RESEARCH ARTICLE

Outlier detection and robust plane fitting for building roof extraction from LiDAR data

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ABSTRACT

Individual roof plane extraction from LiDAR point-cloud data is a complex and difficult task because of unknown semantic characteristics and inharmonious behaviour of input data. Most of the existing state-of-the-art methods fail to detect small true roof planes with exact boundaries due to outliers, occlusions, complex building structures and other inconsistent nature of LiDAR data. In this paper, we have presented an improved building detection and roof plane extraction method, which is less sensitive to the outliers and unlikely to generate spurious planes. For this, a robust outlier detection algorithm has been proposed in this paper along with a robust plane-fitting algorithm based on M-estimator Sample Consensus (MSAC) for detecting individual roof planes. Using two benchmark datasets (Australian and International Society for Photogrammetry and Remote Sensing benchmark) with different numbers of buildings and sizes, trees and point densities, we have evaluated the proposed method. Experimental results show that the method removes outliers and vegetation almost accurately and offer a high success rate in terms of completeness and correctness (between 80% and 100% per-object) for both roof plane extraction and building detection. In most of the cases, the proposed method shows above 90% correctness.

KEYWORDS

LiDAR; building detection; point-cloud, roof plane extraction; outlier detection; plane fitting

1. Introduction

Building is a fundamental object for different Geographic Information System-based applications such as smart city planning and disaster management (Yang, Byungyun and Jungil 2019; Shirowzhan et al. 2019; Gilani, Awrangjeb and Guajun 2018). Individual roof plane extraction from a building along with other roof parts like chimneys and dormers is important for building reconstruction and 3D modelling (Gilani, Awrangjeb and Guajun 2016a; Awrangjeb and Fraser 2014a). An application of the generated 3D models could be the estimation of solar potential on a building, where suitable roof planes are automatically selected to install the photovoltaic cells (Lukač et al. 2013). Although it seems that buildings are prominent and can be detected easily, it is indeed challenging due to the surrounding environment, architectural complexities and diverse viewpoints. These limitations make accurate building detection,

reconstruction and 3D modelling a challenging and complex task (Gilani, Awrangjeb and Guojun 2016b).

Studies have been conducted over the last two decades on individual building extraction and reconstruction (Awrangjeb, Zhang and Fraser 2013). Building extraction implies the extraction of 2D or 3D boundaries of individual buildings. In reconstruction, roof planes are extracted individually and modelled into 3D objects. Based on the input data, current existing building extraction and reconstruction methods can be divided into three major categories (Zheng et al. 2017). Methods in the first category are based on high resolution aerial images (Turker and Dilek 2015; Chaudhuri et al. 2015). Due to presence of shadows, occlusions and poor contrast, and difficulty in estimating accurate height information, image-only based methods fail to serve the purpose of different applications including 3D building reconstruction and solar potential estimation properly (Gilani, Awrangjeb and Guajun 2018). Methods in the second category use the LiDAR data, which offer accurate height information and does not have the issue of shadows and poor contrast (Awrangjeb and Fraser 2014a,b). However, they offer low planimetric accuracy of the extracted building and plane boundaries due to low input point density. Methods in the third category use complementary information from image and LiDAR to avoid their individual issues (Zarea and Mohammadzadeh 2015). But due to the dissimilar and inconsistent characteristics of LiDAR and image data, integration of these two approaches create additional difficulties. For example, features such as lines extracted from individual data do not align properly (Awrangjeb and Fraser 2014a). Therefore, using a single source LiDAR data, registration errors due to the dissimilarities between multisource data can be avoided. Moreover, the LiDAR-based methods are more automatic than the image-based methods (Shamopath and Shan 2009; Gilani, Awrangjeb and Guajun 2018).

Methods using LiDAR only data have the following three main steps (Gilani, Awrangjeb and Guojun 2016b, 2015; Chen et al. 2014). They initially use a filtering technique based on an elevation threshold to divide the data into terrain and non-terrain groups. Then, they apply a plane fitting algorithm to segment the non-terrain points into planar regions. Finally, they apply a post-processing step to remove spurious planes and refine the actual roof planes. However, the segmentation of homogeneous coplanar points (the second step) for individual roof plane extraction is the most significant and complex step for various reasons. Firstly, LiDAR data are unorganised and have variable point density. This characteristic stops generating a method applicable to different input data. Secondly, there is a stochastic and systematic inaccuracy in the estimated 3D point data (Gilani, Awrangjeb and Guajun 2018). Thirdly, due to the limitation of the LiDAR data acquisition system, unexpected points, i.e., noises or outliers, are often captured by the LiDAR system (Sotoodeh 2006). Presence of outliers is an important factor causing the low performance of LiDAR-based methods such as (Awrangjeb and Fraser 2014a). LiDAR data do not follow any specific statistical distribution pattern which creates difficulties for any statistical assumption about the outliers (Zhang et al. 2009). For example, due to the abnormal and false LiDAR point near the roof edge, spurious and erroneous planes can be generated, thus the correct shape of a roof plane may remain undetected (Zheng and Weng 2015). Finally, points along a roof ridge between two near-flat planes can generate false planes constructed using the points from both of the planes. Consequently, the post-processing step follows a complex rule-based refinement procedure to remove the false planes.

To extract the roof planes using homogeneous coplanar points, many LiDAR-based methods use different robust version of the Principle Component Analysis (PCA)

or the Random Sample Consensus (RANSAC)-based plane fitting algorithms (Nurunnabi, Belton and West 2012a; Schnabel, Roland and Kleing 2007). Different techniques using region-growing approaches are used by many authors (Awrangjeb and Fraser 2014a; Gilani, Awrangjeb and Guajun 2016a). However, the original PCA or RANSAC algorithms are sensitive to noises and ineffective for detecting small planes in large point-cloud data (Deschaud, Jean and Francois 2010). Region-growing algorithms often suffer from selecting the suitable seed points.

This paper propose an improved method for building roof extraction using LiDAR data. We remove the outliers from the non-ground points by a new approach which is based on the relative location of a point to its neighbours along with a robust statistical measurements. After that, we apply a resampling process to the initial outlier-free data followed by a method for coplanar points separation to select the suitable seeds for individual roof planes. After that, we apply an improved plane-fitting algorithm based on M-estimator SAmple Consensus (MSAC) which is less sensitive to noises to the outlier-free point-cloud data to extract more accurate planes. At the last stage we apply some rule-based techniques to remove the false spurious planes. We use standard benchmark datasets with different point densities and scene complexities to evaluate the performance of our proposed method. The major contribution of this paper is summarised as follows:

- Considering outliers are one of the major reason for getting inaccurate roof boundaries and false planes, this paper propose and apply a new method for outlier detection from LiDAR point-cloud data.
- An effective plane fitting method which is less sensitive to noises has been introduced in this paper by selecting proper coplanar points and the method is applied on different benchmark datasets with different point densities and complexities.

The rest of this paper is organized as follows: Section 2 represents a review on the existing prominent approaches for building and roof plane extraction using LiDAR data. Section 3 represents our proposed method, section 4 describes the evaluation of experimental results using the benchmark datasets, and section 5 concludes the paper with necessary discussions.

