AN OBJECT BASED APPROACH FOR LEVEL-OF-DETAIL BUILDING MODEL RECONSTRUCTION FROM AIRBORNE LIDAR AND OPTICAL IMAGERY

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2nd International Conference on Geographic Object-Based Image Analysis (GEOBIA 2008)
University of Calgary, Alberta, Canada, August 6-7, 2008

KEY WORDS: Building objects, 3-D, Reconstruction, Level-of-Detail, LiDAR, Imagery, Least squares fitting

ABSTRACT:

The need to automatically extract topographic objects, especially buildings, from digital aerial imagery or laser range data remains an important research priority in photogrammetric, computer vision and geographic information (GI) communities. This paper begins with an overview of the concept of Level-of-Detail important for adaptive building modelling. Level of detail building modelling involves an adaptable extraction and storage of building objects in a manner that allows generalization of these objects on demand in order to meet lower resolution project requirements. The levels of interest range from prismatic, generic planar and detailed planar type building models.

Building regions of interest are derived from a normalised digital surface model (nDSM) and regularisation of the roof lines is achieved by a set of contextual constraints with particular emphasis on rectangular buildings. For detailed building reconstruction, the main consideration is given to polyhedral building types with limited support for curvilinear shapes. A moving least squares approach for computation of surface normal vectors and texture metrics is employed for planar segmentation of both grid data and unstructured point clouds. Delineation of homogeneous planar segments is based on a robust plane growing technique that employs a parametric distance metric as a determinant and dual propagation. 2-D edge lines derived from the orthoimage are matched with 3-D lines derived from LiDAR based on adjacent plane intersections and then used for the final building reconstruction. Connected regions which fail the local planarity tests and are sufficiently large, are segmented using curvature measures based on least squares quadric surface fitting. Multiple representations of the same building object are obtained by following different routes in the building reconstruction schema. Storage of the building objects is currently based on a multipatch data schema. A high level of automation and robustness in the extraction of building objects was possible from LiDAR data however the integration of image data for detailed modelling required operator intervention. Further work on the implementation of the building object model is in progress.

1. INTRODUCTION

1.1 Background

The need to automatically extract 3-D building data from digital aerial imagery or laser range data remains an important research priority. 3-D building data is important for applications such as city modelling, environmental engineering, disaster mitigation and management and emerging civilian and tactical applications such as virtual and augmented reality and homeland security. Significant success has been achieved so far with semi-automatic building extraction systems using either imagery or LiDAR data, however in restricted domains. The need for an integrated data approach for building extraction has been realised however not yet fully tested. To meet the varying demands in terms of capture of building detail and representation, incorporation of Level-of-Detail (LoD) mechanisms into the building extraction schema has become a necessity. This paper presents an integrated approach for LoD building model reconstruction using airborne LiDAR data and optical imagery and discusses the prototype implementation of the proposed model.

1.2 Related Work

Several algorithms have been proposed for enhancing the level of automation in the three-dimensional reconstruction of buildings however a robust and versatile solution is yet to be found although significant progress has been made. A discussion of systems based on and accuracies obtainable with photogrammetry and laser scanning in building extraction is contained in Kaartinen et al. (2005). To date, building extraction has largely been based on single data sources, in most cases either LiDAR data alone (Verma et al., 2006; Vosselman, 1999) or images alone (Kim and Nevatia, 2004; Scholze et al., 2001) however the current trend is on integrated data paradigms. Integration of data sets provides multiple cues that can ease the problem of building reconstruction and result in significantly higher levels of automation in the algorithms. The data bases for integrated approaches have included multiple geometric data, GIS layers and bespoke or scene specific knowledge. A number of researchers have demonstrated approaches for combining data for building modelling, for example LiDAR and aerial images (Rottensteiner et al., 2004), LiDAR and three-line-scanner imagery (Nakagawa and Shibasaki, 2003), LiDAR and high resolution satellite images (Sohn and Dowman, 2001), LiDAR and 2-D maps (Overby et al., 2004), aerial images and 2-D maps (Suveg and Vosselman, 2004) and LiDAR, 2-D maps and aerial images (Vosselman, 2002). Schenk and Csatho (2002) discuss theoretical frameworks for multi-sensor data fusion for generic surface description. Not many researchers however have incorporated LoD modelling into their approaches, important for catering for diverse users and applications.
1.3 Level-of-Detail Modelling

The concept of level of detail has been used in computer graphics since the 1970s, mainly for increasing the efficiency of graphic object rendering. Rendering efficiency is achieved by decreasing the visual and geometric detail of 3-D objects as a function of distance from the viewpoint or the perceived object importance. The concept has been adapted and extended for city modelling by the Special Interest Group on 3-D Modelling (Sig3D). LoD building modelling involves adaptable and scalable extraction and representation of building model information. This enables the capture of building information to be varied depending on the specific project requirements. The five levels of detail range from a simple block (2.5-D) model right up to a walkable model, which takes into account both internal and external geometric detail. Figure 1 below illustrates the concept of LoD modelling as modified for this research. For this research, the aim was to work up to LoD2 only.

