Disease detection system for olive trees using unmanned aerial vehicles (drones)

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1 Introduction

In Europe alone, an average of 26% of olive grove production is lost annually due to plant pests and diseases, with a direct economic cost of more than 7.8 billion euros per year, with an upward trend. Of these diseases, two are particularly important because of their potential impact or their current extent: Xylella Fastidiosa and Verticillium Wilt. Xylella Fastidiosa in particular has been devastating for Italy in recent years. Its rapid spread threatens European arboriculture. In all cases, early and accurate detection and diagnosis of plant diseases are key factors for plant production and reduction of qualitative and quantitative crop yield losses.

Moreover, accurate detection and diagnosis can lead to localised and individualised treatment, applying doses of plant protection products as strictly necessary, avoiding their massive and indiscriminate use (their overuse is estimated at 31%). Both objectives, i.e. avoiding crop yield losses and reducing the overuse of pesticides, are addressed by the key component of the European Green Pact "Farm to Fork".

However, despite the huge economic, environmental, and social impacts this entails, there is a lack of solutions to improve disease risk and treatment management towards early detection and smart product application.

Therefore, the objective of this project is to develop a high-precision, low-cost, real-time system for diagnosing the state of health of olive tree crops. The system will also include a digital platform to show whether the plants analysed have the Xylella Fastidiosa or Verticillium Wilt disease and their degree of progress, as well as their spatial location.

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2 Methods

To achieve said objective, the team has used a drone with built-in hyperspectral and thermal cameras to capture information, which is then processed through an algorithm to obtain a diagnosis of the health of the plants of a given crop. The two main innovations of the system are described below:

2.1 Optimisation of data acquisition from drone flight parameters to improve the quality of hyperspectral and thermal images

A correct selection of the drone flight parameters is extremely important in relation to the usefulness of the captured information. Therefore, the influence of the flight parameters on the quality of the images from the hyperspectral and thermal cameras must be determined. The objective is to create a flight plan by selecting the optimal parameters that minimise the flight time and number of images needed to perform the analysis, while maximising the quality of the images.

The flight parameters considered are 5: i) flight altitude; ii) lateral image; iii) flight speed; iv) flight direction; and v) solar elevation (which depends on the time of day at which the flight is performed). The flight height, in turn, can be replaced by 4 other variables that can be analysed and depend on it: ground pixel size (GSD), forward image overlap, mean image area and mean tilt angle.

To determine the influence of the selected flight parameters, the methodology described by Tu et. al. (2020) [1] will be used, in which partial least squares (PLS) regression is applied, considering the 8 variables described above as independent variables (X) and the following as dependent variables (Y):

- Alignment quality: RMSE and tie point acceptance rate.
- Point cloud quality: normalised point cloud density.
- Hyperspectral indicators: R^2 and RMSE of NDVI

2.2 Diagnosis of the state of health of the plants that make up an olive grove, identifying diseased plants, type of disease affecting them and degree of progress

First, the images are atmospherically corrected, orthorectified and tree crowns are segmented.

Secondly, the 21 spectral indices shown in Table 1 are analysed to obtain statistical regressions between said indices and the assessment of the diseases X. Fastidiosa and V. Wilt.

Table : Overview of the vegetation indices that contribute most to the model conducted in this study and their formulations.	
Vegetation Indices	**Equation**
Structural indices	
Normalized Difference Vegetation Index	N D V I = (R 800 − R 670) / (R 800 + R 670)
Renormalized Difference Vegetation Index	R D V I = (R 800 − R 670) / (R 800 + R 670)
Enhanced Vegetation Index	E V I = 2.5 · (R 800 − R 670) / (R 800 + 6 · R 670 − 7.5 · R 400 + 1)
Optimized Soil-Adjusted Vegetation Index	O S A V I = ((1 + 0.16) · (R 800 − R 670) / (R 800 + R 670 + 0.16))
Triangular Vegetation Index	T V I = 0.5 · [120 · (R 750 − R 550) − 200 · (R 670 − R 550)]
Modified Triangular Vegetation Index	M T V I = 1.2 · [1.2 · (R 800 − R 550) − 2.5 · (R 670 − R 550)]
Modified Simple Ratio	M S R = R 800 / R 670 − 1 (R 800 / R 670) 0.5 + 1
Xanthophyll indices	
Photochemical Reflectance Index (570)	P R I 570 = (R 570 − R 531) / (R 570 + R 531)
Chlorophyll a+b indices	
Vogelmann	V O G 1 = R 740 / R 720
Gitelson &Merzlyak indices	G M 1 = R 750 / R 550
Pigment Specific Simple Ratio Chlorophyll b	P S S R b = R 800 / R 650
Transformed Chlorophyll Absorption in Reflectance Index	T C A R I = 3 · [(R 700 − R 670) − 0.2 · (R 700 − R 550) · (R 700 / R 670)
Transformed Chlorophyll Absorption in Reflectance Index/ Optimized Soil-Adjusted Vegetation Index	T C A R I / O S A V I = 3 · [(R 700 − R 670) − 0.2 · (R 700 − R 550) · (R 700 / R 670) ((1 + 0.16) · (R 800 − R 670) / (R 800 + R 670 + 0.16))
R/G/B indices	
Redness index	R = R 700 / R 670
Blue/green indices	B G I 1 = R 400 / R 550
Lichtenhaler index	L I C 3 = R 440 / R 740
Carotenoid indices	
Pigment Specific Simple Ratio Carotenoids	P S R R c = R 800 / R 500
R515/R570	R 515 / R 570
R515/R670	R 515 / R 670
Fluorescence	
FLD	F L D 3 (747 ; 762 ; 780)
Plant disease index	
Healthy-index	H I = R 534 − R 698 R 534 + R 698 − 1 2 · R 704

