EVALUATION OF UAV-BASED FOREST INVENTORY SYSTEM COMPARED WITH LIDAR DATA

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ABSTRACT

Forest spatial structure is essential for researches on forest ecosystem dynamics. Considering that the field measurement of forest structures over large field plot is labor-intensive and time-consuming, a forest inventory system is developed based on unmanned aerial vehicle (UAV). This study presented the initial evaluation of this system by comparisons with LiDAR data. Results showed that most trees appeared in LiDAR canopy height model (CHM) could also be detected in UAV CHM. The UAV system could measure forest height at plot level with R^2=0.87 and RMSE=1.9 m taking CHM from LiDAR as reference data.

***Index Terms*—**forest biomass, forest structures, UAV, stereo image, photogrammetry, computer vision

1. INTRODUCTION

Forest spatial structure plays an important role in forest ecosystem dynamics, significantly determining regeneration, growth, mortality, resource use, gap creation, and understory development [1]. Tree competition processes result in a specific spatial pattern [2]. It is possible to infer some information of forest ecosystem dynamics from the stand spatial structure [2]. Besides, insight into forest spatial structure is also important for understanding the links between forest ecosystem structure and function [3]. Therefore, there are many studies in forest ecology focusing on describing and modeling the forest spatial structure. Although some studies point out that vertical structure plays an important role in forest ecosystems[1], most of these studies only consider the relative horizontal positions of trees by the spatial point pattern analysis such as the Ripley's K or L function frequently used in recent years [4-6]. The main reason is the unavailability of detailed forest height over field plot with sufficient size. It is time and labor intensive to manually measure tree height in dense forest over large field plot due to the shading between neighboring trees. Although tree height could be calculated using allometric equations, allometric equation should firstly be calibrated under different forest stand conditions.

Remote sensing dataset directly measuring forest vertical structures provides a powerful tool for the research community of forest ecology. Boutet *et al* [7] investigated the change of forest canopy structure caused by hurricane using airborne laser scanner data (LiDAR) acquired by SLICER sensor developed at NASA Goddard Space Flight Center. Kane *et al* [8] assessed the fire effects on forest spatial structure using airborne LiDAR data. However, spaceborne LiDAR system works on point sampling. For example, the Geoscience Laser Altimeter System (GLAS) onboard ICEsat (Ice, Cloud, and land Elevation Satellite) acquires LiDAR waveform within a footprint of 70 m in diameter. The acquisition of airborne LiDAR data is costly because most LiDAR should be carried by airplanes.

Photogrammetry or computer vision is another technique to derive the vertical distributions of ground objects through the stereoscopic processing of photos. The rapid development of stereoscopic processing software and unmanned aerial vehicle (UAV) in recent decades makes the application of photogrammetry much easier than ever before. UAV-based photogrammetry system is able to acquire data at the relative height lower than 500m covering the area of 1 km by 1 km within half an hour. UAV-based photogrammetry system is quite appropriate for exploring the forest dynamics because it can acquire data at any time intervals (one day, one month or one year) by repeating the fixed route at a low cost. Therefore, this study mainly assesses the performance of UAV-based photogrammetry system in characterizing forest spatial structures by comparing with LiDAR data.

2. TEST SITE AND DATA ACQUISITION

The test site of this study is located at Genhe forest bureau in Inner Mongolia Autonomous Region of China. 83.76% of the area is covered by forest. The dominant tree species are *Larix gmelimi* (Dhurian larch) and *Betula platyphylla* (birch). Dhurian larch is deciduous conifer with 83.6% biomass within trunks while birch is broadleaf deciduous. The maximum height of dhurian larch could be 35m and the maximum diameter at breast height (DBH) could be 90cm.

The data used in this study was acquired between 08/21/2014 and 09/07/2014. Parameters for image acquisition is shown in Table 1. Fig.1-a shows the UAV system while Fig.1-b shows its landing scene.

Table 1. The parameters used in image acquisition

Camera	Sony NEX-5T
Focal length	16mm (fixed)
Pixel size	4.89089 x 4.89089 um
Image size	4912*3264
Height (m)	300
Speed (m/s)	10
Longitudinal overlap	95%

Fig 1. The UAV system (a) and Landing after a flight (b)

Airborne Laser Scanner (ALS) data was collected using the Leica ALS60 system onboard a Yun-5 aircraft from 08/30/2012 to 09/14/2012 [9]. The system operated at a 166 kHz pulse rate at 1800m Above Ground Level. The point density is about 2–4 points/m^2.The point cloud data were classified using TerraScan software by TerraSolid Ltd [10]. Points were classified as ground, vegetation, and noise (points located below the ground surface or higher than vegetation canopy top). Then a digital elevation model (DEM) of ground surface and a digital surface model (DSM) with 0.5 m spatial resolution were created.

