CHANGE DETECTION OF URBAN OBJECTS IN MULTI-TEMPORAL LIDAR DATA

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ABSTRACT

Change detection of urban objects is an important process that provides basis for: documentation of urban development, map updating, disaster evaluation and illegal building detection; because it highlights areas that have changed over time. The municipal of Rotterdam acquired airborne laser datasets for years 2008, 2010, and 2012. In this research only 2008 and 2010 datasets are used and the main aim is to analyse the differences between the two data sets. Both datasets are classified into building, water, ground, vegetation, and undefined objects in advance. The objects of interest in this research are buildings, vegetation and ground with main focus being development of a class-based change detection approach. An inventory of expected changes per class is first made and this serves as a basis for developing the change detection approaches. Surface separation map is generated based on 3D neighbourhood for building and vegetation whereas for ground it is based on 2D neighbourhood. Visualization of the separation map is done to identify the appearance of the expected changes per class. Further, the changes in each class are verified by applying different thresholds that are defined based on knowledge of classes. The changes detected are further classified into relevant and irrelevant changes. Building changes with an aerial coverage of above $2m^2$ are identified as relevant; cut and planted trees are the relevant changes in vegetation class and in ground class only changes occurring on the road surfaces are relevant.
Finally accuracy assessment of building and vegetation change results is done with an aerial photograph of 2010 as the reference dataset while for ground it was done by visually comparing the change results with the surface separation map.

ACKNOWLEDGEMENTS

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I would like to thank my supervisors Dr. Ir. S.J. Oude Elberink and Dr. K. Khoshelham for their positive comments, constructive criticism, brilliant suggestions, guidance and support throughout the thesis period. Thank you so much this thesis would not have been a success without your generous support.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

LiDAR	Light Detection and Ranging
ALS	Airborne Laser Scanning
RANSAC	Random Sampling Consensus
SSM	Surface Separation Map
2D	Two Dimensional
3D	Three Dimensional
TP	True Positive
FP	False Positive
FN	False Negative
DSM	Digital Surface Model

1. INTRODUCTION

1.1. Motivation and problem statement

Change detection of urban structures is an important step that provides basis for monitoring and planning with some of the applications being: documentation of urban development, surveying of construction sites, map updating, disaster evaluation and illegal building detection (Hebel et al., 2013). Illegally built or demolished building structures are difficult to identify, especially among other buildings in urban areas. These structures can be identified by use of change detection information in combination with other building records at the municipal authority offices. Local governments are mandated to collect taxes on real estate and buildings in their jurisdiction. However, urban landscapes are subject to dynamic changes demanding regular update of GIS databases, by detecting changes and revising building data accordingly; this is one of the most challenging tasks to the local governments because of lack of fast and automated methods to carry out these regular updates. A number of ways to manually do database updates have been proposed in researches before. One of them being by overlaying an ortho-image of the study area with the change map and existing database; this will show clearly the areas that have changed for example buildings as shown in figure 1-1. Overlaying only the parts of ortho image where changes have taken place would facilitate faster data revision and updates by the human operator (Murakami et al.,1999). However, improving the degree of automation of change detection and updating the databases is essential in a dynamic urban environment.

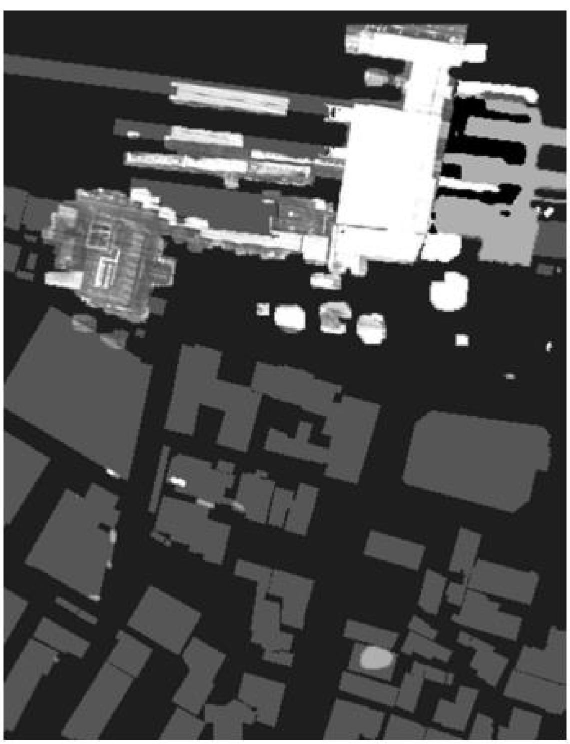


Figure 1-1: Grey areas are building data in a building database, white areas are change results, the ortho image is displayed only for the changed areas (Murakami et al., 1999).

Conventional methods of urban change detection employ aerial images and manual photo interpretation techniques. Use of manual processes can cause omission errors in the detected changes because human errors are present and the processes are costly and time consuming. Also, automated approaches of detecting changes from aerial or satellite images have not yet reached the stage where they can perfectly identify changes (Murakami et al., 1999). Other methods of change detection either use maps or DSMs, and this poses a problem of information loss, because if there is a change under other objects like vegetation, neither maps nor DSM can track. Also changes detected in difference images are generally affected by commission errors. Chen and Lin (2010) used aerial images and LiDAR data for detection of building changes by applying double threshold strategy. However, this technique was faced by detection challenges due to registration errors of the two datasets.

Multi-temporal airborne LiDAR data has been used for change detection in past studies, for example study by Murakami et al., (1999). Xu et al., (2013) also designed an algorithm for building change detection using both geometric and classification information; the data was first classified as explained in Xu et al., (2014).

Having identified the importance of change detection in urban areas and problems of techniques applied in previous researches, this study is motivated towards developing an approach of change detection in airborne LiDAR point clouds that utilizes geometric and classification information to identify changes. The major focus will be to identify the type of changes in different classes by developing a multi-class change detection method. Airborne laser scanners provide a reliable way of 3D change detection because they generate point clouds with accurate 3D coordinates; changes in both coverage and height can be detected (Xiao et al., 2012).

1.2. Research identification

1.2.1. Research objectives and questions

The main objective of this research to develop a change detection approach, that detects changes in airborne LiDAR data by utilizing classification and geometric information to separate false changes from real changes in urban areas.

The specific objectives and associated research questions are:

1. To identify the characteristics of the objects in the classified datasets.
   - What are the properties of objects in an urban area?
   - What geometric properties can be used as constraints in change detection?
2. To use the knowledge of classes and geometric information to detect and classify changes.
   - What kinds of changes occur per class?
   - How to identify a real change?
   - How do false changes appear in the results?
3. To perform quality assessment.
   - What is the performance quality of the change detection method in terms of accuracy?
   - How do classification errors affect the quality of detected changes?

1.2.2. Innovation

The proposed method of change detection will use classification and geometric information as constraints to separate false changes from real changes. Moreover, this approach will utilize knowledge of classes and the kind of geometric changes per class for change detection

1.3. Thesis structure

This thesis is organized in 5 chapters.

Chapter one introduces the problem and motivation of the research; the objectives, research questions and innovation of this research are also identified.

Chapter two is the review of the related work that has been done in the previous researches which includes various approaches of change detection both in remote sensing and LiDAR datasets.

Chapter three describes the research framework. This shows the workflows followed in the research together with explanation of each stage of the methodology.

Chapter four describes the datasets used and the results obtained.

Chapter five describes the conclusions drawn from the study and makes recommendations for future research.

2. LITERATURE REVIEW

2.1. Approches of change detection in imagery

There are various approaches of change detection using imagery. According to Chan et al., (2001) change detection techniques can be grouped into change enhancement techniques and nature-of-change detection techniques. Enhancement techniques only show and locate magnitude of changes but do not show the nature of changes that have taken place. Enhancement methods in remote sensing include: image differencing, principal component analysis and post classification analysis as reviewed in the paper of Lu et al., (2004). Other categories of change detection techniques include: direct comparison, model method, object-oriented methods, time series analysis, visual analysis and hybrid methods. Each of the methods has strengths and weaknesses and no single one is optimal and applicable in all cases (Doxani et al., 2010).

Doxani et al., (2010) in their research used an object-based classification method to automatically monitor changes in urban areas. Morphological scale filtering was used to improve the quality of the objects obtained and multivariate alteration detection transformation was used to identify the changes. However, this method was faced by challenges due to occlusion of some objects especially building walls. Li et al., (2010) applied one class support vector machine method to monitor the damaged buildings from very high resolution imagery after a disaster. Although conventional methods of change detection could be used to assess such damages, analysis is normally done both on damaged and undamaged classes of objects which could be time consuming. One-class support vector machine proved to be efficient in assessing damages in one class only for example buildings.

Sharma et al., (2006) employed unsupervised change detection using RANSAC; they modelled signals received from objects at two different times as a linear function that resulted as an amplification of the image dynamic range. RANSAC was then used to estimate the shift in the dynamic range of the images.

2.2. Approaches of change detection in lidar data

Various approaches of change detection have been applied in previous studies; some using multi-temporal ALS data and others combination of ALS data and aerial imagery. Traditionally, change detection for urban environments was done by spectral analysis of aerial images without putting 3D information embedded in urban objects into consideration. Although 3D information can be extracted from imagery by methods such as stereo-matching, the height information extracted is still less accurate in comparison to ALS data. Vosselman et al., (2005) demonstrates how laser scanning data is useful for change detection and semi-automated 3D mapping of urban environments. From this research laser scanning was seen to be useful for detecting changes as well as errors in mapping. The results of the research proved that automated change detection using laser scanning can also be used as a way of quality control. Matikainen et al., (2010) demonstrated that laser scanner data is useful for updating large scales city maps. The initial step involved detection of buildings from LiDAR data based on region-based segmentation and classification. Change detection was done by comparing the detected buildings with those on the map. They recommended that to improve the change detection results, testing of new and potentially useful datasets like full-wave form laser data would improve automatic classification of objects in the scene.

Chen & Lin, (2010) used double-threshold strategy for find changes in 3-D building models using LiDAR data. Changes were identified by height comparison between LiDAR data and the estimates of the building models. The double threshold strategy helped to cope with the high sensitivity of thresholding that is normally a challenge in rule-based approaches and also improved the detection accuracy. The detection errors that were in the final results achieved were mainly due to registration errors and tiny roof variations. The main limitation of this method was in the areas occluded mainly by vegetation. Choi et al., (2006) used DSM subtraction method to detect changes. The DSMs were generated for individual LiDAR datasets acquired in different dates. Their approach involved three main steps including: identification of change areas, derivation of clues of changes and lastly comparing the clues as shown in figure 1-2. This method was able to detect the type of changes with a sufficient degree of accuracy and reasonable processing time. However, there was no quantitative evaluation carried out.

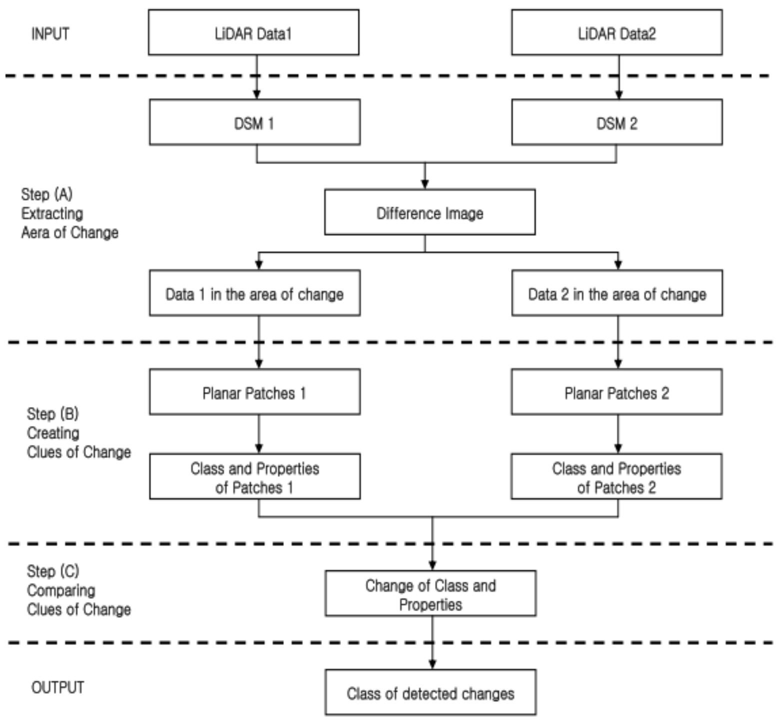


Figure 2-1 Urban change detection approach(Choi et al., 2006)

Hebel et al., (2013) employed object-based analysis and on-the-fly comparison of multi-view ALS data to detect changes. In this study, Dempster-shafer theory was applied to identify conflicting evidence in the laser pulse propagation path. Other attributes were used to distinguish between man-made and seasonal changes. According to study by Khoshelham et al., (2010) Dempster-Shafer method proved to have a better performance than other methods of building detection. Murakami et al., (1999) in their study did a comparison between DSMs acquired in different epochs to detect building changes without omission errors. This method proved that errors of commission can be easily detected in the results obtained. Rottensteiner, (2007) in his research of building change detection compared building detection results to a vector map in order to detect and classify changes. The method took into consideration topological differences between buildings extracted from laser data and the vector map. The building detection method was adopted from previous work of Rottensteiner et al., (2007) on automatic building detection by fusion of laser scanner data and multi-spectral images.

Stal et al., (2013) also detected 3D changes by DSM subtraction. The two surface models derived from ALS data and aerial Photogrammetry acquired in two different dates, were compared to detect and quantify 3D changes in buildings using a pixel-based method of differencing as in the equation below:

$$\mathrm{DSM_D}(c, r) = \mathrm{DSM_{LiDAR}}(c, r) - \mathrm{DSM_{PHG}}(c, r), \qquad \text{(Stal et al., 2013)}$$

The main task was to differentiate unchanged parts, noise, and errors from real significant changes. The results obtained were within reasonable accuracy. However, DSM errors, model noise and insufficient detail due to low spatial resolution had a significant impact on the accuracy and performance of this method. Szostak et al., (2013) in their paper employed nDSM to monitor land cover changes. Use of LiDAR dataset allowed automation of the detection process and the assessment of the land cover dynamics. Teo & Shih, (2013) employed geometric analysis to perform object-based changed detection and change-type determination based on object properties. This was done by generation of a shape difference map by subtracting two digital surface models acquired in two different epochs. The method utilized height differences and above-ground objects to extract the changed objects. Four classes of changes were obtained including: changed building, newly built building where there was a building before, newly built building where there was no building before, and demolished building. 80% correctness in change classification was achieved with most of the errors being in small and the vegetated areas; change detection using full waveform LiDAR would solve these errors.