Two main approaches for incorporating the LoD schema into the building reconstruction process can be identified. Firstly, a bottom-up approach where a multi-level strategy is adopted for reconstructing each level more or less independently varying the data sets used, their resolution and the algorithmic detail. Secondly, the initial reconstruction effort might be aimed at a detailed level with lower levels derived by progressive building generalisation. A hybrid approach is also possible. In this research, a modular bottom-up approach is adopted for the multi-level building reconstruction.

1.4 Study Area and Datasets

The study area for the research is Portbury, a small agricultural village, approximately 11 kilometres North West of Bristol, England. Portbury is one of the test sites identified by the Ordnance Survey (OS) Research Labs, source of LiDAR data and digital imagery, for research on automated building extraction. The data sets available for the test site are as follows: LiDAR data [16 points/m²]; digital orthoimagery [GSD 10cm] and OS MasterMap Topography data.

2. ROOFLINE DETECTION

The rooflines are detected from a normalised DSM (nDSM) obtained by differencing an optimised DTM derived from the LiDAR data using the adaptive TIN algorithm (Axelsson, 1999) implemented in the commercial software TerraScan and an interpolated DSM. A three-metre threshold is applied to the nDSM to detect above ground objects however these include buildings and vegetation. The options followed for vegetation removal included use of intensity data, generic tree point classification and least squares planar fitting differences. The minimum building size was considered to be 12m² according to OS specifications. Building segment simplification is achieved using the modified sleeve algorithm and rectangular enforcement is achieved by deriving a moments-based orientation and enforcing building line segments to be perpendicular or parallel to this orientation within a defined tolerance. The extracted rooflines define the regions of interest for the geometrical roof reconstruction for all LoDs.

3. BUILDING RECONSTRUCTION

3.1 LoD Reconstruction Schema

Reconstruction of LoD0 (block models) requires building rooflines and representative roof and ground heights. The building heights are derived from differences of roof and ground heights obtained from a DSM/DTM. LoD1 requires rooflines and LiDAR data for generic roof modelling based on robust planar intersections. LoD2 additionally requires high resolution image data for accurate edge and sub-feature detection.

3.2 Types of Building Surfaces

For this research, consideration is given to two types of surfaces, planar and curvilinear surfaces as shown in Figures 2. Planar surfaces form the initial hypothesis for the reconstruction algorithms because they are more common. For curvilinear surfaces, consideration is only given to quadric surfaces although this could be extended to more generic superquadric surfaces.

Figure 1. Level-of-Detail modelling schema.

Figure 2. Planar (left) and curvilinear (right) surface.
3.3 Planar segmentation

For planar segmentation of the LiDAR data, a moving least squares plane fitting algorithm is employed. For each point, a cluster of neighbouring points is determined depending on whether a grid or an unstructured point cloud is used. For gridded data, the algorithm searches for the 8-connected neighbours of each point however the grid resolution can be changed. For unstructured point clouds, the neighbourhood of each point is defined based on either a search radius or a defined number of nearest neighbours within a set maximum distance.

![Workflow for planar segmentation](image)

Figure 3. Workflow for planar segmentation.

A least squares plane is fitted to the neighbourhood of each point. For each point, a normal vector and texture metrics are computed together with tests for local planarity. Figure 3 illustrates diagrammatically the steps in the planar segmentation phase of the algorithm. Figure 4 illustrates the vector dispersion and computation of a normal vector for a planar patch. The requirement for this algorithm is to work with both airborne and terrestrial LiDAR data in order to meet the requirements of the different levels of detail.

Figure 4. Planar patch normal vector (Parker, 1996).

Applying the planar segmentation to gridded data makes the neighbourhood search easier and allows other image based metrics such as texture coefficients to be calculated however interpolating the point data introduces some unwanted artefacts. Working on scattered point data introduces a computational overhead and requires appropriate adaptation for image based metrics. The computational overhead can be minimised by pre-sorting the data points. A search radius of 1m was employed.

