OPTIMAL PARAMETER DETERMINATION FOR MEAN-SHIFT SEGMENTATION-BASED SHORELINE EXTRACTION USING LIDAR DATA, AERIAL ORTHOPHOTOS, AND SATELLITE IMAGERY

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ABSTRACT
A method for shoreline extraction has been developed that is based on mean-shift segmentation and the integration of LiDAR data, satellite imagery and aerial orthophotos. This method first classifies LiDAR points as belonging either to a water surface or to land. The classification criterion is the homogenous nature of the Near-Infrared (N-IR) reflection of the water surface, the elevation, and color distribution. Subsequently a shoreline can be extracted by tracing the boundary between these two categories, water and land. However, each mean-shift process requires bandwidth to be used as the parameter to classify the dataset. Also, all data sources having different units of measurement need to be normalized. In this research, we focus primarily on the training phase of this method. Three parameters are necessary for the mean-shift bandwidth (one for each of the three classification stages). In addition, seven normalization scales are used for the data sources including 3-D coordinates (X, Y, Z), RGB values (R, G, B) and N-IR values in this classification phase. A small region of ground truth is needed to provide a reference for the classification performance in the training phase. We obtained this ground truth by manually classifying LiDAR points as either water or land and then manually tracing a shoreline from an orthophoto. When processing, the scale of elevation from the LiDAR points is set to one. Then a mean-shift algorithm with only the elevation feature is used to run the classification with the bandwidth from 0.1 m to 1 m in 0.1-meter steps. The classification result is then evaluated by looking at the rates of true positives, false positives, and false negatives and by the accuracy of the shoreline within the region of ground truth. The best bandwidth is selected based on statistical tests looking at the previously described evaluation factors. All other parameters and scales are resolved one-by-one in a similar manner. The parameters and scales resolved by this systematic training procedure can assure the accuracy and stability of the extracted shoreline.

INTRODUCTION

Along the Lake Erie shore, heavy erosion forces impact both shorelines and blufflines (Ali, 2003; Li, 2004). Bluffline erosion in the region of our experiment (Painesville, Ohio) can reach as much as six feet (Srivastava, 2005). Finding cost-effect ways to extract shorelines and blufflines are important issue in monitoring coastal erosion. Bluffline extraction done by Liu et al. (2009) and Choung (2009) using LiDAR point clouds show promise, but in shoreline extraction, the level of complexity is much higher.

The shoreline is a constant changing line due to the effects of waves, tides and many other factors (Li et al., 2002a). There are two types of shoreline that people are most interested in extracting, the Instantaneous Shoreline and the Tide-Coordinated Shoreline. The Instantaneous Shoreline means extracting the shoreline at the moment in time when the data source is acquired. This is usually been done using aerial photographs, orthophotos or satellite images (Li et al., 2002b). There are two ways to extract Tide-Coordinated Shorelines. One is extracting the Instantaneous Shoreline from aerial photographs (NOAA, 2003; Woolard et al., 2003) or satellite imagery (Li, 2002b; Di, 2003) that is acquired during certain tide-coordinated water levels; this is how NOAA made the current shoreline. The other way is to create a Coastal Terrain Model (CTM) by combining DEM and bathymetry and intersect this with a certain tide-coordinate water surface (Li 1998; Li 2002a; Sault et al., 2005; Robertson et al., 2004; Stockdon et al., 2002). In this research, we extract Instantaneous Shorelines based on LiDAR data, aerial orthophotos and QuickBird Near-Infrared band images as input data.

This Mean-Shift Segmentation-Based Shoreline Extraction method first classifies LiDAR points as belonging either to a water surface or to land. The classification criterion is the homogenous nature of the Near-Infrared (N-IR) reflection of the water surface, the elevation, and color distribution. However, each mean-shift process requires bandwidth to be set aside as the classification parameter. Parameter training for Mean-Shift Image Segmentation is usually done using empirical values. That is because in the color space of an image, the units are the same (gray value) and the domain of value (0~255) is also the same. In our case, the factors include color space, distance, height, point density and normal vector direction. These values are in different units and domains; quality of normalization and parameter determining will be crucial to the classification result.

