DETECTION, SEGMENTATION AND CHARACTERISATION OF VEGETATION IN HIGH-RESOLUTION AERIAL IMAGES FOR 3D CITY MODELLING

NN for anonymity

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ABSTRACT:

An approach for tree species classification in urban areas from high resolution colour infrared (CIR) aerial images and the corresponding Digital Surface Model (DSM) is described in this paper. The proposed method is a supervised classification one based on a Support Vector Machines (SVM) classifier. Texture features from the Gray Level Co-occurrence Matrix (GLCM) are computed to form feature vectors for both per-pixel and per-region classification approaches. The two approaches are presented and results obtained are evaluated and compared both against each other and also against a manual defined ground truth. To perform tree species classification on high-density urban area images, trees must previously be segmented into individual objects. All intermediary methods developed to segment individual trees will also be shortly described. Tree parameters (height, crown diameter) are estimated from the DSM. These parameters together with the tree species information are used for a 3D realistic modelling of the trees in urban environments. Results of the described system are presented for a typical scene.

1 INTRODUCTION

3D city modelling is an active research topic in distinct application areas. Although researches have reached maturity concerning building reconstruction, there is a growing need for a detailed representation of other urban objects such as vegetation areas. Urban vegetation investigation plays a very important role in urban planning, environmental protection and consistency development policy making.

The first step in 3D reconstruction of urban vegetation consists in the segmentation of vegetation areas followed by a classification of each previously identified region. An accurate automatic reconstruction of such types of vegetation areas is a real challenge due to their complex nature and to their intricate distribution between man-made objects in dense urban areas.

Many researches deal with the automatic detection, delineation and classification of tree crowns from aerial or satellite images. Among the different approaches proposed for tree crown delineation, a first class of algorithms uses object-based methods, which model tree crown templates to find tree top positions [Perrin et al., 2006, Larsen, 1997, Pollock, 1996].

Another class exploits shadows around tree crowns to delineate their contour [Gougeon and Leckie, 2001], such as valley-following algorithms [Gougeon, 1995] or region growing methods [Erikson, 2004]. Other contour based methods use multi-scale analysis [Brandtberg and Walter, 1998] or active contours [Horvath et al., 2006] to delineate tree crowns. Applied to forest stands, this kind of algorithms often perform well as neighbour trees often are of same species and age. Applied to urban environments, where neighbour trees greatly vary in size and species, the same algorithms perform poorly. This is mostly due to the different resolution of the input data which can induce false detections for the tree tops. Consequently, tree crowns are often over-segmented during the region growing step.

A third class uses local maxima information to estimate tree top position and the number of trunks [Pinz, 1998, Wulder et al., 2004]. This kind of techniques are mostly applied on forest stands and are based on detecting local maxima on a smoothed image. Provided that the detection filter size is appropriate for the size of the trees and the image resolution, this technique usually produces good results on medium or dense forest stands as estimated tree tops often coincide with real ones.

Urban areas analysis from aerial images received considerable attention in recent years, still studies mainly deal with the automatic extraction of vegetation structures from aerial images [Straub, 2003, Brandtberg and Walter, 1998] and of tree parameters [Song, 2007].

Tree species classification in urban areas is a very challenging area of study, due to the great spectral heterogeneity in the urban environment, to crown shadowing, differential crown illuminations, the great mixture of tree species in a stand, the great variety of tree ages and shapes.

The tree species classification approach proposed uses a supervised classification method based on SVM's. Texture features are computed to form feature vectors for both per-pixel and per-region classification approaches. The two approaches are presented and results obtained are evaluated and compared both against each other and also against a manual defined ground truth.

The strategy of our approach consists of several steps: detection of vegetation areas, segmentation of vegetation types according to their height followed by individual tree crown delineation. Tree species classification is later on performed for each individual tree crown previously segmented. The following section describes the data used in our research. The methods developed to detect vegetation areas, to separate lawns from treed areas, to delineate tree crowns and to perform tree species classification are presented in the third section. Results obtained on our study area are presented and evaluated in the fourth section of this paper. Conclusions and perspectives of our work are presented in the last section of this paper.

2 STUDY AREA AND DATA

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.

Tests were carried out on digital colour infrared aerial images, taken in November 2004, with a ground resolution of 20cm per pixel. The Digital Surface Model (DSM) was derived from the multi-view aerial images using a multi-resolution implementation of Cox and Roy′s optimal flow image matching algorithm [Roy and Cox, 1998]. Figure 1 depicts sample images of our study area.

