Utilising Large Footprint Full Waveform Range Data for Urban Scene Classification

Darshana Rathore (1), Poonam S. Tiwari (2), Hina Pande (2), Shefali Agrawal (2)

[1]Banasthali Vidyapeeth, Rajasthan, India
[2]Indian Institute of Remote Sensing, ISRO, Dehradun
E-mail: poonam@iirs.gov.in

Abstract: Land cover assessment and monitoring of its dynamics are essential requirements for sustainable management of natural resources and for environmental protection. Remotely sensed images are the main source of data used for land cover classification. Generally, landuse/landcover classification is attempted using optical satellite data. Compared to traditional scanning systems, a full waveform system retrieves more information that should still be extracted though from the waveform shape. The shape of the full waveform contains information on the characteristics of the illuminated footprint, like object height, canopy structure and ground surface roughness etc. The study was carried out with an objective to improve urban feature extraction using high resolution satellite imagery and Icesat-1 (Ice cloud and elevation satellite) data of parts of Chandigarh city.
Icesat GLAS waveforms were decomposed into a sum of echoes to characterize the different individual targets along the path of the laser pulse. Since the data collected on different dates was being used in the study, to neutralize the effect of atmospheric conditions or changes in the behaviour of the instrument the waveforms were normalized. To extract the relevant data from the waveform, it was subjected to thresholding. The waveform was decomposed into constituting components by identifying the peaks and fitting Gaussian curve into it. The parameters to be used for rule based classification such as peak height, surface intensity and reflectivity of surface material are extracted for individual component. To analyse the urban land cover information content of full-waveform data, the waveforms from ICESat-1 release 29 tracks over Chandigarh, India were used for study. A total number of 56 footprints were analysed. It was observed that five major land use classes were predominant in the available footprints namely Buildings, Roads, Natural Ground, Trees and Grasses. Each feature has its own property of transmittance, reflectance and absorbance. Thus, the amplitudes of the returns of the waveforms, width and shape of pulse, Δr (difference between pulse range and highest range), Δz (altitude difference between first and last pulse in waveform) and number of echoes in a waveform were selected as suitable parameters for urban scene classification. It was observed that high amplitude values were found for buildings roofs irrespective of the roof material. Similar values were reported for sandy open areas. Low amplitude values corresponded to vegetation and Tar roads, which can be differentiated based on pulse width as trees records greater pulse width. The echoes for grass were less scattered than those of large trees. Extracted features were compared with classified results obtained using the Worldview-2 image dataset. The estimated accuracy for intra footprint classification of urban scene was found to be 79.31%.
The study highlights the possibility of utilizing waveform parameters from full waveform data for enhancing the classification results.

Key words: full waveform, ICESat-1, classification, intra footprint classification

1. Introduction: Creating land cover databases is one of the most important targets in remote sensing. Land cover assessment and monitoring of its dynamics are essential requirements for sustainable management of natural resources and for environmental protection. Remotely sensed images are the main source of data used for land cover classification. Generally landuse/landcover classification is attempted using optical satellite data. Full waveform range instrument sends out a pulse of a certain width and amplitude. After reflection of the pulse on the objects surface, the system records the complete returning pulse signal. This complete signal is the so-called full waveform. Compared to traditional scanning systems, a full waveform system retrieves more information that should still be extracted though from the waveform shape. Full waveform systems brings two important contributions and advantages for additional investigations possibilities. First the processing of the received signal can be used to recover all individual echoes. This enhances the point cloud density with regard to multiple echos (particularly on forest area) as well as the quality of the extracted features within the laser beam corridor. Second by modelling the received waveforms, additional features can be extracted from them. This is for example the amplitudes (also called intensity) and the pulse width derived by the standard deviation of a Gaussian-based decomposition of the waveform. These two values provide mixed information about the geometry and the reflectance properties of the illuminated surface. The shape of the full waveform contains information on the characteristics of the illuminated footprint, like object information (tree and building height), forest structure and ground surface characteristics (e.g. forest species surface roughness and slope) as well as a land cover type (water, bare earth, or urban areas).

