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Detection, Characterization and Modeling Vegetation in Urban Areas from High Resolution Aerial Imagery

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Abstract

This paper presents a complete image analysis system which, from high-resolution color infrared (CIR) digital images, and a Digital Surface Model (DSM), extracts, segments and classifies vegetation in high density urban areas, with very high reliability.

The process starts with the extraction of all vegetation areas using a supervised classification system based on a Support Vector Machines (SVM) classifier. The result of this first step is further on used to separate trees from lawns using texture criteria computed on the DSM. Tree crown borders are identified through a robust region growing algorithm based on tree - shape criteria. A SVM classifier gives the species class for each tree-region previously identified. This classification is used to enhance the appearance of 3D city models by a realistic representation of vegetation according to the vegetation land use, shape and tree species.

Index Terms

image analysis, image segmentation, pattern classification, remote sensing, vegetation

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I. INTRODUCTION

ONE of the primary challenges to understand the dynamics of the Earth system is an accurate assessment of the relationships between human population and the other components of the system. As the global rate of urbanization increases [1], so does the relative importance of the urban environment to the global population. One of the keys to managing assets (vegetation or buildings) is knowing the state of those assets (the quantity and condition) and their trends (are they growing or declining).

The vegetation component of a city is a dynamic entity and its management is a considerable challenge. Residential and business development can have significant adverse effects on the extent and condition of urban vegetation.

Urban vegetation includes individual trees and groves of trees, areas of bush, parks, and reserves. It includes vegetation in either public or private space and/or the combination of these areas.

A good knowledge of the vegetation type, of the tree species are of great importance to all local communities for disaster management, urban planning, environmental protection or urban development policy making. Precise, reliable and meaningful measurement of urban vegetation covers helps decision makers and urban researchers to reach their goals.

In this paper we present a complete hierarchical system to analyze urban vegetation from very high resolution imagery. The proposed system extracts all vegetation areas, separates them into high- and low-height vegetation, delineates individual tree crowns, extracts 3D tree parameters (such as crown diameter, height, trunk localization) and classifies them according to their species. The result of this system is used to create realistic urban virtual environments.

The remainder of this paper is organized as follows: datasets and study area of our system are presented in section II. In section III we review main approaches developed during the last decades to deal with such problems. Section IV presents the techniques used by each of system's modules starting with an overview of the proposed system. Section V presents the output of the entire system for modeling vegetation in urban areas, integrated in a 3D city model. The last section of the paper draws a few concluding remarks and states future work perspectives.

II. DATA AND STUDY AREA

A. Data

The dataset is made up of high-resolution georeferenced aerial images with a resolution of 20 cm per pixel and having 4 channels (red, green, blue and near infrared). The overlap between the images is of 60% within each strip and 60% between two strips. This ensures that all the points of the studied area are visible on at least four to nine images.

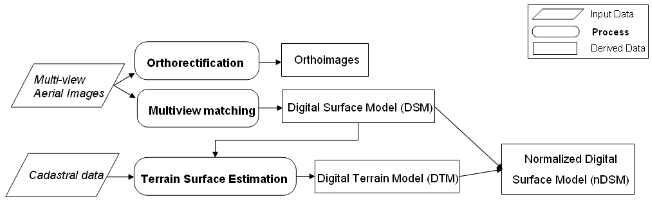


Fig. 1. Overview of the methodological process for dataset creation. Aerial images and cadastral data are used to obtain additional data. Due to the important overlap between aerial images, the DSM obtained is accurate enough for 3D object analysis problems.

Additional data used by our system are derived from these multiple view images, as depicted by the flow diagram of Fig.1.

