Voxel-based vegetation change detection using multi-source data

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Abstract

Detecting vegetation changes finds its application in several important areas, including city planning and urban science, climate change and ecological research. Several sensors and approaches can be used to measure the 3D geometry of vegetation, including aerial, mobile and terrestrial laser scanning, and photogrammetry. Other historical data sources, such as 2D shapefiles might also be available, however, the use of multi-source data presents challenges for vegetation change detection. This study presents a voxel-based approach to vegetation change detection from multi-source datasets, including laser scanning and 2D shape files from different years. A novel Octree data structure is utilised in this work that supports different operations for efficient vegetation change. We demonstrate the strengths of the approach with a case study to discuss the challenges and the future directions.

1. Introduction

Vegetation has inter-annual and seasonal variations and is a natural connection between soil, atmosphere and water. Vegetation change, to some extent, can represent the change in urban land use and reflect the trend of climate change (Sarkar and Kafatos, 2004). A good urban greening layout can not only improve air quality but also improve the urban microclimate or the mental health of residents. Additionally, vegetation resources have certain social and cultural values. For example, the protection and rational utilisation of historical vegetation, and ancient and famous trees are of great significance to the inheritance of culture and history (Stilla and Xu, 2023). Therefore, real-time monitoring of vegetation changes helps to assess the rationality of urban planning and the health of urban ecosystems. As a rapidly developing technology, digital twins provide an opportunity to dynamically display vegetation changes and summarise historical changes (Zhao et al., 2022). This can provide scientific support for ecological protection research.

Vegetation has complex morphological and distributional characteristics, resulting in occlusions, and limiting traditional photogrammetry in dense forests. 2D image-based change detection is also prone to distortions in the process of recovering 3D spatial information (Abellan et al., 2016). Several laser scanning platforms are available, each having its advantages and limitations. Airborne Laser Scanning (ALS) has a wider coverage and provides additional information regarding the tree structures and the terrain, however, the ALS projects are extremely costly, the point density might be very low and the accuracy is inferior to other platforms (Homainejad et al., 2023). Terrestrial Laser Scanners (TLS) provide extremely precise and very high-density points of the trees, however, they are limited by occlusions, very low coverage and high time requirements for scanning. In contrast, a Mobile Laser Scanner (MLS), such as the backpack mobile measurement system has the characteristics of flexibility, portability, high accuracy and wide coverage, and the acquired point cloud data can accurately reflect the 3D structure of vegetation. The derived point clouds facilitate the calculation of individual tree and forest parameters, such as tree height, DBH, canopy cover, etc., to achieve refined forestry management (Hirt et al., 2021), and can be used for change detection tasks as well.

The modelled urban vegetation can be integrated with digital twin platforms to construct high-fidelity 3D urban green space models. This provides great convenience for the comparison of historical data and newly collected data for the dynamic monitoring of urban vegetation change. However, the unstructured nature of point cloud data presents several limitations for the comparison of data coming from multiple sources (platforms), having significant variations in point density and precision. Converting point clouds into voxels and then detecting their changes has proven to be very effective in many studies. Voxel-based representations are particularly beneficial for organising the spatially dense, irregular data found in point clouds, facilitating neighbourhood and value operations. A voxel represents a cubic unit in 3D space, akin to a pixel in 2D imagery, which can help with segmentation, classification, and further analysis (Poux and Billen, 2019). The process of voxelisation involves mapping point cloud data into a regularly spaced grid, where each voxel encompasses points that share similar characteristics or spatial proximity. Voxels have been used in many studies for vegetation modelling either for volume estimation to support preventive burning (Barton et al., 2020) and tree reconstruction (Gorte and Winterhalder, 2004) or for investigating the effect of trees on microclimate (Xu et al., 2021).

In this paper, we present a voxel-based approach to compare scans of urban trees from different years coming from other sources (aerial and mobile laser scanning and 2D footprints of the trees in the form of shapefiles) and estimate changes in vegetation cover. We voxelise the point clouds from two or multiple years with a specific voxel resolution, which is determined by the point density of the scans, and organise them in an octree-data structure designed for processing large datasets. We use existing vegetation footprints to roughly identify the voxels that belong to the vegetation cover extension. We perform morphological and overlay operations to estimate vegetation changes. Depending on the area to be processed and

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the voxel resolution, the voxel models can become very large and can affect the performance time and lead to memory overload. The approach presented in this paper relies on a novel octree data structure, organised in SQLite as presented in Gorte et al. (2024). The octree structure supports several operations for voxel processing, which are to be employed for vegetation change detection. The paper elaborates on the approach, presents the results of the experiments merging multi-source data, and outlines directions for future improvements.

Section 2 introduces the point cloud and voxel-based vegetation change detection approaches. Section 3 presents the method, and we present experiments and results in Section 4. This is followed by discussions and conclusions.