Backscattered laser intensity measurements have largely escaped attention and have not been used as extensively as the three dimensional structure data represented by laser returns. Reflective objects on earth's surface which fall under the diffraction cone have different geometries and different reflectance characteristics. These objects imprint their characterstics in form of backscattered energy and signal return shape (Fig1).

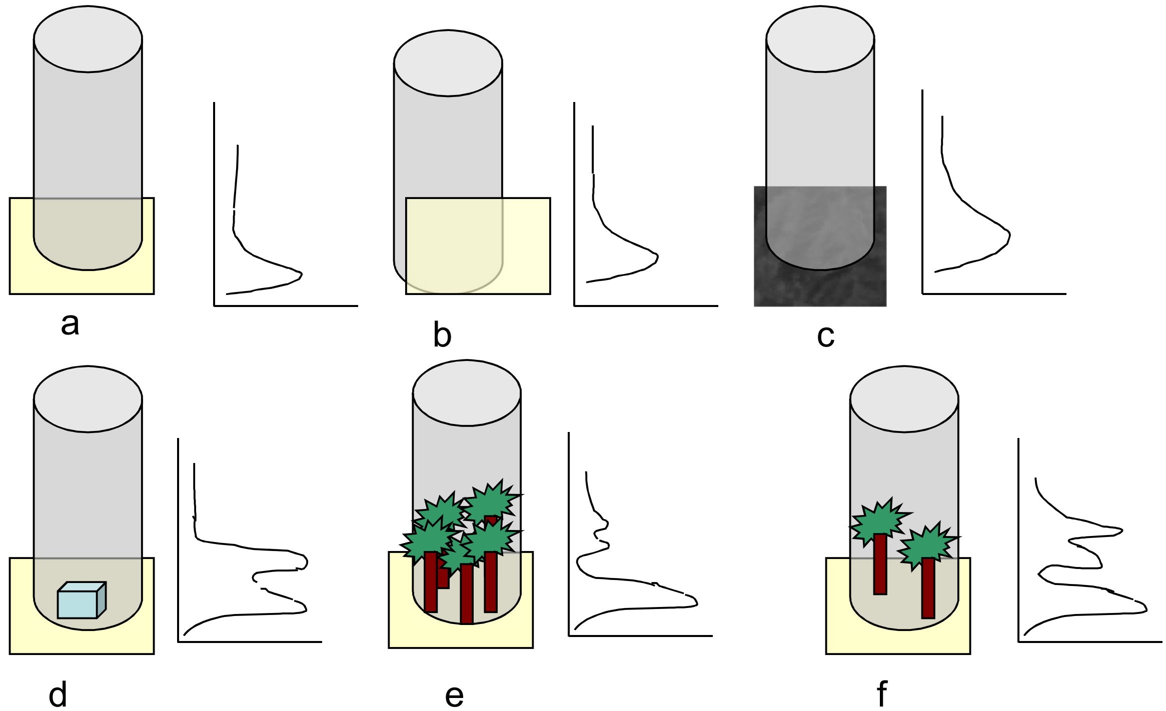

Fig 1: Pulse shape on varying terrain conditions. a: Flat terrain. B: sloped terrain. C: rough terrain. D: mixed flat terrain and building. E: terrain with dense vegetation. F: Terrain with low density vegetation. (modified after Pirotti,2010)

The reflecting objects can be classified in two groups, ground and above ground. Bare ground influences the shape of the pulse with its topographic characteristics. Above ground objects can be buildings, low and high vegetation and other man-made artifacts. Building roofs, sand and gravel areas will record high amplitude values, while the lowest values correspond to vegetation points due to higher target heterogeneity and attenuation. Tar roads will also tend to record low amplitude values.

