Detection of Individual Trees in Urban Areas Using the Point Cloud Produced by Dense Image Matching Algorithms

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Key words: photogrammetry, aerial photographs, image matching, point cloud, classification, clustering, point based, tree detection, urban tree

SUMMARY

Urban environment is the principal habitat for the human population. Trees in urban areas play an important role in modern urban spatial data management, local micro-climatic conditions, the ecosystem and air quality. The distribution and number of trees impact the health and life quality of urban residents considerably. Timely and accurate acquisition of individual tree information is very crucial for the decision makers to supply better living conditions for the residents. Today, LiDAR point cloud with high point density and accuracy is widely available in particular for urban areas for different studies such as 3D city modelling, chance detection, object extraction as well as the delineation of individual trees. Although LiDAR systems have various advantages in recent years, they are still expensive for data acquisition especially in small areas. The cost-effective alternative of the LiDAR systems is the 3D dense point clouds generation with aerial photogrammetry using image matching algorithms such as semi-global matching. This study concentrates on the detection of individual trees in urban environments, which is very difficult task because of structural complexity of urban environment includes various objects such as buildings, roads, trees, temporary objects, power lines and cables. The high density point cloud data obtained with semi-global matching using aerial photographs was used to acquire detailed and accurate information about urban trees instead of LiDAR point cloud. First, a point-based classification has been performed to classify the dense point cloud data automatically which based on hierarchical rules. In this step, the detailed analysis in different pilot areas has been performed for the determination of most suitable parameters used in hierarchical rules. The ground, low vegetation, medium vegetation, high vegetation, building, low point, air point and default classes were obtained with proposed point-based classification approach. After the classification step, a point-based segmentation with advanced clustering techniques carried out using the points in high vegetation class to detect individual urban trees. The dense point cloud data of the test side, which is situated in Zekeriyakoy, Istanbul, were generated with dense image matching algorithms within the scope of High Resolution Digital Surface Model (DSM) and Real Orthophoto Production Project by the Directorate General of Geographic Information Systems of the Republic of Turkey Ministry of Environment and Urbanization. The obtained detection rate of individual trees in the study area verified that individual trees in urban environment can be obtained successfully using the dense point cloud data produced by dense image matching algorithms using aerial photographs.

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1. INTRODUCTION

Today, most of the world population prefers to live in urban areas with the current expansion of cities. Urban forests are of huge importance for humanity because of having aesthetic, environmental, economic, and health benefits in urban ecosystems. Trees, the most dominant elements in urban forests, play an important role within the urban environment as oxygen producers, improving air quality by trapping CO_2 emission, reducing the urban heat island effect with their evapotranspiration, supporting biodiversity, isolating noise, alleviating urban flood risk, etc. (Liu et al., 2017; Yilmaz and Gungor, 2018; Hartling et al., 2019). Besides these ecological and environmental benefits, urban trees also provide many psychological and social benefits to urban residents, such as getting rid of daily life stress, potentially reducing crime, encouraging people to build stronger social relationships, and improving residential property value (Liu et al, 2017). Furthermore, trees, structuring elements of the cities, decorate the roads, pavements, parks, gardens and create shades. Thus, detection, identification and monitoring of urban trees are necessary. The local administrators of the urban environment have to consider the distinctive characteristics of the trees for a sustainable urban planning and monitoring, and a first step is the individual tree identification (Aval et al, 2018). Nowadays, this type of procedure is carried out manually, by field sampling or photo interpretation. These methods are really difficult to cover large scales of continuous urban area in a short time and also generally labor-intensive. Contrary to extensive field sampling, remote sensing opens the way to automate the delineation of individual urban trees. The airborne laser scanners (ALS) in other word Light Detection and Ranging (LiDAR), the most advanced active systems in these remote sensing technologies, provides point cloud in particular for urban areas for different studies such as 3D city modelling, chance detection, object extraction as well as the delineation of individual trees. LiDAR is a powerful technology that enables an accurate characterization of urban structure, and it has been currently incorporated as an operational technology in several studies (Navarro et al., 2018). LiDAR systems collect point cloud data with high accuracy by actively measuring distance to a surface through time of flight of laser beams in a high-frequency (Huang et al, 2018). LiDAR point clouds also include multi-returns from the visible surface of Earth together with the intensity values, and data collection with LiDAR has been performed by multi sensor system including digital camera and GPS/IMU positioned on the same platform (Baltsavias, 1999; Yastikli et al., 2014). However, airborne LiDAR systems, although smaller and lighter than they were some years ago, are usually expensive and cumbersome today (Remondino et al., 2014). Their updating periods are long or data update is not expected because of high cost. The need to improve temporal resolution at a low cost has led people to look for alternative technologies to LiDAR systems. Data collection by aerial photogrammetry is a more cost-effective method of data collection than LiDAR. Photogrammetric techniques have been widely used for 3D data acquisition due to the advantages of high-quality imaging, a short revisit time, and lower costs (Ye and Wu, 2018). In recent years, the production of dense 3D point clouds from aerial stereo images has become possible because of the recent innovations in image matching algorithms and hardware systems. So, today dense image matching point clouds are a significant alternative to ALS-based point clouds in many professional and amateur applications such as 3D modelling and mapping, object extraction, robotics, medical imaging, surveillance, tracking and navigation (Remondino et al., 2014; Yastikli et al. 2014; Navarro et al., 2018).

