4

# LIDAR Remote Sensing Applications in Automated Urban Feature Extraction

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## 1. Introduction

Terrain elevation is a key input in numerous environmental applications and its quality plays a critical role in understanding various earth surface processes (Kenward et al., 2000; Clarke and Burnett, 2003; Neeson et al., 2008). Laser altimetry, also called lidar (light detection and ranging), is a frontier remote sensing technology for mapping earth surface elevation with high vertical resolving ability (Sun et al., 2003; Lefsky et al., 2005; Hofton et al., 2006; Chen, 2007; Simard et al., 2008).In recent years LIDAR has emerged as an important mapping tool and is finding a niche in GIS. LIDAR is a relatively new technological tool that can be used effectively in geospatial decision making. LIDAR is an acronym for Light Detection And Ranging and in some literature it is referred to as laser altimetry. A LIDAR system is composed of a laser scanning system, global positioning system (GPS), and an inertial measuring unit (IMU).

Airborne *LiDAR* has established itself as a standard method for the acquisition of precise and reliable digital elevation data. The main application of airborne *LiDAR* technology is topographic surveying. Airborne LiDAR has found application in an increasing number of mapping and geo-data acquisition tasks. Apart from terrain information generation, applications such as automatic detection and modeling of objects like buildings, roads or vegetation for the generation of 3-D city models have been extensively explored. In the present chapter airborne Lidar data has been used for semiautomatic detection of buildings and roads.

## 2. Principle of LiDAR

### 2.1 Laser

Laser (Light Amplification by the Stimulated Emission of Radiation) light is highly monochromatic, coherent, directional, and can be sharply focused.

Laser Scanning is an active remote sensing technique which provides range measurements between the laser scanner and the illuminated object (most commonly earth topography). Laser altimeter produces short or continuous pulses of laser light, which is captured by a telescope after bouncing back when they are intercepted by a target. Laser system enables day and night observation and also range measurement in textureless areas. Observations from single direction are sufficient, unlike photogrammetric technique where at least two

perspective views are required. In addition it provides data with high vertical accuracy. While LIDAR is an active system that can be, theoretically, used 24 hours a day, it cannot be used above cloud cover or when fog, smoke, mist, rain, or snow storms are present. Additionally, high winds and turbulence will cause problems with the inertial system.
Mostly laser systems are Nd:YAG emitting in NIR (1064nm) wavelength in a narrow spectral width (0.1-0.5nm). Some systems emit at 810 nm (ScaLARS), 900 nm (FLI-MAP), 1540 nm (TopoSys, Riegl). Laser systems generally emit in one wavelength only however bathymetric lasers emit at1064 and 532 nm, to measure both water surface and water bottom.

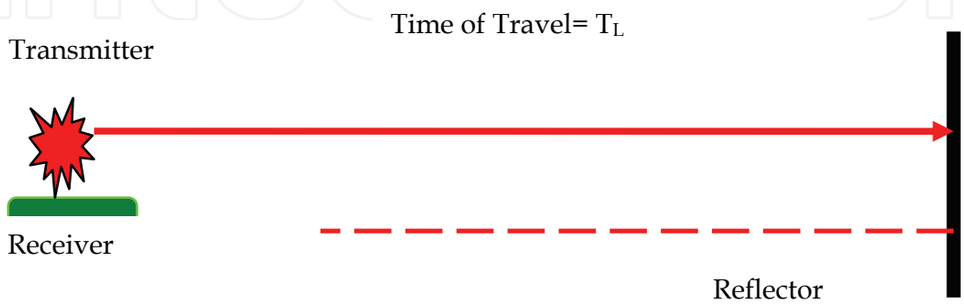



Fig. 1. Principle of Laser

### 2.2 Basic components and functioning

Typical system components include a position and orientation recording unit, a laser measurement system and a control and data recording unit.
The pulsed laser is optically coupled to a beam director which scans the laser pulses over a swath of terrain, usually centred on, and co-linear with, the flight path of the aircraft in which the system is mounted, the scan direction being orthogonal to the flight path. The round trip travel times of the laser pulses from the aircraft to the ground are measured with a precise interval timer and the time intervals are converted into range measurements. The position of the aircraft at the epoch of each measurement is determined by a phase difference kinematic GPS. Rotational positions of the beam director are combined with aircraft roll, pitch, and heading values determined with an inertial navigation system (INS), and with the range measurements, to obtain vectors from the aircraft to the ground points. When these vectors are added to the aircraft locations they yield accurate coordinates of points on the surface of the terrain.

