MONITORING OF TREES' HEALTH CONDITION USING A UAV EQUIPPED WITH LOW-COST DIGITAL CAMERA

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ABSTRACT

Invasive insect pests and fungi, which are introduced accidentally to forests and affect tree growth and survival, constitute a serious threat for the forests and trees acting on climate change and its impacts. Thus, the need for early and accurate health determination process of forest regions, has significantly increased the interest in automatic monitoring methods. In this paper, in order to overcome the great variety of trees' characteristics and forests' heterogeneity that affects the diversity of their color and texture making the detection of diseases a difficult task, a methodology for individual tree detection applying energy minimization, visualizing HOG features across tree canopies and using a dynamically clustering method is proposed. Then, in order to achieve classification based on their health condition, multi-pyramid textural features are proposed and extracted. The experimental results presented use images of a forest area in Greece that include fir trees and show the great potential of the proposed methodology.

Index Terms— Remote sensing, forest monitoring, tree diseases detection, forest health surveillance

1. INTRODUCTION

The environmental challenges the world faces nowadays have never been greater or more complex. Natural disturbances and disasters in conjunction with climate change give rise to the population of insect pests and fungi [20] and simultaneously reduce the resilience of forest ecosystems and their capacity to deliver essential services. Generally, trees purify the air, modify ambient temperatures, reduce storm water runoff, and make cities nice places to live [11]. To this end, it is necessary to efficiently protect trees and forests, by the occurrence of natural disturbances such as the aforementioned threats and in this way to maximize the role of nature in absorbing and avoiding greenhouse gas emissions.

Traditionally, experts recognize tree diseases by measuring and identifying visually irregularities of trees. The main challenge lies in the great variety of trees' characteristics and forests' heterogeneity that affects the diversity of their color, texture and thus aesthetic properties making the detection of diseases a difficult task. Indeed, sometimes only a limited number of infected trees are found by visual inspection, with the remainder being detected only after they have fallen [26]. Furthermore, the needs of reducing the cost and time required to be spent for the training of staff to achieve the necessary skills and expertise to accomplish this health determination process, has significantly increased the research interest in remote sensing and automatic forest monitoring methods.

Remote sensing technologies combined with computer-aided signal and image analysis has become one of the major research subjects in forest surveillance [23]. Numerous approaches for environmental monitoring have been proposed recently to assist foresters and experts in the early detection of natural hazards and disturbances [8]. To date, most researchers have attempted to address the remote species identification and disease recognition challenge using expensive and customized multispectral cameras and estimating health indicators features [6]. Furthermore, in order to extract more spectral bands, researchers have exploited the significant role of hyperspectral cameras and Fabry-Pérot interferometer (FPI) technology [18], [19]. However, all the previously computer-based methods for forest health surveillance suffer from some limitations. Most of the approaches use ground sensors or require expensive and specialized hardware (e.g. using small Cessna-type aircraft platform), with complex standard protocols for data collection and complex analysis methods [14], [22], limiting their potential eventual widespread use by local authorities, forest agencies and experts.

In this paper we present an accurate and affordable approach to detect individual trees and identify their health condition through UAV data in an operationally, time and power cost efficient manner. Specifically, we propose the segmentation of trees applying an energy minimization approach and localization of top parts of trees combining the visualized feature space of HOG descriptors and a dynamically clustering method. Then, in order to rate the health of trees based on the appearance and dynamics of their canopies we propose and extract multi-pyramid (multi-scale and multi-orientation) textural features using linear dynamical systems. To evaluate the efficiency of the proposed methodology, we created a dataset of fifty images, consisting by fir trees.

This paper is organized as follows. Section 2 details the proposed methodology. Experiments are presented in section 3 and finally, discussion and conclusions are provided in section 4.

