CHANGE DETECTION BY THE COMBINATION OF 2D MAPS AND HEIGHT DATA

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ABSTRACT

The advantage offered by laser altimetry (such as high accuracy, fast acquisition and processing, canopy penetration, weather/light independence, and minimum human dependence) for change detection has become glaring as it has become an active area of research in the last decade. However, not much have been done in combining LiDAR data and 2D map for change detection. This work describes the use of LiDAR data and 2D map for change detection. The aim was to detect changes in four classes such as; building, terrain, water, and road. This research proposed a method that could minimize change detection error due to misclassification. The two datasets of different dates were fused to generate initial classification with the points within the map polygon inherits the class label of the polygon. The initial classification is verified and change is detected based on the characteristics of the points within each polygon by making rules. These rules are derived from analysis of the values of the selected attributes to verify and detect change per class. The detected changes are further classified into real change and fake change. The result shows that building was reliably verified and the change detection was not optimal due to a false alarm. The accuracy of the change detection results was done by visual inspection of the comparison of the change polygon with a reference data.

Keywords: change detection, LiDAR, data fusion, 2D map, verification.

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1. INTRODUCTION

1.1. Motivation and problem statement

Change detection is of great importance in most urban studies such as; land use monitoring, illegal building detection, resource management and damage assessment. Timely and accurate change detection of the earth surface (e.g. urban areas) provides the foundation for better understanding of the relationship and interaction between features and human to effectively plan and manage resources (Afify, 2011). Singh (1989), defined change detection as "the process of identifying differences in the state of an object or phenomenon by observing it at different times". The Urban environment is subject to continuous change resulting from several anthropogenic activities such as construction, demolition, and industrialization etc. However, the requirements of sustainability in the present-day urban environment creates the need for continuous, accurate and up-to-date resource data.

The local authorities and mapping agencies are faced with the challenge of the increasing demand for a regular update of the topographic database for effective monitoring and management of the dynamic urban landscape. To keep the database as up to date as possible municipalities are looking into the possibilities of an efficient and automated change detection techniques. Several methods have been adopted for change detection. Consequently, researchers are of the view that there is no universal method for change detection. Automated mapping is a challenging task and different studies have been done on which method is more reliable. However, quite a number of technologies have been employed for monitoring and detecting changes in the urban environment, the application of data from remote sensing with it's synoptic and regular coverage at a multi-temporal scale provides a viable source of information for change detection. New technology like Laser scanning for change detection has proven to have an edge over conventional approach as it can detect object under trees and give information in 3D perspective.

Several methods have been employed in urban change detection by quite a number of authors using LiDAR (Light Detection and Ranging) data. These were done by comparing multi-temporal data as described by Xu (2015) or by comparing a single epoch data with a medium scale map (Vosselman et al., 2004). Other methods of change detection, either using maps or DSMs, are faced with the problem of information loss due to occlusion. When a change occurs under another object like vegetation, neither maps nor DSMs could detect such change (Xu et al., 2013). Nevertheless, the approach of occupancy grid for comparison of ALS data proposed by Hebel et al. (2013) have been used by researchers to avoid information loss.

The use of laser scanning data as the only data source for change detection has been proven to be faced with problems like occluded points in one epoch, gaps in data, due to water absorption and difficulties in separating real change from fake change (Xu, et al., 2013b). The problem of change detection goes beyond just identifying what has changed rather distinguishing real changes from fake changes is an issue faced by researchers in classifying the detected changes, elements attached to building such as window are dynamic and could appear as extended building which is not real changes; the problem of lack of data could be misclassified as change as shown in Figure 1-1.

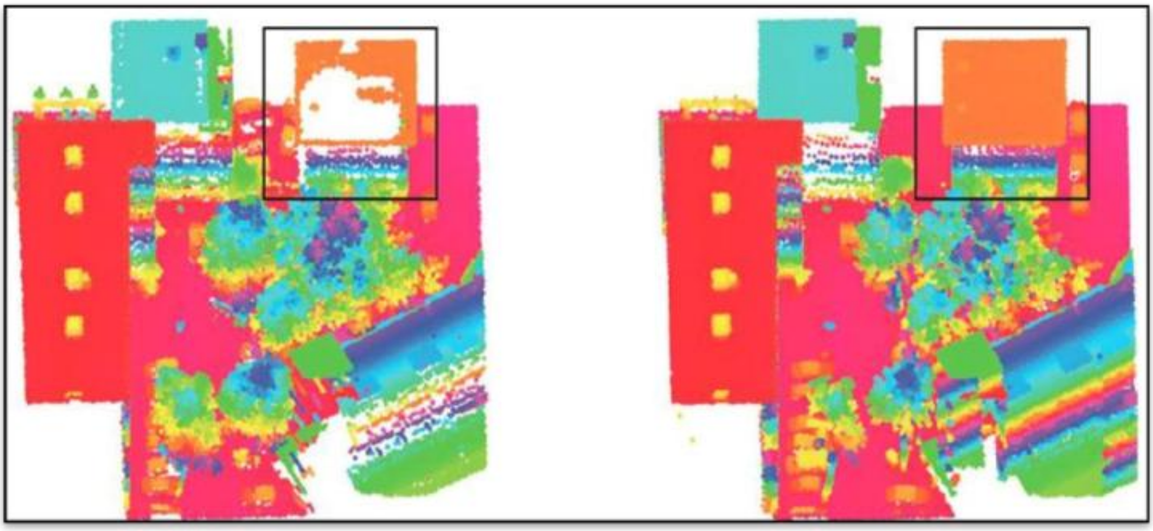

Figure 1-1: Fake changes cause by lack of data in one epoch(Source: Xu., 2015)

Some method uses additional information; like 2D maps as an additional data in their approach. The correct combination of height information with 2D maps have great potentials for fast and efficient automated change detection. Topographic maps provide semantic information, building-outline, classified polygons, and topology. Integrating 2D maps and LiDAR data has a great advantage in improving filtering process (Oude Elberink and Vosselman, 2006). Combining these datasets gives broader insight on the similarities and differences as the LiDAR data gives information on the geometry while 2D map delivers thematic and topographic information, which will help to improve the classification process for effective detection and classification of change into what are real and fake changes. The advantage of integrating 2D map and LiDAR data for 3D urban model was further explained by Haala et al. (1998). In their approach integrating 2D map and LiDAR data, detail reconstruction of the buildings were achieved automatically even in areas of low point density.

In integrating 2D maps with LiDAR data for change detection, several questions are raised such as; the accuracy of the 2D map, how to deal with the map generalization effect and the offset between the datasets. The effect of map generalization was demonstrated in Figure 1-2.

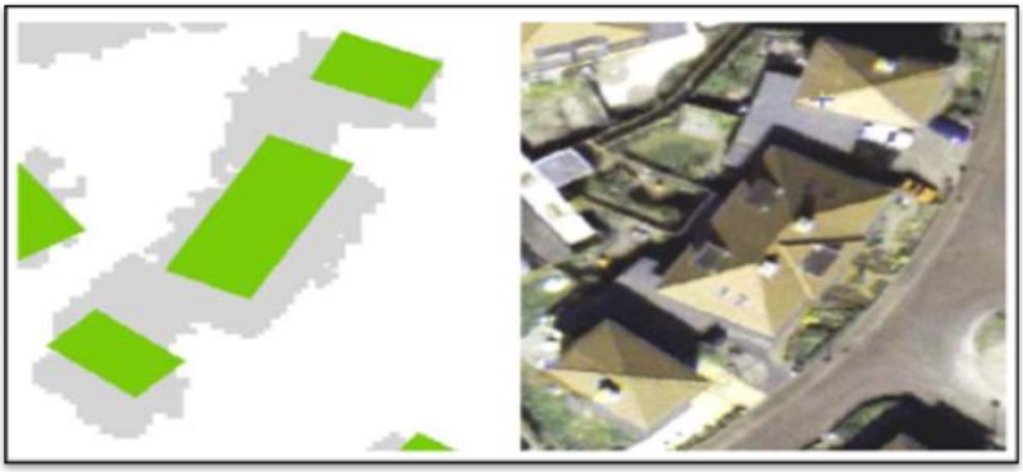

Figure 1-2: Detected mapping error, operator mapped three separate buildings the LiDAR data shows that buildings were connected by lower part with flat roofs (Source: Vosselman et al. 2005).

Oude Elberink (2010) explained the need for proper examination during the data fusion so as to appropriately assigning laser points to 2D map, stating that the 2D map may not represent what is in the LiDAR data, for example building outline in a 2D map represent the boundary wall while the LiDAR data represent the roofs.

Furthermore, (Vosselman et al., 2005) presented an approach to detect changes in building by comparing the contour of classified building segment of LiDAR data to the contour on the map. The result shows new and demolished buildings were properly detected but their results showed some level of inaccuracy in detected change due to a false alarm caused by misinterpretation of mapping rules and incorrect classification caused by vegetation adjacent to buildings.

Change detection using LiDAR data have been an active area of research with a focus on building and vegetation, not much work have been done in detecting changes in other classes of the topographic map. However, having identified the problems in past research works and the advantages of combining two data sources for change detection. The motivation for this work lies on the need to develop an automated change detection technique by fusing LiDAR data and 2D map. My focus on this work is to identify changes in the urban landscape in four classes(water, road, terrain and building). The techniques should be capable of minimizing classification error propagated to the change detection stage which is a major limitation of previous work.

1.2. Research identification

1.2.1. Research objectives and questions

The main objective of this research is to detect changes in an urban area by combining 2D maps and LiDAR data of different date. The fusion of the 2D map and the LiDAR data generate an initial classification which is used for change detection. To achieve the set objective, these sub-objectives should be accomplished;

The sub-objectives and associated research questions

1. To verify the initial classification.

- what are the attributes to be used?
- What is the combination of the features that is useful?

2. To classify change.

- How to decide a change in class?
- How are real change and fake change differentiated?

3. To determine an appropriate measure for quality assessment of detected change.

- What suitable measure can be used to assess the accuracy of the detected change?

1.2.2. Innovation

In the last decades, change detection in urban areas has been explored by various researchers. Most of them approach this task with a different motive and with different sensors. The advent of Laser altimetry has addressed some limitation of conventional method as it tracks changes that happen under vegetation. However, not much work has been done in change detection in an urban area by the combination of 2D map and LiDAR data. Previous work looked mostly at only building change detection. The novelty of the proposed approach goes beyond that, changes in other classes (water, road, and terrain) in the 2D map will be detected. In this thesis a rule-based approach to detect change within polygon is a new insight; our method will use the points in polygon operation to combine point clouds and 2D map to generate an initial classification and perform verification based on the statistics of the attributes to detect changes between the 2D map class and the point cloud within the polygons.

1.3. Thesis structure

This thesis is organized into five chapters

Chapter one introduces the motivation and problem of the research, the objectives of the research and questions and the innovation of the research. Chapter two is a review of literature of related research work to this research work. Chapter three introduce the research methodology. Chapter four present the study area, preparation of data and the result and discussion. Chapter five describe the conclusion drawn from the research and make some recommendation for future.

2. LITERATURE REVIEW

2.1. Principle of LiDAR

The emergence of LiDAR (Light Detection and Ranging) altimetry have impacted greatly on the accuracy and acquisition rate of topographic data. This technology offers enormous possibilities over other conventional methods for topographic data collection in terms of high accuracy, high density, efficient data collection, weather, and light independent. In light of the stated characteristics, LiDAR has been an active research area as it also has the advantage to be used to complement other conventional techniques.

The principle of LiDAR and Electronic Distance Measuring Instrument (EDMI), are similar. Airborne and terrestrial laser scanners usually classified as a time of flight optical 3D measurement systems captures and record the geometry and sometimes the textural information of the earth surfaces. The principle behind LiDAR technology(see Figure 2-1) is the measurement of the time delay created by the traveling laser pulse from the source to the target and back to the scanner. The laser pulse travels with a known velocity which offers a convenient method to calculate the distance. The ranging LiDAR in addition to the distance measurement also has other measurements such as coordinates(x, y and z), orientation integrated into the system (Lohani, 2009).

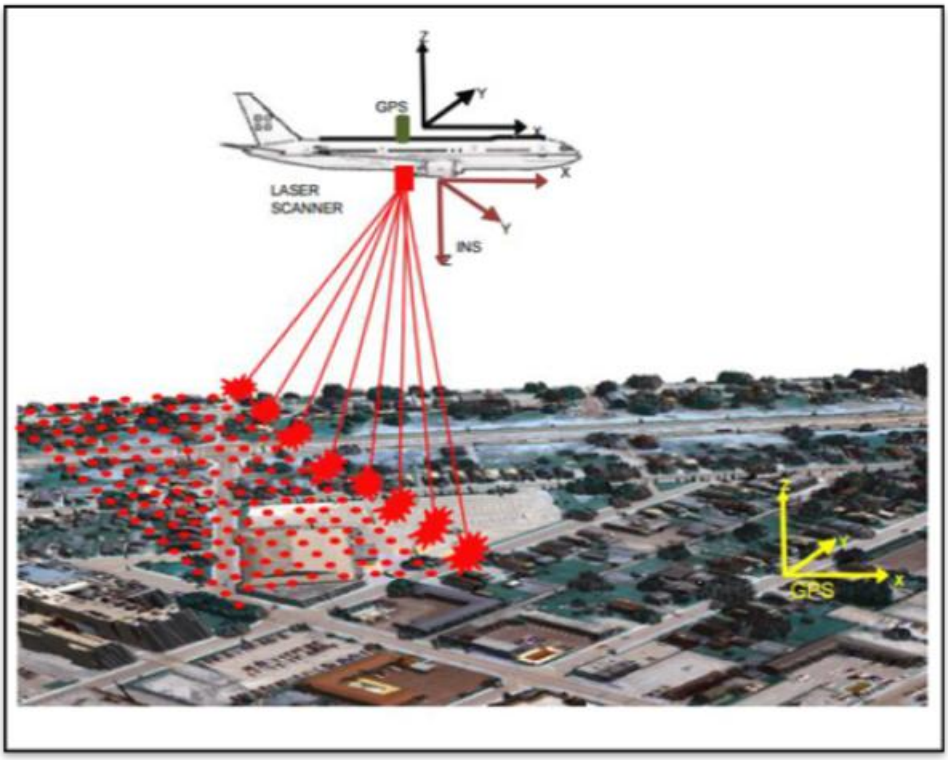

Figure 2-1: Principle of topographic LiDAR (Source: Lohani, 2009).

2.2. Change detection with imagery

Conventionally, change detection was done by visual interpretation of change maps and images. (Fröjse, 2011) in his research compared two algorithms (image differencing and post classification) using satellite imagery from two different sensors to detect changes in an urban area. Unsupervised k-means classification and supervised maximum likelihood classification were used to classify the images for Image differencing and post classification algorithm respectively. Visual inspection was used to classify the difference image into change and no change. However, this approach is time-consuming and not cost-effective when change is frequent and large area needs to be analyzed. Automated approach for change detection was implemented using the Combine Edge Segment Texture analysis(CEST) based on the fact that algorithm like image differencing was not optimal for detecting changes in building in the study area (Ehlers et al., 2012). Their method incorporated frequency based filtering, image segmentation, and texture analysis. The result of the approach yield improved accuracy compared to the image differencing techniques.

Several methods and techniques for change detection have been published in the last decades. (Hussain et al., 2013) For example combined both the pixel base and object base techniques for change detection while (Dal & Khorram, 1999) used artificial neural networks for change detection. However, different methods have been developed with differences in robustness, flexibility and efficiency, researchers are of the view that there is no single best technique for change detection, reviews of various techniques can be found in (Lu et al., 2004). Furthermore, the summary and review of change detection techniques by Gang et al., (2008) categorize change detection approach into two groups: bi-temporal change detection and temporal trajectory analysis. In their review, change detection methods were grouped into seven categories; classification, direct comparison, object-oriented method, time series analysis, visual analysis, and hybrid method (see Figure 2-2).