In this study, we aimed to develop an approach to detect individual urban trees in our Zekeriyakoy, Istanbul test side using dense point cloud data produced with dense image matching algorithms using aerial photographs. For this purpose, a point-based classification approach has been proposed based on hierarchical rules to automatically classify dense point cloud data. The detailed parameter analysis has been performed in different pilot areas in the test side for the determination of most suitable parameters which used in hierarchical rules. Eight classes including the ground, building, low vegetation, medium vegetation, high vegetation, low point, air point and default were acquired with proposed point-based classification approach. A point-based segmentation with mean shift clustering technique was carried out to detect individual urban trees in the study area using the points from high vegetation class. Finally, an accuracy assessment process was performed to determine the detection rate of the urban trees acquired as a result of the segmentation.

The rest of this paper is organized in four sections. The brief information about methodology of dense image matching, classification, segmentation and accuracy assessment approaches are given in the next section. In session to follow, the details of performed classification, segmentation and accuracy analysis processes for individual tree detection using point cloud data from dense image matching of Zekeriyakoy, Istanbul test side. The results and discussions are given in the last part of the paper.

2. METHODOLOGY

In this section, basic information about dense image matching methods, point-based classification and point-based segmentation approaches, and accuracy assessment is included.

2.1 Dense Image Matching

Dense image matching can be defined as generating the 3D point clouds of the overlap area between the image pairs using a pair of stereo images and corresponding camera parameters (Yuan et al., 2019). Generally, the techniques of dense matching are categorized into two main categories, local methods and global methods (Laraqui et al., 2018). The classical SSD (the Sum of Squared Differences), SAD (Sum of Absolute Differences), NCC (Normal Cross Correlation) are some of the local methods, and belief propagation, graph cut, Markov random field (MRF) are also some of the global methods (Su et al., 2018). While local methods use an implicit assumption of surface smoothness since they compute a constant parallax for a window with a certain number of pixels, in contrast, global methods use an explicit formulation of this smoothness assumption, which is then solved a global optimization problem (Szeliski, 2010; Halaa, 2013). In most cases, the matching accuracy by global methods is better than that by local methods (Su et al., 2018). A very popular and well performing example of global methods is semi-global matching (Hirschmüller, 2005; Hirschmüller, 2008) which is used for a variety of applications and measurement tasks, ranging from close-range and real-time applications to aerial image matching (Halaa, 2013; Bethmann and Luhmann, 2017). Semi-Global Matching (SGM) stereo method uses a pixel-wise, Mutual Information (MI)-based matching cost (a global cost function) for compensating radiometric differences of input images (Hirschmüller, 2008). The SGM method aims to minimize the defined global cost function (Hirschmüller et al., 2012). In SGM, one dimensional optimization from all directions through the image have been performed (Yastikli et al., 2014) Semi-global matching combines good performance with reasonable computational time using hierarchical matching strategies and techniques of parallelization on special hardware (GPU, FPGA) (Bethmann and Luhmann, 2017; Dominik, 2017). Besides its advantages, the main drawback of SGM is its memory consumption that depends on the number of pixels and the disparity range like for all global methods. Therefore, SGM based dense matching can be implemented on a computer cluster (Hirschmüller, 2011; Yastikli et al., 2014).

