AN AUTOMATED SUPERELEVATION MEASUREMENT METHOD FOR HORIZONTAL CURVE SAFETY ASSESSMENT USING A LOW-COST MOBILE DEVICE

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ABSTRACT

The horizontal curve is one of the focal points of roadway safety because it plays a critical role in smoothly transitioning vehicles among tangent roadway sections; more importantly, vehicle crashes frequently concentrate on horizontal curves despite their disproportional length in the road network. As one of the most critical safety properties of horizontal curves, adequate superelevation is crucial to vehicle safety because it counteracts the lateral acceleration produced in vehicles when they travel the curve. Despite several sensing-based methods having emerged in recent years, labor-intensive and time-consuming manual superelevation evaluation is often carried out by transportation agencies because emerging methods usually demand expensive equipment (e.g., high-resolution cameras, mobile light detection and ranging (LiDAR) sensors etc.), and complicated operations. Therefore, transportation agencies are still urgently searching for low-cost, reliable alternatives to improve their data collection practices. This paper proposes an automated superelevation measurement method using inexpensive mobile devices (e.g., smartphone, tablet). The proposed method integrates and processes sensing data from a mobile device (including a global positioning system (GPS), an accelerometer, and a gyroscope), and derives superelevation values by employing the fundamental vehicle kinematics at a horizontal curve. Kalman Filtering-based noise reduction, regression-based radius computation, and complementary-filtering-based rolling angle computation methods are introduced to achieve accurate and robust results in spite of low-frequency, noisy signals from the inexpensive devices. An experimental test on State Route 2 in Georgia demonstrates that the proposed method delivers results with accuracy comparable to the LiDAR-based method. A case study of applying the proposed method in high friction surface treatment (HFST) site selection using ball bank indicator (BBI) shows that the proposed method provides a promising alternative for transportation agencies to achieve low-cost, yet reliable data collection for safety analysis and improvement.

Keywords: Superelevation, Geometry, Horizontal Curve, Mobile Device, Automation

INTRODUCTION

Horizontal curves have become one of the critical focal points in roadway safety because a disproportionate number of serious vehicle crashes occur at horizontal curves, despite the fact that curves only represent a small fraction of the roadway network (1). While each crash that is attributed to a combination of factors, transportation agencies have been actively focused on improving the physical safety properties (such as roadway geometry improvement, roadway surface treatment, roadway signage enhancement, etc.) at horizontal curves, attempting to reduce the number of crashes and minimize the severity of crashes.

As an essential component of the physical safety properties at horizontal curves, superelevation plays an indispensable role in enabling vehicles to safely navigate through a horizontal curve by counteracting the lateral acceleration. Although superelevation is usually carefully designed with curve radius, surface fiction, and regulated speed to ensure safety at each horizontal curve, many factors (such as sub-standard construction, aging road surfaces and structures, etc.) may produce inadequate superelevations that potentially lead to serious roadway departure crashes. Although many transportation agencies have been actively collecting physical safety properties at horizontal curves, including superelevation, most of the methods demand manual measurement by field engineers. These manual methods are not only labor-insensitive and time-consuming but are, also, more importantly, produce sparse, error-prone measurements along each horizontal curve; such methods are impractical for supporting a reliable safety assessment. There is an urgent need for a continuous and reliable superelevation measurement method for transportation agencies.

To address such a need, several sensing-based roadway geometry extraction and measurement methods, such as those employing computer vision, light detection and ranging (LiDAR), pavement scanning lasers, etc., have emerged in recent studies. Many of these methods have shown promising results for continuous and reliable extractions of critical safety properties, such as curve radius (2), horizontal and vertical grade (3), sight distance (4), and other issues at horizontal curve locations. However, most of these methods demand a substantial investment in equipment instrumentation and consist of complex calibration and operation processes. Under stringent funding situations, transportation agencies are still seeking low-cost alternative methods for safely collecting data that can deliver accurate and productive performance.

With the advancement of mobile computing technologies, mobile devices (e.g., smartphones, tablets, etc.) have become highly integrated, computationally efficient, and extremely low-cost. By taking advantage of the integrated sensors in these devices (e.g., GPS, and video cameras), many transportation applications have been successfully developed and implemented (5, 6, 7, 8). With other integrated sensors, e.g. accelerometers and gyroscopes, these mobile devices have also become excellent candidates for supporting cost-effective, safe property data collection at horizontal curves. This study aims at harnessing the huge potential of mobile devices to develop an automated superelevation measurement method by integrating the signals from location-aware sensors and computing superelevation values by employing the fundamental vehicle kinematics at a horizontal curve.