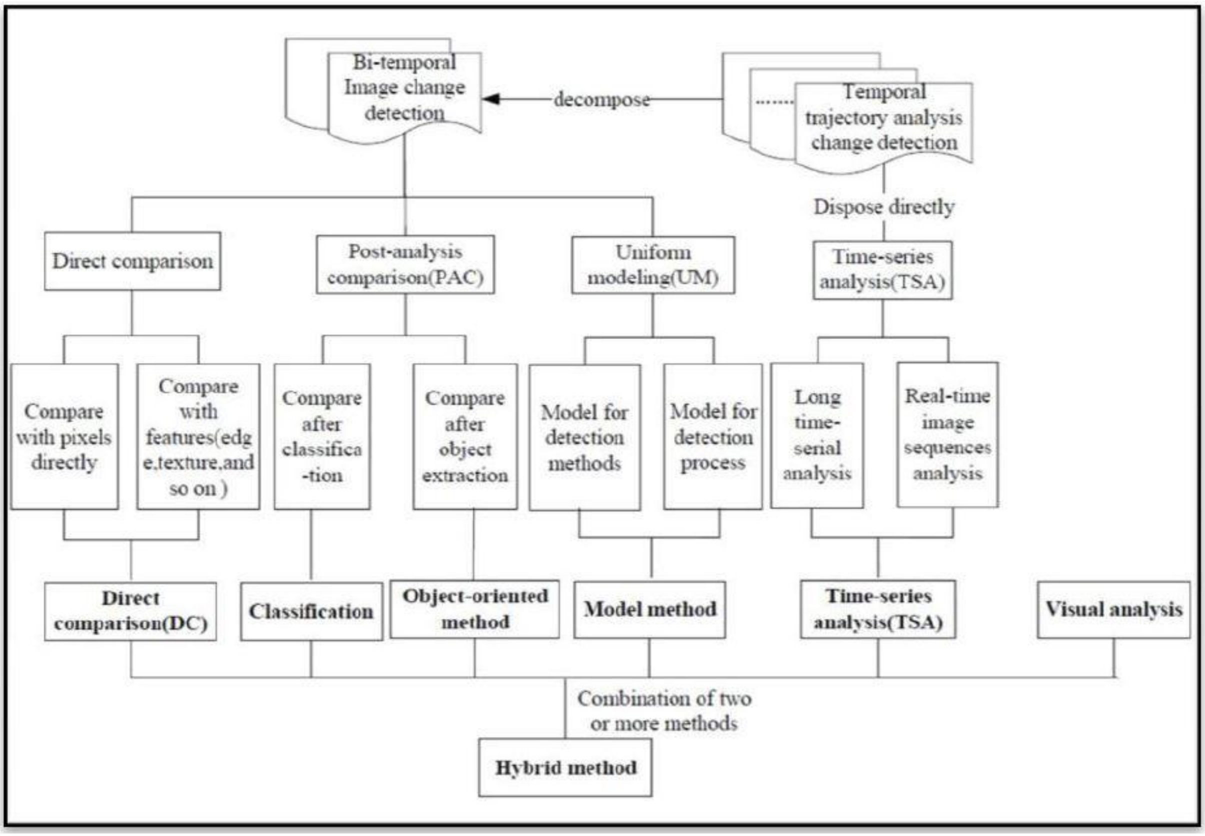

Figure 2-2: Classification concepts of change detection algorithm (Source: Gang et al., 2008).

However, new methods are still been developed and adopted in change detection. The conditional random field was used to detect change from multi-temporal images by classification of pixel of the different images (Chen et al., 2007). Besides the use of multi-temporal images for change detection (Tian et al., 2011) presented an approach that used stereo pair images to detect changes in building in 3D.

2.3. Change detection with LiDAR data

The advantage offered by laser altimetry (such as high accuracy, fast acquisition and processing, canopy penetration, weather/light independence, and minimum human dependence) for change detection has become glaring as it has become an active area of research in the last decade. Using LiDAR data for change detection have an edge over the conventional method as it provides more accurate 3D information. The pioneer work on building change detection in an urban area using ALS data can be traced back to (Murakami et al., 1999). Their approach was to generate multi-temporal Digital Surface Model(DSM) by interpolating the 3D point cloud to a 2D grid. Changes were detected by computing the difference of these DSMs. The difference map generated was overlaid on ortho-image to identify the change in buildings.

Girardeau-Montaut and Roux (2005) presented a method for change detection by direct comparison of point clouds to point clouds acquired with a ground laser scanner. Their approach was an octree-based comparison process of multi-temporal point cloud data by computing three parameters such as average distance, best fitting plane orientation, and Hausdorff distance. Change was detected by the difference of the computed parameters of the point clouds. Gikunda (2015) developed a class based change detection technique. The knowledge of the characteristic of objects and expected change was an important information in the development of her approach. Change was detected from the separation map generated by calculating point-wise geometrical differences between the LiDAR data of two epoch.

For the purpose of change detection, the need for classification of laser point cloud into ground and non-ground points is of great important for the production of Digital Terrain Model(DTM).Several filtering algorithm were examined in (Sithole and Vosselman, 2005) and also they implemented a new filtering algorithm which segments point cloud into smooth-segment and still preserves height discontinuities. Compared with other algorithms their new approach generated a good result in a flat landscape. The results from the filtering were classified into bare earth or object in accordance with the geometric association with the neighbouring segment. However, multi-spectral data could be used as an addition to improving the classification result (Haala and Brenner, 1999).

Similar to the conventional method of using imagery it is obvious that the quality of change detection result depends on the result of the classification.(Khoshelham et al., 2013) described the segment based approach for point cloud classification of damaged building roof. The performances of three classifiers were evaluated and they came up to the conclusion that not enough training set would lead to poor classification result. (Oude Elberink et al., 2010) used a rule-based classification method to classify point cloud into collapsed and non-collapsed building. For their approach, five segment-attributes (Number of points per segment, Mean height above the digital terrain model, Number of segmented to un-segmented points ratio, Planarity of segments and standard deviation of intensity) were computed and the threshold for the classification was determine based on the value of the training sample of the two classes. A reported 70% overall accuracy was achieved with this approach. Another approach for point cloud classification includes object-based and feature-based method. The advantage of using a rule-based approach was further described by Xu (2015). In her work five different classifiers were used and she claimed that the classification result from the rule-based approach has the highest accuracy (see table 2-1) and also a 90% accuracy for change detection in buildings was reported in her work.

Table 2-1: The overall accuracy result and kappa accuracy of five classifiers used to classify point cloud (Source: Xu, 2015).

	Random tree	AdaBoost	ANN_MLP	SVM	Rule based
Overall accuracy	95.5%	94.3%	95.0%	94.1%	97.0%
Kappa accuracy	93.4%	91.6%	92.6%	91.3%	95.7%

In general, there are two basic approaches for detecting changes using LiDAR data (Vosselman et al., 2004). The first approach involves comparison of two datasets of different epoch to detect change. This has been applied in comparing two datasets and changes are inferred by employing surface separation (Xu et al., 2013a). (Choi et al., 2006) presented a feature based approach to detect changes in an urban area using multi-temporal LiDAR dataset. A difference image was obtained by subtracting DSMs generated from the data of two epoch. The difference image was converted to a binary image and opening operator was applied to minimize the commission error caused by occlusions. The second approach, a single epoch of LiDAR data was compared with a 2D map to detect changes

2.4. Change detection with LiDAR data and 2D map

Previous studies have highlighted the advantage of the combination of two datasets in change detection. The fusion of LiDAR data and 2D map for 3D road and building reconstruction was described by (Oude Elberink, 2010). The combination of 2D map and LiDAR data for change detection was implemented by (Vosselman et al., 2004). Change detection was performed by comparing the building segment to the medium scale map. This approach is faced with the generalization effect. To minimize the effect of generalization on the map, dilation and erosion were an additional step introduced in the approach see(Figure 2-3).

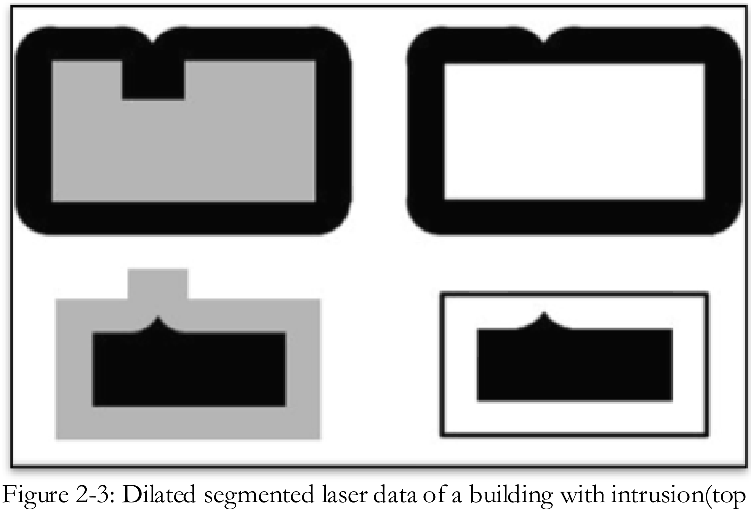

Figure 2-3: Dilated segmented laser data of a building with intrusion(top left) and fitted generalized database object inside dilated building segment(top right). Eroded laser data segment of building with a protrusion (bottom left) and eroded laser data segment fits inside generalized database object (bottom right); (Source : Vosselman et al., 2004).

The kernel size used for the erosion and dilation depends on the specification of generalization process. However, the notable problem faced by the approach is misclassification caused by vegetation adjacent a building. This method was improved by using aerial image to distinguish between building and tree (Matikainen and Kaartinen, 2004).

2.5. Attribute selection

Parameter derivation for characterizing point cloud entails some set criteria for grouping points. In adopting attributes for classification of a point cloud, it's necessary to understand the characteristics of the classes to be analyzed (Xu, 2015). Attribute or feature extraction is an important step for recognition and classification of a point cloud. The selection of relevant attribute subset from a list of attributes is important for effective pattern recognition and classification. Several attributes have been proposed for classifying point clouds by several researchers but the optimum task is to identify the relevant ones. Weinmann et al., (2014) used Filter-based approach to select relevance attributes for classification in their work. The attribute for recognition are used in combination of more than one attributes to improve the classification or recognition of a class.

2.6. Quality assessment in change detection

Quality assessment is an important task for understanding generated results and a deciding factor on employing them. Several factors affect change detection results such as quality of data, complexity of study area, algorithms adopted, miss-classification and quality of reference data. Several methods have been employed in assessing the quality of change detection result. Gikunda (2015) used three possible outcomes of prediction to evaluate the quality of her results. This outcome includes True positive , False negative, and False positive. True positive is when change correctly detected and false negative happens when change is detected in a class that was not correctly and false positive is when change is wrongly classified.

3. RESEARCH METHODOLOGY

In this chapter, the proposed methodology for achieving the set goal and objectives of this research will be explained sequentially. Our work involves detecting change in four classes of interest; building, water, terrain, and road. In order to achieve this attributes for characterizing classes need to be known and at what combination is it optimal to recognized each class. To detect change in each polygon class, a rule-based approach was adopted.

3.1. Framework of the methodology

The proposed methodology is introduced with respect to the set objectives with the following procedures in Figure 3-1 below.

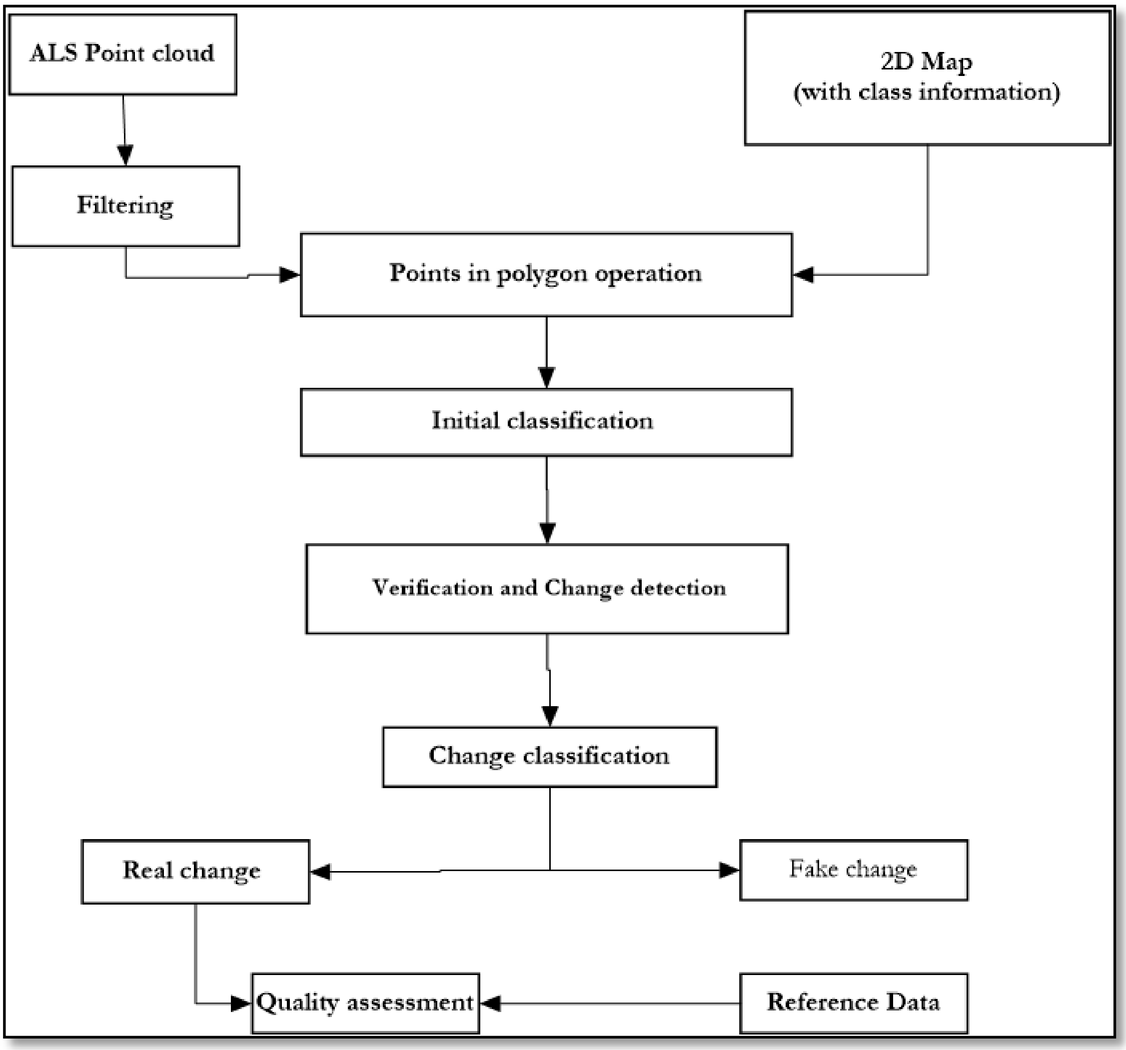

Figure 3-1: Flowchart of methodology.

As illustrated in the framework, the general workflow starts from the combination of LiDAR data and 2D map of different year to detect changes in each class. A combination of attributes is used to recognize how each class looks like. The entire process will be explained sequentially.

3.2. Filtering of LiDAR data

Filtering involves the classification of LiDAR data into ground and non-ground points. Several method exist but the filtering algorithm proposed by Sithole and Vosselman (2005) shows a reliable performance in terrain where there is no much slope and height jump. This is an important step to determine terrain information and it's a prerequisite step for the generation of the initial classification. The filtering of the point cloud in our work was already implemented in data provided. The outputs of the filtering were visualized and most points were correctly classified as ground and non-ground points.

3.3. Classification of 2D map

The 2D map is made of closed polygons. The 2D map polygons were labeled into different classes. This is a prerequisite step for points in polygon operation. The polygons of the 2D map have class labels in the data provided.