Multiple aerial overlapping images with high spatial resolution and high overlap between the images are needed to achieve an adequate image-based dense point cloud using dense image matching algorithms (Navarro et al., 2018; Yastikli and Cetin, 2019a). An overlap of 80 % or more along track overlap and 70 % across track overlap should be provided between the images for very good stereo matching results (Hirschmüller and Bucher, 2010). Several software tools for image-based 3D point cloud production are currently developed by photogrammetric software vendors and research institutes based on semi-global matching (Halaa, 2013). The Microsoft UltraMap V3.0. Dense Matcher, Astrium GEO-Information Pixel Factory are examples of the commercial software tools for dense image matching. The French National Mapping Agency (IGN) developed the software system MicMac and the German Aerospace Center (DLR) developed own software based on SGM algorithm (Yastikli et al., 2014).

2.2 Point-Based Classification

Classification is the first step in extracting productive geo-information for several studies such as building extraction, 3D modelling, tree detection, etc. In addition to pixel-based and object-based classification methods, point-based classification has emerged with the widespread use of LiDAR systems today (Yastikli and Cetin, 2019a). Point-based classification is quite a challenge because of irregular point distributions and complex observed scenes. However, data loss during interpolation to the grid format, to be used pixel-based and object-based classification methods, has made point-based classification methods more attractive for classification applications (Yastikli and Cetin, 2016).

Point-based classification methods use the information of each individual 3D point with reference to its neighbor to obtain accurate classification results (Kim and Sohn, 2013; Niemeyer et al., 2014; Yastikli and Cetin, 2016; Yang et al., 2018). The features that use in the point-based classification algorithms can be categorized into three groups which are spatial-based, echo based and waveform-based features (Mallet et al., 2011). Echo-based and waveform-based features can only be used in LiDAR point cloud classification because of obtaining using multiple-return specifications of laser systems and full-waveform LiDAR data. Only spatial based features including height features, the local environment, local plane features, eigenvalues, surface-based features, vertical profile features, point density and density ratio, can be used in point-based classification of dense point cloud acquired with dense image matching algorithms (Mallet et al., 2011; Yastikli and Cetin, 2019a). The spatial-based features used in point based classification of dense point data are identified in accordance with the targeted classes and the best suited parameters of the features frequently determined as a result of training stages (Yastikli and Cetin, 2016). In addition to geometric features, color information can also be used in the point-based classification of the dense point cloud to acquire the appropriate classes in the test areas.

2.3 Point-Based Segmentation and Accuracy Assessment

Segmentation is a key task in the processing of 3D point clouds acquired using LiDAR systems or dense image matching approaches. Segmentation process group points according to the similar attributes with respect to geometric, color, radiometric, or other information to be used several studies such as feature extraction, classification, modeling, analysis, etc. Existing segmentation approaches can be categorized into image-based and point-based approaches (Che and Olsen, 2018). Point-based approaches segment the data primarily using 3D geometric features. Three important strategies have been commonly adopted for the point-based segmentation approaches which are geometric fitting, region growing and clustering (Zolanvari et al., 2018). Unlike geometric fitting, multi-plane and 3D facades can be divided into segments without need to fitting planes or lines into the dense point cloud using clustering methods. Similarly, unlike region growing, grouping can be initiating without need to seed points or regions using clustering methods. Therefore, cluster-based methods are some of the most recent and popular approaches to directly extract individual trees from the point cloud data (Li et al., 2012). Among many existing clustering algorithms, mean shift is a functional automatic algorithm that is often used in individual tree delineation (Hu et al., 2017). Mean shift, proposed in 1975 (Fukunaga and Hostetler, 1975), is a non-parametric and iterative procedure that shifts each data to local maximum of density function (Wen and Cai, 2006). The method first selects a random point from the dataset as the cluster center (Du et al., 2019). Mean shift is a centroid based clustering algorithm, which works by updating candidates for centroids to be the mean of the points within a given region. Mean shift clustering does not rely upon a priori knowledge of the number of clusters and does not constrain the shape of the clusters (Cabria and Gondra, 2012; Anand et al., 2014). The algorithm automatically determines the number of clusters based on bandwidth, a parameter that determines the size of the region to search.

Accuracy assessment is an important step to evaluate the accuracy of the clusters obtained by segmentation. Pixel-based segmentation errors are measured by establishing the relationship between pixels and their corresponding segments according to the overlaps of segments and the reference polygons (Li et al., 2012). Several methods have been proposed to assess the accuracy of a segmentation (or classification) process. Confusion matrix, error of commission, error of omission, producer's accuracy, user's accuracy, overall accuracy and Kappa coefficient are the prominent methods in statistical measurement of accuracy (Navulur, 2007). Today, although many approaches are available to test the accuracy of pixel-based segmentation or classification methods, no approach are available for the accuracy assessment of point-based methods. Therefore, it is considered that the error matrix created using points instead of pixels and the variables calculated from this matrix may be a suitable approach to test the accuracy of the point-based methods (Yastikli and Cetin, 2019a). Alternatively, completeness and correctness (Equation 1 and 2) analyses can be used for accuracy assessment of the point-based methods (Uzar and Yastikli, 2013).