Four channel orthophotographs are obtained by transforming the aerial images from a conical perspective into a parallel perspective, with the light rays in the vertical direction. A dense Digital Surface Model (DSM) is computed from multiple images using a multi-view matching algorithm [2]. Buildings are masked on the DSM, and the resulting depth map is further on used to estimate the terrain surface, thus obtaining a Digital Terrain Model (DTM) [3] which is a digital representation of the topographic surface. A Normalized Digital Surface Model (nDSM), containing the height of above ground objects, is computed as the difference between DSM and DTM.

B. Study Area

The study area is located in the city of Marseille, situated in the south-east of France. Marseille′s climate is Mediterranean, with a great variety of vegetation species. It is a complex urban area, with many greened and treed resting places, highly intermingled with buildings.

Fig.2 depicts sample images of our study area. The area covered by this image is of approximately 54.800 square meters, and contains all types of above-ground objects present in a city (e.g. buildings, lawns, trees). It contains two species of trees, namely lime trees (Tilia) and plane trees (Platanus Hispanica).

III. PREVIOUS WORK

With the technological improvements of the last generation of very high spatial resolution sensors, and the growing availability of Earth observation images acquired by these sensors great attention is devoted to the analysis of urban scenes.

Numerous studies have focused on the analysis of human settlements, either to monitor urban sprawl, to map urban land use patterns and infrastructure or to automatically reconstruct urban environments. Although research has reached maturity concerning the reconstruction of man-made objects [4] a lot of challenge still exists concerning the modeling of other objects present on the terrain surface, such as trees, shrubs, hedges or lawns.

A. Vegetation Extraction

Traditionally, field surveys and visual interpretation from aerial imagery were used to extract vegetation cover maps. These time-consuming and expensive methods, evolved during the last decades to high-level machine vision systems.

Remote sensing imagery is introduced into applied areas and vegetation indexes are developed to extract vegetation information. Although a great number of such indexes were developed during the years, the most widely used is the NDVI (Normalized Difference Vegetation Index) [5] which is representative of the plants photo-synthetic efficiency and provides per-pixel vegetation distribution.

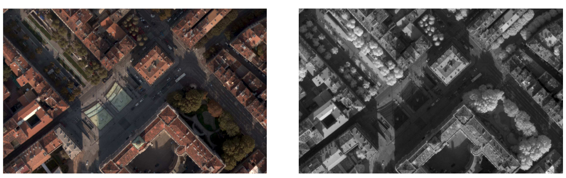
While all these indexes were developed for different applications and particular type of input data and acquisition conditions (which can be incompatible with the urban environment), there is no ideal index designed to characterize the urban vegetation environment.

The urban environment is a mixture of different proportions of lawns, shrubs, treed areas, bare soil, building areas as well as streets. Therefore, the spectral response of urban vegetation is altered by the presence of such different types of elements, having similar spectral signatures. Moreover, the atmospheric conditions over urban areas are greatly influenced by the presence of pollutants and dust issued from industrial plants which are mainly located around big cities. All these factors induce great variations in the spectral reflectance of the same urban material.

B. Tree Detection

Vegetation has an unique spectral signature which enables it to be distinguished from other type of land cover using spectral reflectance properties in different spectral bands. But the reflectance properties of different types of vegetation, such as trees and grass, are very close and other characteristics have to be exploited to distinguish between such classes.

An alternative solution is to incorporate texture properties into the classification process [6] [7]. Texture classification highly depends on the illumination conditions (the position of the solar light source) and the position of the sensor view angle relative to the imaged area. We therefore propose a method to analyze the texture of vegetation areas by exploiting its 3D height information.