This paper is organized as follows. The first section presents the research need and objective of this study. The second section presents a brief literature review on state-of-the-art superelevation measurement methods. The third section presents the proposed method, including an overview of the fundamental vehicle kinematics at a horizontal curve and the detailed superelevation computation approach. The fourth and fifth sections present a detailed experimental test to evaluate the performance of the proposed method and an on-going high friction surface treatment (HFST) ap-

plication to demonstrate the capacity of the proposed method. Finally, the last section summarizes the conclusions of this study and suggests future research.

LITERATURE REVIEW

Recognizing the inefficient and impractical nature of manual measurement of individual safety properties at horizontal curves, many transportation agencies use ball bank indicator (BBI) values as a composite safety indicator, representing the combination of superelevation, unbalanced lateral acceleration (i.e., side friction), and vehicle body roll (9, 10). The measurement is then used to suggest safety improvement strategies, e.g., advisory speed (11). However, the BBI data collection is still an error-prone and time-consuming process because it requires the operator to drive at a constant speed during the data collection and to follow a âĂIJtrial-and-errorâĂİ approach until the lateral acceleration limit is reached (12).

With the development of the emerging sensing technologies, several recent studies have emerged that can measure superelevation more accurately and efficiently. Computer vision techniques are first used to automatically extract the road sections (13). Mobile LiDAR and airborne LiDAR are then used to formulate the 3-D model of the roadway surface so that the cross slopes (i.e., superelevation at horizontal curves) can be derived using surface regression (3, 14). The integrated systems with pavement line-scanning laser and inertial measurement units (IMU) are also introduced to measure superelevation (15, 16). The superelevation is estimated for each scanning line based on the depth measurement derived by the line-scanning laser with the compensation of vehicle rolling angle dictated by the IMU. As high-resolution high-accuracy points, point clouds and scanning lines are acquired through LiDAR sensors and line scanning laser sensors, dense and accurate superelevation measurements can be achieved with an error rate as low as 0.13% (i.e., 0.08°) (3). However, the drawbacks of these methods are a high equipment cost and a complex calibration and operation process, which prevent these methods from being implemented by transportation agencies.

Recently, Denigan et al. (17) have developed a methodology for superelevation measurement using a GPS-equipped digital inclinometer (i.e., digital BBI) and a laptop computer. The measured superelevation is used to suggest safe speeds at curves. The system was utilized to derive roadway radius using the "least square regression method for a quadratic curve" and the vehicle speed. The digital inclinometer was utilized to derive the superelevation along the curve by computing different force components along and perpendicular to the banked surface as the vehicle was cornering. However, the drawback of the method is that measurement may not deliver consistently accurate results, which is attributed to three primary factors: 1) the derived curve radius is computed based on a three-point quadratic regression, which may be easily biased by any inaccurate GPS coordinates; 2) the method simplifies the force component by ignoring the rolling effect of the vehicle body, which may contribute up to three degrees in the final superelevation results (10); 3) the low data acquisition frequency (i.e., 3Hz (18)) adds noise to the acquired signals, e.g., lateral acceleration, which propagates to the computation of superelevation.

In summary, the existing methods have demonstrated the potential for semi-automated or automated superelevation measurement. However, the current methods lack an effective balance between the measurement accuracy and the instrumentation cost. Consequently, this paper is aimed at developing a practical method that conducts low-cost superelevation measurement accurately and automatically at horizontal curves using inexpensive mobile devices.

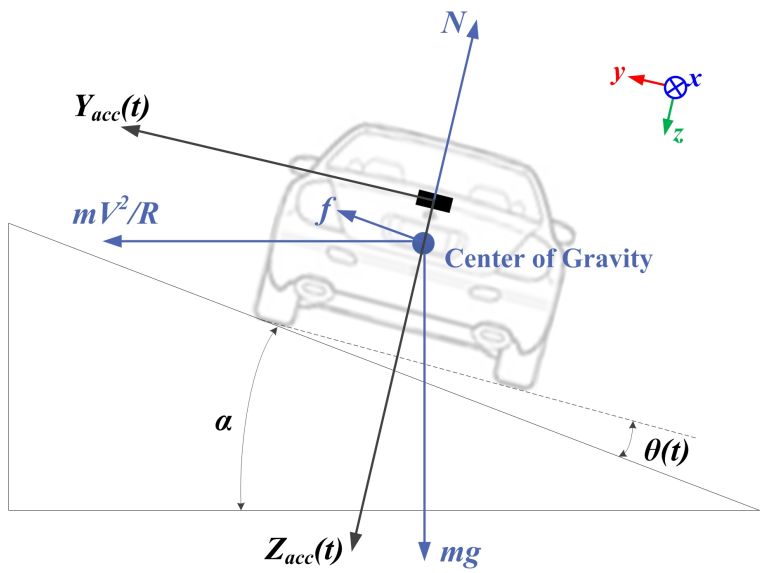

FIGURE 1 : Illustration of the vehicle kinematics at a horizontal curve with bank