The planar segmentation algorithm can be summarised as follows:

1. For each data point, locate corresponding points falling within the defined neighbourhood of the point based on the appropriate search criteria.
2. For each defined neighbourhood, compute coefficients of the plane and from that compute the normal to the plane for that neighbourhood and the azimuth of the projection of the normal on the x,y plane.
3. Compute metrics for assessing local planarity (section 3.5) together with a texture descriptor for each neighbourhood and numerical checks for validating the least squares computation.
4. Data points assumed locally planar are further clustered and grown into consistent planar regions. The robust plane growing algorithm is summarised in section 3.6.

3.4 Localised planar fitting of 3-D points

Given a defined neighbourhood \{(x_\text{i},y_\text{i},z_\text{i})_{i=1..m}\} of a point, we want to fit a plane which satisfies the relationship:

\[ z = Ax + By + C \]  \hspace{1cm} (1)

where \( z \) represents height, \( A \) and \( B \) are slope parameters in the \( x \) and \( y \) direction respectively and \( C \) is the offset at the origin.

In the implementation of the algorithms, we consider two forms of minimisation of the residual sums. The first form minimises the error measured orthogonal to the plane and requires use of eigensystem solvers.

3.5 Tests for local planarity

A number of metrics are computed during the point classification phase in order to check if the point is locally planar and weed out erroneous points. The numerical tests are as follows:

- Centre point residual

For each point under consideration, the difference between the actual height value and the height computed using the determined plane parameters should be below a set threshold (Figure 5). In our case, we set the threshold to 0.09 metres based on the average error computed from the LiDAR point data based on photogrammetric control points. Equations 2 and 3 mathematically describe the computation of plane coefficients and the centre point residual respectively.

![Centre point (p_5) and connected neighbours](image)

Figure 5. Centre point (p_5) and connected neighbours.

\[
p_i = (x_i, y_i, z_i)_{i=1..9}
\]

\[
E(A,B,C) = \sum_{i=1}^{9} [(Ax_i + By_i + C) - z_i]^2
\]

\[
\forall E = (0,0,0)
\]

\[
p_i (\text{actual} - \text{calculated}) \leq \text{threshold}
\]

- Eigen-analysis
The smallest eigenvalue of the dispersion matrix $A$ (Equation 4) computed by reducing neighbourhood points to centre and taking product sums expresses the deviation of the points from the fitted plane. Local planarity is assumed if the smallest eigenvalue is less than a set threshold.

$$A = (P - M)^T (P - M)$$

where $P$ is a matrix of points $(x_i, y_i, z_i)$ and $M$ the mean matrix. A threshold value can be set for the smallest eigenvalue. This measure of planarity works well for gridded data however a more useful and standardised measure for planarity testing is the ratio of the smallest eigenvalue to the total variance given by the sum of all eigenvalues. Fransens (2006) employs a similar method of comparing eigenvalues of the covariance matrix for planarity testing of data in an octree.

### 3.6 Plane clustering and segmentation

The next step is to determine if neighbouring sub-planes defined at each data point could lie on the same planar surface. The planar segmentation and growing algorithm works in an unsupervised mode where the number of clusters is not specified beforehand but determined automatically. The algorithm involves a forward propagation, meant to detect the number of separable plane clusters based on the input tolerance parameters (minimum plane size and sigma threshold for plane fit) and a backward propagation phase for classifying each point data into one of the determined seed clusters or none. A seed plane consists of a set of points within a defined neighbourhood (search radius) that fits well to a plane. Figure 6 shows an example of the segmentation result. The planar segmentation algorithm consists of the following generic steps:

1. Automatic determination of seed planes in forward mode based on the point-plane orthogonal distance criterion and variance of data fit to a plane.
2. Labelling points in backward propagation mode using the identified seed planes and plane growing criterion.
3. Logical filtering for weeding out aberrant points and mixed labelling. The dual propagation serves to minimise the need for logical filtering.
4. Checking the planar segmentation for oversegmentation and undersegmentation then splitting and merging as necessary.

### 3.7 Planar adjacency and 3-D lines

Planar adjacency graphs are determined for clusters found for each building region of interest. Adjacency is based on the distance between the outer boundaries of the clusters.

Adjacent planes are then intersected to determine 3-D breaklines from LiDAR data, which are then verified and matched against edge lines from the orthoimage. Figure 7 illustrates the basic concept of a 3-D line description derived by intersecting planar patch pairs determined on the basis of clustered point cloud data with the circle representing the support point. The handling of step edges requires further consideration.

Reconstruction of LoD1 building objects is completed by constructing a consistent polygon topology from the roof lines and enclosed 3-D line segments determined by planar intersections. The 3-D line segments are further matched to image edge lines and the composite polygon topology used for LoD2 building reconstruction.