(a) (b)

Fig. 2. An aerial image of Marseille (France) representing a high density urban area, where 1 pixel corresponds to approximately 20cm. **(a)** RGB channels **(b)**IR channel

C. Individual Tree Crown Delineation

Many researches deal with automatic tree crown delineation from aerial or satellite images. Among the different approaches proposed, we identify a first class using object-based methods, which model tree crown templates to find tree top positions [8] [9] [10]. Although this kind of approaches give good results, prior knowledge about tree crown size and shape has to be exploited, which can be rather difficult in an urban environment. Another class of methods exploits shadows around tree crowns to delineate their contour [11], such as valley-following algorithms [12] or region growing methods [13]. Other contour based methods use multi-scale analysis [14] or active contours [15] to delineate tree crowns. A third class uses local maxima information to estimate tree top position and the number of trunks [16] [17]. Applied on optical imagery, the performances of these methods are easily influenced by illumination conditions, occlusions or shadings due to intensity variations. We propose an approach to delineate individual tree crowns which exploits tree height information.

D. Tree Species Classification

The problem of tree species classification was first issued in the field of forestry where digital interpretation techniques of aerial/satellite imagery have been used for the inventory and monitoring of forested areas [18]. Depending on the spatial resolution of the input data, the goals of these studies cover a large range of applications. High resolution imagery was used in pixel-based classification of individual tree crowns [13], [19]–[21] yet low spatial resolution imagery was mostly used to extract single species stands [22]. The method we propose to perform tree species classification exploits beside spectral information also texture of high resolution images.

IV. METHODOLOGY

Our objective is to extract all vegetation areas present in an urban environment, and to characterize them according to type and species composition. This section provides an overview of all processing steps of our approach. All different components of the proposed system are discussed in detail in the following subsections. An overview is given in Fig.3.

A. Vegetation Extraction

The first step of our approach is the extraction of vegetation areas.

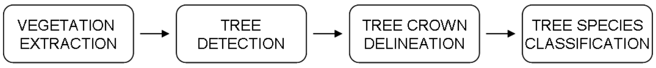


Fig. 3. Block scheme of the proposed system. First, vegetation areas are extracted, then, treed areas are separated from lawns according to one's height. Subsequently, tree crown borders are delineated and finally tree species classification is performed.

The method we propose is robust to the nature of the urban surface and to the atmospheric conditions. It is based on a supervised classification method using a SVM (Support Vector Machines) [23] classifier. The training dataset is made up manually and contains both vegetation and non vegetation areas. For all pixels in the training dataset, the feature vector contains four characteristics, namely, the reflectance values of each pixel in the infrared(IR), red(R), green(G) and blue bands(B). As most of the spectral indices used in literature to detect vegetation areas are linear combinations of the pixels reflectances, we chose a linear-kernel for the classifier.

Results of the proposed approach for vegetation identification in urban environments by means of supervised classification techniques are presented in section V-A of this article. A comparison to results obtained by applying state-of-the-art techniques for vegetation detection will also be presented and the relevance of the proposed method will be highlighted.

B. Tree Detection

The next component of the system deals with the segmentation into grass and trees. The proposed method exploits texture characteristics on the DSM to segment vegetation according to height variation.

To extract treed areas from the vegetation areas previously delineated we compute the local height variance on the vegetation areas corresponding to the Digital Surface Model. This texture feature accentuates large changes in height values between adjacent pixels. Variance texture is computed using

$$V = \sum \frac{(x_{ij} - M)^2}{(n-1)} \tag{1}$$

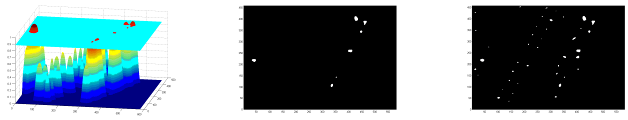
where x_{ij} is the height value of pixel *(i,j)* on the DSM; n equals the number of pixels in a sliding window and M is the mean value of the moving window computed by:

$$M = \frac{\sum x_{ij}}{n} \tag{2}$$

Height local variance was computed using a 11×11 pixels sliding window to capture both fine-scale and coarser-scale height characteristics of urban vegetation. The variance texture data was separated into low and high level values using a histogram-based thresholding method. Results obtained using this method on our data will be presented in section V-B.