3.4. Points in polygon

The underlying principle for detecting changes within polygon class is to use the laser points inside the polygon. This can be implemented by points in polygon algorithm developed by Oude Elberink (2010). However, the algorithm should be able to handle problems with few points within a polygon. This task was implemented using the FME workbench software. In fusing the two data set we ensured that the point cloud and 2D maps were on the same reference plane so that both data are spatially equivalent. The output of this approach will generate the initial classification which will serve as input for the other steps.

3.5. Segmentation of point cloud

Segmentation of point cloud groups points that belong together based on some set criterion. The surface growing method developed by Vosselman et al., (2004) was employed to segment the point cloud into planar segments. The surface growing approach can be regarded as an extension in three dimensions of the region growing algorithm used in image processing to group neighboring pixels into a region (Kamdi and Krishna, 2011).

The surface growing algorithm is implemented in two steps; seed detection and growing. Seed points are detected from a neighbourhood of an arbitrarily selected points that form a planar surface, these points are analyzed with a Hough transform to identify if the points fit a plane. In the next stage, these seed surfaces are grown if it meets set co-planarity criterion. In this work, the parameter value was chosen by repeatedly adjusting the parameter value until the best segmentation result is achieved. The selected parameter value for this work can be seen in Table 3-1. For the 1.0m and 0.2m for the growing parameter, it implies that points are grouped into a segment if they are within 0.2m to the plane and the points are within 1.0m to another point in the segment. While the seed selection parameter value of 10points and 1.0m respectively is the minimum required numbers of points to fit a plane and the points should be within 1.0m from the seed points.

Table 3-1: Parameter for surface growing segmentation.

Parameter for seed selection	Value	Parameter for growing	Value
Seed neighbourhood radius	1.0m	Growing radius	1.0m
Minimum number of seed point	10	Maximum distance of point to the plane	0.2m

Unlike the surface growing segmentation which groups point into planar surfaces if they fulfil the set criteria. The connected component segmentation algorithm is implemented to group points into segments based on their connectivity and their distance. The assumption is that points of an object will be closest to each other than points from other objects. It is expected that points of an object will form a component. However, this may not always be the case if objects are close to each other, for example when cars are closely parked may form a very big component depending on the threshold selected. In this work, the parameter value was chosen by repeatedly adjusting the parameter value until the best segmentation result is achieved. The maximum distance between points is set as 0.5m in this work.

3.6. Verification of initial classification and change detection

The initial classification is the output from data fusion of the 2D with the class label and the point cloud. The point cloud within each polygon inherits the class label of the polygon. To verify the initial classification, there is the need to build statistics describing point clouds of the four classes of interest. In our work attributes were selected for class recognition, selection was done based on the properties of the classes to be examined and the likely changes that could exist within each class. In this work each polygon was verified by comparing the characteristic of the point cloud within in each polygon if it corresponds with that of the class label of the 2D map. In doing so changes are expected as the two datasets are of different dates and when the point cloud characteristics mismatch the 2D map class such polygon is tagged changed. To verify the initial classification and detected changed polygon, a rule-based approached was employed.

3.6.1. Training samples

In order to verify and detect change within each class. Training samples from known polygon need to be selected to understand the characteristics of each class. The training sample in this work is a set of polygons with known class label. Point cloud within each polygon was visualized and their size and shape was analyzed in selecting the training sample for every class. The same number of training samples were selected per class to avoid bias toward a class with a higher number of training sample in training (Chen et al., 2001). The training samples were selected based on human interpretation and samples are selected to represent variability within each class, for example, both big and small building polygon were selected with the view that points of big buildings could show a slightly different pattern to those of small buildings.

3.7. Attribute selection

The extraction of attributes is a critical step in verification of the initial classification. Previous works have used different attribute in the classification of LiDAR data. The task is to select the relevant set of attributes that best describe the classes. These attributes are proposed based on the characteristics of each class and the likely change that are expected per class as explained in section 3.7.1-4. It is quite difficult to choose one suitable attribute for verification due to the variability within class and similarity among classes. To be able to determine the combination of attributes for recognizing and verification of class, there is the need to learn from a number of training samples of known labels how each class signature so as to select the attributes that describe each class better.

3.7.1. Building class

Since the two datasets are of different dates there could be differences between the datasets. These differences need to be taken into account in the verification of the initial classification and change detection. Several reasons that could result to change needs to be taken into account so that unchanged polygon will not be wrongly presented as change. Buildings are static object and an important part of an urban environment. Change in this class takes a particular pattern such as newly constructed, demolished or extended building. The aim of this research is to detect changes in building class based on the geometric characteristics of points within each polygon and how the point cloud differs with the 2D map label. However to achieve this in our work we proposed some attributes based on the characteristics of a building which are: (1) buildings should have most of its points as non-ground. (2) building are mostly made of planar surfaces. These properties of the building class will be used as a basis for the proposed attributes so as to be able to distinguish building from other class like vegetation and another man-made object(cars) which could be on the non-ground points.(1) Number of segmented to un-segmented points ratio(NSUR) (2) Mean relative height (3) Number of non-ground to ground points ratio; these three attributes are proposed to verify and detect changed building polygon. The need to combine more than one attribute is drawn from the fact that one attribute only cannot clearly discriminate between building class and other class. As learned from the data building class and man-made object like cars show notable similarity in NSUR value(see figure 3-2) if this attribute is used alone object like car would be wrongly verified as building so in this work mean relative height is a combining attributes for change detection in the building class having in mind that the mean relative height of a car is less than that of a building.

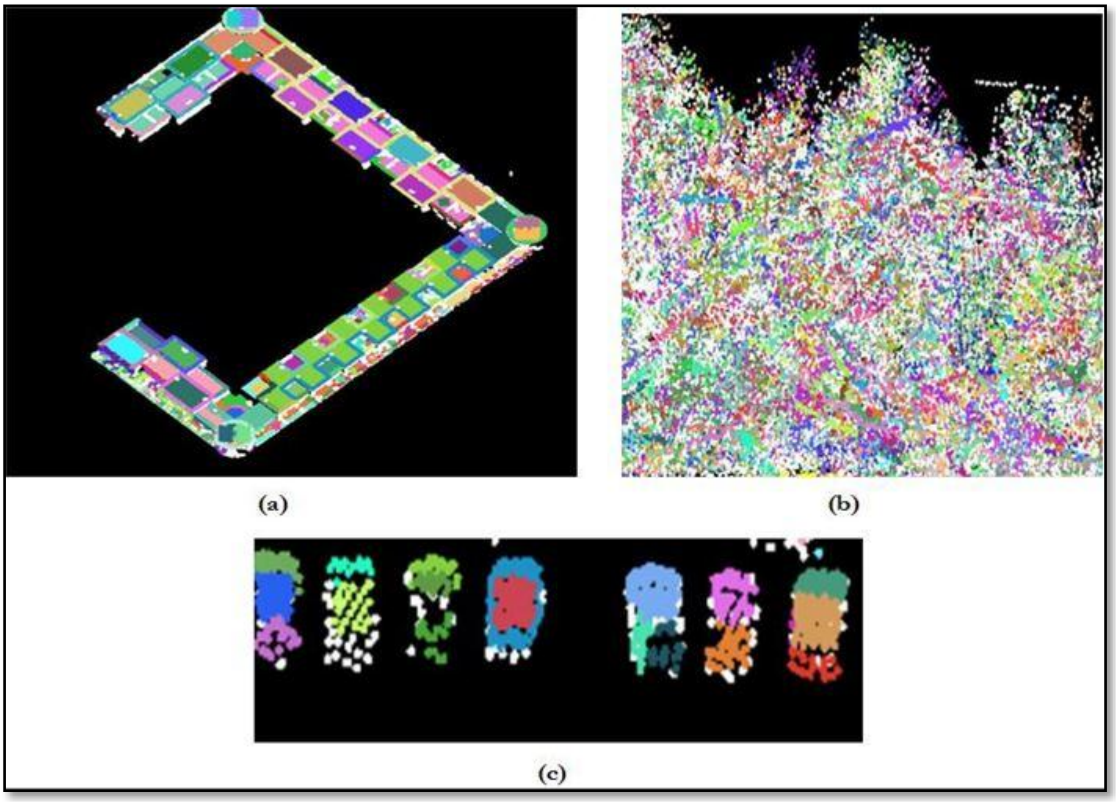

Figure 3-2: (a) Example of a building class surface growing segmentation result, different colour shows different planar segment, (b) planar segmentation result of vegetation with the colour points representing the segmented points and the white points are the un-segmented points, (c) segmentation result of cars.

3.7.2. Water

Water class shares similar characteristics like the terrain and road in a point cloud as these three classes are mostly planar except in cases where a terrain has features like grasses on it. Water tends to absorb laser pulse and thereby causing gaps in the point cloud. These may not always be the case in a scenario where there is high strip overlap and high specular reflection(Xu,2015). In this class, the likely change to happen in a water class could be a reduction in water size due to season variation. Another change that could be experienced in a water class is the construction of object like bridge in a water polygon. The attribute for this class were proposed based on these characteristics of the class: (1) water will be mostly ground points except for cases where there is change or vegetation in a water polygon.(2)Most of the points of a water class will fall as the minimum height value as there is very little height difference. Having these feature in mind it is logical to expect differences in the height histogram distribution. The height histogram distribution of the road, water, and terrain class was inspected by first looking at the histogram of all three classes (see figure 3-3).

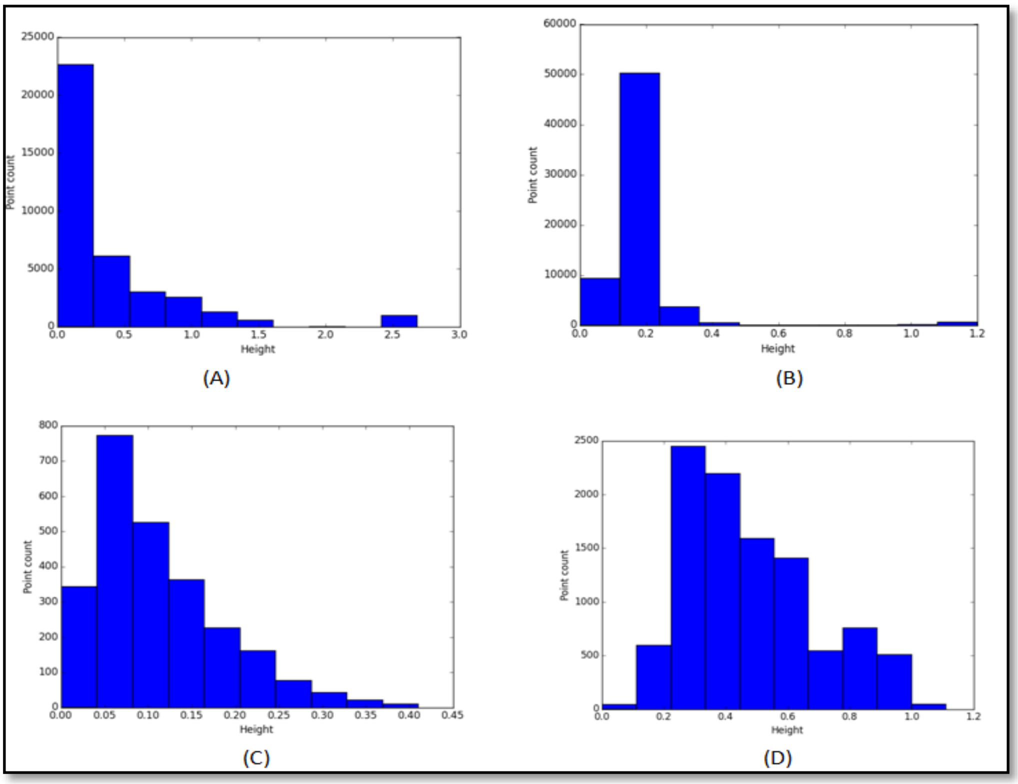

Figure 3-3: Histogram of relative height distribution for the water class.

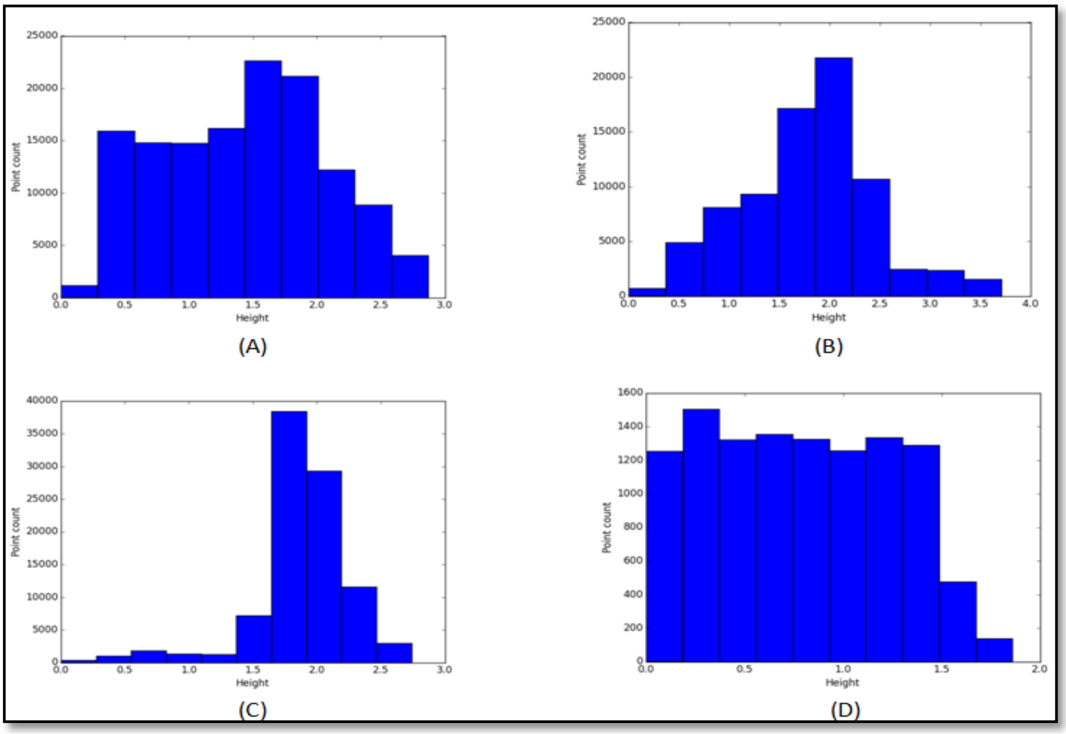

Figure 3-4: Histogram of relative height distribution for the road class.