SHORELINE EXTRACTION PROCEDURE

The first issue that we are dealing with here is characterization of LiDAR points on the water surface. Sun glint characteristics could be found in the LiDAR data, but in this case, it's not the sun causing the effect, it is the laser beam itself. This problem not only causes the intensity to become brighter directly under the flight path, but also causes the LiDAR point to fade away where points are further away from the flight path. Currently, intensity has not been used due to the effect described above. Instead, the 3-D position information and the corresponding color information were employed.

Input data used in our method are LiDAR point clouds, Near-Infrared (N-IR) bands from the satellite images and orthoimages. The procedure for generating an Instantaneous Shoreline is illustrated below (Figure 1). First, color information (R, G, B) from orthophotos and N-IR intensity is assigned to every LiDAR point. Second, a learning procedure is performed to determine the parameters of the Mean Shift Algorithm. Third, mean-shift filtering is applied to the LiDAR elevation (Z) and color information (R, G, B) to minimize the segment numbers. Fourth, point density (PD), normal vector direction (ND) and normal vector direction variation (NV) is calculated for every LiDAR point. Fifth, the LiDAR point information (X, Y, Z) and corresponding color information from the satellite image (N-IR) and orthoimages (RGB) plus PD, ND and NV are used to segment the LiDAR points. Sixth, the parameters calculated from the learning procedure are used to group the segmented points into two classes: points on land or points on water (only two classes are considered in this procedure). Finally, an Instantaneous Shoreline is extracted by tracing the boundary of the land. The following sections describe this method in detail.

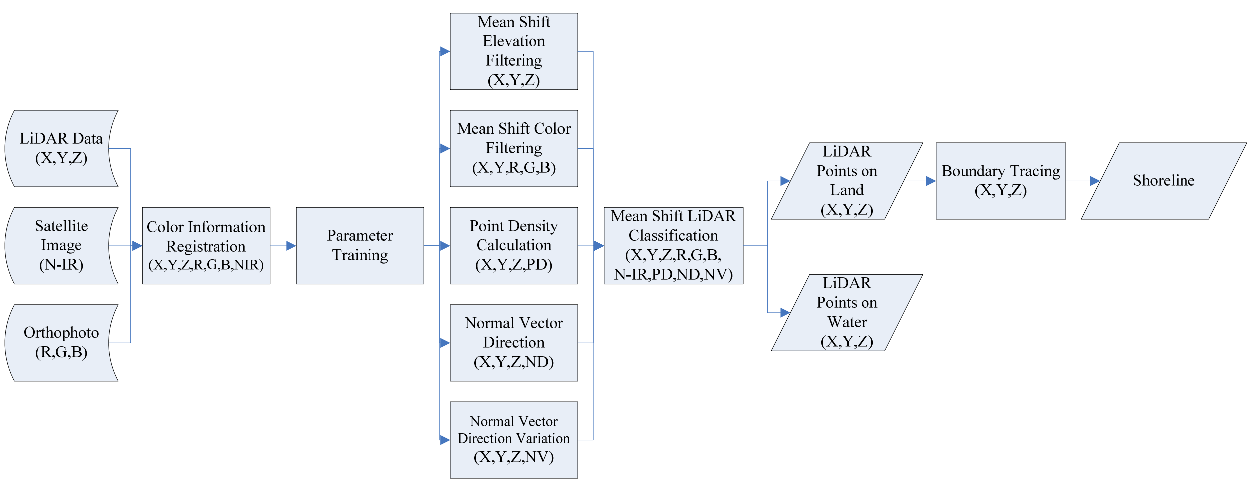

Figure 1. Flow chart of the shoreline extraction procedure.

Registration of LiDAR Data, Orthoimages and Satellite Imagery

In our current test area, the LiDAR data, orthoimages and satellite images were not acquired simultaneously, or even in the same year. There are definite changes during these years, but some of the data sources (e.g., N-IR band form satellite images) play basically a supporting role to make the classification result robust, not necessarily to increase the level of accuracy.