Harding (1998), and Blair et al. (1999) showed that using observations from a full waveform laser system it is possible to achieve accurate forest structure and biomass estimates. However, the system considered in this case was just operated from an airplane flying at a low altitude of a few kilometers above the ground surface with a medium footprint size of about 10-20 m. Moreover, data acquisition could only be performed in a small area. Some typical systems used in these days were the Scanning Lidar Imager of Canopies by Echo Recovery system (SLICER), the Laser Vegetation Imaging Sensor (LVIS), and the commercial airborne full waveform scanning system from RIEGL the LMS-Q560 (2003). Icesat system acquired data between 2003 and 2009 over the entire earth from 600 km altitude, with a footprint size of about 70 m and a distance between consecutive footprints of approximately 175 m. However, due to high operational altitude, this system is also affected by many error sources, like instrumental and operational problems, atmospheric effects and surface conditions.

Song et al. (2002) applied filters to a gridded representation of intensity data and evaluated its potential to classify different materials such as asphalt, grass, roof, and trees. Hasegawa (2006) investigated the characteristics of LIDAR intensity data for land cover classification and indicated that it is difficult for extraction of trees without supplementary information because trees have a wide intensity range and the range overlaps with the range of other height objects. Brennan and Webster (2006) utilized LIDAR height and intensity data to classify various land cover types using an object-oriented approach. They concluded that through the use of spectral and spatial attributes of LIDAR data they were able to classify a variety of land cover types using derived surfaces, image object segmentation, and rule-based classification techniques. Recently, LIDAR intensity data were found to be directly related to spectral reflectance of the target materials (Ahokas et al., 2006). These authors studied the relationship between calibration of laser scanner intensity and known brightness targets. They concluded that intensity values were directly related to target reflectance from a variety of altitudes (200 m, 1000 m, and 3000 m) after correcting errors due to range, incidence angle (both Bidirectional Reflectance Distribution Function, BRDF, and range correction), atmospheric transmittance, attenuation using dark object addition and transmitted power (difference in Pulse Repetition Frequency, PRF, will lead to different transmitter power values). Comparative studies on leaf-on and leaf-off situation have shown that a significant correlated difference can be detected on the pulse shape (Duong 2006 a). Duong et al (2006 b) utilized full waveform ICESAT data for landcover classification. Kim et al (2009) differentiated tree species using intensity data derived from leaf-on and leaf-off airborne laser scanner data. Mallet and Bretar [2009] have specifically documented the behavior of small-footprint and large-footprint lidar over building and vegetation covers, showing that differences are to be found in the scale and position of diffraction cone in respect to the object. Pirotti (2010) analysed the relationship between geometric/radiometric surface parameters and pulse shapes in respect to potential utilization of GLAS data for land cover classification and concluded that buildings effect laser waveform differently depending on their height and size compared to the size of the laser diffraction cone and on the percent of laser spot area reaching the ground versus hitting the building. GLAS systematically samples the energy profile returned from the surface as a full waveform (Harding and Carabajal, 2005). ICESat data can therefore only be used for classifying profiles, as compared to regions mapped by area-sensors. The full waveform data gives new possibilities to extract more information about land cover of the earth surface. In this study, the full waveform analysis is investigated in the context of land cover classification. The study was carried out with an objective to improve urban feature extraction and adequate classification of urban domain using high resolution satellite imagery and LIDAR data of Icesat (Ice cloud and elevation satellite) of parts of Chandigarh city in India by adapting rule set on basis of various normalized difference indices on segmented object in image and retrieved laser data of GLAS instrument (geoscience laser altimeter system).