Vögtle & Steinle, (2004) also applied differencing of laser scanning derived DSMs acquired at different dates. Segmentation based on region growing algorithm was first done to generate separate 3D objects; this was to avoid ambiguities. However, this method could not provide the full information required for disaster management which was the main aim of the study. Vosselman et al., (2004) carried out a study for automatic change detection of buildings in medium scale map using ALS data. The method applied in this study involved segmentation and classification of ALS data, followed by matching of building segments obtained with the building objects on the vector database. This was to facilitate updates of the topographic database.

Vu & Matsuoka, (2004) employed global histogram thresholding method on LiDAR data for change detection of buildings in dense urban areas. The changes detected in this study were not only of buildings but also trees due to seasonal changes and newly planted trees. However, their methods were not able to differentiate changes due to trees and building using only LiDAR data. This wrong detection was eliminated by mismatching in the building database. Reasonable results were obtained but there was need for improvements in future. Xiao et al., (2013) applied a combination of methods based on consistency between the occupancies of space computed from different datasets and Weighted Dempster-Shafer theory (WDST). This approach allowed detection of changes in large urban areas while separating real changes from occlusions. Xiao et al., (2012) applied tree to tree matching algorithm using overlapping bounding boxes and point to point distances for change detection of urban trees. Comparison of the two methods was done to evaluate constancy and stability of parameters. The detected changes showed the two methods can be used for monitoring tree growth and pruning in urban areas. From the research it was noted that since mobile laser scanning is good in acquiring data on tree trunks, combining it with ALS data would be more efficient for tree change detection. Yu et al., (2004) also examined the feasibility of tree-tree matching method in the detection of harvested trees and determination of forest growth in LiDAR data.

Xu et al., (2013) employed surface separation map for building change detection. 3D surface separation map indicates the differences between two epochs of ALS data. In this research the focus was changes occurring on building elements especially on the roof. After the generalization of the surface separation map, changes were verified by making rules on the separation map; changes larger than 10cm were detected. Several attributes were used to classify the changes including: area, height to the nearest roof, normal of nearest roof (type of roof) and the class labels of the changed points. The changes were classified into roof, wall, dormers, vehicles, construction above the roof and undefined objects. The result of the study showed that 80% of the changes were correctly interpreted. Most errors occurred in the classification of changes due to vehicles and dormers which were confused for constructions above the roof.

Various change detection methods have been applied to study changes in urban areas in the past and results have been obtained with reasonable accuracy. However, class-based change detection methods have not been applied before. Class-based approaches are necessary due to the fact that a single approach is not sufficient for detecting changes in different kinds of objects present in urban areas; changes occurring in different objects vary in geometric nature, pattern and magnitude. Development of different approaches to detect changes in different classes of objects is the main focus of this research.

3. RESEARCH METHODOLOGY

3.1. Introduction

The focus of this research is to detect changes of various urban objects in ALS data. The main objects of interest are buildings, ground and vegetation. The idea is use of knowledge and characteristics of the objects to develop a change detection approach for each class of objects. In order to develop the change detection approaches proper knowledge of the object characteristics and expected changes is required beforehand. This will make it easy to develop an approach that's fit for each object category. Furthermore, a visit to the municipal of Rotterdam was made to find out the changes of interest to the user. This information was also used as a reference during the development of the class-based approaches. Section 3.2 lists the characteristics of the objects of interest as well as the changes of interest to the user as specified by municipality of Rotterdam.

3.2. Inventory of the expected changes per class

As mentioned earlier, the municipal of Rotterdam officials indicated that they would be interested in changes occurring in classes building, ground and trees. Changes in water class will not be of focus in this research since it would be difficult to detect changes using ALS data because water absorbs most LiDAR pulses so most parts on water lack data. The expected changes per each class of objects are as follows:

3.2.1. Building

Buildings are amongst the static objects in urban areas. Over short periods of time there are no major changes that could occur on the buildings. Changes occurring on buildings take a particular geometrical pattern. The possible changes include: newly built or demolished building extensions that take the same orientation as the main building; additional floors to a storey building/ increasing building height; reduction/ demolishment of some building floors leading to decrease in building height; a building may be demolished and replaced with a new one with the same dimensions; a building could be completely demolished and not replaced; new buildings are built; construction of new roof elements like dormers etc. All these are real changes. Some false changes could occur in this class, for example absence of points in one epoch due to occlusion or presence of water on a surface could appear as a change. Xu et al., (2013), in their research focused on changes in building roofs, wall, and roof elements which are larger than 10 cm and area larger than $4m^2$; fake changes resulting from lack of data which were identified as unknown.

The focus of this research in this class will be to detect both small and large changes and later show the implication of both cases using the approach developed. The municipal of Rotterdam is interested in changes greater than $2m^2$. Although other smaller changes would be detected they will not be relevant to the user.

3.2.2. Ground: Roads

The roads are classified as part of ground in the input data. The road surface itself is more or less static, but the surface level can change like in cases where objects like speed bumps and curbs are introduced or removed; these could cause changes as small as 15cm to 30cm or when the street as a whole is reconstructed and raised to reach a certain level. This is common in the Netherlands because the ground level sinks over time. Curbs mainly occur at the edges of the roads or between car lanes and bicycle lanes while speed bumps run across the road. There are also other objects present along the roads like road furniture for example traffic light, lamppost etc. These are expected to have changes over time too.

However, changes due to road furniture are not of interest in this research. The only changes the user is interested in are changes occurring on the road surface. Dynamic objects also occur on the roads like vehicles; these could cause changes in height of between 0.5m to 3m. However, since vehicles are classified to a different class, they will be separated from the ground during analysis to solve the problem of false changes. Other false changes left will also be eliminated by the approach adopted.

3.2.3. Vegetation: Trees

Vegetation in urban areas is found mainly in the parks and the trees planted along the roads. Trees planted along the roads in Netherlands appear at particular intervals; this could be an important factor in monitoring their changes. Also vegetation has a very unique and irregular point distribution in ALS data; this factor is considered while developing a change detection approach for this class. Some of the changes that occur on the vegetation include: vegetation growth, this can be increase in width or height. Growth of vegetation like trees does not occur in any specific pattern, it's random. Also new trees could be planted where none existed before; trees could also be removed/ cut. Xiao et al., (2012), described a tree oriented change detection approach, by identifying the location of trees in both epochs then applied tree to tree matching method using a distance threshold of 0.5 meters. In his research he focused on four categories to analyze the changes as shown in the table 3.1 below.

Table 3-1: Change detection categories, Xiao et al., (2012).

Categories	Cut	Planted	Area Change	Volume Change
Change	Only in data 1	Only in data 2	Area ↑ Area ↓	Volume ↑ Volume ↓

The focus this research will be to detect planted trees and cut/removed trees; this is in accordance to the interest of municipal of Rotterdam. Changes in volumes and area occupied by trees are out of scope of this study.

3.2.4. Summary

Table 3-2 below gives an overview of the magnitude of changes under study per class.

Table 3-2: Magnitude of changes under study per class

Class	Magnitude	Location of change
Building	Changes above 10 cm	Change on whole or part of a building
Ground	Changes above 15 cm	Changes on road surface
Vegetation	Changes above 2 meters	Change on a whole tree (cut or planted trees

Having identified the geometric characteristics and the nature of the changes per object it is clear that different approaches of change detection will need to be developed for different classes; hence class-based change detection method as shown in the methodology frame-work in figure 3-1 below.
It is noted that the focus of this research is not to detect the smallest changes in a particular object; rather the main aim is to develop different approaches for change detection per class.

3.3. Methodology frame-work

The methodology of this research is class-based change detection; this is because the expected changes per class are already known. The methodology workflow is executed with respect to three sub-objectives following the steps in the in figure 3-1. Class-based three-dimensional surface separation map is generated by calculating point-wise geometrical difference between the two input point clouds. Workflows are developed to detect changes for different objects, the results are assessed and the methods are revised if necessary. Finally error analysis is carried out on the results.

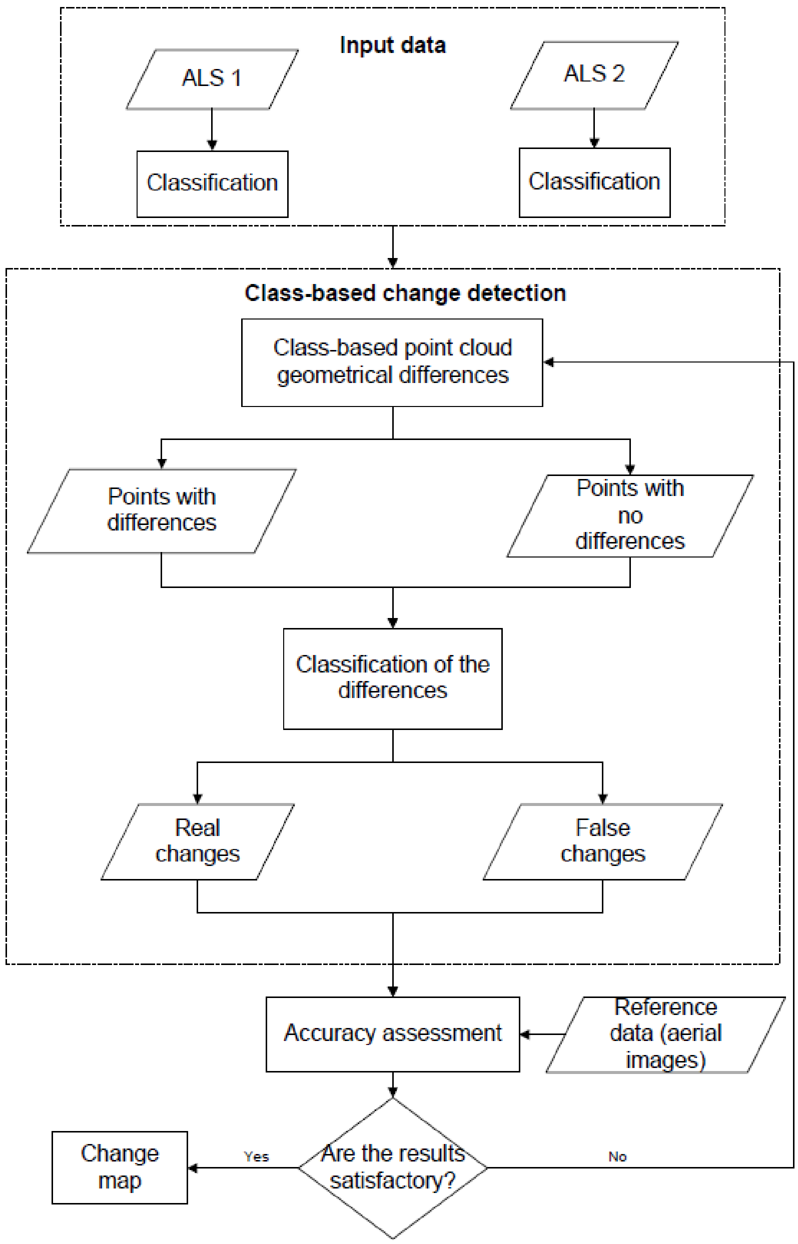


Figure 3-1: Methodology framework

3.4. 3D Surface separation map generation

The separation map contains geometric indication of whether there is a change or not. Surface separation map has been applied before by Vosselman, (2012) in his research on automated planimetric quality control in high accuracy airborne laser scanning to evaluate the quality of data in overlapping strips. Xu et al., (2013) also applied surface separation map to detect and classify building changes in airborne laser scanning data.

To generate surface separation map, the two input datasets were merged and edges derived with the scan numbers being the distinguishing attribute. The differences between the two epochs were calculated as the distance from a point in the first epoch to its nearest fitted plane in the second epoch (point to plane distances). For every point in the first epoch a search is made within a range of 1 meter in 3D or 2D depending on the class to check if there is a point in the second epoch. The separation values between the two epochs were recorded as residuals stored in the first epoch. If no nearby point is found in the other epoch due to lack of data, a separation value of 100 is assigned. Calculation of surface separation map was done based on 3D neighbourhood for building and vegetation, whereas for ground it was done based on 2D neighbourhood. All separation values are positive float values. Figure 3-2 shows surface separation map calculation workflow. Figure 3-3 shows an example part of input datasets and the resulting surface separation maps.