Completeness = $(TP)/(TP+FN)$ (1)
Correctness = $(TP)/(TP+FP)$ (2)

TP is the number of true positive entities segmented (classified) correctly, FN is the number of false negative entities identified as correct in the reference data that were not segmented in the segmentation process, FP is the number of false positive entities that were segmented in the segmentation process but were not exist correctly in the reference data (Yastikli and Cetin, 2019b). The detection rate is the basis criteria for completeness and correctness analysis especially in segmentation process for individual tree detection studies (Lee et al., 2010).

3. DETECTION OF INDIVIDUAL TREES

This section contains detailed information about the study area, the data set, the workflow of the study, performed point-based classification of dense point cloud, performed point-based segmentation of high vegetation points and accuracy assessment of the segmentation for the purpose of the study.

3.1 Study Area and Data Set

In this study, Zekeriyakoy, located in Sariyer district of Istanbul, was determined as an urban study area (Figure 1). The dense point cloud data generated with semi-global matching in the study area within the scope of High Resolution Digital Surface Model (DSM) and Real Orthophoto Production Project by the Directorate General of Geographic Information Systems of the Republic of Turkey Ministry of Environment and Urbanization has been used as the test data. Details about the test data can be found in Yastikli and Bayraktar (2014).

Figure 1. General view of the study area in Zekeriyakoy

The workflow of the proposed the point-based classification approach consisting of hierarchical rules to automatically classify dense point cloud data, and the point-based segmentation with mean shift clustering technique to detect individual urban trees in the study area is given in Figure 2.

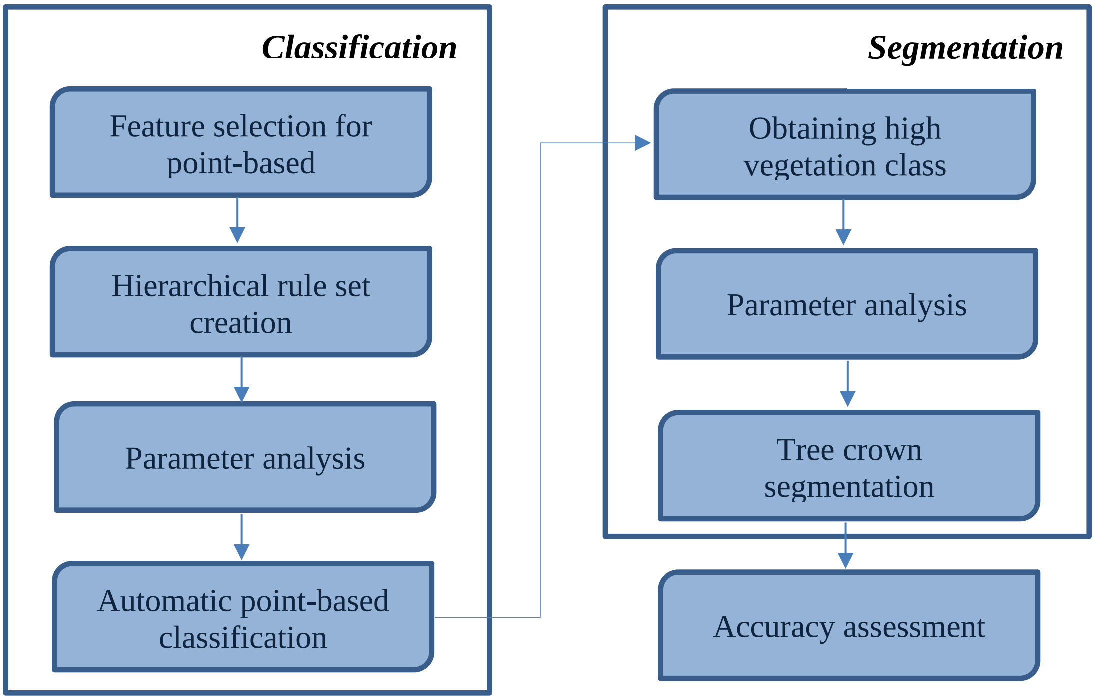
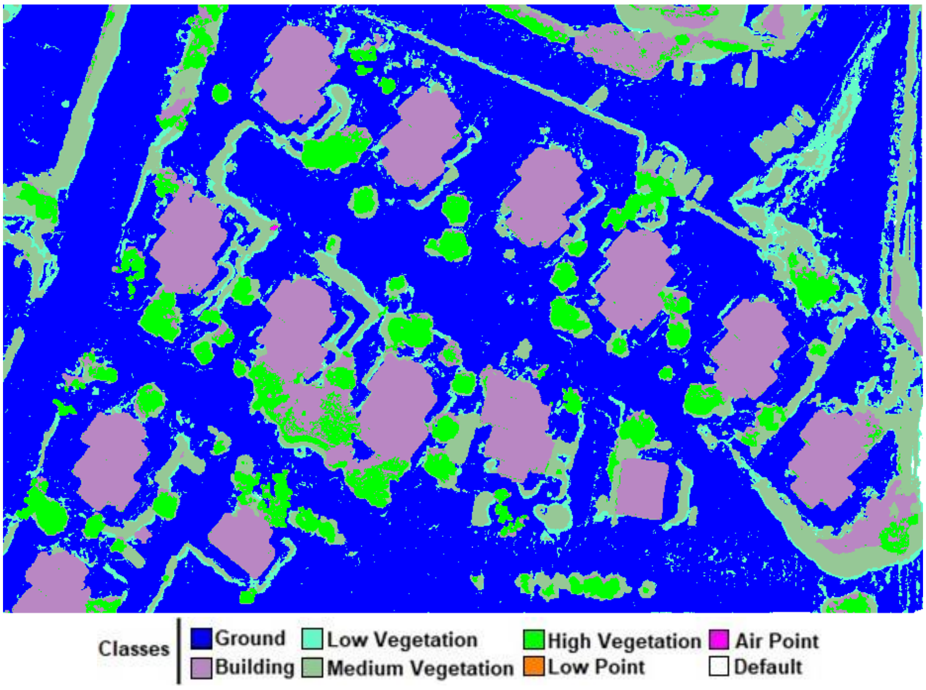