### 2.3 Lidar system classification

Laser systems are categorized on the basis of:

1. Method of recording the return pulse:
    a. Discrete
    b. Full Waveform
2. Size/Area of illuminated spot
    a. Small footprint (few cm)
    b. Medium to large footprint (tens of m)
3. Sampling Rate/ Scanning pattern

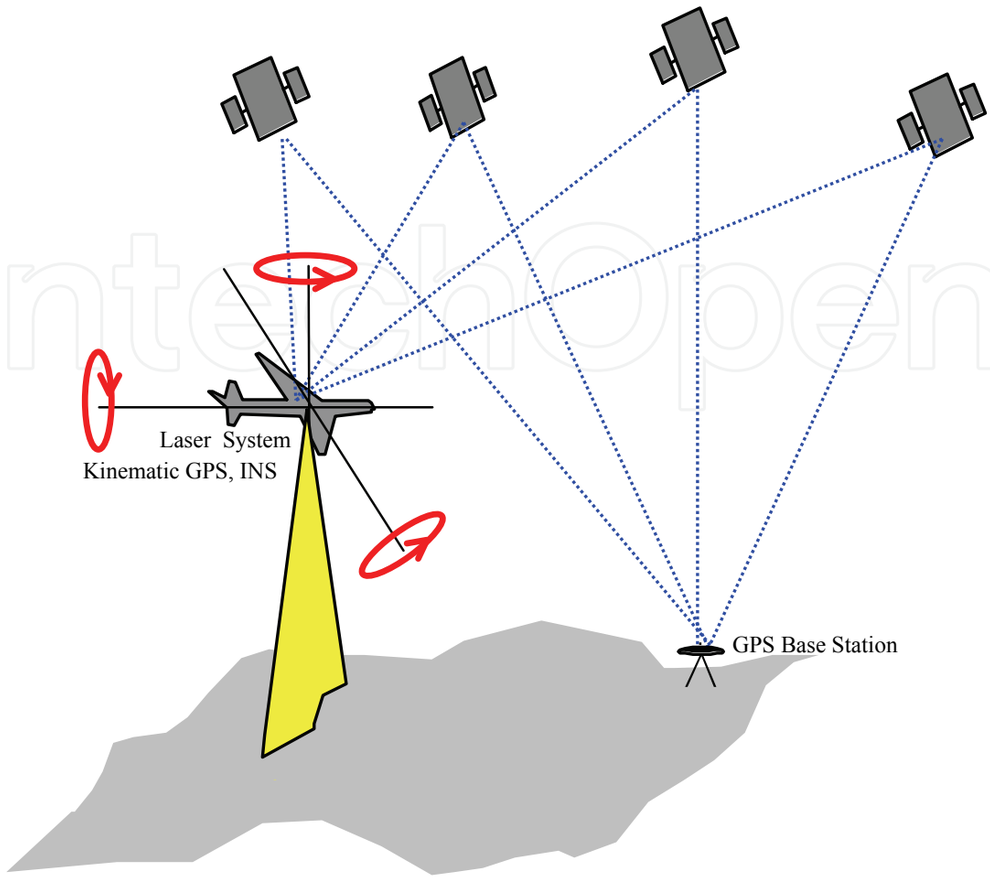



Fig. 2. Components of a Laser Altimeter

4. Pulsed and continuous wave
5. Platform Based
    a. Aerial
    b. Satellite
    c. Terrestrial

Discrete Lidar system measures the time of flight of Laser pulse until its first or last echo arrives. They can only differentiate a first, several intermediate and a last echo. Full waveform systems on the other hand sample the return signals very rapidly and store the entire echo waveform. Small footprint lidar illuminates a few cm area on the ground whereas the footprint size for medium to large footprint systems cover tens of meters. Small footprint systems provide high density data and an accurate altimetric description within the diffraction cone. However mapping large areas require extensive surveys. Besides small footprint systems often miss tree tops. Large footprint systems increase the probability to both hit ground and canopy top (Mallet & Bretar 2009). Pulsed systems measures the round trip time of the light pulse from the laser to the target and back to the receiver. Continuous wave systems use phase difference between transmitted and received signal for range measurements.

Apart from range, several other physical properties like width of backscattered echo, amplitude and cross section of backscatter are also measured.