2. Related Works

Building reconstruction and individual roof plane extraction from LiDAR data can be categorised into two main approaches: data-driven and model-driven (Tarsha-Kurdi et al. 2007). The first approach tries to find out the shape of a building from the provided data and the second approach finds the most similar model previously stored on the database to the input data. The data-driven approach works in general for any building shape and does not depends on the predefined building roof models. In this paper, we review the data-driven approaches. However, for both approaches outliers or noise cause low accuracies. Because of the outliers, sometimes erroneous surface patches can be detected which are devious from the actual roof planes (Shen et al. 2019). For these reasons, removing outliers is an active and long-standing research field (Cheng, Siu and Lau 2017). Both supervised and unsupervised approaches have been developed and implemented to detect and remove the outliers from point-cloud data (Rusu and Cousins 2013; Amer et al. 2013). According to Chandola, Arindam and Vipin (2018) outlier can be classified into three categories: point, collective and contextual. A point outlier shows significant difference from the rest of the datasets. A group of data

shows deviation in collective outlier while data behave differently in some context in contextual outlier. Stucker et al. (2018) used a supervised approach using standard Random Forest (RF) classifier. They classified the LiDAR data into several classes for Multi-View Stereo (MVS) point-cloud and find out the label (inlier or outlier) of each input 3D points. However, supervised approach for outlier detection is not popular since creating labelled datasets to train a classifier is difficult and complex because of the unpredicted nature of point-cloud data. Nurunnabi, West and Belton (2015) proposed two methods for outlier detection by using robust statistical techniques. The first method is based on a robust z-score and the second method used the Mahalanobis distance. Zhang et al. (2009) calculated the outlier-ness of a point in scattered data by proposing the Local Distance-based Outlier Factors (LDOF). This method identified the relative location of the point to its neighbours and found the degree to which the point deviated from the neighbours. However, this method performed well for 2D point data only.

To detect buildings from LiDAR data in urban area Awrangjeb, Guojun and Fraser (2014) introduced a method for complex building structures. Considering reflected points from side walls of buildings, they first divided the LiDAR points into ground and non-ground categories using bare-earth Digital Elevation Model (DEM) and then removed the points reflected from the walls using a plane fitting technique. They firstly considered a fictitious horizontal plane and then construct another plane using the neighbouring points of each non-ground point. Some rule-based procedure is applied to remove falsely detected roofs. Building boundary is extracted using a binary mask and the Canny Edge detector. However, the planimetric accuracy of their method is lower because of the LiDAR point density and the method does not works for curved roof planes.

Considering the planner surfaces are the candidate roof planes, most of the methods use PCA-based plane fitting approaches which are sensitive to noises (Hubert, Rousseeuw and Karlien 2005). Gilani, Awrangjeb and Guojun (2016b) proposed a point-cloud segmentation method combining PCA and a robust normal estimation method LRSPCK (Zang et al. 2013). The authors tried to preserve the sharp salience features by their method. Using a height threshold the author separated the non-ground points. A region growing approach on the non-ground points followed by plane refinement and boundary approximation method extract the individual roof planes. However, their method did not consider the noises and suffered from lower planimetric accuracy.

Shamopath and Shan (2009) presented a framework for segmentation and reconstruction of building roof from LiDAR data. They first calculated the eigenvectors and eigenvalues to determine the planarity and applied Voronoi neighbourhood of a point P to construct the covariance matrix. From eigenvalues λ_1 λ_2 and λ_3 they determined the planarity of a specific point P . A normalize eigenvalue λ' is applied to hypothesized the inherent noise (breakline points) to be planer. They introduced topologic information to the clustering process and applied potential based clustering introduced by Yoger and Filey (1994) to determine the cluster centre. However, performance of their method degrades when buildings are complex in nature. Tarsha, Landes and Pierre (2008) used an extended RANSAC algorithm for robust building roof plane detection but their method could not construct plane with area less than 50 m². RANSAC algorithm sometimes can not distinguish two close planes and generate false segments consisting of points from the near coplanar surfaces (Xu et al. 2015).

Awrangjeb and Fraser (2014a) constructed a building mask using the separated ground LiDAR points which correspondence to individual buildings and trees. Each

non-ground objects are then clustered and separated using the ground mask. Coplanar points in each cluster are detected using a procedure proposed by Shampath and Shan (2009). This separates all individual clusters into different parts based on their planarity. Delaunay Triangulation (DT) algorithm is used for finding the neighbours of each point in the calculated cluster. A seed is randomly selected from a group of co-planar points and iteratively construct a plane. The authors applied six different steps to refine the extracted planes. Though the proposed method fails to detect the small buildings and roof planes, it performed very accurate for the large building and separate roof plane extraction.

Mongus et al. (2013) proposed a morphological based algorithm to detect flat regions from LiDAR data assuming that the flat regions are the candidates for buildings. To remove the non-building objects points the authors used multi-scale levelling schema (MSLS)-segmentation which is based on differential morphological profiles. Later, the same authors used Differential Morphological Profiles (DMPs) to perform multi-scale data decomposition and a new algorithm for local fitting surface (LoFS) to extract planar points for the building was proposed (Mongus, Lukač and Žalik 2014). However, their method can only detect flat building roofs. Individual building with non-flat roofs can not be detected.

Contour-based boundary extraction for a building area was proposed by Awrangjeb and Fraser (2014b). Edge points were detected by canny edge detection algorithm on a binary image mask and then converted to the corresponding nearest LiDAR points. Incorporating density variation information, Santos et al. (2015) recently used α -shape algorithm introduced by Edelsbrunner, Kirkpatrick and Seidel (1983) to extract the boundaries for building roofs from LiDAR data. Their method mainly consists of three major parts. They first determined an adaptive value for α . Secondly, they applied the α -shape algorithm on the LiDAR data. Finally, a refinement process was performed on the detected boundaries.

Huang et al. (2018) proposed a top-down strategy for building extraction. This method takes an object and its surrounding neighbour points as a unit for analysis. Smooth region are considered as probable building candidates and segmented from separated non-ground points. Based on some geometric and penetrating features they classified the building regions. Again, using some topological, geometric and penetrating features they removed the non-building points around buildings. However, their method does not consider about individual roof planes.

Recently, machine learning approaches based on LiDAR data for building extraction and roof shape classification have been used by many authors (Maltezos et al. 2018; Nahhas et al. 2018; Jeremy and Ella 2018). Zhou and Jie (2018) used point-cloud data with different densities to detect the buildings. LiDAR data were first converted into grey-scale images using the height values of the corresponding LiDAR point. A deep Convolutional Neural Network (CNN) was trained using the images of buildings. They applied some morphological operations after the grey-scale conversion to avoid the exhaustive sliding windows and train the network well. Although recently deep learning based approaches perform well for building detection. However, most of the cases their planimetric accuracies are low and individual roof plane extraction is not considered.