Figure 2. The workflow of the proposed approach for individual urban tree detection

3.2 Point-based Classification of Dense Point Cloud

In the proposed automatic point-based classification approach, each 3D point is classified according to its individual characteristics, and automatically assigned to the belonging class with the created rule sets. Firstly, feature selection was carried out, and then the rule set was created for point-based classification of dense point cloud. The color information of the single points were used in the rule set as well as various important geometric features such as height features, local plane features, etc. Detailed parameter analyses, which were used in the classification rules, was performed for ground, building and vegetation classes in order to ensure high classification accuracy. The automatic point-based classification of the dense point cloud was carried out with the proposed classification approach, consisting of the hierarchical rule set, using the most appropriate parameters determined with parameter analyses. Eight classes, which are ground, building, low vegetation, medium vegetation, high vegetation, low point, air point and default, were obtained as a result of the point-based classification process. The dense point cloud of the study area, and the classification results, obtained with proposed automatic point-based classification approach using geometric features and color information, are given in Figure 3. The hierarchical rule sets for point-based classification, proposed in this study, was created, and the classification was performed using TerraScan module of TerraSolid software.

(a)



(b)

Figure 3. The dense point cloud of the study area colored according to the real point color (a) and results of the point-based classification of dense point cloud (b)

When the point-based classification results of the dense point cloud generated with semi-global matching is analyzed, it is seen that the ground class including roads and open areas is classified quite well. In addition, all the buildings in the study area were classified completely. The vegetation points were also generally classified correctly as low, medium and high vegetation. However, high vegetation points which are close to the buildings were assigned to the building class in some part of the study area. The points which belong to fences or walls between parcels that should be assigned to the ground class were classified into the middle or high vegetation classes. The confusion exists between ground and vegetation classes, and vegetation and building classes. However, the general classification results revealed the fact that, the 3D point cloud produced with dense image matching algorithms has been successfully classified with the automatic point-based classification approach using the geometric features and color information with the proposed approach in this study.

3.3 Point-based Segmentation and Accuracy Assessment

For the detection of individual trees in the study area, all single vegetation points must be segmented. The high vegetation class obtained as a result of the classification was separated from the other data to be used in tree crown segmentation (see Figure 4).