C. Individual Tree Crown Delineation

The following module performs individual tree crown delineation. It is based on treed areas delineated by the previous module and exploits tree shape to segment tree crowns.



(a) (b) (c)

Fig. 4. Detecting tree tops from the DSM **(a)** 3D view of the DSM: all points higher than the analysis altitude h are evaluated for tree top estimation **(b)** 2D view of the 30th iteration **(c)** Seed points detected after the final iteration: we can notice that we obtain one seed region for each tree.

To individually delineate tree crowns, we developed a segmentation method based on a seeded region growing approach, taking into consideration the treed areas previously detected. Our approach consists of two steps: the first one is used to detect seed points which are grown to regions corresponding to individual tree crowns in the second step.

Traditionally, region growing (RG) methods developed for image segmentation start by arbitrarily choosing seed pixels which are grown into regions composed of all neighboring pixels satisfying a similarity criterion. This process continues until all pixels belong to some region. It is possible to split the segmentation procedure in two steps, one in which seed points are chosen, and a second one, when a region is grown.

The performance of this type of segmentation method is highly dependent on the number of seeds (as the number of detected regions is equal to the number of seed points) and on the choice of the similarity criteria used (which can be based on any characteristic of the regions in the image).

The method we developed uses a set of seed points with a one-to-one correspondence with the number of trees in the image, which are grown into regions made of pixels lying on the same surface.

1) Seed Points: To obtain one seed point for each tree crown, we use the DSM to estimate tree tops. To reduce the number of possible candidates for a tree top, a Gaussian filter is used as a smoothing filter on the DSM with an empirically determined mask, approaching the average size of the trees in the image. To determine tree tops, we evaluate the maximum height of the trees present in the DSM and we consider all points having the same height as tree tops. In the first iteration we obtain points corresponding to the highest trees in the stand. Therefore, we iteratively decrease the analysis altitude, h. At each step, we analyze all points at greater heights than h and detect a new seed when a new region appears and it doesn′t touch pixels previously labeled as seeds. A graphical illustration of this algorithm is presented in Fig.4.

2) Region Growing: Starting from the previously labeled tree tops, tree crown borders are obtained by a region growing approach based on geometric criteria of the trees. This approach is similar to the previous one, based on a height descent. The altitude analysis h is iteratively decreased, and for each step, the pixels corresponding to a height of $h \pm \triangle h$ are iteratively aggregated to the adjacent region.

The results of the above presented method are exemplified in section V-C. An evaluation of the accuracy of the results obtained using the automatic segmentation algorithm and a manual tree crown delineation method will also be presented.

D. Tree 3D Parameter Estimation

Tree crown diameter and tree height, are estimated for each tree using the segments obtained from the tree crown delineation method presented above. Fig.5 depicts the parameters estimated for a tree, from the corresponding tree crown segment.

(a) (b) (c)

Fig. 5. 3D scale factors estimated for each tree. **(a)** Crown surface estimation **(b)** Tree crown diameter **(c)** Tree height

The width of a crown (diameter) can be measured by vertically projecting the edges of the crown on the ground and measuring the length along one axis from edge to edge through the crown center (cf. Fig.5 -(a) & (b)). Tree height (cf. Fig.5 -(c)) is estimated as the distance from the base of the tree to the tree top and is directly computed on the nDSM (cf. II). We estimate the position of the trunk of the trees on the ground as corresponding to the barycenter of the crown surface.

E. Tree Species Classification

Tree species discrimination in urban areas using remote sensing data is a difficult task, for several reasons :

- $complexity$: tree stands are very complex, having great height and shape variance (in urban areas trees of different ages, thus height, are often adjacent and crowns are often cut to different geometric shapes);
- $density$: the high density of trees, often intermingled to each other, leads to many hidden parts of crowns, to crown shadowing and differential crown illuminations;
- $diversity$: the great number of species in one genus form difficult cases and their discrimination can be difficult even on the field.