2. **Experimental Approach:** The approach followed in the study comprises of following steps:

2.1 Waveform Signal Processing and Initial parameter Estimation: Icesat GLAS full waveform data allows determining the vertical distribution of targets within the diffraction cone with a temporal sampling of 1ns. The understanding of such waveforms requires a pre processing step. These waveforms can be decomposed into a sum of echoes to characterize the different individual targets along the path of the laser pulse. Waveform processing maximizes the detection rate of relevant peaks within each signal in order to facilitate information extraction from the raw signal. Also best fit of a waveform is selected from a class of functions which allows to extract additional information regarding the target shape and its reflectance. For the present study, the product GLA01, the global full waveform data was investigated. The waveforms over urban areas were processed and intial parameters such as amplitude, width of echo, shape of echo, reflectivity etc were calculated. These parameters were used for generating knowledge base for classification of urban landcover features. A probability based classification was carried out and accuracy was evaluated. The detailed methodology is shown below in Fig 2.

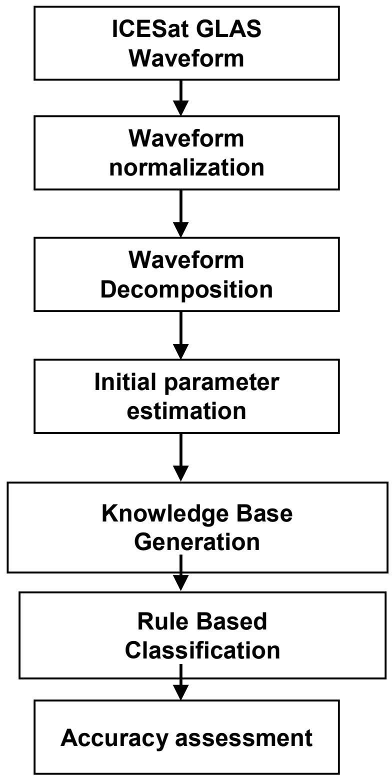

Fig 2: Methodology Adopted

2.2. Waveform normalization: Due to different atmospheric conditions or changes in the behaviour of the instrument, the amount of energy in the laser return pulse may vary with time, even if there is no significant change in the ground scenario. These effects altered the comparison of absolute energy levels of particular constituents of different waveforms. Thus for comparing waveforms captured in different epochs the voltage needs to be normalized. The normalization step required a division of the received energy Vi by the total energy VT, at moment i (equation 1). After normalization the area under any waveform equaled

$$VN(i) = Vi / VT \quad \text{where} \quad VT = \sum_{i=1}^{544} Vi \qquad \text{Eq 1} \quad \text{(Doung, 2006)}$$

2.3 Waveform Thresholding: A waveform contains significant noise at the begin and end of the signal. The actual waveform can be obtained using a suitable threshold value. The threshold value is individually identified by calculating the mean and standard deviation of the noise in the first 150 bins of the raw waveform. The signal value less than the threshold was set to zero in the beginning and end of the waveform (Fig 3).