3. Proposed Extraction Method

Figure. 1 shows the general flow diagram of the proposed method for building roof plane extraction. LiDAR point-cloud data are firstly divided into ground and non-ground points based on a height threshold. Non-ground points contain the buildings roofs, trees and other elevated objects. A building mask is generated using the ground points. A void area in the ground mask indicates a tentative building and its corresponding non-ground points represent a candidate building. A robust outlier detection algorithm is applied to obtain points that can be true outliers or other points (e.g., edge and ridge points) that can make the plane fitting algorithm unsuccessful. These points are kept separated from the non-ground point set. Based on the neighbouring point relationship and co-planarity characteristics, the outlier-free non-ground points are divided into different clusters, each of which is segmented using an improved plane fitting method. Using some selected properties including area and neighbouring information, small and falsely detected planes are removed. Remaining planes represent the true building roof planes. To obtain the boundary of a building, neighbouring planes are grouped and the points on each group of planes are used. At last, each outlier point is tested if it fits well with a true roof plane. Otherwise, it is removed as a true outlier. This step helps keep the edge and ridge points with the corresponding planes.

Figure 1. General architecture of the roof plane extraction method. Shaded area within dashed rectangles indicate the improved modules

In this section, we will describe the steps in detail. Figure 2 shows a simple scenario of our working procedure and illustrates the different steps for roof plane detection using a part of the datasets we have used in this paper with point density 40 points/m².

Figure 2. A simple scenario from Aitkenvale (AV) dataset: (a) orthoimage of a sample area (b) separated raw LiDAR data into ground and non-ground points; (c) generated mask M_g using ground points; (d) resampled non-ground points with outliers; (e) removed outliers and grouped into clusters (group of red points); (f) separated roof candidate clusters with wrong planes indicated by separate colors. Small probable trees area also removed; (g) refined roof planes; (h) detected boundaries of individual roof planes.

3.1. *Classifying Raw LiDAR Data into Ground and Non-ground Points*

For any building detection or roof plane extraction method, ground and non-ground points are first separated. Buildings and trees which have certain minimum height is enough for separating the input LiDAR data into two different groups. For our

method, we are provided with the bare-earth DEM, so we use the corresponding DEM height (H_g) as the ground height. We use a constant height threshold $h_c = 1$ m, which was used by Awrangjeb and Fraser (2014a) ($T_h = H_g + h_c$). Points with height values greater than T_h now represent the elevated objects including buildings, trees and bushes. The ground points having height less than T_h are used to generate the building mask M_g of resolution 0.25 m (Awrangjeb, Zhang and Fraser (2012)). Figure 2(b) shows the separated ground (yellow) and non-ground (blue) points for sample input area of Figure 2(a). Figure 2(c) shows the generated mask using the ground points where, white areas represent the roads, water area, ground furniture and cars, while the black regions represent the buildings and trees.

Using a connected component analysis, the individual black regions are obtained from M_g . The non-ground points within each black region are found using its boundary on a resampled non-ground points. After outlier detection, the outlier-free non-ground points for each black region are employed to extract individual planar segments.

3.2. Outlier Removal

Before extraction of roof planes of individual buildings, it is important to detect points that can make any plane extraction method less effective. These points can be noises which do not represent any real objects. They can also be real edge and ridge points which cannot be used as the seed points in the plane extraction method, otherwise, they may lead to extraction of false planes. These points are called commonly outliers in the rest of the paper. In this section, we present our proposed outlier detection method from the non-ground points.

Most of the existing outlier detection methods remove outliers but some inliers are also incorrectly removed. For 3D building reconstruction and roof plane extraction missing inlier data is usually more harmful than some few remaining outliers close to the true surface (Stucker et al. 2018). The method we propose in this paper tries to keep the inliers as many as possible.

Outliers in point-cloud data can be divided into two categories: local outliers and global outliers (Chandola, Arindam and Vipin 2018). Because of the sparse nature and lack of distinctive geometric attributes finding the global outliers is not an amenable way. When the global outliers are sparsely distributed and do not form any micro-cluster in point-cloud, then a method designed for detecting local outliers can also detect the global outliers (Stucker et al. (2018)). The method we propose and use in this paper tries to find out the local outliers using the information of the neighbours of each 3D point. We mainly adopt the methods based on Maximum Consistency with Minimum Distance (MCMD) using Robust z -score (R_z) (Eq.(1)) and LDOF (Eq.(2)) proposed in Nurunnabi, West and Belton (2015) and Zhang et al. (2009), respectively. We observe that the R_z score of a specific point along with its relative distance to neighbours provides a significant score for a specific point's outlier-ness. MCMD algorithm using R_z considers an imaginary plane using the provided 3D point data and then calculates the orthogonal distance for each of the points from that plane. The points which stay only on the constructed imaginary plane or within a specific distance threshold are considered as inliers. For this reason, it can misclassify some points including edge and ridge points when the plane is not detected and constructed correctly. Again, LDOF was originally designed for 2D point data and using only the relative distances with neighbours it takes the decision about a point; whether, it is an outlier or inlier. A point which is actually an inlier can be misclassified as an outlier

(or vice versa) when it only satisfies the provided relative distance threshold from its neighbour; especially where the points are on the same plane but density varies. We try to combine these two methods to detect inliers and outliers correctly using the proposed method.

Let $N_p = \{q_j\}$, where $j \geq 1$, be the set of all neighbours of a point p_i in the point-cloud data, n be the cardinality of N_p , d_{p_i} be the average distance from all neighbours in N_p to p_i and D_{p_i} be the average distance among all points in N_p and $|\cdot|$ indicate the absolute value. The Robust z -score (R_{z_i}) and LDOF (L_{f_i}) of P_i can be defined as:

$$R_{z_i} = \frac{|p_i - \text{median}(N_p)|}{a.\text{median}_i |p_i - \text{median}(N_p)|}, i = 1 \dots n. \quad (1)$$

$$L_{f_i} = \frac{d_{p_i}}{D_{p_i}}, \quad (2)$$

where

$$d_{p_i} = \frac{1}{n} \sum_{q_j \in N_p} \text{dist}(q_j, p_i)$$

and

$$D_{p_i} = \frac{1}{n(n-1)} \sum_{q_j, q_{j'} \in N_p, j \neq j'} \text{dist}(q_j, q_{j'}) .$$

Figure 3. Detected inliers and outliers (a) using R_z ; (b) using L_f and (c) proposed-where most of the outliers detected correctly. Red star indicates detected outliers and black circle indicates detected inliers

We generated some synthetic data (inliers and outliers) for a real roof plane. Figures 3(a) and 3(b) shows the detected inliers and outliers using the corresponding methods of R_{z_i} and L_{f_i} , respectively. Red star indicates the detected outliers and the black circle indicates the detected inliers. In Figure 3(a) it can be observed that some probable inliers inside the plane detected as outliers and vice versa. In Figure 3(b), we can also see that many outliers were detected inside the plane because of the relative distance

threshold using L_{f_i} , although those points were supposed to be inliers. To solve these problems we propose Algorithm 1 as follows:

Algorithm 1 Outlier and Inlier Detection Process

Input: P : All non-ground 3D LiDAR points with outliers

Output: $inliers (P_{in})$: Outlier free non-ground point-cloud

$outliers (P_{out})$: Detected outliers

- (1) Find the neighbours N_p of a input point p_i from P
 - (2) $\forall i \in N_p$
 - Find robust z -score R_z using MCMD_Z and use Delaunay triangle for neighbourhood calculation in all cases
 - Find L_{f_i} score for each of the points with respect to their neighbours
 - (3) if $R_z(i) < T_z$ and $LDOF(i) < T_l$
 - (4) $P_{in} \leftarrow i$
 - (5) else, $P_{out} \leftarrow i$
 - (6) Repeat step 1 to 5 for all non-ground points (P) in the input data
 - (7) Return unique P_{in} and P_{out}
-

Algorithm 1 first calculates the R_z score of a specific point using MCMD_Z algorithm proposed by Nurunnabi, West and Belton (2015). To choose the value of a in Eq. (1) as a correction factor, we follow the work proposed by Rousseuw and Hubert (2011) to make the R_{z_i} score consistent; where, they choose $a = 1.483$. Next, the algorithm finds the L_{f_i} score for each of the 3D points in a cluster. If a point exceeds the predefined thresholds $T_z = 2.5$ and $T_l = 1$ for R_z and L_{f_i} , respectively, then we consider the point as an outlier.

Most of the neighbourhood searching method use the k -NN (Nurunnabi, West and Belton 2015) or different varieties of Fixed Distance Neighbourhood (FDN) (Sotoodeh 2006) for LiDAR data analysis. We use the Delaunay triangulation in all the cases to calculate neighbourhood for outlier detection as it gives the natural neighbouring points and is free from choosing the values like k or thresholds for distance. Although, for a higher value of k (more than 200) some existing methods of outlier detection show good results, for our datasets we found that Delaunay algorithm chooses approximately 10 to 15 times fewer points to make the decision. Figure 3(c) shows the detected inliers and outliers using the proposed algorithm.

3.3. Clustering and Co-planar Point Separation

We use M_g for clustering the LiDAR points following the method proposed by Awrangjeb and Fraser (2014a). Figure 2(e) shows the results of clustering which includes both buildings and tree points. Next, the points of small trees are removed and boundaries of each probable building clusters are extracted using the same method. All outlier free non-ground points are then assigned to each of the clusters.

To extract the individual roof planes from each cluster a seed must need to be selected first. Proper selection of the seed is important. The non-planar or sharp points which represent edge, boundary or corner points should be excluded from selecting the seeds. If a sharp feature point is selected as a seed then it causes the wrong roof plane extraction. So, a method need to be developed correctly that can separate sharp features and other non-planar points from the most likely planar points in each cluster. Some isolated 0-D points which do not have any neighbours (e.g. single noise or return

signal from chimneys) can be separated easily by the outlier removal process. Building roofs are mainly the 2-D planar points so these should be correctly identified to select the seeds for separate planes. Most of the existing methods use a normalised eigenvalue 3 proposed by Shampath and Shan (2009). In Eq.(3) λ_1, λ_2 and λ_3 are eigenvalues and $\lambda_1 \leq \lambda_2 \leq \lambda_3$. To balance over-removal and under-removal of planar points they choose a threshold value of 0.005. When λ' in Eq.(3) is less than 0.005 then the LiDAR point is considered as a planar point.

$$\lambda' = \frac{\lambda_1}{\lambda_1 + \lambda_2 + \lambda_3} \quad (3)$$

We found that a fixed threshold for λ' sometimes misclassifies the LIDAR points for our datasets. According to Nurunnabi, Belton and West (2012a) λ_1 values for a planer surface is sufficiently consistent. So, we consider an adaptive threshold based on only λ_1 values calculated for each neighbours of a point P instead of λ' . Delaunay triangulation algorithm is used for finding a natural neighbourhood for each point in a cluster. The threshold Th_n is based on the standard deviation (std) and mean of the λ_1 values.

Let $N_n = \{L_i\}$, where $i \geq 1$, be the set of all calculated λ_1 values for every neighbour of a point P . Then, Th_n is calculated by using the following equation:

$$Th_n = (std(N_n) - mean(N_n))/2 \quad (4)$$

When λ_1 is less than Th_n for a specific point, then we consider the corresponding point is planer and include it in set X_1 , otherwise, it is considered and included as sharp features or non-planer point in X_2 .

3.4. Plane Fitting for Roof Plane Extraction

For each extracted cluster we have now separated co-planer points (X_1) and rest of the other non-ground points (X_2). To find a plane, an unused point (P) from X_1 is selected first for each plane as a seed. To select the point, best fit straight lines are extracted along each cluster boundaries and nearest coplanar point from X_1 of each straight line is selected for each roof plane according to the method described in Awrangjeb, Zhang and Fraser (2012).

To initialise a plane, the neighbouring points of P are selected from X_1 using the Delaunay neighbourhood. Let X_p be the set of neighbours chosen from X_1 including P . Planar segment extraction is initialised using X_p . The number of points to initialise is not less than 3. The M-estimator SAmple Consensus (MSAC) algorithm (Torr and Andrew 2000) is now used which is a variant of RANSAC plane-fitting algorithm to find a plane with inliers points and this process executes iteratively for all points in X_p for each plane.

We choose MSAC to initialise because it is less sensitive to noises and uses a loss function rather than fixed thresholds to the point-to-plane distance thus it is more robust to outliers (Torr and Andrew 2000). It minimise the robust cost function $C_f = \sum \rho(e_i^2)$, where $\rho(e_i^2)$ is defined as:

$$\rho(e_i^2) = \begin{cases} e_i^2 & e_i^2 < T^2 \\ T^2 & e_i^2 \geq T^2 \end{cases} \quad (5)$$

The symbol e_i indicates the error term for i -th observation and T is the distance threshold defined previously. MSAC has less computational burden and it provides hefty benefit for robust estimation Nurunnabi, West and Belton (2015).

In this stage, MSAC initially constructs a plane by the detected inliers discarding the remaining outliers from X_1 and it continues until no co-planar points found along the selected boundary line. After making decisions about all co-planar points for a plane, we find the other neighbours from X_2 for each of the inlier points of the initial plane constructed. Let, the set of neighbouring non-co-planar points from X_2 be Y_n . Distances from the initially constructed plane using the co-planar points are calculated for each points in Y_n . If the normal distance (T_p) for a point from Y_n to the plane is less than 0.15 (Awrangjeb, Zhang and Fraser 2013) then the point is considered as an inlier and included to the group of inlier planar points detected using MSAC. Next, the plane (Υ) is updated and constructed using the equation ($\alpha_x + \beta_y + \gamma_z = \delta$) on all the detected inlier points.

Algorithm 1 detected the outliers (P_{out}) from the initial non-ground data. The algorithm may misclassify some inliers as outliers. At this point, we again recheck the distances of each point in P_{out} to the constructed plane Υ . If the distance satisfies the threshold T_p for any point in P_{out} we add it to that plane and remove from P_{out} . Finally, we again update the plane (Υ). This process stops until no further points can be added from X_2 and P_{out} for a plane. Figure 4 demonstrated the overall steps for planar segment extraction.