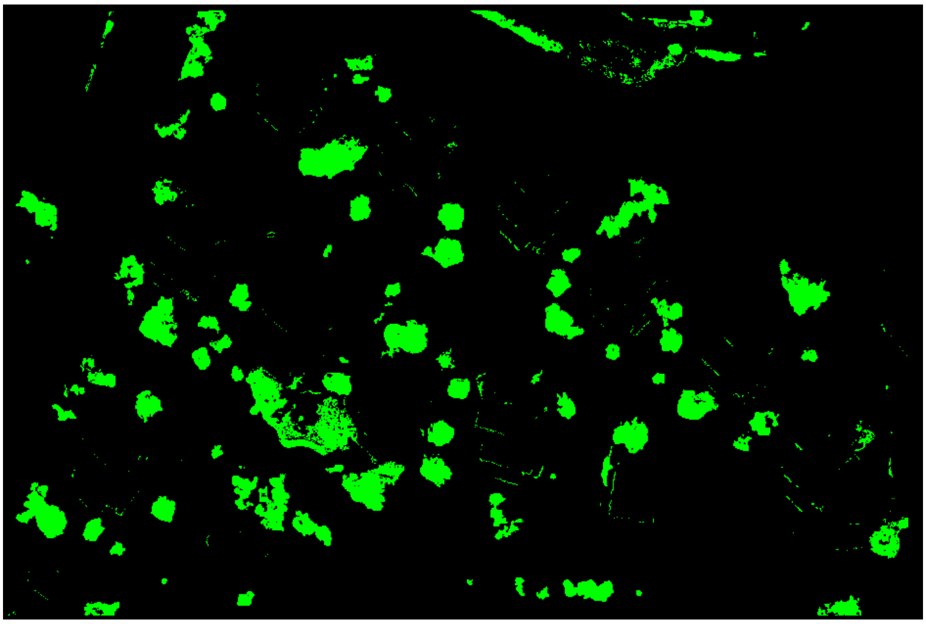


Figure 4. The high vegetation points in the study area

Trees in the high vegetation class of the study area have been segmented automatically with the mean shift clustering algorithm using geometric features of dense point cloud for individual tree detection. 168 individual trees (clusters) were obtained by segmentation. The graphical representation of mean shift clustering results including cluster centers are shown in Figure 5, and the results of the mean shift clustering are shown in Figure 6. The highest points, define the midpoints of tree crowns, for 168 clusters and the highest points and other tree points in each cluster are seen in Figure 7. Mean shift clustering process was conducted using Python programming language in Jupyter Notebook which is an open-source web application.

