A HYBRID APPROACH FOR TREE CLASSIFICATION IN AIRBORNE LIDAR DATA

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ABSTRACT

In this paper we propose a hybrid approach for tree classification in airborne LIDAR (Light Detection and Ranging) data by integrating the point based supervised classification with region-based unsupervised clustering method. Furthermore we propose a novel 3D robust statistics-based shape feature that can overcome the limitations of existing methods in separating building boundary points from tree points. Experimental results show the new algorithm is very effective and can achieve very high accuracy.

***Index Terms*—** Airborne LIDAR, Classification, Tree, Robust Statistics.

1. INTRODUCTION

Airborne LIDAR data has become more and more important in 3D urban scene modeling and understanding applications. One of the essential tasks in these applications is to accurately classify tree points from the airborne LIDAR data. Recently Charaniya et al. [4] and Lodha et al. [5] applied machine learning techniques such as AdaBoost and expectation maximization to perform airborne LIDAR classification that separates the data into four main categories. Carlberg et al. [6] performs segment wise classification of airborne LIDAR data based on PCA based saliency features. Chen et al. [7] performs 2D tree classification in airborne LIDAR data by combining over-segmentation and under-segmentation followed by classification. Despite significant success, existing methods still have difficulty in separating the building boundary points from tree points as described in [7].

In this paper we propose a hybrid approach for tree classification by integrating point based supervised classification with region-based unsupervised clustering. Furthermore we propose a novel 3D robust statistics-based shape feature that can overcome the limitations of existing methods in separating building boundary points from tree points.

The rest of the paper is organized as follows. Section 2 describes the details of the proposed algorithm. The experimental results are presented in Section 3. Section 4 draws the conclusion and discusses some future work.

2. THE PROPOSED HYBRID APPROACH

The proposed hybrid approach intends to address the problem of misclassification of building boundary points and tree boundary points often observed in prior works.

There are three main steps in the proposed hybrid approach:

1. Clustering by spatial and range affinity
2. Classification using supervised machine learning leveraging a proposed 3D shape feature
3. Refined classification based on unsupervised clustering

We elaborate on each of the three steps in the following sub-sections.

2.1. Clustering by Spatial and Range Affinity

We first convert the 3D LIDAR points into a depth image by projecting the 3D points onto a uniform grid on the (x, y) plane. The intensity of the pixel in the grid will be determined by the average of the z values (height) of all the 3D points projected onto the same grid point. Figure 1(a)-(b) shows an example.

Next we conduct region-growing based clustering [3] on the depth image. Starting with a seed pixel of a cluster, we iteratively include its neighboring pixels into the current cluster if: (1) the intensity difference between the neighboring pixel and the current pixel is within a threshold, and (2) the difference between the neighboring pixel's intensity and the mean intensity of the pixels in the current cluster is within a threshold. Fig.1(c) shows the result after the clustering. Here the same color indicates the same cluster. The largest cluster is extracted as the ground cluster and will be used in the subsequent classification step. As can be seen from the figure, there are still some remaining pixels (shown in black) that are not assigned to any clusters. For example pixels belonging to trees generally have large depth variations thus may not join any clusters. After clustering we conduct connected component analysis on the remaining pixels to group them together based on spatial proximity. Fig.1(d) shows the result after connected component analysis.

2.2. Supervised Classification

After clustering we conduct classification using Support Vector Machine (SVM) to train a classifier that can separate tree points from building points. The features we used in training include the following four features: normalized height, normal vector, normal vector variation, and the LIDAR return intensity.

Normalized height is calculated by subtracting the height value at the current point by the corresponding height value of the ground. The ground height is obtained from the ground cluster extracted in the previous clustering step with a hole-filling step [3] to fill in holes that represent other clusters in the ground cluster.

