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Forest area Segmentation from LiDAR images

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Abstract— LiDAR (Light Detection And Ranging) is a remote sensing technology used for a wide variety of applications and multi-scale LiDAR image analysis is a promising tool for forestry and terrain related studies. The segmentation of forest area is possible from LiDAR images, which is very much useful in forest management. Due to some disadvantages of conventional segmentation schemes, the attentive vision method can be used for this purpose, which is based on our visual attention mechanism. In this, primitive feature map is generated as the initial step. Primitive feature map is created by applying a LoG (Laplacian of Gaussian) filter on the input image. Attentive vision method involves the detection of feature point. Then, a ring region and a disk region are defined on image with arbitrary radii and detected feature point as center for calculating some parameters like isotropic local contrast, height variance, mean value of pixels in disk region and the total number of points in the ring region. For object area recognition, a descriptor vector is formed to represent the current disk area centered at feature point. The difference between this vector and the reference vector is compared with a threshold vector to recognize whether the considered area is an object area. Forest area segmentation is completed by doing a region growing segmentation with the feature point as seed point. This method provides an effective segmentation of forest areas using attentive vision method to remote sensing image analysis.

Keywords— LiDAR images, Feature point, Attentive vision method, Region growing, LoG, Isotropic local contrast, Descriptor vector.

INTRODUCTION

Remote sensing is the process of collecting information related to objects without being in physical contact with them. In most of the remote sensing techniques, the process involves an interaction between incident radiation and targets. There are two main types of remote sensing: active remote sensing and passive remote sensing. Passive remote sensors detects radiations reflected or emitted by the objects whereas in activeremote sensing, the source emits energy to scan objects andsensor analyses the reflected or backscattered radiation fromthe target. Light Detection And Ranging (LiDAR) is an active remote sensing technique because they emit pulses of lightand detect the reflected light. This characteristic allows LiDAR data to be collected at night when the air is usually clearer andsky contains less air traffic than in daytime. LiDAR equipment is typically mounted in aircrafts to rapidly collect points overa large area. It is also placed in ground based stationary ormobile platforms. Collection of elevation data using LiDAR has several advantages such as high resolution and grounddetection in forested terrains over other techniques[2]. Remote sensing has been applied to forest ecosystem managementfor many years. The LiDAR technology has become popular in forestry during past decade. LiDAR can provide high resolution representation of objects. Very good resolution andavailable radiometric data make LiDAR a most acceptable tool for studying forests. LiDAR uses shorter wavelength ofelectromagnetic spectrum. It fires rapid pulses of light towardsa surface and analyzes each returned pulse. LiDAR allows the direct measurement of three-dimensional structures and theunderlying terrain.

In forestry, LiDAR can be used to measure the three dimensional structure of a forest. LiDAR penetrates the tree canopy to return an accurate interpretation of ground surface. LiDAR technology provides horizontal and vertical information at high resolution and accuracy. The first return will begenerated from uppermost limit of canopy, followed by lessintense returns through the canopy, down to the underlyingterrain. Returns are classified based on whether it is fromground or aboveground source. Ground return can generate a detailed terrain of the interested area while aboveground returns such as canopy return can be filtered to provide foreststructure. LiDAR images in forest areas have some different featurescompared to images from other regions. First, the objects have irregular shape. Second, the presence of multiple objects of interest. Third, in dense forests tree-tops cannot be easily distinguished from each other. Fourth, estimation of digital terrain model (DTM) images is difficult in dense forest areas.In these conditions, image segmentation cannot be handled in a conventional manner. For object segmentation task, three common methods are used such as pixel-wise thresholding in which a height threshold is used to separate objects of interest,pixel classification method which considers pixels as a vector belongs to one of two classes-objects and background and thirdmethod is the extraction of object feature points. For object detection from LiDAR images in a computational manner, two major approaches have been widely used such as the direct processing of LiDAR data and segmentation of surfaces as point clouds and the second one is the object detection and segmentation on Digital Surface Model (DSM) images.
Several methods of tree detection and forest segmentation based on airborne LiDAR data have been recently developed.A combination of surface reconstruction with watershed segmentation was applied to full waveform data to delineate trees[7]. Another example is the method of gray-scale morphology used to detect treetops in dense forest areas[8]. Fusion of LiDAR data and high

