LEAF DEVELOPMENT INDEX ESTIMATION USING UAV IMAGERY FOR FIGHTING APPLE SCAB

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ABSTRACT

This paper describes the use of Unmanned Aerial Vehicle (UAV) technology to fight apple scab. Specifically, it shows how it is possible to improve the scab risk evaluation basing on the actual apple leaves development status, yielded from UAV images, as input to the infection model. For this purpose, we introduce a new index, called Leaf Development Index (LDI), which is evaluated during the main growth phases of the apple trees using an UAV equipped with both multispectral and thermal sensors. Preliminary results are reported and discussed.

***Index Terms*—** Apple Scab, Leaf Development Index, Unmanned Aerial Vehicles.

1. INTRODUCTION

Scab is one of the most relevant disease in apple farms. It is caused by the Ascomycete fungus *Venturia inaequalis* and manifests first as dull black or grey-brown lesions on the surface of tree leaves and then on fruits damaging apple's quality and aspect. The main problem with this kind of disease is that there are no efficient curative treatments to apply. Only preventive treatments can lead to the absence of this disease from fruits [1] The purpose of this work is to exploit UAV technology to improve the scab infection risk evaluation. Indeed, to make the most efficient scab preventive treatments, it is necessary to know the exact period on which the infection could develop. There are various mathematical models that can make good risk evaluation analysis using local weather data (temperature, humidity, rainfall, wind speed, solar radiation, etc. …) as input [2] The problems with this kind of models are that they do not have feedback from the orchard and they strongly depend from the position and distance of the closest weather station. To give to the model an environmental feedback, an improved risk evaluation mathematical model, called *A-Scab*, has been introduced in [3] . In this model, the infection efficiency during an infection period is computed as follows:

$$Risk_{inf} = \sum_{i=1}^{n} SRA_{dis} \cdot IE_{inf} \cdot HOST_{inf} \cdot 100 \qquad (1)$$

where *n* is the number of days including the infection period, SRA_{dis} and IE_{inf} are parameters that depend only on weather data; $HOST_{inf}$ represents a parameter that depends exclusively on the Leaf Area Index (LAI). The LAI is computed using a mathematical model that takes into account only the daily average temperature (base 4 [°C]) multiplied by an empirical factor [4] .

In this work, we improve this empirical model, that could be inadequate in some cases, through the introduction of a new index: leaf development index (LDI) that takes into account the area of the leaves and the presence of new leaves (which, according to the literature, is a parameter playing a fundamental role in the scab infection) from a day to another. This index is automatically estimated on each UAV survey, then it is converted with a mathematical filter to fit the range of the previous LAI index and used as fixing point for the LAI model. In this way, we obtain an environmental feedback on the status of apple trees that takes into account not only the leaves area but also the new leaves appearance, thus improving the risk computation of *A-Scab* model.

The model and the image analysis algorithms have been developed using *Matlab*® environment and *C++* language.

2. TOOLS AND METHODS

The evaluation of the *LDI* using an UAV requires specific sensors and platform. In our tests, we have used an octocopter with a 3-axis gimbal which carries a six-band multispectral camera and a thermal camera as well. The multispectral camera acquires data from bands of 410 [nm] to bands of 900 [nm] with a resolution of 1280x1024 and the thermal camera acquires and stores radiometric data for each pixel with a spectral band in the range of 7.5-13.5 [μm]. Due to the fact that the multispectral camera requires a distance from the object greater than 60 [m] to have a perfect overlap of each band image, we have performed acquisitions at a height of about 65 [m] (above ground level) to have the maximum *IFOV* possible that is: 32.50 [mm] and with a field of view of 41.844 [m] for the horizontal view and 33.516 [m] for the vertical view. All the UAV survey has been done according to the prescription of the Italian Civil Aviation Authority (ENAC) about the usage of UAV between 4 [kg] and 25 [Kg] [5]

The LDI evaluation process could be summarized as follows:

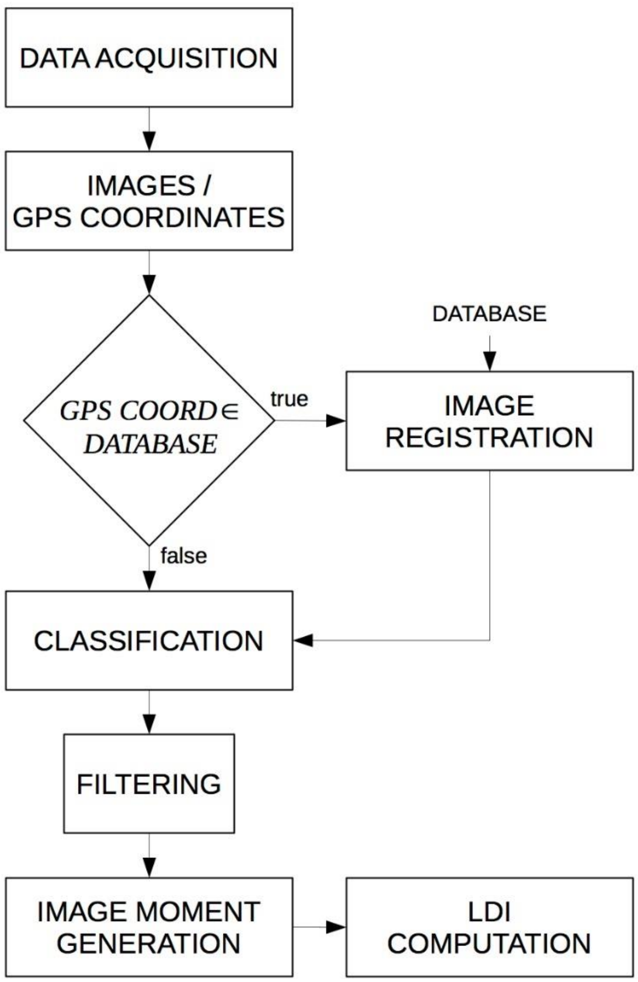

Fig. 1. Leaf development index evaluation flow chart.

First of all, different data are acquired as follows:

- **Multispectral Camera:** Acquires a 1280x1024 image for each of its six spectral bands with a radiometric resolution of 10 bit. This sensor is used to classify the multispectral images, to extract the bounding box features and to evaluate the LDI index.
- **Thermal Camera:** Acquires a 640x512 image which associates to each pixel a thermal value. The images are stored with a radiometric resolution of 14 bit. This sensor is principally used to identify apple trees row at the beginning of the trees growth stage.
- **GPS Sensor:** Stores geolocation data for each acquired i2mage.

The acquired GPS data are then compared with previous geolocation data stored in our database considering possible errors due to sensor precision and *Kp* index. If matches are found, an image registration process between the current images and the previous flight images is required in order to estimate the LDI of the same target during a whole season. Therefore, a classification algorithm, which will assign to each pixel a class, takes place analyzing the spectral features of each pixel of the image and associating it to the class which has the most similar spectral characteristics to it. This classification process is based on the multispectral images and it is used to infer two classes, namely ‘tree’ and ‘soil’ classes. For such purpose, it has been used a simple algorithm based on the Bayesian decision theory [6]
Clearly, the worse is the classification of the elements present in the image, the worse may be the features extraction of the bounding box, the LDI evaluation and consequently the risk infection index. After the classification process, the images are filtered using median and morphological filter. The median filter allows reducing noise, whereas the morphological filter with circular structuring elements permits to preserve the regions that have analogue shape to the structuring element and to erase all other regions.

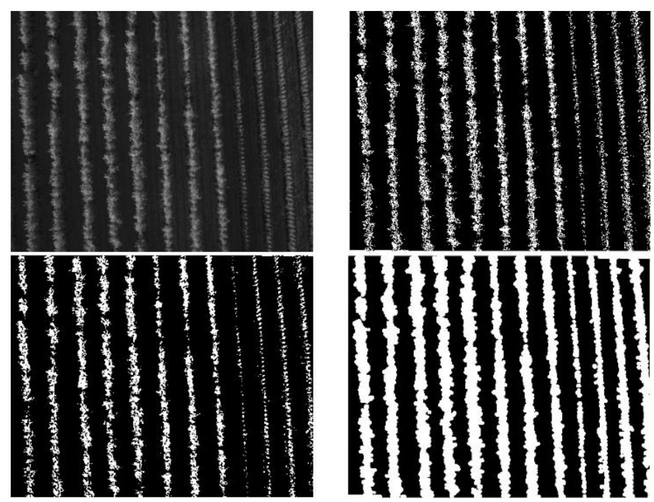

Fig. 2. Example of filtering process: original image [NIR band: 800 [nm]] (top left), binarized image (top right), outcome of median filter (bottom left), result of morphological filter (bottom right).