The satellite images may be in the geographic coordinate system, and orthoimages and LiDAR data in the projected coordinate system. As there will be errors during transformation, manual translation offset must be adjusted after the transformation. In order to assign color information for each LiDAR point, we project the LiDAR points onto the orthoimages and then the color information (R, G, and B components) can be derived from the orthoimages and assigned to each of the LiDAR points. Retrieval of the N-IR data is achieved by the same process, but using the satellite imagery. In the test area, LiDAR data and orthoimages were registered by the data provider, Ohio Geographically Referenced Information Program (OGRIP), created by Woolpert, Inc. The satellite image was registered manually.

Mean Shift Segmentation

The Mean Shift Algorithm (Fukunaga and Hostetler, 1975; Cheng, 1995) is a non-parametric classification algorithm. It is usually considered as a segmentation algorithm rather than a classification algorithm because there is no direct link with one class to a segment. The procedure for Mean Shift Algorithm is given below.

1. Create a kernel with a predefined radius;
2. Calculate the center of mass for the points in this kernel;
3. Move the kernel center to this center of mass. Repeat Steps 1 to 2 until the center of mass converges.
4. The converging coordinate of the kernel center defines a segment. Each point within the radius of the trajectories that converges to the same location belongs to this segment.
5. Steps 1 to 4 are repeated until every point in the dataset belongs to a segment.

This Mean Shift Algorithm has been used in our method for data filtering and segmentation. The elevation of the LiDAR data and the color information from the orthoimages are filtered using the mean-shift filtering procedure. This filtering procedure is a modification of Comaniciu's image-filtering algorithm (Comaniciu and Meer, 2002). Afterwards, the data is imported into the Mean Shift Segmentation Algorithm. Details of this procedure are described below.

When we use the Mean Shift Algorithm for data filtering, the above-mentioned procedure has been employed. An additional step in this procedure, designed to minimize the number of segments, is to assign a new value (elevation or color, for example) to every point in a particular segmented group. For example, for all the LiDAR points segmented as a group, the same elevation value is assigned to each point in the group. A similar procedure is used when the color information is filtered. We assign every point in the group the same color as the mode. In this procedure, one parameter needs to be defined for each step of elevation (Elevation Filtering Bandwidth, EFB) and color filtering (Color Filtering Bandwidth, CFB). These parameters are the radius of the kernel.

After data filtering, the Mean Shift Algorithm is employed again for segmentation. The input for the segmentation is the eleven-dimensional feature vectors [X, Y, Z, R, G, B, N-IR, PD, HV, ND, NV] corresponding to the LiDAR points. X and Y are the horizontal coordinates from the LiDAR point cloud. Variable Z is the height of the LiDAR point and is used directly as a classification feature. Strip adjustment needs to be done prior to the classification if the region is contributed to by several LiDAR strips. Variables R, G and B are the color information gathered from the registration of LiDAR data and orthoimages. Variable PD is the point density. LiDAR point density will be different on land and or on a water surface, as we mentioned before, so we consider it as a feature in our segmentation method. This feature is especially useful in tidal flat regions. In this research, only the last return of each laser beam has been used; therefore, multiple returns of the LiDAR point will not create point density variance. Variable HV is the elevation variation; its value is calculated from the LiDAR point clouds as the largest height difference within a predefined window size. This parameter could easily determine a breakline in the data set. Variable ND represents the normal vector direction. This is calculated by generating a TIN model and averaging all the normal vectors of triangles that are connected to the point. Variable NV is the normal vector direction variation. It is the opposite of the ND; instead of averaging the triangles, NV finds the largest angle difference of triangle surfaces between the connecting triangles.

