Quantitative Evaluation of GPS Performance under Forest Canopies

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***Abstract*—There is an increasing demand for use of the Global Positioning System (GPS) to navigate or track objects in the forest. However, objects near a GPS receiver antenna, such as tree leaves and branches, can reflect GPS signals and result in large position errors. Canopies in the forest will also block satellite signals and cause the GPS receiver to stop updating data. This is of practical significance for evaluating the performance of GPS in the forest environment. A field test was conducted to understand how large the position errors are and how long the position updates may be deferred under different levels of canopy densities. A digital camera was used to record the canopies over the test site. Image processing techniques, especially Otsu's algorithm, were used and the canopy density was classified into three levels. The ANOVA was used to analyze the effect of canopy density on the GPS position errors. The result shows that the GPS position errors are significantly different under different canopy density levels. The GPS data-update frequency was also analyzed, and the result indicates that the scheduled position update intervals are lengthened due to the existence of forest canopies.**

***Index Terms*—Forest, Global Positioning System, Image processing, Otsu' algorithm**

I. Introduction

There is an increasing demand for use of the Global Positioning System (GPS) in the forest environment. For example, tree harvesters must be navigated accurately to maintain proper distances from property lines, streams, and other natural resources. Forest fire fighters need to know the positions of themselves, their teammates, and the fire to work effectively and safely. The management of fire-fighting will be more efficient with the position data provided by GPS. More and more hikers are equipped with GPS devices for positioning themselves. New generations of GPS receivers are small, light, cheap, fairly accurate and easy to use. GPS has great potential for these applications.

The GPS is a worldwide radio-navigation system enabled by a constellation of operating satellites and their ground stations. GPS provides specially coded satellite signals that can be processed in a GPS receiver, enabling the receiver almost anywhere on the earth to compute position, velocity, and time. At least four GPS satellites are needed to calculate a 3D user position. Signals from the GPS satellites must travel a long distance until they reach the earth's surface. Many factors, such as the ionosphere and the troposphere delays, can cause errors in position calculation. Multipath propagation of GPS signals is one of the main sources of GPS errors in the forest. Objects near a receiver antenna, such as trees, larger boulders, and canyon walls, can reflect GPS signals and result in one or more secondary propagation paths. These secondary-path signals can interfere with the signal that reaches the receiver directly from the satellite, distorting its amplitude and phase significantly. The magnitude of pseudorange error caused by multipath propagations can be as high as 230~260 feet [1].

Another problem with the use of GPS in the forest is that tree canopies may block satellite signals. If, due to this blockage effect, only three or fewer satellites are visible from a GPS receiver, the receiver cannot calculate the 3D positions of the receiver. This will result in a longer data update interval and, hence, cause problems for applications that require constant position updates.

These problems are of practical significance for evaluating the performance of GPS in a forest environment. A field test was conducted to understand how large the position errors are and how long the position updates may be deferred under different levels of canopy densities. In this paper, we describe the design and report the findings of this field test.

II. General Test Information

A. Test Site

The site selected for the field test is in the Capitol State Forest, Washington State. The Capitol State Forest is located near the southern end of Puget Sound, just west of Olympia, on the Black Hills that rise nearly 3200 feet. At the test site, some of the forest timber has been harvested by thinning, partial cuts, and clear cuts. The test trail runs through both harvested and reserved areas. Figure 1 shows the test trail and the position of the test control points.