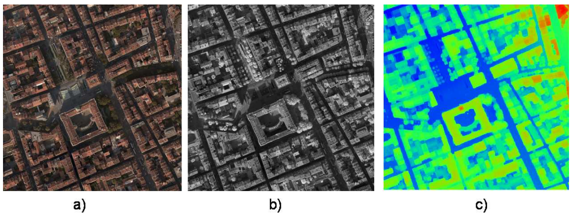

Figure 1: An aerial image of Marseille (France) representing a high density urban area, where 1 pixel corresponds to approximately 20cm (a)RGB channels (b)IR channel (c)DSM for the same area

The following section presents the algorithms we developed to perform tree species classification.

3 METHODOLOGY

Detection of a class of objects in large images and classification of objects in segmented images have intensely been researched in computer vision in recent years. Given a set of distinguishable objects, their classification can be performed. Before such a task can be undertaken it is first necessary to partition the image into regions corresponding to individual objects.

To perform tree species classification, trees must previously be identified as individual objects. In this section, we summarise our approach to extract vegetation areas, separate lawns from trees and delineate individual tree crowns. For a detailed description of methods developed for this processing steps please refer to [for anonymity, 2007].

3.1 Vegetation Detection

A supervised classification system using a linear-kernel Support Vector Machines (SVM) classifier was used to identify vegetation areas. The method we propose is robust to the nature of the urban surface and to the atmospheric conditions. The training data set is made up manually and contains both vegetation and non vegetation areas. The feature vector we used contains four characteristics, namely, the reflectance values of each pixel in the infrared, red, green and blue bands. The output of this processing step is depicted in Figure 2 and is further on used to mask out all non-vegetation areas.

3.2 Tree Grass Segmentation

The goal of this second step is to identify treed areas from the vegetation areas previously delineated. We developed a method based on texture characteristics of the vegetation areas on the Digital Surface Model (DSM). Treed areas are characterised on the DSM by a higher gray-level variance compared to lawn areas. To segment trees from lawns, we compute the local height variance as this feature accentuates large changes in height values between adjacent pixels. The resulting image is thresholded

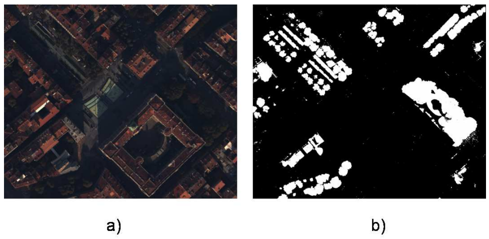

Figure 2: Vegetation detection based on linear-kernel SVM classification (a)Input image (b)Vegetation mask

using a histogram-based method to obtain masks for grass and treed areas. Figure 3 shows the results obtained for grass/treed area separation for the test area depicted in Figure 1.

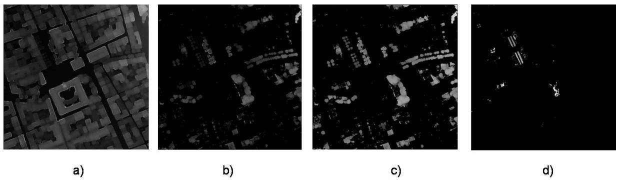

Figure 3: Differentiation between grass and treed areas (a)Local variance computed on the DSM (b)Vegetation areas on the DSM (c)Treed areas (d)Lawns

3.3 Individual Tree Crown Delineation

To segment individual tree crowns we work on the treed areas previously identified corresponding to the DSM, further on called Canopy Height Model (CHM). We developed a robust region growing algorithm to segment individual tree crowns on the CHM. We extract seed points with a one-to-one correspondence with the tree tops on the CHM. For this step, we first smooth the CHM by a Gaussian filter. We then evaluate the maximum height of the trees present in the CHM 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 analyse all points at higher heights than h and detect a new seed when a new region appears and it doesn′t touch pixels previously labelled as seeds. A graphical illustration of this algorithm is presented in Figure 4.

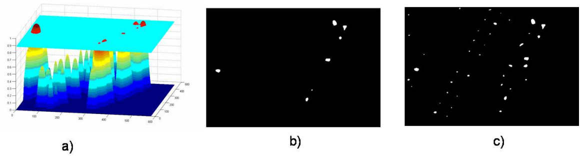

Figure 4: Detecting tree tops from the DSM (a)3D view of the DSM: all points higher than the analysis altitude h are evaluated for tree top estimation (b)2D view of the 30th iteration (c)Seed points detected after the final iteration: we can notice that we obtain one seed region for each tree.

Tree crown borders are obtained by an approach similar to the previous one, based on a height descent. The altitude analysis h is iteratively decreased, and for each step, pixels corresponding to lower height than the seed's height are aggregated to the adjacent seed. The results of this algorithm for tree crown delineation for the test area presented in Figure 5 - (a) can be seen in Figure 5 - (b).