PROPOSED METHOD

Background of Vehicle Kinematics

The core of the proposed method for superelevation measurement is to derive or acquire signals from the low-cost mobile devices to solve the fundamental vehicle kinematics when a vehicle is cornering on banked roadways. Figure 1 illustrates the kinematics when a vehicle is negotiating a super-elevated roadway with a horizontal curve radius R and superelevation α. The vehicle has a mass m and is traveling at speed V. The pavement surface provides the perpendicular support force N to the vehicle, and it also provides side friction f, as the vehicle has the potential of lateral motion without skidding. Therefore, when the vehicle is traveling along the curve without lateral motion, the combination of the gravitational force (mg), the support force (N) and the side friction force (f) act through the vehicle's center of gravity to balance it with the fictitious centrifugal force ($\frac{mV^2}{R}$). Meanwhile, the acceleration of the vehicle and the rotation angles are captured by the accelerometer and the gyroscope in a mobile device. As shown in Figure 1, the lateral and vertical accelerations are recorded as $Y_{acc}(t)$ and $Z_{acc}(t)$ on the vehicle frame, while the rolling angle is recorded as $\theta(t)$ (t indicates the instantaneity of different forces and accelerations).

Therefore, the lateral acceleration Yacc can be represented by the balancing forces along the y direction in the vehicle frame when there is no lateral motion (i.e., side skidding), written as in Equation 1.

$$Y_{acc}(t) = \frac{V(t)^2}{R(t)} \cdot \cos(\alpha(t) - \theta(t)) - g \cdot \sin(\alpha(t) - \theta(t)) \tag{1}$$

Equation 1 can be rewritten as Equation 2 after certain rearrangements. Therefore, superelevation (α) is a function of four parameters, including the vehicle speed (V), the curve radius (R), the lateral acceleration ($_{Yacc}$), and the rolling angle (θ) at any given timestamp t. Therefore, the proposed method is aimed at accurately obtaining the four essential parameters using a low-cost mobile platform so that the superelevation can be reliably derived.

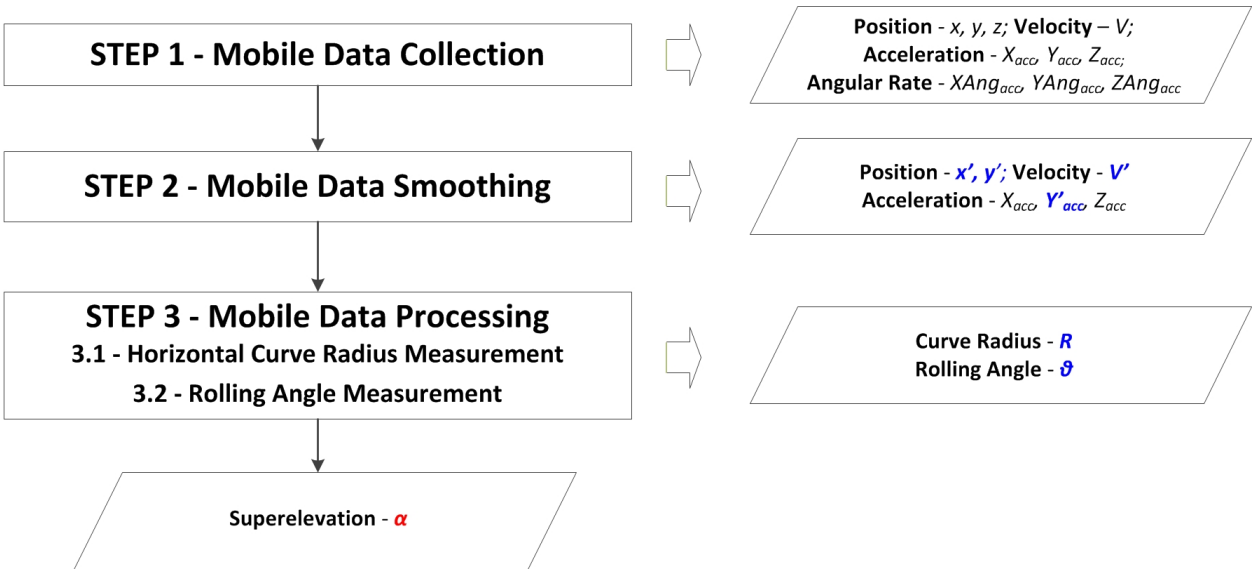

FIGURE 2 : Flowchart of the proposed method

$$\alpha(t) = \arccos\left(\frac{Y_{acc}(t)}{\sqrt{\left(\frac{V(t)^2}{R(t)}\right)^2 + g^2}}\right) - \arccos\left(\frac{\frac{V(t)^2}{R(t)}}{\sqrt{\left(\frac{V(t)^2}{R(t)}\right)^2 + g^2}}\right) + \theta(t) \tag{2}$$

Overview of the Proposed Method

The proposed method consists of four steps for deriving the necessary parameters from the computed superelevation, including the vehicle speed (V), the curve radius (R), the lateral acceleration (Y_{acc}) and the rolling angle (θ). Figure 2 shows the flowchart of the proposed method. The raw data is first collected using a low-cost mobile device that is mounted in the data collection vehicle. Then, a Kalman Filter-based data smoothing scheme is conducted to compensate the errors introduced due to the low acquisition frequency and the sensor noise. Using the smoothed position data and acceleration data, a circular-regression-based method and a complimentary filter-based method are introduced to compute horizontal curve radius and rolling angle. Finally, the superelevation measurement is conducted by inputting the four parameters into Equation 2.

