Automatic Extraction of Trees for 3D-City Models from Images and Height Data

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ABSTRACT: The automatic extraction of trees from aerial imagery in an urban environment is the main focus of this paper. Aerial color infrared images and a dense digital surface model are used as sources of information for the automatic extraction of individual trees and their characteristics. The strategy of our approach is to reduce the complexity of the image content by means of different abstraction levels. The extraction starts on a global scene level with the detection of hypotheses for tree and building regions, describing the coarse content of the given scene. The tree regions are further analyzed on the local level. Trees in the tree regions are detected, and a first rough estimation is made of the 3D centers of the crowns and their radii. For each tree the 3D position and the shape of the crown is refined at a last stage.
The paper describes the developed algorithm in detail and proves its feasibility using real imagery and height data.

1 INTRODUCTION

Geographic information systems (GISs) have received major attention over recent years. A particularly important challenge is the task of populating the GIS databases with geo-objects. Due to their history existing GISs are often two-dimensional. At least in urban environments, however, the extension to the third dimension is necessary in order to meet the users' demands as demonstrated by a survey conducted under the auspices of the European Organization for Experimental Photogrammetric Research (OEEPE). 55 institutions – users and producers - from 17 European countries took an active part in the OEEPE survey on 3D city models (Fuchs et al., 1998). Applications mentioned in the survey included architecture, tourist information systems, the telecommunication, and the computer game industry. The analysis of a questionnaire answered by the participants showed that there exists a relatively high demand for vegetation data: currently 78 % of the producers and 71% of the users are concerned with vegetation. In future, the user requirements will mainly be directed towards vegetation, refer Fuchs et al. (1998).

It is well known that the GIS data constitute the most valuable part of any GIS, partly because of the high cost involved in data acquisition and update. Therefore, major research efforts have been concentrated on partly, at least, automating the data acquisition. The automatic extraction of vector data from aerial images (also called image analysis) is one of the main research topics in photogrammetry and computer vision; Ebner et al. (1999) and Förstner et al. (1999) give an overview of its current status. About two decades ago, Rosenfeld (1982) defined image analysis as "the automatic derivation of an explicit meaningful description of physical objects in the real world from images". Advances in technology and research will probably lead to the integration of image analysis and GIS into one single system, in the future this development may lead to an even more automated updating process of geo-data by means of imagery.

In this paper we describe our current work on automatic extraction of trees from aerial CIR images and normalized digital surface models. Our focus on trees is motivated by the fact that trees constitute an important object class for applications of 3D city models (see above). For our work, the application consists in building a simulation system for training emergency force officers to better respond to crisis situations (CROSSES, 2001).

We start with an overview of the current work about the extraction of trees from images in different contexts. In chapter 3 we present the employed strategy for extracting topographic objects from images. Then, we describe how this strategy is applied to the extraction of trees in an urban environment including examples of obtained results. The paper concludes with an outlook onto future developments.

Regarding the terminology, we use the term *image* as a generic term for raster data in a regular grid, every pixel can have a height value or one or more reflectance values. A *digital surface model* (DSM) is an image consisting of height values including vegetation, buildings and other objects. A *digital terrain model* (DTM) consists of only those points lying directly on the terrain. The difference DSM - DTM is called *normalized DSM* (nDSM). *Scene* is used for the domain of the real world which is mapped in the images, the *scene description* consists of the instances of objects visible in the scene.

2 RELATED WORK

2.1 *Forest*

The extraction of trees for forest inventory purposes was investigated by different researchers. Regarding the user requirements the height of the tree and the radius of the crown are most important, mainly due to the fact that the stem diameter is correlated with the height and the radius (Borgefors, 1999, Hyyppä et al., 2000). The stem diameter, in turn, is an economic factor in forest management and can also be used for visualization of the whole tree in other applications. Pollock (1994, 1996) proposed a generic model for a tree divided into a geometric part, a function for the leaf density distribution, and an illumination model. The outer envelope of a crown is described by a surface of second order, a generalized ellipsoid of revolution (GER). The GER has the following form:

$$\frac{(z-z_0)}{a^n} + \frac{\left((x-x_0)^2+(y-y_0)^2\right)^n}{b^n} = 1 \tag{1}$$

x, y, and z describe a co-ordinate system with the z-axis pointing up. b is the radius of the crown, and a is the height of the tree above the terrain. The parameter n characterizes the shape of the surface. Values for n smaller than 2 lead to a cone, if n increases beyond 2 the resulting shape becomes more and more cylindrical. The co-ordinates x_0, y_0, and z_0, translate the local co-ordinate system to the scene co-ordinate system, and thus describe the position of the tree in the scene.