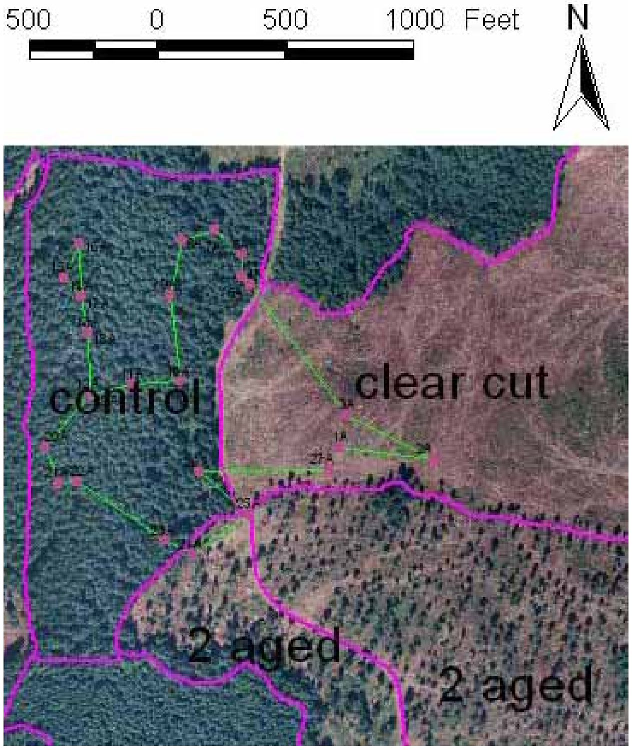

Fig. 1 Test trail in the forest.

B. *Test Time*

The field test in the forest was performed on May 21 and 22, 2002. In the late spring, most of the plant leaves in the Puget Sound area have already grown up. The weather is still cloudy or rainy during this season. These conditions presented one of the worst scenarios for navigation in forests.

C. *Test Device and Settings*

The GPS equipment used in the field test was a Pro XR manufactured by Trimble Navigation Limited. The Pro XR is a 12-channel, real-time DGPS receiver working on single frequency. The PRO XR was applied for navigation on a trail with 26 control points. Some preliminary tests were performed to find the most suitable settings for the navigation task. The Position Dilution of Precision (PDOP) mask was set to be 7.0 in the test, which was a fairly high value. PRO XR would disregard the position data when the PDOP value was higher than the threshold of 7.0. With a higher PDOP mask, the PRO XR can still calculate the position data even though the satellites are poorly positioned in the sky. However, the position accuracy of GPS would be decreased in this case. The Signal-to-Noise Ratio (SNR) mask was set to be 3.5, which was a fairly low value. SNR indicates the signal strength of a satellite. PRO XR would disregard the signal from a satellite when the SNR value of this satellite was lower than the threshold of 3.5. With a lower SNR mask, the PRO XR can still use a signal from a satellite even though the satellite's signal is poor; however, the position accuracy of GPS would become lower because of the lower SNR mask. The Elevation mask was set to 14º, which was a low value. PRO XR would disregard the signal from a satellite when the elevation of this satellite above the horizon was lower than the threshold of 14º. The real-time-differential mode was set to auto. In this mode, the PRO XR will automatically apply a real-time differential correction and log the Differential GPS (DGPS) data if it receives correction signals from base stations; when no correction signals are received, the PRO XR will log the GPS data without applying the real-time differential correction.

The position mode was set to be "Manual 3D". In this mode, PRO XR always needs at least four satellites to compute one 3D GPS position. If there are fewer than four satellites available, the PRO XR will not log any GPS position. The Real-Time Kinematic (RTK) mode was set to be "on," which means PRO XR applied RTK in the test. The logging interval for positions was set to be 5 seconds. The measurement units were feet (one foot is equivalent to 0.305m), and the antenna height was 6.0 feet (1.83m). The coordinate system was NAD83, Washington State South Zone State Plane Coordinate System.

A digital camera (Olympus C-3040, focal length 7.1~21.3mm) was used to record the canopy over each stake. The focal length was set to 7.1mm to record a wide scope of canopies. The camera was vertically held by hand over each of the stakes to photograph the canopies. The canopy pictures were used for classifying the level of canopy density at each control point.

There were 26 surveyed points with marked stakes in the test trail (Figure 1). The PRO XR was navigated along the trail six times.

To evaluate the real-time navigation ability of the devices, all the data used in this paper are those logged in real-time.