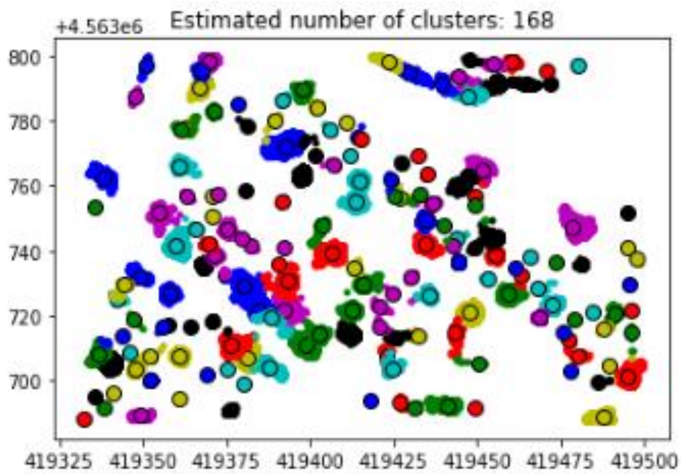
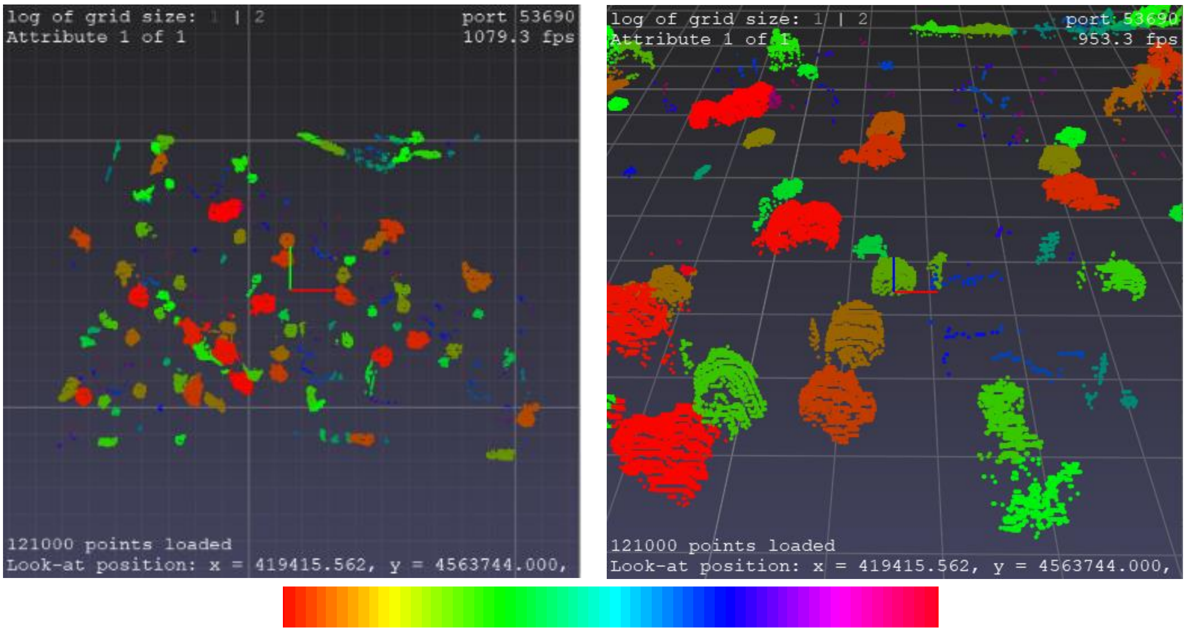
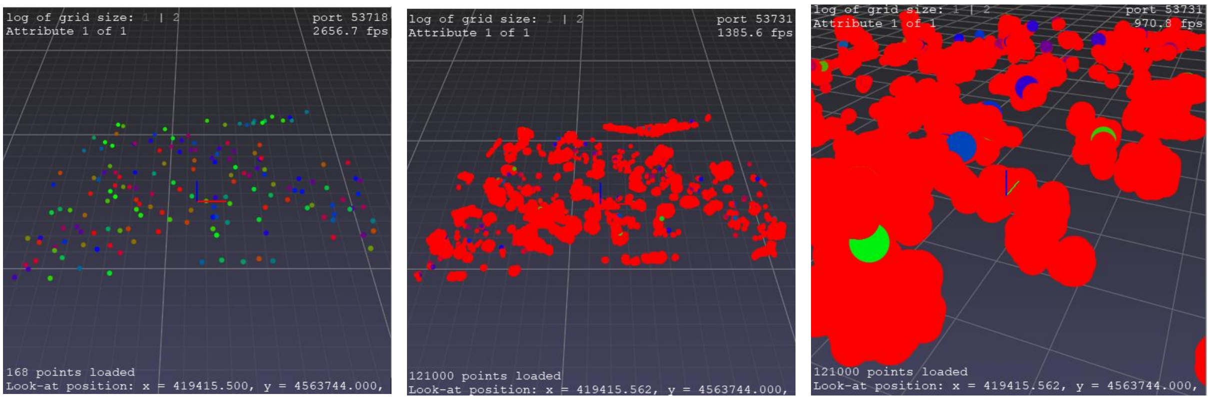


Figure 5. The graphical representation of mean shift clustering (including cluster centers)



(a) (b)

Figure 6. Results of the mean shift clustering process (168 clusters) in general view (a) and the close view (b)