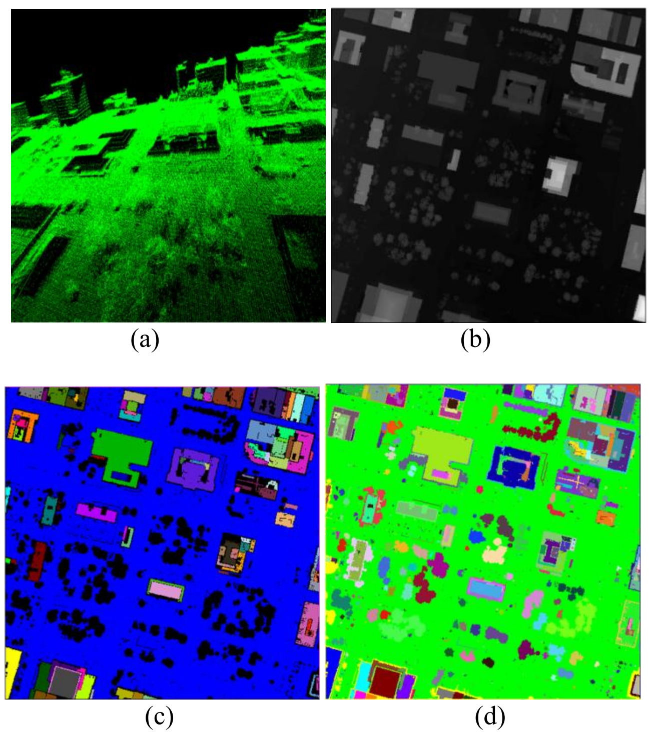


Figure 1: Depth image clustering based on spatial and range affinity. (a) Original LIDAR points; (b) Depth image converted from the LIDAR points; (c) Depth image clustering by region-growing based on the depth affinitiy. Different clusters are shown in different colors; (d) Connected component analysis for the leftover pixels from the previous clustering step. Different components are shown in different colors.

Normal vector is the eigenvector of the smallest eigenvalue from the covariance matrix of the local neighborhood [1].

Normal vector variation measures the variations of normal vectors within the local neighborhood of the current point and is defined as the mean cosine measure of the normal vectors in the local neighborhood.

Laser returned intensity is the scalar value reflected from the object back to the LIDAR scanner that relates to the material reflectivity of the object.

The above four features are very effective in separating typical tree points from typical building points (i.e. when the data does not contain points in the building boundaries or tree boundaries). As shown in Table 1 (a)-(c), the training accuracy can reach over 99% when we train the classifier on tree/non-tree points, building/non-building points and ground/non-ground points, respectively. However since points near the building boundaries often have large normal variations, the above features cannot separate building boundary points from tree points very well. Figure 2(a) shows the classification result on downtown St Louis using the classifier trained by the four features. Here the ground points are colored in yellow, building points are shown in blue while tree points are shown in green. The red circle highlights one of the areas where building boundary points are misclassified as tree points. If we include building boundary points in the training data and retrain the classifier using the four features, the test accuracy reduces to 92% as shown in the confusion matrix listed in Table 2. To overcome the difficulty in separating tree points from building boundary points, we propose a new 3D shape feature based on robust statistics in the next subsection and Fig 2(b) shows the result after using the new feature.

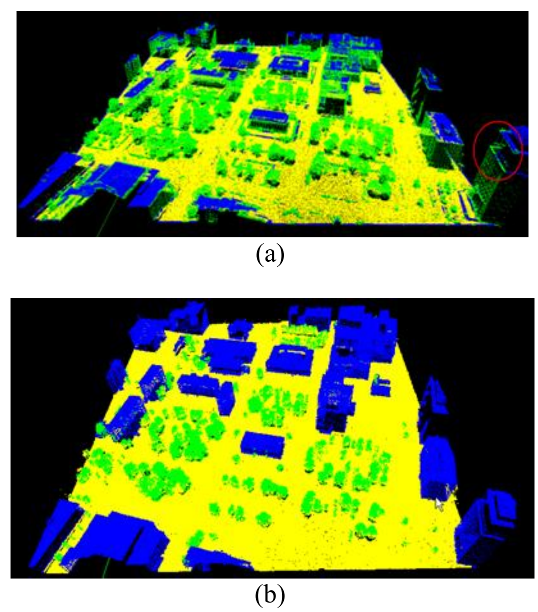
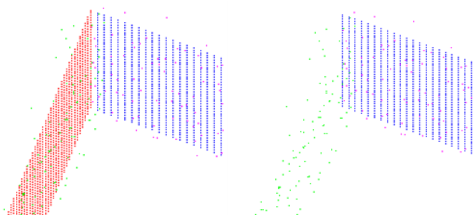


Figure 2: An example of the classification results on around $420000 m^2$ of downtown St Louis (a) using models trained without the new 3D shape feature. Red circle highlights one of the areas where building boundary points are misclassified as tree points due to high normal variations. (b) Result after using the new 3D shape feature.

2.3. Proposed 3D Shape Feature

The new 3D shape feature is based on the observation that there are generally multiple dominant planar structures near the building boundaries while there are no dominant structures in tree points. We employ iterative plane fitting with RANSAC (RANdom Sample Consensus) [8] to explicitly detect the multiple dominant planes in the neighborhood of building boundaries. Figure 3 shows an example. In Fig.3(a) one dominant plane is fitted (based on the red points), while Fig.3(b) shows another dominant plane is fitted (based on the blue points). After the fitting, we will compute the percentage of the points in the neighborhood that are inliers of one of the fitted planes and use it as a 3D shape feature in the tree classification. With this new feature added, the classification accuracy increases from 92% to 98.77%.