2. METHODOLOGY

The framework of the proposed methodology is shown in Fig. 1. In this, a commercial quadcopter mid-priced UAV is used to capture forest areas. For the segmentation of trees in the captured images, we apply an energy minimization approach based on graph cuts. Then, we estimate the visualized feature space of HOG descriptors noticing that higher layers of a tree appear brighter white than the lower layers in the HOG-based visual world. Subsequently, in order to split the overlapped trees and to identify their top parts, a dynamically clustering method is applied. Finally, we apply a novel multi-pyramid feature extraction approach and classify the identified trees in the following categories: a) trees with normal appearance, b) trees with total or partial defoliation and c) decolorized trees.

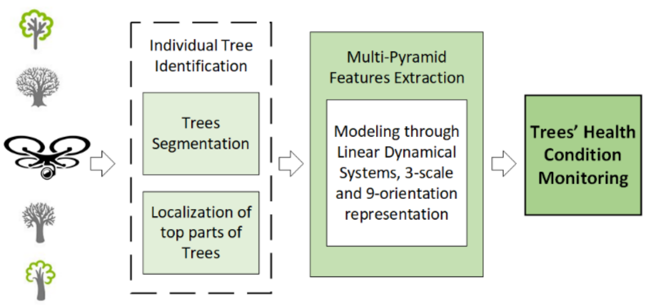

Figure 1. The proposed methodology

2.1. Individual tree identification

2.1.1. Trees segmentation

For the segmentation of trees in an aerial image (Fig. 2a), an unsupervised energy minimization technique that is based on graph cuts was applied [16]. In this labeling problem, the image is represented as a graph $G = \langle V, E \rangle$, where V is the set of all nodes and E is the set of all edges connecting adjacent nodes. Nodes and edges correspond to pixels and their adjacency relationship, respectively. The graph also contains two terminal nodes, which are referred to as the source and the sink. The labeling problem is to assign a unique label x_p for each node V, so as to minimize the following energy:

$$E = \sum_{p \in V} C_p(x_p) + \sum_{(p,q) \in E} S_{p,q}(x_p, x_q) \qquad (1)$$

where C_p is the color consistency cost which depends on the label x_p. The $S_{p,q}$ is the smoothing cost between two neighboring pixels (p, q) and it depends on the labels (x_p, x_q). The cost of the cut which partitions the graph into two disjoined subsets, is defined to be the sum of weights of the edges crossing the cut, whereas the minimum cut problem is to find the cut with the minimum cost, that minimizes the energy either globally or locally. The algorithm results the labeling that minimizes the energy of Eq. (1) leading to the segmentation of canopy parts of trees, of lower parts of trees and soil. Then, we used the four central moments rejecting the part of image that represent the soil (Fig. 2b). For the initialization of the algorithm, a k-means approach was adopted for assigning an initial label to each pixel.