Pollock generates templates based on this geometry, the leaf density distribution, and the position of the sun. The templates, which are looked upon as an idealization of an image of the real crown, are varied by means of the parameters of the GER and matched in the image. The approach was tested using one channel of the Canadian MEIS II scanner, images had a ground sampling distance (GSD) of 36 cm. Another approach was proposed by Gougeoun (1995), also using similar data. Tree outlines are extracted by means of a method which interprets the shadow areas between the trees as valleys in the gray value distribution. In a second step the tree outlines are extracted more precisely with a rule based approach on the pixel level. Brandtberg & Walter (1998) have developed an approach for the extraction of trees from aerial images with a GSD of 10 cm. After a Gaussian smoothing of the image with different kernels, edge extraction using zero-crossings is performed in all resulting images. Valid edges are selected by means of their gray level curvature and length. The curvature centers of the extracted edges are accumulated over all used images scales and are interpreted as the centers of tree crowns. A region growing is performed as last step for the delineation of the individual tree. The same approach was also applied with good results to height data with a GSD of 10 cm (Borgefors et al., 1999).

2.2 *Settlement and Open Landscape*

The extraction of individual trees in urban environments is also addressed by a number of authors. Here the main applications are 3D city models and tree cadastre. Brunn & Weidner (1997) proposed to use the variance of DSM surface normals to detect vegetation regions. Laser scanner data and a color infrared image are used in combination by Brenner & Haala (1998, 1999) for the classification of an urban scene. A pixel based unsupervised classification algorithm is employed to perform the segmentation of the image. The skeleton of each region classified as trees is computed, and the junctions within the skeleton are looked upon as center points of trees. In their work the authors show that the combination of CIR image and height data leads to reliable results for the detection of vegetation and buildings in an urban environment. However, the work is mainly focused on the extraction of buildings, vegetation is not treated in any great detail.

Mayr et al. (1999) investigate the suitability of DSM data for the classification of trees, they use a GER, as proposed in (Pollock, 1994). The GER parameters are estimated by a least squares adjustment, coniferous and deciduous trees are differentiated by means of their geometry using the GER parameter n . The position of the tree in the scene is assumed to be known. Panchromatic high resolution aerial imagery, taken in spring, is used by Bacher & Mayer (2000) for the extraction of deciduous leafless trees in urban environments. The shadows of the trunks are used as hypotheses for tree positions. After line extraction, valid lines are selected by means of a Hough transform, then the individual branches are searched. An approach for the extraction of rows of trees in combination with roads in open landscape from color infrared images with 0.8 m GSD is described in (Heipke et al., 2000). The description for the row of trees is taken from a GIS data model. After a separate processing of roads and trees, the rows of trees are used as possible road candidates, which leads to a refinement of the road network.

2.3 *Consequences for our work*

Most of the authors make use of a geometric model of the tree. The 2D surrounding of the crown is generalized to a circle, (Pollock 1994, 1996, Mayr et al. 1999, Bacher & Mayer 2000, Heipke et al., 2000) or an ellipse (Brandtberg & Walter, 1998). In 3D Pollock (1994, 1996) and Bacher & Mayer (2000) use a GER as geometric description. Based on the presented analysis of the published references we have chosen to also use the GER geometric model proposed by Pollock (1994), and adopt the idea of template matching in an adaptive refinement step.

Similar to Brenner & Haala (1999) we combine CIR and height data. Developments in imaging sensors show, that this combination of data will be available on a routine basis in the near future. These sensors are laser scanner combined with an optical line scanner, for example the Toposys II instrument (TOPOSYS, 2001), or multiple view CIR digital images in combination with an automatically generated DSM.

In contrast to the work by Brenner & Haala we focus on trees in urban environments, motivated by the fact, that relatively little work was done in this domain up to now, and that there is a growing demand for 3D vegetation objects.

3 HIERARCHICAL IMAGE ANALYSIS

In our work the scene to be interpreted is subdivided into four super classes: *settlement*, *water*, *forest* and *open landscape*. These super classes can then be used as global context knowledge about the scene. In many GIS data models similar classes can be found as the highest level of abstraction in a hierarchically structured data model. An example for an object hierarchy is given in Figure 1, ordered by the abstraction level. The highest level of abstraction is given by the landscape, level 2 contains the super classes, different areas are placed in level 3, the next level consists of the objects and the lowest level of abstraction is given by the level of object components.