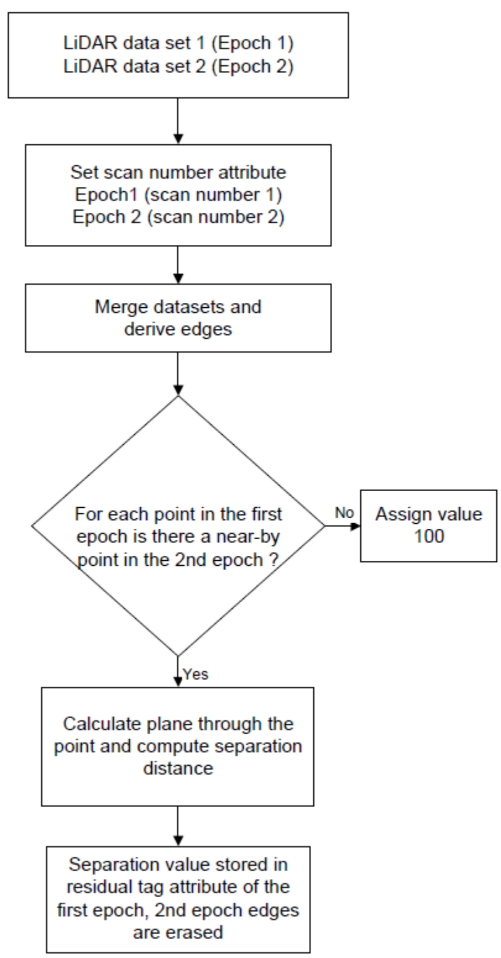
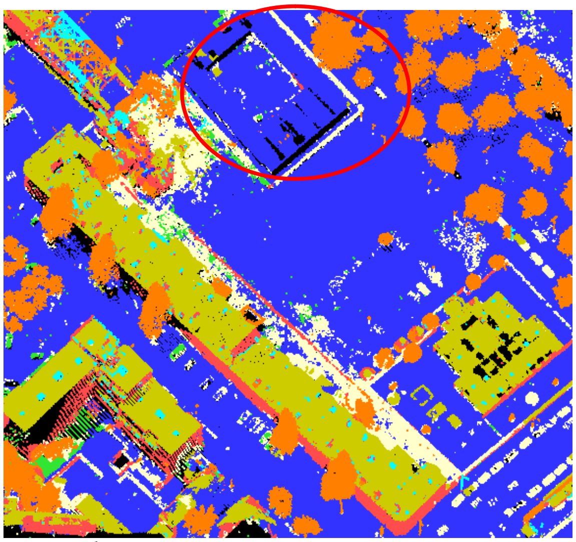
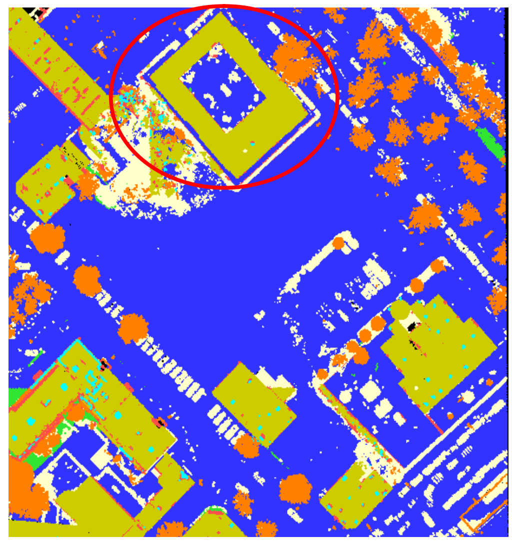


Figure 3-2: SSM generation workflow

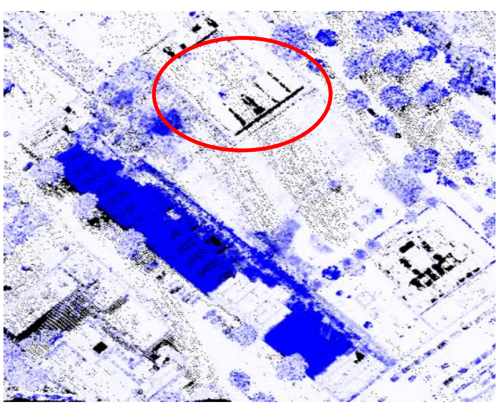
This workflow was executed twice by reversing the order of input datasets; this makes it easy to interpret various types of changes that occur within the time of study. Further explanation of this is in section 3.5. It was noted some objects like newly built buildings with heights above 100 meters were assigned separation values of 100 since nearest point is not found. This problem was solved by increasing the number of neighbours for edge generation. It was also observed that even if there is classification error in one of the datasets, if there is no geometric change there will be no consequence. Example is the building in red circles in figure 3-3; it was wrongly classified as ground in 2008 but correctly classified in 2010. Since there were no geometrical changes on the building, corresponding separation values are close to zero.



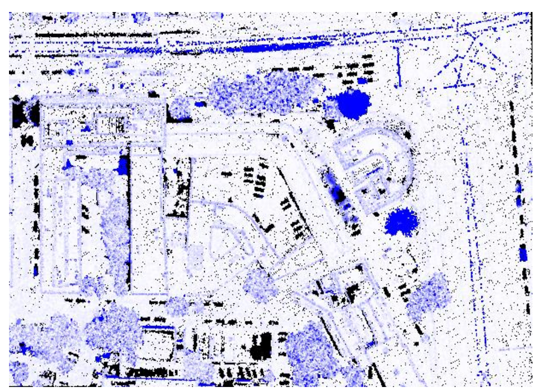
a. 2008 dataset



b. 2010 dataset



c. Separation map (2008 vs. 2010) with all classes based on 3D neighbourhood



d. Separation map (2008 vs. 2010) with vegetation & building based on 3D neighbourhood and ground based on 2D neighbourhood

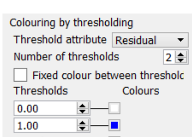


Figure 3-3: (a) and (b) Are classified 2008 & 2010 datasets respectively and (c) is separation map with all classes based on 3D neighbourhood (d) separation map with vegetation & building based on 3D neighbourhood and ground based on 2D neighbourhood

As mentioned earlier, surface separation map for ground was calculated based on 2D neighbourhood. Referring to figure 3-3 d, undefined objects which includes vehicles on the ground were left out during calculation of 2D ground surface separation map to avoid their influence to the changes detected on the ground.

3.5. Class-based change detection

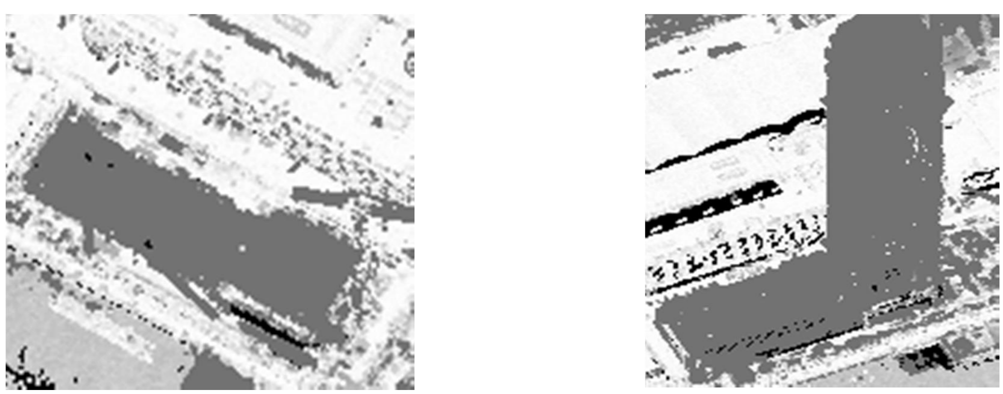
An important task in this research is to identify nature and appearance of the expected changes in the surface separation map. Since the appearance of changes in the separation map for different objects is different, separate interpretation approaches were adopted as follows.

3.5.1. Building

Appearance of expected changes in the surface separation map

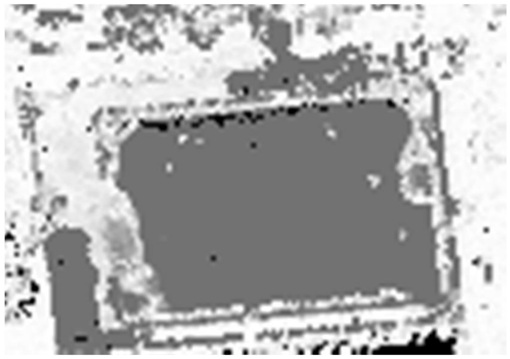
Calculation of the SSM was done with two epochs as inputs in the order 2008 vs.2010 and 2010 vs.2008. Changes in buildings exhibit high separation values in the two epochs (both when the separation map is generated in the order 2008 vs.2010 and 2010 vs.2008); this is because the distance to nearest point in the other epoch is large in both cases. In all the diagrams below the SSM is visualized by colour thresholding showing all changes greater than 1 meter; all separation values are positive.

Newly constructed buildings have high separation values in 3D separation map in both epochs. The only difference is the visualization in both epochs; the building is visible in the epoch where it is present. In figure 3-4a, the part of the building existed in year 2008. In year 2010 the building was built to its full height. Figure 3-5 also shows visualization of similar cases where in (a) the building was completely not present in year 2008; (b) it was present in year 2010.
Existing buildings that have increased in height have high separation values only in the parts that have been newly built within the time of study; while the parts of the building that already existed has low separation values as in figure 3-5 c and d. Demolished and newly built building extensions also have high separation values in both epochs as in figure 3-5 e and f.

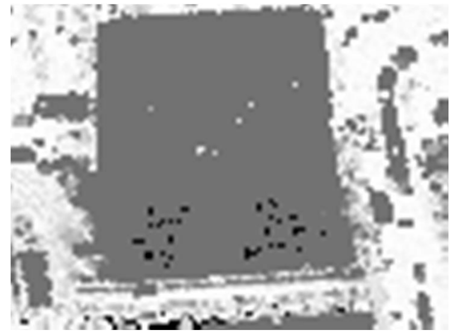


a. 2008 b. 2010

Figure 3-4: (a) Part of building in yellow square present in year 2008; (b) building fully built in year 2010

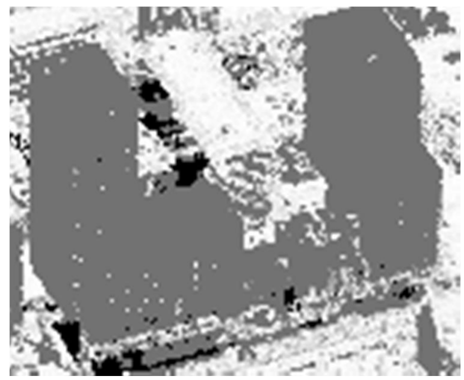


a. 2008

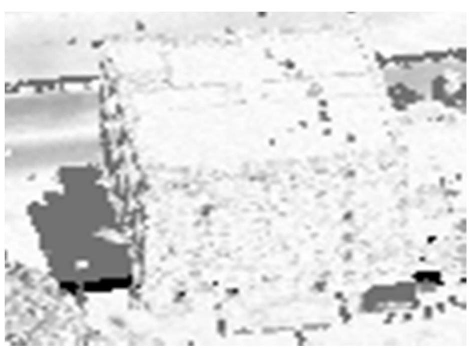


b. 2010

c. 2008



d. 2010

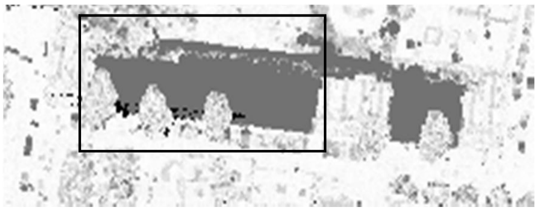
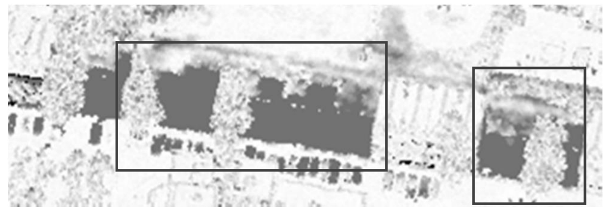


e. 2008

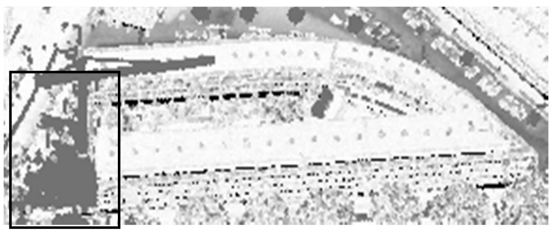
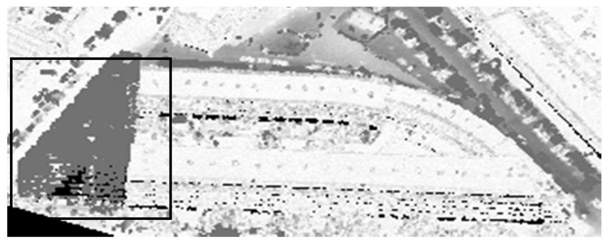
f. 2010

Figure 3-5: (a) Building absent in year 2008; (b) building built in year 2010; (c) &(d) the building increased in height in 2010. Some parts in the lower parts of the building have high separation values because of occlusion in year 2008; (e) building extension present in year 2008; (f) building extension demolished in year 2010.

Parts of buildings demolished or newly built have high separation values in the 3D surface separation map as shown in figure 3-6.

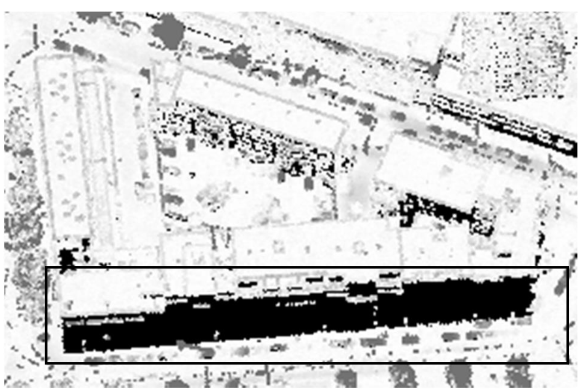
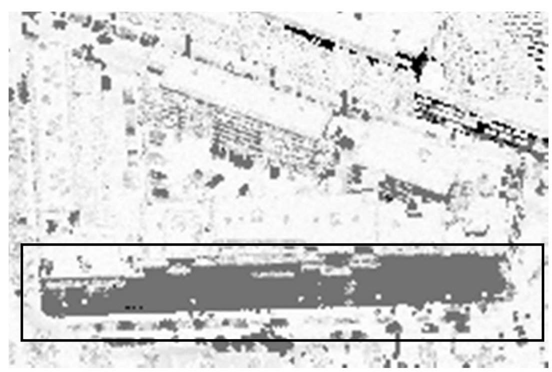
a. 2008 b. 2010

c. 2008 d. 2010

Figure 3-6: (a) shows parts of the building in squares that were present in year 2008; (b) same parts of the building demolished in year 2010; (c) shows part of a building that was not present in year 2008; (d) part of the building built-up in year 2010

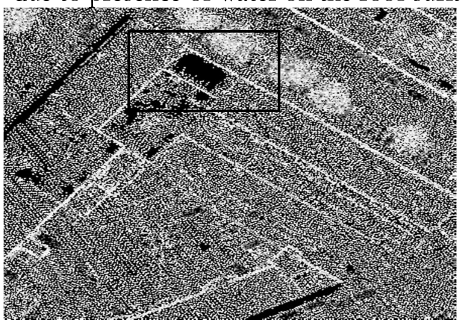
Points with high separation do not always denote a change, for example this could occur due to lack of data as a result of occlusion of some parts of the building like the walls in one of the datasets as shown in figure 3-7. As a result these points are assigned high separation values. It is observed that the high separation values only occur in the epoch where data is present. In 2D neighbourhood nearest points in the other epoch will be found too the only difference is that the separation values will be larger than in the case of where the separation map is calculated based on 3D neighbourhood. This case of occlusion will further be confirmed by checking whether the corresponding roof of that building has changed or not.