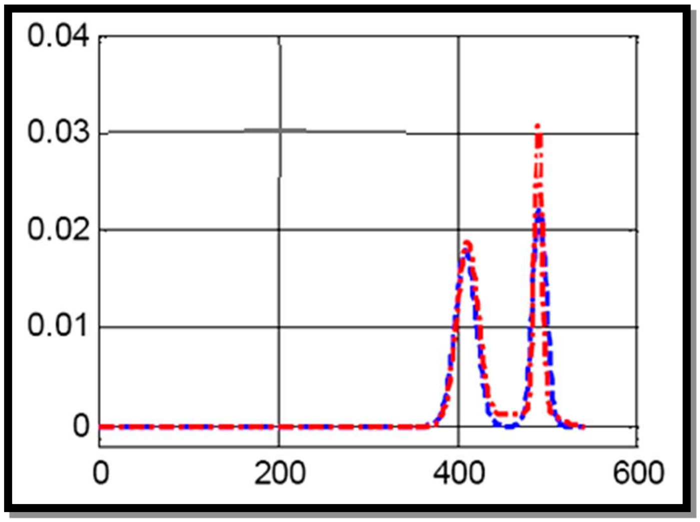

Fig 3: Waveform Denoising

2.4 Waveform decomposition: The raw waveform exhibits a rough shape and requires considerable smoothing. Peaks of the waveform are identified by comparing the amplitude of a point with neighbouring points. A function is fitted to the identified peaks. Generally Gaussian wave is fitted to the estimated peaks. If the transmitted pulse is expected to be Gaussian, the waveform can be modeled as a sum of Gaussians (Brenner et al., 2003). Also if the height distribution within the diffraction cone follows Gaussian law, the reflected waveform can be approximated by sum of Gaussian. This is true for large footprint systems. Generalized Gaussian allows tomodel flattened, narrow and high pulses. Log Normal does not improve the fitting globally. Non parametric methods fail to provide signal maxima location. Since other available functions do not exhibit significant improvement in fitting results, the Gaussian components are fitted to the smoothed waveform w(t). Every Gaussian component Wm corresponds to one Gaussian bell curve. So, it was assumed that the smoothed waveform w(t) is a sum of Gaussian components Wm. That is,

$$w(t) = \sum_{m=1}^{Np} Wm\,(t), \quad \text{where:} \qquad Wm\,(t) = Am\, e^{-(t-tm)^2 / 2\sigma^2 m}$$

where w(t) is the amplitude of the waveform at time t, Wm (t) is the contribution from the m-th Gaussian component, Np is the number of Gaussians found in the waveform, Am is the amplitude of the m-th Gaussian, tm its position and σm its standard deviation. The least squares approach is used to compute the model parameters, that is, the values for Am, tm, and σm in the above equation are obtained by fitting the theoretical model to the observed waveform in such a way that the difference between model and observation is minimized in the least-squares sense. The square sum of the residuals itself can be used to quantify the quality of the fit. And due to our normalization step this minimal sum and therefore the quality of the fit can be compared between the different waveforms (Duong et al, 2006).The fitting step results in a number of Gaussian components with Gaussian parameters (Fig 4).

