the ellipse fitting algorithm of FitzGibbon is applied to every subset, and only the best fitting is kept, according to a quality criterion.

The quality criterion is defined as:

$$C = \int_E \|\nabla I\| ds \quad (1)$$

where E is the ellipse curve and I is the original image. C is directly obtained by summing the pixel-values in the gradient image for every ellipse point.

⁵ Respectively ellipse center (2 parameters), 2 ellipse radii (small and large axes), and ellipse orientation.

The main potential problem with such a procedure is the risk of combinatorial explosion. For a set of n compatible segments, the total number of subsets is $2^n - 1$ (excluding the empty one). In the present case, the maximum number of segments has been set to 8 (i.e. 127 possible subsets). If this number is exceeded, shorter segments in the subset are removed .

Image scanning

In order to apply the fitting algorithm described above, a starting point inside each berry must be defined. This is presently achieved by setting arbitrary starting points in the image using a regular square grid of 10x10 pixels. Because starting points that are close to each other often generate similar or overlapping ellipses, a selecting process is applied after the scanning: ellipses that have a common portion of contour⁶ are detected, and only the one with the better quality criterion is kept (see equation (1)).

Finally, a last selection step is applied, that takes into account the ellipse dimensions.

Results and discussion

Figure 4 shows the results obtained on the image of figure 2.a, using the whole process described above. The initial edge detection is also given for analysis purpose. A total processing time of a few minutes has been necessary, using a standard Pentium 4 PC computer, and concerns essentially the image scanning phase.

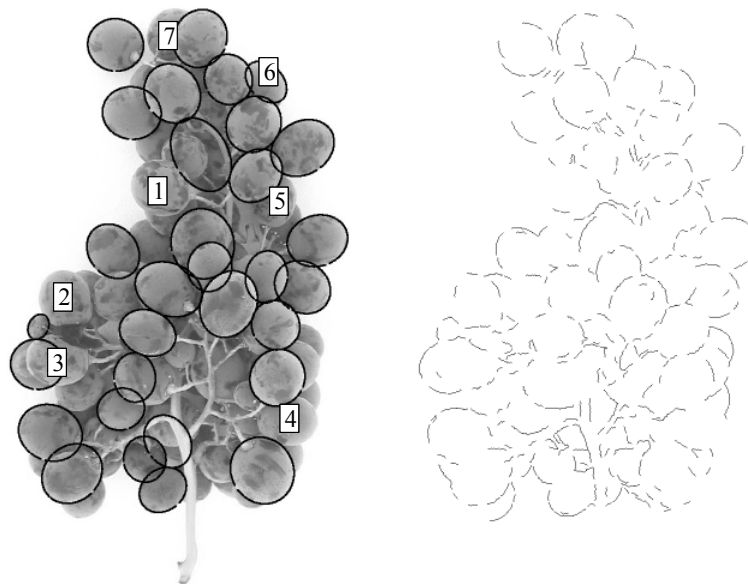


Figure 4. Example of ellipse fitting
a) *Algorithm output.* b) *Initial edge detection*

⁶ A tolerance of 3 pixels in the contour position is used for this test

As a first remark, these results show that the ellipse model is well-adapted to berry profiles: ellipse curves redraw the berry contours very accurately. However, about 1/3 of the visible berries on the grape vine are not detected, and some erroneous ellipses are present.

Various reasons explain the non-detection of visible berries. In cases 1 to 5 (see figure 4.a), it is due to the insufficient number or quality of the initial edges (Figure 4.b), leading to erroneous ellipses that have been rejected on quality criterion. In cases 6 and 7, a detailed analysis shows that *the correct ellipses have been found*, though they do not appear in the results: they have been replaced by erroneous ones in the selection process (in case 7, the selected ellipse, which included two berries, has finally also been removed on dimension criteria).

This illustrates the two main critical points of the proposed method. First, the performance of the initial edge detection step is determinant. Second, a substantial improvement might be obtained using a more elaborate quality criterion in the final model fitting selection

Conclusion

A complete image processing algorithm has been proposed to recover the berry profile in vine grapes, for various agronomic purposes. The ellipse fitting approach has shown its ability to provide very satisfactory results. However, further work is still necessary to achieve an operational system. It will concern:

- The improvement of the primary edge detection process: adaptive thresholding will be included in the watershed computation step, taking into account the local grey-level distribution.
- The improvement of the model fitting quality criterion: a multivariate classification will be introduced, taking into account the ellipse dimension, the gradient value distribution among the ellipse curve, etc. A learning step will thus be necessary.
- The algorithm optimisation in order to reduce the processing time.

By applying this new algorithm to grape images acquired in the field with the REV device (figure 1), non destructive quality assessment will become available, and replace destructive berry size measurement operations presently made in laboratory. According to the existing protocol, a set of about 25 grape images per parcel should be sufficient. The images will be stored and post-processed.

After a first phase of validation and calibration in ITV research laboratories, expected users are mainly the wine growing cooperatives, consulting companies or large vine producers.

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