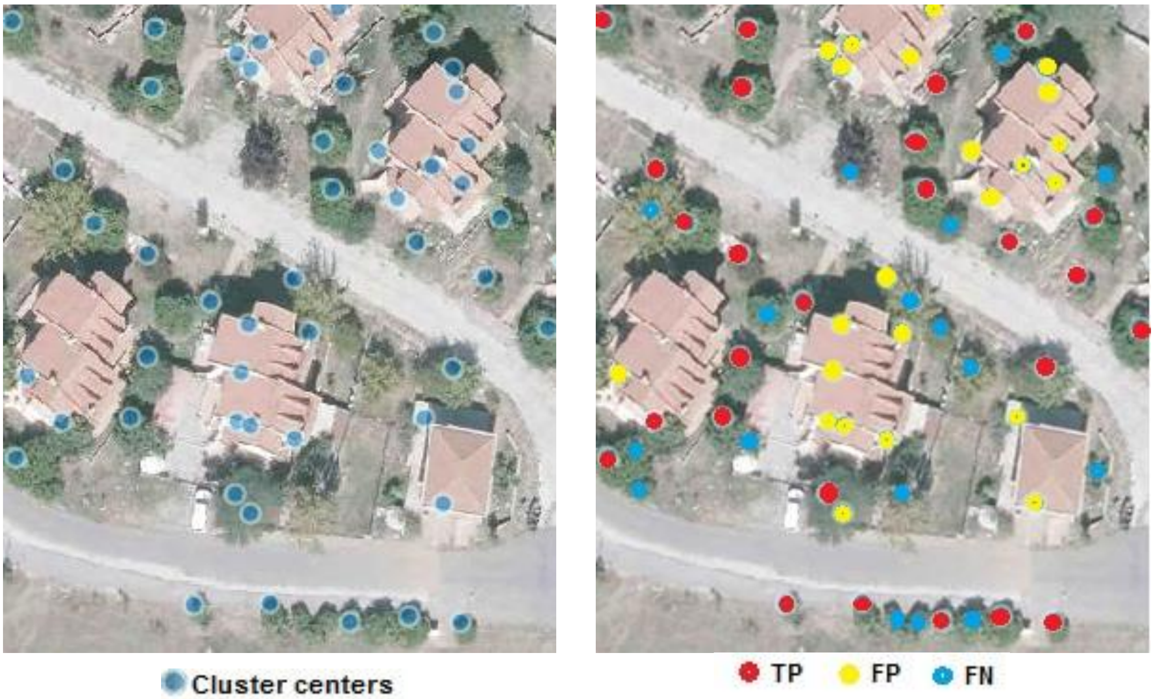


(a) (b) (c)

Figure 7. The highest points for 168 clusters (a), the highest and the other tree points (b) and the close view of the highest and the other tree points (c)

When the segmentation results with the mean shift clustering method are examined, it is seen that the high vegetation class is segmented successfully. However, there are a lot of clusters segmented as individual trees that are not individual trees in the segmentation results due to presence of other points in high vegetation class not belong to high vegetation class. Especially the points of the side walls of the buildings are among the incorrectly segmented individual tree points from high vegetation points. Insufficiently classification of the high vegetation class in urban areas affected segmentation results negatively.

An accuracy assessment of the segmentation has been carried out according to detection rate in a small pilot area which located in the test side. The trees, exist on the orthoimage (2013), has been used as the reference data. In Figure 8, the determined pilot region for accuracy assessment of detected individual trees overlapped the cluster centers and the pilot region overlapped TP, FP, FN tress is given.



(a) (b)

Figure 8. Determined pilot region for accuracy assessment with cluster centers on orthoimage (2013) (a) and TP, FP, FN trees (b)

The 26 clusters were determined as individual trees correctly (TP) and 23 clusters were determined as individual trees wrongly (FP) in the pilot region. The points of 17 trees couldn't be segmented as clusters (FN). Therefore, the achieved results were 60.47% completeness and 53.06% correctness. The correctness and completeness results are not satisfactory as expected because of insufficient classification of high vegetation class.

4. CONCLUSIONS

In this study, a point-based approach based on hierarchical rules for automatic classification of high density point cloud, produced with semi-global matching algorithms using aerial photographs, has been proposed. The detailed parameter analysis has been performed in different pilot areas in test side for the determination of most suitable parameters to be used in hierarchical rules, and the ground, low vegetation, medium vegetation, high vegetation, building, low point, air point and default classes (total eight) was obtained with proposed point-based classification using geometric features and color information of the points in the study area. A point-based segmentation with mean shift clustering technique carried out with points from high vegetation class to detect individual urban trees in the study area using geometric features of points, and 168 individual trees (clusters) were obtained by segmentation. An accuracy assessment process was performed according to the detection rate of the urban trees, and the correctness and completeness result is achieved 60.47% and 53.06% respectively.

The classification of 3D point clouds, produced with dense image matching approaches at a more affordable cost compared to LiDAR, which is a more expensive method, has been carried out successfully with the point-based classification approach. After classification step, the point-based segmentation with mean shift clustering method was carried out using high vegetation points obtained as a result of classification for the detection of individual urban trees. However, the segmentation results to obtain individual trees are not satisfactory because of the insufficient classification of the high vegetation class. The improvement of the point-based classification accuracy will positively affect segmentation accuracy and detection of individual trees in urban areas. The success of the point-based classification approach, which consists of hierarchical rules that allow automatic classification, mainly depends on the determination of geometric features and detailed analysis of the parameters used in the hierarchical rules. Therefore, the determination of more effective geometric features and color information will increase the classification and also segmentation accuracy

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