INDIVIDUAL TREE DETECTION BASED ON DENSITIES OF HIGH POINTS OF HIGH RESOLUTION AIRBORNE LIDAR

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KEY WORDS: Airborne LiDAR, densities of high points, tree detection, Inverse Watershed segmentation, Canopy Height Model (CHM), Digital Terrain Model (DTM)

ABSTRACT:

The retrieval of individual tree location from Airborne LiDAR has focused largely on utilizing canopy height. However, high resolution Airborne LiDAR offers another source of information for tree detection. This paper presents a new method for tree detection based on high points' densities from a high resolution Airborne LiDAR. The advantage of this method is that individual trees are detected based on the densities of high points which distinctively separates crown centers from crown edges. Therefore, regardless of the crown shape, the center of a crown has a higher density than the edge of the crown. The densities of high points for each point in a dataset are calculated in a column with a specified window size. At the beginning, all points in the dataset are selected as candidate point for tree locations. The tree locations are further refined by using Inverse Watershed segmentation in which higher weights will have better chances to be selected as tree locations than points with lower weight. The method is tested on different tree species and tree conditions for a floodplain area in the Netherlands. The results of the tree detection are compared with the actual tree locations. It is found that this method can correctly predict more than 70 percent of trees under different tree conditions. This method is sensitive to the density of undergrowth vegetation, vegetation type, size of trees, and density of crown cover caused by overlapping tree crowns. Further work is required on using this information to optimize this method.

1. INTRODUCTION

Various studies concentrated on individual tree detection from Airborne LiDAR. Pitkanen, et al (2004) developed adaptive methods for individual tree detection based on Canopy Height Model (CHM) of Airborne Laser. The CHM in the first method was smoothed using a Gaussian filter and the degree of smoothing is defined by the height of pixel. Subsequently, local maxima on the smoothed CHM were considered as tree locations. In the second method, an abundant number of possible tree locations was selected based on local maxima or almost local maxima. The candidate pixels were then reduced based on slope within the assumed crown center area and based on the distance and valley depth between a location and its neighboring locations. The second and third methods used crown width and tree height model as a parameter to adapt with tree size. The third method was modified from scale-space method used for blob detection. The CHM was divided into several region based on height ranges and each region the center height value was used to predict crown diameter. The scale for Laplacian filtering for each region was determined based on the predicted crown diameter. Local minima found in the image were considered as tree locations. It was pointed out that the results from above methods were not good as only 40% of all trees could be found and it was reported that this is mainly caused by the large number of small trees. About 60-70% of the dominant trees were found. About half of trees were found on the un-filtered CHM but it contained huge number of false predictions. The results for fixed scale Gaussian filtering and height-based Gaussian filtering were almost similar. The filtering process had slightly moved the predicted location of trees compared to the original image. However, for the method that is dependent on tree height and crown size relationship, the relation of tree height and crown width is not so often modeled, probably due to lack of crown measurement . Another disadvantage is differences of tree species in tree height and crown width relation. In another study, Popescu, et al., (2002) and Popescu, et al., (2003) used variable window size of local maxima filtering with square and circular shape filter. The appropriate window size for the Local Maxima filter is defined based on the assumption that there is a relationship between crown size and tree height. Tree species information was derived from multi-spectral image. Kini (2004) used variable window of Local Maximum filter with the assumption that there is a relationship between crown size and tree height. However, it was shown that the regression coefficients of deciduous, pines and combined trees (deciduous and pines) are less than 0.6.

Weinacker, et al., (2004) used local maximum of smoothed CHM and delineation of single tree is done using pouring algorithm. It was observed that the segmented trees still contained a lot of wrong segments, in which the regions are too small to be a tree, inappropriate crown shape, and crown regions that cover another trees and canopy gaps. The segments were refined based on their shapes and distance between tree tops. Falkowski, et al.,(2006) introduces a new technique based on spatial wavelet analysis (SWA) to automatically estimate location, height and crown diameter of individual trees within mixed conifer using Airborne LiDAR. In this study, two-dimensional Mexican hat wavelet was used to convolve over the dataset and local maxima of the resultant wavelet transformation image are used for tree location determination. The performance of this method is comparable to variable window filtering based on priori knowledge of tree height and crown diameter relationship. The advantage of this method is no priori knowledge on tree height and crown diameter relationship required. In another study, Straatsma and Middelkoop (2006) in their study used image contouring and some manipulations on the resulting polygons to extract tree tops from CHM and aerial photograph.