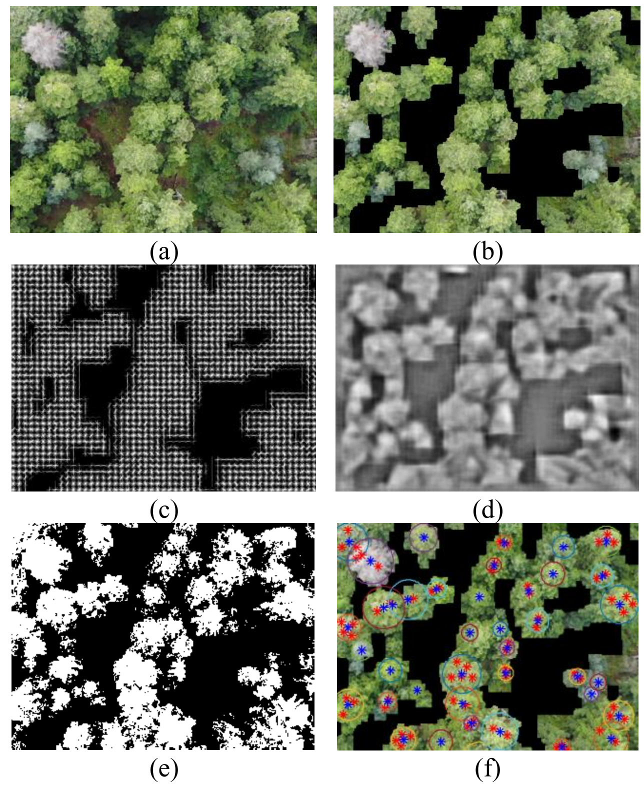

Figure 2. Methodology of the individual tree identification: a) UAV captured image, b) trees segmentation c) extraction of HOG features d) visualized feature space of HOG features e) mask of trees f) estimation of top parts of trees.

2.1.2. Localization of the top parts of trees

Using satellite or airborne remote sensing technology, the localization of the top part or layer of a tree of a canopy, which is composed of branches and leaves or needles is a significant process especially when dealing with tree health issues that are, in many cases, firstly become visible in these parts of trees [17]. To this end, after the initial segmentation and in order to find the points of the top parts of tree canopies the proposed methodology consists of two main steps: a) the estimation of mask of trees and b) the dynamically localization of trees.

As HOG features (Fig. 2c) are changing for the different layers of trees in aerial photography [25], we used visualization of HOG descriptor $h \in \mathbb{R}^d$, where the d is the size of it, in order to achieve their separation. Specifically, we jointly calculate a couple of bases for each image and HOG descriptor [24] with shared coefficients $\alpha \in \mathbb{R}^L$ using a super resolution sparse coding approach and sparse modeling software optimization. Given a pair of bases $U(t) \in \mathbb{R}^{D\times L}$ and $V(t) \in \mathbb{R}^{d\times L}$ the image and the HOG descriptor can be decomposed as follows:

$$I = Ua \text{ and } h = Va \tag{2}$$

Thus, the visualization of the HOG features (Fig. 2d) can be obtained by projecting the HOG features h onto the HOG basis V and then projecting a into the natural image basis U:

$$H = Ua^* \tag{3}$$

$$\text{where } a^* = \underset{\alpha\in\mathbb{R}^L}{argmin} \|Va - h\|_2^2 \tag{4}$$

Then, in order to make clearer the differences between the layers of trees, we applied a histogram equalization rejecting the regions of lower intensity and creating a binary mask of trees that will be used in the subsequent detection process (Fig. 2e).

For the localization of trees, we used the above extracted mask and we applied a distance transform estimating the distance image D and the regional maxima. Subsequently, we applied a regional H-maxima transform [21] in order to suppress all local maxima in a neighbourhood with radius equal to the value v. The result of this step allows us to identify a list of k trees (Fig. 2f, red asteroids) driven by the morphology of the extracted trees' mask.

Then, as each tree canopy and specifically fir canopies can be spatially modelled as circles, the pixel coordinates of each tree in the mask can be modelled using a Gaussian distribution and the number of each tree can be dynamically estimated. More specifically, an iterative Gaussian mixture model [1] was applied with the number of detected trees to being equal to the predicted number of clusters. The method attempts to compute the overlapping of neighbouring clusters and uses an overlap threshold to purge all redundant clusters. Specifically, we initialize the algorithm using the list of k trees and we compute the responsibility of each Gaussian component for itself relative to the set of remaining clusters:

$$\rho_{i,K} = \frac{\hat{\gamma}_{ii}}{\hat{\gamma}_{ii} + \sum_{j\in K}\hat{\gamma}_{ij}} \tag{5}$$

where $\hat{\gamma}_{ij} = \hat{\gamma}_j(p_i) \in [0,1]$ is the generalized responsibility of component j for component i:

$$\hat{\gamma}_j(x) = \frac{\pi_j N(p|\mu_j, \Sigma_j)}{\Sigma_{j\in C}\pi_j N(p|\mu_j, \Sigma_j)} \tag{6}$$

Then, clusters expand towards empty space. Furthermore, to ensure that the overlapping trees have been correctly detected we propose a validation criterion. As the canopies of fir trees are generally circular, we estimate whether a detected cluster is redundant or not, estimating if the cluster areas are covered almost exclusively by the tree data of the previous step estimated mask. If not, the overlap threshold is reduced estimating new parameters and clusters (Fig. 2f, blue asteroids).