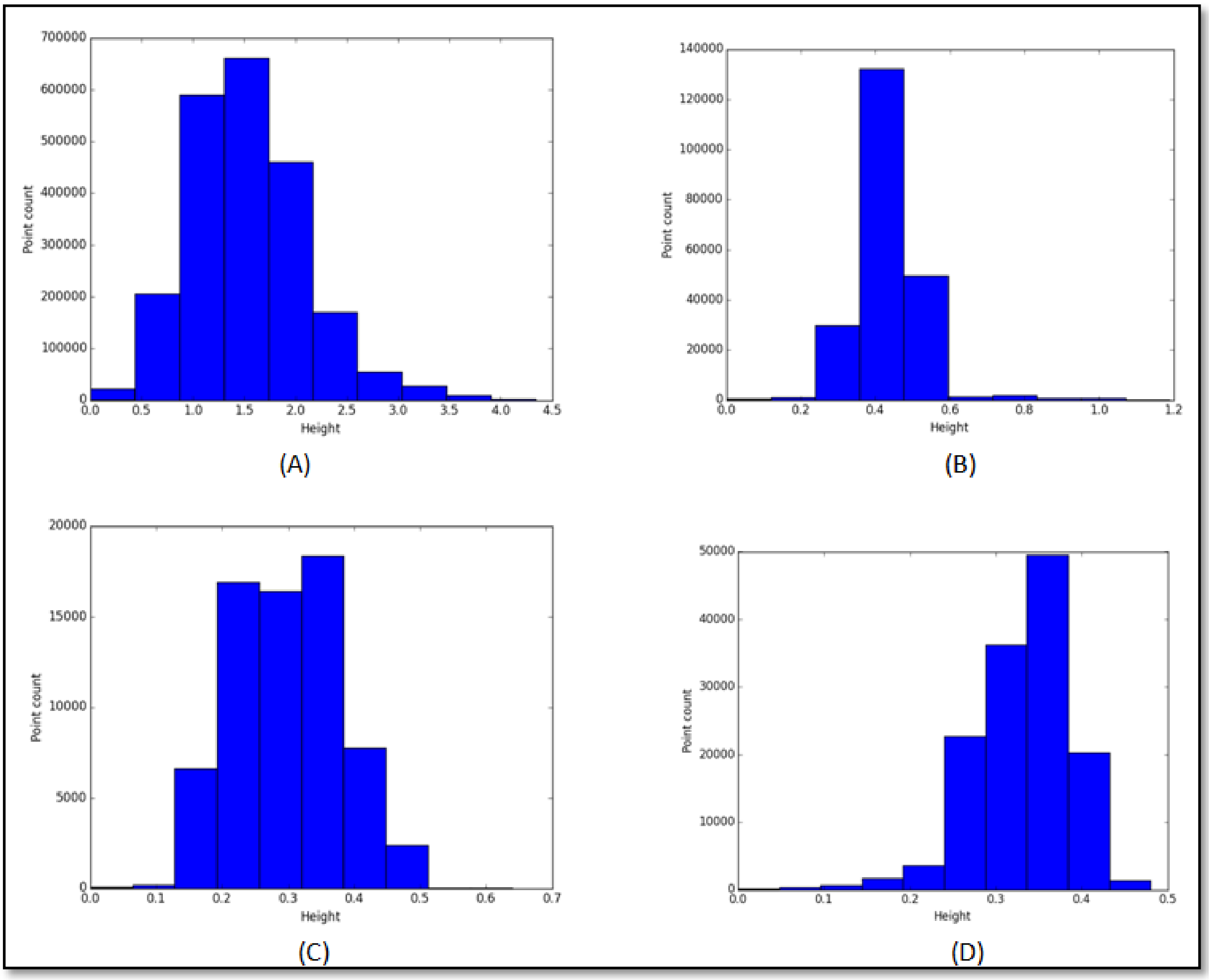

Figure 3-5: Histogram of relative height distribution for the terrain class.

The histogram represents the relative height distribution of some selected training sample of the road, terrain and water which are mostly ground features. It is logical to say that the histogram distribution of a clear water class is quite distinct from the other classes which made it a good attribute to verify and detect change in water class. However, it was observe that ditches and swamp shows similar characteristic like the terrain class due to the presence of grasses in most ditches in the study area. In trying to factor for water class which is not clearly water in our work the non-ground point will be used to detect possible change in water polygon. Having identified the variability in water class and how distinct a clear water class is from other class, these attributes are proposed to implement the rule-based approach for verification and change detection in this class. (1) Ground point ratio of the height histogram (2) Local height difference.

3.7.3. Road

The road class is characterised by diversity as road in the 2D map includes roads, parking lots, road furniture and trees. This class is contrast in characteristics including both natural and man-made objects in a point cloud which makes it quite challenging in selecting the right attributes to factor for this variability within class and detect changes. Change in these class includes newly constructed road, speed bumps and new road furniture and new trees planted by roadside. However, in this work our interest is only on detecting road polygon which has changed from been a road. The attributes for the road recognition and change detection were proposed based on the following characteristics: (1) Road are flat surfaces (2) Road points are both ground and non-ground points as in the case of presence of cars, trees and road furniture. Having in mind these characteristics of the road class the following attribute are proposed for the rule-based approach: (1)Local height difference (2)Mean relative height (3)Number of segmented to un-segmented points ratio (4) Number of ground to non-ground point ratio.

3.7.4. Terrain

The terrain class includes both bare soil, low plant covers like grass in the parks as well as vegetation cover and individual trees. The likely change in this class could be newly constructed building in a terrain polygon and new road constructed on a terrain polygon. To detect changes in the terrain class attributes are proposed based on the following characteristics: (1) Terrain non-ground points are mostly trees and vegetation which are irregular in shape except in the scenario where there is change or presence of another man-made object like car e.t.c. (2) Ground points include both flat surface and low vegetation. Base on these characteristic and the contextual knowledge of the likely change within this class the following attribute are proposed: (1)Local height difference (2) Number of segmented to Un-segmented points ratio (3) Relative height.

3.7.5. Calculation of attributes

To calculate the attributes value for each class in this work, it is important to select an appropriate group of points of the initial classification to be used. For the water, road and terrain class both ground and non-ground points. While the building class non-ground points were used as building points will be above the ground. Since change is detected per polygon, for every polygon per class their attribute values are calculated. These proposed attributes were selected to be able to detect changes within class by determining signature for each class from the calculated attribute values of the training sample for each class.

3.7.5.1. Number of segmented to un-segmented points ratio(NSUR)

This attribute represents the number segmented points and non-segmented points ratio. The segmented points are points within each polygon class that fulfills the criteria for surface growing segmentation explained in section 3.5. While the points that do not fulfill the set criteria are un-segmented. The attribute is a good indicator of the presence of vegetation and tree since they are irregular in shape while planar object like building and cars will have most of their point grouped into a planar segment. It is expected that building and another man-made object like cars will have high value of NSUR compare to vegetation. The non-ground point was used in calculating this attribute values.

Table 3-2: Number of segmented to un-segmented points ratio value per class

Class	NSUR	Class	NSUR	Class	NSUR
Building1	0.93	Terrain1	0.62	Road1	0.6
Building2	0.96	Terrain2	0.47	Road2	0.64
Building3	0.97	Terrain3	0.72	Road3	0.78
Building4	0.89	Terrain4	0.88	Road4	0.59
Building5	1	Terrain5	0.24	Road5	0.89
Building6	0.88	Terrain6	0.16	Road6	0.65
Building7	0.97	Terrain7	0.69	Road7	0.64
Building8	0.83	Terrain8	0.77	Road8	0.8
Building9	0.9	Terrain9	0.61	Road9	0.68
Building10	0.89	Terrain10	0.73	Road10	0.71
Building11	0.92	Terrain11	0.79	Road11	0.6
Building12	0.94	Terrain12	0.59	Road12	0.77
Building13	0.97	Terrain13	0.64	Road13	0.54
Building14	1	Terrain14	0.72	Road14	0.81
Building15	0.99	Terrain15	0.79	Road15	0.78

Building16	0.98	Terrain16	0.76	Road16	0.79
Building17	0.96	Terrain17	0.51	Road17	0.65
Building18	0.89	Terrain18	0.78	Road18	0.75
Building19	0.94	Terrain19	0.56	Road19	0.87
Building20	0.99	Terrain20	0.43	Road20	0.64
Building21	1	Terrain21	0.65	Road21	0.76
Building22	0.94	Terrain22	0.71	Road22	0.74
Building23	0.93	Terrain23	0.88	Road23	0.62
Building24	0.9	Terrain24	0.8	Road24	0.77
Building25	0.95	Terrain25	0.31	Road25	0.61

3.7.5.2. Ground points ratio(GPR)

This attribute is computed based on the insight gotten from the height histogram distribution of the three classes(see Figure 3-3-5). Number of bin was set as 10 for all class as it shows varying appearance between classes. The ground ratio is computed with the assumption that water class will have most of its point in the first three bin of the histogram as observed from the histogram. The histogram distribution of the water class was observed to show some higher level of similarity within the class and different from the histogram shape of other classes. The attribute value per class of some selected training sample can be found in Table 3-3. For the computation of the ground points ratio the ground points of the classes was used the expression is illustrated below.

Ground points ratio = No of points in the first 3bins/ total number of point in all bin.

Table 3-3: Ground points ratio value per class of training samples

Class	GPR	Class	GPR	Class	GPR
Water1	0.98	Road1	0.42	Terrain1	0.46
Water2	0.92	Road2	0.48	Terrain2	0.07
Water3	0.92	Road3	0.14	Terrain3	0.62
Water4	0.91	Road4	0.1	Terrain4	0.3
Water5	0.72	Road5	0.35	Terrain5	0.6
Water6	0.98	Road6	0.29	Terrain6	0.42
Water7	0.89	Road7	0.05	Terrain7	0.23
Water8	0.84	Road8	0.2	Terrain8	0.42
Water9	0.92	Road9	0.34	Terrain9	0.32
Water10	0.94	Road10	0.7	Terrain10	0.56
Water11	0.47	Road11	0.48	Terrain11	0.67
Water12	0.52	Road12	0.14	Terrain12	0.29
Water13	0.49	Road13	0.11	Terrain13	0.6
Water14	0.73	Road14	0.35	Terrain14	0.72
Water15	0.47	Road15	0.29	Terrain15	0.005
Water16	0.61	Road16	0.04	Terrain16	0.88
Water17	0.11	Road17	0.34	Terrain17	0.45
Water18	0.53	Road18	0.11	Terrain18	0.29
Water19	0.55	Road19	0.06	Terrain19	0.19
Water20	0.49	Road20	0.42	Terrain20	0.92

Water21	0.46	Road21	0.42	Terrain21	0.34
Water22	0.61	Road22	0.07	Terrain22	0.18
Water23	0.61	Road23	0.72	Terrain23	0.28
Water24	0.43	Road24	0.34	Terrain24	0.14
Water25	0.41	Road25	0.42	Terrain25	0.4

3.7.5.3. Number of non-ground to ground points ratio(NNGR)

This attribute represents the number non-ground points and ground points ratio within each polygon. It is logical to argue that for road and water class will have small non-ground to ground points ratio except in polygon with objects within the same polygon while the building class will have a higher value. The terrain class will be based on the characteristics of the terrain. The attribute value per class of some selected training sample can be found in Table 3-5. The NNGR attribute is proposed to be able to discriminated areas with building and areas with no building.

Table 3-4: Number of non-ground points to ground points ratio value per class of training sample

Class	NNGR	Class	NNGR	Class	NNGR	Class	NNGR
Building1	0.99	Terrain1	0.34	Water1	0.25	Road1	0.11
Building2	0.99	Terrain2	0.23	Water2	0.41	Road2	0.003
Building3	0.86	Terrain3	0.47	Water3	0.002	Road3	0.3
Building4	0.98	Terrain4	0.68	Water4	0.52	Road4	0.22
Building5	0.99	Terrain5	0.003	Water5	0.72	Road5	0.009
Building6	1	Terrain6	0.3	Water6	0.32	Road6	0
Building7	0.97	Terrain7	0.46	Water7	0.06	Road7	0.001
Building8	0.96	Terrain8	0.27	Water8	0.09	Road8	0.13
Building9	0.96	Terrain9	0.68	Water9	0.41	Road9	0.06
Building10	0.99	Terrain10	0.77	Water10	0.31	Road10	0.05
Building11	1	Terrain11	0.23	Water11	0.0025	Road11	0.009
Building12	0.96	Terrain12	0.3	Water12	0.0013	Road12	0.003
Building13	0.97	Terrain13	0.37	Water13	0.0028	Road13	0.25
Building14	0.98	Terrain14	0.011	Water14	0.46	Road14	0.0013
Building15	0.98	Terrain15	0.47	Water15	0.72	Road15	0.75
Building16	0.94	Terrain16	0.12	Water16	0.038	Road16	0.037
Building17	0.99	Terrain17	0.37	Water17	0.54	Road17	0.31
Building18	0.98	Terrain18	0.54	Water18	0.32	Road18	0.45
Building19	1	Terrain19	0.48	Water19	0.46	Road19	0.017
Building20	0.98	Terrain20	0.051	Water20	0.063	Road20	0.083
Building21	0.99	Terrain21	0.012	Water21	0.11	Road21	0.048
Building22	0.97	Terrain22	0.68	Water22	0.0028	Road22	0.64
Building23	0.98	Terrain23	0.011	Water23	0.038	Road23	0.068
Building24	0.98	Terrain24	0.54	Water24	0.016	Road24	0.12
Building25	0.99	Terrain25	0.72	Water25	0.003	Road25	0.083

3.7.5.4. Local height difference(LHD)

This attribute represents the median of the plane fitting residual of points in a polygon. To compute this attribute per class. Planes are fit within a local neighbourhood size of 15points(see illustration in Figure 3-6).The distance of each point from the fitted plane is calculated as the residual of each point. The median of the distance of the points from the plan is used to measure the local height difference. However there might be variation in the local height difference between classes but it's expected that this attribute value will be relatively low for very planar surfaces and high for irregular surface. If a polygon gets a low residual value the polygon is considered to be of planar surface.

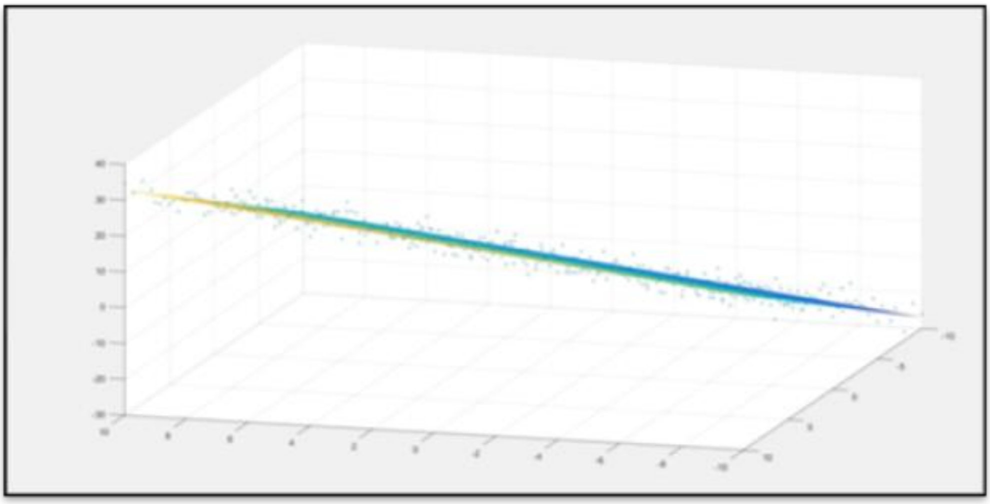

Figure 3-6: Schematic representation of plane fitting of points.

Table 3-5: Local height differences value per class of training samples

Class	LHD	Class	LHD	Class	LHD
Terrain1	0.013	Water1	0.013	Road1	0.0119
Terrain2	0.009	Water2	0.014	Road2	0.016
Terrain3	0.022	Water3	0.025	Road3	0.016
Terrain4	0.01	Water4	0.022	Road4	0.011
Terrain5	0.021	Water5	0.014	Road5	0.012
Terrain6	0.009	Water6	0.029	Road6	0.01
Terrain7	0.016	Water7	0.012	Road7	0.012
Terrain8	0.013	Water8	0.016	Road8	0.015
Terrain9	0.014	Water9	0.024	Road9	0.009
Terrain10	0.012	Water10	0.03	Road10	0.007
Terrain11	0.013	Water11	0.019	Road11	0.008
Terrain12	0.014	Water12	0.033	Road12	0.011
Terrain13	0.017	Water13	0.012	Road13	0.018
Terrain14	0.011	Water14	0.034	Road14	0.009
Terrain15	0.014	Water15	0.018	Road15	0.013
Terrain16	0.015	Water16	0.018	Road16	0.011
Terrain17	0.013	Water17	0.03	Road17	0.007
Terrain18	0.014	Water18	0.014	Road18	0.008
Terrain19	0.022	Water19	0.036	Road19	0.017
Terrain20	0.019	Water20	0.05	Road20	0.012
Terrain21	0.014	Water21	0.017	Road21	0.007
Terrain22	0.014	Water22	0.016	Road22	0.008

Terrain23	0.013	Water23	0.027	Road23	0.013
Terrain24	0.014	Water24	0.028	Road24	0.012
Terrain25	0.017	Water25	0.017	Road25	0.008

Table 3-5 shows the LHD value of training samples three class. The attribute value was calculated using the ground points of these classes on the basis that in trying to detect change there is a need to be able to discriminate within their attribute value.