Above it is clearly shown that most of the tree detection studies were based on height of the canopy. For some approaches the relationship between crown size and tree height is needed beforehand. The aim of this study is to examine another source of information from high resolution LiDAR data for tree detection. This study will discuss in detail the following issues to optimize the method.

1. How this method performs for different tree species (with different crown shape)
2. How significantly each parameter contributes to the final result of tree location
3. What are the advantages and disadvantages of this method

2. MATERIAL AND METHODS

2.1 Study site

The study site is in The Duursche Waarden floodplain, the Netherlands (see figure 1.0). This floodplain is located along the IJssel River, the smallest tributary of the Rhine River in the Netherlands . The area is partly covered by meadow and arable land and a large part of the areas has become nature. The vegetation comprises of (1) softwood forest Willow (Salix abla, Salix viminalis), poplar (Populus nigra, Populus x canadensis), (2) hardwood forest oak (Quercus robur), ash (Fraxinus excelsior) and a small pine stand (Pinus sylvestris) on a river dune, together with (3) reed marshes (Phragmites australis), and (4) herbaceous vegetation with sedge (Carex hirta), sorrel (Rumex obtusifolius), nettle (Urtica dioica), thistle (Crisium arvense) and clover (Trifolium repens).

Figure 1.0: The Duursche Waarden floodplain

2.2 LiDAR data

The LiDAR data in this study were captured by a FLI-MAP 400 system. The FLI-MAP 400 is a helicopter mounted LiDAR system designed to capture highly detailed terrain features with high accuracy. It is claimed that the absolute accuracy of FLI-MAP 400 data measured over hard and level surfaces is 2.5 to 3.0 cm. The system is capable of scanning in three directions and this increases the chance of capturing a significant amount of reflected pulses from the ground even in a quite densely vegetated area. The FLI-MAP 400 data records maximum four laser reflections with an unmatched distance of 0.9 m, which enables optimal interpretation of a detailed terrain model even in vegetated areas. The Airborne LiDAR of FLIMAP-400 data with a density of 70 points per meter square were acquired in 2007. The leaf-off LiDAR data allows better penetration through canopy and thus the vertical structure of tree could be easily revealed. In this study, four different areas have been selected for tree detection. These datasets differ in crown shape and density of undergrowth vegetation. Two datasets contain quite dense undergrowth vegetation (a and d in figure 2.0), while the other two datasets (b and c) contain less undergrowth vegetation or an almost clear ground surface.

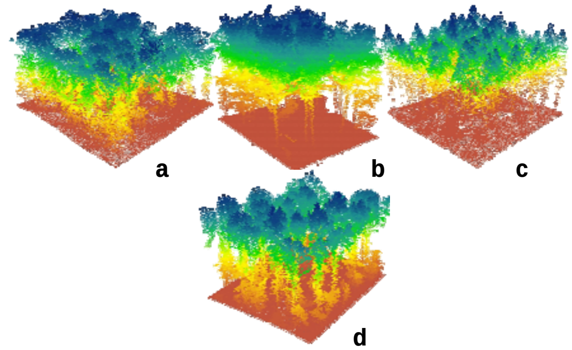


Figure 2.0: LiDAR dataset; dataset 1 (a), dataset 2 (b), dataset 3 (c) and dataset 4 (d)

2.3 Tree detection

2.3.1 High points densities of tree crown

Airborne LiDAR acquired during leaf-off conditions has a better penetration through tree crown and reflected pulses could be from major and minor braches of tree. Referring to the physical structure of tree crowns, the surface area of branches in the center of a tree crown is commonly larger than the volume of the branches towards the outside. Therefore, it can be expected that with small footprint Airborne LiDAR, more laser pulses are reflected from branches at the center of tree crown and the number of pulses reflected by branches decreases towards the edge of crown. High resolution Airborne LiDAR data therefore gives an opportunity to detect individual tree crowns on the basis of high point densities. Thus, regardless of crown shapes, this property still can be used to distinctively separate parts of tree crowns. Figure 3.0 shows theoretically how this assumption is applied for tree crowns with different shapes.