resolution aerial images isan effective way for the successful reconstruction of forestareas[9]. Forest area segmentation and individual tree detection are also possible in a GIS environment[10]. 2-D wavelet analysis is also useful in determining the position and height of individual trees [11]. Most of these methods are based ona single-scale analysis and object detection is implemented through time-consuming and unstable prior segmentation of LiDAR images. So there is a need for developing a method for object detection from LiDAR images. The goal of this work is to develop a method for effective segmentation using feature point extraction method from LiDAR images and object detection using DSM images.The method is based on visual attention model of image segmentation[13],[14] which concentrates on salient regions inan image. Object detection is performed by locating the feature points and these feature points are used for final segmentation. Region growing segmentation with some modifications is usedhere for final segmentation.

METHODOLOGY

Forest area segmentation from LiDAR images is a promisingtool for the studies related to forestry. Fig. 1.shows the workflow of proposed method for detecting forest areas from LiDAR images. It consists of primitive feature computation, feature point detection,object area recognition and a region growing.

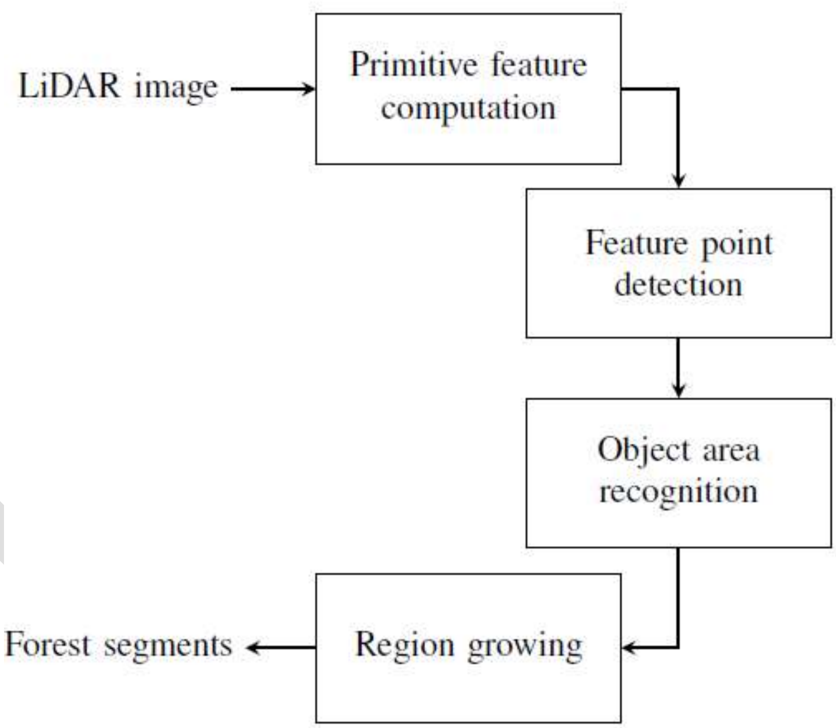

Fig.1:Work flow for forest area segmentation

The basic block diagram for the object segmentation of LiDAR images in forest areas is shown in Fig.1. LiDAR image of a forest area is given as the input image. Primitive feature iscomputed as the first step. It is calculated as the sum of square of Laplacian of Gaussian filtered image in which the filter is applied on a windowed section of input image. Using visual attention model, the feature points are detected on input image. These feature points are considered as the centers of object area. Object area can be recognized by a descriptor vector comparison. Finally region growing is performed to segment the entire object region.