III. Methodology

A. *Canopy Density Index*

Figure 2 is a typical picture taken in the forest for canopy density analysis. Based on the picture, the canopy density can be quantified using the Canopy Density Index (CDI). The CDI is defined as the ratio of canopy representing pixels, such as leaves and branches, to total pixels in a picture.

Fig. 2 Canopy in the forest

The color pictures were in the Joint Photographic Experts Group (JPEG or JPG) format when they were taken in the forest. Every pixel in a JPG picture contains three channels: intensity, hue, and saturation. Intensity is decoupled from the color information in the image. The intensity channel is often used for image processing. In the JPG format, the intensity values are integers ranging from 0 to 255. A JPG picture can be easily converted to a gray-scale picture by only preserving the intensity channel of each pixel. Figure 3 shows the gray-scale picture converted from the color picture of Figure 2. It is easier to analyze the canopy density with only the intensity channel.

Fig. 3 Canopy in the forest in gray-scale

However, as the intensity value varies from 0 to 255, it is necessary to find an intensity value threshold to determine whether a pixel is a canopy-representing pixel or a sky pixel. In gray-scale pictures, a darker object has a lower intensity value. If the intensity value of a pixel is lower than the threshold, the pixel will be identified as a canopy pixel. Otherwise, it will be a sky pixel. A global threshold was selected using Otsu's method [2]. Otsu's algorithm chooses a threshold value that minimizes the intra-group variance. In this study, we need to find a threshold value that separates the canopy pixels from the sky pixels so that we can calculate the CDI for each studied control point.

B. Application of Otsu's Method

One measure of group homogeneity is variance. A group with low homogeneity will have high variance [3]. One possible way to choose the threshold is to find a gray-scale value that minimizes the intra-group variance. Otsu (1979) developed such an algorithm for threshold selection. Here, we show how Otsu's algorithm can be applied for classifying image pixels into one of the two categories: canopy and sky.

Suppose an image has L gray levels. For each gray-level value i, P(i) is the normalized frequency of i. Assuming that the threshold is T, the normalized fraction of pixels that will be classified as canopy (denoted by qc(T)) and sky (denoted by qs(T)) are:

$$q_c(T) = \sum_{i=1}^{T} P(i) \text{ and } q_s(T) = \sum_{i=T+1}^{L} P(i)$$

(1)

The mean gray-scale values of the canopy pixels, μc(T), and the sky pixels, μs(T), are:

$$\mu_c(T) = \frac{\sum_{i=1}^{T} iP(i)}{\sum_{i=1}^{T} P(i)} = \frac{1}{q_c(T)} \sum_{i=1}^{T} iP(i) \text{ and}$$

$$\mu_s(T) = \frac{\sum_{i=T+1}^{L} iP(i)}{\sum_{i=T+1}^{L} P(i)} = \frac{1}{q_s(T)} \sum_{i=T+1}^{L} iP(i) \quad (2)$$

The variance of the canopy pixels is:

$$\sigma_c^2(T) = \frac{\sum_{i=1}^{T} (i-\mu_c)^2 P(i)}{\sum_{i=1}^{T} P(i)} = \frac{1}{q_c(T)} \sum_{i=1}^{T} (i-\mu_c)^2 P(i)$$

(3)

Similarly, the variance of the sky pixels is:

$$\sigma_s^2(T) = \frac{\sum_{i=T+1}^{L} (i-\mu_s)^2 P(i)}{\sum_{i=T+1}^{L} P(i)} = \frac{1}{q_s(T)} \sum_{i=T+1}^{L} (i-\mu_s)^2 P(i)$$

(4)

The intra-group variance is defined as:

$$\sigma_W^2(T) = q_c(T)\sigma_c^2(T) + q_s(T)\sigma_s^2(T)$$

(5)

The threshold can be determined by testing each gray-scale value from the beginning of the histogram for the threshold T that minimizes σ_W^2.