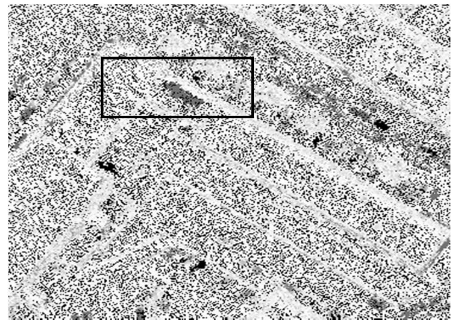
a. 2008 b. 2008

Figure 3-7: 3D neighbourhood (a) the wall in black square was occluded in 2008; (b) The wall has high separation values because of absent in year 2008

Lack of data in one epoch could also be as result of surface absorption and this mainly occurs on the roof of a building; presence of water on a building roof absorbs laser pulses. This will too have high separation values in the separation map based on 3D neighbourhood. However, in the 2D neighbourhood a nearest point is not found for these areas, since it is the roof hence a value of 100 is assigned to the points as specified in the SSM calculation algorithm. Figure 3-8 shows and example of part of roof with data gaps due to presence of water on the roof surface.



a. 2008 dataset

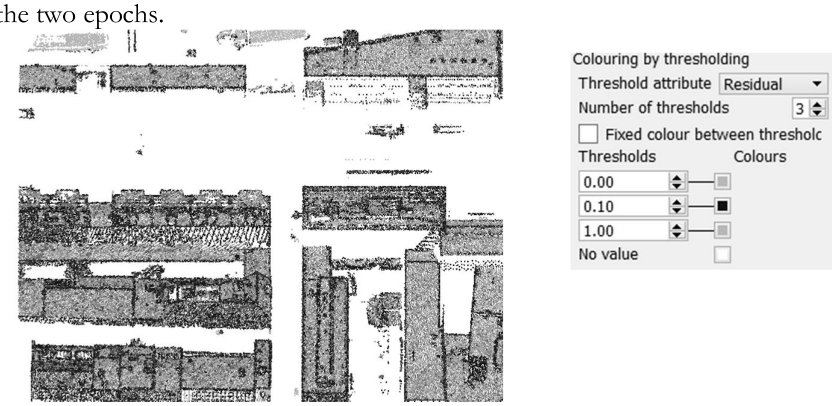


b. 2010 dataset

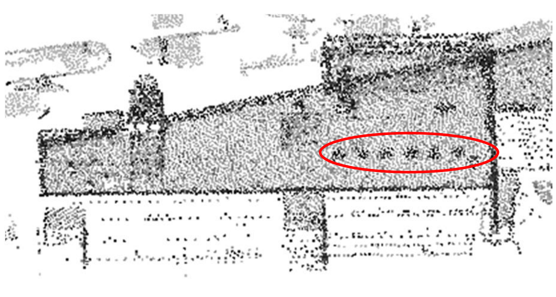
Figure 3-8: (a) Absence of LiDAR points on a roof in 2008 data; no separation values when 2008 is input as the first epoch, (b) absence of LiDAR points in 2008 data; leads to high separation values in 3D neighbourhood when 2010 is input as the first epoch.

Changes between 10cm and 1m

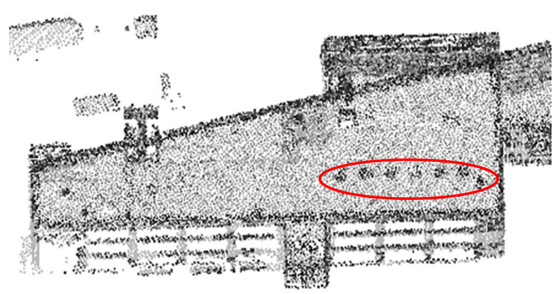
All the above visualized changes are above 1 m (points with separation values above 1 meter). Small changes up to 10 cm can also be detected, for example on roofs due to changes on dormers. Figure 3-9 below shows some of changes with separation values above 10cm and below 1 meter. In (a) it is observed that building edges have separation values greater than 10 cm; this is due to differences in point density of the two epochs.



a. 2008 vs. 2010



b. 2008 vs. 2010



c. 2010 vs.2008

Figure 3-9: (a) Overview of points with separation values greater than 10 cm; (b)& (c) points on the roof with separation values above 10 cm,

Change detection workflow

Since changes cannot be extracted and interpreted by only thresholding the separation map, a workflow was developed to separate the changed points and the unchanged points from the surface separation map as shown in figure 3-12. All points classified as building (roof, wall and roof element) in the scene classification were selected from the surface separation map the result is as shown in figure 3-10. This was followed by grouping of the points into planar segments using surface growing method(Vosselman et al., 2004). Surface growing algorithm is the most common method of segmenting planar surfaces in point clouds. This algorithm is similar to region growing used in images. There are two steps involved in surface growing; first step being identification of the seed surface point. This is done by plane fitting and analysis of residuals between the points and other points within some threshold distance. Points with residuals below the threshold distance are considered as part of the plane. However, there are always outliers in LiDAR data; robust least squares adjustments or Hough transform methods are used to fit planes in these cases. For this research seed selection is done by direct neighbourhood method, within a radius of 1 meter.

The second step of surface growing is growing the seed surface which involves fitting of a plane equation and points are added to the plane depending on whether they are within the threshold value set. Planar surface model was used and maximum distance to plane set at 0.2 meters. The reason for doing surface growing is to have compact segments instead of points and this make is easy for further analysis of changes per segment. The results for surface growing are as shown in figure 3-11. For changes above 1 meter, the percentage of point points with separation greater than 1 meter per segment is calculated with the formula:

% of points with separation values > 1 m = (number of points with separation >1m)/ (Total of points with separation values)

If a segment has over 80% of the points with separation larger than 1 meter, it is labelled as changed. The rest of the segments were labelled as unchanged; these change values are stored in plane number tag attribute. 80% value was chosen as the optimum after trying several thresholds. The workflow was executed a second time; the separation value threshold was lowered to 10cm. Further, the changed and unchanged segments were separated and connected component analysis done separately. 2D connected component analysis is done on changed segments. Changes on an entire building are expected to be grouped as one object hence 2D neighbourhood is preferred. The changed components are further inspected and any component with a roof segment greater than 2sqm is labelled as a relevant change and the others are labelled as irrelevant changes. At this stage false changes as a result of lack of data on occluded walls are eliminated. The roofs are identified by using the class labels. The idea is if the roof has not changed the whole building is considered as unchanged. In that the walls cannot change without the roof changing. Xu et al., (2013) treated areas that lack data due to occlusion in a different way; the algorithm created labelled the wall points as "unknown" instead of changed if the roof of the same building is not changed. These walls are labelled "unknown" due to lack of evidence as to what happened with the wall. These unknown points were excluded from the datasets in further analysis. In this research occlusion is confirmed by reversing the order of the epoch during SSM calculation as mentioned earlier.

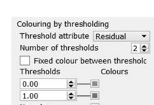
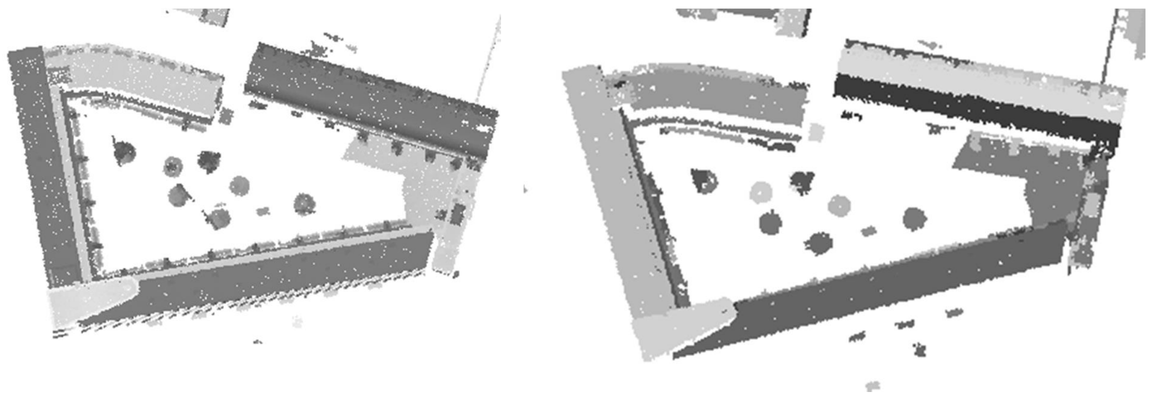


Figure 3-10: Building points selected using class labels



a. Unsegmented building points b. Segmented building points

Figure 3-11: Building segmentation process (a) input labelled by height colour (b) labelled by segment number

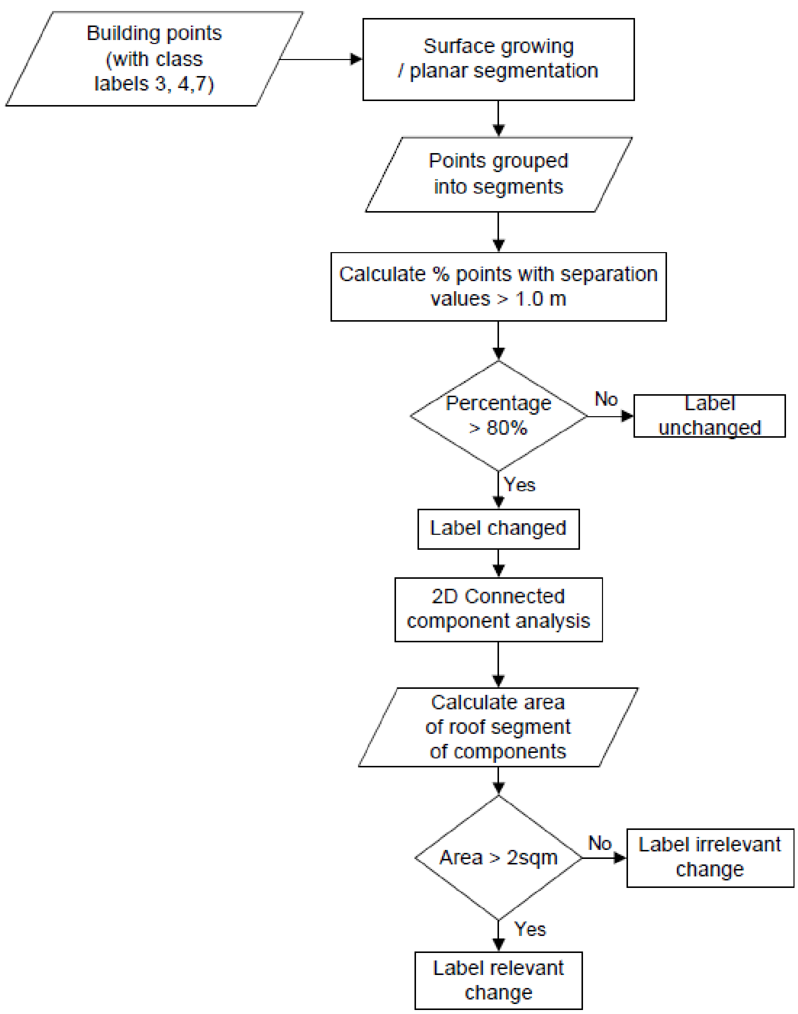


Figure 3-12: Building change detection workflow

After changed and unchanged segments of the building were separated, 2D connected component analysis was done on the changed segments only and the outputs were as in figure 3-13.

(a)Part of changed segments before 2D connected component analysis

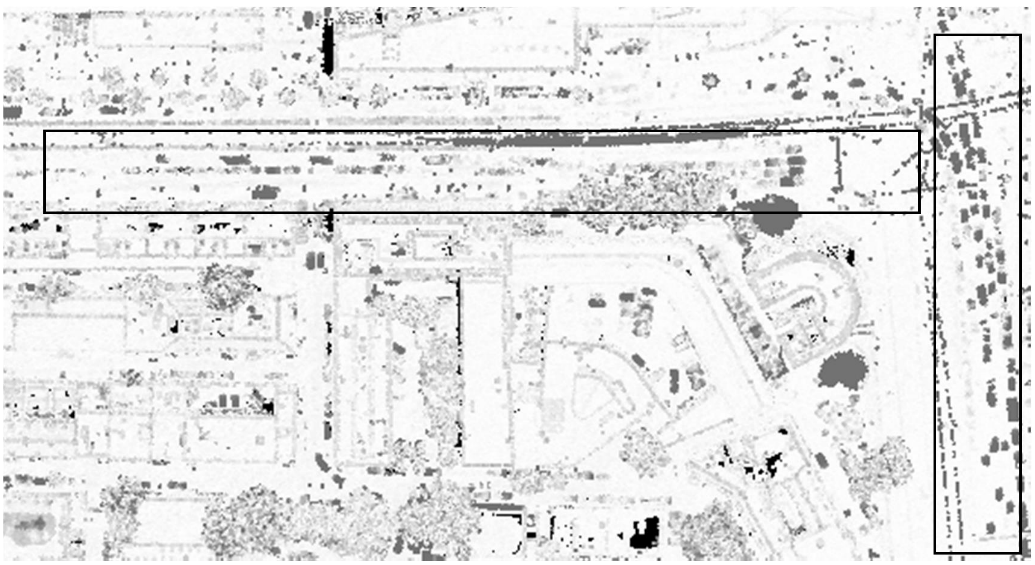
(b)Changed components after 2D connected components analysis

Figure 3-13 (a) changed points labelled by plane number, (b) changed points labelled by component number

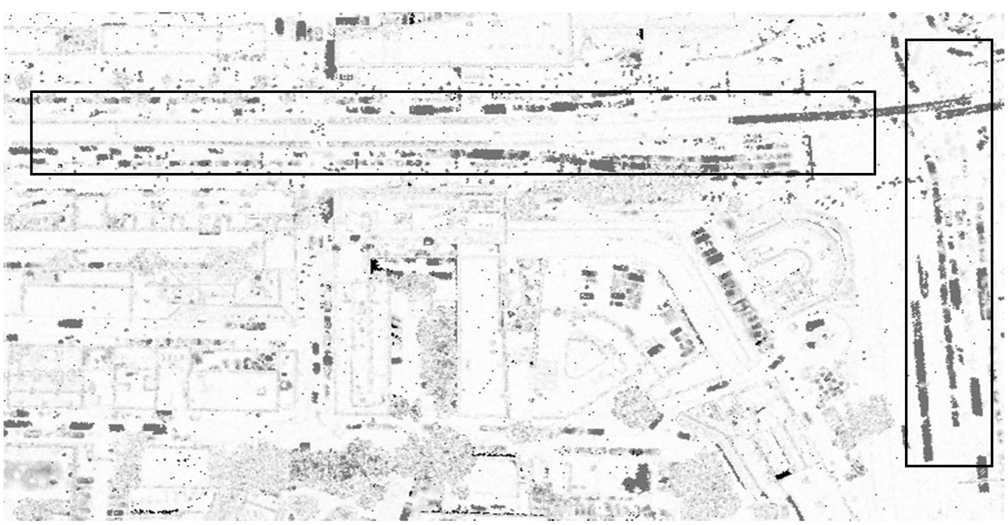
3.5.2. Ground

Appearance of expected changes in the surface separation map

In this class the changes of interest are those occurring on the road surfaces. The roads are classified as part of ground in the input datasets. Changes on the roads could be as a result of changes on the surface and changes due to the dynamic objects like cars present on the road. However, the user is interested with the changes occurring on the road surface. The idea is to separate changes occurring on the road surface from the changes resulting from dynamic objects like cars. The first step is interpretation of the surface separation map by thresholding the separation values. The same 3D surface separation map generated in section 3.4 is used first. It was noted that points on dynamic objects like vehicles on the ground have high separation values in the SSM as shown in figure 3-12 below in the black squares.



a. 2008 vs. 2010



b. 2010 vs. 2008

Figure 3-14: 3D Surface separation map showing changes on roads/ground due vehicles in the black

Generation of surface separation map with presence of dynamic object on the road surface was observed to introduce false changes on the road surface. A different approach was adopted for generation of surface separation for this class.

