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Automatic detection of bunches of grapes in natural environment from color images

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ABSTRACT

Despite the benefits of precision agriculture and precision viticulture production systems, its rate of adoption in the Portuguese Douro Demarcated Region remains low. We believe that one way to raise it is to address challenging real-world problems whose solution offers a clear benefit to the viticulturist. For example, one of the most demanding tasks in wine making is harvesting. Even for humans, the environment makes grape detection difficult, especially when the grapes and leaves have a similar color, which is generally the case for white grapes. In this paper, we propose a system for the detection and location, in the natural environment, of bunches of grapes in color images. This system is able to distinguish between white and red grapes, and at the same time, it calculates the location of the bunch stem. The system achieved 97% and 91% correct classifications for red and white grapes, respectively.

1. Introduction

Variable management practices within the field according to site-specific conditions can be promoted through the concept of Precision Agriculture (PA) and Precision Viticulture (PV). It is based on new tools and information sources provided by modern technologies, such as yield monitoring devices, soil, plant and pest sensors and remote sensing [3]. PA and PV generally have two main objectives: to render the production more cost-effective and to reduce its environmental impact. The first objective can be achieved by reducing production costs and improving productivity. The second objective relates to the accuracy and the ability to control the application of production factors, such as chemicals, which should be done within a fair measure of the real needs of crops.

The rate of adoption of these technological tools varies considerably from country to country, and from region to region [23]. In addition to environmental benefits, such as those related to better water and nutrient management, PA and PV systems can increase worker productivity, augment product throughput and improve selection reliability and uniformity. Additionally, the use of robotic systems in agriculture has seen a sharp increment in recent years. Many systems

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have been described for the automation of various harvesting processes, such as for fruit location, detachment and transfer, among other, [22]. They have been used in the harvesting of, for example, melons [11], cucumbers [12], tomatoes [16] and oranges [18]. For a survey of several aspects of these systems see, for example, [14] and [20].

According to the report of the US Department of Energy [1], the wine industry is interested in using autonomous robotic systems for grape harvesting, phytosanitary treatments, among other very time and human resources consuming tasks, for multiple reasons; this also happens to be true for the Douro Demarcated Region (DDR) of Portugal, as explained below. Harvesting conditions, in particular, affect wine quality, and several techniques need to be used in order to produce quality wines, and including scheduling details [2], and ending up with production details [15].

Soft computing methods and techniques have been used in virtually all fields of science. They have been successfully applied to the detection of lifetime building thermal insulation failures [21], neural visualization of network traffic data for intrusion detection [8], identification of typical meteorological days [6], enhanced data visualization [7], to name only a few. Visual inspection methods can also be used to locate grapes for harvesting. Unfortunately, the location process is much easier for fruits than for vine grapes (see, for example, [19]), even if soft computing techniques like the ones listed above are used. The environment makes grape detection difficult even for humans, especially when the grapes and leafs have similar colors, as is the case for white grapes. To an automatic recognition application, the grapes can appear at different scales, they can be partially hidden by leafs, the luminance of images can vary widely due to the sun, clouds, leafs, and so on.

We have tried different pattern recognition techniques in order to try to solve these problems. Many works have been devoted to the definition of object invariant descriptors for simple geometric transformations; see, for example, [13]. The Zernike moments [5] have been developed to overcome the major drawbacks of regular geometrical moments regarding noise effects and image quantization error. Zernike moments were successfully used in the detection of red grapes [4], but nothing is known about their performance in connection with white grapes. Moreover, besides the difficulties associated with the calculation of the Zernike moments, the method proposed by [4] implies two distinct phases, training and recognition, the training phase being crucial to the results of the whole system. The computation time for the learning step, for 17 images, is reported to take 5 minutes on a 2.8 GHz Pentium 4. The computation time for the recognition step (identification of each block of size 16×16 pixels) takes less than one second. We have tried to use Zernike moments to detect white grapes but the results were disappointing (less than 50% of correct classifications).