It is easy to enumerate cases, which are most likely unsolvable. Suppose we want to know the species of each of the tree crowns depicted by Fig.6. Which are the features suitable to discriminate between the two?

Fig. 6. Tree crowns belonging to two different species. Assigning the correct species to each tree is a very difficult task, even for an advised photo interpreter. Finding features suitable to discriminate between two such similar textures is even more difficult.

We computed texture characteristics to form feature vectors for a supervised classification approach based on SVM's. We study both per-pixel and per-region classification approaches, and results obtained for the two approaches are evaluated and compared both against each other and also against a manual defined ground truth.

The texture of an image contains information about the spatial and structural arrangement of objects [24]. There are two classes of Texture Measures (TM): first order (occurrence), and second order (co-occurrence) statistics [25], [26]. First-order statistics are derived from the histogram of pixel intensities in a given neighborhood (i.e. moving window), but don't take into consideration spatial relationship between pixels. Second-order statistics are computed from the Gray Level Co-occurrence Matrix (GLCM) which indicates the probability that each pair of pixel values co-occur in a given direction and distance [25], [26].

We focused on first- and second- order measures to characterize tree species. Many texture features can be computed from the GLCM matrix. Each element of the GLCM, $g(i,j|d,\theta)$ describes the relative occurrence of two pixels with gray level (i) and gray level (j), respectively, and separated by inter-pixel distance (d) in the angle direction (θ). A GLCM is defined as:

$$G(d,\theta) = [g(i,j|d,\theta)] \tag{3}$$

We computed the following **Texture Measures (TM)**: *Mean, Standard Deviation, Range, Angular Second Moment, Contrast, Correlation, Entropy, Inverse Difference Moment.*

The use of the GLCM method requires an appropriate window size, inter-pixel distance and direction. Classification results greatly depend on the selected window size: if it is too small, the spatial information extracted is not statistically reliable, whereas a too large window allows the overlapping of different classes.

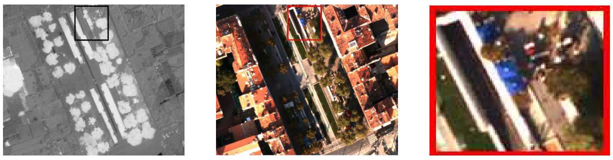
We use the tree crown delineation results as additional information to compute the second order statistic parameters of the GLCM method. This allows us to overcome the overlapping classes problem. We propose two approaches to compute texture measures : a pixel-based one in which texture measures are computed for each pixel over a square-neighborhood centered on it and a region-based one where texture measures are computed on all pixels belonging to a tree crown. The size of the window for the pixel based approach was chosen of 31×31 pixels to make statistically reliable the measurements. As for the region approach we compute second order features for all pixels inside a tree crown border.

The choice of an appropriate distance between pixels is closely related to the coarseness or the fineness of the texture being analyzed. The coarser the texture, the more the distance between pixels can be increased. As we are interested in preserving all possible differences between species, we decided to consider a distance of 1 pixel and thus to characterize texture in its finest level of detail.

Direction is important in the case of anisotropy in the texture. This is not the case for tree crowns, therefore we

(a) (b) (c)

Fig. 7. Vegetation detection based on linear-kernel SVM classification **(a)** RGB input image **(b)** IR input image **(c)** Vegetation mask



(a) (b) (c)

Fig. 8. Spectral indices used for vegetation detection **(a)** NDVI image highlighting vegetation areas **(b)** RGB channels for the same area as the one presented in Fig.(a). **(c)** Excerpt from the RGB image presenting parasols classified as vegetation

decided to compute second order statistics over a direction of 0°.

Since we want to separate vegetation regions which look similar, it seems that using perceptually relevant color spaces is important. Texture classification was done using feature vectors computed on four different color spaces: *RGB, XYZ, Lab, HSV* [27].