Otsu's method works well when an image's gray-scale values are bimodally distributed. If the gray-scale values are not bimodally distributed, multiple applications of Otsu's algorithm may be necessary. In this particular study, almost all the images were bimodal in terms of gray scale values. Figure 4(a) shows three example images used in this study. Gray-scale histograms, pixel thresholds obtained from Otsu's algorithm, and CDIs corresponding to the three sample pictures are shown in Figure 4(b). The resulting binary images, in which canopy pixels are in black and sky pixels are in red, are provided in Figure 4(c). Intuitive comparisons between the original pictures and the binary images indicate that the proposed method for CDI calculation works very well.

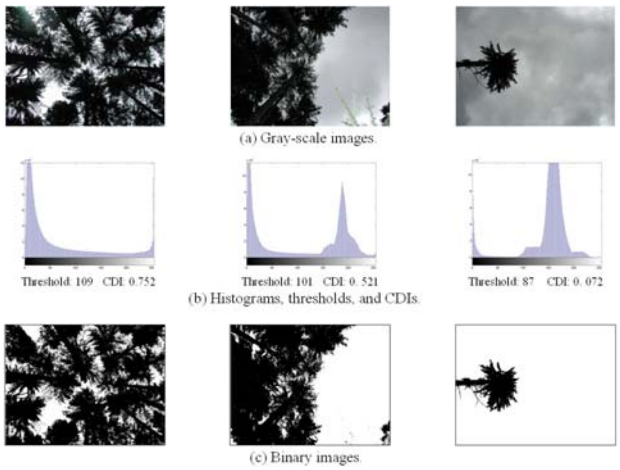

Fig. 4 Examples of CDI calculation using Otsu's algorithm

Another limitation of Otsu's method is that it does not work well with variable illumination. For example, if the gray-scale values depend strongly on the locations within the image, the global threshold determined by Otsu's method may not the best threshold. In this study, the pictures were taken on a cloudy/shower day, and the illumination within one image is quite homogenous. Therefore, Otsu's method was still appropriate for the analysis.

C. Canopy Density Levels

Once the global threshold of a picture is determined, the CDI can be easily calculated. Figure 5 shows the distribution of CDIs for the 26 control points. Based on the distribution, the canopy density can be classified into three levels: low-canopy, medium-canopy, and high-canopy. The CDI value of the low-canopy level is zero or less than 0.1. For the medium-canopy level, the CDI varies from 0.45 to 0.55. The CDI of high-canopy level is about 0.75, ranging from 0.67 to 0.86. The following section will show whether GPS performed significantly differently under these three canopy levels.

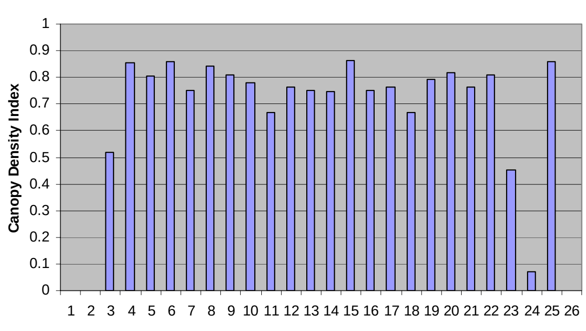

Fig. 5 Canopy density levels

IV. Analysis and Results

The GPS performance in this test is considered to have two aspects: position accuracy and data update frequency. A GPS position error is calculated as the distance from the surveyed position to the position logged by the PRO XR. All the control point coordinates in the test site are known and were verified using a Topcon 1 second total station by researchers at the University of Washington in 1999.

TABLE I
THE GPS POSITION ERRORS FOR THE ANOVA

Runs	Mean PDOP	Position Error (ft)		
		Low density	Medium density	High density
Run 1	4.69	3.4096	4.6647	4.6591
		4.6266	9.9130	3.0817
Run 2	5.40	3.5500	8.0293	21.3180
		3.5367	4.2208	3.1175
Run 3	4.36	3.1746	5.3756	15.9841
Run 4	5.00	3.5530	5.5511	2.8333
		5.0403	9.0329	5.5469
Run 5	4.52	1.8053	3.2011	17.9765
		4.9881	5.2154	12.6545
Run 6	4.80	3.1209	6.4687	22.3075
		1.5620	4.0468	26.1575

The method of analysis of variance (ANOVA) was used to analyze the effect of canopy density levels on position errors. The GPS position error data used for the ANOVA are shown in Table 1.