In this paper we present a simple method for the detection and location, in natural environment, of bunches of grapes in color images, using only very simple and basic image processing techniques. The system is able to distinguish between white and red grapes, and also to work at night (with very little, or none, light/brightness variation). Additionally, the system can calculate the location of the bunch stem, which can be used to help guiding a harvesting robot. The system presented here represents part of an effort that is being made by our team to help introducing PA and PV in the farmers' everyday practices in the DDR [17], and is intended to be used in an autonomous harvesting robotic system.

The paper is organized as follows. In the next section we present the DDR unique characteristics, which definitely shaped and constrained the system. Section 3 is used to present the proposed system. Its performance and efficiency are discussed in Section 4, where experimental results obtained with real images are given. Section 5 presents some conclusions and discusses future work.

2. The DDR unique characteristics and their impact on the system

The DDR is a UNESCO World Heritage Site. It is the oldest Wine Demarcated Region of the World, where Port wine is actually produced and then shipped to the city of Oporto. Due to its unique characteristics, it poses very specific challenges, mainly connected with its topographic profile, pronounced climatic variations and complex soil characteristics. It is located in northeast Portugal, and consists mostly of steep hills (slopes reaching 15%) and narrow valleys that flatten out into plateaux above 400 m. The Douro river dug deeply into the mountains to form its bed, and the dominant element of the landscape are the vineyards, planted in terraces fashioned from the steep rocky slopes and supported by hundreds of kilometers of drystone wall.

Vineyards in the DDR are characterized by their small area size, and by having more than one caste per parcel and even for bard, particularly in the case of old vines. The more recent vines were projected and organized having in mind better control of the number and type of castes. Still, more than 120 (both white and red grapes) different castes are used in the region. Grape harvest and disease predictions, as well as the assessment of the grape value, are currently left to the grape-growers, without the help of decision-support mechanisms, in an environment where no significant irrigation systems exist.

Traditionally, vineyards have been harvested by humans. However, harvesting is a hard work, particularly in a region with the topographic and climatic characteristics of the DDR. The manpower needs are large and it is more and more difficult to find qualified workers. Autonomous systems could not only reduce the harvesting cost and manpower needs but they could also be conceived to work during the night. There is however one important constraint: although it is not essential that the workpower of the harvesting robot surpasses that of a human, it is crucial that they satisfy quality control levels at least similar to those achieved by humans. Also, the existing machines harvest grapes by striking the vine, a process that is not recommended for some wines, such as champagne, for chemical reasons (e.g., oxidation) but also because of some deposits being collected with the grapes. These harvesting machines need, at least, one operator. They also require previous preparation of the vineyard, such as cutting the tips.

(a) (b)

Fig. 1. Processing steps: (a) original image containing bunches of red grapes; (b) color mapping.

By contrast, the system presented in this paper is intended to be used in an autonomous robotic system, without previous preparation of the vineyard, which helps to keep the cost of the solution down to a minimum. It is part of an effort made by our team to help introducing or spreading PA and PV in the farmers' everyday practices in the DDR [9,17]. We wanted a system able to work during the night, with very little, or none, light/brightness variation. We also wanted the system to distinguish red from white grapes, because in the DDR red and white grapes are commonly found in the same parcel and even the same bard, and therefore telling one from the other is essential for correct harvesting.

3. The grape recognition system

We came to realize early in our work that if we could solve the problem of detecting bunches of white grapes we could also solve the problem of detecting red grapes. The reasons will become clear from the results section. Consequently, we have focused our efforts on the detection of bunches of white grapes. For the reasons explained in the previous section, we wanted the whole system to be able to work at night (i.e., in the darkness, with very little, or none, light/brightness variations), and also have the ability to distinguish between red and white grapes.