3.7.5.5. Mean Relative height(MRH)

This attribute represents the mean relative height of the points within each polygon. Its calculated by taking the mean of all height value minus the least height value within each polygon. This attribute is a good indicator of the height of object and proposed as a good discriminator between man-made objects like cars and buildings.

3.8. Rule-based verification and change detection

An important task of this research is to identify how each class appears in a point cloud based on the calculated attributes and to verify the initial classification. The points within the polygons could be different due to change over time from the 2D map label. The polygon class which has changed will be detected. Having identified the geometric characteristics for each class and the differences in attribute combination per class, it is clear that the verification and change detection will be implemented per class. For this step, a rule-based approach for verification and change detection was employed. The rule-based approach was implemented as it showed high accuracy result as explained in chapter two.

The training samples of the classes were analyzed to determine the signature of each class based on their attributes values for verification and change detection per class. From the statistics of the training samples, the thresholds were chosen to create the rules for the verification and change detection of the initial classification. The thresholds were chosen by considering the range of attribute values of the training samples, insight on how threshold was chosen see in figure3-7. The arrow shows the region of the of threshold value.

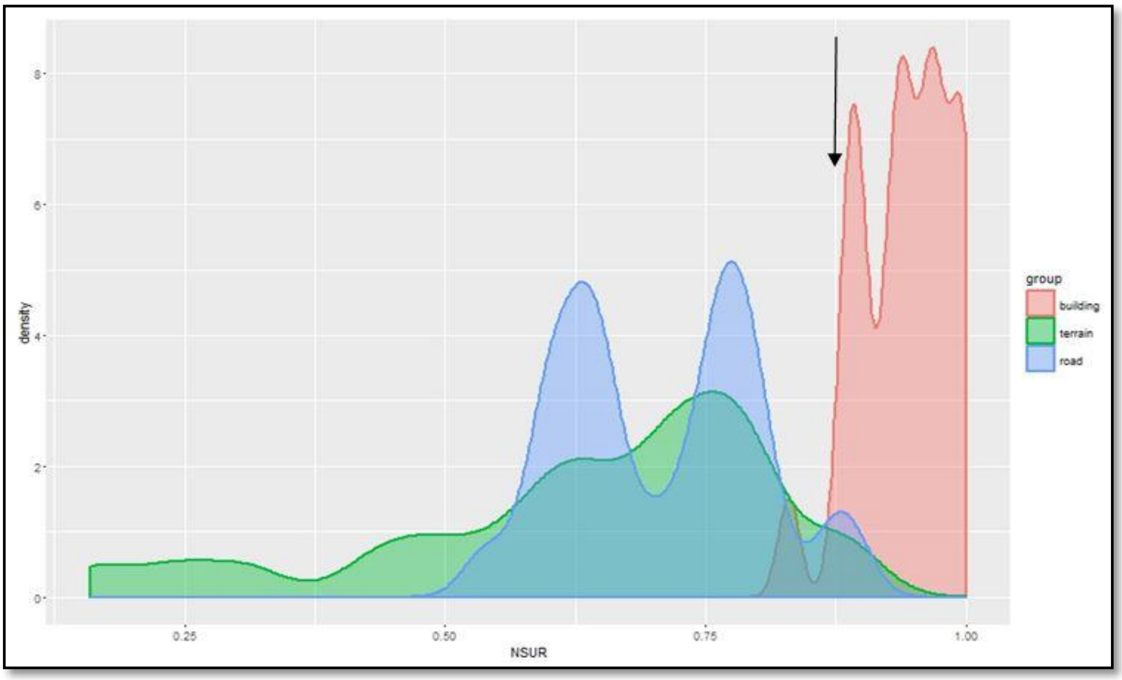

Figure 3-7: NSUR value of three classes.

In determining the threshold value this was done based on the attribute value of the selected training set. This training set which was selected manually, for this case samples of buildings were selected, samples of terrain with vegetation were selected and samples from the road class which includes both tress and cars were selected. The reason behind the selected training sample is to depict features that are most likely to be on the non-ground points. From the figure, it can be observed that there is some level of overlap between the road class and the building class which is expected because cars and building would have similar NSUR value. To be able to discriminate this two classes in our work additional attribute (mean relative height) was included.

However from the statistics, the values per class tend to show some pattern, in selecting the threshold from the calculated attribute values of the training samples the presence of some outlier was observed in attribute values. In our work further investigation was done for those samples and it was discovered that the outliers are due to the variability within classes. To accommodate such cases the threshold were adjusted to factor for this variability. For instance from the table 3.3 "water5" sample tend overlaps with terrain class for ground point ratio attribute value due to a lower value, which calls for further observation of the sample. It was observed that the sample has some vegetation on top of a water surface see figure3-8.

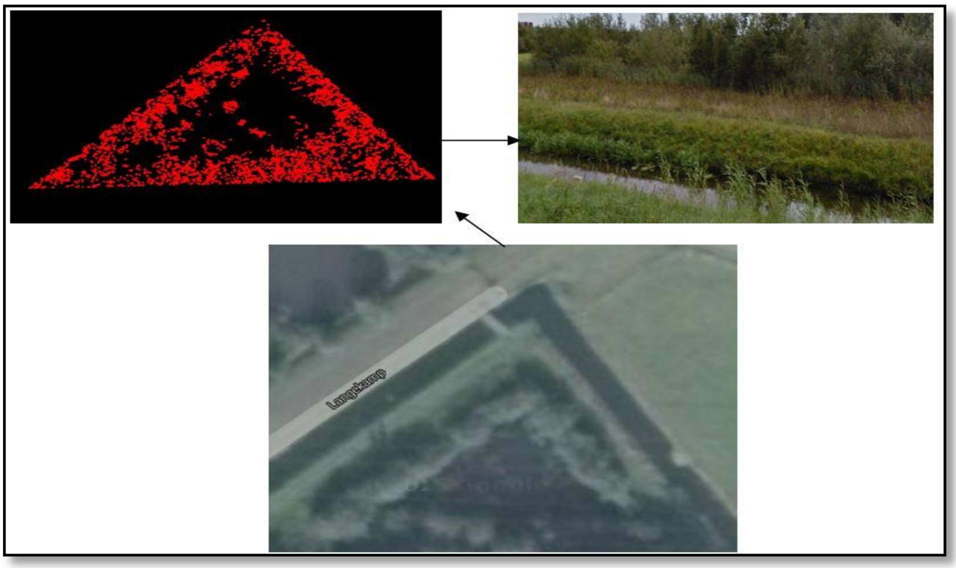

Figure 3-8: Supposed water class with low GPR value due to the presence of trees.

3.8.1. Verification and Change detection in building class

To verify and detect change in building class, this is done by comparing the attribute value for each polygon with the threshold of the training samples. The algorithm is created to compute attribute value for all building class and check if they meet the set condition. If they fulfil the condition it is un-change if not such polygon were labelled change. The procedure for verification and change detection in buildings can be seen in figure3-9.

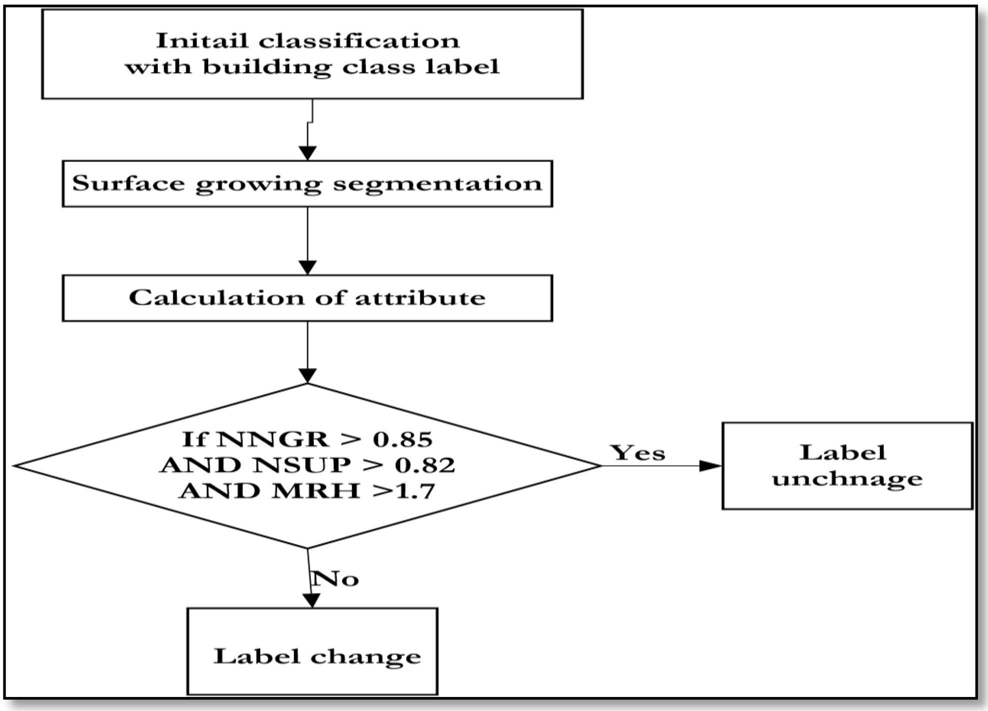

Figure 3-9: Building class verification and change detection workflow

3.8.2. Verification and Change detection in water class

To verify and detect change in water class, this is done in two stages due to the variability within water class. As observed from the calculation of attributes of the training samples of the water class, this class tend to show different characteristics in the point cloud which were investigated to be water and ditches covered with grasses. It is expected that water and ditches covered with grasses cannot share similar signatures so in this work the verification and change detection will be done in two stages. Firstly, the NNGR and GPR value will be used to verify and detect changes in real water class and the NSUR of the non-ground point will be used to verify and detect changes in ditches. The workflow for the procedure can be visualised in figure3-10. The algorithm is created to compute attribute value for all water class and check if they meet the set condition. If they fulfil the criteria it is un-change if not such polygon were labelled change. The procedure for verification and change detection in building as in figure3-10.

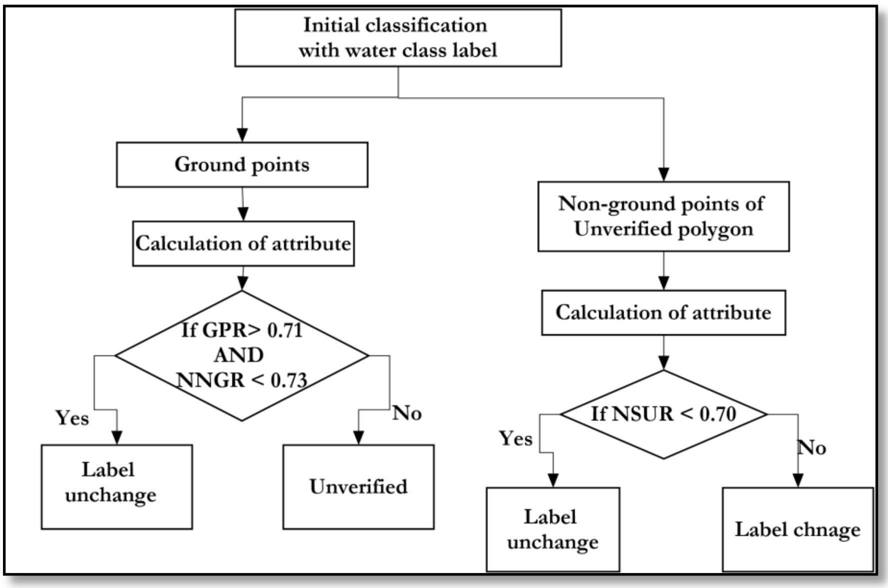

Figure 3-10: Water class verification and change detection workflow

3.8.3. Verification and Change detection in road class

To verify and detect change in road class shows to be complicated due to the close overlap with the attribute value of the road and the terrain class on the group points. To be able to verify the road class and possible detect possible changes the non-ground point was used also. The algorithm computes the local height difference of the ground point of the road class and compares the attribute value with that of the set threshold from the training samples. While for the non-ground points the NSUR is computed to be able to discriminate within natural features like trees in parking lots from man-made objects like cars and building, trees are an irregular object and will have low NSUR value compared to a man-made object which is planar . As some polygon will still be unverified due to the presence of only man-made feature which results to high NSUR value. In order to be able to verify such polygon, the mean relative height would be computed per polygon if it fulfils set condition of a man -made object like car such polygon will be labelled unchanged or else it is tagged change. The figure shows the workflow for verification and change detection in road class.

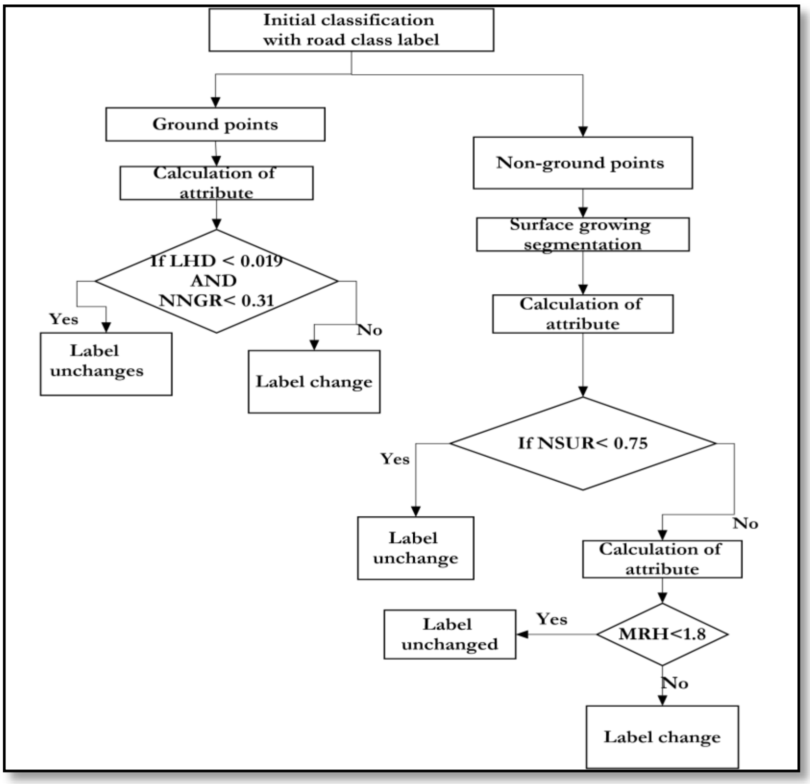

Figure 3-11: Road class verification and change detection workflow

3.8.4. Verification and Change detection in terrain class

The terrain is characterised with both flat surfaces on the ground and vegetation points above the ground. In learning process the terrain and road tend to shared close similarity with the road class in the ground points and also slightly above the ground, which makes it difficult to differentiate a road from some terrain. In verifying and detecting change on the ground would be very tricky as the algorithm may wrongly represent flat terrain as change. In theses research, the non-ground points will be considered more in detecting change as discussed earlier that change in terrain class could be represented in both ground as in newly constructed road and non-ground points of the point cloud in cases of the newly constructed building and building extension. The procedure for change detection can be found in figure3-12. The algorithm computes attributes for each polygon and compares the attribute value of each polygon with the set threshold from the training samples if polygons fulfil the threshold it is tagged Unchanged.