Using this eleven-dimensional analysis, the Mean Shift Algorithm initially divides the point cloud into multiple groupings of water or land areas. These areas must be further refined into water bodies or land areas. In the learning process, described later in this paper, we manually digitized a partial shoreline segment as ground truth. This was used as prior knowledge to determine which groups belong to water and which belong to land. For example, if we know that there are three groups of water points within the region where we have ground truth, then we can assign these three groups as a water surface class. These three groups are not only distributed over the training area; but also appear throughout the entire test region. As a result, we can find all the points belonging to the water surface in this entire test region.

Boundary Tracing

At this point, all the LiDAR points have been segmented and classified as points either belonging to water or to land using the above-mentioned Mean Shift Algorithm. The next step is to trace the boundary of the segmented LiDAR point groups to obtain a shoreline. As there may be no LiDAR points on the water surface (due to the scattered and weak reflection of the water surface), many error boundaries may be created if we trace the boundary of the LiDAR points belonging to the water surface. Therefore, we select all the points that are classified as not belonging to the water surface class (i.e., all points classified as belonging to the land) for tracing the boundary and finally extracting the shoreline.

The algorithm used to trace the boundary is a Modified Convex Hull Algorithm (Sampath and Shan, 2007) that is based on the Convex Hull Algorithm proposed by Jarvis (1977). Due to the complexity of the LiDAR point distribution within the coastal area, one constraint has been added to this algorithm: that the angle between two edges must be large than 60 degrees.

Training Procedure

Training procedure is one of the most important elements that make this shoreline extraction method work. In this method, there are eleven factors in total including red, green and blue bands from orthoimages (R, G, B), elevation from the LiDAR data (Z), and N-IR band intensity value from the satellite imagery (N-IR) along with point density (PD), elevation variation (HV), normal vector direction (ND), and normal vector direction variation (NV) calculated from the LiDAR point cloud. All of these measures are in different units, thus normalizing all of these measurements is a major task. All of the parameters are normalized based on elevation. There are three parameters in this classification system, Elevation Filtering Bandwidth (EFB), Color Filtering Bandwidth (CFB), and Overall Classification Bandwidth (Mean Shift Classification Bandwidth, MSCB). The training procedure is described below.

1. A small region is selected as the training area. This area should have a relatively complex terrain containing the most distinct feature in the whole area.
2. The shoreline is traced manually and acts as ground truth in later steps.
3. The ground-truth shoreline is used to divide the LiDAR points into two sets, points on a water surface or points on land.
4. The MSCB parameter is determined by taking elevation Z into the mean-shift classification and giving it a reasonable parameter value. In this case, as the unit of elevation is in feet, 0.5 feet seems a reasonable starting number for testing the parameter (because of the wave height in the LiDAR dataset). Then, mean-shift classification is applied and the shoreline obtained by tracing the boundary. After these steps, we will have two sets of LiDAR points, points on a water surface and points on land. This data is compared with ground truth. A number indicating the correctly classified points along with the rate and error classification is obtained. In this case, we combined Type 1 and Type 2 errors. Meanwhile, the generated shoreline is also compared to the ground-truth shoreline. An RMSE is calculated to present the accuracy of this generated shoreline. After obtaining all these accuracy indicators, we add an interval to the MSCB parameter and perform the entire process again, repeating this step until the total number of effective classes (points within a class that is more than 5 points) after classification reaches 100. We assume that over 100 classes would mean that the classes will be too small to correctly determine land or water surfaces. Usually there will be a relationship trend between the three accuracy indicators and the value of the parameter; if there is, we could fit a function to it and pick the best parameter value where the accuracy is the best. If there is no trend in the accuracy, we can simply pick the parameter with the highest accuracy.
5. The horizontal normalization scale (XYS) is determined. First, X and Y need to be normalized between 0 and 1 and then multiply the scale XYS later in the mean-shift classification. This scale value is what we need to determine in this step. Using the MSCB that we have just determined, we put X, Y, Z into the classification with multiplication of XYS to X and Y. XYS is the power of 2, (i.e., XYS = 0, 2, 4, 8, …). A smaller interval is implemented if the parameter is inconclusive due to the large interval. Then we use the same procedure in Step 4 to determine the best value for XYS.
6. The EFB parameter is determined using the X, Y, and Z after horizontal normalization. Procedure 4 is also used to determine this EFB parameter.
7. The color normalization scale (CS) is determined in a procedure similar to Step 5.
8. The CFB parameter is determined is a procedure similar to Step 4. After this procedure all parameters have been determined.
9. The N-IR normalization scale (N-IRS) is determined in a procedure similar to Step 5.
10. The Elevation Variation normalization scale (HVS) is determined in a procedure similar to Step 5.
11. The point density normalization scale (PDS) is determined in a procedure similar to Step 5.
12. The normal vector direction normalization scale (NDS is determined in a procedure similar to Step 5.
13. The normal vector variation normalization scale (NVS) is determined in a procedure similar to Step 5.