First step was to select all points labelled ground (label 2) in the two epochs during the scene classification. The vehicles were excluded; they have a different class label. The surface separation map was generated based on 2D neighbourhood using the same workflow as in figure 3-2. However, some gaps are left on the roads in the areas where cars/vehicles were present during data acquisition. For this reason 2D neighbourhood is chosen for surface separation map generation; this is because a nearby point will be found in the second epoch within a search radius of one meter eliminating high separation values on the gaps. This will eliminate high separation values/ false changes caused by dynamic objects or data gaps on the road surface. Figure 3-15 shows surface separation for ground generated in 2D neighbourhood.

a. 2008 vs.2010

b. 2010 vs.2008

Figure 3-15: Ground SSM generated in 2D neighbourhood (black areas are software background areas where there were buildings and other objects)

From figure 3-15 it is observed that the points with high separation values due to dynamic objects like cars are not present. So, false changes as a result of the dynamic objects have been eliminated. However, there are points still with high separation values, these are points on water or occluded areas by buildings; points that were absent in one epoch.

Change detection workflow

To detect changes points are grouped into two categories depending on the separation values as in figure 3-16. Points with separation values of 0 to 0.15 metres are considered to be unchanged and points with separation values above 0.15 to 0.5 metres are considered to be changed. Points with separation values above 0.5m are discarded at this stage because they are likely to be located on water or occluded areas; changes on the road surfaces are expected to be less than 0.5 metres. Connected component analysis is done on the two classes of points separately. Connected component analysis was chosen since the ground surface is not perfectly planar. Connected component analysis clusters nearest points to form individual segments that represent an object. The clustering is influenced by the distance between points. The algorithm first selects a seed point, then the points are connected to the selected seed points based on the parameters set by the user. Both sets of components are then combined together and components with over 85% of points with separation values greater than 0.15 m are labelled as changed. These are the changes on the ground surface; relevant to the user. Percentage of points per component is calculated by the formula:

% of points with separation values > 0.15 m = (number of points with separation >0.15)/ (Total of points with separation values)

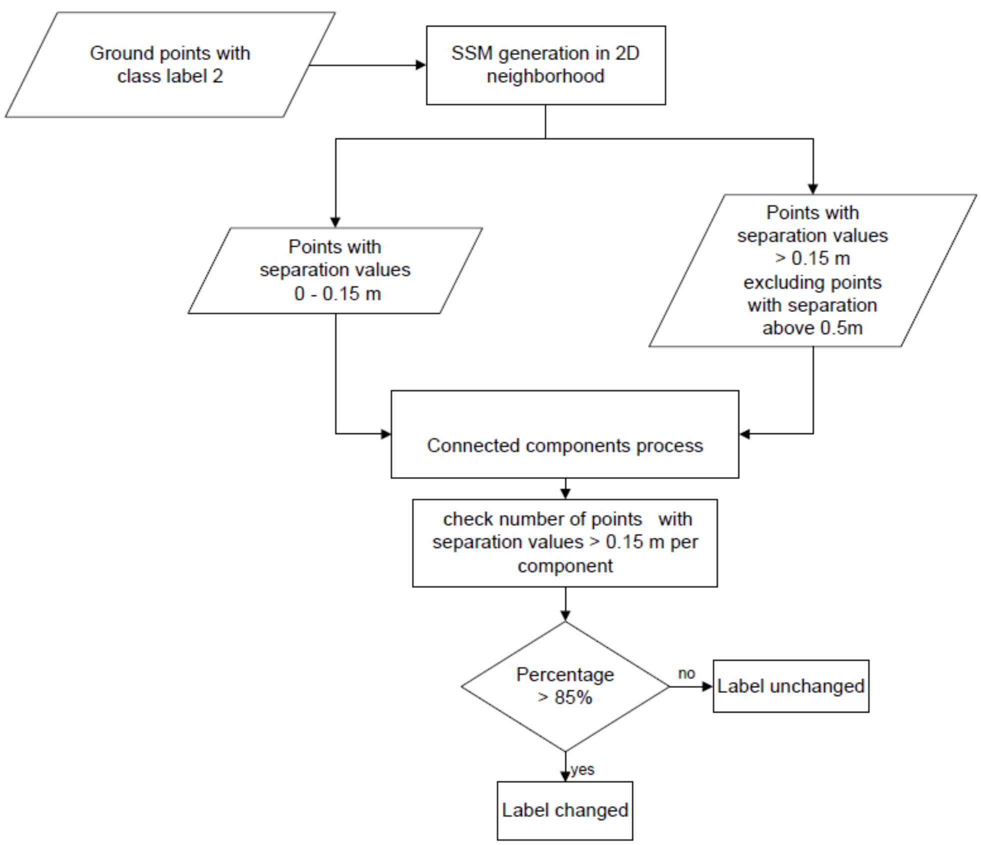
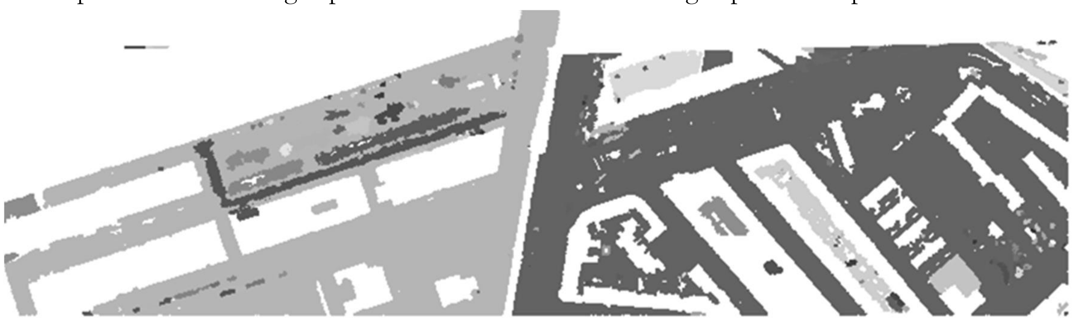


Figure 3-16: Ground change detection workflow

Figure 3-17 shows results of connected component analysis on the ground points. Grouping the points before connected components ensured that that points considered to be changed are grouped together and the unchanged are grouped together for efficiency in further analysis.

a. Components of unchanged points

b. Changed points components



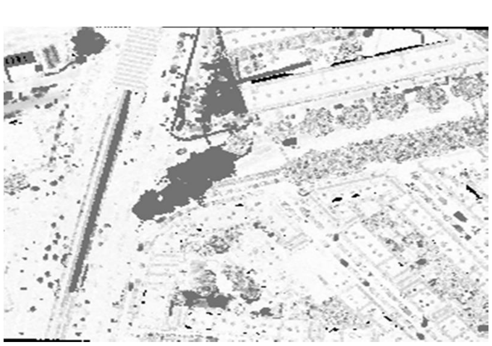
c. Combined components of changed and unchanged points

Figure 3-17: Ground points connected component analysis

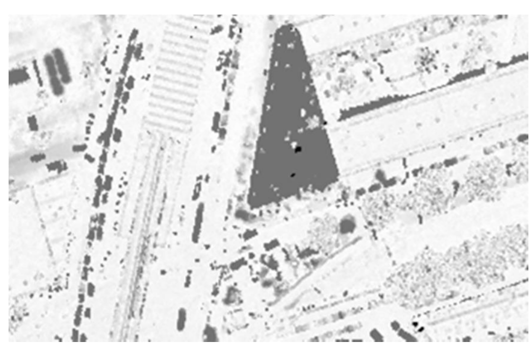
3.5.3. Vegetation

Appearance of expected changes in the surface separation map

As mentioned earlier changes of interest in this class are only planted and cut trees during the time of study. These exhibit high separation values in the 3D surface separation map. However, since in these cases a tree is absent in one epoch, high separation values don't show in both epochs. The high separation values only show in the epoch where the trees are present. In the epoch without trees there are no large separation values because the distance to the nearest point in the other epoch is less than a meter no matter whether there is a tree or not in the other epoch. Below are some example separation maps; grey colour represents point with separation values above 1 meter and white represents points with separation values below 1 meter, the separation values are all positive.

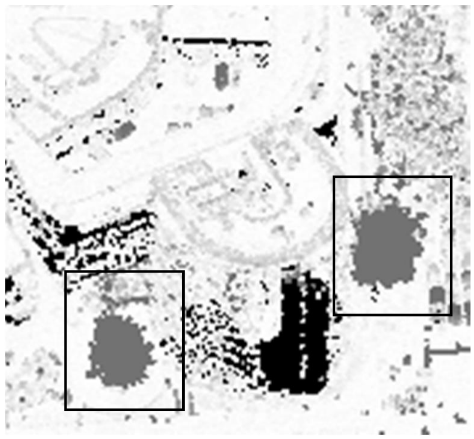


(a) SSM with 2008 dataset

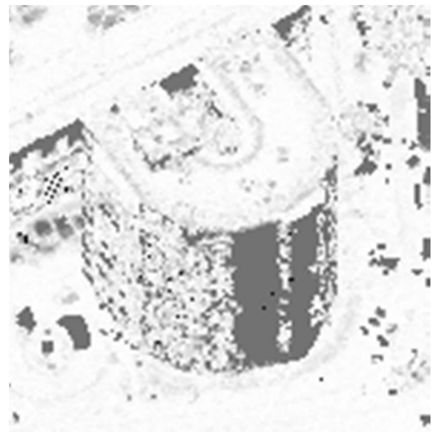


(b) SSM with 2010 dataset

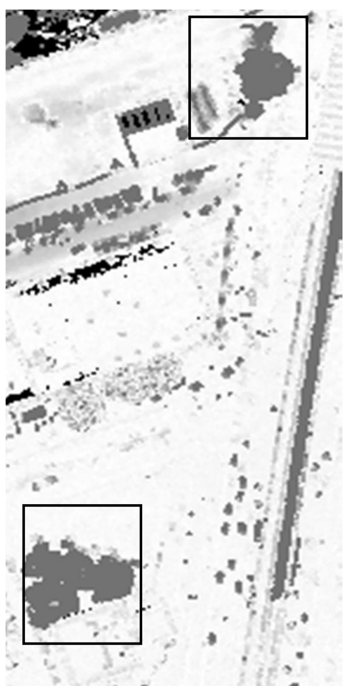
Figure 3-18: Trees in black squares were present only in 2008; there other trees with low separation values were present in both epochs



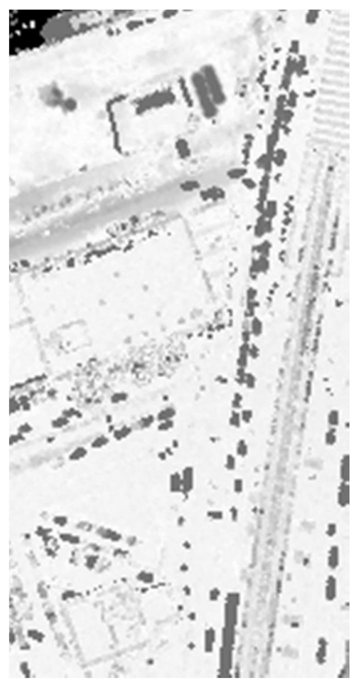
a. SSM with 2008 dataset



b. SSM with 2010 dataset



c. SSM with 2008 dataset



d. SSM with 2010 dataset

Figure 3-19: (a) Trees in black squares were present only in 2008 do show high separation values in this case; (b) The trees are not present in year 2010; (c) Trees in black square were present only in 2008; (d) The trees are not present in year 2010

Change detection workflow

The procedure followed for change detection is as in figure 3-20. To interpret the changes from the 3D separation map, points classified as trees (label 4) are selected like in figure 3-21. If high separation values greater than 2 meter are observed only in year 2008 from 3D surface separation map and not observed in year 2010; this means the changes detected by the SSM are of cut trees (trees that existed in 2008 but cut in 2010) and vice versa. Selection of vegetation points is followed by segment growing on the points. Since the segmentation results had a large number of isolated points majority filtering was done to assign the points to a segment. The most frequent segment number within a fixed neighbourhood is assigned to these points. Most trees still had multiple segments in them; connected component process was done to group the points of each tree into compact components. A Kd-tree was generated from the points and each component was labelled with a component number. The result of this process is as shown in figure 3-22.

An algorithm was created to calculate the percentage of points with separation values greater than 2 meters per component. Components with percentage greater than 90% were labelled as changed while the rest of the components were labelled as unchanged. 90% value was chosen because the changes we are looking at involve a change in the whole tree as a component. After trying several threshold values 90% was chosen as the best. The value is sufficient enough for detection of cut and planted trees while allowing for some error margin in the datasets. At this stage all changes detected in trees/ vegetation (cut and planted trees) are relevant to the user; so no need to further label the points.