2.2. Multi-Pyramid Features Extraction

As can be noted tree canopies contain spatial characteristics that reflect the canopy structure and can be used as an indicator for the health condition of trees. Inspired by the dynamic texture analysis techniques that have been widely used for time and spatially evolving signals [12], [10] and textures classification in forestry applications [2], [4] we consider each tree canopy as a spatially evolving multidimensional signal. Here, due to the variant heights and orientations of trees and different flight altitudes of UAVs we propose a new modeling method through the construction of a multi-pyramid i.e., twenty-seven representations in different scale and orientation (Fig. 3), and the use of higher order linear dynamical systems. Thus, we consider each individual multi-pyramid tree representation as a multidimensional signal evolving in the spatial domain and model it through the following dynamical systems.

$$x(t+1) = Ax(t) + Bv(t) \tag{7}$$

$$y(t) = \bar{y} + Cx(t) + w(t) \tag{8}$$

where $A \in \mathcal{R}^{n\times n}$ is the transition matrix of the hidden state and $C \in \mathcal{R}^{d\times n}$ is the mapping matrix of the hidden state to the output of the system. The quantities $w(t)$ and $Bv(t)$ are the measurement and process noise respectively, while $\bar{y}$ is the mean value of observations. The LDS descriptor, $M = (A, C)$, contains both the appearance information of the observation data modeled by C, and its dynamics that are represented by A.

The multidimensional spatial signal can be represented by tensor $Y \in R^{nxnxm}$, where n is the size of the examined tree and m is equal to the number of *rgb* image channels. For the estimation of the system parameters, we apply a higher order singular value decomposition [15] to decompose the tensor:

$$\boldsymbol{Y} = S \times_1 U_{(1)} \times_2 U_{(2)} \times_3 U_{(3)} \tag{9}$$

where, $S \in R^{n\times n\times m}$ is the core tensor, while $U_{(1)} \in R^{n\times n}$, $U_{(2)} \in R^{n\times n}$ and $U_{(3)} \in R^{m\times m}$ are orthogonal matrices containing the orthonormal vectors spanning the column space of the matrix and $\times_j$ denotes the *j*-mode product between a tensor and a matrix. Given the fact that the choice of matrices A and C is not unique, we consider $C = U_{(3)}$ and $\boldsymbol{X} = S \times_1 U_{(1)} \times_2 U_{(2)}$. Hence, equation (9) can be reformulated as $\boldsymbol{Y} = X \times_3 C \Leftrightarrow Y_{(3)} = CX_{(3)}$ where $Y_{(3)}$ and $X_{(3)}$ indicate the unfolding along the third dimension of tensors $\boldsymbol{Y}$ and $\boldsymbol{X}$ respectively. Thus, the transition matrix A, can be easily computed by using least squares as:

$$A = X_2 X_1^T (X_1 X_1^T)^{-1} \tag{10}$$

where $X_1 = [x(2), x(3), \dots, x(n)]$ and $X_2 = [x(1), x(2), \dots, x(n-1)]$. After the estimation of the systems parameters, each multi-pyramid tree representation can be described by the $M = (A, C)$.

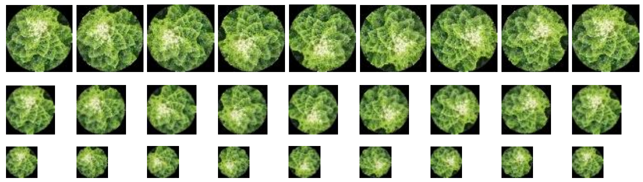

Figure 3. Texture analysis through multi-pyramid (multi-scale and multi-orientation) analysis.