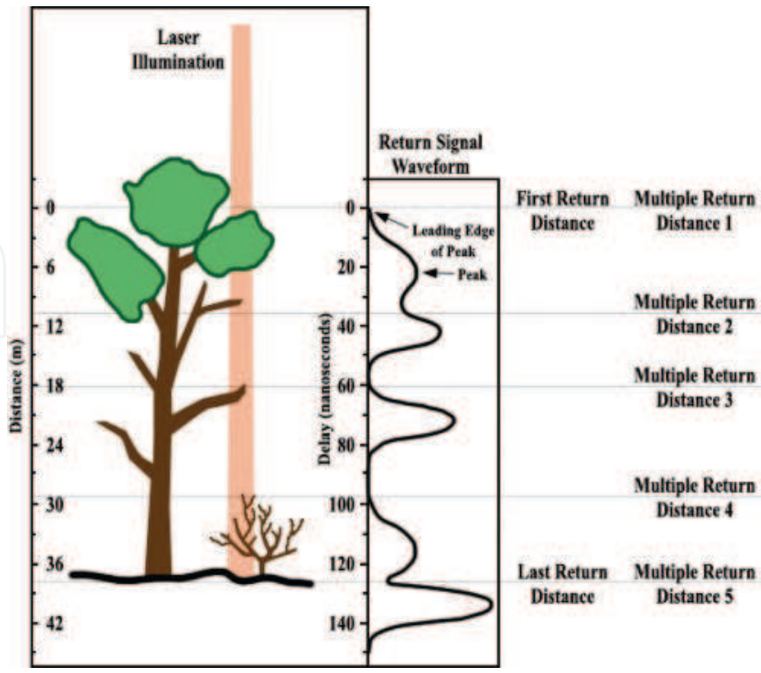



Fig. 3. **Discrete and Full Waveform Lidar** (In a waveform lidar, the entire return pulse is digitized and recorded. In a discrete multiple-return lidar, only the peaks would be recorded) Source: ASPRS

### 2.4 Lidar accuracy and error sources

The various sensor components fitted in the LiDAR instrument possess different precision. For example, in a typical sensor the range accuracy is 1-5 cm, the GPS accuracy 2-5 cm, scan angle measuring accuracy is 0.01°, INS accuracy for pitch/roll is <0.005° and for heading is < 0.008° with the beam divergence being 0.25 to 5 mrad. However, the final vertical and horizontal accuracies that are achieved in the data are of order of 5 to 15 cm and 15-50 cm at one sigma. The final data accuracy is affected by several sources in the process of LiDAR data capture (Lecture notes from International School on LiDAR Technology, IIT Kanpur, India2008). A few important sources are listed below:

1. Error due to sensor position due to error in GPS, INS and GPS-INS integration.
2. Error due to angles of laser travel as the laser instrument is not perfectly aligned with the aircraft's roll, pitch and yaw axis. There may be differential shaking of laser scanner and INS. Further, the measurement of scanner angle may have error.
3. The vector from GPS antenna to instrument in INS reference system is required in the geolocation process. This vector is observed physically and may have error in its observation. This could be variable from flight to flight and also within the beginning and end of the flight. This should be observed before and after the flight.
4. There may be error in the laser range measured due to time measurement error, wrong atmospheric correction and ambiguities in target surface which results in range walk.
5. Error is also introduced in LiDAR data due to complexity in object space, e.g., sloping surfaces leads to more uncertainty in X, Y and Z coordinates. Further, the accuracy of laser range varies with different types of terrain covers.

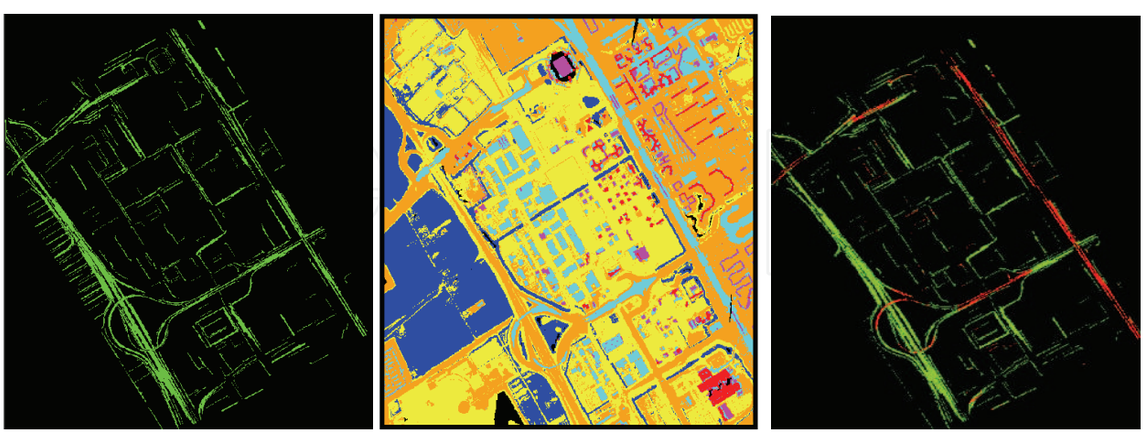
6. The divergence of laser results in a finite diameter footprint instead of a single point on the ground thus leading to uncertainty in coordinates.

## 3. Discrete airborne LIDAR for urban feature extraction

### 3.1 Road extraction

Automatic road extraction from remotely sensed images has been an active research in urban area during last few decades. But it is quite difficult in urban environment due to mix of natural and man-made features. An integrated approach of airborne laser scanning (ALS)/altimetry and high-resolution data has been used to extract road and differentiate them from flyovers. An integration of high-resolution satellite data and airborne laser scanning data offer exciting possibilities for automatically and accurate road extraction (Zhan et al., 2003). The urban area chosen for addressing the study problem is Amsterdam in The Netherlands. Aerial LiDAR and IKONOS PAN and XS dataset were utilized for road extraction.