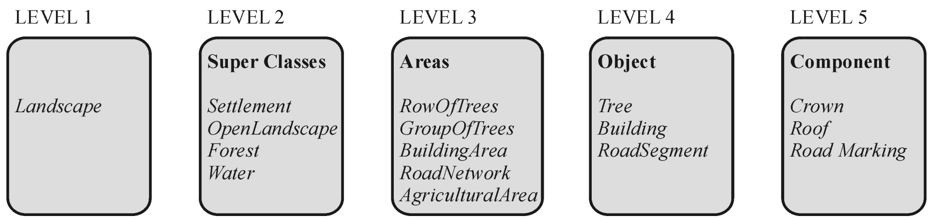

Figure 1: Different abstraction levels in the hierarchical structure of the landscape

Following a proposition made by Suetens et al. (1992), also used by Mayer (1998), the existing methods of image analysis can be mapped into a two dimensional solution space. One axis describes the suitability for complex models and the other axis the suitability for complex image data. Methods for processing either simple models or simple images are available. However, complex models in conjunction with complex image data cannot be handled appropriately with existing methods. Thus, a reduction in complexity is necessary. Since the model complexity is usually dictated by the application, only the image complexity can be manipulated. It can be reduced by means of a scale-space transformation (Lindeberg, 1994) and by a reduction of the processing domain.

In order to solve a problem with complex models and complex images, it can be argued that the following hierarchical strategy is feasible (see again Figure 1): At some level L of the hierarchy the image complexity is reduced using a scale-space transformation. The related object classes of level L+1 are searched for only in the parts of the scene, in which the context – given by the instances of the level L objects - is known. This procedure is repeated until the last level is reached, leading to a stepwise reduction of the complexity of the images. Therefore, simple object models can be applied in the actual level to be processed. The context always defines the domain of the scene relevant for the actual level and is also used to set initial parameters for the object extraction.

4 MODELS FOR TREE EXTRACTION

4.1 *Scene description*

In this chapter we describe how the presented strategy can be used to successfully extract trees in aerial CIR images and height data. We present a scene description based on a semantic net which captures the different abstraction levels of the landscape mentioned above, additionally we introduce the concepts we have defined for the extraction of trees, refer to Figure 2. A *Tree* appears in different context, as part of a *RowOfTrees* concept in the *OpenLandscape*, and also in the context of *settlement* as a part of a *GroupOfTrees*.

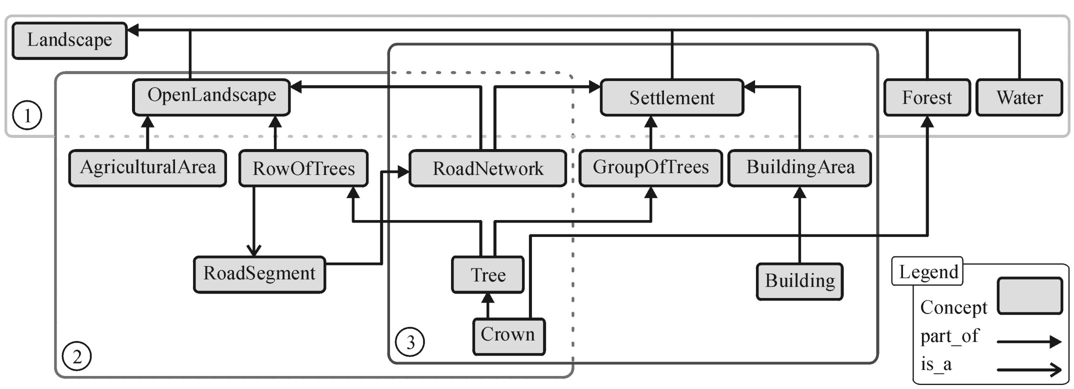

Figure 2: Partial scene description based on semantic nets, decomposed into sub graphs

The whole graph representing the scene description can be decomposed into sub-graphs. These sub-graphs are the *Landscape (1)* sub-graph, the *OpenLandscape (2)* sub-graph and the *Settlement (3)* sub-graph, refer to Figure 2. The sub-graphs represent different parts of the landscape, but overlap where an object can appear in more than one sub-graph. In this case, however, the object "knows" from the context into which sub-graph it belongs. Therefore, models and methods relevant in this very sub-graph can be chosen for the extraction. In previous work we have described how the super classes of the *Landscape* sub-graph *(1)* can be automatically extracted from CIR images (Heipke & Straub, 1999) and how the *OpenLandscape* sub graph can be used to simultaneously extract roads and trees/rows of trees in open areas (Heipke et al., 2000). For the latter case we have also presented an evaluation of the achieved results (Straub & Wiedemann, 2000). In the research presented here we further consider the settlement sub-graph only.