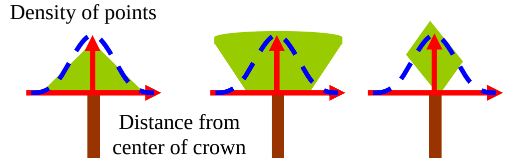


Figure 3.0: High points' densities for different shape of tree crowns

In this study, the density of high points for each point in the dataset is calculated by the number of points in a column with a specified (horizontal) window size. Regardless of crown shape or tree species each tree crown is expected to have a distribution of densities of high points as shown in figure 4.0.

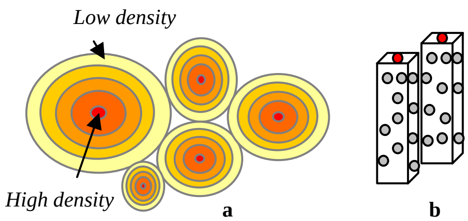


Figure 4.0: Densities of high points each tree (a) and number of points in column for each point in dataset. The red point is the point that holds number of points in column (b)

2.3.2 Tree detection based on high densities of high points and Inverse Watershed segmentation

At the beginning, all points above specified reference level are selected as candidates for tree locations. The reference level is defined as the average level below tree crowns for the trees in a dataset (figure 5.0). This is necessary to avoid that the calculation of point densities contains too many errors caused by undergrowth vegetation and on the other hand, it would speed up the tree detection process.

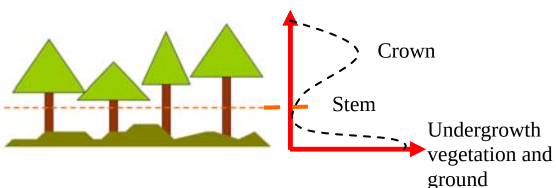


Figure 5.0: Reference level

The candidates of tree locations are refined by using an Inverse Watershed algorithm and for each tree only a single location remains (refer figure 6.0). The detailed explanation of the processing steps is as follows:

1. Calculate a histogram for the entire dataset and define the appropriate reference level
2. Select points with height above the reference level
3. Calculate the number of points in a column with a specified window size for each point in the dataset. In this study, different window sizes are tested between 0.1 and 5.0 meter.
4. Convert the points to raster format with a specified cell size (spatial resolution). Each raster cell contains the number of high points within that cell. In this study the cell size ranges from 0.1 to 1.0 meter.
5. Normalize the cell values to weights from 0.1 to 1.0.
6. Apply 3x3 mean filtering to the raster data;
7. Select all pixels as candidates for tree locations
8. Sort candidate pixels based on their weight values and give a rank to each point
9. Refine candidates for tree location based on Inverse Watershed segmentation
    a. Start segmentation from seed pixels (those with the highest weight)
    b. Grow pixel to 8 neighboring pixels and remove pixels if their weight values are lower than the seed pixel. Stop the growing process if there is no other lower neighboring pixels
    c. Repeat step 8a to 8b for the next largest pixel.

The reason of selecting window size for calculating number of point for each point, and for selecting a cell size for the raster conversion, is to give a full view of how the tree detection process performs. This would allow the method to converge at certain values. The raster conversion only takes the maximum weight value within a specified window for each pixel and no interpolation introduced to avoid errors by this process. Simple mean filter is applied on the raster data with assumption that it would help the refining process of the candidate points by removing irregularities of weight values within a crown. The Inverse Watershed segmentation method is used as a basis to choose final points that mark the location of trees (see figure 6.0).

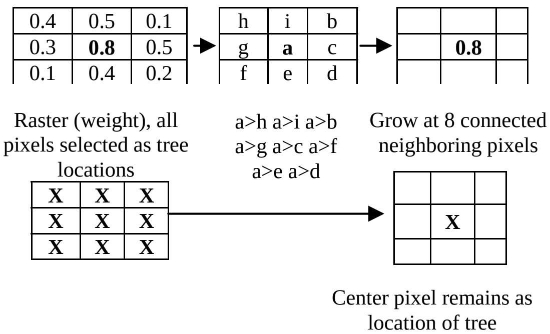


Figure 6.0: Inverse Watershed segmentation as a basis to refine tree locations

Table 1.0 shows the reference level selected for each dataset. According to the histogram, the first peak of higher elevations represents the pulses received from tree crowns and the second peak, if any, would be from the ground and undergrowth vegetation.