Multiresolution segmentation allows the segmentation of an image into a network of homogeneous image regions at any chosen resolution. These image object primitives represent image information in an abstracted form serving as building blocks and information carriers for subsequent classification, beyond purely spectral information, image objects contain a lot of additional at-tributes which can be used for classification: shape, texture and – operating over the network – a whole set of relational / contextual information. Knowledge Base provides an intelligent and integrated knowledge solution that promotes easy image information extraction. Various rules were applied for classifying road segments. Spectral, shape, textural and contextural properties of the objects were utilized for formulating rules for road extraction (Fig 4a). Lidar Data was processed to generate Digital surface model. Lidar point cloud was filtered to classify ground and non ground points (Fig 4b). Height threshold was applied to extracted roads using lidar point cloud to separate out ground road and elevated roads (Fig 4c).



(a) (b) (c)

Fig. 4. a: Roads extracted with object oriented rule based classification
b: Filtered Lidar Data
c: Ground and Elevated Roads

To evaluate the success of the results of road extraction, the extracted roads were subjected to an accuracy assessment. Accuracy is the degree of conformity with a true reference. Wiedemann et al., (1998) have suggested that the quality of each road can be evaluated by contemplating the completeness and correctness of the extracted road network. The contiguity of the two road networks (reference and extracted road) may lack in coherence, hence the accuracy cannot be judged directly. Buffer method can be used for accuracy assessment of automatically extracted data with respect to reference data. For assessment of road extraction accuracy, a buffer of constant predefined width is constructed around the reference and extracted road data. (Fig 5).

The parameters are defined and calculated using these formulas:

***Completeness*** is the ratio of the correctly extracted records to the total no of relevant records within the ground truth data, and can be calculated as-

$$\textbf{\textit{Completeness}} = \frac{\text{length of matched reference}}{\text{length of reference}} \tag{1}$$

$$\text{Completeness} \in \{0; 1\}$$

***Correctness*** is the ratio of the number of relevant records extracted to the total number of the relevant and irrelevant record retrieval, and can be calculated as-

$$\textbf{\textit{Correctness}} = \frac{\text{length of matched extraction}}{\text{length of extraction}} \tag{2}$$

$$\text{Correctness} \in \{0; 1\}$$

***Quality*** is the measure of final result combining completeness and correctness, and can be calculated as-

$$\text{Quality} = \frac{\text{(length of matched extraction)}}{\text{(length of extraction} + \text{ length of unmatched reference)}} \tag{3}$$

$$\text{Quality} \in \{0; 1\}$$

The optimum value for completeness, correctness and quality is 1.

In the case of road, completeness of 76.26% and correctness of 50.78% was achieved. The overall accuracy observed for the road extraction was 43.85%. With this result it was evaluated that more than 3/4th part whole of the road network was completely extracted with the correctness of nearly half of the total road network.

While in the case of elevated road/ flyover, a completeness of 88.61% and correctness of 85.71%. The overall accuracy of the elevated road extraction was examined as 77.21%. The output result shows that most of the part of elevated road network was completely and correctly extracted to the total road network. In the study area, urban scene was highly complex and contained high-rise buildings, open-grounds, medium-rise buildings etc, which mainly affected the accuracy of road extraction. To overcome such problems an integrated approach of high-resolution satellite data and LiDAR data have been studied, which can extract urban road efficiently.