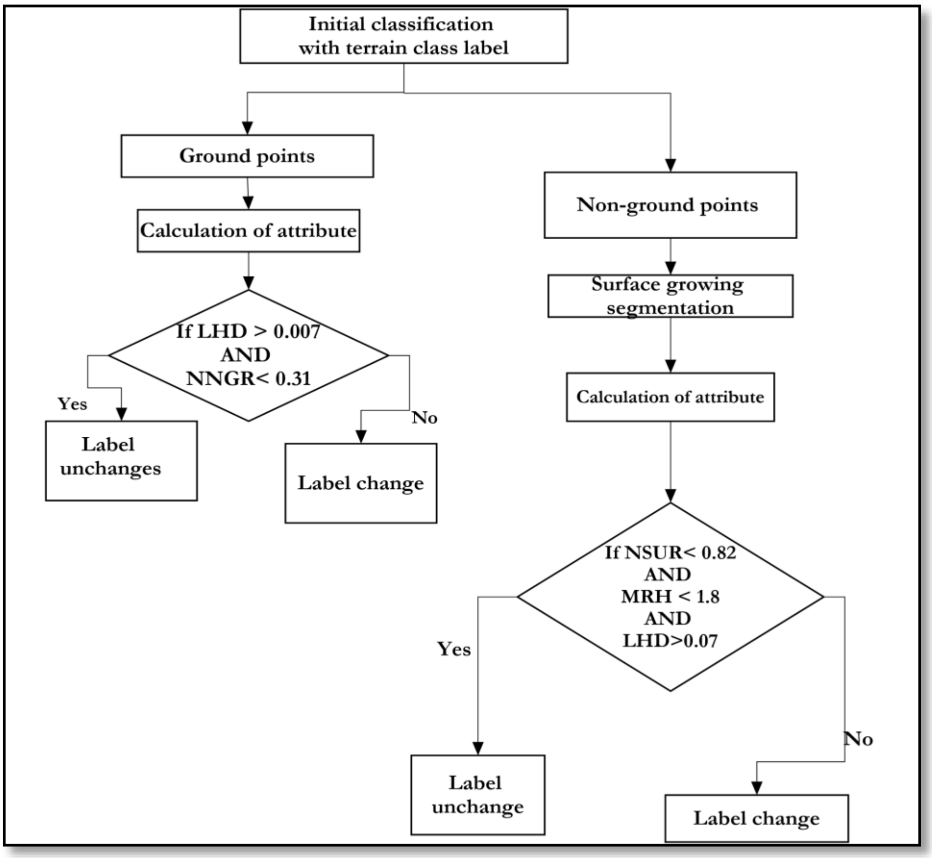

Figure 3-12: Terrain class verification and change detection workflow

3.9. Classification of detected change

The polygon classes which did not fulfill the set rules were detected as change. The detected changes were extracted and further classified into real and fake change. Nevertheless, certain factors need to be taken into accounts which could affect the change detection result so as not to present unchanged object as change. Some the factors which could affect these process have been identified:

(a) Change detection error due to few point within polygon: The cases of few points within a polygon was observed to give quite a contradicting attribute value. In this research, such effect was minimized by setting the criteria for the local plane fitting of points to fifteen neighbourhood points and such polygon class were tagged unknown class.

(b) Change detection error due offset between datasets: The misalignment between the two datasets could impact on the change detection result. As a part of a part of the point of a class could be found in the neighbouring polygon giving rise to false alarm. These cases were observed mostly in cases where a building polygon is next to a terrain polygon part of the building roof and some wall points will be found in the terrain polygon. In another instance part of terrain points where within a water polygon. This cases were checked in our work but was considered in the workflow.

The final interest is to distinguish real change from fake changes. In this research, a connected component of points within changed polygon was implemented and the components were examined to determine if it's indeed a change or not. Visual inspection was used to classify changes into real and fake changes.

3.10. Quality assessment of the detected change

To assess the quality of the change detection. The detected change polygons were compared with some form of reference data. In this work Google map was used as the reference data and the comparison was done by visual inspection of the results. Google map was used due to lack of availability of ground truth data. To determine the quality of the change detection results the percentage of the real change to the total change detected was computed.

4. DATASETS AND RESULTS

4.1. Data

The 2D map and LiDAR data of the municipality of Den Bosch were the datasets used in this research. The selected area covers approximately 0.8km². The study area is mostly a flat terrain with newly constructed buildings and several lakes and canals around the city(see Figure 4-1).

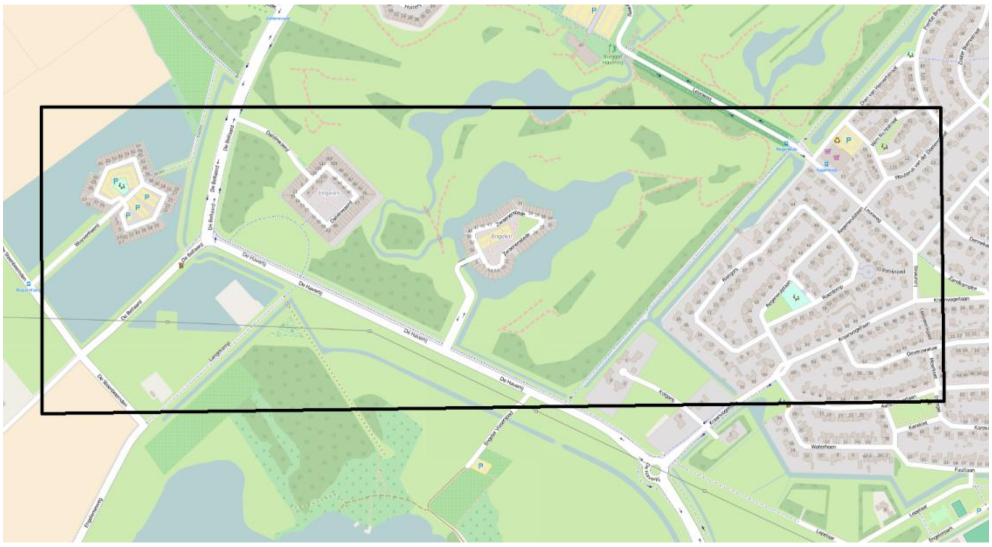

Figure 4-1: Location of the study area on Google map

4.1.1. LiDAR data

The point cloud used in this research is the national height model(AHN2) of the Netherlands with an average point density of 12points/m² (see Figure 4-2).

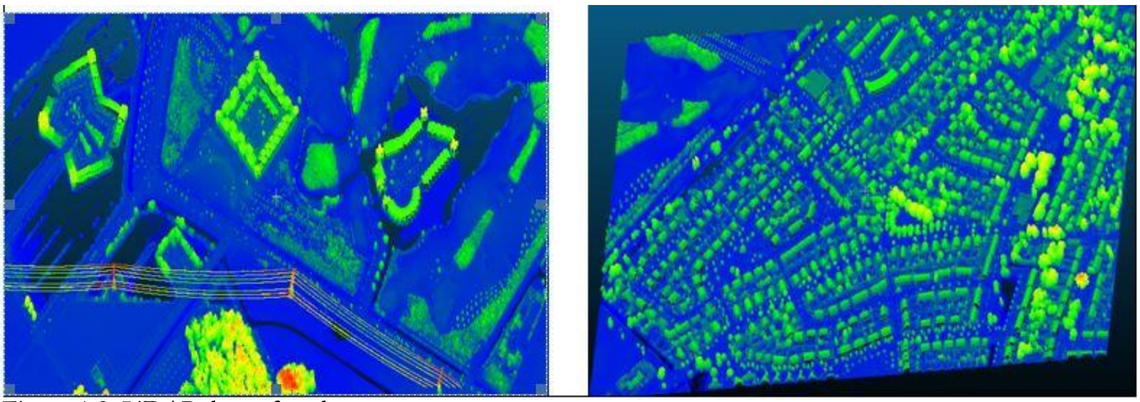

Figure 4-2: LiDAR data of study area.

4.1.2. 2D map data

The IMGeo is the Information Model for Geography in the Netherlands. The IMGEo is the definitions for 2D large scale representations of objects such as water, land use and land cover, roads, buildings and tunnels. The 2D used in this research is a large-scale map of scale 1:1000 with an accuracy of about 10cm.(see Figure 4-3).

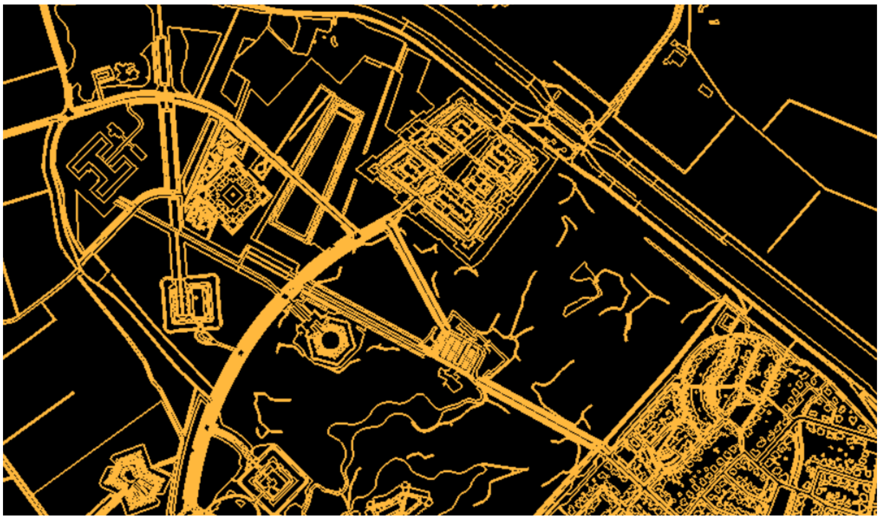

Figure 4-3: 2D map data of study area

4.2. Data preparation

Using point cloud and 2D map for change detection starts with data fusion. The data fusion was implemented as described in section 3.4 to properly fuse the datasets in this work both datasets were of the same reference plane to minimize miss-alignment of the datasets. However, the slight systematic offset was observed of about 10cm between the two dataset which was not constant but in rare cases, so this will not have an influential impact in our work. The 2D map used were topologically valid and was classified by the data provider into different class labels. The description of the features classified as each class can be seen in Table 4-1. In our research, our interest is only in four classes (water, building, road and terrain) from the map.

Table 4-1: Classified 2D map class description

Class	Description
Water	Sea, waterway, plain water, ditches
Road	Drive-way, lane motorway, bicycle path, parking surfaces, pedestrian-street, footpath
Terrain	Tree, low vegetation, grassland, hedge plant
Building	Houses

4.3. Results

The change detection between the 2D map and point cloud, filtering of the point cloud into ground points and non-ground points is a prerequisite step for the generation of the initial classification. The initial classification is the output of fusing the filtered point cloud and the 2D map. The point clouds within each polygon of the initial classification inherit the label of the 2D map. It is expected that since the two datasets are of different dates there could be change between the point cloud and the map. However the initial classification is verified by using the points within the polygon classes to generate statistics to recognize each class and based on these statistics the initial classification is verified to be correct if the attributes value fulfill the condition of that class else such classes were tagged as change.

4.3.1. Initial classification

As explained in chapter three the points in polygon operation was implemented to generate the initial classification after the point cloud filtering(see Figure 4-4). Different class uses different points to generate statistics for the verification process. For building non-ground points within the polygon, class was used and for the terrain, road and water both ground points and non-ground points were used to calculate the attribute value respectively.

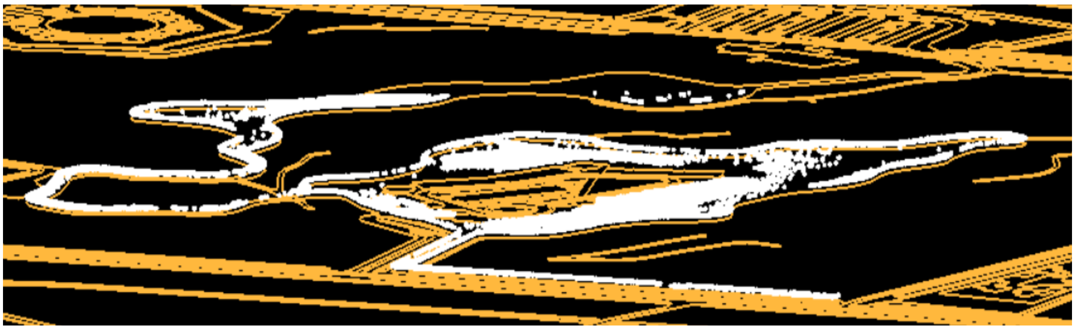

Figure 4-4: Initial classification of selected water points in a polygon.

4.3.2. Building class verification and change detection result

Using the rule-based verification approach explained in chapter three the building classes were verified into buildings if it fulfills the set condition else the polygon is tagged changed. The verification and change detection result are shown in Figure 4-5. From the figure, it is observed that out of the 111building polygon class all fulfill the conditions of the rule-based algorithm with no change detected.

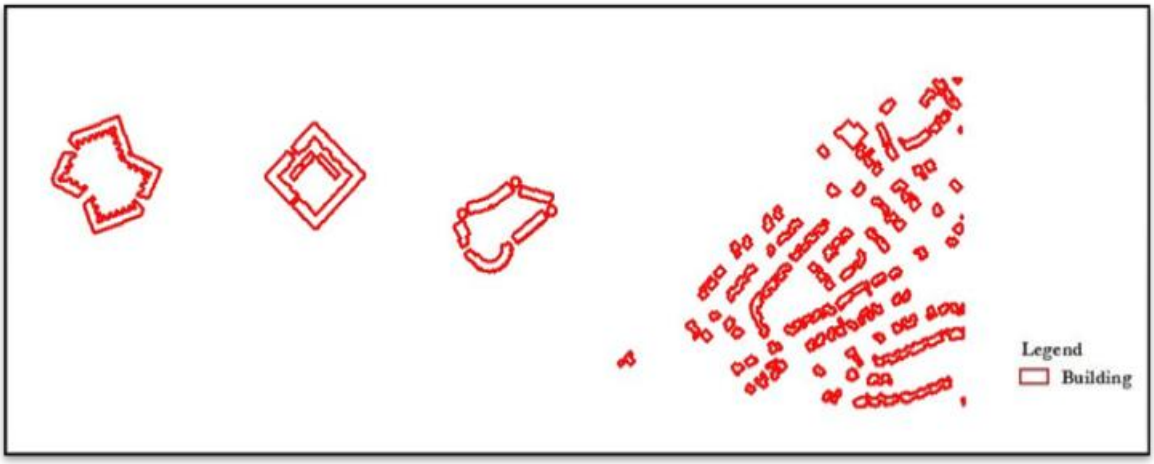

Figure 4-5: Verification and change detection result of building class(the red polygon shows the buildings verified as buildings).

4.3.3. Water class verification and change detection result

The water class originally is characterized with variability as the description of water class from the classified 2D map includes lakes, ditches, sea, plain water and water-way. The rule-based verification considered this wide range of features grouped as water. The water polygons were verified and tagged water if they meet the set criteria and was tagged change if the polygon class does not fulfill the condition for a water class. From the study area, 28 polygons were all verified (see Figure 4-6). Analysis of the change detected result will be discussed in Section 4.4.

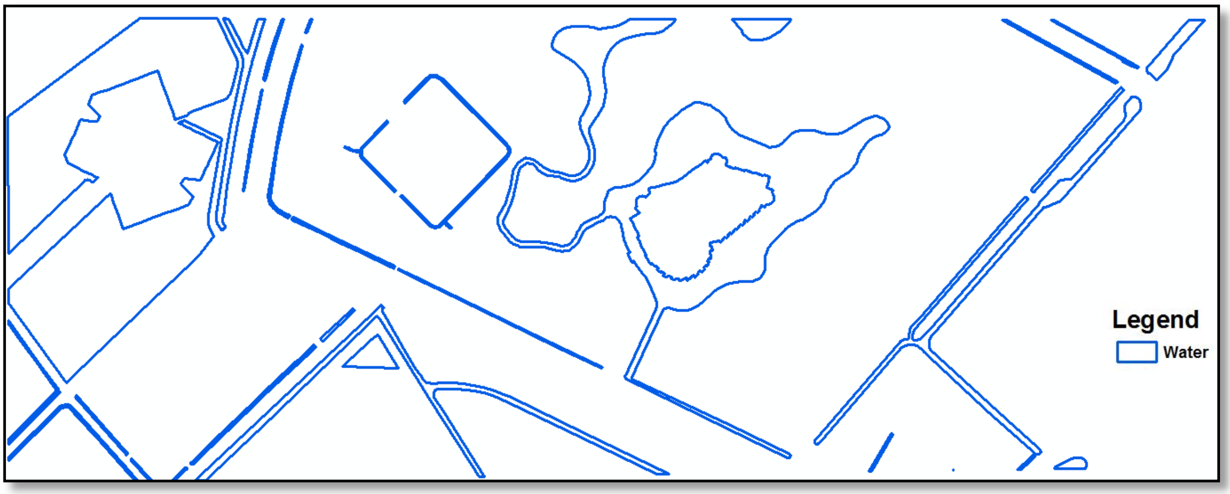

Figure 4-6: Verification and change detection result of water class(Blue polygon are water class that fulfilled the condition of the rules and are tagged water).