Figure 4. A planar segment extraction from a LiDAR point-cloud cluster

3.5. Refining and Removing Non-roof Planes

The plane fitting module provides segmented candidate building roofs. But all segments may not represent true roof planes. We apply some rule-based techniques to remove the non-roof planes. Firstly, we assume that a roof plane has a minimum allowable size of 1 m^2 . Some planes can be detected which do not satisfy this size. Planes extracted with an area less than 1 m^2 are removed. Secondly, we consider the harmonic mean of the points height differences for each of the extracted planes. Height difference indicates the entropy of selected points. Constructed planes using the points over the tree leaves naturally have greater entropy than a man-made flat roof. If the height difference is greater than 0.5 m , we consider the plane as a tree (false) plane.

Thirdly, sometimes a single plane segment can be extracted twice or more because of wrong seed selection. To solve this issue, we find the percentage of matching between every extracted plane to other planes according to Awrangjeb and Fraser (2014a). If we find more than 80% match of points between two planes then merge them into a single plane. Fourthly, we use the ratio r for a number of unused points to the total number of non-ground points of a detected plane within an area with at least 1 m width. For plane fitting, we selected seed from the co-planer points X_1 and then added the other compatible points from the non-ground point (X_1 and X_2). The unused points are the remaining non-ground points. If r is greater than 20% then we assume that the extracted plane is a tree plane.

So finally, a plane with minimum 1 m^2 area with a height difference less than 0.5 m and with used point ratio (r) greater than 20% is considered as true roof plane. Sometimes small planes like vents and chimneys can be removed by the refinement procedure. To avoid these removals we adopted a test criterion from Awrangjeb and Fraser (2014a). If a plane resides within the boundary area of an accepted true plane, that test mark these misclassified plane as true roof plane.

One of the main interesting thing of this proposed method is that due to less outliers, the rate of small and false planes is very few. Most of the abnormal points are removed by the outlier removal method thus false planes are generated less, which leads the refinement procedure less time consuming but more effective. Figure 5 shows the refinement and non-roof plane removal result. Figure 5(a) shows all the extracted planes including tree planes and small roof parts. Figure 5(b) shows the correct roof plane extracted after removing non-roof planes.

To detect a building from the roof planes we concatenate all the planes in a cluster. An individual building is a collection of separate adjacent roof planes. Using this concept we group all the points from a group of planes which are adjacent and extract the corresponding boundaries representing the individual building.

4. Performance Evaluation

In this paper, we evaluate our proposed outlier detection method as well as the improved building roof extraction method and finally detected the building boundary. To evaluate the outlier detection method we use synthetic datasets. For roof plane and building boundary extraction we use the Australian benchmark and the International Society for Photogrammetry and Remote Sensing (ISPRS) benchmark datasets. Three different sites of Australian benchmark and three areas from Vaihingen, Germany area in ISPRS benchmark with different resolution are selected for evaluation. In this section, we first describe the datasets. After that, experimental results of the proposed

Figure 5. Demonstration of non-roof plane removal by proposed technique. (a) all extracted planes before refinement (b) detected roof plane after refinement

outlier detection method followed by roof plane and building extraction results are described. Finally, we analyse the results.

4.1. Datasets

For outlier detection, we first construct labelled datasets with inliers and outliers taking help from the method proposed by Awrangjeb, Gilani and Fasahat (2018) which is originally an approach for 3D building reconstruction using LiDAR data. We first generate 3D roof models of Aitkenvale (AV) area and Hervey Bay (HB) from Australian benchmark datasets. After that synthetic inliers and outliers on each of the roof planes is created. Total 3924 inliers and 612 outliers (approximately 15%) for 22 roof planes of AV datasets and then 21850 inliers and 2549 outliers for 30 different buildings with 166 roof planes in HB area is manually generated. Inliers are created randomly with orthogonal distance between 0 to ± 0.05 meter from each roof plane and outliers are generated randomly with orthogonal distance between 0.06 to ± 0.45 m. Figure 6 shows the created 3D building roof models where Figure 6(a) shows the generated inliers and outliers for a building with 8 roof planes from AV datasets and Figure 6(b) and Figure 6(c) show the generated 3D roof models of AV and HB respectively.

AV area has high point density 29 to 40 points per square meter and the HB has medium point density, which is 12 points per square meter. AV dataset has two different sites. First one (AV1) covers $66 \text{ m} \times 52 \text{ m}$ area with $40/\text{m}^2$ point densities. The second one (AV2) have point density $29/\text{m}^2$. AV1 has five different buildings with 26 roof planes and the AV2 has 63 buildings with 211 roof planes and it covers $214 \times 159 \text{ m}^2$ area. Four of the buildings in AV2 have the area between 4 to 5 m^2 and 10 of the buildings with the area between 5 to 10 m^2 . The Hervey Bay (HB) is the second area of Australian datasets. It is a single site and covers $108 \text{ m} \times 104 \text{ m}$ area. This area contains 28 different buildings with 166 roof planes. 3 of the buildings are

Table 1. Accuracy measures of proposed outlier detection using the Aitkenvale (AV1) dataset

Methods	TPR	TNR	FPR	FNR	Acc
LDOF	53.2	54.5	49.5	48.3	54.6
MCMD_Z	81.0	79.2	18.6	19.6	86.2
MCMD_MD	72.3	73.2	26.5	27.3	76.5
Proposed	79.2	98.2	2.4	19.0	96.5

less than 5 square meters in area and six of the buildings are in between area of 5 to 10 m². LiDAR datasets of HB is collected from a moderately hilly area. Bare-earth DEMs are available for all of these areas.

ISPRS benchmark datasets has three different sites from Vaihingen (VH) area. The first area (VH1) is named as *Inner City*. It is dense developed and consists of complex historic buildings. The second area (VH2) consists of high rising buildings and third area (VH3) is characterized as a residential area. LiDAR point density of VH1 is 3.5/m², VH2 has 3.9 points per square meter and finally, VH3 has point density 3.9/m². VH1 has 37 buildings larger than area of 2.5 m², The second area contains 14 large buildings and finally, VH3 contains 56 buildings with an area greater than 2.5 square meters.

To evaluate the roof extraction method, the reference data is created for each individual area from the datasets. The reference data indicates each individual roofs and buildings of the selected area. Reference roofs were generated from the orthoimages using Barista software (Barista, 2016). Detected roofs and buildings by the proposed method are then compared with the reference datasets. Figure 8 shows the reference roofs of Australian Benchmark datasets and Figure 7 shows the same for VH datasets. Reference boundaries of the roof planes and buildings are sketched using blue colours.