Table 1.0: Reference level for each dataset

Dataset	Reference level (m)
Dataset 01	18.449
Dataset 02	16.220
Dataset 03	13.839
Dataset 04	16.143

2.4 Evaluation

The predicted tree locations for each dataset are compared with the real locations, which were manually extracted. The evaluation method takes into account both correctly predicted tree locations and the false predictions (see equation 1.0).

Score = (NoCPT/NoT) + (NoCPT /NoPT) …1.0

Where,
NoCPT – Number of correctly predicted trees
NoT – Number of trees
NoPT – Number of predicted trees

The score ranges from 0.0 to 2.0, in which low scores indicate poor tree prediction results and high scores correspond to good predictions. Good prediction means that the method is able to correctly predict a considerable number of trees with little false prediction, and poor predictions in most cases contain many false predictions with a small number of correctly predicted trees. The distance between predicted tree locations and the real tree locations should be less than 1.5 meter. Figure 7.0 shows the overall methodology of this study.

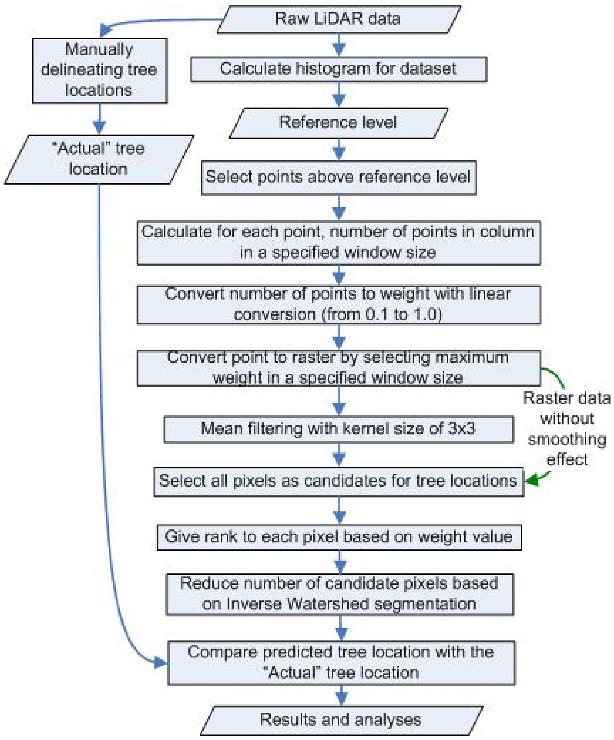
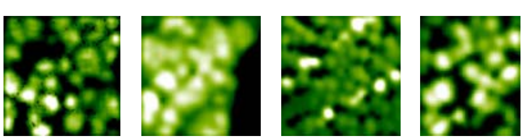


Figure 7.0: Overall methodology

3. RESULTS AND DISCUSSION

In this study, three smoothing methods are used to reduce irregularities of weight values within a tree crown, namely 1) different size point buffer to calculate number of points, 2) cell size for raster conversion and, 3) mean filtering. Figure 8.0 shows the example of a raster datasets that have been used for the tree detection process. In general, it is found that the point buffer size and the mean filtering have less effect on the tree location prediction error than the cell size for raster conversion. This is probably because the cell size determines the scale of raster data. A small cell size would produce a huge number of zero value pixels in raster data and this subsequently affects the performance of the Inverse Watershed segmentation method. Meanwhile, a large cell size decreases the number of pixels, which converts the raster data to a smaller scale and subsequently leads to a loss of information. On the other hand, mean filtering helps in producing better prediction results compared to un-filtered raster data.



a **b** **c** **d**

Figure 8.0: Example of weight values in raster for, dataset 1 (a), dataset 2 (b) dataset 3 (c) and dataset 4 (d)