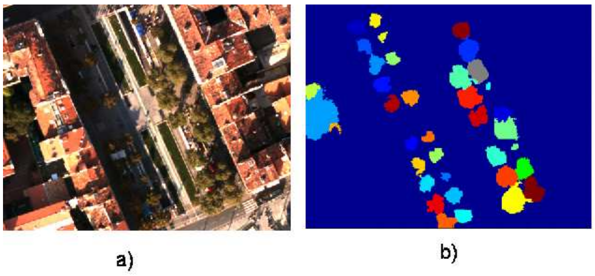

Figure 5: Tree crown delineation results. (a) Input data (b) Segmentation results for the proposed region growing method

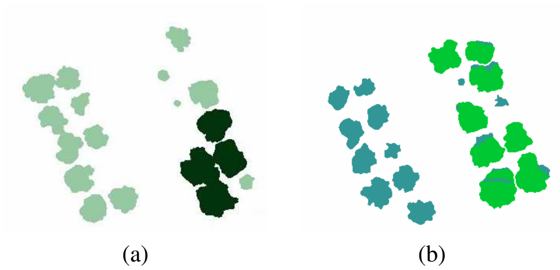

Figure 7: Tree species classification: training and test data-sets (a)Training area (b)Test area

3.4 Tree Species Classification

3.4.1 Feature Extraction Tree species are defined by several characteristics, such as average height, crown shape, leaf shape and color, stem density, crown spectral characteristics, and so on.

Images are composed of tone (i.e. spectral information) and texture (i.e. tonal variability in a given area), two interdependent characteristics [Baraldi and Parmiggiani, 1995, Harralick et al., 1973]. The texture of an image contains information about the spatial and structural arrangement of objects [Tso and Mather, 2001]. There are two classes of texture measures: first order (occurrence), and second order (co-occurrence) statistics [Harralick et al., 1973, Mihran and Jain, 1998]. First-order statistics are derived from the histogram of pixel intensities in a given neighbourhood (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 pixels values co-occur in a given direction and distance [Harralick et al., 1973, Mihran and Jain, 1998].

Other methods used to characterise image texture include Fourier analysis, wavelets, variograms, fractal dimension [Tso and Mather, 2001].

In this study we focused on first- and second- order measures to characterise tree species. We computed the following texture measures: *Mean, Standard Deviation, Range, Angular Second Moment, Contrast, Correlation, Entropy, Inverse Difference Moment*. 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:

$$G(d,\theta) = [g(i,j|d,\theta)] \tag{1}$$

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-neighbourhood centred 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 analysed. 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 characterise 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 decided to compute second order statistics over a direction of $0°$.

3.4.2 Texture Classification The supervised classifier used is a linear-kernel SVM one in a one-against-one configuration. Support Vector Machines demonstrated in recent years excellent performance in a variety of pattern recognition problems. For a detailed analysis of SVM's please refer to [Vapnik, 1995, Li and Kwok, 2003].

Texture classification was done using different feature vectors computed on four different colour spaces: *RVB, XYZ, Lab, HSV*. Since we want to separate vegetation regions which look similar, it seems that using perceptual relevant colour spaces is important. For a review of colour spaces in the context of image segmentation, please refer to [Ceccato et al., 2001].

The training and test databases will be presented in the section 4, together with the experimental results obtained.

4 RESULTS AND EVALUATION

We computed fist- and second- order texture measures in several colour spaces for each of the segments previously identified. 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 analysed 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.

Figure 7 presents 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 1, for feature vectors composed from *Texture Measures (TM)* computed on different colour spaces. Results are presented both for pixel-based approaches and for region-based ones.

Table 1: Accuracy of Tree Species Classification

Feature vector	**Pixel-based approach Classification accuracy (%)**	**Region-based approach Classification accuracy (%)**
TM on RVB	58,19	73,68
TM on Rlabel	68,09	68,42
TM on Vlabel	52,77	68,42
TM on Blabel	62,10	68,42
TM on IR	52,49	57,89
TM on DSM	70,35	63,16
TM on XYZ	61,61	68,42
TM on Xlabel	62,59	68,42
TM on Ylabel	58,62	68,42
TM on Zlabel	63,13	63,16
TM on HSV	95,84	94,74
TM on Hue	61,91	57,89
TM on Saturation	90,53	89,47
TM on Value	93,42	100
TM on Lab	53,13	57,89
TM on Llabel	81,42	89,47
TM on alabel	79,61	57,89
TM on blabel	76,71	73,68

As we can notice results obtained are very promising, with a classification accuracy varying from 93,42% for texture measures computed for pixel-based approach on the Value component of the HSV color space representation to 100% for the region-based one for the two class separation problem mentioned above.