2. Background

2.1 Point Clouds for vegetation change detection

The capability of LiDAR to provide high-resolution, 3D spatial data allows for detailed analysis of vegetation structures. Recent studies have explored various applications of LiDAR in monitoring urban trees and analysing forest dynamics over time. Tompalski et al. (2021) provided a comprehensive review of methods for estimating changes in forest attributes using airborne 3D point cloud data. They highlighted the potential of bi-temporal and multi-temporal point clouds for detailed analysis of forest structure changes that offer valuable insights for both analysis and future projections. LiDAR-based matrices and multi-temporal ALS point clouds have also been utilised for continuous forest mapping by performing change detection using vegetation height and canopy cover (Szostak, 2020). Additionally, automated tree segmentation and change detection in large urban areas have been performed using ALS data for robust quantification of tree heights and value variations using dynamic scaling to extensive regions (Fekete and Cserep, 2021). Holopainen et al. (2013) compare ALS, MLS and TLS data for tree mapping in an urban setting and analyse several well-established approaches for tree detection and localisation, however, they did not perform any change detection or utilise voxel-based approaches.

2.2 Voxel-based vegetation change detection

Several approaches have been proposed in the literature that utilise voxels for vegetation change detection. Liu et al. (2016) perform change detection using Apache Spark-based cloud computing and voxels, where they use MLS data from two different sensors, however, their study involved testing the algorithm on simulated and building data only. Gehrung et al. (2018) proposed a voxel-based metadata structure for change detection in large-scale urban areas using MLS data. Their method employs a plane-filtered raycasting algorithm to eliminate discretisation artefacts near planar structures, significantly improving the accuracy of volumetric representations. Wu et al. (2018) compare MLS and ALS data for mapping individual trees by utilising voxels for segmenting tree parts into single trees. Further, they mapped the vitality of the trees using infrared imaging. However, they did not perform any change detection.

Zieba-Kulawik et al. (2021) calculate urban indices such as Vegetation 3D density index and Vegetation Volume to building volume modelling urban space, and use voxel-based point cloud processing using only ALS data. Hirt et al. (2021) use MLS data from two different systems in tracking changes in urban tree structures, where they introduced an object-based change detection approach using occupancy grids to compare point cloud data across multiple time epochs. By segmenting tree objects and analysing geometric variations, the research demonstrated the ability to monitor tree growth, health, and potential hazards affecting urban infrastructure. Fang et al. (2023) proposed a semantic-supported change detection method using ALS point clouds, achieving high-precision segmentation and detection by integrating an improved PointNet++ framework with voxel-based comparison. Their approach effectively filters out non-target changes, enhancing detection accuracy.

Li et al. (2024) proposed a voxel-based method for modelling 3D forest scenes by integrating terrestrial and airborne LiDAR data. The authors combine high-density, fine-scale details from TLS data with the broad coverage of ALS data to generate detailed forest models over large areas. This method faces challenges such as computational cost and species classification accuracy, which require further optimisation and data integration. D'hont et al. (2024) use MLS, TLS and ALS data for estimating several parameters of trees, such as DBH, tree height, crown area, etc., and analysed how each sensor contributed to the errors in estimating the parameters. They used voxelisation for preprocessing the data and comparing it with ground truth, however, they did not specifically perform any change detection.

3. Methods

As mentioned above, an octree data structure is pivotal. Voxels create a regular grid that is used to map the point clouds. Fine-resolution voxels are advantageous when high accuracy is required, but the size of the voxel space can grow exponentially when large areas are considered. As a result, the performance can be affected and the computer memory might become insufficient. Therefore, the storage and processing of the octree has to be on the disk.

Instead of creating one large octree, we subdivide the entire area of interest into cells each containing 64x64x64 voxels, where each cell is an independent octree. The octree is designed to maintain volumetric objects but can accommodate any unstructured data. A geo-reference is maintained, which relates 'real world' coordinates (X, Y, Z) (in metres) to integer grid coordinates (x, y, z). For example, (X, Y, Z) = (X_0, Y_0, Z_0) + R $*$ (x, y, z), where R is the voxel resolution. The range of (x, y, z) is between (0, 0, 0) and $(x_{max}, y_{max}, z_{max})$, which defines the size of the particular voxel layer.

The octree mechanism allows to maintain a multi-resolution voxel pyramid. The voxel pyramid has seven levels with resolutions: 0.2m, 0.4m, 0.8m, 1.6m, etc. The finest resolution is at the bottom of the octree, i.e. level 0. The resolution gets coarser as the level goes up. Each voxel has one value, which is converted to a key via a Key-formula, which is then linked to the voxel value (V): (x, y, z, L) $\longleftrightarrow$ key (K) $\rightarrow$ value (V). The values are stored in SQLite database.