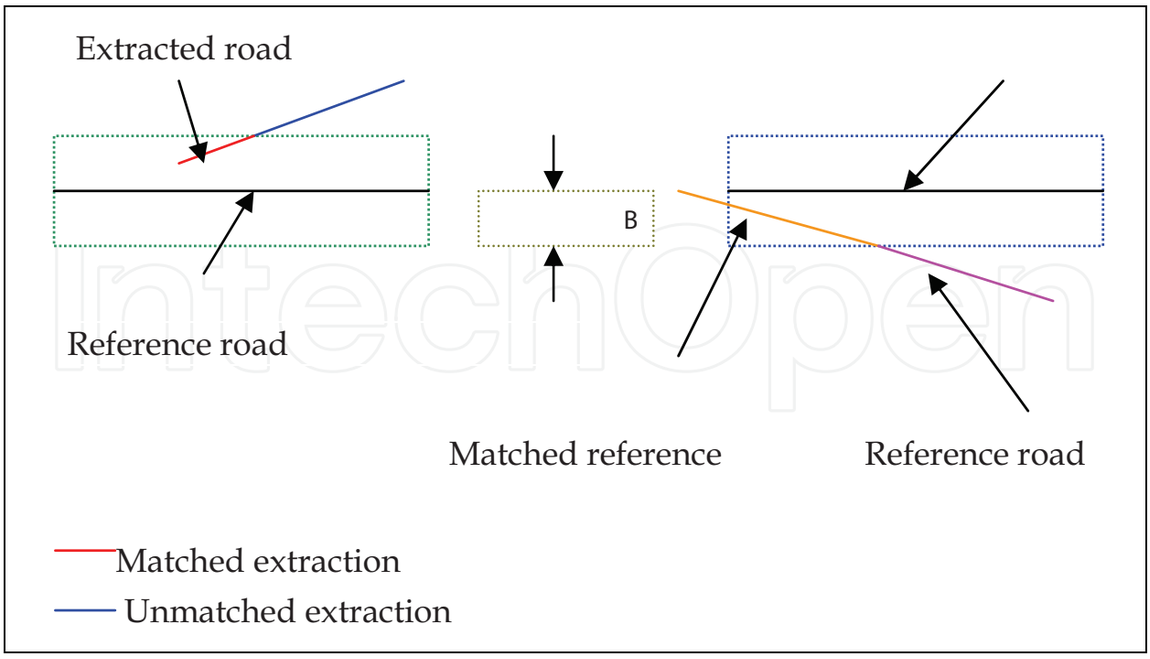



Fig. 5. Accuracy Assessment strategy

### 3.2 Building extraction

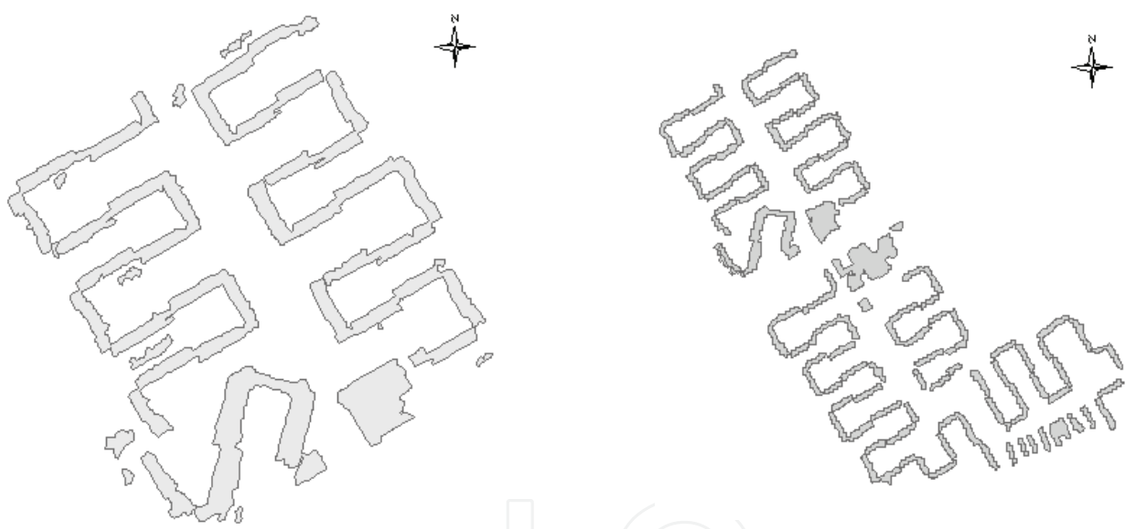
#### 3.2.1 Integrated use of high resolution spatial data and aerial laser data

The automatic building extraction from remotely sensed imagery has attracted much attention during the last decade. Generally the building extraction is based on different kinds of knowledge of buildings: geometry, spatial, spectral, radiometry. Many computer-aided, GIS and remote sensing techniques are currently in use to allow a faster building extraction, development, updating, maintenance and urban planning. Different kinds of techniques are being used for building extraction. Most of them are pixel based, using multi source data alone.

The increasing availability of high spatial resolution satellite images has provided a new data source for building extraction. When compared with the aerial photographs, the high resolution satellite images provide several advantages that include the cost and the accessibility. In the recent studies the spectral reflectance values have been used to detect the buildings *[Lee, S., et al., 2003)*.

High resolution satellites image provides a good basis for reorganization and monitoring of structural changes to map urban details. Higher the resolution of the imagery, more man made features such as buildings, roads, moving objects, etc. can be identified. But even in high resolution image, the feature extraction suffers from the background objects. Airborne laser scanning is an emerging technique to identify the height objects. An integration of high-resolution satellite data and airborne laser scanning data offer exciting possibilities for automatically and accurate building extraction. *(Zhan, Q,. 2003)*. One single sensor technology seems unlikely to produce detailed and varying characteristics of building models. Combining the geometry, photometry, and other sensing sources can compensate for the shortcomings of each sensing technology and appears to be a promising methodology.