4.1 3D Tree Modelling

Tree height is estimated as the distance from the base of the tree to the tree top. We estimate the position of the trunk of the trees on the ground as corresponding to the barycenter of the tree crown surface. The ground altitude at the base of the tree is computed in this point, from the Digital Terrain Model (DTM) which is a digital representation of a topographic surface. Tree tops are estimated as corresponding to the location of the seed points previously extracted for each tree. The height of the tree tops is thus directly computed on the Normalized Digital Surface Model (nDSM). The nDSM is computed as the difference between DSM and DTM.

Tree height, tree position and tree species information are used to enhance 3D city models with realistic representation of vegetation. Figure 6 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 Figure 6. 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.

5 CONCLUSION AND FUTURE WORK

We presented our approach for tree species classification in high density urban areas. We uses colour infra-red aerial images and a DSM to extract vegetation, separate lawns from trees, delineate tree stands into crowns, classifying tree crowns according to their species, and analyzing tree crowns to determine physical information about individual trees which will in the end be integrated into 3D city models.

Research in the field of urban remote sensing often lacks the tree species level identification. Our study describes a novel application of image texture analysis to classify tree crowns according to species. The first results are promising, pointing towards future large-scale classification of vegetation in urban areas from high-resolution aerial imagery. Two main conclusions can be drawn from our study. First, both first- and second- order texture measures were 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.

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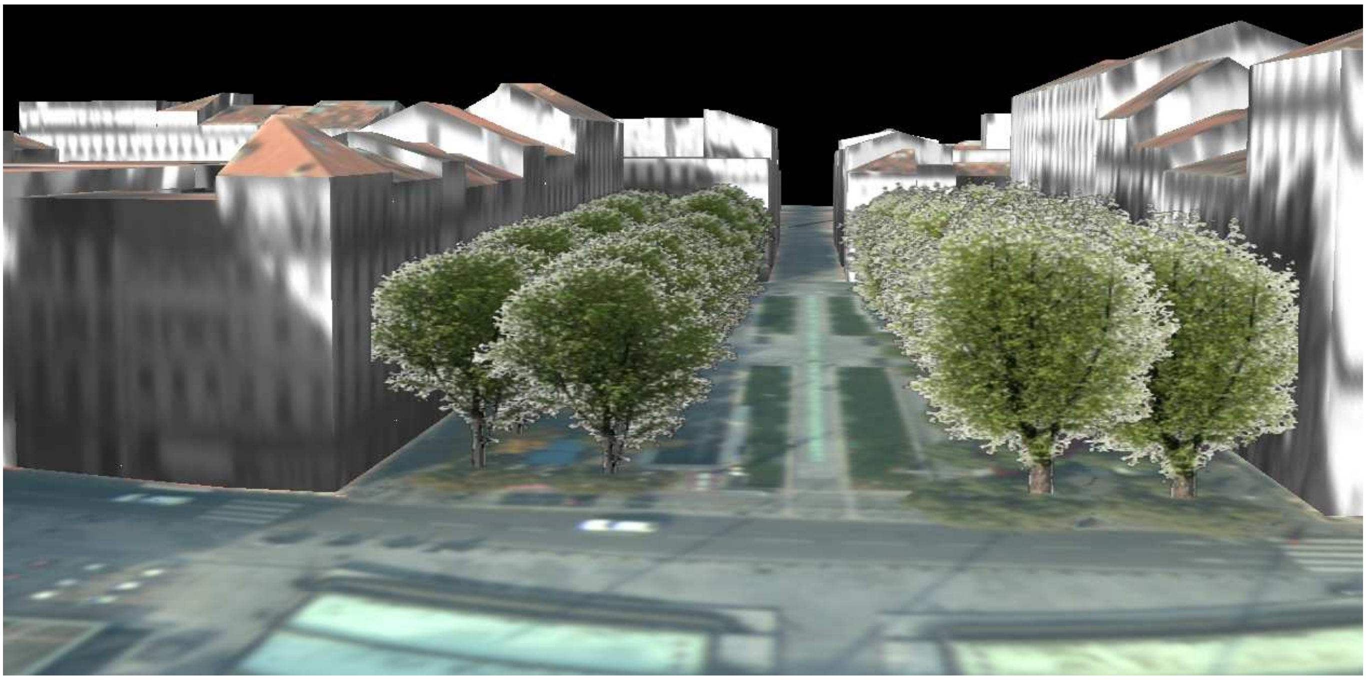

Figure 6: 3D tree modelling over Marseille