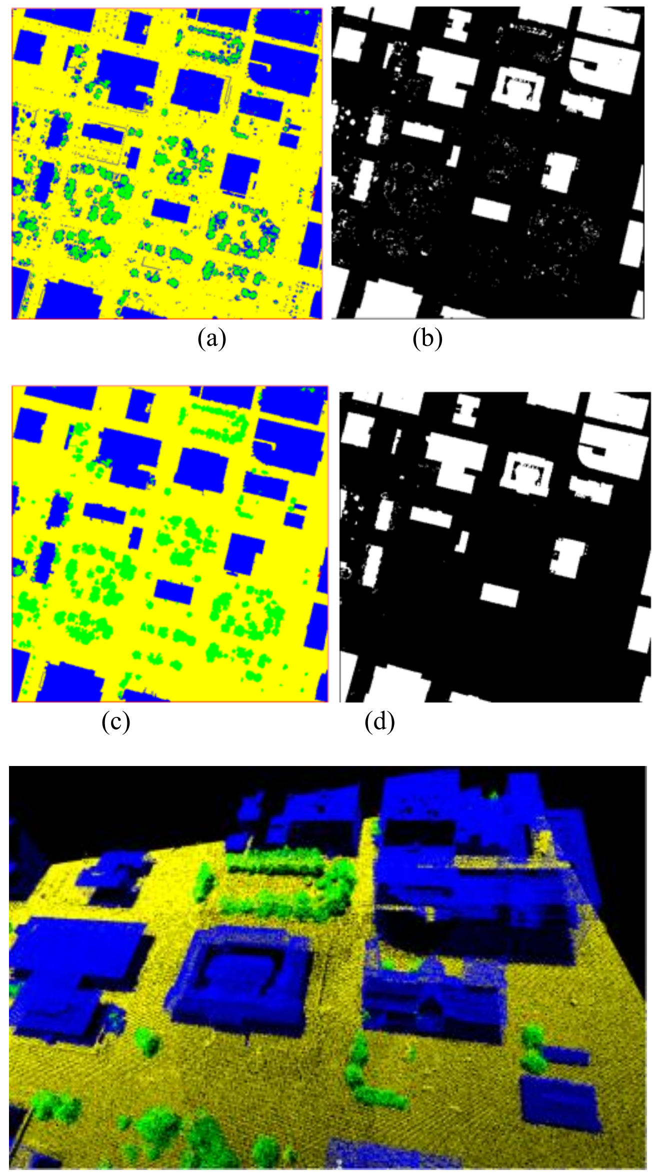


(a) (b)

Figure 3: 3D shape feature. Synthetic data points to simulate building boundary points (red points and blue points) with some noisy green and purple points added. We employ RANSAC based iterative plane fitting to detect the main dominant planes. (a): One of the planes is extracted based on the red points; (b): Remove the inliers (the red points), the other plane is extracted based on the blue points. The percentage of the points in this neighborhood that are inliers of one of the two fitted planes will be used as a 3D shape feature in the tree classification.

2.4. Clustering Based Classification Refinement

In this paper the classification is performed on 3D points directly. However the training data is based on the 2D depth image instead of 3D points. This implementation simplifies the training process greatly but it also results in the difficulty in providing training data that includes points in the boundary of trees. This is due to the fact that several 3D points could be projected onto one 2D pixel, thus it is possible to have both tree points and non-tree points projected onto the same 2D pixel. The lack of training data in the boundary of trees can result in some of the misclassification near the boundary of trees as can be seen in Fig.4 (a) and (b). To overcome this limitation we propose to employ results from the previous clustering step to conduct classification refinement. More specifically if a point is classified as tree then it will be labeled as tree; if a point is classified as non-tree points, then we will check its corresponding cluster obtained from the previous clustering result. If the current point is located in a cluster of which the majority members are trees then the current point will be labeled as trees. Figure 4 shows the classification result with the refinement step. Figure 5 shows the flow chart of the complete classification process.



(a) (b) (c) (d) (e)

Figure 4: Classification result. (a) Result based on the supervised classifier only. Some of the tree points are misclassified; (b) Binary depth image (building points are shown as white, non-building points are shown as black) of points after removing tree points classified in (a); (c) Result after clustering based classification refinement; (d) Binary depth image of points after removing tree points classified in (c). It shows that tree boundary points are classified accurately by comparing with (b). (e) 3D view of the classification result.

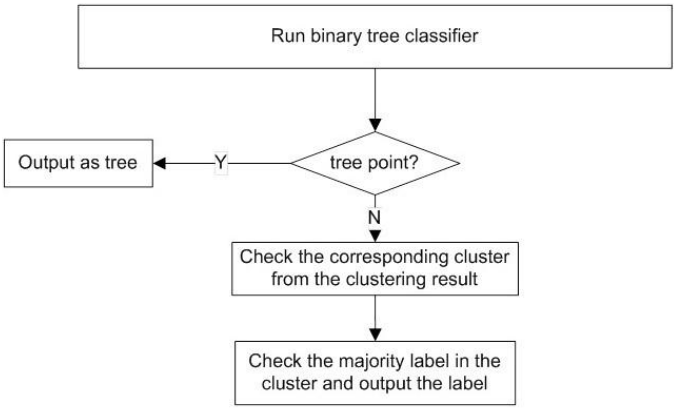


Figure 5 Flow chart of the tree classification process.