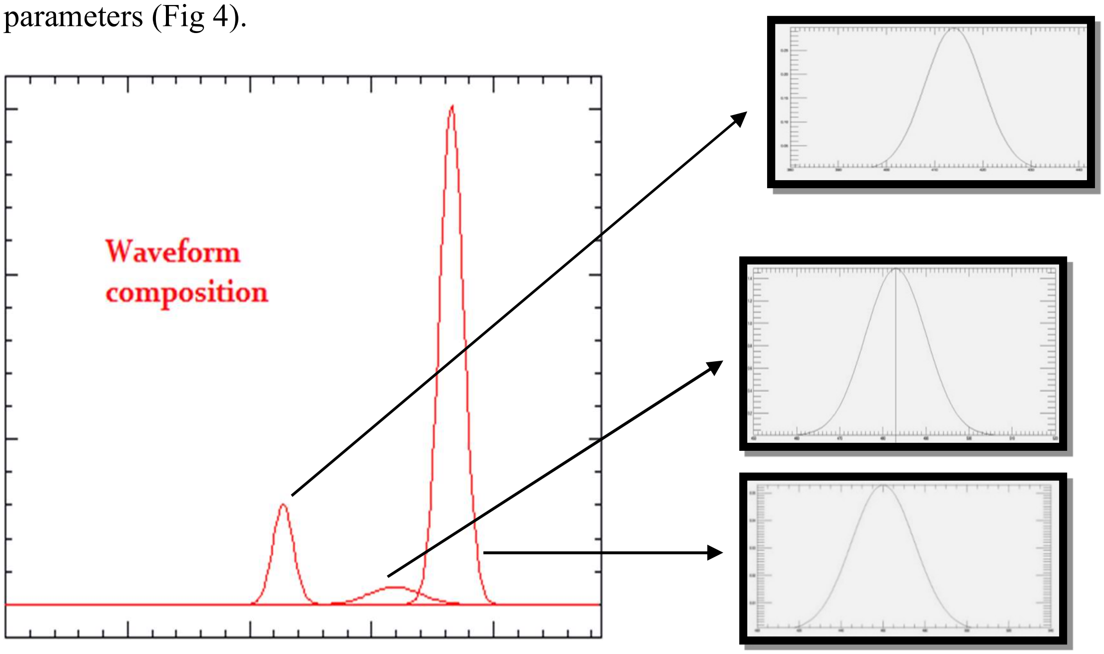

Fig 4: Waveform Decomposition

2.5 Parameter Estimation: After decomposition and Denoising of waveform we calculated peak height, surface intensity and reflectivity of surface material. To straighten waveform processing capabilities by fostering information extraction from the raw signal and maximize the rate of detection applicable peaks is the main aim of this approach. Table 1 gives parameters for curve analysis

Table 1: Parameters for curve analysis.

(a)Reflectivity	$= \dfrac{\textbf{Uncorrected surface reflectivity}}{\textbf{Roundtrip Atmospheric Transmission}}$
(b)Uncorrected Surface Reflectivity	$= \dfrac{(3.14 * \text{Energy (received)} * (\text{Range})\ \hat{}\ 2)}{(\text{Energy (Transmitted)} * \text{Area of Telescope} * \text{Optics Transmission}}$
(c)Round-trip Atmospheric Transmission	$= \mathrm{e} - 2(\text{cloud Optical depth} + \text{Aerosol optical Depth} + \text{Molecular optical Depth})$
(d)Height	=Centroid of last return – Starting time of return * 0.15

2.6 Knowledge base generation and Rule based classification: To analyse the urban land cover information content of full-waveform data, the waveforms from ICESat release 29 tracks over Chandigarh, India were used for this research (Fig 5). The data was acquired on 23-02-2003. A total number of 56 footprints were analysed.