3. METHOD

The data was processed using a purchased copy of Agisoft Photoscan which is a commercial computer vision software package [11]. The main processing steps include:

(1) Load aerial photo recorded in Exchangeable image file format (EXIF). The camera parameters is always automatically provided together with images if no additional modification is applied. Camera calibration is needed if EXIF data is unknown. The parameters used in camera calibration include pixel size and focal length.

(2) Photo alignment. This step is used to estimate the relative positions and attitudes of photos based on the identified common points from these photos.

(3) Building dense point cloud. This is the critical processing step. The dense point cloud is generated by automatic image matching. Three filtering method is provided to remove noise points including aggressive, mild and moderate. Mild method is preferred if there is small meaningful features exist.

(4) Building mesh. Two types of surfaces are provided including arbitrary and height field. For earth observing, height field is preferred.

(5) Placing markers. The above four steps works in relative coordinate systems. Ground control points are needed to transform it into georeferenced coordinates.

(6) Point cloud classification. Automatic classification procedure in Photoscan consists of two steps. Firstly, the dense point cloud is divided into cells of a certain size. The lowest point in each cell is detected. The terrain model is approximated by triangulation of these lowest points. The second step is to determine whether other points also belong to ground points. Ground points should satisfies two conditions: (a) it lies within a certain distance from the terrain model; (b) the angle between terrain model and the line to connect this point with a point from a ground class is less than a certain degree. The second step is repeated until all points are checked.

(7) Results export including point cloud, digital surface model, and orthophoto.

4. RESULTS

Totally 41 photos covering an area of 0.469 km^2 are processed in this study. Fig. 2 shows the locations of cameras and image overlap. Different colors indicate different numbers of photos are used. Fig.3 is the digital surface model (DSM) reconstructed from the dense point cloud. The average point density is 137.9 point/m^2. Fig.4 is the orthophoto through the mosaic of 41 photos ortho-rectified by the extracted digital surface model with a resolution of 0.085m. Fig.5 is the digital elevation model (DEM) of ground surface built from point cloud of ground.

Fig.6 shows the canopy height model derived by the difference between DSM and DEM. While Fig. 7 shows the canopy height model derived from LiDAR data. It is clear that Fig.6 and Fig.7 looks quite similar. Most trees appeared in LiDAR CHM could also be detected in UAV CHM. Their difference mainly appeared near boundaries because less points from ground surface degraded the quality of UAV DEM.

In order to evaluate the performance of UAV forest inventory system at plot level, both the CHM from UAV and that from LiDAR are resized to a resolution of 30m by pixel averaging. Fig. 8 shows the scattering plot between UAV CHM and LiDAR CHM. They are highly correlated with R^2=0.87 and RMSE=1.9 m.

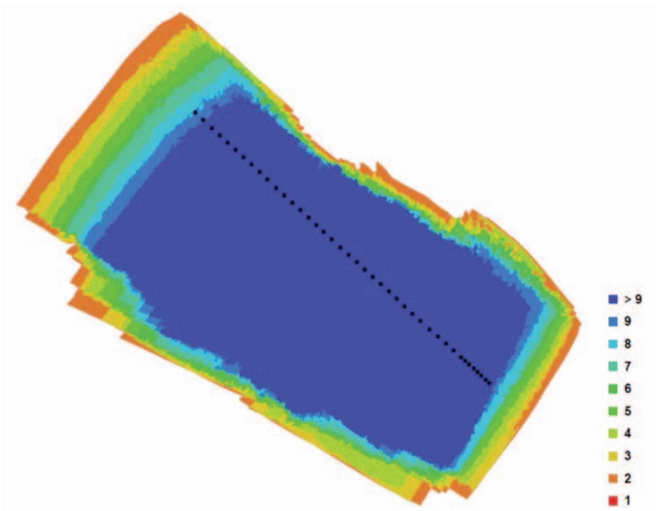

Fig.2 Camera locations and image overlap

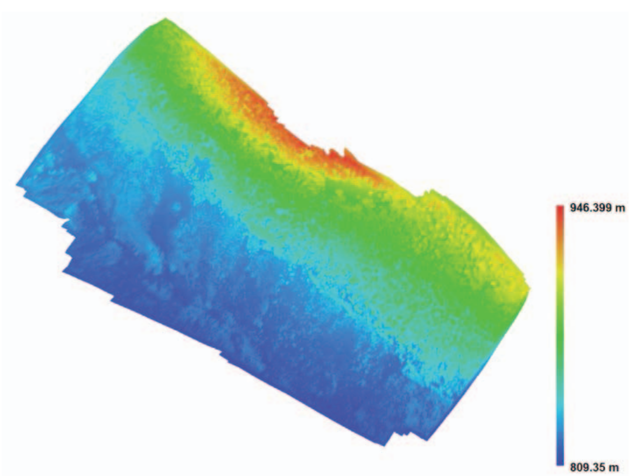

Fig.3 Digital surface model (DSM)