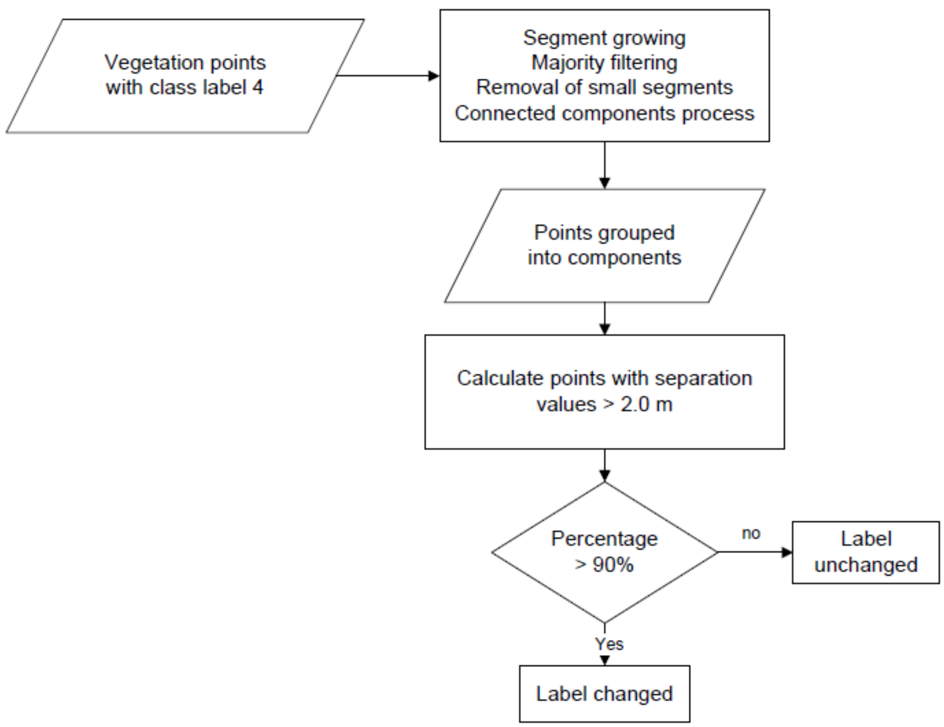
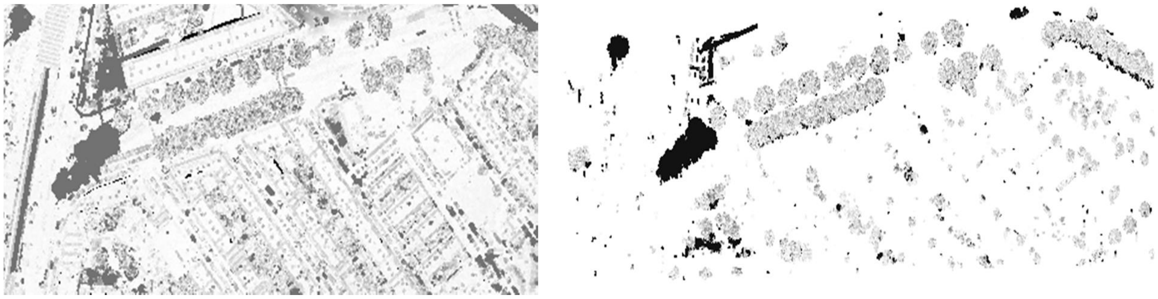


Figure 3-20: Vegetation change workflow



a. 2008 dataset b. Trees/vegetation from 2008

Figure 3-21: (a) shows a section of 3D SSM visualized by separation values; (b) vegetation visualized by separation values.

It observed that trees some trees (in black squares) in figure 3-22 (a) have multiple segments hence connected components is done as in (b)

a. Part 2008 dataset segmented (b) Part of 2008 dataset connected components

Figure 3-22: (a) Result of segment growing, (b) Result of connected component analysis

3.6. Quality assessment

The quality assessment of the change results achieved in buildings and vegetation is done by comparing them to ground truth points obtained from an aerial photograph that was acquired in year 2010. Assessment of ground changes is done by visual inspection and comparison of the changes to the SSM. This is because acquiring ground truth points for ground would be difficult since all parts of the ground are not well visible on the image.

3.7. Differences in change detection approaches for different classes of objects

Since the main aim of this research is to develop different approaches for change detection per class, we note the main differences in the approaches adopted as below:

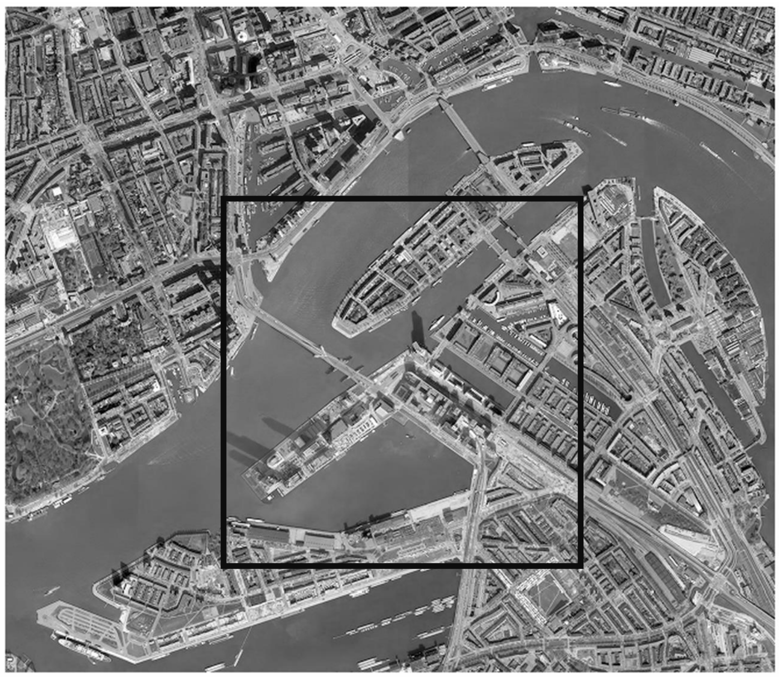
Table 3-3: Difference in change detection approaches used

Differences in change detection approaches	**Classes**		
	Building	Ground	Vegetation
SSM calculation	Based on 3D neighbourhood	Based on 2D neighbourhood (other objects are excluded)	Based on 3D neighbourhood
Appearance of changes in SSM	All real changes have high separation values in both epochs	All real changes have high separation values in both epochs	High separation values present in the epoch where the vegetation is present.
Grouping points together for change analysis	Surface growing algorithm	Connected components algorithm	Connected components algorithm
Threshold values for change detection	10 cm for small changes and 1 meter for large changes	15cm for changes on the ground surface	2 meters for cut and newly grown trees
Location of changes	Whole building/part of building/building element	On the surface of the roads/streets	Change of the trees as a whole component
Relevance of changes detected	Changes above 2 square meters in aerial coverage are relevant	Changes on the road/ street surface are relevant	Cut and planted trees are relevant changes

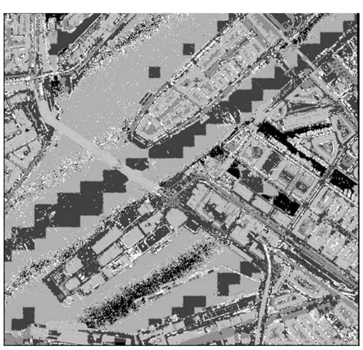
4. DATASETS AND RESULTS

4.1. Dataset

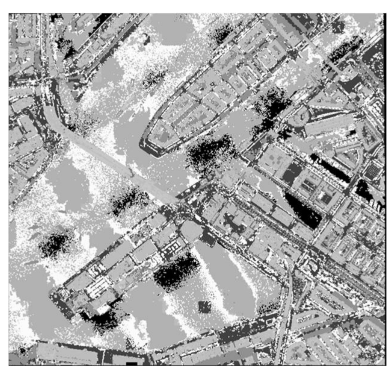
The input Airborne Laser Scanner (ALS) datasets were classified using multiple-entity classification strategy approach by Xu et al., (2014). Both datasets are classified into building, ground, vegetation, water and undefined objects as shown in figure 4-1 b & c below. The two datasets are located in the commercial area of Rotterdam. The point density for 2008 and 2010 are 30 pts/m2 and 35 points/m2 on average respectively. An aerial image acquired in 2010 was used for assessing the accuracy of the results obtained. The square black square on the aerial photograph shows the location of the study area.



a. location of the study area



b. 2008 data



c. 2010 data

Figure 4-1: (a) Location of study area on the aerial photograph acquired in year 2010 (b) & (c) classified input LiDAR datasets

Before starting any analysis some data preparation was done which involved creation of pyramid levels to make it easier to work with the data. Linear reducing factor was left default as 2, minimum 3D distance between points based on original points spacing of 0.2 reduction method was used. Both datasets have 6 pyramid levels. Further to prevent the surface separation map algorithm from crashing, a thinning factor of 2 was introduced.

4.2. Results

The change detection procedure for all the classes is composed of change detection, classification of the changes and assessment of the accuracy with which the changes were detected. The first steps include generation of a surface separation map and change identification using different approaches for different classes. All results are shown with the changes stored to one epoch depending on what kind of change is on display.

4.2.1. 3D Surface separation map for all classes

As mentioned earlier in chapter 3 generation of the surface separation map was done differently for different classes of objects. For building and vegetation the surface separation map was based on 3D neighbourhood and for ground class it was based on 2D neighbourhood. The surface separation map gives clues of where there are changes but further interpretation is applied to separate the changed from the unchanged points. The output separation values are saved in the first epoch for display

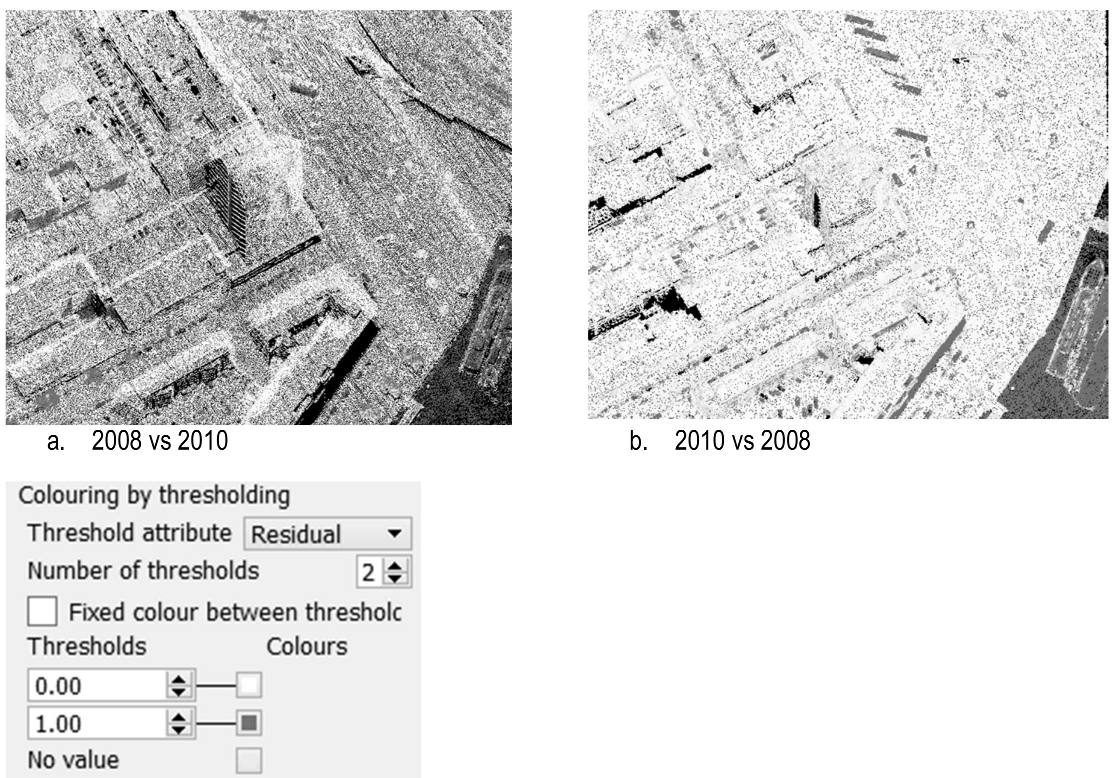


Figure 4-2: 3D Surface separation map calculated inclusive of all classes

Larger differences between the two datasets can be observed where the grey colour gets deeper. These are the areas where large changes have taken places. Large differences are also observed in places where there is lack of data in one dataset especially on water surfaces and occluded parts of buildings. In water high separation values are seen in both epochs, this is because point density on water is not the same for both epochs resulting to high separation values. The surface separation maps are the inputs of the change identification.

4.2.2. Building change detection

After the generation of surface separation map the expected changes are visually identified as they appear the separation map as discussed in section 3.5. This is followed by labelling the changed and unchanged parts of the buildings as shown in figure 4-3; changes visualized in this figure are greater than 1m.

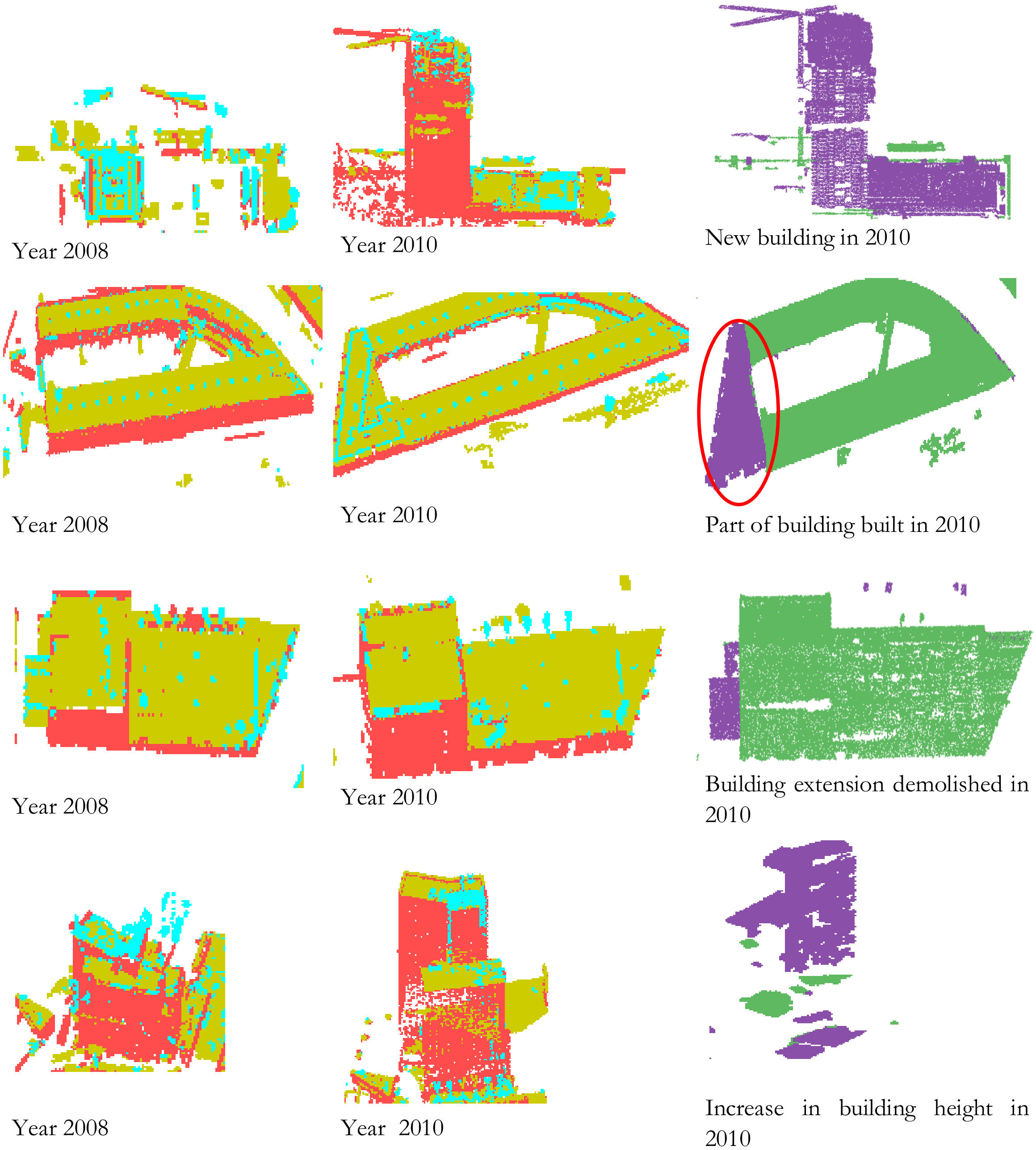


Figure 4-3: Examples of changes detected; the 1st and 2nd columns show the input datasets visualized by class labels and the 3rd column show change detection results, purple colour represents changed parts and green colour represents the unchanged parts of the buildings.