1.Primitive feature computation

Primitive feature can be different characteristics of return pulses such as pulse intensity or width of return pulses in the case of multiple returns LiDAR data. Density of particular return pulse can also be used as a primitive feature since it characterizes the object area to be detected. But in this case only a single component initial image is given as input. The value of primitive feature in point (i,j) is computed as

$$g(i,j)=\frac{1}{|A_k|}\sum_{(m,n)\epsilon A_k(i,j)}(L_k[G_k[f(m,n)]])^2 \quad (1)$$

where f(m,n) is the input image, $A_k(i,j)$ is the local window centered at (i,j), L_k is the Laplacian operator and G_k is the Gaussian operator. Laplacian filters are derivative filters used to find areas of rapid change in images. Since derivative filters are sensitive to noise it is common to smooth the image before applying Laplacian. This is LoG filter. This preprocessing step will reduce the high frequency noise content present in the image prior to differentiation. Laplacian operator generally operates on a grayscale image and generates a grayscale image as output. A discrete convolution kernel which can approximate the second derivatives in the definition of Laplacian should be formed.

Since convolution is an associative operation we have to first convolve the Gaussian filter with Laplacian mask at first and then convolve this with the input image. The 2-D Gaussian smoothing operator is a convolution operator that removes the details and noises present in the input images. Since Gaussian filter is a smoothing filter it reduces the range of scales over which intensity can change. Intensity change can be detected based on the assumption that wherever a change occur there will be a corresponding peak in the first directional derivative or a zero-crossing in the second directional derivative of intensity. To detect the direction of changes a second-order differential operator Laplacian is used.

2. Feature point detection

Feature detection is the process where an image is automatically examined to extract features that are unique to objects in the image. The process can be divided into three steps:

- Detection: Identifies interesting points (feature point). Same feature should be always detected irregardless of viewpoint.
- Description: Each feature point should have a unique description that does not depend on the features, scale and rotation.
- Matching: Determines the objects contained in the input image and possibly the transformation of objects based on predetermined feature points.

Speeded-Up Robust Feature (SURF) detector is used here to detect feature points. The technique to achieve scale invariance is to examine the image at different scales, scale space using Gaussian kernels. SURF divides scale space into levels and octaves. The octave is divided into uniformly spaced levels.

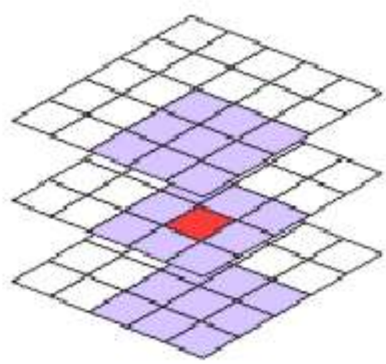

Fig.2: Three octaves with 3 levels

Figure 2 shows three octaves with three levels. Then interest points are the points that are the extrema among 8 neighbors in the current level and its 2x9 neighbors in the below and above levels. This is a non-maximum suppression in a 3x3x3 neighborhood. The neighborhood for the 3x3x3 non-maximum suppression used to detect features is highlighted in figure 2. SURF uses a Hessian based detector to detect interest points. Determinant of Hessian matrix represents the local change around the area.

$$H(X,\sigma) = \begin{bmatrix} L_{xx}(X,\sigma) & L_{xy}(X,\sigma) \\ L_{xy}(X,\sigma) & L_{yy}(X,\sigma) \end{bmatrix} \quad (2)$$

$$L_{xx}(X,\sigma) = I(X) * \frac{\partial^2 g(\sigma)}{\partial x^2} \quad (3)$$

$$L_{yy}(X,\sigma) = I(X) * \frac{\partial^2 g(\sigma)}{\partial y^2} \quad (4)$$

$$L_{xy}(X,\sigma) = I(X) * \frac{\partial^2 g(\sigma)}{\partial xy} \quad (5)$$

$L(X,\sigma)$ is the convolution of image with the second derivative of Gaussian. Since the convolution is very costly to calculate it is approximated and speeded-up with the use of integral images and approximated kernels. Integral image I(X) is an image where each point $X=(x,y)^T$ stores the sum of all pixels in a rectangular area.

$$I(\mathbf{X}) = \sum_{i=0}^{i\leq x} \sum_{j=0}^{j\leq y} \mathbf{I}(\mathbf{x},\mathbf{y}) \quad (6)$$

The SURF algorithm approximates the second order Gaussian kernels with box filters[15]. The use of integral images enables calculating the response in a rectangular area with arbitrary size using 4 look-ups as illustrated in Fig. 3.