The supervised classifier used is an SVM [23], [28] classifier with a linear kernel and in a one-against-one configuration. The training and testing databases contain two species of trees, namely lime tree (Tilia) and plane tree (Platanus hispanica). Both per-pixel and per-region classification approaches are analyzed using the same feature vectors. A manually defined ground truth serves as data support for the training and evaluation steps. Training is performed on a set of 18 trees while tests are carried out on a stand of 19 trees.

V. Results and Evaluation

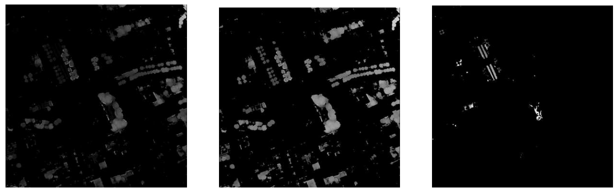
A. Vegetation Extraction

Fig.7-(c) presents the vegetation mask obtained by applying the proposed supervised classification algorithm to the test area presented in Fig.2.

We compared the results obtained by our method to results obtained using state-of-the-art methods to detect vegetation. The vegetation mask obtained for the study area using a NDVI decision-based method is depicted in Fig.8-(a). At a first glance, there are no major differences between this vegetation mask and the one depicted in Fig.7-(c).

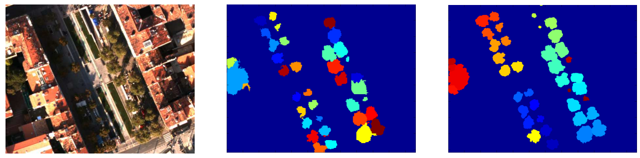
The highlighted patch in Fig.8-(a) presents an area classified as vegetation by the NDVI index, which in fact corresponds to non-vegetation areas (blue parasols) as can be noticed in Fig.8-(b) & (c).

Vegetation classification rates are high for the two methods, from 87.5% for the NDVI based method to 98.5% for the SVM classification method. The main drawback of the proposed method compared to NDVI based method, lies in the fact that training areas have to be defined and the classifier has to be re-trained when data acquisition conditions change.



(a) (b) (c)

Fig. 9. Differentiation between grass and treed areas **(a)** Vegetation areas on the DSM corresponding to the height local variance **(b)** Treed areas **(c)** Lawns



(a) (b) (c)

Fig. 10. Tree crown delineation results. **(a)** Input data **(b)** Automatic tree crown delineation results for the proposed RG method **(c)** Reference manual delineation of tree crowns

The results of this module of the system give localization areas for urban vegetation and will be used to mask all other objects present in the urban area.

B. Tree Detection

Fig.9-(a) depicts the variance image computed on the vegetation areas extracted from the DSM. Fig.9-(b) & (c) depict the result of the segmentation of treed areas from lawns.

The accuracy of the grass/lawn segmentation was evaluated against a manual delineation and the results are very promising. More than 97% of the grass surface in the reference delineation was correctly classified as lawn.

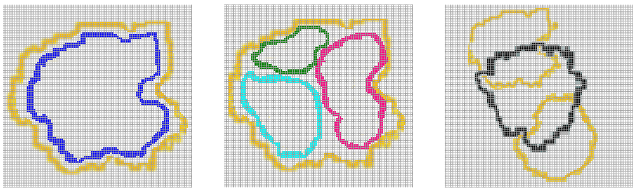
Lawns will be masked in the vegetation areas extracted by the first module, to accurately delineated individual tree crowns.

C. Individual Tree Crown Delineation

Tree crown delineation will be performed on tree stands previously identified. The segmentation algorithm proposed in section IV-C belongs to the family of region growing algorithms and uses tree seed regions depicted in Fig.4-(c) as input.