The octree is storage optimised by applying a dedicated function which compresses repetitive voxel values of lower levels. In the case of unclassified point clouds, only two 1-voxels contain one or more laser points, and the 0-th voxel is 'empty'. The compression works as follows: Assuming at level L_1 only two (out of eight) voxels are explicitly stored with values 1, and the other six are assumed to be 0. The values 1 and 0 are the values for the corresponding cells at level L_2. This means that if a voxel (x, y, z, L) is present in the octree database, so is its value, otherwise, we have to go up the levels until we find a cell that contains (x, y, z) and take the value from there. More details for cases, when more than two values are available in the points, can be found in Gorte et al. (2024).

Several generic functions are provided to analyse the data in the data structure. For this paper, OTover, OThist and OTras are of primary interest. Additionally, the processing of point cloud data invokes several 2D raster operations as well.

OTover (octree Xin, octree Yin, octree out, function O (x,y), function A(a)). The operation OTover takes two input voxel layers and produces an output by applying a function with two parameters. For example, if we have two voxel layers representing vegetation point clouds obtained in time T_1 and time T_2 (where T_1 ¡ T_2), the operator allows us to integrate them and compute 1) overlapping voxels, 2) the voxels that exist in layer T_1 but not in T_2 and 3) the voxel that exists in T_2 but not in T_1. The result can give indications for change detection in the case of volumetric objects as follows: 1) noting has been changed, 2) some (parts of) objects might have been removed and 3) some (parts of) objects might have been added.

OTras (octree in, 3D raster out, boundB, resL, dataT). OTras operator performs an octree-to-raster conversion and thus prepares the data for visualisation or manipulation in the computer memory. Furthermore, OTras handles parameters, which allow one to specify a bounding box (BoundB), a resolution level (ResL), and an output data type (byte, short, int) (dataT).

OTfilter is a generic algorithm to perform 3D neighbourhood operations on voxel datasets. The operator has several parameters such as an array of coefficients, which is used as a kernel in convolution operators, or as a structuring element for mathematical morphology use.

OTprofile collects the vertical profile at each (x, y) position of a voxel and passes it as an array of voxel values to a user-specified profile-analysis function. For example, to encode the lowest voxels of trees into DTM.

OThist (octree in, hist out, resL) produces the histograms of a voxel data set at a specified resolution level. For example, the histogram of the number of points within voxels.

4. Experiments and Results

4.1 Dataset

Mobile LiDAR backpack, 2024: The data collection system utilised in this study is a backpack-based mobile mapping platform. This system, designed and built by our laboratory at PolyU, incorporates two Hesai XT LiDAR sensors, each capable of achieving an accuracy of up to 3 cm. The configuration consists of a 32-channel LiDAR mounted horizontally and a 16-channel LiDAR positioned at an oblique angle, a high-resolution panoramic camera, and a precise GNSS module. It is worth noting that the horizontal LiDAR field of view experiences partial obstruction due to the presence of two structural support columns. Positioned directly above the horizontal LiDAR is a high-performance 3DM-GX5-25 IMU, which offers pitch and roll errors of 0.25 degrees and a yaw error of 0.8 degrees, ensuring a reliable baseline for motion estimation. The IMU operates at an output frequency of up to 500 Hz. With integrated SLAM and GNSS navigation technology, it can obtain georeferenced high-resolution panoramic images and high-precision 3D point cloud data even with high accuracy.