The study area selected is a very small part of Amsterdam, but having well planned buildings. When using images characterized by a higher spatial and spectral resolution, it is difficult to obtain satisfactory results using traditional classification methods. Object oriented approach utilizes group of pixels instead of individual pixels for classification process. Objects are created by segmentation which makes this step the most crucial in the methodology used. Segmentation results can be improved by iteratively selecting appropriate parameters like scale, smoothness and compactness to identify various objects in the image. In multi segmentation, different scale parameters were analysed to identify the scale value at which the image could be segmented. If the parameters are not optimally chosen, the features may merge producing complex polygons having parts of adjoining features merged with them hence producing erroneous results. Accuracy of extraction was analysed using the above mentioned parameters. IKONOS fused image and LIDAR data were segmented based on scale, shape, compactness and smoothness. An object-oriented knowledge base was generated to extract building (Fig 6).

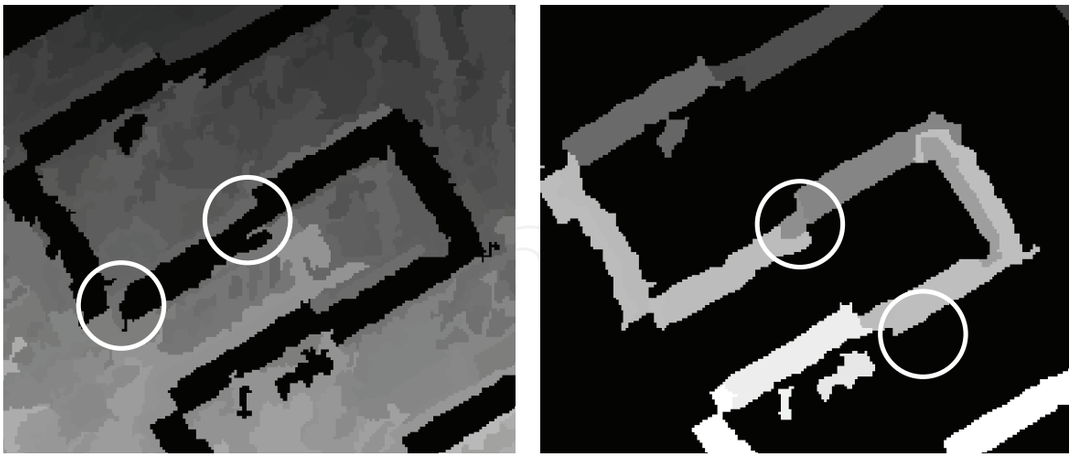



(a) (b)

Fig. 6. Buildings extracted from a: IKONOS b: IKONOS+LiDAR

After extracting the object of interest, it was found that the extracted objects did not show accurate and defined boundary. To remove these defects and regularize the building boundaries, mathematica5l morphological operators were applied (Fig 7).

In addition to completeness, correctness and quality, area and positional accuracy were calculated for the extracted buildings. The area accuracy using IKONOS is 95.05% and the area accuracy for the buildings extracted using IKONOS and LiDAR is 99.84%. In case of qualitative assessment, completeness correctness and quality of the extracted buildings was calculated. For IKONOS data the completeness was 84 %, correctness 100% and quality was found to be 86 %. For IKONOS and LiDAR data completeness is 90.9%, correctness is 100%



(a) (b)

Fig. 7. a Before using Closing Operator b. After using Closing Operator

and quality 90.9%. The buildings extracted using IKONOS data have well defined building boundaries so the error in X and Y direction are very less. While in LiDAR and IKONOS, the buildings extracted have not defined building boundaries. The edges and the corners of the extracted building boundaries using LiDAR and IKONOS are not matching. Thus, there is more positional error in X and Y direction in the extracted buildings. The results indicate a definite improvement in accuracy by utilizing complementary datasets. In high contrast areas buildings extracted using only high resolution intensity data gave satisfactory results, while in low contrast and shadow areas incorporating range data is necessary for proper boundary detection.

The present study indicates the usefulness of integrating LiDAR data for building extraction. It was found that in low contrast areas where IKONOS image was not giving good results, integration of LiDAR has improved the correctness and quality of the extracted data to a great extent. Though positional accuracy was higher with IKONOS dataset as it gives proper edges of the buildings.

### 3.2.2 Use of laser range and height texture clues

Detecting buildings directly from the raw LiDAR data is not a straightforward problem. This is due to the ambiguity of other vertically extended features which are not buildings in the raw data. (Alharthy & Bethel 2002). The raw LiDAR point cloud consists of a mixture of terrain, vegetation, buildings and other natural and man-made structures. Different types of objects require different methods for modeling, analyses and visualization. An inherent source of information of *LiDAR* point data is the analysis of height texture defined by local variations of height. Depending on the type of sensor used, objects to be classified show different behaviour in texture measures derived from these variations.