4.3.4. Road class verification and change detection result

As discussed earlier that the initial classification generated by fusion of the two datasets was used to verification and change detection within classes. After implementing the rule-based verification, approach explained in chapter three. Results of the verification and change detection for road class can be seen in Figure 4-7.

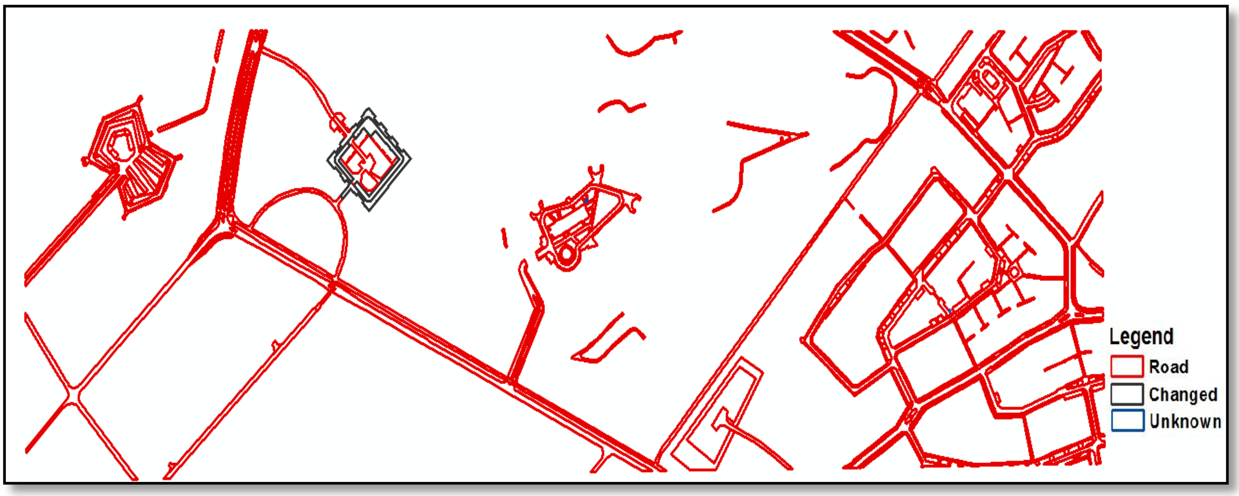

Figure 4-7: Verification and change detection result of Road class. (Red polygons are verified road polygon that fulfilled the set conditions of a road class while the grey colour polygons did not fulfil the conditions and were tagged changed and blue polygon are road polygons with few points).

Looking at the result most of the road class were verified with few polygon tagged as changed and unknown. The Unknown class is due to insufficient or lack of points within the polygon to compute the attribute for verification. These problems were observed to be associated with small sized polygons of the road class.

4.3.5. Terrain class verification and change detection result

The verification and change detection in the terrain class were done as described in section3.8.4. As mention earlier class with few or no points were tagged as "Unknown". It was observed that the attribute value for both terrain class shows variability between flat terrain on the ground and vegetation. The non-ground points and ground points of the terrain were used so as to include the variability in the verification. The verification and change detection result(see Figure4-8) shows more change were detected in the terrain class as well as few polygon were tagged unknown because of the problem associated with few or no points within a polygon. Further discussion on the result will be described in Section 4.4.

Figure 4-8: Verification result of Terrain class(red polygon shows the polygon that meets the condition of terrain class and the grey polygon shows polygon that fails to meet all the condition of the terrain class and was tagged change and the blue polygons are polygons are polygons with few points).

4.4. Classification of change detection results

In chapter three the method for classification of change to determine real changes from fake changes was describe. If change is correctly identified within any class it was classified as real change. However, some factors as described in Section 3.8 could affect the change detection results due to fake change. To be able to investigate such cases the points within the changed polygon were further analyzed.

4.4.1. Road class change detection classification

The polygons detected as changed were further classified into fake change and real change. The reason behind this step is to properly ascertain what led to the change and classify the change. In other to distinguish the real change from fake change a connected component of points within polygon was visually evaluated and the changes was classified. The result of the classification of road class detected change can be visualized in Figure 4-9.

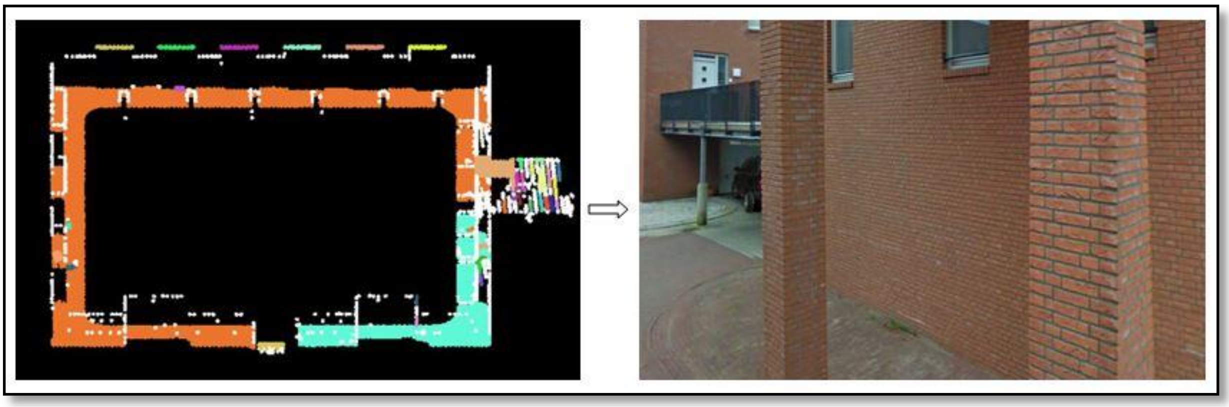

Figure 4-9: Shows the presence of misclassified road class as change. A connected component of points shows the presence of building parts in the road polygon causing false alarm as a result of high NNGR causing fake change in road class.

The results of the change classification of road class as shown in Figure 4-9 it is observed that the change detected in the road class were fake changes. This is due to the nature of the parking lot which is within a building. The polygon then to have the signature of a building while in reality it is a parking lot built inside a building.

4.4.2. Terrain class change detection classification

By visual inspection of the connected component of the points in the changed terrain class was employed to classify detected change into real change and fake change(see Figure 4-10-12). The unknown polygons were further examined and it was observed that the polygon tagged "unknown" were polygons with few points. The result of the classification shows that most change detected in terrain was due to the presence of building in a terrain polygon class. All new building in the terrain class were correctly detected as change in this class.

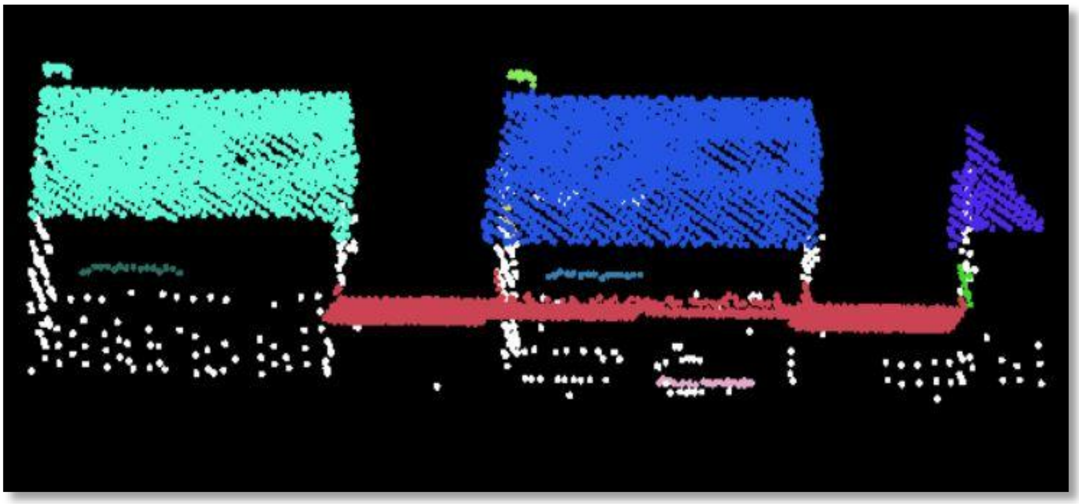

Figure 4-10: Shows a building component in a terrain polygon. Most changes in terrain class are due to the presence of building points resulting to high NSUP (observed to be above 0.9) value. The change was classified as a real change.

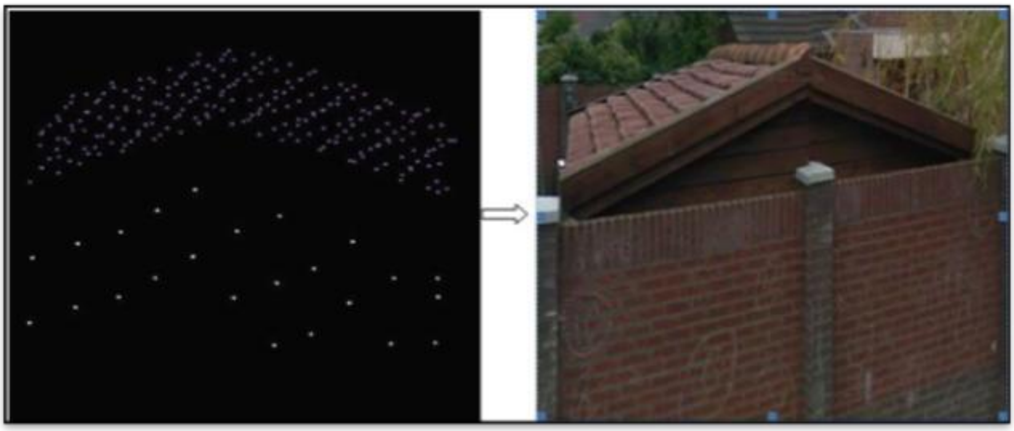

Figure 4-11: Shows component of an extended building in a terrain polygon. Real change in terrain class due to building extension. The building point gives a high NSUP value which does not meet the condition of a terrain class. The change was classified as a real change.

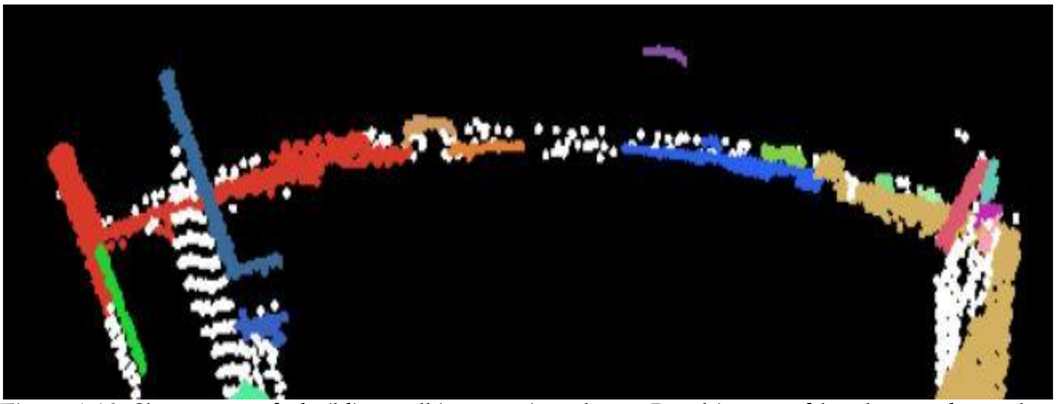

Figure 4-12: Shows part of a building wall in a terrain polygon. Resulting to a false alarm and was classified as Fake change.

From the result of classification of change, it was observed that most real changes were due to the presence of buildings in the point clouds which were not present in the building class. These are new buildings constructed after the 2D map creation. Furthermore, the terrain class tagged as "unknown" were polygons with few points due to the small size of the polygon.

4.5. Analysis of the result

The research work describes a new approach to change detection by fusion of LiDAR data and 2D map to detect changes in four classes. The 2D map provides a prior class label of the entire polygons. The proposed algorithm for the verification of the initial classification offered by the 2D map and also detect possible changes was implemented per class. The approach involves deriving rules that best describe each class from selected training sample, this makes the results sensitive to the thresholds derived from the training samples. The effect of the thresholds value can be seen in the result as it cannot completely factor for all variability within a class and some changes are missed and fake changes were detected.

4.5.1. Building class

All the verified building class polygon were overlaid with the reference data (see Figure 4-13). This was implemented in ArcGIS. By visual inspection, it was observed that all the building class was accurately verified with no change detected in the building class these can be further supported by the fact that since change was detected per polygon the change to be detected by the approach are change caused due to building demolition. If new buildings are constructed or extended, such change will be represented by another polygon of a different class and cannot be detected as a change in a building polygon. Furthermore, change detection by fusion of 2D map and point cloud detects only changes in two dimension that is, change in building height cannot be represented in the results.

Figure 4-13: Buildings polygon(red) overlaid on the reference data

From the overlay of buildings polygon and the reference data, it can be observed that some buildings were missing from the building class. This could be due to the absent of such building at the point of map creation. However, it will be expected that such building should be detected in the terrain class as change.

4.5.2. Water class

The result from the water class was compared with the reference data to assess the accuracy of the verification result(see Figure 4-14).

Figure 4-14: Water polygon overlaid on the reference data. Water class(blue).

The verification result showed that all polygon of the water class were accurately verified. The reason behind no change detected change in this class is related to the study area which depicts no change and also to the fact that change is water is mostly unlikely. The common change in water class is mostly accredited to seasonal variation leading to decrease in water size and volume. However, change is detected per polygon and change in water volume is outside the scope of this research.

4.5.3. Road class

The road polygon was compared with the reference data (see Figure 4-15). It was observed that most of the road polygons were verified accurately and the change detected where false alarm due to the complexity of the polygon class where parking lots are connected to a building. The false alarms were observed to be mostly building points within the road class. No real change was detected in road class as changes in road class are rare, to have a road changed into a different class is difficult except in cases where building are constructed on a parking site which was not observed in the study area. However if new road is constructed it will be reflected in another polygon and not detected in road class as a change.

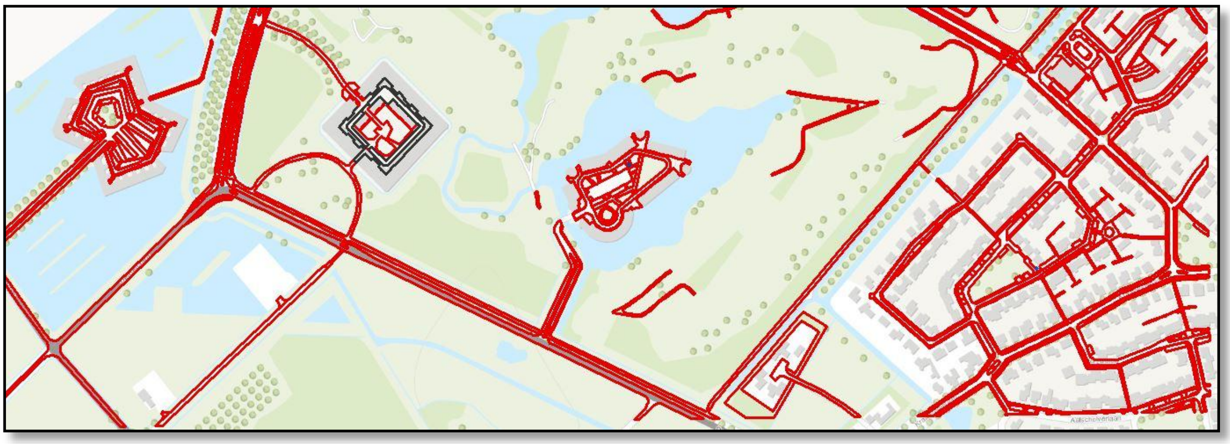

Figure 4-15: Road polygon overlaid on the reference data. Verified road class(red), change(grey) and unknown(blue).