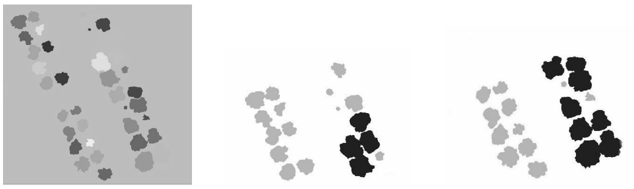
The results of this algorithm are illustrated in Fig.10-(b) on a small crop of our test area depicted in Fig.10-(a) . The reference manual delineation presented in Fig.10-(c) for the same tree stands will be used for evaluation purposes.

1) Evaluation Measures: The approach used for the evaluation is similar to the one presented in [29]. A statistical analysis is first performed taking into consideration the total number of trees in the ground truth and the omission (omitted trees) and commission errors (segments not associated with a tree). We take into consideration the following cases for the spatial analysis of the segmentation : pure segments, over-segmented trees, under-segmented trees. Fig.11 illustrates these evaluation measures. Pure segments (Fig.11-(a)) correspond to correctly identified trees. We consider that a segment is 100% pure if



(a) (b) (c)

Fig. 11. Evaluation measures defined for tree crown delineation accuracy assessment. Yellow shapes represent ground truth delineation of tree crowns. **(a)** Pure segments **(b)** Over-segmented trees. **(c)** Under segmented trees



(a) (b) (c)

Fig. 12. Tree species classification: training and test datasets **(a)** Input data: tree crown delineation results **(b)** Training area **(c)**Test area

it corresponds to one and only one segment in the ground truth and vice versa, with an overlap area greater than 80%. Over-segmented trees (Fig.11-(b)) correspond to the case when more then one segment is associated with the ground truth delineation. Under segmented trees (Fig.11-(c)) correspond to segments which include a significant part ($> 10\%$) of more than one tree.

The accuracy assessment results are presented in table I.

TABLE I
TREE CROWN DELINEATION ACCURACY ASSESSMENT

	Quantity	**% of the total number of trees**
Trees correctly segmented	32	78.0
Trees over-segmented	1	2.4
Trees under-segmented	4	9.7
Trees omitted	4	9.7
Total number of trees in the stand	41	
Total number of detected trees	37	

Tree crown delineation is performed on 3D height information of trees and is therefore not influenced by shadings, occlusions or intensity variations. Nevertheless, a precise DSM is needed to obtain accurate tree crown delineation results. Given such a DSM, the limitations remaining are the ones corresponding to particular tree shapes. This is the case with road-alignment trees, having highly intermingled tress crowns and which may be delineated as an unique tree crown.

D. Tree Species Classification

Fig.12-(b) & (c) present tree crown regions used for classification purposes. Plane trees are represented with darker tones than lime trees.

Results obtained for tree species classification are presented in Table II. The feature vectors are composed of the **Texture Measures (TM)** previously presented (i.e. *Mean, Standard Deviation, Range, Angular Second Moment, Contrast, Correlation, Entropy, Inverse Difference Moment*). Feature vectors

TABLE II
ACCURACY OF TREE SPECIES CLASSIFICATION PERFORMED ON DIFFERENT COLOR SPACES

Color space and component	**Pixel-based approach Classification accuracy (%)**	**Region-based approach Classification accuracy (%)**
RGB	58,19	73,68
Rlabel	68,09	68,42
Glabel	52,77	68,42
Blabel	62,10	68,42
IR	52,49	57,89
DSM	70,35	63,16
XYZ	61,61	68,42
Xlabel	62,59	68,42
Ylabel	58,62	68,42
Zlabel	63,13	63,16
HSV	**95,84**	94,74
Hue	61,91	57,89
Saturation	90,53	89,47
Value	93,42	**100**
Lab	53,13	57,89
L_label	81,42	89,47
a_label	79,61	57,89
b_label	76,71	73,68

were computed on different color spaces (i.e. *RGB, XYZ, Lab, HSV*) and on each of the their components separately. Results are presented both for pixel-based approaches and for region-based ones.