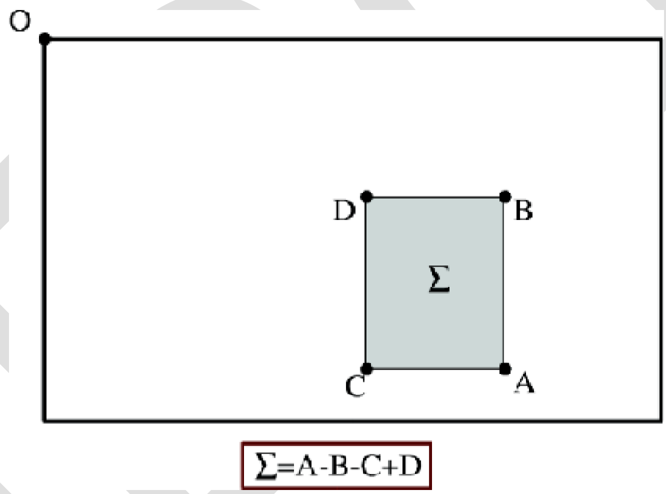

Fig. 3: Four memory look ups is sufficient to calculate the sum of an rectangular area with an integral image

3. Object area recognition

For object area recognition, a model-based approach[16] can be used. This model-based approach can be implemented with the help of Salient Disk Model(SDM)of high-contrast homogeneous regions. A Salient Image Disk is defined as a circular image fragment of a variable diameter, which is inscribed into a homogeneous region and has the local maximum of contrast-to-homogeneity ratio. A region is called high-contrast homogeneous if the ratio of the regional contrast to intensity variance inside the region is higher than a certain threshold. It involves the assumption of representing the object regions by homogeneous and high-contrast disk areas inscribed into the object regions. Then the feature points are set as the centers of the disk areas[17]. The structure of a Salient image disk is shown in Fig. 4.

Two non-overlapping regions centered at point (i,j) are involved in the estimation of Salient Image Disk homogeneity and local contrast. Disk region S is a maximal-diameter disk centered at (i,j) with its diameter equal to σ, and inscribed in the homogeneous region. The ring region Q_σ has its outer diameter equal to $\delta+2\delta_{min}$, where δ_{min} is the minimal scale diameter. Ring region is introduced for contrast calculations.

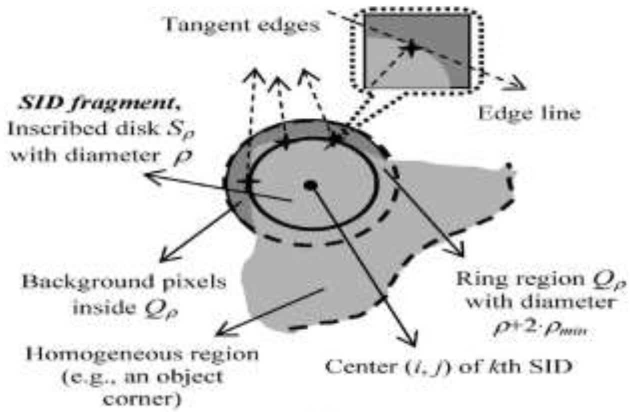

Fig.4: Salient image disk of a homogeneous region

The image area description for object area recognition involves the creation of a descriptor vector which represents the current disk area centered at feature point. Three descriptors are used for creating the descriptor vector:

- Planar pose parameter
- Area shape descriptor
- Intensity parameter

Planar pose parameters include two coordinates of the feature point, local scale and dominant direction and intensity parameters include mean value, root-mean-square deviation d(x,y) and local isotropic contrast c(x,y). Determination of local scale includes the selection of greatest by diameter disk centered at (x,y) and inscribed into the current homogeneous region. Local scale value is the diameter of inscribed disk. Area shape descriptors play a key role in image matching since they determine the local uniqueness of image fragments containing objects of interest. Shape descriptors are some set of numbers that are produced to represent a shape feature. Usually the descriptors are in the form of a vector.