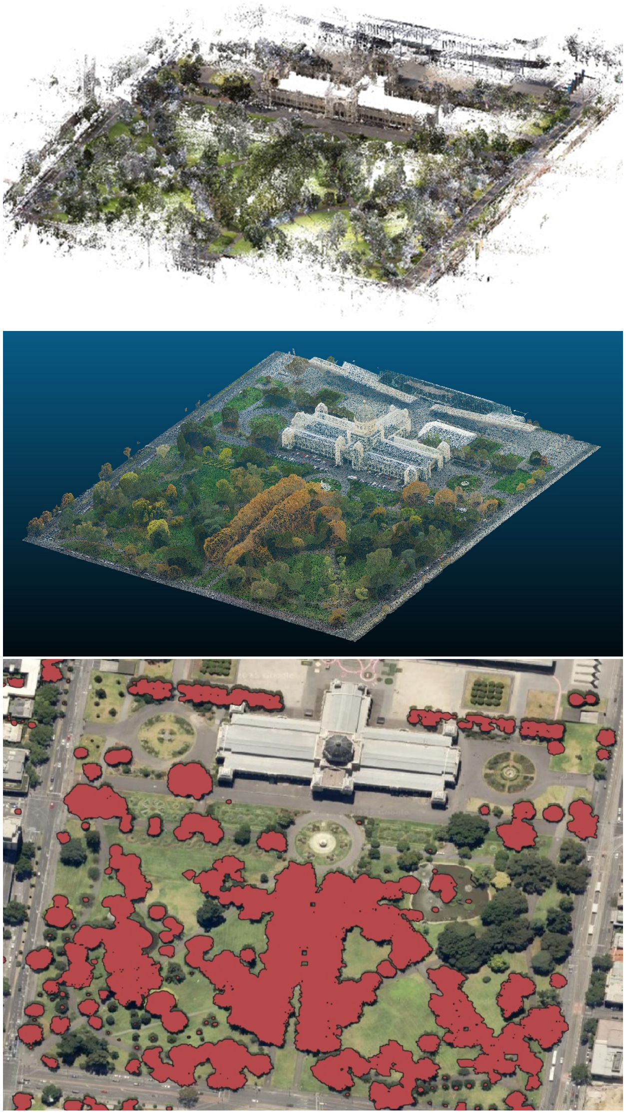

Figure 1. Top: 3D point cloud of Carlton Gardens captured by the backpack mobile mapping system. Middle: Aerial LiDAR data. Bottom: Canopy footprints derived from shapefile.

A dataset was captured using the backpack mobile mapping system in Carlton Garden, a historic public park located in Melbourne, Australia. This UNESCO World Heritage-listed site features diverse vegetation, including large trees, manicured lawns, and ornamental flower beds, making it an ideal location for testing vegetation change detection methods. The garden's complex structure, with varying canopy densities and different plant species, provides a challenging yet valuable environment for evaluating the effectiveness of MLS-based change detection. The processed point cloud data, visualised in Figure 1 (top), showcases the detailed 3D representation of the garden, enabling voxel-based vegetation analysis.

City of Melbourne Aerial LiDAR. 2016[1]: This data covering

[1] Data download available at: https://www.land.vic.gov.au/maps-and-spatial/imagery/elevation-data/major-lidar-projects/greater-melbourne-lidar-2017-18

Figure 2. Aerial point cloud with spurious points floating above and below the scene

Figure 3. After removal of spurious points

the Carlton Gardens was collected from Department of Transport and Planning (DTP), Victoria. This data was collected during 2017-2018. The dataset covers all of Melbourne's urban and peri-urban regions, representing the most accurate and consistent depiction of Melbourne's ground surface, tree cover, and built environment. For quality assurance, the project utilised the QA4LiDAR software developed by FrontierSI, for automated quality checks to ensure consistency throughout the 13,000 km^2 extent. The data is a classified and geo-referenced point cloud having a density is 8/m^2 (first return). Figure 1 (middle) shows the visualisation of the aerial LiDAR data.

Tree Canopies 2016 (Urban Forest)[2]: This data was collected from the public website of Data Victoria. This dataset contains tree canopy polygons that represent actual tree canopy extents (footprints) on both private and public property across Melbourne City. The mapping was done using aerial photos and LiDAR in the year 2016. The frequency of new data collection is approximately every year. Figure 1 (bottom) shows the location of the tree canopies.

Based on the available aerial and mobile point cloud data, as well as vegetation footprints, a workflow was established to transform the data into a database of voxel layers.

4.2 Geo-referencing, voxelisation and cleaning

The voxel layers in the database share a common geo-reference w.r.t. the EPSG:7855 CRS. The aerial point clouds were already given in EPSG:7855, but the mobile point cloud used its local coordinate system and therefore had to be geo-referenced first. This was done using CloudCompare software, by selecting tie points in the mobile and the aerial datasets and applying an affine transformation. Next, a rectangular window was chosen from the aerial point cloud that precisely covers the mobile points (although these do not fill the entire rectangle).

After this, the 2 point clouds are voxelised by applying the following steps:

- Subtract the minimum window coordinate (left-front-lowest corner of the voxel space) from all coordinates
- Divide by the voxel resolution - we used 0.2 m (i.e. the high-resolution in the octree database)
- Truncate to integers
- Remove duplicates (alternatively: count how many times each truncated coordinate occurs, if an occupancy grid were desired)
- Submit the results to be stored in the voxel database system

The voxelised point clouds allow for tackling the unexplained "noise" in the aerial dataset: spurious points floating above and below the scene (Figure 2). Those points can now be removed quite effectively: we removed each point that has no other points present within a certain distance (we chose 4 voxels = 0.8 m), see the cleaned output in Figure 3. This could be implemented as a local (neighbourhood) operator, or (as was done here) by using nearest neighbour software like FLANN[3]. Below we use the "cleaned" point cloud.