To this end, the system simply makes a first pass through the original (night captured) image, counting the number of pixels that are "inside" limits of the Red, Green and Blue (RGB) components of $(044, 051, 064)$, $(033, 041, 054)$, $(055, 062, 075)$, and $(018, 024, 036)$, for red grapes, and $(102, 108, 089)$, $(095, 104, 085)$, $(076, 090, 078)$, and $(083, 089, 038)$ for white grapes. These four central values (colors) were experimentally (trial and error) determined during the development phase. The system looks for pixels within the "limits" of these central values: the default limit contains all the values within 8% of these central values for red grapes and 15% for white grapes (these were the values experimentally determined from the night captured images). The largest counts indicate the type of grape, i.e., red or white.

However, if initial conditions are known, i.e., if we know that a parcel consists of a single type of grape (say white), then the system can be switched to that type of grape mode (say white mode), skipping the grape identification phase. Most vineyards in the DDR have small areas, and, as said before, they may also contain more than one type of grape (red or white and even different castes) per parcel and even per bard, particularly in the case of old vines.

Once the type of grape (red or white) is established, the system follows three additional steps: color mapping, morphological dilation, black areas and stem detection. The color mapping step is done based on the conditions established during the grape identification step. At the end of this step we will have a binary image (black for the pixels in the range and white for the other pixels). Fig. 1(a) shows the original image, containing bunches of red grapes, and Fig. 1(b) presents the resulting image of the application of color mapping step.

The resulting image from this step does not generally have a uniform (continuous) black region, see Fig. 1(b), but several regions, where the concentration of black pixels is greater. The morphological dilation operation is meant to fill in the gaps between the pixels, yielding uniform black regions. We have used a square of 3×3 pixels as the structuring element, typically one of the most simple and used structuring elements. We should recall that the shape of this structuring element is not very far from the shape of a grape berry. Because the regions resulting from the color mapping step when applied to red grapes and white grapes are very different, with a greater sparsity when dealing with white grapes, we have typically used 60 iterations of the morphological dilation for red grapes, and 100 iterations for white grapes. Fig. 2(a) shows the resulting image after the dilation operation, applied to the image presented in Fig. 1(b). Obviously, we have tried different sizes for the structuring element, but when its size was increased, even with a lower number of morphological dilation iterations, the number of overlapping uniform black regions tends to increase; these overlaps will correspond to incorrect overlapping bunches, leading to incorrect identifications.

The final step is used to detect and numbering the black regions, and locate the bunch stem. First, the number of contiguous regions are counted and labeled (numbered) using 8-connectivity. Then, for each region, its width, height and area are calculated (in pixels) so that we can discard false detections of very small bunches or very large regions to contain only one bunch of grapes. Note that in this last case the region will be composed of two or more bunches and the system will need to capture more images (from different angles) to correctly handle these situations. Now, these parameters, and also the total number of admissible areas, are all adjustable. Next, we count the number of regions, center, area, width, height,

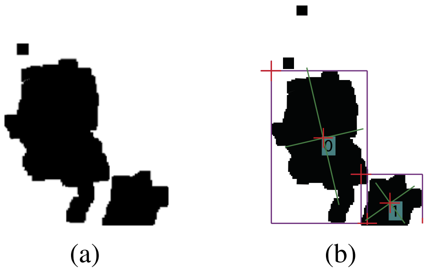


Fig. 2. Processing steps: (a) morphological dilation; (b) black areas (bunches) and stem detection step.

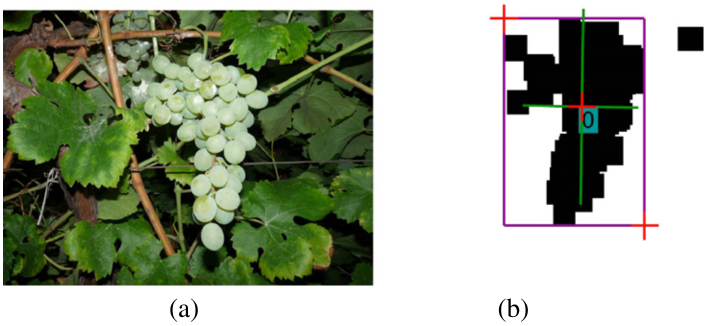


Fig. 3. Example of identification final result: (a) original image; (b) identification result.