4.2 *Geometric and radiometric model for individual trees in the settlement sub-graph*

The extraction of trees in the settlement context is based on a model, which includes geometric and radiometric features, as well as neighborhood relations, refer to Figure 3. Regarding the geometry of an individual tree we use the GER as mentioned before. The radius b is set to a minimum value of 2.5 m, and the minimum value for the height of the tree a is set to 5 m. The shape parameter n is set to n = 2 leading to a shape, which mainly fits to broad-leafed trees, as this is the kind of trees we expect to be found most often in images of settlement areas flown after the leaves have come out.

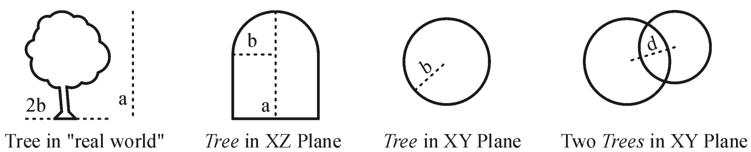

Figure 3: A tree in the "real world" and the geometric parts of the concept *Tree*

In the radiometric tree model two aspects are used, (1) we assume that a tree has a spectral signature different from the one of the neighboring trees, and (2) the NDVI value must be characteristic for vegetation. The first assumption is needed to separate neighboring trees, the second one to differentiate vegetation from non-vegetation areas. As in an urban environment the trees are often planted by humans, trees usually stand at some distance. In our model we assume that the distance d between trees is larger than their radius b (see Figure 3, right).

4.3 *Detection of GroupOfTrees instances in Settlement Regions*

The settlement sub-graph consists of a *settlement* concept as the level 2 base node, refer to Figure 2. Level 3 consists of three nodes, *BuildingArea*, *GroupOfTrees* and the *RoadNetwork*. In the following we will use vegetation as a material property due to its scale independency, therefore vegetation is not mapped into the settlement sub-graph as a concept. We start with the concept *GroupOfTrees*, which can be extracted from the scene by means of the material property *Vegetation* and the geometric property *3DObject*. We use the term *3DObject* for the objects in the scene having a height above the terrain, for example a building in contrast to a road. The NDVI is used as feature for vegetation, and the nDSM as feature for *3DObject*, refer to Figure 4. The different objects are ordered by means of their concepts´ life cycle - from left to the right - and by the abstraction level from top to bottom. The "Material and Geometry" layer is used for class properties, which are independent of the abstraction levels. The "Image" layer contains the low-level features, which are extracted from the original image data.