4.2. Outlier Detection Results

To evaluate the proposed outlier detection method we compute precision, recall and F_1 -scores. Using conventional formula, True Positive Rate (TPR) (Ratio of the number of correctly detected outliers to the total outliers), True Negative Rate (TNR) (ratio of the number of correctly detected inliers to the total inliers, False Positive Rate (FPR) (ratio of the number of inliers identified as outliers to the total inliers), False Negative Rate (FNR) (ratio of the number of outliers identified as inliers to the total outliers) are also calculated. We compared the method with three other existing methods: LDOF (Zhang et al. 2009), MCMD_Z (Nurunnabi, West and Belton 2015) and MCMD_MD (Nurunnabi, West and Belton 2015). Table 1 and Table 2 show the comparative results of the proposed method in terms of TPR, TNR, FPR, FNR and Accuracy (Acc). Again, Table 3 shows the comparisons in terms of precision, recall and F_1 -scores. Proposed method shows better result in most of the cases. Although, a little bit lower precision for inliers and recall for outliers are observed compared to MCMD_Z for AV datasets, it means our method give emphasis on inliers which is one of major goal discussed earlier. We get high F_1 scores in all cases.

Figure 6. Created 3D building roof model using method proposed by Awrangjeb, Gilani and Fasahat (2018). (a) Inliers and outliers for a single building. Red star (*) indicates outliers and black dot (.) indicates inliers (b) 3D roof model of Aitkenvale datasets (b) 3D building roof of Hervay bay datasets.

Table 2. Accuracy measures of proposed outlier detection using the Hervey Bay (HB) dataset

Methods	TPR	TNR	FPR	FNR	Acc
LDOF	59.5	62.5	36.6	41.0	57.8
MCMD_Z	82.1	85.0	15.2	17.3	84.0
MCMD_MD	71.0	76.2	23.2	29.5	72.9
Proposed	77.4	93.2	8.7	23.2	92.6

Table 3. Comparison with different methods A1 = LDOF Zhang et al. (2009), A2 = MCMD_Z Nurunnabi, West and Belton (2015), A3 = MCMD_MD Nurunnabi, West and Belton (2015)

Using AV roof planes					
Inlier	Precision	87.2	99.0	95.0	97.6
	Recall	53.4	72.4	73.1	98.1
	F_1 -score	66.0	82.2	83.1	97.4
Outlier	Precision	20.2	60.1	26.0	84.4
	Recall	52.7	89.1	71.2	84.8
	F_1 -score	28.5	71.7	39.8	83.4

Using HB roof planes					
Inlier	Precision	82.1	95.4	91.6	96.8
	Recall	59.4	69.2	70.8	95.9
	F_1 -score	68.4	79.5	79.7	95.6
Outlier	Precision	25.8	68.9	29.7	82.7
	Recall	62.1	85.1	80.4	80.8
	F_1 -score	35.4	78.7	42.2	80.8

4.3. Roof Plane Extraction Results

We show both quantitative and qualitative evaluation of roof plane extraction using the proposed method. Table 4 and Table 5 show the object-based and pixel-based evaluation of roof plane extraction respectively for AV1, AV2 and HB areas of Australian benchmark. Figure 9 shows the extracted roof planes using the proposed method. The result is evaluated using the system proposed by Rutzinger, Franz and Norbert (2009). Table 5 shows area-omission and commission errors instead of over-segmentation and undersegmentation properties. For Australian benchmark datasets, we mainly compared our method to the approach of Awrangjeb and Fraser (2014a). Our method shows better results especially in correctness. We show the comparison of roof plane extraction using Table 11. For the Vaihingen area, Table 6 shows the object based roof extraction results and Figure 10 shows the extracted roof planes using the proposed method.

From Table 4 and Table 5 we can see that for AV1 and HB the results are better in roof extraction than AV2. This is because AV2 is a large area with complex building structures and trees. Last two columns of Table 4 show the results of over-segmentation and under-segmentation. Our method shows outstanding performance in this case. Over-segmentation rate is only 1%, although for AV2 area the under-segmentation rate (C_{rd}) is high because of the complex nature of the building roofs. Because of some misregistration between the reference data and extracted roof planes the omission and commission errors in Table 5 are high. Orthoimage and LiDAR data registration errors are 1 to 2 m² which cause the high omission and commission errors. Table 4 also shows that the average completeness and correctness for roof plane area over 10 m² are 84%

Table 4. Roof plane extraction: object-based evaluation for Aitkenvale (AV1, AV2), Hervey bay (HB). C_m indicates completeness, C_r indicates correctness, Q_l indicates quality, ($C_{m,10}$, $C_{r,10}$, $Q_{l,10}$) for plane with area over 10 m². C_{rd} indicates detection cross-lap and C_{rr} indicates reference cross-lap rates.

Areas	C_m	C_r	Q_l	$C_{m,10}$	$C_{r,10}$	$Q_{l,10}$	C_{rd}	C_{rr}
AV1	0.89	1	0.89	0.96	1	0.93	0.12	0
AV2	0.64	0.96	.67	0.77	0.97	0.79	0.30	0.01
HB	0.84	0.89	0.74	0.92	0.90	0.76	0.11	0.02
Average	0.79	0.95	0.77	0.84	0.96	0.83	0.18	0.01

and 96%, respectively, for object-based evaluation. For pixel-based evaluation average completeness and correctness for Australian datasets are 76% and 80%, respectively, shown in Table 5.

Table 6 shows the object-based evaluation of roof planes for VH datasets. Area 3 (VH3) contains less vegetation and large buildings. It is a residential area and the houses maintain enough distance from each other. Therefore, completeness and correctness are comparatively higher than other two areas (VH1 and VH2). We get average correctness of 93% for all types of roof and 95% correctness with building roof size at least 10 m². Over-segmentation rate is only 3% on average which means only a few roof planes are separated as two or more planes, although we can see many under-segmentation and on average it is 39%. Because, most of the time small roof planes are merged with the close large neighbouring planes.

Figure 7. Vaihingen area with reference roofs and building: (a)Area-1 (VH1), (b) Area-2 (VH2) (c) Area-3 (VH3)

4.4. Building Detection Results

We generate the building outlines by combining all the adjacent roof planes in a cluster. Table 9 and Table 10 show the object-based and pixel-based building detection results, respectively, for Australian Benchmark. The average object-based completeness and

Figure 8. Australian Benchmark datasets with reference roofs and buildings : (a) AV2, (b) AV1 (c) HB

Table 5. Roof plane extraction: pixel-based evaluation for Aitkenvale (AV1, AV2), Hervey bay (HB). C_m indicates completeness, C_r indicates correctness, Q_l indicates quality, $(C_{m,10}, C_{r,10}, Q_{l,10})$ for planes over 10 m². A_{oe} indicates omission error and A_{ce} indicates commission error.

Areas	C_m	C_r	Q_l	$C_{m,10}$	$C_{r,10}$	$Q_{l,10}$	A_{oe}	A_{ce}
AV1	0.89	0.88	0.80	0.89	0.88	0.78	0.11	0.13
AV2	0.73	0.80	0.63	0.77	0.80	0.65	0.26	0.20
HB	0.80	0.69	0.62	0.74	0.70	0.58	0.32	0.35
Average	0.76	0.79	0.65	0.76	0.80	0.68	0.25	0.24

correctness for all building are 86% and 97%, respectively. When the buildings are at least 10 m² in size, we get 90% completeness and 97% correctness on average for the three areas. For the AV1 area, we can see that our method is 100% accurate for building detection both in object-based and pixel-based evaluations. This is because the area of AV1 is small and contains a few if vegetation. Average completeness and correctness are 85% and 95%, respectively, in pixel-based evaluation. The buildings are situated by keeping a moderate distance from each other and the datasets have high point densities thus the over-segmentation is only 1% for both object-based and pixel-based evaluation and the under-segmentation rates are 13% and 10%, respectively.