4.3 Footprints

The vegetation footprints were given in a shapefile in a geographic (latitude-longitude) coordinate system. Using OGR and GDAL software (`www.gdal.org`), the coordinates were converted to EPSG:7855, and a window was selected covering the area of the study. This produces a new shapefile, where all objects (i.e. footprints) that intersect the window are entirely present. The result may be larger than the specified extent. It can be cut to size in the subsequent 2D rasterisation step, such that the (x, y)-extent exactly fits the point clouds, and has the same 0.2 m resolution. The rasterised footprints were dilated by three pixels (0.6 m) in $\pm$ x and y directions, to account for the possibility of trees widening during the period between footprint and point cloud production. After storing the pixels (as voxels with z=0) in the database, the footprints are elevated multiple times to cover the entire height of the voxel space.

4.4 Height shifts and correction

Combining aerial (grey) and mobile (blue) point clouds in a single image (Figure 4) demonstrates the effect of the different viewing directions of both sensors, emphasising the top vs.

[2] Data download available from `https://discover.data.vic.gov.au/dataset/tree-canopies-2016-urban-forest`

[3] Available at: `https://github.com/flann-lib/flann`

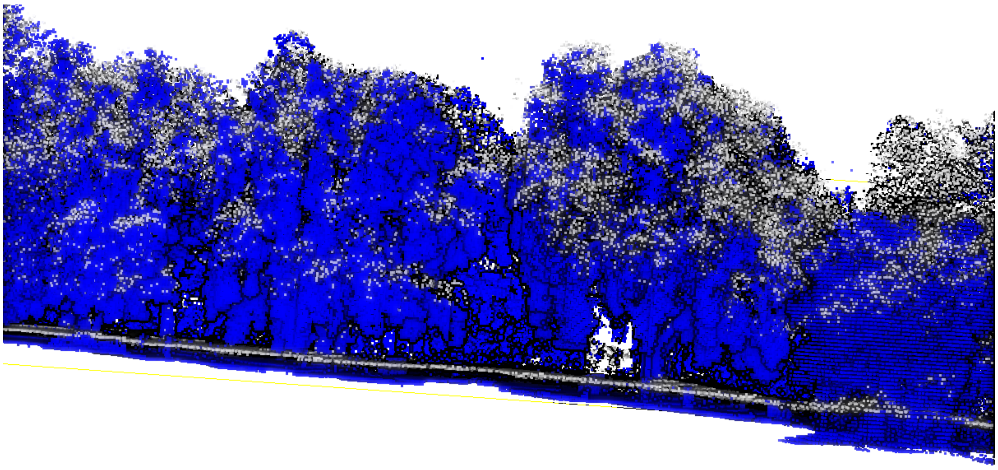

Figure 4. Visualising aerial (grey) and mobile (blue) points from a different viewpoint for top and bottom point analysis.

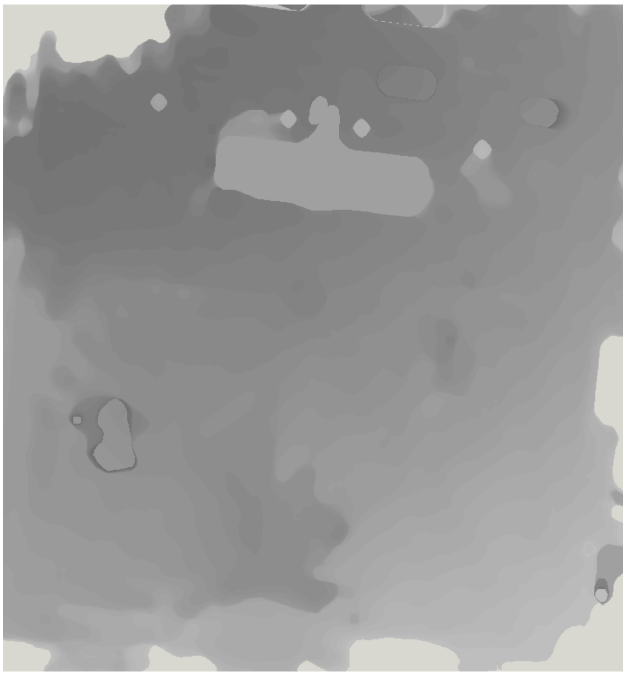

Figure 5. Spatial distribution of height differences between ground points in aerial and mobile point clouds

the side and bottom of objects, respectively. Furthermore, it appears from the ground voxels that the blue cloud is shifted down w.r.t. the grey one. This will become an issue when trying to assess tree growth between data acquisitions. At first, this shift looks like a tie point selection issue while georeferencing the mobile point cloud. However, we have the impression that the mobile point cloud is slightly deformed w.r.t. the aerial one – it is not just shifted and/or tilted (which could be explained by the affine transformation). We do not observe any horizontal shifts, only vertical ones, and these are slowly varying over the scene. This leads us to the following correction procedure:

- Identify ground voxels in both datasets: the height of the lowest voxel at each (x, y) position (using OTfilter). The result is two raster images.
- Apply local-minimum filtering in a sufficiently large neighbourhood to ensure that we get only ground heights (instead of variable things like bushes). We used 127x127 neighbourhoods.
- Subtract the two results, mask according to the footprint area, and remove outliers.