2.3. Trees' health identification

For the representation of each tree through the extracted descriptors, we adopted the Martin distance as a similarity metric. Specifically, we estimate the subspace angles [9] between two descriptors and solve the Lyapunov equation $A^{\intercal}PA - P = -C^{\intercal}C$, where:

$$P = \begin{bmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{bmatrix}, A = \begin{bmatrix} A_1 & 0 \\ 0 & A_2 \end{bmatrix}, C = [C_1 \quad C_2] \qquad (11)$$

The cosine of the subspace angles is calculated by the following formula:

$$cos^2\theta_i = i^{th} eigenvalue(P_{11}^{-1} P_{12} P_{22}^{-1} P_{21}) \qquad (12)$$

Then, the Martin distance between M_1 and M_2 is defined as:

$$Martin_{distance}(M_1, M_2) = -ln \prod_i cos^2\theta_i \qquad (13)$$

Then, through the definition of K representative codewords, we create a Term Frequency (TF) histogram representation for each tree that corresponds to its extracted representations. Thus, each TF histogram corresponds to an examined tree [2]. Furthermore, for the classification of each tree, we calculate the distances of test tree TF histograms with the histogram representations of the training dataset. By ranking the similarities across all training trees, the majority rule of the c labels with the minimum distances is adopted in order to classify the examined tree.

3. EXPERIMENTAL RESULTS

To evaluate the efficiency of the proposed methodology, we created a dataset, consisting of 50 forest images and containing in total 1548 trees (Fig. 4). The research was conducted at a part of AUTH university forest in central Greece which mainly is consisted by fir trees. In this area, the annual average rainfall is 885 mm and the average annual temperature is 9.6 °C. This climate is considered to be Csb according to the Köppen-Geiger climate classification. In this research, the study area covers approximately 200 ha of fir trees. For the validation of the proposed methodology results, we manually labelled the trees in the images. From the annotation we excluded shrubs and trees that are at the edges of the images and the biggest part of them is not shown in them. The goal of this experimental evaluation is two-fold: a) Initially, we aim to show that the proposed methodology improves the identification of individual trees using UAV images and b) we want to demonstrate the superiority of the proposed multi-pyramid texture analysis approach against other state of the art approaches.

(a) (b) (c)

Figure 4. Tree images of the dataset with: a) normal/regular appearance, b) total or partial defoliation and c) discoloration.

With respect to number of annotated trees, an overall detection rate of 92.1% was obtained, while the identification rate of individual trees using the wide-used watershed algorithm [13] is 84.2%. In Table I, we present experimental results for the proposed method against a number of well-established wood and forest-level state-of-the-art approaches for texture analysis. More specifically, as the most health monitoring developed methods use spectral indices, we compared the identification rates of trees health condition of the proposed method against four approaches that widely have been used to overcome environmental challenges. Table I, show that the proposed method outperforms all other methods achieving improvements up to 3.6%. As was expected all approaches improve the classification rate of GLCM, that is 82.96%. Furthermore, the classification rate using RGB-LCM is 84.1%, the rate using CNN is 88.1% while the rate applying i-BGLAM is 90.2%.

Table I. Comparison results of trees health condition identification rates

Method	Detection
Proposed	**93.8%**
i-BGLAM [27]	90.2%
CNN [7]	88.1%
RGB-LCM [3]	84.1%
GLCM [7]	82.9%

4. DISCUSION AND CONCLUSION

The wide variety of different sensors in combination with the modern signal processing and communication systems enables the near real-time environmental data acquisition, assessment, processing and analysis for the ultimate goals of ecosystem protection and monitoring. The proposed method will allow experts and scientists to achieve a better-coordinated global approach that will contribution in limitation of forest degradation and negative impacts of climate change on air, water, food, soil erosion, floods and timber supplies. In the future, more data from a variety of tree species will be collected in order to assess the effectiveness of the proposed methodology.

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