As we can notice results obtained are very promising, with a classification accuracy varying from 95,84% for texture measures computed for pixel-based approach on the HSV color space to 100% for the region-based approach on the on the Value component of the HSV color space representation.

Two main conclusions can be drawn from this study. First, both first- and second- order texture measures are strong predictors of tree species. Second, models that included all pixels of a tree crown for texture measures computation explained better class variability. Future work is needed to evaluate the possibility of extending tree species classification methods to several classes.

Results of all of the above presented modules are exploited to enhance 3D city models with realistic representation of vegetation. Fig.13 depicts the 3D view of our study area with automatically inserted tree models according to real tree species. As we can observe two different tree models are present in Fig.13. If we take a closer look at the image, we notice that tree trunks are correctly positioned on the ground as we can see the projection of the tree crown on the ground, underneath the tree model.

VI. CONCLUSION AND FUTURE WORK

We presented a complete hierarchical image analysis system to characterize urban vegetation. It works on color infra-red aerial images and contains components dealing with vegetation in urban areas, from extraction to tree species classification. After identifying vegetation areas, lawns are separated from trees, then tree crown borders are delineated and trees are classified according to their species.

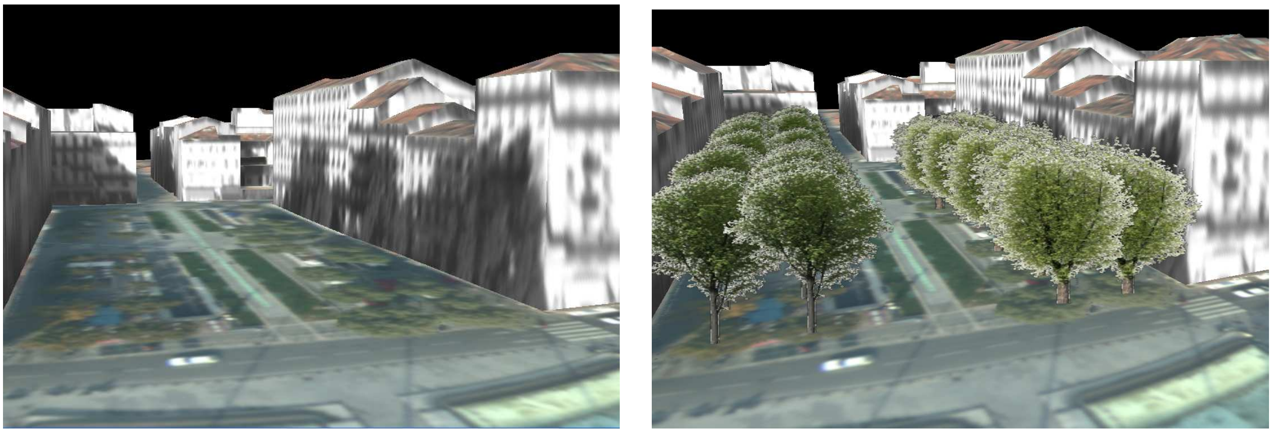


Fig. 13. 3D tree modeling over Marseille. Left: 3D city model containing buildings. Right: Automatic generated 3D city model containing buildings and realistically rendered trees according to vegetation information obtained using the proposed system.

The proposed approach operates on standard aerial data and performs a complete characterization of vegetation in urban areas without any supplementary source of information, such as hyper-spectral or LIDAR (LIght Detection and Ranging) data.

Research in the field of urban remote sensing often lacks tree species information. Our study describes a novel application of image texture analysis to classify tree crowns according to their species. The first results are promising, pointing towards future large-scale classification of vegetation in human settlements from high-resolution aerial images.

In the next step, we will use this system on images from other acquisition campaigns to check its performance when the acquisition conditions change. The output of the system will be used to enhance 3D city models, with a realistic representation of urban vegetation according to its characteristics.

VII. Acknowledgment

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