STEP 1 - Mobile Data Collection

The objective of mobile data collection is to acquire the signals that describe a vehicle's instantaneous position and motion, including position, velocity, acceleration, and rotation. A typical low-cost mobile device (e.g., a smartphone or a tablet) usually integrates three sets of location-aware sensors, including GPS, an accelerometer, and a gyroscope. The GPS sensor can acquire the position information by recording the vehicle's coordinates and velocity. The accelerometer sensor can acquire the linear motion information by recording the vehicle's three-directional acceleration. The gyroscope sensor can acquire the vehicle's rotational motion information by recording the vehicle's angular velocity. Figure 3 shows an example of the acquired signals along a sharp horizontal curve, where the red curves indicate the signals that correspond to the curve. It can be

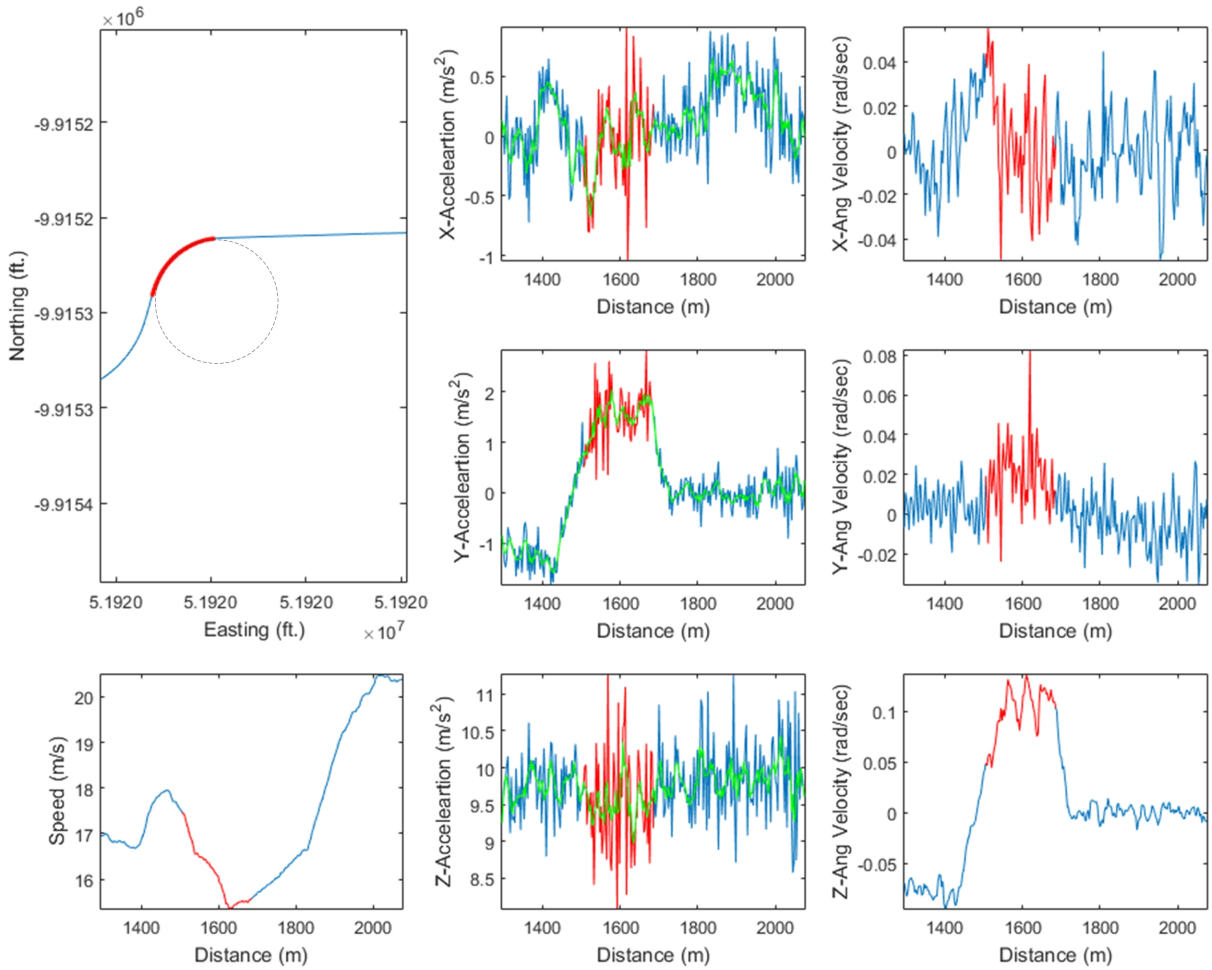

FIGURE 3 : Sample signals when a vehicle enters a super-elevated horizontal curve

observed that the signals reflect the general trend of the vehicle's behavior with reduced speed and cornering on the banked roadway. However, the extensive noise was also observed.