The use of a morphological filter on the binarized image also allows to merge neighboring regions with similar shape improving the extraction of the bounding box features and the apple trees row identification.
To define the LDI, it is necessary to introduce the bounding box concept, that is the minimum geometric shape that

contains a region of interest. The definition of the bounding box features depends on the growth phase of apple trees at the moment of the first survey. The maximum leaf coverage is considered to be about at the same day of the apple harvest. If the leaf coverage is not at the maximum growth stage possible, then the bounding box is defined using the acquired thermal images to identify the position of apple trees rows and assigning to them a fixed dimension value defined as follows:

- **Bounding box shape:** Rectangle centered on the apple trees row.
- **Bounding box length:** Dimension of the apple trees row.
- **Bounding box width:** Distance between the nearest apple trees row.

Otherwise, if the leaf coverage is at the maximum growth stage then the bounding box characteristics are defined as follows:

- **Bounding box shape:** Rectangular
- **Bounding box centroid:**

$$[C_x, C_y] = \left[\frac{M_{10}}{M_{00}}, \frac{M_{01}}{M_{00}}\right] \qquad (2)$$

where M_{ij} is the image spatial moment.

- **Bounding box orientation:** It is computed from the covariance matrix of the second order central moment:

$$cov[I(x,y)] = \begin{bmatrix} \mu'_{20} & \mu'_{11} \\ \mu'_{11} & \mu'_{02} \end{bmatrix} \qquad (3)$$

where I(x,y) is the pixel intensity matrix and μ'_{pq} are the second order central moment. The eigenvectors of this matrix correspond to the major and minor axes of the image intensity, so the orientation Θ can be extracted from the angle of the eigenvector associated with the largest eigenvalue towards the axis closest to this eigenvector [7] :

$$\theta = \frac{1}{2} arctan\left(\frac{2\mu'_{11}}{\mu'_{20} - \mu'_{02}}\right) \qquad (4)$$

The obtained bounding box are then checked to find intersection between elements. If this happens, the bounding box involved are merged.

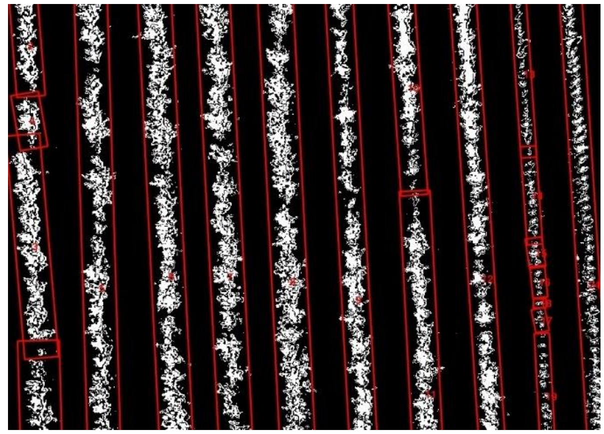

Fig. 3. Example of bounding box extraction result in the case of maximum leaf growth stage.

The features of each bounding box are then stored in a database and used to compute the LDI during a whole season. If the definition of the bounding box has been done using the thermal images, at the end of the season when the leaf growth stage is at its maximum value the actual bounding box would be replaced and stored using the image centroid and second order central moment method.
Once the bounding box features are defined, it is possible to compute the LDI for each region as follows:

$$LDI_\alpha = \frac{pixel^{(1)} \subseteq B.BOX_\alpha}{pixel^{(tot)} \subseteq B.BOX_\alpha} \qquad (5)$$

where α ϵ [0, *N*] is the index of the bounding box of interest from the *N* extracted boxes. $Pixel^{(0)}$ are pixels with logical value equal to 0, $pixel^{(1)}$ are pixels with logical value equal to 1 and $pixel^{(tot)} = pixel^{(0)} \cup pixel^{(1)}$.
This value is then multiplied by a conversion factor to fit the LAI range defined in the *A-Scab* Model.