Table 1
Summary of grape detection results. Correct means that all bunches present in each image were correctly identified. Incorrect means that the system had classified some areas of the image as if they were bunches although no bunches at all were present, or missed the identification of an existing bunch.

	White	Red
Correct	172 (91%)	34 (97%)
Incorrect	18 (9%)	1 (3%)
Total	190 (100%) images	35 (100%) images

perimeter and boundaries, for each region. For each region, and based on the pixel distribution and density around its center, it is determined the "horizontal" (width) and "vertical" (height) axes of the bunch, i.e., the bunch orientation. Then, with these axes (and orientation), and with the region's limits, we locate the bunch stem. Fig. 2(b) shows the resulting image after the final step and Fig. 3 shows another example consisting of the original image and the resulting identification.

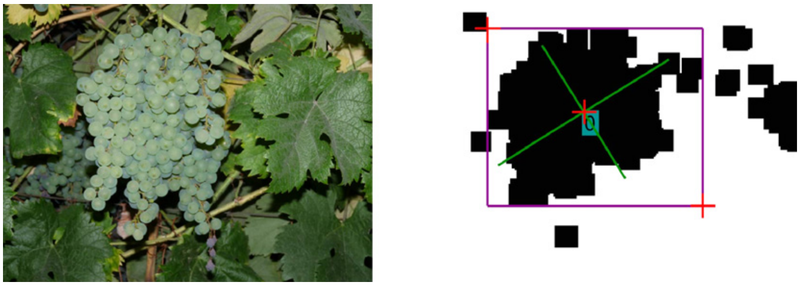
4. Results and discussion

All images presented here and used to test the system were captured during the night, with a Panasonic FZ28 camera (http://www.panasonic.co.uk/html/en_GB/1258590/index.html), simply using its internal flash, i.e., no other lightning system was used. By capturing the images during the night we avoid any spurious reflections or bad illumination during sunny day time, like momentary presence of clouds, but also, as explained above, some important wine chemical properties (e.g., oxidation). In total, there were 190 images containing bunches of white grapes, and 35 images of red grapes (the number of images containing bunches white grapes is much higher than that of red grapes because the identification of bunches of red grapes is much simpler, as explained above). A summary of the results can be seen in Table 1. As we can see, there were 172 correct results for bunches of white grapes; this means that all bunches present in each of these 172 images were correctly identified. We emphasize this fact, because we want that in a near future this system can be part of a harvesting robot, and we know that most of the infield images captured by this robot could contain more than one bunch per image, which clearly is not an optimal situation, but rather real. Recall that in a practical infield situation the robot can take as many images as needed to ensure that no more bunches are present for harvesting. However, we also have 18 images with incorrect or false detections. This means that the system classified some areas of the image as if they were bunches although no bunches at all were present, or missed the identification of an existing bunch. Also, if two regions were merged during the morphological dilation process they were counted as an "incorrect" result.

As we have foreseen, the system's performance, in percentage, is better for bunches of red grapes than for white grapes. Recall that the color of red grapes is very different (contrasting) from their surroundings (e.g., color of the leaves); however one must note the small number of red grape sample images.

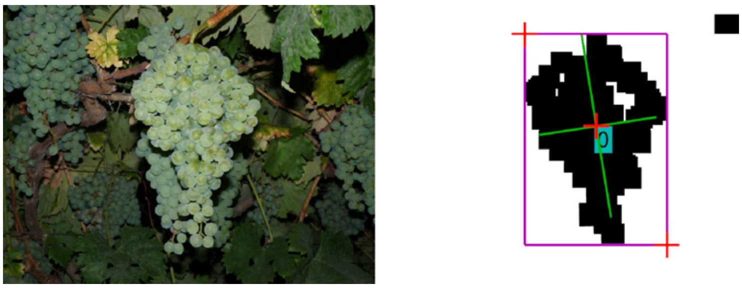
(a) (b)

Fig. 4. Example of a possible robot's positioning correction by noticing "how far" it is from the bunches: (a) original image; (b) identification result.