STEP 2 - Mobile Data Smoothing

The objective of mobile data correction is to obtain reliable vehicle position, velocity, and acceleration values by compensating for the errors introduced due to low acquisition frequency and sensor noise. In previous studies, several signal processing methods have been developed for smoothing vehicle navigation data, such as the least-square spline approximation (19), kernel-based smoothing (20), Discrete Kalman Filter (21), etc. It was identified by Jun, Guensler and Ogle 2006 that the Discrete Kalman Filter could provide the best performance in terms of estimation accuracy and noise reduction capability. Kalman Filter assumes that the state of the target is predictable based on the past state only when the target makes a gradual transition. In the context of horizontal curve navigation, it is reasonable to assume that the vehicle is traveling through the horizontal curve without any sudden maneuvering or disruptive actions. Therefore, the Discrete Kalman Filter is selected in this step to smooth the raw vehicle position, velocity, and acceleration data acquired by the mobile device. One of the critical inputs using Kalman Filter is to determine the correct values

of the measurement noise and process noise, e.g. errors for GPS position, velocity computation, and acceleration measurement. In this study, the square of the mean error values from the manufacturer's technical specifications for the mobile device are used (a Broadcom BCM4751 GPS receiver and an Invensense MPU-6050 gyro and accelerometer are used in this study). The parameters obtained from the technical specification provide a conservative baseline for implementing the proposed method. However, for practical implementation, different transportation agencies need to revise these values according to the specific devices deployed in their projects. If further improvement of the performance is desired, a more detailed calibration process for different parameters is recommended (22). After this step, the smoothed position (x', y', z'), velocity (V'), and acceleration (X'_{acc}, Y'_{acc}, Z_{acc}) can be derived. The green curve in Figure 3 shows an example of the difference between the raw acceleration signals and the smoothed results.

STEP 3 - Mobile Data Processing

Among the four necessary parameters for computing superelevation, curve radius (R) and rolling angle (θ) are not immediately available from the raw data acquired by the mobile device. Therefore, the purpose of this step is to process the mobile data and derive these remaining two parameters.

Horizontal Curve Radius Computation

In previous studies, the GPS points are sequentially processed using a three-point quadratic regression (17) or a fixed number of points for circular regression (23, 24, 25). However, the results of such a regression method are sensitive to the positional accuracy of any of the selected points, and the results usually split a curve into different sections due to the varying regression results in adjacent sections. In this paper, an iterative circular fitting algorithm proposed by Ai and Tsai 2015 is introduced to automatically identify the curved segment and compute the corresponding radius. Instead of selecting a fixed number of neighboring points for fitting, an incremental number of adjacent points are attempted until arriving at the least fitting error. Once the number of adjacent points is selected for the current group of GPS points, the next circular fitting will be started by skipping the current group of points. Hence, optimized numbers of GPS points are selected for each group of GPS points through iterations. Figure 4 shows an example of the results using the proposed method (red curve), the three-point quadratic regression method (blue curve), and the ground truth digitized from satellite images (green curve). It can be observed that using the three-point quadratic regression, the performance is significantly distorted by the random location noise from the GPS, while the proposed method remains robust by utilizing a larger population of locations.

Rolling Angle Measurement

Most of the commercial gyroscopes embedded in mobile devices report only the angular velocities of each rotational angle. Therefore, the rolling angle serves as an integral of the rolling angular velocity over time. Although a gyroscope obtains accurate measurements for the angular velocities at each moment, the integration over a longer time will produce accumulated errors (i.e., drift). On the contrary, although an accelerometer obtains an accurate overall trend the vehicle, the measurement at each moment may be distorted by noise (e.g., small disturbance of forces). To minimize drifting errors from the gyroscope and the disturbance of noise forces from the accelerometer, a complementary filter (26) is introduced by combining both angular velocity measurements from