Some changes detected in buildings are not real changes. These are as a result of occlusion. For example only part of the wall of a building has changed like shown in figure 4-4. These were eliminated at a later stage by checking if the roof of the building has changed.

Figure 4-4: Changes due to occluded walls in red circles

Further the change results are separated into relevant and irrelevant changes based on the size of the roof of changed components. Components with a roof greater than 2 m2 meters which was found to be equivalent to 10 points in the data used (reduced version of the dataset) were labelled as relevant changes. The rest of the components were labelled as irrelevant, as shown in figure 4-5. The false changes resulting from occlusion were classified as irrelevant since the roof of the building is not changed. However, some of them were still labelled as relevant changes, this because parts of building roofs greater that 2 m2 have changed. This could have been as a result occlusion of some parts of the roof resulting to change on the roof. This could also be a result of a change of a building element on the roof.

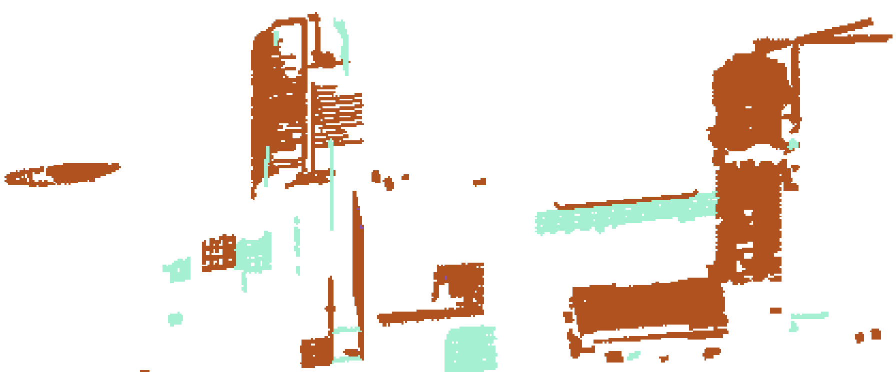
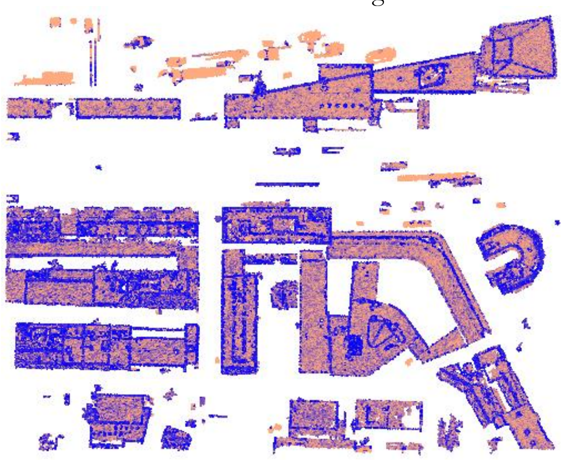
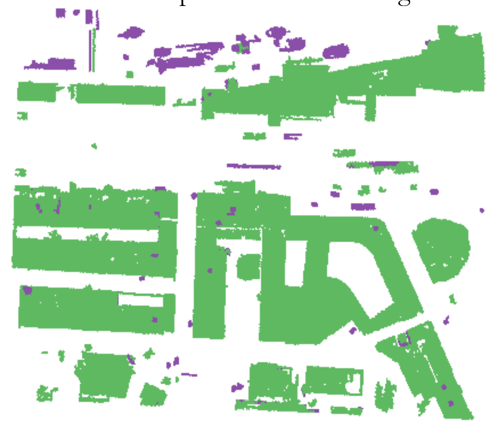


Figure 4-5: Brown components are the relevant changes and the cyan components are the irrelevant changes

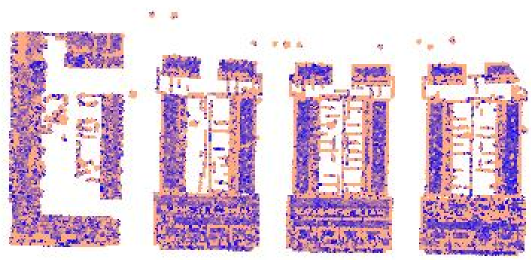
Small changes below one meter were also investigated. Small changes were detected by lowering the detection threshold to 10 cm. It is observed some of the small changed seen from on the SSM are not detected. This because they are due to small differences in point densities of the two epochs. By inspecting the separation values of the left out small changes; most of them were found to be close to 10 cm. It is also observed that lowering the threshold introduces more false positives in the change results.



a. 2008 vs. 2010 SSM

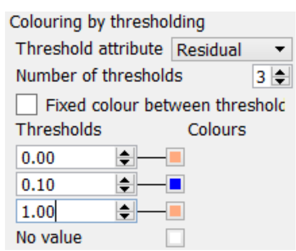


b. changes corresponding to SSM in (a)



c. 2010 vs. 2008 SSM

d. Changes corresponding to SSM in (c)



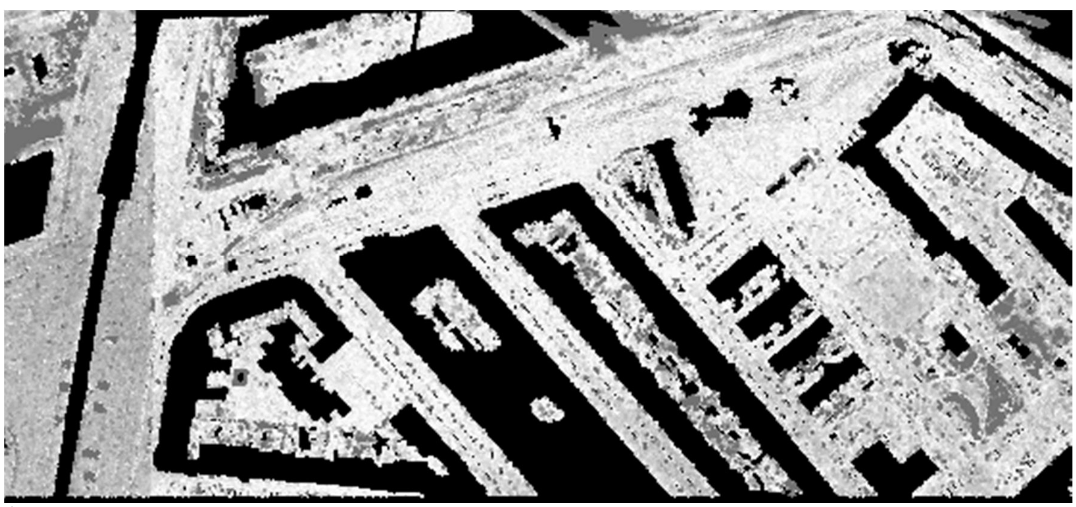
e. SSM thresholds in display

Figure 4-6: Result of detection of the small changes; in b and d purple represents changed components while green represents unchanged components.

4.2.3. Ground change detection

As discussed earlier ground SSM was generated separately in 2D neighbourhood. This helped eliminate false changes/ points with high separation values due to presence of dynamic objects on the ground surface. Results of the surface separation map are as below. Larger differences are observed in areas where there is deeper grey colour. Looking at the road surface most of it is more or less unchanged.

(a)2008 vs. 2010



(b)2010 vs.2008

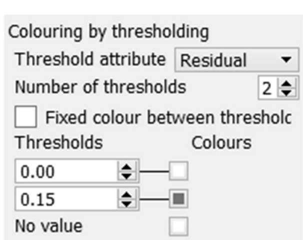
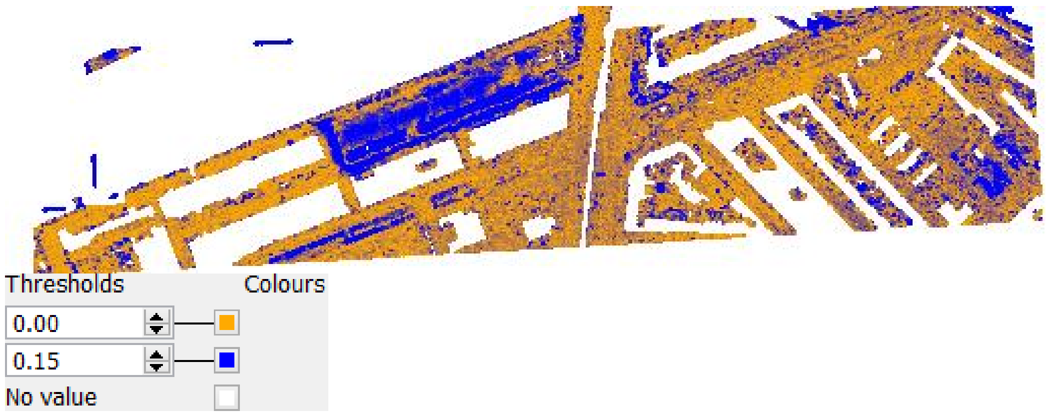


Figure 4-7: Ground SSM based on 2D neighbourhood

Changes on the ground were labelled by looking at the percentage of points per segment with separation values above the threshold set in the change detection workflow. Results of change detection are as in figure 4-8; it is clear there are a few changes on the ground surface this is due to differences in height values on those particular areas between the two epochs. However, the changes don't show any pattern. These changes could be as a result of small repairs on the road surface causing height differences. Comparing the SSM and the change results, it is observed that all the changes as per SSM are depicted in the change results.

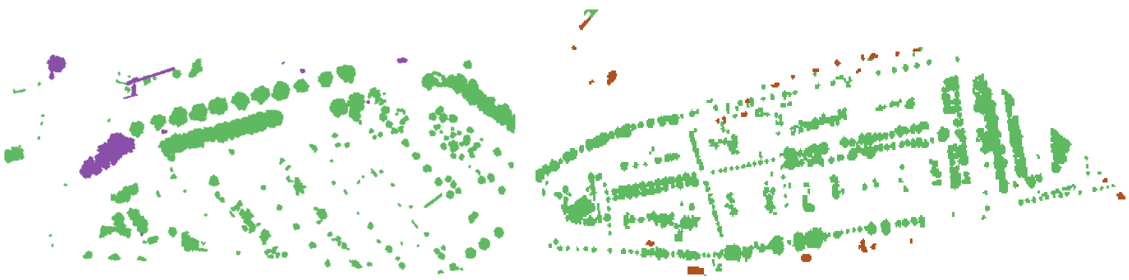


a. 2008 vs. 2010 SSM showing separation values

b. Ground changes green represent unchanged while purple represents changed components
Figure 4-8: Ground changes

4.2.4. Vegetation change detection

The expected changes were identified as they appear in the separation map as highlighted in section 3.5. As mentioned earlier cut and planted trees are the changes of interest in this research. It is observed that cut or planted trees have high separation values (greater than 2 meters) which are observed in the epoch in which the trees are present. For example, if a tree was present in 2008 and cut in 2010, high separation values area observed in 2008; whereas there will be no separation values observed when 2010. So to detect cut trees in the period 2008-2010, separation values stored in 2008 dataset are used and to detect planted trees, separation values stored in 2010 data are used. The points of cut or planted trees are labelled as changed and the other trees that were present in both datasets are labelled as unchanged.



a. Part of 2008 data cut trees shown in purple colour

b. Part of 2010 data planted trees are shown in brown colour

Figure 4-9: (a) shows some of the trees that were cut (in purple colour) during the study period in; (b) shows some of the trees that were planted (in brown colour) during the study period; in the diagrams green colour represents unchanged trees

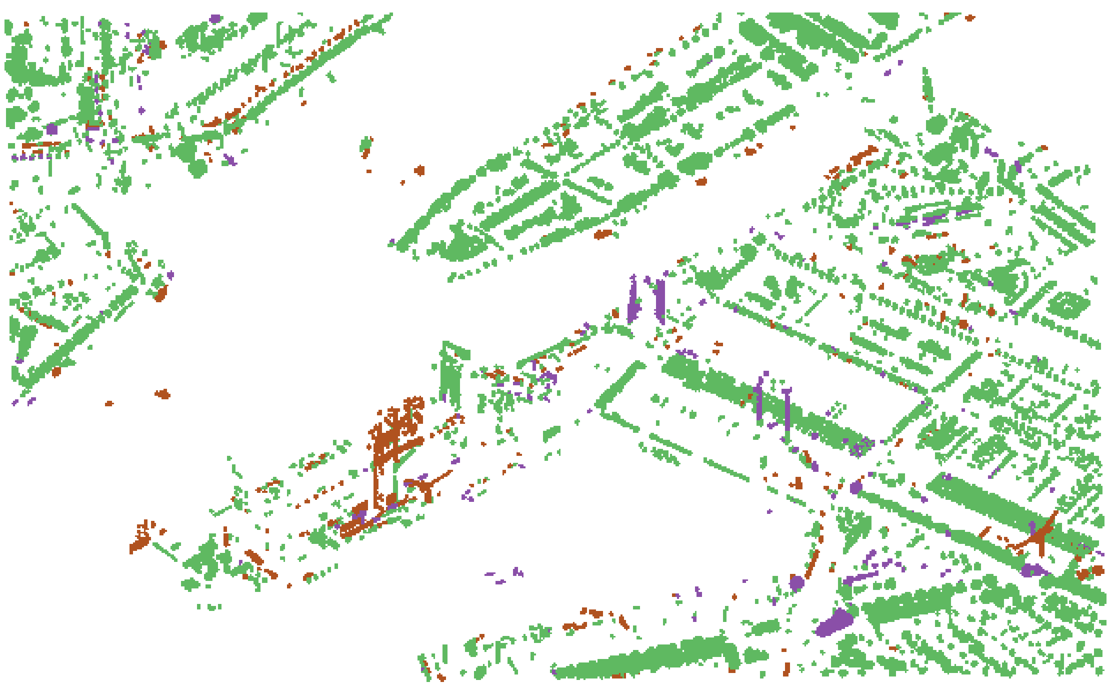


Figure 4-10: Overview of the trees in the whole study area, purple colour represents cut trees, brown colour represents planted trees and green colour represent unchanged trees

From figure 4-10 it is observed that some of the objects detected as cut and planted trees are not really trees, this is due to classification errors in the input data as discussed later in the document. Elimination of these errors can be done by different methods for example use such attributes as component size, height span, minimum height, colour, reflectance, normal and plane residual (Wen Xiao et al., 2012). However, this is out of scope of the objectives of this research.

