Assessment of lidar data for instream flow type classification

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Abstract

The information of instrem biotype, i.e., types, location, distribution, etc, are important for estuary environment management. Field observations carry out by ecology surveyor is the standard procedure to gather that information, which is time consuming and is difficult to be applied to a large spatial extend. The instream biotype is classified according to the flow type, water depth, substrate material, and bottom topography. The roughness characteristic of the water surface can be extracted from the high density point cloud acquired by airborne topographic lidar, which can then be used for flow type classification. This implies a great potential of using lidar for instream biotype classification to a large spatial extend in a timely manner. We employed semi-variogram for the water surface roughness characterization. The principle component analysis is then used for the flow type classification. The results show that the first and second principle components are closely related to the flow type considered in this study, i.e., unbroken standing wave, ripple and no perceptible flow.

1. Introduction

The instream biotype classification is based on the associated flow type, water depth, substrate material, and bottom topograph. The information regarding the locations and extend of biotype is important for river management.

Remote sensing images, with image resolution ranging from 0.25 to 3 m, has been used for instream biotype classification (Winterbottom and Gilvear, 1997; Wright et al., 2000; Zhang, 2000; Legleiter et al., 2002). More recently, airborne lidar system has also been applied for data collection of estuary topography (Carbonneau et al., 2004).

Semi-variogram is one of the means to represent the texture features of remote sensing image (Maillard, 2001; Carbonneau et al., 2004). Following the same procedure, the semi-variogram can be applied to lidar point clouds, which 3D values can be used for calculation.

2. Materials and Methods

The study area

The study area is located near the confluence of Nan-Shih River and Pei-Shih River, northern Taiwan. The study area, denoted by the red rectangle in Figure 1, is 504 m x 504 m. The above ground features include gravel, low vegetation, forest, bridge and buildings.

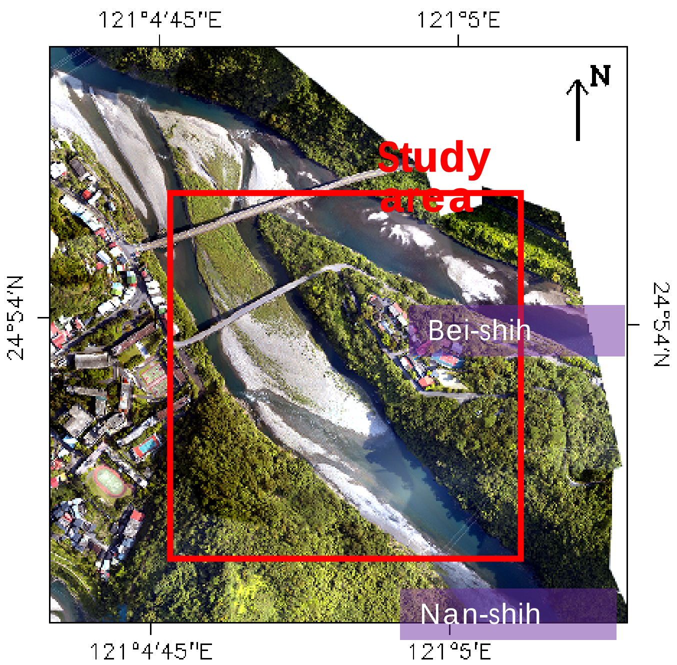

Figure 1. The study area

LiDAR data

The LiDAR dataset of the study area was flown on 13 May 2008 at the altitude of 400 m. The dataset was delivered as an ASCII file containing xyz coordinates. The mean density in the resulting dataset is about 100 points per square meters.

Semi-variogram

Because of different water depth and bottom topography, flow types in the study area, i.e., broken standing wave (BSW), unbroken standing wave (USW), ripple (RP) and no perceptible flow (NP), have different water surface roughness and texture. A semi-variogram is a function of the spatial dependence of semi-variance, it groups semi-variance values at different lag distances. Semi-variogram shows the water surface height dependence at different distance, which represents the texture of flow types.

Figure 2 shows the representative semi-variograms of gravel and four different flow types, including BSW, USW, and NP. Nugget values of BSW, denoted as red line in Figure 2, and USW , denoted as green line in Figure 2, are larger than gravel and NP. In the study area, the difference between BSW and USW are quite consistent, which suggests that nugget value is useful for classification. In addition, the slope is also a useful parameter as an added criterion for classification. For example, the nugget difference of gravel and NP is not consistent in this study area, while their slopes are distinctively different.