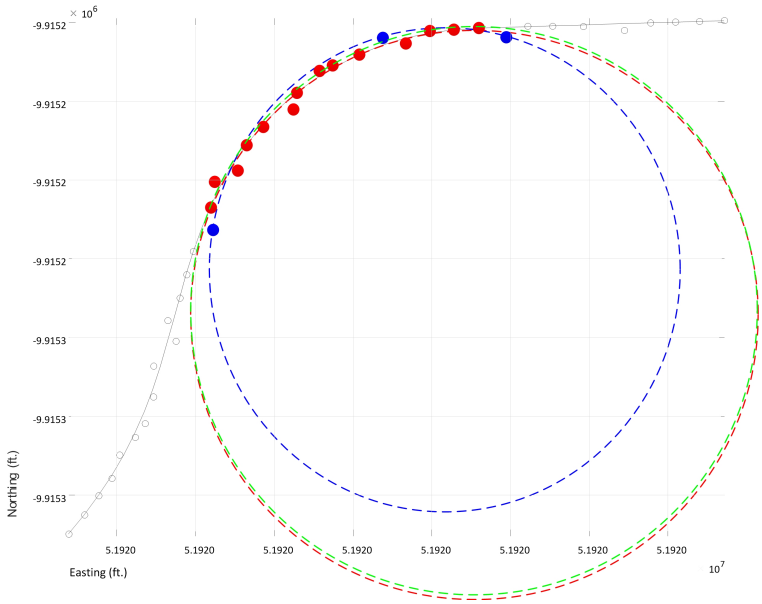

FIGURE 4 : An example of computed curve radius using the proposed method and the three-point regression method

the gyroscope and acceleration measurement from the accelerometer. A general formulation of the complementary filter is as shown in Equation 3.

$$\theta(t+\Delta t) = \lambda \cdot (\theta(t) + XAng_{acc} \cdot \Delta t) + (1-\lambda) \cdot \arctan\left(\frac{Y_{acc}}{Z_{acc}}\right) \cdot \frac{180}{\pi} \tag{3}$$

Where Δt is the data acquisition frequency of the gyroscope and the accelerometer in the mobile device, $XAng_{acc}$ is the rolling angular velocity, and λ is a normalization weight that reflects the confidence of the angle integration. Such a complementary filter is designed to take advantage of the momentary measurement from the gyroscope and the accumulative measurement from the accelerometer so that an accurate rolling angle could be derived. The weight of the λ was calibrated in a way that the gyroscope is heavily weighted for taking advantage of the accurate momentary measurement (i.e., $\lambda > 0.90$), while the accelerometer is lightly weighted (i.e., $1-\lambda < 0.10$) for taking advantage of the accumulative measurement without overwhelmingly distorted by the inaccurate momentary disturbance of forces. In this study, a trial-and-error calibration process was conducted to determine a desirable λ (i.e., $\lambda = 0.95$). Figure 5 shows an example that was collected on a tangent road section with minimal cross slope, where the results using the complementary filter (red curve) and the direct integral of rolling angular velocity (blue curve). It can be observed that the direct integral of the rolling angular velocity starts to drift significantly after approximately 800 seconds of data collection, while the rolling angle using the proposed complementary filter controls the drift well (i.e., bouncing around the anticipated zero rolling angle (green line)). If directly using the rolling angle computed from the direct integral, the computed superelevation may be significantly distorted by the drifting.

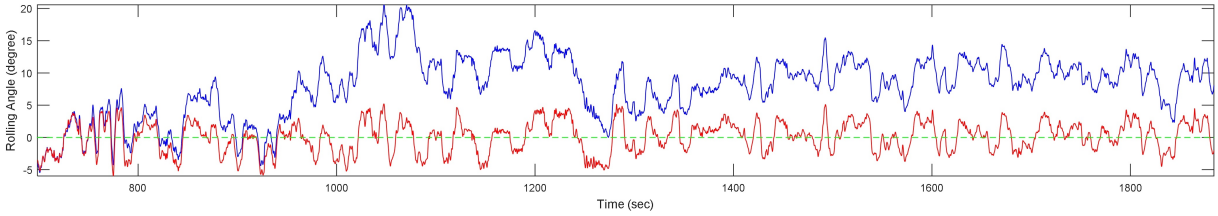

FIGURE 5 : An example of computed rolling angle from the proposed Complementary Filter and the direct integral

FIGURE 6 : Instrumentation of the experimental test using different devices

EXPERIMENTAL TEST

A 22-mile road section on State Route 2 in Rabun County, Georgia, was selected for conducting the experimental test, including a wide range of horizontal curve radius and different posted speeds. A commercial Android Tablet (i.e. a Google Nexus 7) was used for the data collection by setting up the acquisition frequency at 1Hz. Because of the long distance of the testing section, it was not feasible to establish the ground truth using a manual survey. Therefore, the ground truth was established based on the data collected using the Georgia Tech Sensing Vehicle (GTSV) (27, 28). The mobile LiDAR was processed using an existing algorithm to obtain the superelevation with a validated accuracy (3). To comprehensively evaluate the performance of the proposed method, the data collection vehicle was also equipped with a Rieker digital BBI so that the superelevation derived from the proposed method could also be compared with the ones from the method patented by Denigan et al. 2014. Figure 6 shows the instrumentation of the data collection vehicle. The tablet was placed in a customized bracket and attached vertically to the vehicle's radio panel, while the digital BBI was placed on the dashboard of the vehicle.