Table 3.0 shows the results of tree detection with maximum score value for datasets filtered with mean filter. It is shown that the method has been able to correctly predict more than 70 percent of trees with different crown shapes and sizes. Dataset 3 has the highest prediction accuracy (84%) and also the lowest prediction error (5%). This is followed by dataset 2 (accuracy 75%, error 42%), dataset 1 (accuracy 73%, error 12%) and dataset 4 (accuracy 70%, error 13%) (refer appendix B). Dataset 1 contains quite dense undergrowth vegetation that affects the calculation of the numbers of points above the reference level. The undergrowth vegetation would create false signs of tree locations, so we might get more than one tree within a tree crown. In all datasets the tree detection method misses some small trees, especially those that very near to another large tree. This is because of the over-smoothing effect, in which the smoothing steps have better surfaces of large trees but at the same time small peak of weight values from small trees disappear. Furthermore, tree branches which start lower then the reference level seem to be misinterpreted as trees.

In dataset 2 it is shown that the trees have a quite dense canopy cover, which allows only small gaps between the tree crowns. In this situation it is also observed that some branches overlap with other branches of neighboring trees. The laser pulse densities received from these areas are quite high and sometimes even higher than at the center parts of trees. Therefore, instead on detecting center of tree, the tree detection method marks this area as tree and eliminates the real tree location. Another issue is that non-symmetric distributions of branches also move the locations of detected trees compared to the real location of the trees. The tree detection process for dataset 3 also faced some problems with overlapped tree crowns. However, the tree detection in dataset 3 is still higher than in datasets 4, 2 and 1, and this is due to less undergrowth vegetation, and each tree having an almost symmetric cone shape of pine tree crown structure (table 2.0). The study area is rather flat, thus the points are not normalized with the DTM. However, for areas with rugged terrain, it is strongly recommended to normalize the point clouds.

Table 2.0: Tree detection results

Dataset	Mean filtering	Mean	Minimum	Maximum
1	Yes	1.021	0.287	1.592
	No	0.962	0.310	1.478
2	Yes	0.954	0.283	1.393
	No	0.900	0.250	1.288
3	Yes	1.069	0.527	1.791
	No	1.041	0.469	1.675
4	Yes	1.049	0.314	1.540
	No	1.038	0.400	1.485

NOCPT – number of correctly predicted trees
NOWPT – number of wrongly predicted trees
NOT – number of trees
Pb – point buffer, Cs – cell size

The graph (refer appendix A) shows that the tree detection method has difficulty to converge in dataset 2 without mean filtering, but this is quite easy for another datasets. In addition, the graph shows quite distinct part of convergence of each dataset. For the datasets filtered with mean filter, the fastest convergence of tree detection process is for dataset 3 followed by dataset 1, 3 and 4. In general datasets without mean filtering would be able to detect more trees but it contains many false predictions of tree location.

4. CONCLUSIONS

The tree detection based on densities of high points is able to detect at least 70% of the dominant trees. The false prediction of tree location is caused by several reasons such as density of undergrowth vegetation, vegetation type, size of trees, and density of crown cover, which causes overlapping of tree crowns. This information should be used to further optimize the method and to ensure that it will be able to work efficiently in different forest conditions. More importantly further studies should be focused on deriving this information directly from high resolution LiDAR data.

The existing methods for tree detection are based on a local maximum filter, with the assumption that there is a relationship between size of tree crown and tree height. However, this relationship needs to be established for different tree species, forest density, different climatic conditions and etc. Future work is needed to compare both methods for tree detection since some of the required parameters can be directly determined from the high resolution Airborne LiDAR. In this study, the selection of reference level is done manually, and this process can be automated by applying Gaussian fitting routine.