The resulting difference image shows how much the mobile voxels have to be shifted vertically at each (x, y), to coincide (at ground level) with the aerial point cloud (Figure 5). The image still shows ”irregularities”, but at those places, there are no trees (for example, at a building we have no ground points, and roof points only in the aerial data). The ”regular” grey values, which are used as height shifts, range from -10 to 10 (± 2m).

5. Change detection

Now we overlay the voxel layers (using OTover) into Figure 6 (left), showing the aerial data in grey and the mobile data in blue, both selected according to the (dilated) footprints. Only the mobile point cloud voxels are shown in Figure 6 (right) for reference, which is from a later date. It can be seen that three trees, which were marked in Figure 6 (left) have disappeared. Trees with blue tops in Figure 6 (left) became higher, however, for trees that are still with grey tops, we cannot be sure. Either they did not grow, or there were no reflections from the top of those trees in the mobile point cloud because the laser beams reflected in the interior of the trees. Figure 7 shows the aerial (green), mobile (brown), and combined voxel sets above a single footprint of polygon. They demonstrate the effects of acquisition geometry. Whether the tree became higher between the ”green” and ”brown” acquisition remains doubtful. The situation at another footprint polygon, which spans a group of trees, is shown in Figure 8. The same observations as above apply. One tree was removed between the two acquisition dates.

5.1 Automatic analysis

Part of the goal of this study was to explore possibilities for automatic analysis of the available data. Consideration was given to the estimation of tree crown volumes, as well as, change detection. Another interesting subject is tree classification (to distinguish between tree and non-tree parts of point clouds), but currently, this is considered a “deep learning” application, outside our current scope.

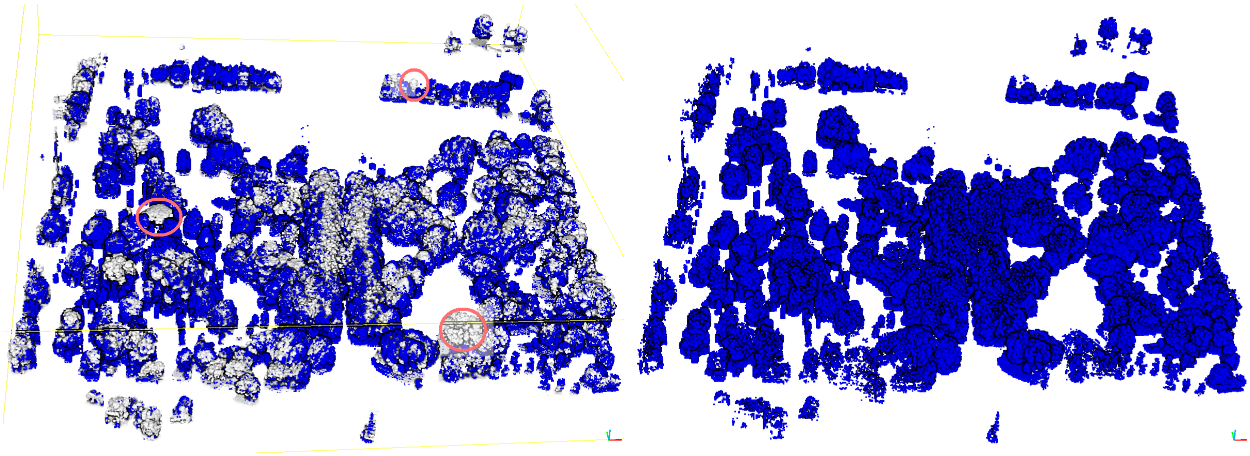

Figure 6. Left: Combined aerial (grey) and mobile (blue) point clouds. Marked trees are only present in the aerial dataset. Right: Showing only mobile-scanner points of the same scene.

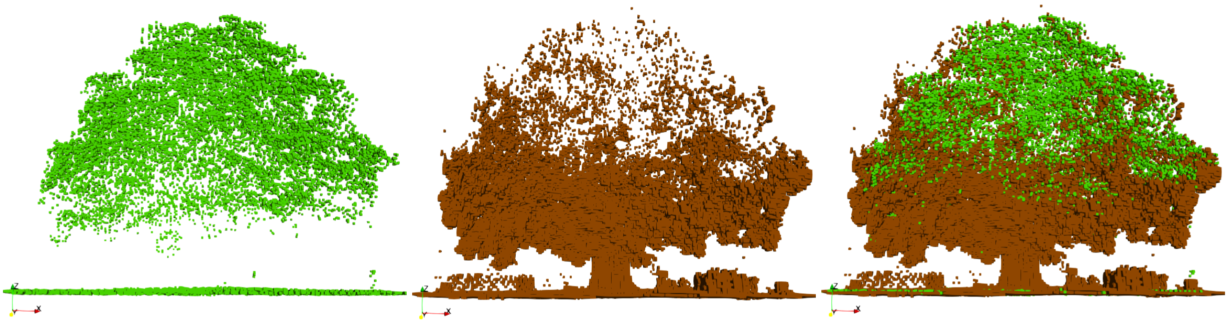

Figure 7. A single tree as seen by the aerial scanner (green) and the mobile scanner (brown), as well as combined.