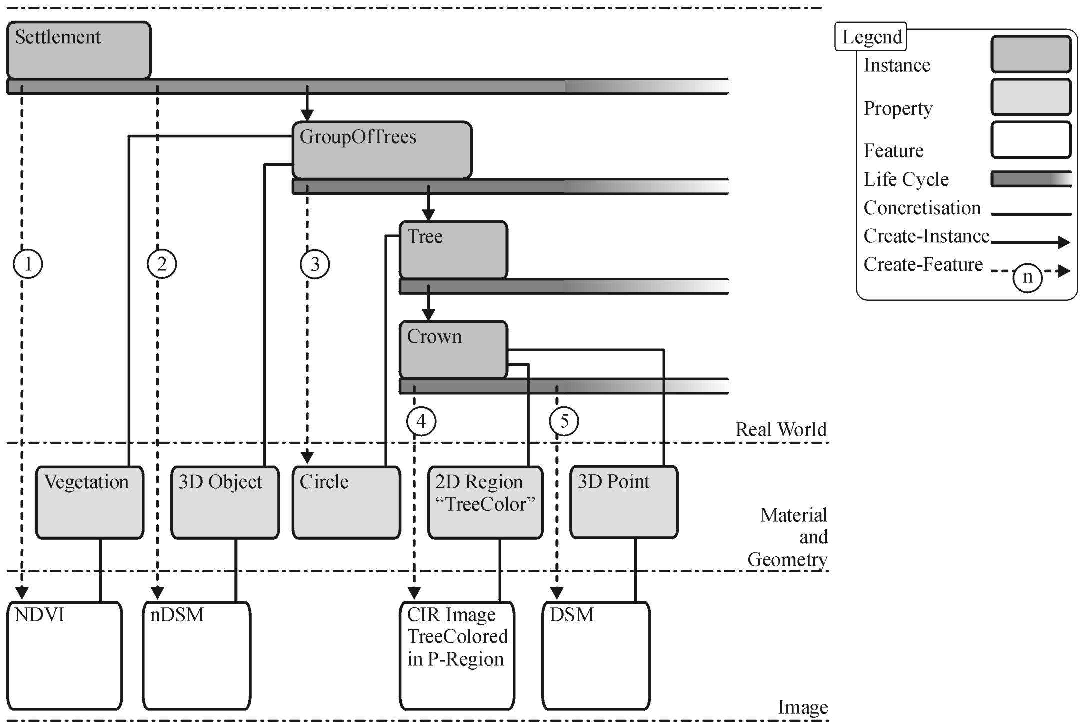

Figure 4: Model and sequence diagram for the extraction of trees in settlement context

In order to detect vegetation in the CIR image the NDVI image is segmented into the two regions vegetation and non-vegetation. This segmentation is based on a histogram analysis of the NDVI image under the assumption that there exists a clear local minimum close to zero which represents the threshold necessary for the segmentation.

In the nDSM[1] *GroupOfTrees* are searched for as local maxima having a minimum size. The local maxima are easily found using a threshold of 5 m, corresponding to the minimum height of a tree (see section 4.2), and the resulting areas are tested for size, areas larger than one single tree, i. e. $\pi(2.5\text{m})^2$, are selected for further processing. After creation of the necessary features (marked as (1) and (2) in Figure 4), instances of the concept *GroupOfTrees* are generated by intersecting the vegetation areas with the detected *3DObjects*.

4.4 *Decomposition of GroupOfTrees to individual Trees*

After the instantiation of a *GroupOfTree* object the extraction of individual trees is performed, assigned with (3) in Figure 4. A *GroupOfTrees(i)* region, called GOT_i in the following, is depicted in Figure 5. GOT_i consists of four individual *Trees(j)*. The decomposition of this region into individual tree hypotheses is carried out by means of mathematical morphology: a circular structuring element SE with radius r_k is created, called $SE_k(r_k)$ with r_k = 1.5 m (equivalent to 15 pixel). Then, an opening of GOT_i with $SE_k(r_k)$ is carried out, the result is assigned as $\gamma_{SE(k)}(GOT_i)$, following the notation proposed by Soille (1999), r_k is then increased in steps of one pixel, and after each increase the opening is repeated. The result of $\gamma_{SE(k)}(GOT_i)$ becomes empty if r_k is larger, then the largest circle which fits into GOT_i. The first *Tree*(j = 1), is then instantiated with the initial values b = r_{k-1} at the position (x_0, y_0) of the center

[1] As mentioned earlier we consider an nDSM as input to our approach. There are various methods to reduce a DSM to a nDSM, in general these are used for the processing of laser data to derive a DTM (e. g. Kraus & Pfeifer, 1998, Vosselman, 2000, Lohmann et al., 2000). A discussion of these techniques is beyond the scope of this paper. In order to actually produce a nDSM for our work we have adopted the method described by Jacobsen & Passini (2001) in which the transformation from DSM to nDSM involves a local analysis of the height differences of neighboring points and profiles followed by linear prediction.

of gravity of $\gamma_{SE(k-1)}(GOT_i)$. The corresponding circular region T_1 of *Tree*(1), is removed from GOT_i, and in the remaining region the described operation is preformed again, as long as $r_{k,j} > b_{MIN}$. The result is a decomposition of GOT_i into individual trees, see Figure 6.