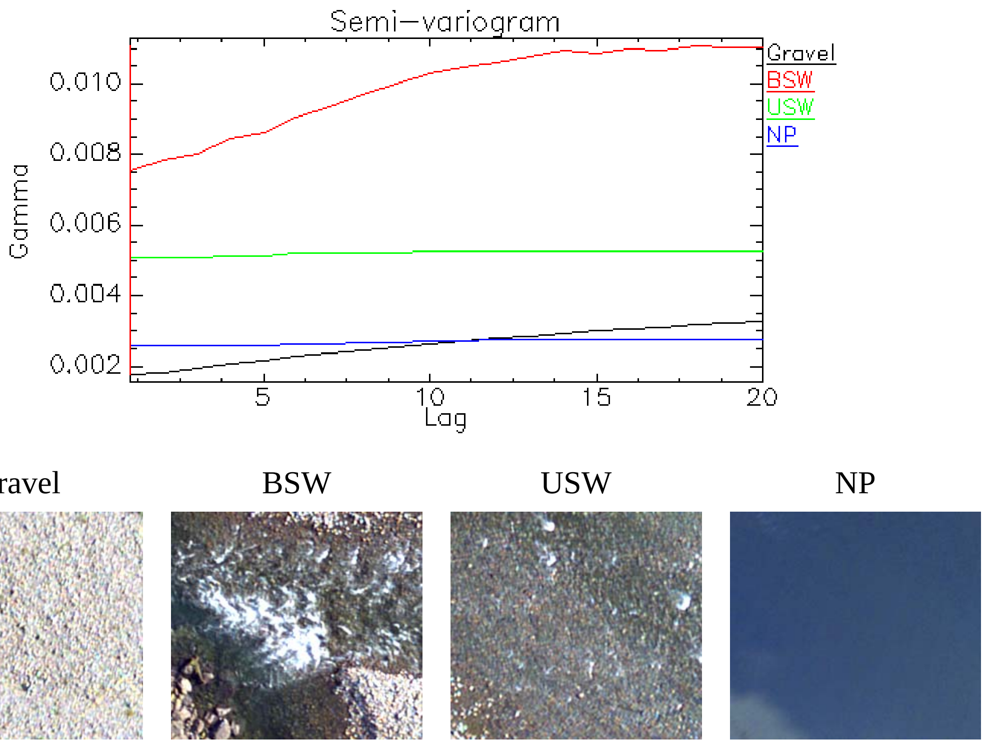

Figure 2. Representative semi-variogram of gravel and flow types in the study area.

The more lidar point clouds are use for semi-variogram calculation, the more stable the semi-variogram will be. For our study area with the point cloud density of 100 point/m^2, including more lidar point clouds mean decreasing the spatial resolution of the resultant texture image. The effect of window size used for semi-variogram calculation will be discussed.

<u>Principle component analysis</u>

Principal component analysis (PCA) performs orthogonal linear transformation onto the data and transfer the data to a new coordinate system, such that and greatest variance of the data is projected on the first coordinate, called the first principal component (PC1). The second greatest variance of the data lies on the second coordinate, called the second principal component (PC2), and so on. The lag distance of the semi-variograms for flow types is setup at 10cm. For the window size of 6m x 6m, the maximum lag distance is 3 m, and there are 30 samples in each semi-variogram. The 30 samples are regarded as 30 bands of an image in order to apply principal component analysis on these data and transformed it to 30 principle components.

Two sequential PCA are performed on the semi-variogram image. The first is to extracted water by building a mask using PC1. After the water is extracted, the second PCA is used for flow type classification.

3. Results

Figure 3 shows the PC1 and PC2 of the semi-variogram image using 1) 6 m x 6 m window size with stepping distance of 6 m, 2) 2 m x 2m window size with stepping distance of 2 m, and 3) 6 m x 6 m with stepping size of 2 m. Due to large window size of 6 m, the feature details are lost in Figure 3a and 3b. When a smaller window size of 2 m is used, more detailed features are preserved. However, the principle component images become noisy, which can be exemplified by the arrows in Figure 3d. When the window size of 6 m x 6 m with stepping distance of 2 m is employed, the detailed features are somewhat fuzzy while remain visually distinctive (Figure 3e and 3f). More importantly, the PC1 and PC2 are more robust to noise.