Shape descriptors should meet the following requirements:

- The descriptor should be possibly complete to represent the information content.
- The descriptor vector should not be too long.

The shape description method[18],[19] called radial shape pattern is based on salient disk model. The algorithm for radial shape pattern consists of two basic steps:

- Determination of dominant direction
- Estimation of L directional descriptor components

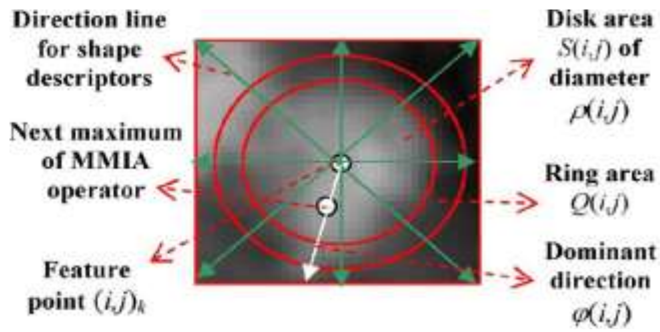

Figure 5:Determination of object area descriptors

Fig. 5 shows the object area descriptors in which the feature point is set as the center of concentric regions. Shape description consists of determination of dominant direction and estimation of L directional descriptor components. Dominant direction can be determined as the maximum of attention operator on a circle with diameter $\delta(x,y)$ centered at (x,y). Second step involves the analysis of directional contrast in L directions lying on a circle of diameter $\delta(x,y)+\delta_{min}$ centered at (x,y) where L is the total number of shape components and δ_{min} is the diameter of minimum scale disk.

4 Region growing

Basic function of region growing is the partition of an image into non-overlapped regions. First it takes a seed and then merges pixels with similar property and then forms a region corresponds to each seed[20]. Output of region growing must satisfy the following constraints:

- $\sum_{i=1}^{L} R_i$
- L is the number of regions. It means that sum of all regions should give the entire image.
- R_i is connected region, i=1,2,3,...n, where n is the number of regions. $R_i \cap R_j$=Null for all $i \neq j$.
- Mutual exclusion of region.

Region growing consists of following steps:

- Selection of initial seeds: Seeds should have some similar features with respect to their neighbors. There should be a seed for each region. No seeds should be connected to each other.
- Growing formula based on stopping criterion: Growing formula decides the homogeneity between the seed and its neighbors. Stopping criteria should be sufficient to differentiate neighbor elements.

There are mainly three goodness-of-seed conditions: the seed point has to be located inside a homogeneous image region, preference is given to the seed point locations whose area intensity has higher contrast with surrounding region and for a non-compact region the seed point has to be located at the center of its largest circular fragment inscribed into the region. Feature points are selected as seed points in this case to satisfy all the goodness-of-seed conditions[21].

In this methodology, a modified version of conventional region growing is used with three modifications to create a more effective segmentation of LiDAR images. First modification is to use an adaptive threshold in stopping criterion in which the threshold depends on the statistical characteristics of growing region. Second one is that region growing proceeds not on initial image but it is based on most relevant component of objects of interest. Third modification is that the growing process is limited by a circular area, whose diameter is comparable to local scale value. Since the threshold selection and region growing conditions depends on local scale value this region growing is also known as scale adaptive region growing.

RESULTS AND DISCUSSIONS

The main aim of this work is to segment the forest area from LiDAR images. For this an input image and a reference image are needed. First the primitive feature is computed on two small sections of smoothed input image. Laplacian of Gaussian filtering is applied for this. Then feature point is located on the same images. For object area recognition, a descriptor vector should be created. Descriptor vector contains feature point coordinates, isotropic contrast and height variance. So for the calculation of these values, a concentric ring and disk region are created on smoothed section of input image. These steps are repeated on reference image also. Then recognition is performed by comparing the difference between descriptor vectors of input and reference images with a threshold vector. Region growing completes forest segmentation. The simulation of project is performed using MATLAB R2014b.

