IDENTIFICATION OF GRAPEVINE CANOPY ELEMENTS BASED ON RGB IMAGES TO QUANTITATIVELY ASSESS THE VINEYARD STATUS

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Background and Aim

Vine vigour and cluster exposure in a grapevine canopy fruiting zone has been shown to strongly correlate with key fruit composition (sugars, acids, flavours and aromas) and diseases incidence (Botrytis, powdery mildew, etc).

The automated image analysis for the identification of plant elements is an important issue to be addressed for vineyard assessment→ IMAGE SEGMENTATION

Optimum segmentation method is strongly application dependent, therefore it needs to be tested for each particular case.

The objective of the present work is to propose and test a simple, rapid and practical method for the identification of the relevant elements of vineyard canopy: clusters, green leaves, yellow-dry leaves, canes and trunk.

Experimental Layout

The analysis was applied to twenty colour images corresponding to Tempranillo *Vitis vinifera* L grapevines from various defoliation treatments in a commercial vertical shoot-positioned vineyard, located in Rioja wine region (Spain).

The set of images was divided in two subsets: 10 for calibration and 10 for testing the classification performance. A wooden frame (1.20m*0.70m) was included in the images as a spatial reference.

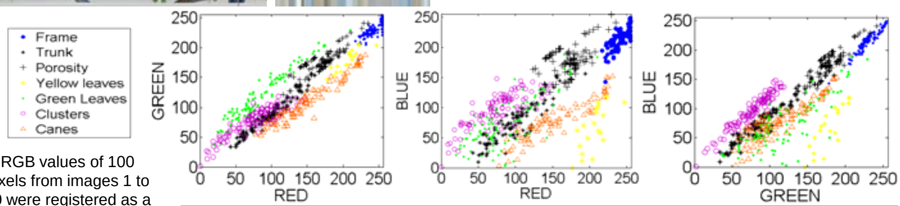
Fig. Some examples of RGB images of grapevine fruiting zone from various defoliation treatments

Image Segmentation and Analysis

1) DEFINITION OF REFERENCE CLASSES

Seven reference areas selected manually on Red Green Blue basis (RGB) for each class present in reference images (1-10):

R	G	B
74	74	86
99	74	69
76	76	88
73	80	98
75	70	76
(...)	(...)	(...)



RGB values of 100 pixels from images 1 to 10 were registered as a reference.

Fig. RGB values used for calibration. The centre of gravity (cog) is computed for each class

2) COMPUTATION OF DISTANCE

On test images (11-20) Mahalanobis distance (MD) was computed between RGB values of each pixel and the cog for each class.

MD takes into account the covariance C between variables X Y and thus improves Euclidean distance, being generally accepted that fro the latter the high correlation among RGB values tends to produce misclassification of objects with uniform colour but different intensities (i.e. differences in illumination or shadows).

Mahalanobis distance: $D_{mah}^2=(X-Y)^T C^{-1}(X-Y)$

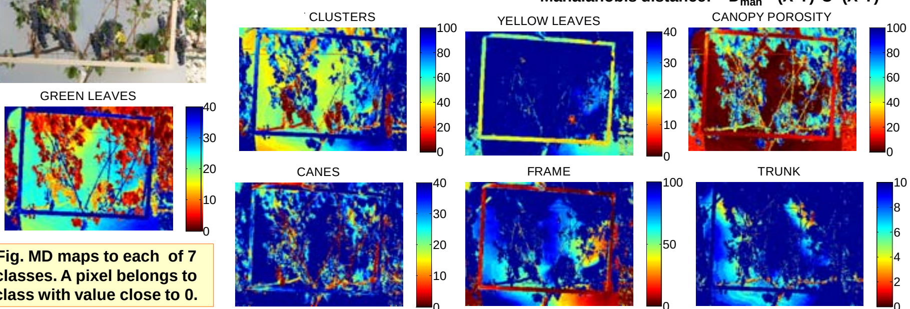


Fig. MD maps to each of 7 classes. A pixel belongs to class with value close to 0.

3) CLASSIFICATION OF PIXELS

Each pixel of the images is assigned to the most proximate class according to MD

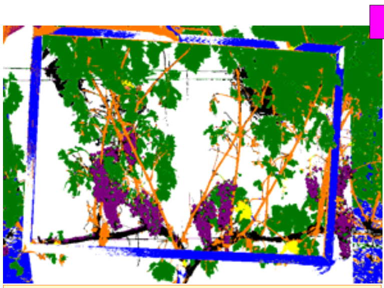


Fig. Classified image

4) REGIONS OF INTEREST (ROIs) FOR CROP STATUS

Several ROIs are defined: global (all pixels within the frame), vine (polygon within initial ROI and above trunk line), vegetative area (polygon including all leaves) .

The number of pixels assigned to each class within each ROI was computed. The image displays an example of polygon for global ROI.

Fig. Minimum polygon defining the region of interest

Conclusions

A simple and computationally inexpensive method for pixel classification was proposed and applied to the identification of elements of the vineyard canopy (clusters, leaves, canes, trunk, and canopy porosity). Image features are defined to reflect crop status and evolution.

Potential applications include yield and fruit quality prediction and diagnostic of canopy status within onboard and robotic systems.

5) FEATURE EXTRACTION

On the global ROI (gROI)

- Size (number of pixels, gROI_s)

On the vine ROI (vROI)

- Size (number of pixels, vROI_s)
- Relative size of vROI (%, vROI/gROI*100) related to the quality of the image -not too high or too low-
- Relative size of trunk (%, vROI_rt=sum(trunk)/ vROI_s*100
- Relative size of canes (%, vROI_rt=sum(canes)/ vROI_s*100

On the vegetative ROI (VROI)

- Size (number of pixels, VROI_s)
- Relative size (%, VROI_rs= VROI_s/ vROI_s*100)
- Relative amount of Green Leaves (%, sum(GL)/ vROI_s*100 related to vine vigour
- Relative amount of Yellow Leaves (%, sum(YL)/ vROI_s*100)
- Canopy porosity (%, sum(Porous)/ vROI_s*100

On the clusters (labeled 4-connected components on binary fruit cluster image)

- Relative Yield (%, sum(fruit clusters))/ vROI_s*100
- Euler number (number of fruit clusters in the image minus the total number of holes in those objects)

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