The ANOVA table for the GPS position error analysis is shown in Table 2. Since there were three canopy density levels, the degrees of freedom between treatments was 3-1=2; there were 33 positions used in the ANOVA, so the degrees of freedom of the total sample was 33-1=32, and the degrees of freedom within treatments was 33-3=30.

TABLE 2
THE ANOVA TABLE OF GPS DATA

Source of Variation	Sum of Squares (ft^2)	Degree of Freedom	Mean Sum of Squares (ft^2)	F
Between treatments	457.5136	2	228.7568	8.153
Within treatments	841.7098	30	28.0570	
Total	1299.2234	32		

At the confidence level of 99% (α=0.01), F0.01 (2, 32)=5.390<8.153. This means the canopy density can significantly affect the position accuracy of GPS receivers at the p=0.01 level.

TABLE 3
CALCULATED TIME CONSUMPTION INDEX (TCI)

Canopy density	Low	Medium	High
Time Consumption Index	1.012	1.970	3.119

Besides position errors, the data update frequency should also be analyzed. Typically, a GPS receiver updates its location periodically at the interval set by the users. However, if the visibility of GPS signals is poor, such update efforts may be seriously delayed. In this study, we use the Time Consumption Index (TCI) to measure the location update performance of GPS receivers. The TCI is defined as the ratio of the actual data collection time to the scheduled data collection time at a survey point using a GPS receiver. Under ideal conditions, e.g. there is no object to block the GPS signals, the TCI should be one. The observed TCIs for the three canopy density categories are presented in Table 3. We can see that the TCI values increase significantly from the low density category to the medium density category and from the medium density category to the high density category. Under low-density canopies, the GPS receiver can log the same amount of position data in about 101.2% of the scheduled time. Under medium-density canopies, the actual data collection time is 97% longer than the scheduled time. When the GPS receiver is under high-density canopies, the actual data collection time is 311.9% of the scheduled time. The effect of canopy density level on the GPS data-update frequency is remarkable.

V. CONCLUSION

In this paper, we described a field test conducted to quantitatively evaluate the performance of GPS under forest canopies. Since canopy density varies from location to location and its impact on GPS performance is different from location to location, a method for measuring the density level of GPS was necessary for this study. We used image processing for measuring canopy densities. In this study, canopies were classified into three levels based on their densities: low, medium, and high. Otsu's algorithm was used to choose the threshold value for identifying whether a pixel represented canopy or sky. The canopy density level of each survey point was determined according to the calculated CDI.

In this study, the GPS performance was measured by two aspects: position accuracy and data update frequency. There is no doubt of the importance of position accuracy. The reason we considered data update frequency as another measure of the GPS performance was because GPS devices are increasingly used in real-time applications in which a consistent data update frequency is required. The ANOVA was used to analyze the effect of canopy density levels on the GPS position errors. The result shows that the GPS position errors were significantly different (at 0.01 significance level) under different canopy density levels, and the higher the canopy density level, the larger the GPS position error. In our analysis of the GPS data-update frequency, we introduced the TCI to measure the GPS performance on position updates. The TCI increased significantly with the canopy density levels. This indicates that the scheduled position update intervals are lengthened due to the existence of forest canopies. The higher the canopy density, the longer the delay.

The result of the test shows that GPS performance is significantly degraded by forest canopies. This problem limits the application of GPS in a forest. Many solutions for this problem are available, such as aerial or van-based technologies. To improve its performance in forest, GPS can be combined with other navigation systems, such as FAA navigation beacons or the Inertial Navigation System (INS). However, further studies are needed to evaluate the effectiveness of these combined systems.

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