3. EXPERIMENTAL RESULTS

In this section we show the preliminary results we obtained on some airborne LIDAR data. We use 5 fold cross validation for the supervised classification based on Support Vector Machine (SVM-light [2]) with RBF kernel. Table 1 shows the confusion matrix when the first four features are used and the training data includes typical tree and building points. It can be observed that the accuracy is above 99%. If the training data includes the building boundaries then the accuracy reduces to about 92% (Table 2). When the new 3D feature is used in addition to the four features the accuracy improves to above 98% (Table 3). We apply the model to multiple unknown datasets and find the result are very accurate. Figure 6 shows another example.

								Accuracy
TP	3150	FP	38	FN	201	TN	48396	**99.54%**
TP	3165	FP	44	FN	186	TN	48390	**99.56%**
TP	3169	FP	32	FN	181	TN	48402	**99.59%**
TP	3152	FP	43	FN	198	TN	48391	**99.53%**
TP	3128	FP	41	FN	222	TN	48393	**99.49%**

(a)

								Accuracy
TP	42485	FP	183	FN	27	TN	9090	99.59%
TP	42492	FP	176	FN	20	TN	9097	99.62%
TP	42490	FP	186	FN	21	TN	9087	99.60%
TP	42496	FP	188	FN	15	TN	9085	99.61%
TP	42499	FP	192	FN	12	TN	9081	99.61%

(b)

								Accuracy
TP	5894	FP	16	FN	29	TN	45846	99.91%
TP	5897	FP	15	FN	26	TN	45847	99.92%
TP	5899	FP	10	FN	24	TN	45852	99.93%
TP	5894	FP	18	FN	28	TN	45844	99.91%
TP	5891	FP	15	FN	31	TN	45846	99.91%

(c)

Table 1. Confusion matrix for training data that includes typical tree, typical building and ground points and use the first four features on: (a) building vs non-building; (b) ground vs non-ground; and (c) tree vs non-tree, respectively.

								Accuracy
TP	44973	FP	2359	FN	1293	TN	2102	92.80%
TP	44995	FP	2333	FN	1271	TN	2128	92.90%
TP	44919	FP	2332	FN	1347	TN	2129	92.75%
TP	44917	FP	2319	FN	1349	TN	2142	92.77%
TP	44908	FP	2336	FN	1357	TN	2124	92.72%

Table 2 Confusion matrix for tree vs non-tree when using the first four features and the training data includes building boundary points.

								Accuracy
TP	46148	FP	505	FN	118	TN	3956	**98.77%**
TP	46150	FP	515	FN	116	TN	3946	**98.76%**
TP	46128	FP	543	FN	138	TN	3918	**98.66%**
TP	46148	FP	549	FN	118	TN	3912	**98.69%**
TP	46136	FP	520	FN	129	TN	3940	**98.72%**

Table 3 Confusion matrix for tree vs non-tree when the new 3D shape feature is used in addition to the four features with the training data includes building boundary points.

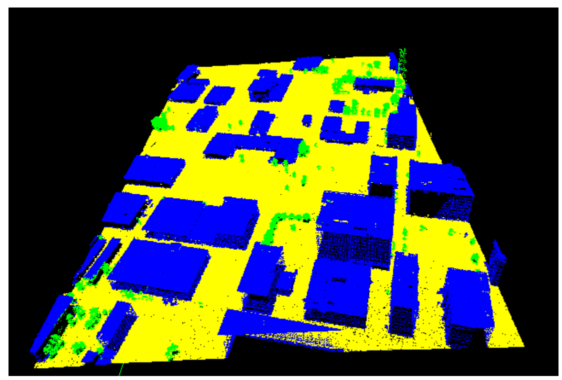


Figure 6: Classification result on another dataset.

4. CONCLUSION

In this paper we integrate point wise supervised classification with region-based unsupervised clustering for tree classification in airborne LiDAR data. Our algorithm overcomes the limitation of existing methods on classifying building boundary points by using a novel 3D shape feature.

5. ACKNOWLEDGEMENT

We would like to thank SVM light for allowing us to use their software [2]. We also thank Tim Haithcoat and Wenbo Song for providing us some of the testing LIDAR data. This work is supported in part by the NSF award#1004606, #0856206, #1039433, #1245795 and NGA award#HM1582-10-1-0012.

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