4.5.4. Terrain class

The overlay of the reference data with the terrain class shows the presence of changes and unknown polygon(see Figure 4-16). The change in this class is mostly due to the presence of new buildings in a terrain polygon which were not originally labelled as building on the 2D map. However, some fake changes were also observed as earlier explained while polygon with few points was tagged as unknown which was observed to mostly in polygon of small size.

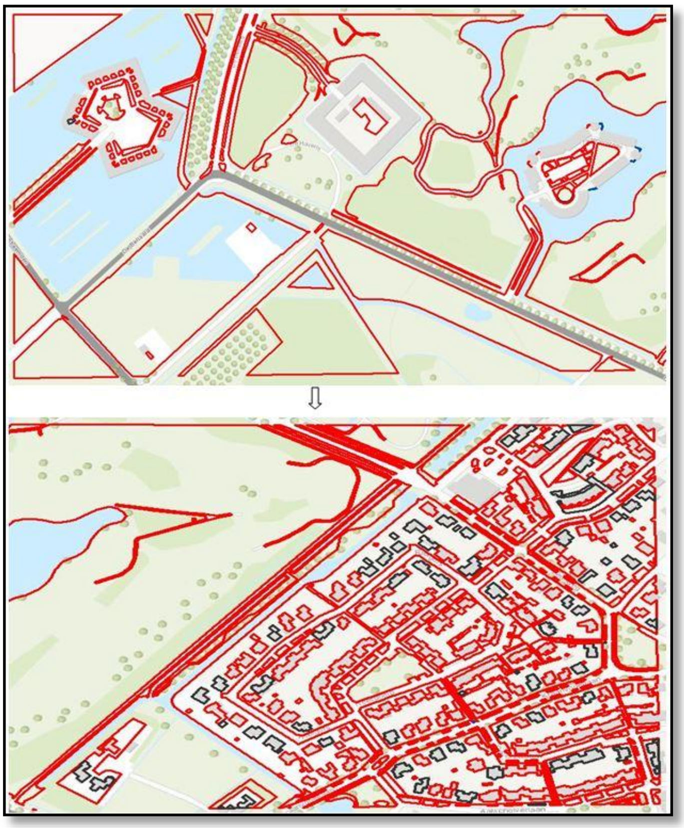

Figure 4-16: Terrain polygon overlaid on the reference data. Red polygons are verified as terrain while the grey polygons were the change polygons in the terrain class and most were observed to be building points in a terrain polygon.

The overlay of the terrain verification and change detection result shows that the missing building present in the reference data but were not included in the building class were actually detected as they appear as change in the terrain class. The attribute value of NSUP proves to be a reliable attribute to distinguish between building and vegetation.

4.6. Accuracy assessment

To assess the accuracy of the verification and change detection results, it is required that the results are compared with some form of reference data. In calculating the final accuracy in this research missed change due to the limitation of the approach were taken into account. The reference data used in this work is gotten from Google map due to lack of availability of ground truth data and information about the exact year of the datasets. By comparing the change detection result with the reference data of different date with the LiDAR data, there could be an error in the final calculated accuracy due to the time differences between the reference data and the LiDAR data.

A typical scenario was observed where a point cloud in the terrain polygon had building points but in the reference data, the polygon was still identified as terrain. However, such cases were negligible and will not strongly influence the final accuracy assessment. The accuracy of the verification and change detection is computed as shown in Table 4-2.

Verification accuracy = [Verified class/(verified class + fake change+ unknown)] x 100

Change detection accuracy = [Real change/ (real change + fake change + missed change)] x 100

Table 4-2: Verification and change detection accuracy assessment.

Class	Verified	Real change	Fake change	Missed change	Unknown	Verification accuracy(%)	Change detection accuracy(%)
Building	111	-	-	-	-	100	-
Water	28	-	-	-	-	100	-
Road	208	-	2	1	2	98	0
Terrain	312	79	3	4	5	97.5	90.8

The accuracy of the results as shown in Table 4-2 for both verification and change detection shows that the results were affected by the missed changes and fake changes detected. The verification result can be translated to 100% for building verification, 98% for road, 97.5% for terrain and 100% for water verification. The accuracy for verification and change detection in both terrain and road class is affected both fake change and Missed change. As observed from the attribute values of the training areas road and terrain class shows strong similarity making it difficult for the algorithm to detect change on the ground points. When a terrain changes to a road such change cannot be detected in this approach based on the observation that there is no clear difference to select the right threshold to separate these two classes. False alarm was recorded in terrain class due to miss registration of the two data where part of building points were found in terrain class.

The accuracy for change detection using our approach is low in road class due false alarm while no change was detected in the building and water class which can be related to both the approach of change detection per polygon as earlier explain. In another instance, no change was detected base on the observation that no change existed in the study area. The 90.8% accuracy recorded for the terrain class were mostly due to the presence of newly constructed buildings. However, the accuracy may be not very satisfactory for detecting change but the result suggests that this approach verified all building present in the study area reliably.

5. CONCLUSION AND RECOMMENDATIONS

In this research, a method was developed for change detection by combining 2D map and LiDAR data of different year. The approach was organised to meet the set objectives of this research. The first step of this research was to generate the initial classification from fusing the 2D map with the LiDAR data. The LiDAR data within the polygon inherits the class label of the map which was now verified and changes were detected.

With respect to the verification of the initial classification in our workflow attributes like mean relative height, number of segmented to un-segmented points ratio, number of non-ground points group points ratio, ground point ratio and local height difference were used to verify and detect changes per polygon. This attribute was proposed for this research based on the characteristics of each class. To verify and detect changes rules were defined from the computation of attribute value from selected training samples and the values were statistically analysed and the rules per class were defined.

Our method was not optimal in change detection in all the classes. The reason is due to the fact that the rule-based approach is directly related to the threshold and the training samples collected to define the rule for verification and change detection. This approach may not be the best as the classes examined shows so much variability and it may not be effective when implemented in another study area.

Despite the accuracy recorded the methodology was faced with some other limitation:

(i) The method requires the point cloud data to be filtered into ground and non-ground points before the verification and change detection.

(ii) The method requires high point density data as polygons with very few or no point cloud not me analysed.

Conclusively, these results suggest that this approach is useful in class detection. Despite the results shows so some missed change and fake change been detected, our approach is still useful as it is logical to argue that it may be better to have fake change than to change detection error due to misclassification of data as the class description shows similarity within classes.

5.1. Recommendations

The implemented method have shown to be unreliable in detecting changes on ground points within a terrain class resulting to missed change and in another case when road change to terrain it cannot be detected as the two class are similar. Nevertheless, some limitation were observed and needs improvement. The method was not robust in terrain and road class. To minimize the false alarm and missed change, I would recommend image could be incorporated to provide colour information and improve the accuracy of the verification and change detection result.

For further work, I would recommend a better method for detecting change with would give an improve accuracy and factor for both the similarity across class and variability within the class. My suggestion would be to try classification of the point cloud separately compare both classes from the point cloud and 2D map.

REFERENCES

Afify, H. a. (2011). Evaluation of change detection techniques for monitoring land-cover changes: A case study in new Burg El-Arab area. *Alexandria Engineering Journal*, *50*(2), 187–195. doi:10.1016/j.aej.2011.06.001

Chehata, N., Guo, L., & Forests, R. (2009). Airborne lidar feature selection for urban classification using Random forests. Laser scanning 2009, The international Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences 38 (Part3/W8), 207-212.

Chen, K., Zhou, Z., Lu, H., & Huo, C. (2007). Change detection based on conditional random field models, WSEAS International conference on Remote sensing, pp93–97. Retrieved from http://www.wseas.us/e-library/conferences/2007venice/papers/570-598.pdf(February 9,2016).

Choi, K., Lee, I., & Kim, S. (2006). A feature based approach to automatic change detection from Lidar data in urban areas, *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences,* Vol. XXXVIII, Part 3/W8, pp.259-264.

Dal, X. L., & Khorram, S. (1999). Remotely sensed change detection based on artificial neural networks. *Photogrammetric engineering and remote sensing ,* 65, 1187-1194.

Ehlers, M., Klonus, S., Jarmer, T., Sofina, N., Michel, U., Reinartz, P., & Sirmacek, B. (2012). Cest Analysis: Automated change detection from very-high-resolution remote sensing images. *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XXXIX-B7*(September), 317–322. doi:10.5194/isprsarchives-XXXIX-B7-317-2012

Fröjse, L. (2011). Multitemporal satellite images for urban change detection. Unpublished Msc Thesis. Royal Institute of Technology, Faculty of Geodesy and Geoinformatics, Stockholm, Sweden.

Gikunda, J. M. (2015). *Change detection of urban objects in multi-temporal lidar data.* Unpublished Msc. Thesis. Enschede, The Netherlands: University of Twente Faculty of Geo-Information and Earth Observation (ITC). Retrieved from http://ezproxy.utwente.nl:2048/login?url=https://webapps.itc.utwente.nl/library/2015/msc/gfm/gikunda.pdf

Guyon, I., & Elisseeff, A. (2003). *The Journal of Machine Learning Research*, *3*, 1157–1182. doi:10.1023/A:1012487302797

Haala, N., & Brenner, C. (1999). Extraction of buildings and trees in urban environments. *ISPRS Journal of Photogrammetry and Remote Sensing*, *54*(2-3), 130–137. doi:10.1016/S0924-2716(99)00010-6

Haala, N., Brenner, C., & Anders, K. H. (1998). 3D urban GIS from laser altimeter and 2D map data. *International Archives of Photogrammetric & Remote Sensing*, *32*, 339–346.

Hall, M., Frank, E., Holmes, G., Pfahringer, B., Reutemann, P., & Witten, I. H. (2009). The WEKA data mining software. *ACM SIGKDD Explorations*, *11*(1), 10–18. doi:10.1145/1656274.1656278

Hebel, M., Arens, M., & Stilla, U. (2013). Change detection in urban areas by object-based analysis and on-the-fly comparison of multi-view ALS data. *ISPRS Journal of Photogrammetry and Remote Sensing*, *86*(August 2015), 52–64. doi:10.1016/j.isprsjprs.2013.09.005

Hussain, M., Chen, D., Cheng, A., Wei, H., & Stanley, D. (2013). ISPRS Journal of Photogrammetry and Remote Sensing Change detection from remotely sensed images : From pixel-based to object-based approaches. *ISPRS Journal of Photogrammetry and Remote Sensing*, *80*, 91–106. doi:10.1016/j.isprsjprs.2013.03.006

Jianya, G., Haigang, S., Guorui, M., & Qiming, Z. (2008). a Review of Multi-Temporal Remote Sensing Data Change Detection. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. Vol. XXXVII. Part B7. Beijing 2008*, *37*, 757–762. doi:10.1016/j.isprsjprs.2003.10.002

Kamdi, S., & Krishna, R. K. (2011). Image Segmentation and Region Growing Algorithm. *International Journal of Computer Technology and Electronics Engineering*, *2*(1), 103–107.

Khoshelham, K., Oude Elberink, S., & Xu, S. (2013). Segment-based classification of damaged building roofs in aerial laser scanning data. *IEEE Geoscience and Remote Sensing Letters*, *10*(5), 1258–1262. doi:10.1109/LGRS.2013.2257676

Lohani, B. (2009). Airborne Altimetric LiDAR: Principle , Data Collection , Processing and Applications 1 Introduction. *Processing*. Retrieved from http://home.iitk.ac.in/~blohani/LiDARSchool2008/Downloads/LiDAR_notes/LiDAR_Full_Notes.pdf

Lu, D., Mausel, P., Brondízio, E., & Moran, E. (2004). Change detection techniques. *International Journal of Remote Sensing*, *25*(12), 2365–2401. doi:10.1080/0143116031000139863

Matikainen, L., & Kaartinen, H. (2004). Automatic detection of changes from laser scanner and aerial image data for updating building maps.*XXth ISPRS Congress,* Istanbul, Turkey.

Murakami, H., Nakagawa, K., Hasegawa, H., Shibata, T., & Iwanami, E. (1999). Change detection of buildings using an airborne laser scanner. *ISPRS Journal of Photogrammetry and Remote Sensing*, *54*(2-3), 148–152. doi:10.1016/S0924-2716(99)00006-4

Oude Elberink, S. (2010). *Automated 3D Road and Building Reconstruction Using Airborne Laser Scanner and Topographic Maps*. Unpublished PhD Thesis. Enschede, The Netherlands: University of Twente, Faculty of Geoinformation Science and Earth Observation(ITC). Retrieved from http://www.itc.nl/library/papers_2010/phd/oude_elberink.pdf

Oude Elberink, S., Shoko, M., Fathi, S. A., Rutzinger, M., & Observation, E. (2010). Detection of collapsed buildings by classifying segmented airborne laser scanner data, ISPRS workshop laser scanning 2011. International Archieves of Photogrammetry and Remote Sensing, Vol. XXXVIII, Part5/W12, pp.307-312.
Oude Elberink, S., & Vosselman, G. (2006). 3D modelling of topographic objects by fusing 2D maps and lidar data. In Proceedings of the ISPRS TC-IV Intl symp. on: Geospatial databases for sustainable development(pp. 199-204).

Singh, A. (1989). Review Article Digital change detection techniques using remotely-sensed data. *International Journal of Remote Sensing*, *10*(6), 989–1003. doi:10.1080/01431168908903939

Sithole, G., & Vosselman, G. (2005). Filtering of Airborne Laser Scanner Data Based on Segmented Point Clouds. *International Archives of Photogrammetry and Remote Sensing*, *36*(Part 3/W19), 66–71.

Tian, J., Chaabouni-Chouayakh, H., & Reinartz, P. (2011). 3D building change detection from high resolution spaceborne stereo imagery. *2011 International Workshop on Multi-Platform/Multi-Sensor Remote Sensing and Mapping, M2RSM 2011*. doi:10.1109/M2RSM.2011.5697371

Vosselman, G., Gorte, B. G. H., Sithole, G., & Rabbani, T. (2004). Recognising strucutre in laser scanner point clouds. *Remote Sensing and Spatial Information Sciences*, 33–38. doi:10.1002/bip.360320508

Vosselman, G., Kessels, P., & Gorte, B. (2005). The utilisation of airborne laser scanning for mapping. *International Journal of Applied Earth Observation and Geoinformation*, *6*(3-4), 177–186. doi:10.1016/j.jag.2004.10.005

Vosselman, G., Sithole, G., & Systems, S. (2004). Change detection for updating medium scale maps using laser altimetry. The International Archives of the photogrammetry, Remote Sensing and Spatial Information Science 34 (Part B3), 207-212

Weinmann Martin, J. Boris, M. C. (2014). Semantic 3d scene interpretation: a framework combining optimal neighborhood size selection with relevant features. *ISPRS Technical Commission III Symposium, Photogrammetric Computer Vision*, *II*(September), 1–8. doi:10.5194/isprsannals-II-3-181-2014

Xu, S. (2015). *Classification and change detection in multi-epoch airborne laser scanning point clouds*. Unpublished PhD Thesis. Enschede, The Netherlands: University of Twente, Faculty of Geoinformation Science and Earth Observation. doi:10.3990/1.9789036538350

Xu, S., Vosselman, G., & Oude Elberink, S. (2013). Detection and classification of changes in buildings from airborne laser scanning data. *ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences*, *II-5/W2*(November), 343–348. doi:10.5194/isprsannals-II-5-W2-343-2013