The input images are downloaded from the website of open topography. The test site is located in Canada. LiDAR raw data were acquired with a LiDAR system having pulse frequency of100 KHz. The points were then converted to a raster of 0.5mper pixel resolution. Fig. 6 shows the input image and Fig.7 is the reference image. Then primitive feature map is created and feature point is detected using SURF algorithm. Corresponding figures are shown in Fig. 8 and Fig. 9 respectively.

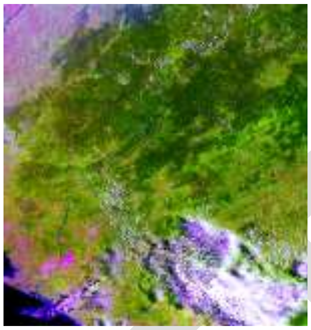

Fig. 6. Input image

Fig. 7. Reference image

Fig. 8. Primitive feature map

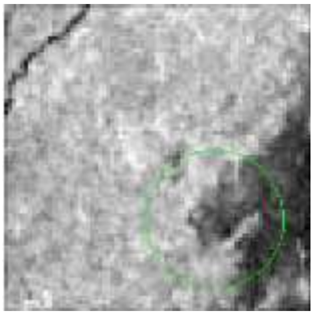

Fig. 9. Windowed input image with detected feature point

Then for creating the descriptor vector, a concentric disk region and a ring region are created on the input image and the parameters like isotropic contrast, height variance number of points in both disk and ring regions, etc. are calculated. Detected feature point is selected as the center of ring and disk and arbitrary radii are selected for both. The ring is setup with a larger diameter than disk. Same step is repeated on reference image also. The calculated values are summarized in Table 1.

Table 1:Calculated parameters of Input and Reference images

Parameter	**Input Image**	REFERENCE IMAGE
Feature point location	[51.82,53.06]	[31.52,24.77]
No.of points in disk region	657	674
No.of points in ring region	818	823
Isotropic local contrast	623.08	602.73
Height variance	0.0087	1.8668

This process is explained for windowed sections of input image. Finally a region growing algorithm is used with detected feature points as seed points for obtaining the segmented forest area from input image. The region growing is applied only for those areas which are recognized as object area through a descriptor vector comparison. The output image with detected forest area is shown in Fig. 10.

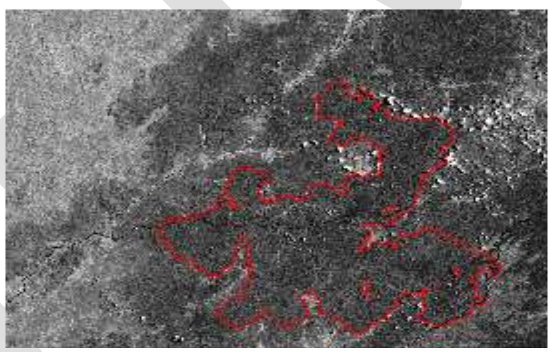

Fig. 10. Segmented forest area

CONCLUSION

LiDAR image analysis has numerous applications in forestry. It can be used to detect forest areas from LiDAR DSM images. For this a segmentation method based on attentive vision scheme is presented here. Compared to existing methods, the main difference is the computation of primitive feature as first step. This method is based on the visual attention model of image segmentation which helps to overcome the disadvantages of existing methods for forest segmentation. The object area recognition is based on the model based approach. Another important advantage is that the final segmentation is based on scale adaptive region growing in which both the threshold selection and stopping criterion are dependent on local scale value. It helps to eliminate the demerits of conventional region growing algorithm. This method also possess some characteristics. First, it is a model-based approach that can include both height characteristics and shape features of objects to be detected. Second, it does not require the ground points and finally, it provides a fast processing of LiDAR images.

REFERENCES:

[1] Roman Palenichka ,Frederik Doyon ,Ahmed Lakhssassi and Marek B. Zaremba,"Multi-Scale Segmentation of Forest Areas and Tree Detection in LiDAR Images by the Attentive Vision Method",IEEE Journal ofselected topics in applied earth observations and remote sensing , Vol.6,No. 3, June 2013.

[2][Online]Available:http://www.lidar-uk.com/usage-of-lidar.