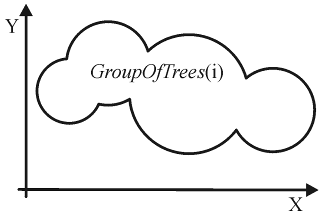

Figure 5: A *GroupOfTrees* object

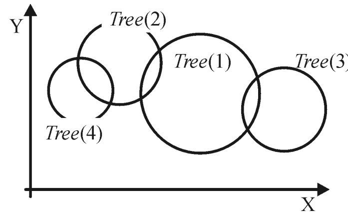

Figure 6: Individual *Trees,* correct position

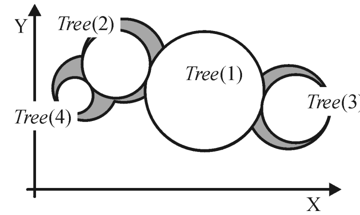

Figure 7: Individual *Trees,* including systematic errors

The removal of T_j from GOT_i lead to a systematic error in position and radius of the next *Tree(j+1)*, refer to Figure 7. This position error is reduced in the following step be means of the spectral information in the CIR image, assigned as (4) in Figure 4. The visible part of the concept *Tree* in aerial imagery is the *Crown*. For every *Crown*(j) of the corresponding *Tree*(j) two regions are defined: a circular *safe region* S with radius *b*/2 centered in (x_0, y_0) and depicted in gray in Figure 8, used for learning the characteristic spectral signature of the tree; and a *possible region* P, with a radius 1.5 *b*, plotted with a dashed line in Figure 8.

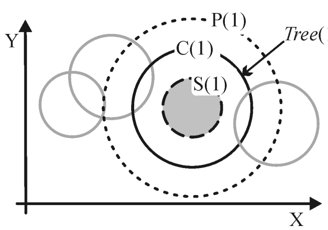

Figure 8: Regions P, C, and S

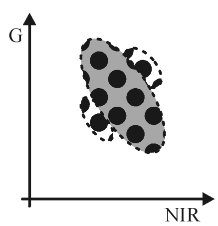

Figure 9: Feature Space

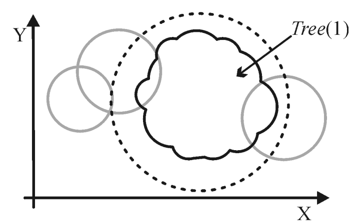

Figure 10: Extracted *Tree*(3)

We assume, that the gray values of the pixels in S are representative for the crown of the tree. These pixels are transformed into a feature space spanned by the gray values of the green and the infrared channel (Fig. 9) and the covered domain is marked as a region in the feature space. This region is extended by means of a morphological dilation with a small circular SE (diameter three pixels). All pixels in region P which fit into the extended domain in feature space are classified as pixels belonging to the crown, refer to Figure 10. This procedure is similar to the strategy which a human operator employs during multispectral classification, if the training area for a specific object class does not show a normal distribution for the gray values (ERDAS, 1997). Next, the tree center co-ordinates (x_0, y_0) are computed as the center of gravity of all pixels belonging to the tree, and the radius is calculated as $r^2 = \text{Area} / \pi$. As a final step of our procedure, assigned as (5) in Figure 4, P is computed again with the refined parameters x_0, y_0, b and a template is generated based on equation (1) with n=2. This template is fitted to the DSM in P, which leads to the missing parameters a and z_0, and the final position x_0, y_0.

5 RESULTS

The approach was applied to image and height data of a test area in Grangemouth, Scotland. The color infrared aerial images were acquired in summer 2000 for the IST project CROSSES. The image flight was carried out with 80% overlap along and across the flight direction. The image scale is 1:5000, which leads to a GSD of 10 cm at a scanning resolution 21µm. Based on these images a DSM and a true orthoimage were automatically derived by the French company ISTAR (Gabet et al., 1994). The orthoimage and the DSM cover an area of 4 km². A large part of the whole test site belongs to an industrial plant with sparse vegetation. We have selected a subset of the data set for our test with relatively typical suburban characteristics. One family houses, some larger buildings, trees and roads are visible in this subset. It is about 2700*2300 pixels large, corresponding to an area of approximately 60,000 m², refer to Figure 11 for an overview of the “Grangemouth” test site.