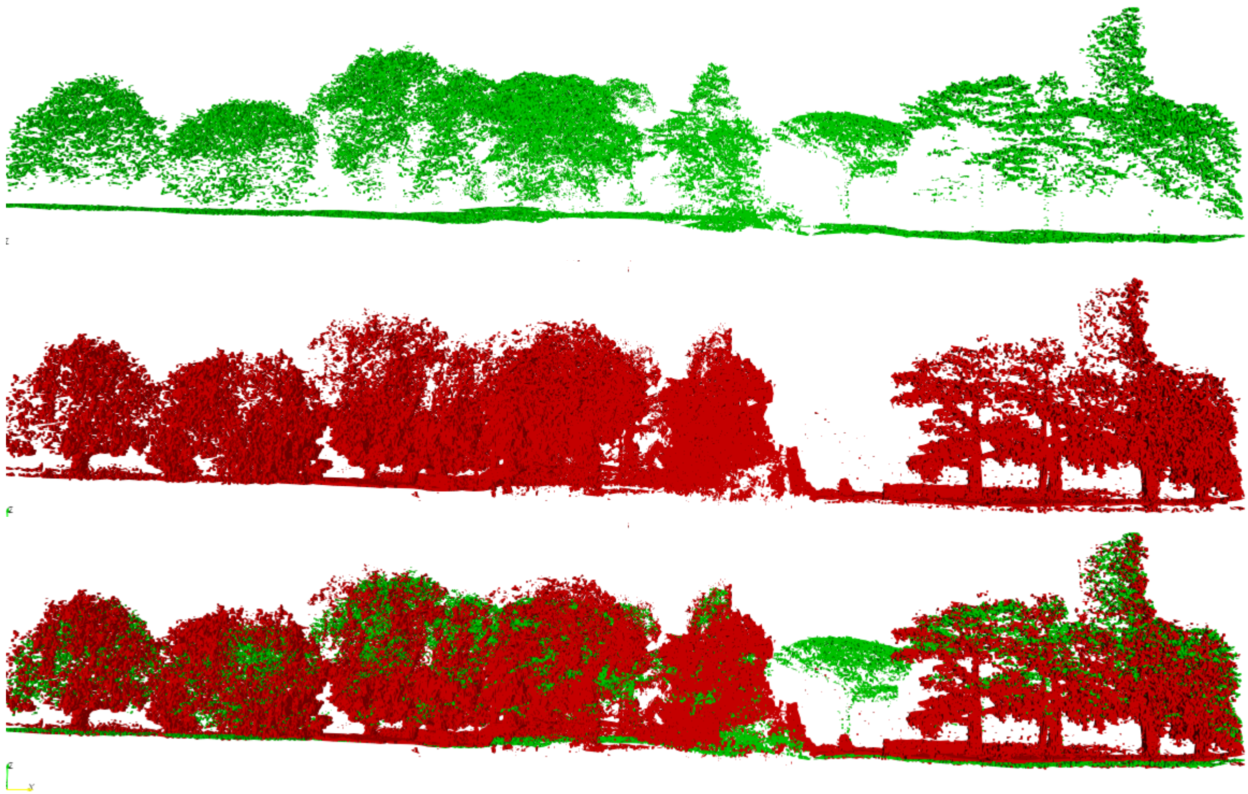

Figure 8. Multiple trees as seen by the aerial scanner (green) and the mobile scanner (brown), as well as combined.