Table 1 Indices considered in the assessment of the diseases X. Fastidiosa and V. Wilt

Finally, trees are classified according to their health status using linear discriminant analysis (LDA) and a support vector machine (SVM), which exploit the combined information of the previously calculated indices. The LDA method is used for the classification of early stages of disease development, while the SVM discriminates against advanced stages.

Linear discriminant analysis (LDA) is a method used in statistics, pattern recognition and machine learning to find a linear combination of features that characterise or separate two or more classes of objects or events. The resulting combination can be used as a linear classifier, or, more commonly, for dimensionality reduction prior to further classification.

In relation to Support Vector Machine (SVM) methods, these are properly related to classification and regression problems. Given a training set of samples, one can label the classes and train an SVM to build a model that predicts the class of a new sample. Intuitively, an SVM is a model that represents the sample points in space by separating the classes into two spaces as wide as possible by a separating hyperplane. When the new samples are put in correspondence with this model, depending on the spaces to which they belong, they can be classified into one class or the other.

3 Results

First, a commercial drone capable of supporting the cameras (DJI Inspire 2) was selected. The flight software it had integrated was analysed and the 8 flight parameters were analysed, determining the percentage of dominance of each flight parameter with respect to the quality indicators. This will improve the quality of the hyperspectral and thermal images captured by the system and, in addition, adjust the number of images per second captured, reducing the amount of data and allowing their transmission in real time.

A hyperspectral camera with 260 bands in the 400-1000nm region and a thermal camera with thermoelectric cooling stabilisation have been selected. Both were calibrated in the laboratory.

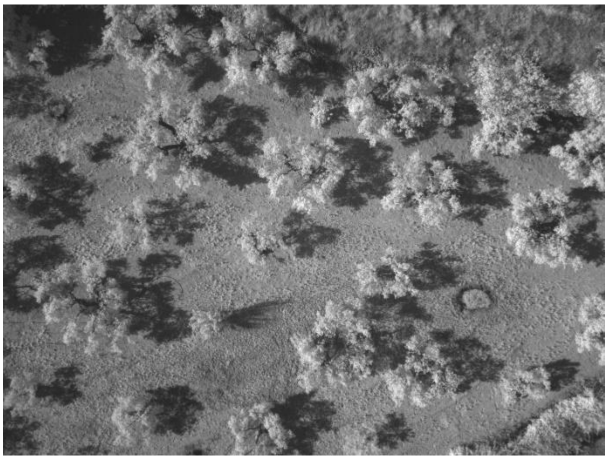

Fig. 1 Images obtained during a flight in Benimantell (Alicante)

The atmospheric correction was performed with the SMARTS irradiance model for the ground surface. The orthorectification of the hyperspectral images was performed using the PARGE software (ReSe Applications Schläpfer, Wil, Switzerland). This is done using the input data acquired with a miniaturised inertial measurement unit (IMU) (model MTiG, Xsens, The Netherlands) installed on board and synchronised to the camera.

4 Conclusions

To date, the system has succeeded in obtaining the optimal flight parameters required to reduce the amount of data processed and the necessary steps to pre-process the spectral images.

Successful development of the system still requires overcoming challenging, such as the ones listed below:

- Laboratory analysis of a sample of olive trees.
- Obtain a relationship between the X. Fastidiosa and V. Wilt diseases with the proposed spectral indices.
- Obtain a map to visualise the health of olive trees in real time.

References

[1] Tu, Y. H., Phinn, S., Johansen, K., Robson, A., & Wu, D. (2020). Optimising drone flight planning for measuring horticultural tree crop structure. ISPRS Journal of Photogrammetry and Remote Sensing, 160, 83-96.