(a) (b)

Fig. 5. Example of overlapping bunches and identification result.



(a) (b)

Fig. 6. Example of a possible robot's positioning correction by noticing the presence of more bunches; (a) original image; (b) in this case, only the central bunch was correctly identified, so more pictures are needed (see text).

The system can also be used to help guiding the robot. As it can be seen in Fig. 4, although the picture was captured very far way form the grape bunches the system manages to identify the presence of bunches of grapes. So, the system can help to tell the robot to move along that direction, adjusting (fine tuning) its position or trajectory. Usually, the presence of many bunches of grapes in one image indicates that the robot is at a considerably far distance from those bunches. Obviously, this can only be a contribution to the robot's trajectories or positioning. In the examples of Figs. 5 and 6, for example, we can see that the bunch in the center of the figure is correctly identified. However, we can see that there are more bunches to be harvested. By capturing one more image after the harvesting of the central bunch the system will detect the presence of more bunches and then correct the robots trajectory, as in the previous situation. As noted before, the presence of leaves may (partially) occlude a bunch; in these cases a mechanic system like the one presented in [10], basically a blower/fan to remove leaves, can be used to help solve this problem.

We have tested the system on a computer running Microsoft Windows XP Home Edition, with an Intel Core Duo Processor T2300 at 1.66 GHz, Mobile Intel 945 PM Express Chipset, 3 GB DDR2 667 MHz SDRAM, and NVDIA GeForce Go 7300 External 128 MB VRAM video card. In order to reduce the identification time, we tested several image resolutions, as presented in Table 2. With a resolution of 1.3 megapixel (MP) the system is able to produce the same results as with a 10 megapixel resolution. Note that the identification of bunches of red grapes takes less time, because it uses a lower number of iterations during the dilation operation step.

Table 2
Summary of grape detection time versus image resolution (seconds versus megapixels).

	10 MP	3 MP	1.3 MP
White	1.5 s	0.22 s	0.16 s
Red	1.0 s	0.15 s	0.08 s

5. Conclusions and ongoing work

Within the context of precision agriculture/viticulture, and because the Douro Demarcated Region has its own very particular characteristics, a vision inspection system was developed in order to identify bunches of grapes, for later inclusion in a robotic system for night conditions harvesting. The system is also able to automatically distinguish between white and red grapes, and has achieved 97% and 91% of correct classifications, for red and white grapes, respectively. Additionally, it can also calculate the location of the bunch stem, and can be used to help the robot's location and guiding system.

Concerning the identification algorithm we are trying to make it more flexible. For example, during the morphological dilation step, the number of iterations should depend on the merging of the different regions, i.e., the iteration process should stop if the regions are already contiguous or if two distinct regions are merged. Also, the tilling and distribution of these contiguous regions should be analyzed in order to prevent incorrect identifications, like two or more staked regions, regions with much greater width than wight, among other. Obviously, a dedicated (specific) lighting system may help in producing better identification results (starting with a simple diffuser), but it would also increase the system cost and needed resources (e.g., power supply). We are also currently testing multi-spectral cameras. This solution is far more expensive, but it could bring information about grapes maturation and alcoholic level. A cheaper alternative may include infra-red cameras, but red grapes yield more thermal information than white grapes, and so, once again, the identification of red grapes seems simpler than white grapes. In addition to the tasks of detection and harvesting, the robotic system may also contribute to mitigate the environmental impact of chemical plant protection products, as its application by robotic systems would be made only at points of interest identified by the vision system, among other possible applications (pruning, trimming the vines, disease detection, etc.).

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