Most of the previous work in classification of aerial LiDAR data has concentrated on unsupervised clustering on a smaller number of classes often resulting in coarse classification while a few have attempted parametric classification with or without segmentation. [Arefi et al ]

The aim of the work presented in the following is to classify raw laser scanner data using height texture measures. Texture is qualitatively and quantitatively defined by height, variation of height in local windows and measures. When a small-area patch has wide variation of gray level primitives, the dominant property is texture (Haralick and Shapiro, 1992). A number of texture measures will be defined and discussed. These texture measures are used as bands in a classification of the dataset.

Following texture measures for the purpose of this study were calculated:

**Data range:** It is the difference between minimum and maximum pixel value in a window around a pixel. It will be zero in homogenous area such as on flat roofs or streets, small on tilted roofs and large within trees.

**Variance:** The variance of height in a window around a pixel will show similar characteristics as the data range, with somewhat different behaviour concerning single outliers.

$$Variance = \sum \frac{(x_{ij} - M)^2}{n-1} \tag{4}$$

where: $x_{ij}$ = DN value of pixel ij , n = number of pixels in a window, M= mean of moving window

**Contrast:** It is a measure of the amount of local variation in the Image. It increases exponentially as (i-j) increases. Contrast increases at the edges.

$$\sum_{i,j=0}^{N-1} P_{ij}(i-j)^2 \tag{5}$$

**Dissimilarity:** Similar to "Contrast", but increases linearly. High if the local region has a high contrast.

$$\sum_{i,j=0}^{N-1} P_{ij}(i-j) \tag{6}$$

i is row and j is column number, i,j is value in the cell i,j of matrix, $P_{ij}$ is normalized value in cell i,j, N is number of rows or columns

**Correlation:** Measures the linear dependency of grey levels of neighbouring pixels.

$$\frac{\sum_{i,j=0}^{N-1} P_{ij}(i-\mu_i)(i-\mu_j)}{(\sigma_i^2)\sqrt{(\sigma_i^2)}} \tag{7}$$

σ is standard deviation

Variance image highlighted the building and tree boundaries. Data range, Contrast and Dissimilarity gave similar results. Correlation highlighted the building blobs and tree pixels. Since the study aimed at automatically extracting the building footprints, hence correlation was found useful. The original Height data, Variance and Correlation were stacked in form of bands to give a composite image. An analysis of the results obtained from the

classification using different combinations of the texture measures discussed showed that good results are obtained when using these three bands, which were further processed to highlight the desired characteristics of buildings

Both unsupervised classification and supervised classification techniques were applied to these three bands. While unsupervised classification did not lead to a satisfactory segmentation, good results were obtained with maximum likelihood classification.

After training the ML algorithm quantitatively evaluates the variance and correlation of the class spectral response patterns when classifying all pixels in the image. The value of the discrimination function of a given pixel, being a member of a particular class, is computed. The pixel is then assigned to the class with the largest probability.

The classified results (Fig 8a) gave objects protruding from the terrain which included both buildings and tree pixels. The differentiation between building and tree classes was based on spectral values. NDVI was calculated and was used as an input for rule based expert classification (Fig 8 b).However few tree pixels were not removed as their spectral values were effected due to factors like shadows etc. The remaining scattered non building pixels were removed by applying morphological filters (Fig 8 c). The improvement achieved by post processing with opening and closing can be observed. The small holes are filled, few isolated pixels are removed or associated with other objects and the edges are smoother and closer to the shape of the buildings than before post processing. However in places few building pixels in close proximity to tree pixels have also been eliminated.