3. LDI-BASED INFECTION RISK EVALUATION

The procedures showed above permit the mathematical model of the infection risk to be strongly tied to the local reality of the orchard. To better understand the relevance of the LDI on the risk evaluation process, in the following figures it has been reported an example of how this index influences the scab infection risk evaluation.

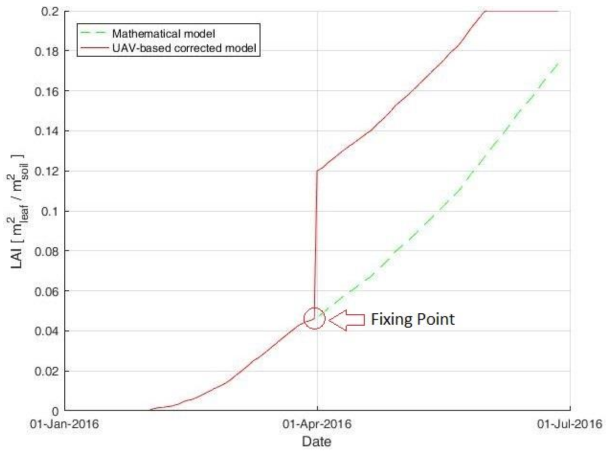

Fig. 4. LAI curve before and after the LDI fixing point.

The fixing point has been applied on the first of April and then it has been proceeded using the LAI model commonly used in *A-Scab* using the fixing point as offset. As could be seen in the figures below, the introduction of the fixing point leads to a readjustment of the risk infection dates and values.

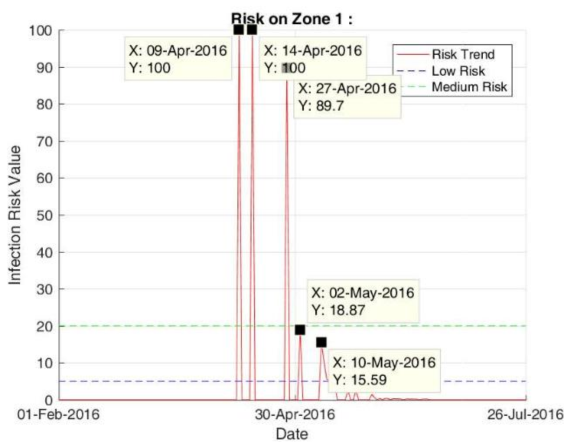

Fig. 6. Risk evaluation without LDI evaluation.

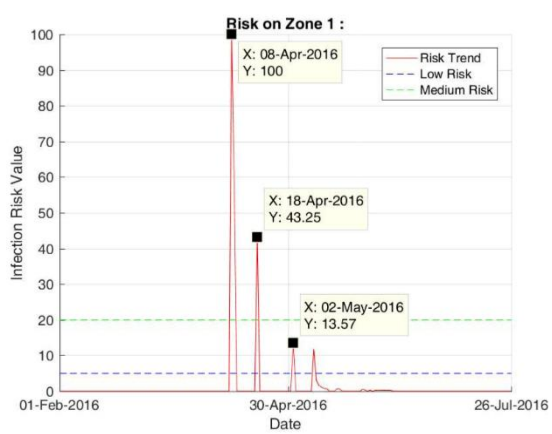

Fig. 7. Risk evaluation with LDI evaluation.

Indeed, our technique permits to better tune the mathematical model values for the LAI computation using information that comes directly from the orchard. This leads to more precise values of the infection risk taking into account the possible heterogeneity of the orchard. Moreover, using only the LAI mathematical model for the risk infection evaluation, it is not possible to discriminate between the infection risk of apple trees row and the infection risk of the entire orchard because it is described only by the acquired weather data at the geographical position of the weather station. Instead, using periodical survey with an UAV to estimate the LDI, it is possible to relate an infection risk index to each apple trees row.

4. ACKNOWLEDGMENTS

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