The derived superelevation results using the proposed method were compared with the ground truth and Denigan's method. Figure 7 on the left shows the overall superelevation results along the road section, which contains 11,774 superelevation measurements at an approximately 3m

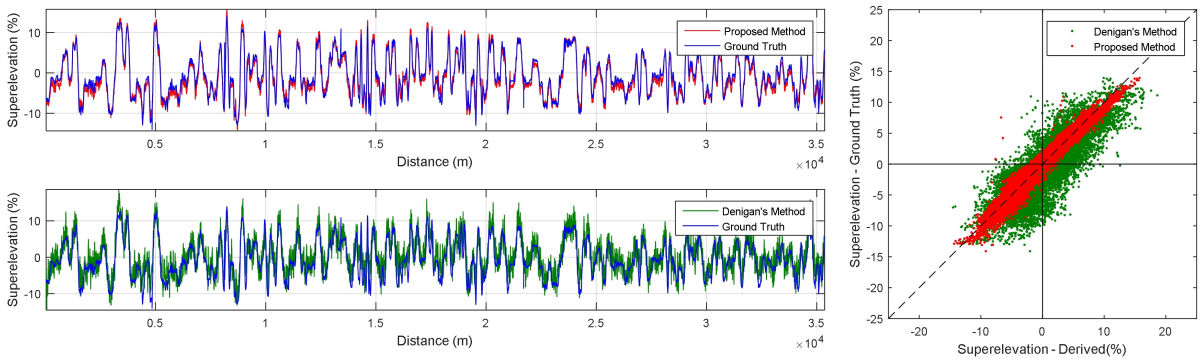

FIGURE 7 : Experimental test results for superelevation measurement
Left: Spatial distribution of the superelevation along State Route 2; Right: Correlation between the derived results and the ground truth

interval. Compared with the ground truth (blue line), it can be observed that the superelevation derived from the proposed method (red line) consistently traces the ground truth established by the mobile LiDAR. The results from Denigan's method (green line) were also compared with the ground truth. It can be observed that although Denigan's method also traced the ground truth well, it produced more noise in the superelevation measurement as a result of the presented drawbacks identified in the literature review. Figure 7 on the right shows the correlation between the derived superelevation and the ground truth. From the results of the proposed method, the R^2 of 0.95 and the error of variance of 1.30 strongly suggest very accurate measurement. In comparison, the same correlation was established between Denigan's method and the ground truth. However, the results derived using Denigan's method show that the R^2 of 0.66 and the error of variance of 8.71 that are indicative of the drawbacks identified in the literature review.

The experimental test has clearly demonstrated that the derived superelevation using a low-cost mobile device is accurate and reliable. The proposed method delivers results comparable to the mobile-LiDAR-based method but at a fraction of the cost. Compared with the results of Denigan's method, the proposed mobile data collection method, and data processing method is shown to be effective in being able to compensate for the potential errors introduced by the low data acquisition frequency and signal noise from the low-cost devices. The proposed method provides an efficient and effective method for transportation agencies to conduct superelevation inventory for their safety improvement programs.

CASE STUDY - HFST APPLICATION

To demonstrate the capacity of the proposed method, a case study on a 30-mile section of roadway with HFST application was conducted with GDOT. GDOT has recently started a statewide sharp-curve safety improvement program using HFST. Instead of relying on historical crash data to identify feasible horizontal curve candidates for HFST (29), GDOT conducts comprehensive BBI measures for each horizontal curve along a corridor. All the curves with a BBI value greater than 12° become feasible candidates for HFST. It is recognized that GDOT's HFST site selection criteria take a proactive approach by investigating the physical safety property of each curve. However, the BBI data collection is a time-consuming process due to the constant traveling speed at the posted speed limit (12).