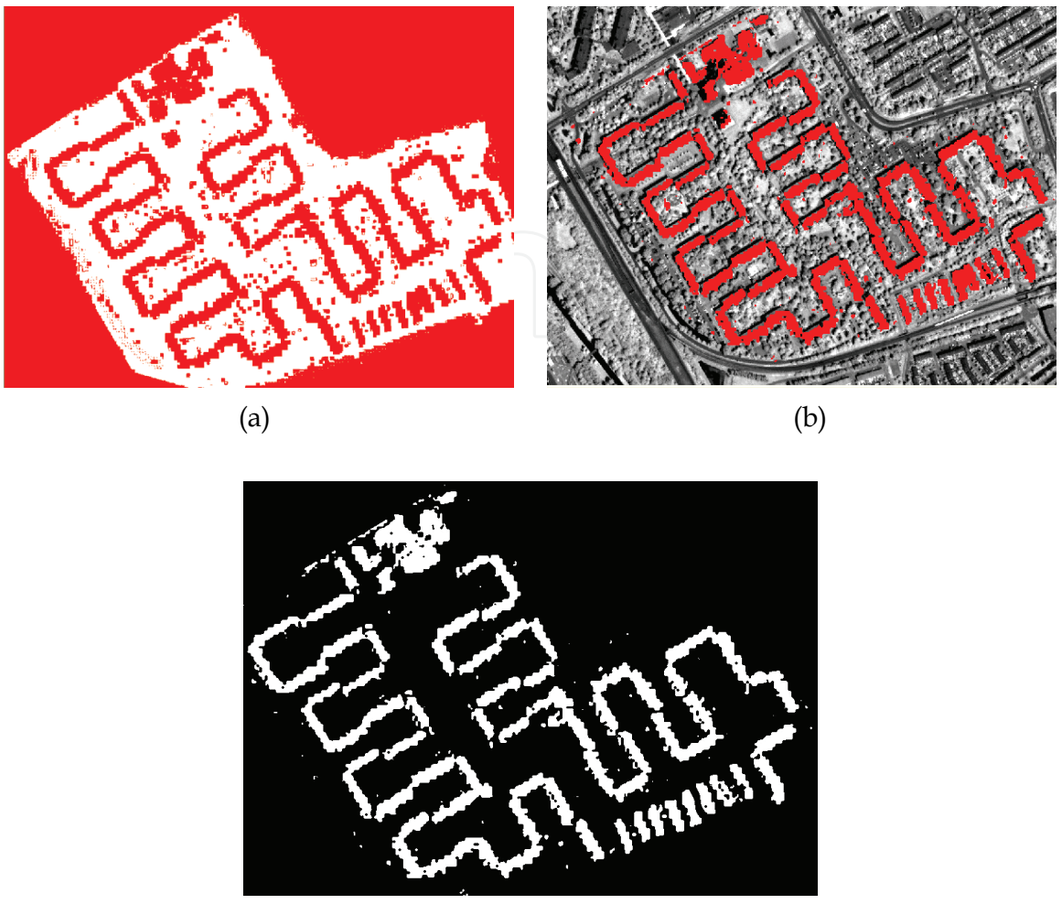
Visual interpretation of the IKONOS image was carried out for use as reference in error evaluation of the extraction process. Accuracy assessment was carried out and a confusion matrix was generated. The error matrix obtained is shown in Table1.

An overall accuracy of 91% was achieved. The error of commission for class buildings was found to be 9% that means 9% pixels which belong to other classes have been wrongly classified into buildings, whereas the error of omission was 6% which indicated that 6% pixels belonging to class buildings have been omitted in the final classification results.

The investigations in the present study have shown that the detection of buildings in laser range data is feasible and indicates a promising quality by just using standard remote sensing and image processing tools.

| | *BUILDINGS* | *TREES* | *OTHERS* | *TOTAL* |
|---|---|---|---|---|
| BUILDINGS | 32 | 3 | 0 | 35 |
| TREES | 2 | 9 | 1 | 12 |
| OTHERS | 0 | 1 | 30 | 31 |
| TOTAL | 34 | 13 | 31 | 78 |

Table 1. Error Matrix for knowledge based classification



(a) (b)

(c)

Fig. 8. a: Supervised classification results, b: Knowledge based classification c: After noise removal

## 4. Conclusions

In high resolution satellite data, urban features are no longer point objects but polygons with prominent shadows and other associated features. Shadows and surrounding objects give different manifestations during the feature extraction. Sometimes the roads parallel to the buildings and the trees mix up and pose a hindrance to the building extraction. Since numerous factors influence the brightness value of the image making it difficult to separate the desired information. To overcome this problem, multiple data sources have been exploited to compensate for these disadvantages. For this purpose LiDAR data has been used as an attractive supplement together with high resolution intensity data due to high vertical accuracy and high point density. LiDAR data have several advantages of feature localization and planer patch extraction compared to image dataset. On the contrary, high resolution imagery provides more accurate break lines information than LiDAR data. Moreover multispectral imagery is useful to identify and classify objects, such as building

and vegetation. Thus, it is proposed to combine LiDAR data and high resolution satellite images for the urban feature identification and detection.

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**Laser Scanning, Theory and Applications**

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Ever since the invention of laser by Schawlow and Townes in 1958, various innovative ideas of laser-based applications emerge very year. At the same time, scientists and engineers keep on improving laser's power density, size, and cost which patch up the gap between theories and implementations. More importantly, our everyday life is changed and influenced by lasers even though we may not be fully aware of its existence. For example, it is there in cross-continent phone calls, price tag scanning in supermarkets, pointers in the classrooms, printers in the offices, accurate metal cutting in machine shops, etc. In this volume, we focus the recent developments related to laser scanning, a very powerful technique used in features detection and measurement. We invited researchers who do fundamental works in laser scanning theories or apply the principles of laser scanning to tackle problems encountered in medicine, geodesic survey, biology and archaeology. Twenty-eight chapters contributed by authors around the world to constitute this comprehensive book.

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