[3] J.C. Fernandez, A. Singhania, J. Caceres,K.C. Slatton,MStarekand R.Kumar,"An Overview of Lidar Point Cloud Processing Software",Geosensing Engineering and Mapping (GEM)University ofFlorida,2007.

[4] Nabil Ouerhani and Heinz Hugli,"MAPS: Multiscale Attention-based Pre-Segmentation of Color Images",Instituteof Microtechnology, Universityof Neuchatel,Switzerland,June 2013.

[5]DimitriLisin,EdwardRiseman and Allen Hanson,"Extracting salientimage features for reliable matching using outlier detection techniques",Department of Computer Science,USA.

[6] NicuSebe and Michael S Lew,"Comparing salient point Detectors",Liden Institute of Advanced Computer science,Netherlands..

[7] J. Reitberger, P. Krzystek, and U. Stilla, Combined tree segmentation andstem detection using full waveform lidar data," Proc. ISPRS Workshop onLaser Scanning 2007 and SilviLaser 2007, Espoo, Finland, Sep. 1214,2007, vol. XXXVI, pp. 332337.

[8] H. Andersen,S.E. Reuterbuch and G.F. Schreuder,"Automated individualtree measurement through morphological analysis of a LiDAR–basedcanopy surface model",Proc. Ist Int. Precision Forestry Symp., 2001,pp.11-22.

[9] Liang-ChienChen,Tsai Wei Chiang and Tee Ann TeoLiang-ChienChen,Tsai Wei Chiang and Tee Ann Teo,"Fusion of LIDAR Data andHigh Resolution Images for Forest Canopy Modeling",Center for Spaceand Remote Sensing Research,Taiwan.

[10] Dirk Tiede,GregorHochleitner and Thomas Blaschke,"A Full GIS-basedworkflow for tree identification and tree crown delineation using laserscanning" IAPRS,xxxvi,Aug.2005.

[11] Michael J. Falkowski, Alistair M.S. Smith, Andrew T. Hudak,PaulE. Gessler, Lee A. Vierling and Nicholas L. Crookston,"Automatedestimation of individual conifer tree height and crown diameter viatwo-dimensional spatial wavelet analysis of lidar data",Can.J.Remotesensing,vol.32,no.2,pp. 153-161,2006.

[12] R.Palenichka and M.Zaremba,"Multi-scale Isotropic Matched Filteringfor individual tree detection in LiDAR images",IEEETrans.Geosci.Remotesens.,vol.45,no.12,pp.3944-3957,2007.

[13] Paul L.Rosin,"A simple method for detecting salient regions",PatternRecognition,pp.2363-2371,2009.

[14] R.Palenichka and M.Zaremba,"A Spatio-Temporal Isotropic Operatorfor the Attention-Point Extraction",Computer analysis of images andpatterns,Vol.5702,2009,pp.318-325.

[15] Jacob ToftPedersen,"SURF: Feature detection and description",Dept.ofComputer Science, Aarhus.

[16] R.Palenichka,MariaPetrou and YannisKompatsiaris and AhmedLakhssassi,"Model-based extraction of image area descriptors using a multi-scale attention opeartor",International conf.on pattern recognition,Nov.2012.

[17]Roman M. Palenichka and Marek B. Zaremba,"Automatic Extractionof Control Points for the Registration of Optical Satellite andLiDARImages",IEEE Transactions on Geoscience and Remote sensing,Vol.48,No.7,July 2010.

[18] Mingqiang Yang, KidiyoKpalma and Joseph Ronsin,"A Survey of ShapeFeature Extraction Techniques",Pattern Recognition, In-Tech,, pp.43-90,2008.

[19] Dengsheng Zhang and GuojunLu,"Review of shape representationand description techniques",Journal of Pattern recognitionsociety,Vol.37,pp.1-19,July 2003.

[20] ShilpaKamdi and R.K.Krishna,"Image Segmentation and Region Growing Algorithm",International Journal of Computer Technology and Electronics Engineering (IJCTEE),Vol.2,Issue 1,ISSN 2249-6343.

[21] ShilpaDantulwar and Prof. R.K.Krishna,"Performance analysis using single seeded region growing algorithm".