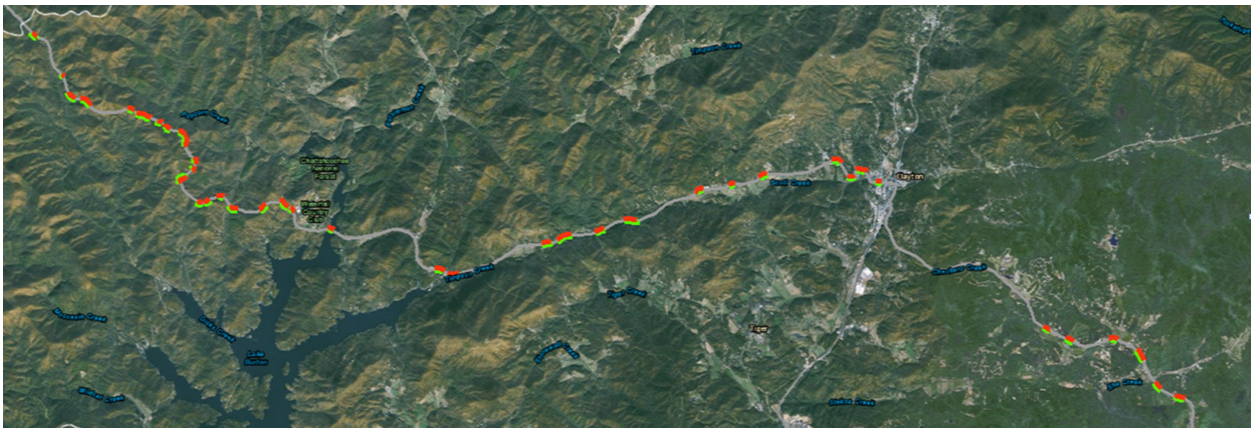

FIGURE 8 : Selected candidate curves for HFST in Rabun County, Georgia

Instead, by integrating the computed superelevation using the proposed method, the BBI values could be accurately computed and then subsequently applied to determine an HFST site. By certain manipulation of Equation 2 (30), the BBI value can be represented by Equation 4.

$$BBI = \arctan\left(\frac{Y_{acc} \cdot \cos(\alpha - \theta)}{Y_{acc} \cdot \sin(\alpha - \theta) + 1}\right) \tag{4}$$

In Figure 8, the green highlighted lines show a map of curves selected for HFST application based on the BBI measurement conducted by GDOT field engineers. It can be observed that the same curves are selected using the proposed method, highlighted in red lines in Figure 8. In this case study (containing 91 curves in 30 miles), it took two field engineers approximately 25-35 minutes to complete each horizontal curve based on the manual BBI data collection (a total of 42 hours). In comparison, it only took less than one hour to complete the entire road section using the proposed method (including approximately 45 minutes to collect the mobile data and less than 10 minutes to compute the continuous superelevation and BBI values). The significant productivity improvement is attributed to two factors: 1) no constant speed is required by the proposed method; 2) the collected mobile data can be processed automatically immediately after the data collection without the need for heavy computation.

CONCLUSIONS AND RECOMMENDATIONS

Horizontal curves pose one of the most pressing safety concerns for transportation agencies. As one of the indispensable safety properties at a horizontal curve, superelevation is carefully designed with curve radius, surface friction, and posted speeds to ensure vehicles safely traverse through the horizontal curve. However, many factors (such as sub-standard construction, aging road surfaces, and deteriorated structures) may separate the actual superelevation from its original design, which could lead to serious roadway departure crashes. Transportation agencies are actively searching for reliable and cost-effective methods to evaluate the safety properties of horizontal curves (including superelevation) to take the place of their existing manual practice. By taking advantage of the significant development of mobile computing platforms, this paper proposes an automated superelevation measurement method using a low-cost mobile device.

By employing the fundamental vehicle kinetics at horizontal curves, superelevation is presented as a function of the four essential parameters collected/derived from a mobile device, in-

cluding the vehicle speed, the curve radius, the lateral acceleration, and the rolling angle. This study used a series of smoothing methods (including the Kalman Filtering Method) and signal processing methods (including the iterative circular regression method and the complementary filtering method) to correct and to derive the four parameters from the integrated sensors equipped with a mobile device. The results from the experimental test conducted on State Route 2 in Georgia demonstrate that the proposed method, despite using a low-cost mobile device, has measurements comparable to the ones using expensive mobile LiDAR systems. The correlation between the proposed method and the LiDAR-based method shows an R^2 of 0.95 and an error of variance of 1.30, which strongly suggests that the proposed method can make accurate measurements. The proposed method, also, outperforms another comparable method developed by Denigan et al. (17), suggesting the effectiveness of the proposed signal smoothing and processing methods proposed in this study. A case study for HFST site selection was conducted to demonstrate the capacity of the proposed method, and the results from the selected sites using the proposed method are consistent with the mechanical BBI measurements GDOT made. More importantly, the proposed method significantly reduces the time and effort to acquire the BBI values.

Recommendations for future studies include the following: 1) a large-scale roadway network is recommended to validate the proposed method; 2) new mobile data- smoothing methods should be studied to improve the accuracy of the proposed method; 3) the sensitivity of the specification and the installation of the mobile sensor should be studied to suggest the optimal configuration for transportation agencies; 4) using automated methods for studying other safety properties at horizontal curves are recommended so that a comprehensive horizontal curve safety inventory can be established to support more effective and productive safety improvement programs; 5) integration of the proposed method with the existing connected vehicle sensors and data is recommended to support future connected vehicle applications, e.g., identification of roadway geometry condition changes for the advanced warning system.

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