After all of these parameters and normalization scales are determined, we add all LiDAR points for the entire test area and begin to extract the shoreline for the region.

EXPERIMENTAL ANALYSIS

The research test area was located in Painesville, Lake County, Ohio. The LiDAR data and orthoimages were provided by OGRIP. The satellite imagery was acquired by QuickBird.

Experimental Data

The OGRIP LiDAR dataset was collected April 11, 2006. The average point spacing was 7 feet; both horizontal and vertical accuracy was about 1 foot. The OGRIP orthoimages were collected in the period March 18 through May 7, 2006. Their resolution is 1 foot with an accuracy of about 5 feet. The QuickBird image was acquired June 19, 2004. It has a resolution of 0.7 m. All datasets were collected in different time frames, but the QuickBird image plays a supporting role in the classification because of its lower resolution. The test region is a 6 -km shoreline along Lake Erie near Painesville, Ohio. Figure 2 shows an orthophoto of the region and the 6-km shoreline that we are testing outlined in red. This region contains beaches, bluffs and man-made embankments.

Figure 2. Test area: Painesville, Lake County, Ohio. Orthoimages provided by OGRIP.

Shoreline Comparison

To compare the shoreline extracted from the Mean Shift Algorithm with the ground truth, the following procedures were employed. This procedure is illustrated in Figure 3.

1) Select the manually digitized shoreline as a reference line;
2) Set an interval for calculating the error distance (one-meter intervals have been used in our experiment);
3) Create nodes on the reference line using the interval defined in Step 2;
4) Draw transects lines on every node perpendicular to the reference line;
5) Search for the intersection point of the transect line and the second shoreline; and
6) Calculate the distance between the intersection point and the node on the reference line.

Analysis of Results

Results show that in the area of the man-made dock, classification error is small, but it does not show a good accuracy because of the low density of the LiDAR dataset. In Figure 4, a red line represents the ground truth that was manually digitized, and a blue line represents the shoreline that was extracted by the algorithm. In an area where a sandy beach is next to a bluff toe (Figure 5), the classifier may snap to the bluff toe instead of the shoreline. Figure 6 shows a region where the bluff toe is not next to a beach area; the extracted shoreline performs relatively well in this region. In comparison with the ground truth, the total length of the extracted shoreline is 6288 m, and the RMSE is about 1.53 m, which is slightly better than the LiDAR point spacing (Table 1).

The maximum error occurred near a small dock in the bluff area (Figure 7). The ground truth was determined by following the highest water mark, but the extracted shoreline is influenced by the LiDAR elevation and the

LiDAR point density. Part of the dock was included in the shoreline. This was the largest difference found between the ground truth and the extracted shoreline.

Table 1. Shoreline comparison results for the Painesville region

Region	*Length*	*LiDAR Nominal Point Spacing*	*RMSE*	*Maximum Error*
Painesville	6288 m	2.13 m	1.55 m	8.24 m

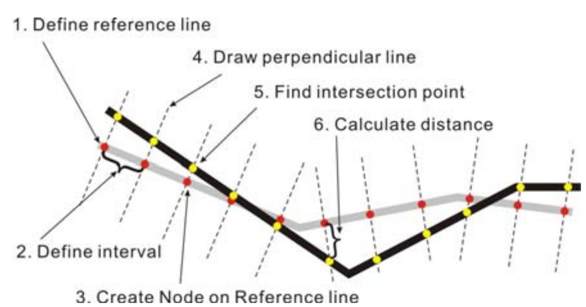

Figure 3. Conceptualization of shoreline comparison.