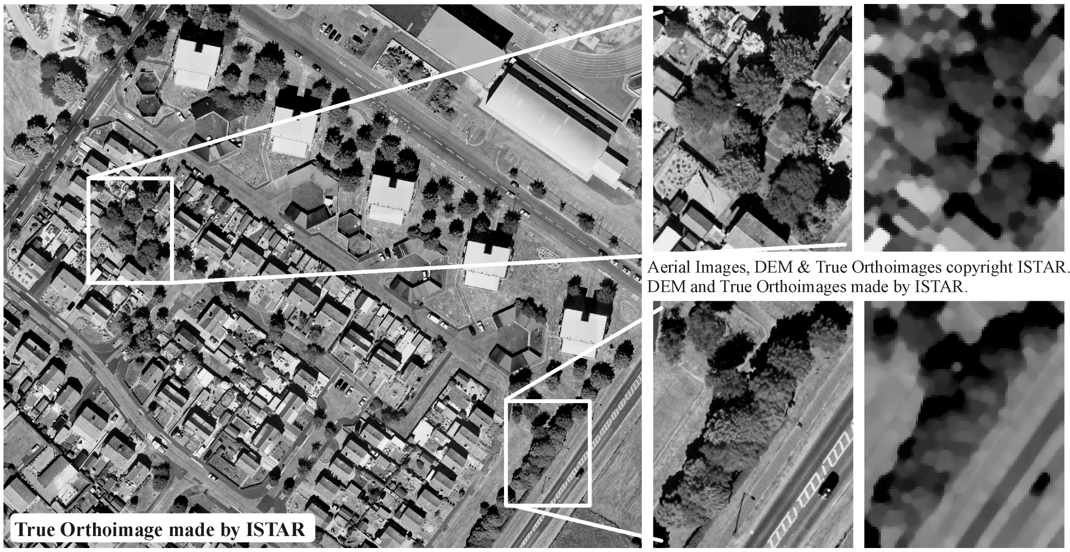

Figure 11: Overview of the test site “Grangemouth”, and enlarged subsets in different scales

Figure 12: Enlarged subsets from the test area, *GroupOfTrees* and individual *Trees* superimposed

For the two examples depicted in Figure 12 the small image on the left shows the surrounding polygon of a *GroupOfTrees* object with the corresponding image. The larger image shows the resulting individual *Trees* by means of a circle superimposed to the image. The first example shows a good case, here the trees are clearly separated, refer to Figure 12 left. In this case the surrounding polygon of the *GroupOfTrees* instance can be decomposed into circles. Additionally, the colors of the trees are different, too, which is not clearly visible in the gray value image. The resulting *Trees* fit the expectations, a human operator would have digitized them in a similar way. The second example (Figure 12, right) shows a more difficult case, here the trees stand close together, and the color is quite similar. Therefore, neither the first morphological step, nor the refinement in feature space lead to a good approximation of the tree position. The larger circle at the bottom contains in fact parts of several trees.

Overall, 235 trees were extracted in the test site with the approach described above. In order to estimate the *completeness* (True Positives / (True Positives+False Negatives)) and the *correctness* (True Positives / (True Positives+False Positives)) as well as the geometric error in position and radius we have compared the obtained results to reference data. A completeness of 95% and a correctness of 89% was reached, refer for example Wiedemann et al. (1998) regarding the quality measures. The latter were captured semi-automatically from the same images. A window was opened at the center co-ordinate of the tree in question, and the extracted tree was indicated to a human operator. He subsequently defined radius and position for the “reference tree”. The corresponding height value was computed automatically as the mean value inside the circular area at the reference position. The error in the position was computed as the mean value of the Euclidian distance between the automatically and the manually captured positions of all 235 trees. The error in the height and radius were derived accordingly. The mean error in the position resulted in 90 cm, the height error in 20 cm, and the radius error in 70 cm. Considering the results of the difficult cases these results – although amounting to 9 and 7 pixels for the planimetric parameters, and thus rather large values – are compatible with our expectations, and they are sufficient for most applications involving trees (Fuchs et al. 1998). Summarizing, one can say, that the method for the extraction of trees in urban environments leads to reliable results in the test site.

6 SUMMARY AND OUTLOOK

We have presented an approach for the extraction of trees from color infrared and height data in an urban environment for the generation of 3D city models. The approach is based on a tree model, using geometric and radiometric features as well as neighboring relations between trees. We have embedded the tree extraction into a hierarchical scene description of a landscape in different abstraction levels. The abstraction levels are used as a control mechanism for the feature extraction in order to simplify the automatic interpretation of images. The approach was investigated in a test site of approximately 60,000 m^2 with promising results.

The internal evaluation of the results will be the main focus of our work in the future, because it is seen as the most critical point in the proposed automatic system. Another point will be the modeling of relations between trees and other objects in settlement areas, first results of this work are presented in (Straub et al. 2001).

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