Figure 4 shows the false color images where PC1 is assigned to red and blue and PC2 is assigned to green. Figure 4i- 4iii shows the typical condition of BSW, USW, and NP shown in the orthophoto. Their corresponding locations are also indicated in Figure 4a – 4c, where BSW appears purple, USW appears purple with lighter tone, NP appears green.

Due to the effect of window size, the overall appearance of Figure 4a is blurry due to large window size of 6 m x 6 m, and that of Figure 4 b is noisy due to insufficient point clouds include for semi-variogram calculation. That of Figure 4c is more visually pleasing and many of the flow type can be more easily identified.

4. Conclusions

The use of lidar data combining semi-variogram analysis and PCA for flow type classification is demonstrated. It is found that PCA is efficient for revealing the texture properties of different flow types. Our results is promising for ecology survey of flow type in large area with short turnaround time.

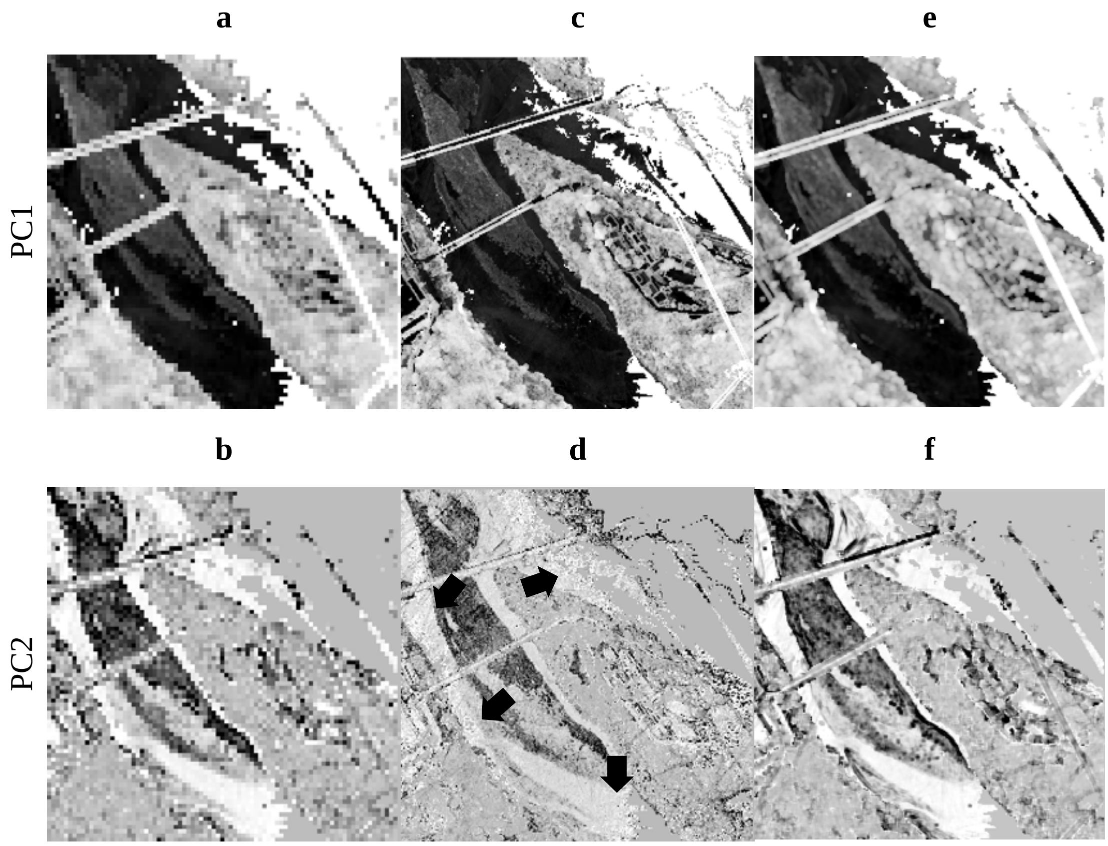

Figure 3. Principle component images for: (a and b) window size of 6 m x 6 m and stepping distance of 6 m; (c and d) window size of 2 m x 2 m and stepping distance of 2 m; (e and f) window size of 6 m x 6 m and stepping window of 2 m. The arrows indicate noisy region.