### 3.8 Quadric segmentation

Connected points that are not locally planar and form a sufficiently large size are further tested for curvilinearity. A second degree 2.5-D polynomial surface is fit to the data points and takes the form:

$$z(x, y) = a_{10}x^2 + a_{20}y^2 + a_{11}xy + a_{02}x + a_{01}y + a_{00}$$

The steps in the segmentation can similarly be summarised as follows:

1. For each locally non-planar point, define a sufficiently large neighbourhood of non-planar points.
2. Use least squares to fit a quadric surface to the local neighbourhood of each point.
3. Compute the derivatives of the surface and the slope of the tangent at each point.
4. Compute the minimum and maximum normal measures (principal curvatures, $\kappa_{min}$ and $\kappa_{max}$) and then derive other curvature measures (Gaussian, Mean and Laplacian).
5. Data points assumed locally quadric are further clustered and segmented into consistent surfaces.

The proposed segmentation algorithm is in some ways similar to the planar clustering algorithm. The quadric segmentation algorithm makes use of the principal curvature measures. Consider two points on a homogeneous non-planar surface $S$. For each point on the surface there are two directions corresponding to the minimum and maximum normal curvatures respectively. Points lying on the same surface will have similar curvature suggesting that the absolute differences between the minimum and maximum normal curvatures will be small. Two thresholds $\Delta\kappa_{min}$ and $\Delta\kappa_{max}$ are set for the purpose of deciding whether neighbouring points can be accepted as lying on the same surface. The algorithm automatically determines the seed surfaces which are then grown until all non-planar points have been labelled. Compensation for segmentation effects is performed after point labelling. Surface modelling is considered additive and applied in a Constructive Solid Geometry (CSG) fashion. The model could be extended to
superquadric surface fitting for more generic curvature modelling.

4. IMAGE DATA ANALYSIS

Image data serves to provide more accurate breaklines for detailed modelling, verify 3-D lines derived from LiDAR and allow texture mapping for photorealistic building modelling. There are three important considerations for the integration of high resolution image data:
- Building localisation
Building roofline polygons are localised in the orthoimage by dilating the minimum bounding rectangle then projecting this into the image. A factor of 1.25 is applied to the areal dimensions of the minimum bounding rectangle. This reduces the search space for matching purposes.
- Edge extraction
2-D linear segments are extracted from the orthoimage using the Canny edge operator (Canny, 1986).

The building outline together with 3-D breaklines both derived from LiDAR data are matched to the extracted image edge information. A feature (relational) matching algorithm is applied under an invariant 2-D affine transformation to project edge information onto the LiDAR framework which forms the basis for vertical integration. A check is made for (nearly) coincident pairs of edges and breaklines considering directions and spatial extents within some tolerance. The composite of building lines with duplicates removed is used for generating closed building topologies which are then used for LoD2 polyhedral building reconstruction. The matching algorithm is a simplified and modified version of the algorithm presented in Stamos and Allen (2000).

5. PROVISIONAL RESULTS AND DISCUSSION

This paper outlined a methodology for level of detail building model reconstruction following an integrated data paradigm. A prototype implementation of the proposed model is in progress however most parts of the algorithm have been tested piecemeal. The prototype implementation of the algorithms was done using the Java language.

Figure 8 shows part of the orthoimage for the test site with a few building regions of interest linked to Figure 9. Normal vectors are most useful for sloped planes and are problematic with flat planes whose normal vectors can be omnidirectional. The robust plane segmentation algorithm described in section 3.6 can work reliably with both sloped and flat planes.

Figure 9. Colour coded normal vector map corresponding to image subset in Figure 8.

Figure 10 shows a sample hip building in the study area. The result of applying the robust plane segmentation algorithm to the sample building is shown in Figure 11 with the 3-D line segments derived by planar intersections shown in red.

Figure 10. A sample hip building in the study whose segmentation result is shown in Figure 11.

Figure 11. The segmentation result of the sample hip building in Figure 10. Shown in red are projections of the 3-D line segments derived by robust planar intersections.
The plane segmentation algorithm was very reliable and efficient for most buildings in the study area. However, to meet the requirements for reliability and robustness, the algorithm is efficient when applied to dense datasets. The point classification phase was useful for determining locally planar points and filtering erroneous measurements.

Reconstruction of block models (LoD0) is achieved with minimal effort after processing the DSM/DTM. LoD1 reconstruction was automated to a significant level however at the present moment some operator intervention is required for LoD2 object reconstruction which incorporates image data.

The curvilinear segmentation algorithm was tested over a different study area with appropriate building types. A significant level of automation in the planar and curvilinear segmentation was possible. Further work is on full implementation and analysis of the algorithms however the results are very promising.

6. REFERENCES