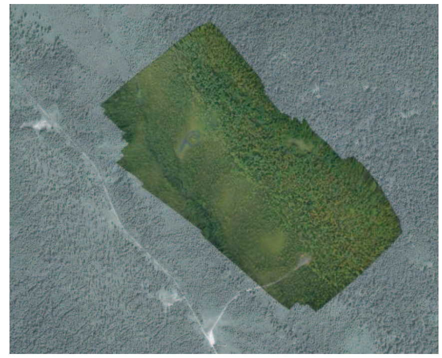

Fig.4 Orthophoto overlaying on Google Earth

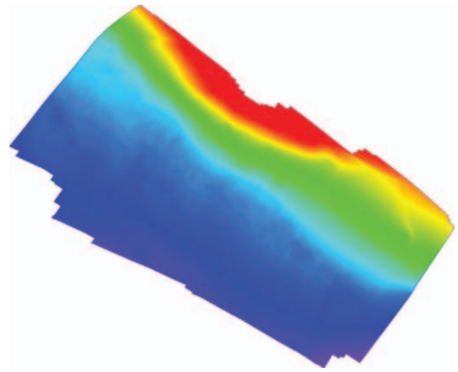

Fig.5 Digital elevation model of ground surface (DEM)

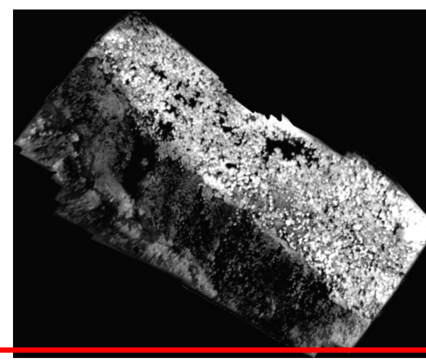

Fig.6 Canopy height model (UAV CHM), i.e. the difference between DSM and DEM

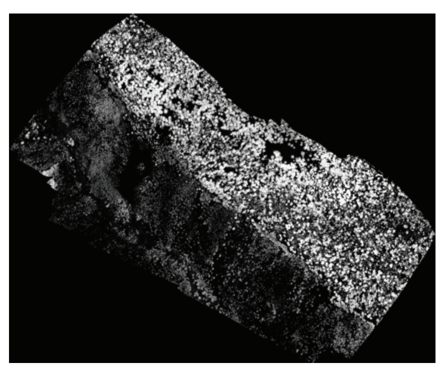

Fig.7 Canopy height model from LiDAR data (LiDAR CHM)

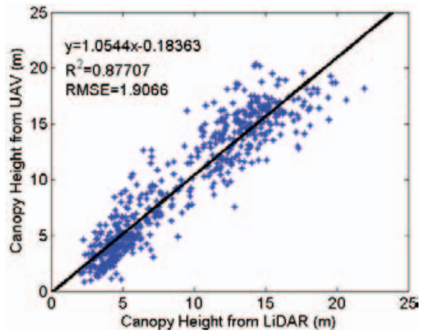

Fig.8 Scattering plot of LiDAR CHM vs. UAV CHM

5. CONCLUSION

Forest inventory is essential for retrieval of forest biomass using remote sensing dataset. Forest spatial structure over field plot with sufficient size is also important for forest ecosystem researches. The study reported the performance of a forest inventory system based on UAV platform by comparing with LiDAR data. The results showed that CHM from UAV looks quite similar with CHM from LiDAR data. Most trees visible in LiDAR CHM could also be detected in UAV CHM. CHM from UAV could measure forest height at plot level with R^2=0.87 and RMSE=1.9 m taking CHM from LiDAR as reference data.

6. ACKNOWLEDGMENT

The LiDAR data was provided by Dr. Yong Pang from Institute of Forest Resource Information Technique of Chinese Academy of Forestry. Mr. Hongliang Chu from Institute of Remote Sensing and Digital Earth of Chinese Academy of Sciences helped us in data acquisition. This work was supported by the National Natural Science Foundation of China (Grant Nos. 41471311), the National Basic Research Program of China (Grant No.2013CB733404, 2013CB733401). The authors thank each of the foregoing supports.

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