Table 3.0: Statistics for tree detection results

Dataset	NOCPT	NOWPT	NOT	Accuracy (%)	Prediction Error (%)	Pb (m)	Cs (m)
1	36	6	49	73	12	2.9	0.4
2	18	10	24	75	42	2.9	0.5
3	54	3	64	84	5	2.2	0.3
4	25	21	30	70	13	3.2	0.6

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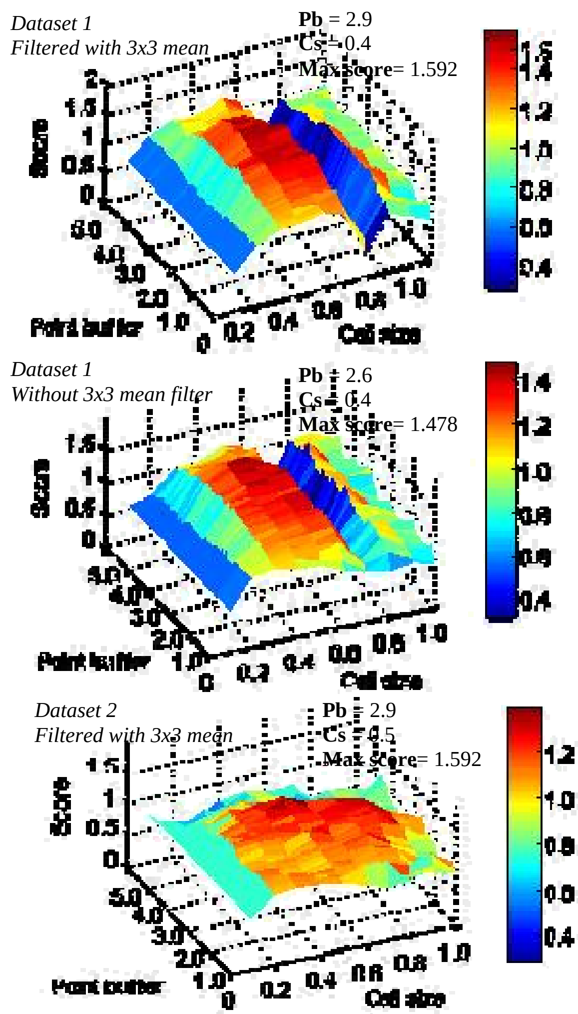
Acknowledgment

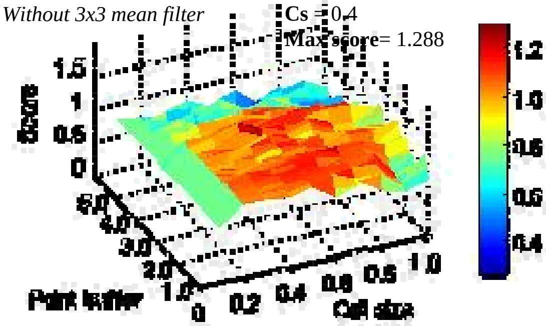
The authors would like to thank Rijkwaterstraat, The Netherlands for giving an opportunity to use FLI-MAP 400 Airborne LiDAR data.

Appendix

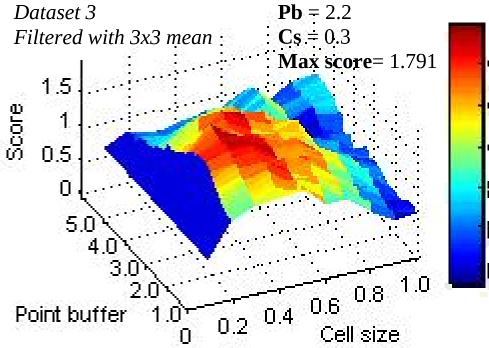
APPENDIX A: Graph for tree detection of all datasets



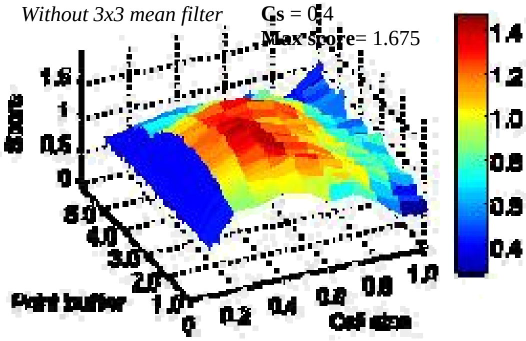
Dataset 2
Without 3x3 mean filter
Pb = 2.6
Cs = 0.4
Max score= 1.288