4.3. Accuracy analysis and error description

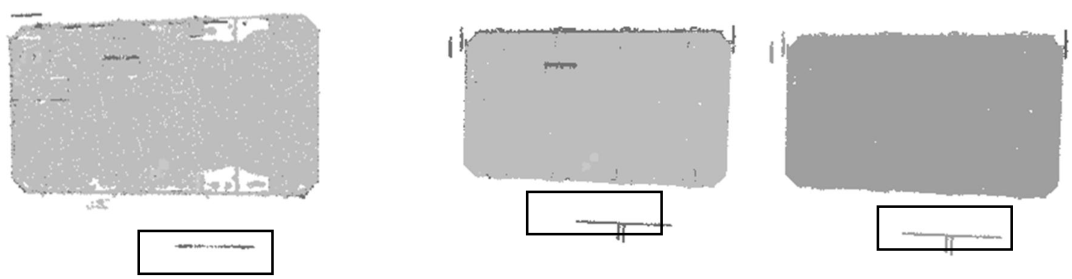
The purpose of performing evaluation of the change results is to help determine the quality of change detection approaches used per class in terms of accuracy and also to determine how classification errors of the input data influence the change results obtained. In this study evaluation of results was carried out using an aerial photograph acquired in 2010 as the reference dataset.

4.3.1. Change detection error due to scene classification error

The surface separation map was generated from already classified input data. To separate the objects in the separation map, selection is done using the classification labels. This follows that classification errors in the scene classification are transferred to the change detection stage.

False positives (for example a non-building object is detected as a change in building)

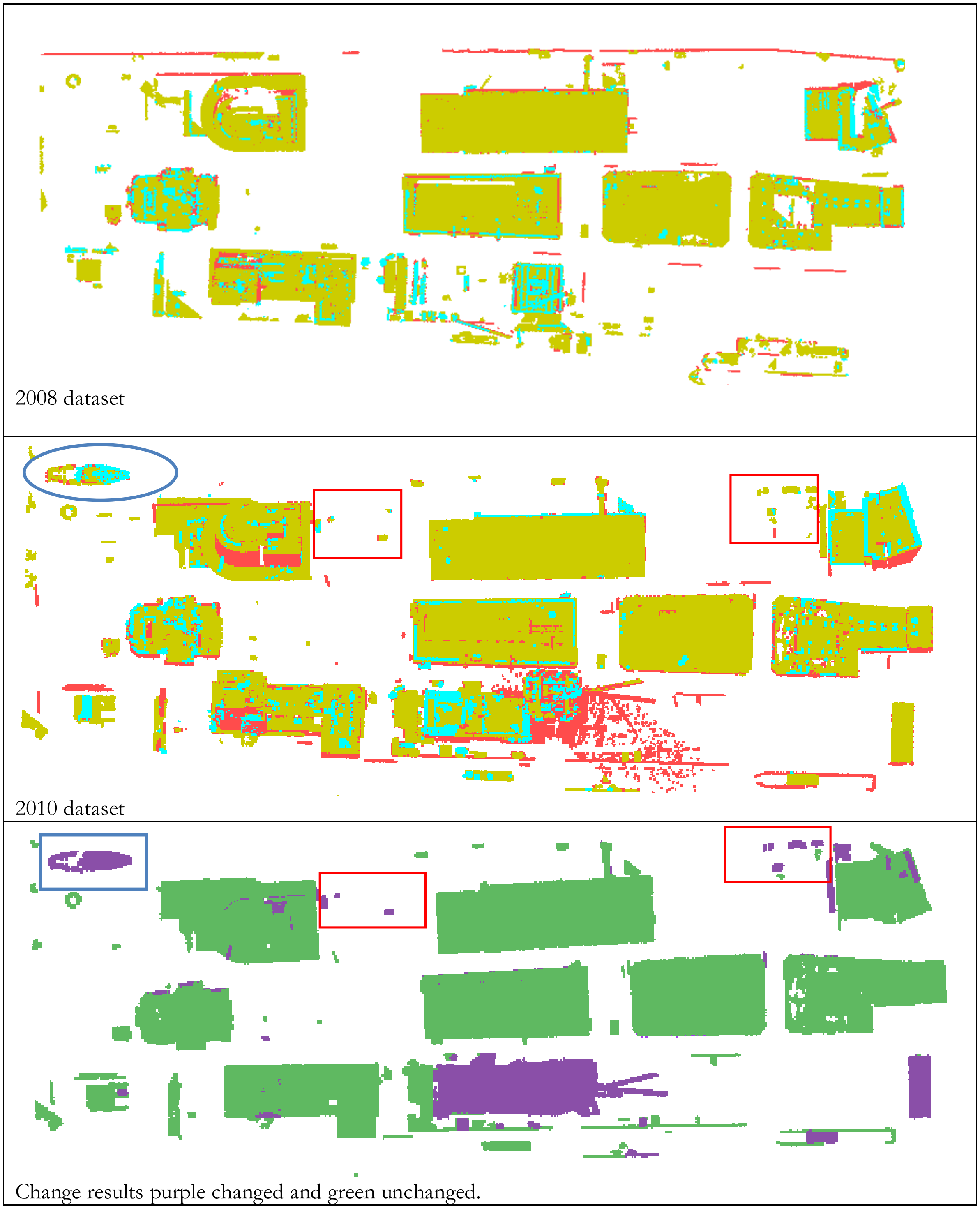
This happens when there is scene misclassification error in one epoch. Since the scene class labels are used for separation of different objects for change detection, wrongly classified objects end up in the wrong class. If there is no change in the wrongly classified objects, false positives will not occur in the output change results as shown in figure 4-11; the object in black squares was misclassified as a building wall (label 7) in both 2008 and 2010 datasets. Because there is no change in the object it did not appear among the changed parts of the building.



a. Year 2008 b. Year 2010 c. No change detected

Figure 4-11: False positives avoided even if there is error in classification; (c) represents unchanged building parts

False positives cannot be avoided if there is a change in the misclassified objects. For example, some vehicles on the ground were classified as buildings during scene classification. These were present in 2010 and absent in the 2008 resulting into a change under class building as shown in figure 4-12 (in red squares). The boat in a blue circle was not present in year 2008 and it was misclassified as a building in 2010. As a result it appeared in change results. These false positives were confirmed from the aerial image that was acquired together with LIDAR dataset in year 2010 as in figure 4-13.



2008 dataset

2010 dataset

Change results purple changed and green unchanged.

Figure 4-12: False positives in building changes due to classification errors

Figure 4-13: Aerial image showing the ground truth of false positives in buildings in 2010 as in figure 4-12

Some false positives are also found in vegetation change results. Some road furniture and part of building walls were wrongly classified as vegetation and hence they appeared in change results since they were present in only one epoch. Some of the false positives were avoided because no change had taken place as in figure 4-14.

Figure 4-14: Features in blue squares are false positives avoided, and features in red square are false positives in vegetation changes

False negatives

This happens for example when a change is detected in an object that was not classified correctly in both epochs during scene classification. This change will not fall in the correct class of objects and this leads to false negatives. In figure 4-15, a real change in building occurred but since parts of the building were classified as vegetation the change ended up in vegetation class. When either of the dataset is correctly classified false negatives can be avoided.

a. 2008 displayed by class label b. 2010 displayed by class label c. Change result

Figure 4-15: Example of false negatives, in (c) brown colour represent changed components and green colour unchanged components

Additionally, some objects like construction cranes were detected as part of building changes. However, further analysis of these kinds of changes is beyond the scope of this research so they were left in the change results. For example the construction crane (in red circle) in figure 4-16 was detected as part of building changes.

Figure 4-16: The part in red circle is a construction crane that was labelled as a building change.

4.3.2. Change detection error due to change detection method

By visual inspection it was noted that some unchanged walls are classified as changed. This was also confirmed from the aerial images as in the figure 4-17. The approach used for building change detection, has the assumption that if the roof of a building has not changed then the walls have not changed; meaning the building is unchanged. In case part of the roof greater than 2 m2 was occluded causing a change, the false changes on the walls were not eliminated by our method. Some of them remained in the final results for example the wall in figure 4-17 a.

a. occluded wall labelled as relevant

b. occluded displayed by class label

c. red walls corresponding to the building in a.

Figure 4-17: False changes on the walls

The wall was labelled as a relevant change by our algorithm because it was connected to a part of changed roof (in black circle) that is greater than 2m2. This could be solved my increasing the threshold.

4.4. Accuracy analysis

Accuracy assessment on the changes detected was done by comparing the changes an aerial photograph that was acquired together with LiDAR dataset of 2010. Since only 2010 aerial photograph is available from municipal of Rotterdam, the task was to compare the changed objects with the 2010 image and verify whether they really exist on the ground on not; depending on the type of change that is detected. For example if a tree was planted in year 2010, the task was to confirm whether it's really there on the aerial photograph or not.

All vegetation and building changed components were converted to CSV files and loaded to ArcGIS. Polygons were created for each of the classes to make overlay with the aerial image easier. 30 and 39 random samples were selected for building and vegetation respectively. Ground truth points were digitized and error analysis carried out as follows: Correctness, completeness and quality of both vegetation and building changes were evaluated. Correctness represents the percentage of correctly detected changes while completeness presents the percentage of the reference data. Quality is a measure of how bad or good change detection results are; it combines both correctness and completeness together. These measures are determined by considering three classes of factors per category of objects including true positives (TP), false positive (FP) and false negative (FN). The formulas are as shown below according to McKeown & Bulwinkle, (2000).

$$\text{Completeness} = TP / (TP+FN)$$
$$\text{Correctness} = TP / (TP+FP)$$
$$\text{Quality} = TP / (TP+FN+FP)$$

Table 4-1: Completeness and correctness of the change results

2008 vs.2010 changes					
	True positive	False positive	False negative	Correctness	completeness
Building	18	12	5	60%	78%
Vegetation	28	11	0	72%	100%

Table 4-2: Percentage of error due to Scene classification and errors due to change detection methods

	False Positive		False negatives		
Building	12	11	5	5	Errors due to scene classification (94%)
		1		0	Errors due to limitation of change detection method (6%)
Vegetation	11	9	0	0	Errors due to scene classification (82%)
		2		0	Errors due to limitation of change detection method (18%)

Accuracy assessment of ground components has not been done using aerial image because it is difficult to obtain reference samples since all parts of the ground are not well visible from the aerial photograph.
In building some of false positive were due to our method, this was as a result of some cases as explained in section 4.3.2. Vegetation some of the errors were due the season when the data was acquired. Some trees were present in the aerial photograph but they had no leaves. These trees had very low point density in the LiDAR data hence were in case there is a change it was not detected by our method.

5. CONCLUSION AND RECOMENDATIONS

5.1. Conclusion

Different change detection approaches for different classes have been presented in this research. These were developed to meet the objectives of the study and answer the research questions. The research began with identification of geometric properties of the objects in urban areas, this involved description of the expected changes per class including their magnitude in section 3.2. Further the appearance of expected changes in the surface separation maps was discussed. This was followed by development of change detection approaches per class of objects in section 3.5. Finally, accuracy analysis and error description was done in section 4.3 including a discussion of how the classification errors affected the quality of the change detection results.

The following conclusion can be drawn from the different approaches applied for change detection:

- Use of 3D Surface separation map method as the first step of getting change clues provided a good basis for change detection for buildings and trees.
- Surface growing has proven to an efficient algorithm to group building points in compact segments for further analysis. 2D connected component analysis on building changed points was efficient enough in grouping a changed building into one compact component.
- Generation of surface separation map method based on 2D neighborhood for ground points was able to avoid false changes due to dynamic objects like cars. Further grouping of ground points using connected component algorithm was observed to be advantages since ground surface are not perfectly flat.
- Connected components algorithm was also found efficient in clustering tree points together for further analysis of changes.

Changes in all the classes i.e. building, ground and vegetation can be correctly detected and classified using our change detection method provided that the input data set is correctly classified. The correctness for building was found to be 60% and for trees/ vegetation was found to be 72%. Separation of relevant and irrelevant changes was faced by errors as a result of scene classification and also some limitations in the methods used.

Our change detection method detected larger changes for example changes on a whole building with higher accuracy. However, reduction the threshold to 10cm to detect smaller changes in building was observed to introduce more false positives in the results. Changes on trees were detected with high accuracy; the errors present are due to scene classification errors. Improvement of scene classification methods would be necessary since the change detection methods developed in this research are class-based.

All the objectives of the research were achieved and the research questions answered by the approaches developed.

5.2. Recommendations

The proposed methods were feasible enough to achieve the research of objectives of this research. However, improvements could still be made since the achieved results are not perfect, hence the following recommendations:

- The study area was only a small part of city of Rotterdam in future analysis could be run on the whole city to achieve more feasible results that would be of help to the municipality of Rotterdam.
- Classification of the input data introduced errors in the change detection results because some objects were misclassified to the wrong classes; the classification method could be improved for better results in future. Also incorporating more factors to separate relevant and irrelevant changes in the results would improve the methods used for change detection.
- For accuracy assessment aerial images of both epoch acquired at the same time with the LiDAR data would be more helpful for accuracy assessment in future. Also having GPS acquired ground truth points for ground class, would be helpful for quality assessment of ground changes.

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