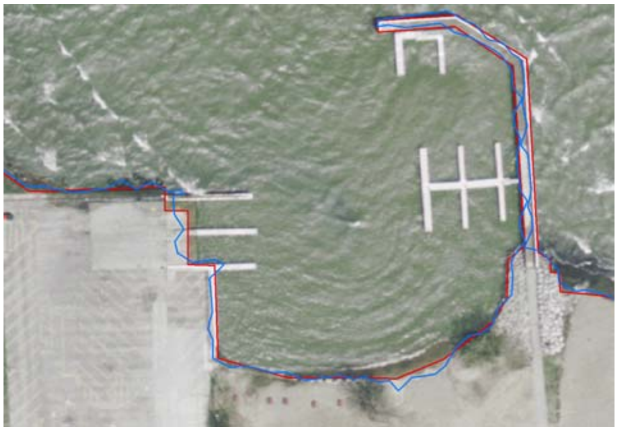

Figure 4. Shorelines along man-made dock.

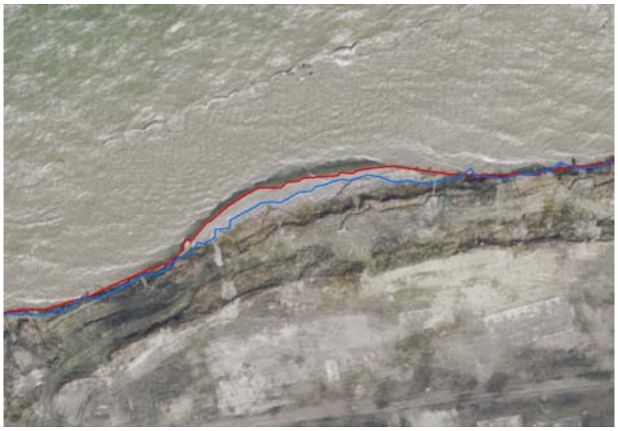

Figure 5. Shorelines in beach area next to bluff toe.

Figure 6. Shorelines in region with steep bluff.

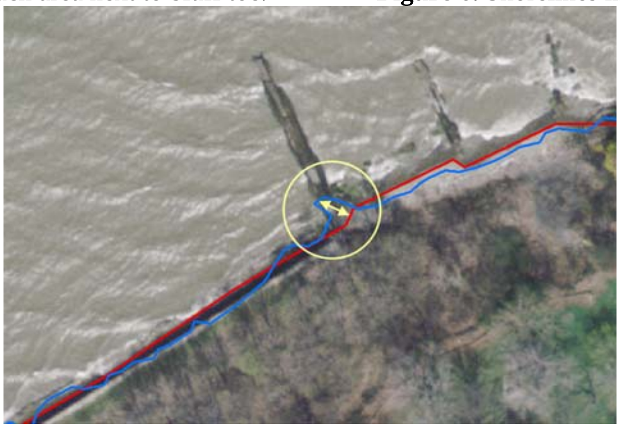

Figure 7. Maximum error found in the area of research (8.24m).

DISCUSSION AND CONCLUSIONS

We have investigated shoreline extraction from the integration of LiDAR data with orthoimages and satellite imagery using a Mean Shift Algorithm. The experimental results show that, with the employment of orthoimages, this method can extract highly accurate shorelines from LiDAR data. The accuracy of the extracted shoreline is better, in general, than the nominal point spacing of the LiDAR data. In a mixed area with different terrain and man-made objects, the accuracy level was found to be around 1.5 m.

The training procedure of resolving the parameters and normalization scales systematically shows a robust result, and this procedure made the algorithm possible for extracting shorelines in a semi-automatic manner.

In current results, the level of accuracy depended highly on the nominal LiDAR point spacing. We are developing an improved method to achieve a higher accuracy through the contribution of additional image information.

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