Classifying Airborne LiDAR Point Clouds via Deep Features Learned by a Multi-scale Convolutional Neural Network

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Methodology

(1) For each point in a LiDAR point cloud, we select its height, intensity, roughness and RGB attributes to predict its label. Here, the height attribute is normalized by subtracting the height of the ground, the roughness attribute is estimated by calculating the distance between the point and the best fitting plane of its neighboring points, and the RGB attribute is obtained from the corresponding orthoimages.

(2) Generate a set of multi-scale contextual images for each LiDAR point from the selected attributes using the natural neighbor interpolation algorithm. In our experiment, the contextual images are generated at three scales by specifying the neighborhood radius of each point as 3.2 m, 6.4 m, and 9.6 m, respectively.

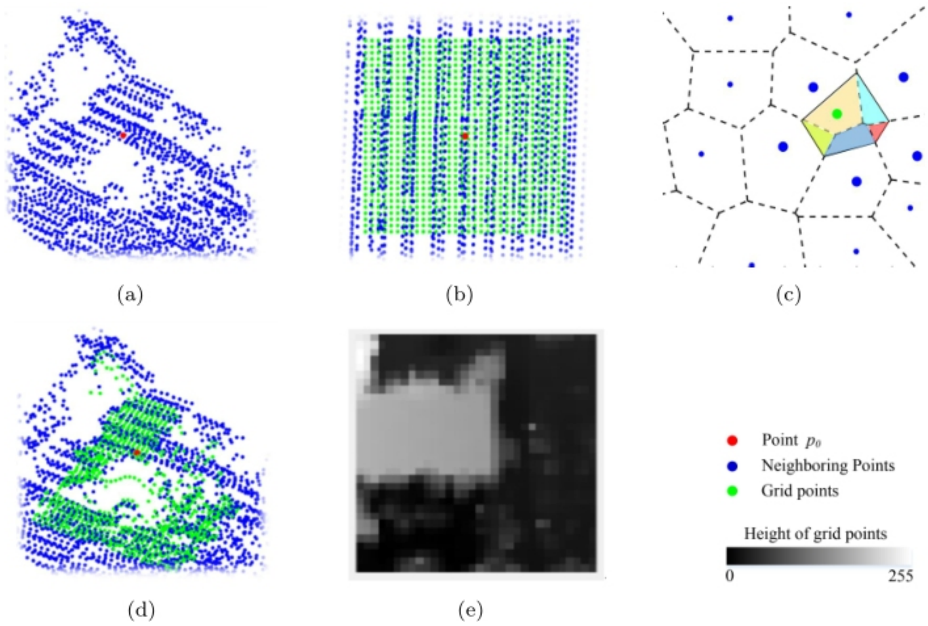

Figure 1 An example for generating a height contextual image for a given point p_0: (a) p_0 (the red point) and its r-neighbor point set (the blue points), (b) grid points (the green points) generated for p_0, (c) natural neighbors (the big blue points) and their weights (the sizes of the colored areas) for a grid point (the green point), (d) grid points rendered with estimated height values, and (e) a height contextual image generated for p_0.

(3) Train a multi-scale convolutional neural network (MCNN) to automatically learn deep features of each point from the generated contextual images across multiple scales. The MCNN is trained using the SGD algorithm with a group of training points, which is obtained by randomly selecting 4, 000 points per category from the training dataset.

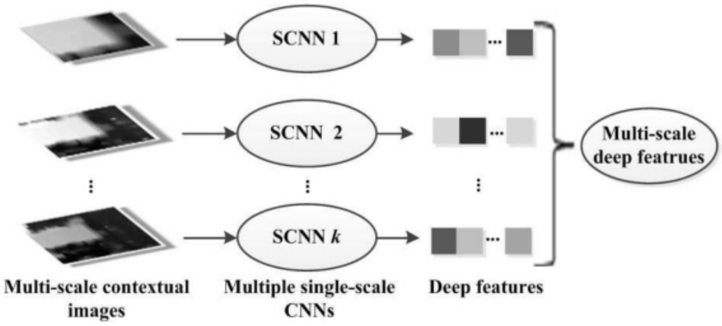

Figure 2. Framework of the MCNN, which is composed of k single-scale CNNs (SCNN) and outputs multi-scale deep features by combining deep features learned by each single-scale CNN.

(4) Classify the point cloud using the softmax regression classifier based on the learned multi-scale deep features. Let v_i represent the learned multi-scale deep features of a LiDAR point p_i, and y_i represent the label of the point p_i, we can estimate the probability $P(y_i \vee v_i)$ of the point for each category by using the softmax regression classifier.

(5) Optimize the classification result of each point by performing a trade-off with the result estimated only using its own attributes, including the height, intensity, roughness and RGB attributes. Given a point p_i, we first use its learned deep feature vector v_i to estimate its probabilities $P_0(y_i \vee v_i)$. Then, only with its own attribute vector $v_i^{'}$, we again estimate its probabilities $P_1(y_i \vee v_i^{'})$ using a bagged decision trees classifier. On this basis, the final label y_i of the point p_i is determined by selecting the category which has the maximum sum of the two probabilities.