To demonstrate the building detection results on the ISPRS datasets, the pixel-based evaluation shown in Table 7 and object-based evaluation on Table 8. From Table 8, we can see that the method performs 100% accurate on completeness and correctness when buildings are at least 50 m² in size. For all types of building the method shows 81% completeness and 100% correctness. Visual inspection tells the

Figure 9. Extracted roof segments for Australian benchmark datasets (a) AV1, (b) HB (c) AV2. Area marked by letters in (a), (b) and (c) magnified in (d) - (j) indicate small, missed, over and under-segmentation cases

Table 6. Roof plane extraction: object-based evaluation for Vaihingen (VH) datasets. C_m indicates completeness, C_r indicates correctness, Q_l indicates quality, $(C_{m,10}, C_{r,10}, Q_{l,10})$ for buildings over 10 m². C_{rd} indicates detection cross-lap (under-segmentation and C_{rr} indicates reference cross-lap (over-segmentation) rates

Areas	C_m	C_r	Q_l	$C_{m,10}$	$C_{r,10}$	$Q_{l,10}$	C_{rd}	C_{rr}
VH1	0.67	0.92	0.62	0.84	0.94	0.76	0.40	0.03
VH2	0.72	0.91	0.71	0.88	0.93	0.89	0.35	0.05
VH3	0.80	0.94	0.81	0.90	0.98	0.91	0.42	0.03
Average	0.73	0.93	0.72	0.87	0.95	0.85	0.39	0.03

method performs well for detecting buildings although some small buildings are missed due to sloped terrain and building region on stilts where LiDAR points have below 1 m height. These points were removed during the process of the ground and non-ground point separation procedure.

Figure 11 demonstrates the results of building detection. Figure 11(a) is chosen from Australian benchmark datasets and Figure 11(b) is chosen from ISPRS benchmark datasets. Figures 11(c)-(d) show the under-segmentation error due to the closeness of different buildings. Due to the undetected building roof planes Figure, 11(e) shows a partially detected building. Figure 11(f) shows missed building due to the occlusion of the tree and Figure 11(g) shows detected small building. Accuracy of building detection directly depends on correct roof plane extraction. This method identifies the building boundaries by adding all adjacent roof planes in a cluster so if some roof planes remain un-extracted, the ultimate detected building boundaries is not accurate.

Table 7. Building Detection: pixel-based evaluation for Vaihingen (VH) datasets. C_m indicates completeness, C_r indicates correctness, Q_l indicates quality, $(C_{m,50}, C_{r,50}, Q_{l,50})$ for buildings over 50 m². A_{oe} = area omission error and A_{ce} = area commission error

Areas	C_m	C_r	Q_l	$C_{m,50}$	$C_{r,50}$	$Q_{l,50}$	A_{oe}	A_{ce}
VH1	0.89	0.96	0.84	0.84	0.96	0.81	0.12	0.04
VH2	0.90	0.98	0.84	0.92	0.98	0.97	0.10	0.03
VH3	0.91	0.99	0.85	0.85	0.99	0.85	0.17	0.01
Average	0.90	0.98	0.84	0.87	0.98	0.88	0.13	0.02

Table 8. Building Detection: object-based evaluation for Vaihingen (VH) datasets. C_m indicates completeness, C_r indicates correctness, Q_l indicates quality, $(C_{m,10}, C_{r,10}, Q_{l,10})$ for buildings over 50 m². 1:M = over-segmentation and N:1 = under-segmentation

Areas	C_m	C_r	Q_l	$C_{m,50}$	$C_{r,50}$	$Q_{l,50}$	1 : M	N : 1
VH1	0.80	1.00	0.76	1.00	1.00	1.00	1	6
VH2	0.82	1.00	0.78	1.00	1.00	1.00	0	3
VH3	0.79	1.00	0.79	1.00	1.00	1.00	1	5
Average	0.81	1.00	0.78	1.00	1.00	1.00	0.67	4.7

Table 9. Building Detection: object-based evaluation for Aitkenvale (AV1, AV2), Hervey bay (HB) datasets. C_m indicates completeness, C_r indicates correctness, Q_l indicates quality, $(C_{m,10}, C_{r,10}, Q_{l,10})$ for buildings over 10 m². C_{rd} = detection cross-lap (under-segmentation) and C_{rr} = reference cross-lap (over-segmentation)

Areas	C_m	C_r	Q_l	$C_{m,10}$	$C_{r,10}$	$Q_{l,10}$	C_{rd}	C_{rr}
AV1	1.00	1.00	1.00	1.00	1.00	1.00	0	0
AV2	0.62	0.96	.68	0.75	0.94	0.72	0.30	0.01
HB	0.95	0.94	0.95	0.95	0.96	0.95	0.11	0.02
Average	0.86	0.97	0.88	0.90	0.97	0.89	0.13	0.01

Table 10. Building Detection: pixel-based evaluation for Aitkenvale (AV1, AV2), Hervey bay (HB) datasets. C_m indicates completeness, C_r indicates correctness, Q_l indicates quality, $(C_{m,10}, C_{r,10}, Q_{l,10})$ for buildings over 10 m². C_{rd} = detection cross-lap (under-segmentation) and C_{rr} = reference cross-lap (over-segmentation)

Areas	C_m	C_r	Q_l	$C_{m,10}$	$C_{r,10}$	$Q_{l,10}$	C_{rd}	C_{rr}
AV1	1.00	1.00	1.00	1.00	1.00	1.00	0	0
AV2	0.82	0.96	.79	0.82	0.95	0.79	0.20	0.01
HB	0.78	0.89	0.76	0.78	0.89	0.76	0.11	0.02
Average	0.87	0.95	0.85	0.87	0.95	0.85	0.10	0.01

Figure 10. Extracted roof segments for ISPRS datasets (a) Vaihingen area-1 (VH1, (b) Vaihingen area-3 (VH3). Area marked by letters in (a), (b) magnified in (c) - (f) indicate small, missed, over and under-segmentation cases

4.5. Comparative Analysis

The improved method performs better both in roof plane extraction and building detection. It is robust in terms of correctness for both building detection and roof plane extraction. That means false positive rate is low. Outliers were one of the reasons for generating FP points for building or roof planes. The robust outlier removal method along with the improved plane fitting methods together make the proposed individual roof and building detection method robust.

The proposed method is a data-driven approach. Therefore, we choose three different methods from ISPRS portal (ISPRS 2019) along with results from (Awrangjeb and Fraser 2014a) and (Liua et al. 2012) to compare our results for ISPRS datasets. In Table 11, we compare our results for Australian datasets with the method proposed by Awrangjeb and Fraser (2014a).