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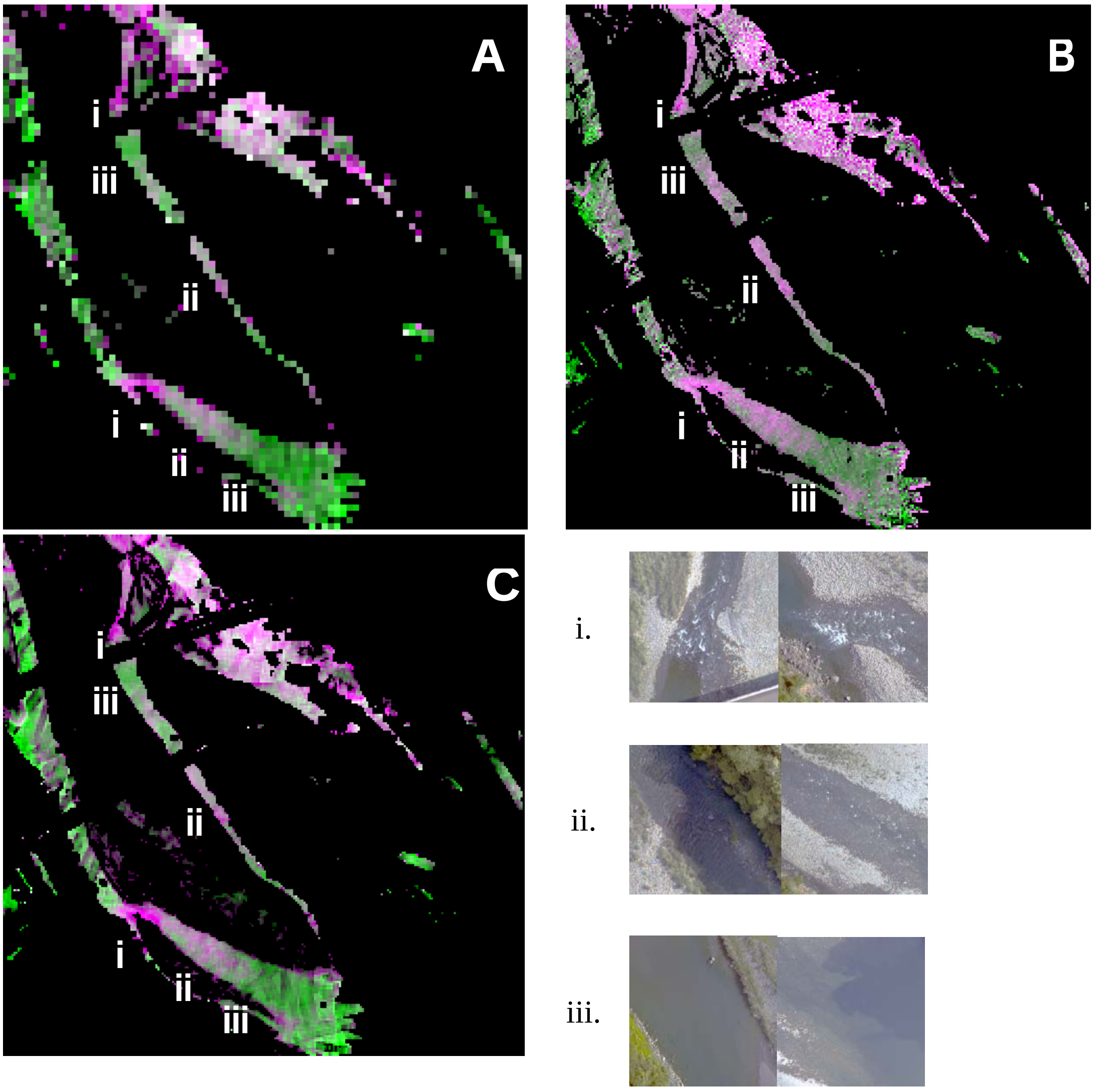

Figure 4. False color images (after masking). R: PC1; G: PC2; B: PC1. (a) 6 m x 6 m window size with 6 m stepping distance. (b) 2 m x 2 m window size with 2 m stepping distance. (c) 6 m x 6 m window size with 2 m stepping distance. Typical conditions of (i) BSW, (ii) USW, and (iii) NP in orthophoto.

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