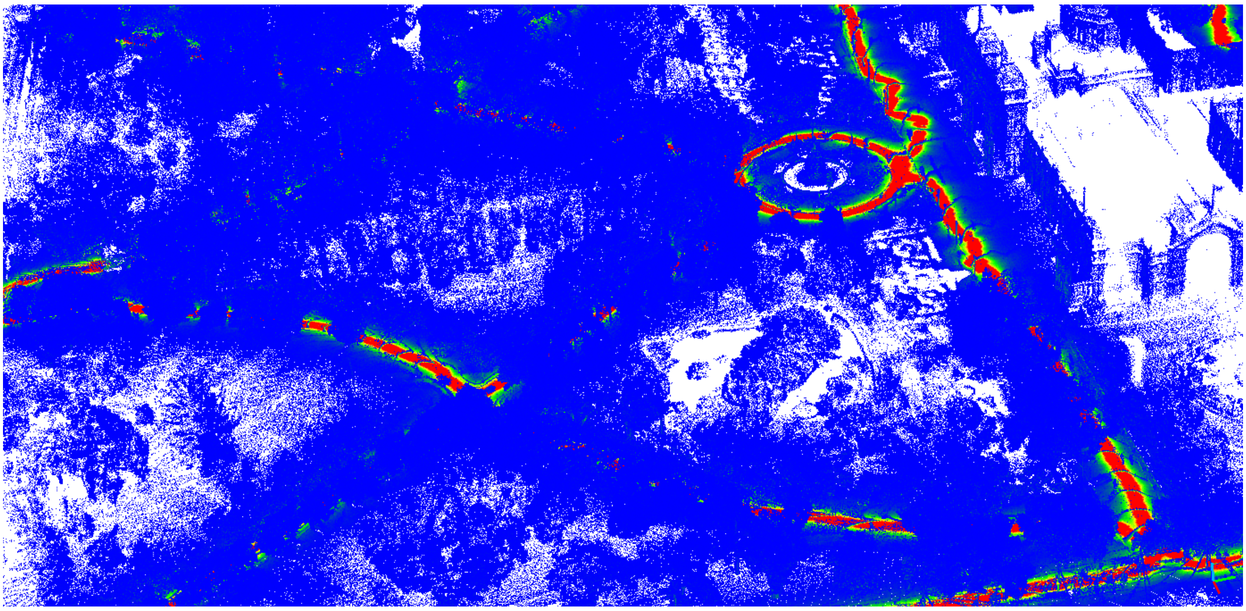

Figure 9. The visualisation of point density of the mobile laser scanning.

When looking at the green (aerial scanner) and brown (mobile scanner) point clouds in the previous subsection, it is difficult to imagine algorithms (or automated workflows) that yield the same outcome in both cases (green and brown), assuming that the scene did not change between the two acquisitions. And it is even more difficult to imagine that small changes, which might be due to growth or damage, would be reliably detected. While current results indicate a slight incompatibility between the aerial and mobile scanners for a reliable change detection approach, further quantitative investigations are required to be performed, which will be a part of future work. Volume estimation might be useful to assess the “amount of green” in an urban precinct, about fulfilment of (for example) climate change mitigation goals. Change detection would support the management and maintenance of urban vegetation by monitoring tree growth and detecting damage.

The detection of tree growth needs further investigation. Point clouds obtained by different sensors create ambiguities and complicate the comparison. As discussed above, the tops of the trees are under-represented in the backpack data set, and the aerial point clouds are missing points under the canopy. Furthermore, the walking path and speed with the backpack need to be carefully planned concerning the objects (trees) to be monitored. The current point cloud contains very high-density points on the paths (i.e. more than 260 per voxel, given in red in Figure 9), while many trees between the paths have much fewer.

A promising approach seems the combination of the two point clouds (aerial and terrestrial) to obtain more accurate crown volume estimates than would be achieved by analysing either point cloud separately. That the datasets were not acquired simultaneously may be forgiven, as long as the obtained estimates are anywhere in between the “true” values at the two acquisition moments. It is also assumed that drastic changes, such as the complete removal of a tree, would be reliably detected. Yet, preliminary experiments show that estimating those volumes is not straightforward. We have dilated the point clouds such that they form a closed hull around a tree crown, which can then be flood-filled, and after that “eroded back” to the original shape. However, large holes require more dilation and too much of the shape is lost during the process. In the multiple-tree scene, some holes are larger than the distance between the trees, causing the trees to “merge”. We currently expect “Reality Mesh” software to be the way forward with future experimentations.

6. Conclusions

In this paper, we process point clouds of trees from two different epochs and detect the changes. The experiments clearly illustrate that using the voxel approach is superior to using the original points clouds. The data sets become significantly smaller (especially the mobile data set having 163 million points and only 9 million voxels)) and easy to process and visualise. Preprocessing and cleaning are also beneficial due to gridded data.

We have used a data structure and operators, which have been primarily created for volumetric objects. Although the point clouds have been successfully imported, analysed and visualised, more considerations have to be taken into account. For example, the aggregation function to build the octree is currently using majority criteria. This might not always be appropriate for point clouds especially when the lower resolution octree nodes are to be used. However, such a uniform octree data structure allows the integration of data with various voxel layers such as buildings, streets, and underground structures for integrated analysis.

Scans from different epochs but collected with the same scanner can give a better estimation of the changes, but they might still be insufficient to compute tree volumes. The experiments have illustrated that a combination of aerial and terrestrial point clouds might be the best option, given they are collected at the same time (e.g. using a mobile backpack and a drone). Then the volume of the trees can be computed as all voxels that contain tree points. Two volumes from two different years will provide a precise estimation of the changes in the tree canopy.

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