Evaluation results of three methods on Vaihingen datasets are available on ISPRS portal under name VSK, UMTF and TON. Results taken from corresponding papers of (Awrangjeb and Fraser 2014a) and (Liua et al. 2012) and we named these by MA and LIU, respectively. From Table 12 we can see that our method shows competitive performances for building detection. We can see that $C_{m,50}$ and $C_{r,50}$ are 100 % for the proposed method in all the cases. That means that our method is 100% accurate in completeness and correctness for detecting buildings over 50 m². In term of correctness, our method performs better than most of the cases. However, VSK shows slightly better in correctness in terms of pixel-based evaluation when all building types are considered. The method performs slightly better sometimes in terms of planimetric accuracy (RMSE).

Figure 11. Detected Buildings: (a) AV2 area from Australian benchmark datasets (b) VH3 area from ISPRS benchmark; area marked by letters in (a) and (b) magnified in (c-g)

For roof plane extraction for VH3 area the proposed method is better than all other methods in terms of completeness. In terms of correctness, it is better than TUD and MA except for ITCE1. For VH2 completeness is better in all cases except ITCE1. Completeness for roof area over 10 m² is higher than all other methods in VH1 shown in Table 13. We can see that the vertical distances (RMSZ) error is lower in every case for our proposed method. It is due to the reason of outlier removal. We had clean LiDAR data for roof plane extraction. That is why the RMSZ distances between the reference data and our result are lower.

Table 11. Comparison of roof plane extraction for Australian datasets. Results from Awrangjeb and Fraser (2014a) named as (AF,2014). C_m , C_r indicates object-based completeness and correctness. ($C_{m,10}$, $C_{r,10}$ are completeness and correctness when planes are atleast 10m²). C_{mp} , C_{rp} indicates pixel-based completeness and correctness respectively ($C_{mp,10}$, $C_{rp,10}$ are completeness and correctness when planes are atleast 10m²).

Method	C_m	C_r	C_{mp}	C_{rp}	$C_{m,10}$	$C_{r,10}$	$C_{mp,10}$	$C_{rp,10}$
Aitkenvale (AV1)								
(AF,2014)	0.90	0.92	0.85	0.80	0.96	0.92	0.89	0.83
Proposed	0.89	1	0.89	0.88	0.96	1	0.89	0.88
Aitkenvale (AV2)								
(AF,2014)	0.60	0.90	0.70	0.77	0.75	0.92	0.74	0.78
Proposed	0.64	0.96	0.73	0.80	0.77	0.97	0.77	0.80
Hervey bay (HB)								
(AF,2014)	0.79	0.84	0.80	0.72	0.90	0.85	0.66	0.52
Proposed	0.84	0.89	0.80	0.69	0.92	0.90	0.74	0.70

5. Conclusions

Individual roof plane extraction and building detection have various application areas. However, it is difficult and challenging to get accurate planes with boundaries because of intrinsic nature of the input data. This paper proposed an improved and automatic data-driven building roof plane extraction method. Three major steps- outlier removal, plane fitting and refinement procedure have been performed sequentially to extract the roof planes. The proposed robust outlier detection module has been applied effectively to avoid the effects of outliers. Where most of the existing outlier detection approaches misclassify many inliers as outliers, using the synthetic data we have shown better performance than the existing state-of-the-art. Next, we applied an improved plane fitting method which is based on the MSAC algorithm on the outlier free data. Preprocessed outlier free data along with the less outlier sensitive plane fitting approach have made the proposed roof plane extraction method more robust with a concise refinement procedure. Better correctness in the benchmark datasets for individual roof plane proved the effectiveness of the proposed algorithm. Besides this, experimentally we have demonstrated the high building detection accuracy in

Table 12. Comparison of building detection results for ISPRS Vaihingen area datasets. C_m , C_r indicates object-based completeness, correctness respectively ($C_{m,50}$, $C_{r,50}$ for building over area 50 m²). (C_{mp} , C_{rp} are pixel-based completeness, correctness respectively. RMSE is planimetric accuracy in meters.

Method	C_m	C_r	C_{mp}	C_{rp}	$C_{m,50}$	$C_{r,50}$	RMSE
Area-1 (VH1)							
VSK	78.4	100	85.7	98.1	96.4	100	0.80
UMTP	78.4	100	89.0	87.3	96.4	100	1.10
TON	75.7	96.7	76.7	95.9	96.4	96.4	1.00
MA	80.0	96.0	92.0	84.0	100	100	1.11
LIU	75.7	93.5	76.7	95.7	93.3	96.7	1.18
Proposed	80.0	100	89.0	96.0	100	100	1.14
Area-2 (VH2)							
VSK	85.7	100	85.4	98.4	100	100	0.90
UMTP	78.6	91.7	94.8	85.6	100	91.7	0.80
TON	71.4	100.0	88.5	98.9	100	100	0.70
MA	83.0	84.0	91.0	91.0	100	100	0.80
LIU	71.4	100	88.5	98.0	90.9	100	0.71
Proposed	82.0	100	90.0	98.0	100	100	0.85
Area-3 (VH3)							
VSK	75.0	100	86.3	98.7	97.4	100	0.80
UMTP	85.7	95.8	93.5	85.2	100	100	1.00
TON	55.4	100.0	67.8	98.4	81.6	100	1.00
MA	72.0	97.0	93.0	86.0	100.0	97.0	0.89
LIU	55.4	100	67.8	98.4	77.5	100	1.17
Proposed	79.0	100.0	91.0	99.0	100	100	1.03

Table 13. Comparison of roof extraction results for ISPRS (Vaihingen area) datasets. C_m, C_r indicates object-based completeness, correctness respectively ($C_{m,10}, C_{r,10}$ for roof area over 10 m²). RMSE is planimetric accuracy RMSZ is height accuracy in meters.

Method	C_m	C_r	$C_{m,10}$	$C_{r,10}$	RMSE	RMSZ
Area-1 (VH1)						
ITCE1	60.8	96.6	64.4	97.2	1.0	0.30
TUD	67.4	96.2	68.0	97.8	0.8	0.20
MA	66.0	83.3	81.4	84.9	1.0	0.41
Proposed	67.0	92.0	84.0	96	1.1	0.03
Area-2 (VH2)						
ITCE1	79.7	73.7	97.9	73.7	1.2	0.10
TUD	68.1	98.1	85.4	100	0.6	0.30
MA	71.0	87.7	93.8	92.6	0.7	0.37
Proposed	72.0	91.0	98.0	97.0	0.8	0.03
Area-3 (VH3)						
ITCE1	67.7	100	73.6	100	0.8	0.10
TUD	74.5	93.0	83.1	98.0	0.7	0.10
MA	77.2	89.2	91.9	96.1	0.8	0.27
Proposed	80.0	94.0	91.0	98.0	0.8	0.02

complex environment. However, sometimes because of low point densities some small true roof planes remain undetected and planimetric accuracy of the detected planes is also limited. In future, we will look how more accurate roof boundaries can be extracted in the cases of low point densities or missing points for a particular area. Integration of aerial images in low point density/missing points area or incorporating the model-driven approaches may lead a more suitable solution.

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