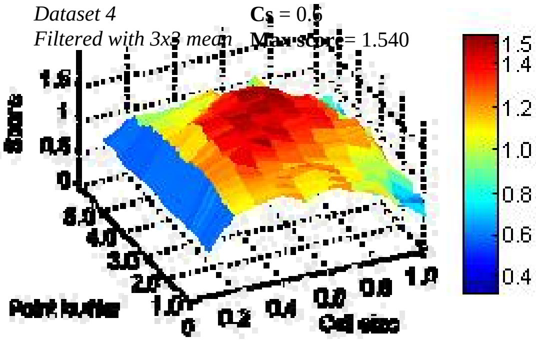
Dataset 3
Filtered with 3x3 mean
Pb = 2.2
Cs = 0.3
Max score= 1.791



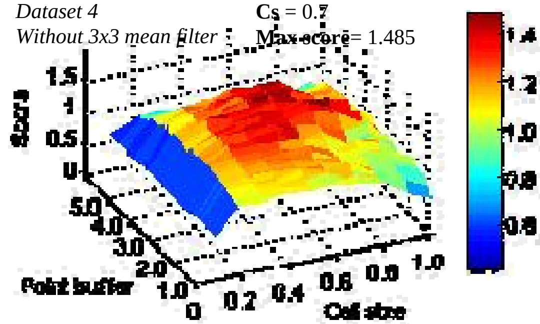
Dataset 3
Without 3x3 mean filter
Pb = 1.9
Cs = 0.4
Max score= 1.675



Dataset 4
Filtered with 3x3 mean
Pb = 3.2
Cs = 0.5
Max score= 1.540

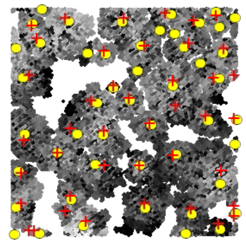


Dataset 4
Without 3x3 mean filter
Pb = 2.5
Cs = 0.7
Max score= 1.485

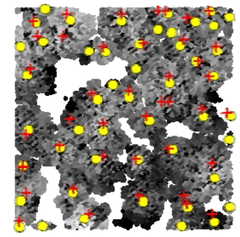


APPENDIX B: Detected and actual trees

Dataset 1 with and without 3x3 mean filter

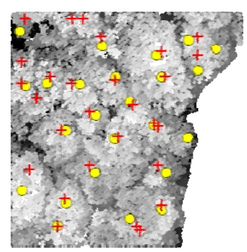


NOPT – 42, NOCPT – 36, NOT - 49

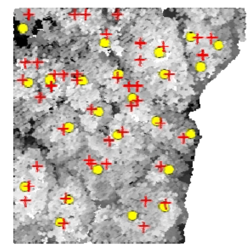


NOPT – 41, NOCPT – 43, NOT - 49

Dataset 2 with and without 3x3 mean filter

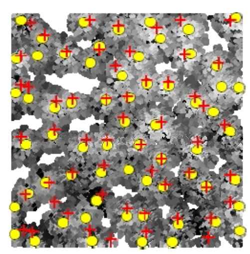


NOPT – 28, NOCPT – 18, NOT - 24

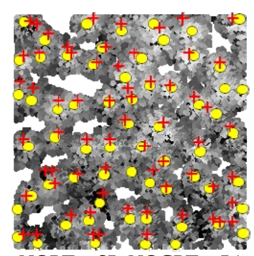


NOPT – 44, NOCPT – 20, NOT - 24

Dataset 3 with and without 3x3 mean filter

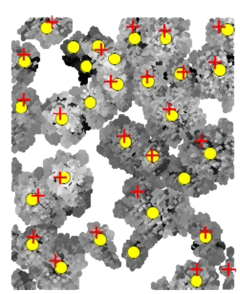


NOPT – 57, NOCPT – 54, NOT - 64

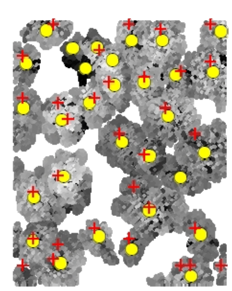


NOPT – 65, NOCPT – 54, NOT - 64

Dataset 4 without 3x3 mean filter



NOPT – 25, NOCPT – 21, NOT - 30



NOPT – 32, NOCPT – 23, NOT - 30

NOPT *– Number of predicted trees*
NOCPT *– Number of correctly predicted trees*
NOT *– Number of trees*