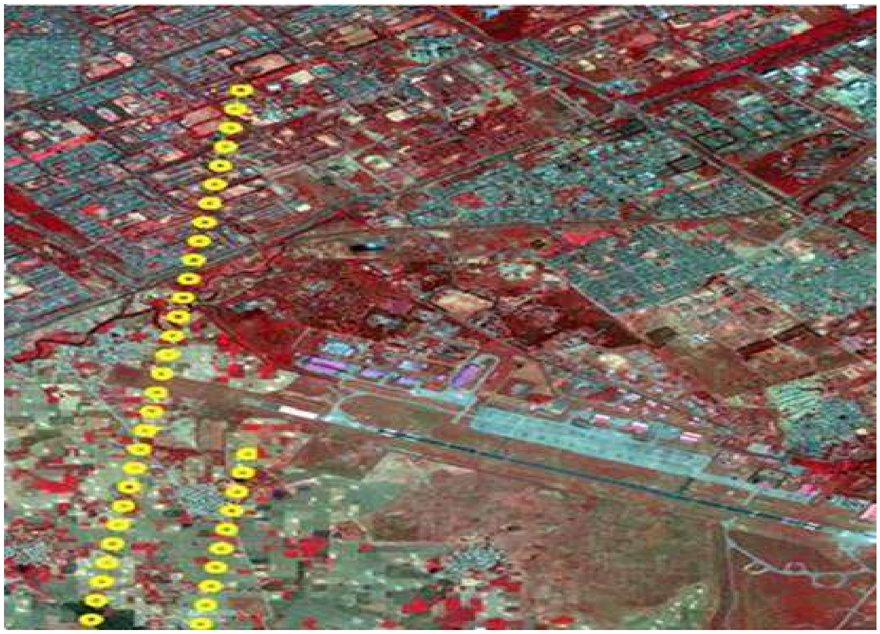

Fig 5: GLAS footprints overlaid on IKONOS PAN of Chandigarh area

3. **Result:** It was observed that five major land use classes were predominant in the available footprints namely Buildings, Roads, Natural Ground, Trees and Grasses. Each feature has its own property of transmittance, reflectance and absorbance. Thus, the amplitudes of the returns of the waveforms, width and shape of pulse, Δr (difference between pulse range and highest range), Δz (altitude difference between first and last pulse in waveform) and number of echoes in a waveform were selected as suitable parameters for urban feature classification. It was observed that high amplitude values were found for buildings roofs irrespective of the roof material. Similar values were reported for sandy open areas. Low amplitude values corresponded to vegetation and Tar roads, which can be differentiated based on pulse width as trees records greater pulse width. The echoes for grass were less scattered than those of large trees. Ground and building features coincide with low pulse width values (Fig 6). For the further analysis of waveform for feature extraction reflectance range for tree and buildings has been developed. Reflectance range for Tree was found to be 0.32 – 0.48 and that for buildings was between 0.008 – 0.28. Based on the analysis the rules were generated for classification of urban features.

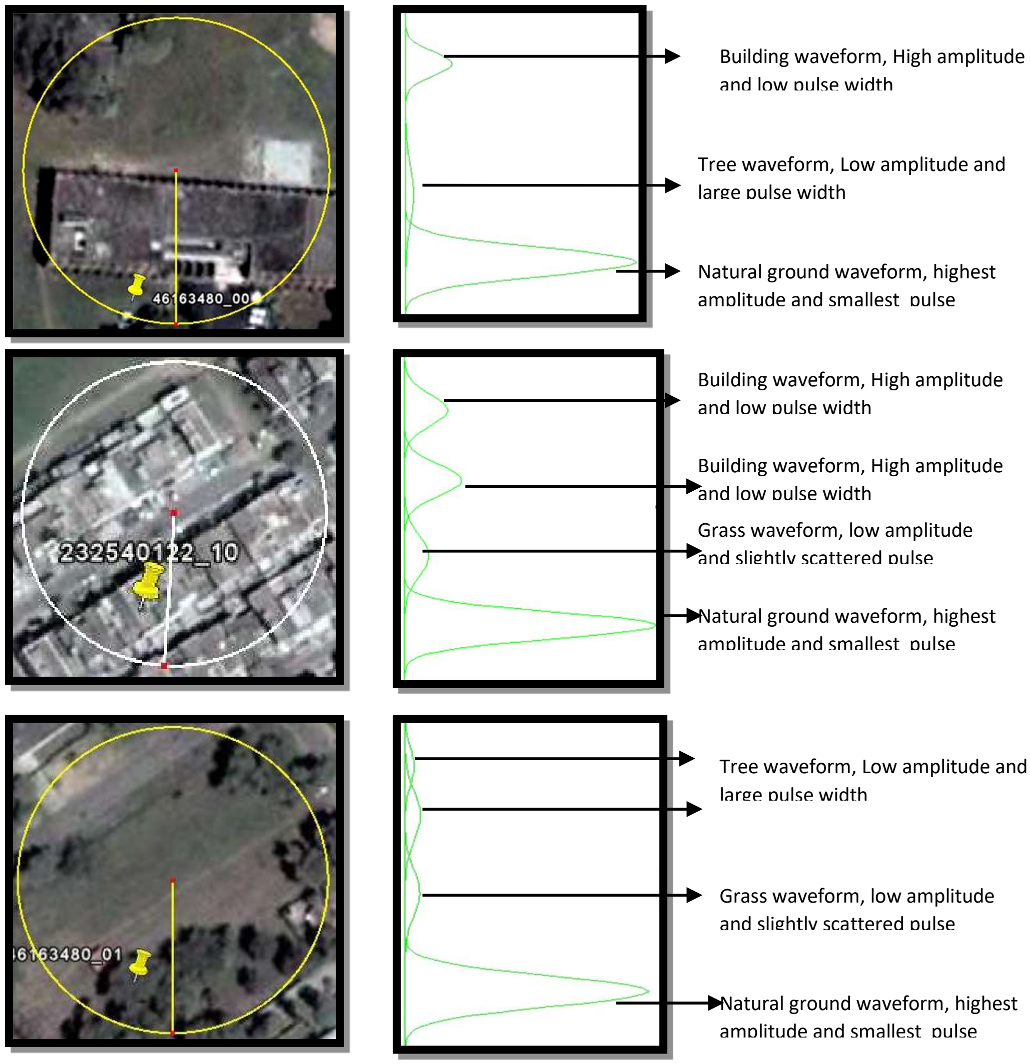

Fig 6: Knowledge Base Generation

Parameters discussed above were calculated and analysed. To access the accuracy of the classification, the classified and the reference information needs to be compared. One of the most common means of expressing classification accuracy is the preparation of confusion matrix. A confusion matrix compares on a category by category basis the relationship between known reference data and classified data. Classified features were compared with worldview-2 classified features for 60 returns of GLAS data. To evaluate the quantitative accuracy of the classification of urban feature, the extracted feature from laser data were compared with visually interpreted features using google earth and optical data of WV-2 satellite. A standard confusion matrix was utilized to quantitatively examine classification outputs. The Kappa statistics, and class wise accuracy were calculated to access the performance of methodology on individual classes and overall classification. It was found that the kappa statistics for classification was 0.71 achieved. The accuracy of individual classes was also found to be satisfactory. Table 2 lists out the users and producer’s accuracy for individual classes.

Table 2: Class wise accuracy statistics

Classes	Producer's accuracy	User's accuracy
Trees	76.92%	71.43%
Buildings	92.86%	65%
Grounds	74.19%	95.83%

The results indicate that the full waveform lidar data provides parameters that can be effectively used for extracting landuse/landcover information. It is observed that these parameters when analysed through a rule based classification method are useful in enhancing the classification results. The study highlights the possibility of utilizing these parameters from full waveform data for improving the classification accuracy.

4. References:

Cheng Wang, Fuxin Tang, Liwei Li, Guicai Li, Feng Cheng, and Xiaohuan Xi, 2013. Wavelet Analysis for ICESat/GLAS Waveform Decomposition and Its Application in Average Tree Height Estimation IEEE Geoscience and Remote Sensing Letters, VOL.(10),1.

Gunho Sohn, Ian Dowman,2007. Fusion of high-resolution satellite imagery and LiDAR data for automatic building extraction ISPRS Journal of Photogrammetry & Remote Sensing 62 (2007) 43 63Data Department of Geomatic Engineering, University College London, Gower Street, London.

Hamedianfar A., Zulhaidi H.M.S., Mansor S. and Noordin 2014. Improving detailed rule-based feature extraction of urban areas from WorldView-2 images and Lidar data, Internation Journal of Remote Sensing, Vol.35 (5).

Manandhar, Dinesh, and Ryosuke Shibasaki, 2002."Auto-extraction of urban features from vehicleborne laser data." International Archives of Photogrammetry Remote Sensing and Spatial Information Sciences 34.4 650-655.

Markus Mollera, Jens Birgerb, Anthony Giduduc and Cornelia Glabera, 2013.A framework for the geometric accuracy assessment of classified objects International Journal of Remote Sensing, Vol.(34), 24, 8685–8698.

Ursula C. Benz, Peter Hofmann, Gregor Willhauck, Iris Lingenfelder, Markus Heynen, 2004. Multiresolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information, ISPRS Journal of Photogrammetry & Remote Sensing 58, 239– 258.

Waghmare Y A, 2012.Urban Feature Extraction Using Space born GLAS/Lidar waveform data and high resolution Satellite Image.

Zuxun Zhanga,Xiangyun Hu a, Zhen Lia,2011. ANALYSIS AND APPLICATION OF LIDAR WAVEFORM DATA USING A PROGRESSIVE WAVEFORM DECOMPOSITION METHOD International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, ISPRS Calgary Workshop, 29-31 August 2011, Calgary, Canada Volume XXXVIII-5/W12