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NCHRP IDEA Program

An Enhanced Network-Level Curve Safety Assessment and Monitoring Using Mobile Devices

Final Report for
NCHRP IDEA Project 214

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AN ENHANCED NETWORK-LEVEL CURVE SAFETY ASSESSMENT AND MONITORING USING MOBILE DEVICES

IDEA Program Final Report

NCHRP-IDEA 214

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Transportation Research Board
The National Academies

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LIST OF ABBREVIATIONS

AASHTO	American Association of State Highway and Transportation Officials
BBI	Ball Back Indicator
CARS	Curve Advisory Reporting System
CSAM	Curve Safety Assessment and Monitoring
CMF	Crash Modification Factors
DOT	Department of Transportation
DEG	Degree
FHWA	Federal Highway Administration
GPS	Global Positioning System
GTSV	Georgia Tech Sensing Vehicle
IMU	Inertial Measurement Unit
MUTCD	Manual on Uniform Traffic Control Devices
NCAT	National Center for Asphalt Technology
NCHRP	National Cooperative Highway Research Program
PC	Point of Curve
PT	Point of Tangent
RMSE	Root Mean Squared Error
SR	State Route
TRAMS	Texas Roadway Analysis and Measurement Software
TTI	Texas A&M Transportation Institute

EXECUTIVE SUMMARY

A disproportionally high number of serious vehicle crashes (25% of fatal crashes) occur on horizontal curves, even though curves represent only a fraction of the roadway network (5% of highway miles) (*1*). This is a high-priority problem that has great interest among transportation agencies throughout the nation because their ultimate goal is to reduce serious vehicle crashes on curves. The in-service curve characteristics, including the curve geometry information (curve radius, point of curve, point of tangent, deviation angle, superelevation, and grade), along with traffic speed, vehicle trajectory, and Ball Bank Indicator (BBI) measurements are vitally important for performing curve safety assessment and analysis, for setting up adequate curve advisory speeds, and for studying driving behavior along a curve. The BBI value shows the combined effect of superelevation, driving speed, and the curvature of the driving trajectory. Based on our communication with state DOT engineers, certain geometric properties of the curve, such as superelevation, may change over time because of new pavement resurfacings. Therefore, understanding in-service curve characteristics is vital to assessing and improving curve safety. Transportation agencies, like the Georgia Department of Transportation (GDOT), use the BBI value as a risk factor to proactively identify the curve sites in need of high friction surface treatment (HFST). However, current transportation agencies' practices use dedicated devices operated by designated engineers to collect and extract the detailed level curve characteristics information for assessing curve safety conditions at the network level. This includes collecting and extracting in-service curve characteristics, acquiring their BBI values, and computing the required advisory speed. The main challenge of current practices is that they are time-consuming, labor-intensive, and costly.

With the advancement of modern sensor technologies, low-cost mobile devices (such as smartphones, tablet PCs, action cameras, etc.) are capable of collecting GPS data, IMU data (accelerometer, magnetometer, and gyroscope data). The sensor data collected by such devices can be used to compute and analyze curve characteristics information and driver behaviors at the network level to identify curves with inadequate advisory speed. Therefore, there is an urgent need to develop an enhanced method to collect and extract in-service curve characteristics, acquire BBI values using smartphones, and compute adequate advisory speeds based on in-service curve characteristics. The development of such an enhanced cost-effective method will support network-level curve safety assessment, analysis, and improvement. The objectives of this research project are 1) to develop an enhanced curve safety assessment method that uses low-cost mobile devices and new data collection and computation methods and 2) to critically assess the feasibility of the proposed method for network-level curve safety condition assessment. The proposed method, using a new intra-agency, crowdsourced data collection and computational framework, leverages a) low-cost mobile devices, (e.g., smartphones, tablet PCs, action cameras, etc.) to collect sensor data, including GPS data and IMU data, and b) transportation agencies' existing vehicles and transportation engineers (who can collect data while simultaneously performing other tasks). The proposed method uses a cost-effective means for transportation agencies to perform a preliminary network-level curve safety screening on a daily or weekly schedule. Once roadway sections in need of curve safety improvement are identified, a detailed curve safety assessment can be conducted to identify and target curve sections for in-depth investigation. This enables transportation agencies to focus their time and attention on targeted roadway curve sections that need improvement, which will save significant time and cost.

The following highlights the findings and results of this research project:

1) A cost-effective method using low-cost mobile devices and an enhanced intra-agency, crowdsourced data collection, and computational framework has been developed to assist network-level curve safety condition assessment. The proposed data collection and computational framework consist of six modules: 1) mobile data collection, 2) mobile data registration and processing, 3) driving kinematics calculation, 4) curve geometry calculation, 5) advisory speed calculation, and 6) curve warning sign design. Key data items computed and acquired using the

proposed method in this research project include BBI angles, curve radius, superelevation, and advisory speed. It can be extended to extract other data items in the future with this framework.

2) The proposed method achieves more accurate superelevation estimation by incorporating the vehicle's body roll angle, which is estimated from vehicle's roll rate, in the calculation of superelevation. In addition, two calibration procedures are proposed to estimate the vehicle's roll rate and enhance superelevation computation accuracy.

3) A data collection application, "AllGather," was built for Android smartphones. "AllGather" is an advanced dashcam-like application that collects a driving video log, GPS data, IMU data, and driving speed.

4) The proposed method has been validated using the data collected on 1.7 miles of roadway at the NCAT test track. Using the data collected by mobile devices, this validation evaluated the feasibility of using the proposed method to compute curve safety assessment-related data items. Results show that the proposed method can achieve accurate results for computing superelevation, curve radius, BBI angle, and curve advisory speed.

    a) With the application of the proposed, enhanced superelevation computation method, the superelevation results from smartphones can consistently achieve an RMSE of 1.4 – 1.5 % slope at different data collection speeds. Without applying the enhanced super-elevation computation method, the RMSE value is 3.2 % slope at high speed. The advisory speed result is about 1 MPH off from the advisory determined from the manually measured superelevation (our ground reference). Thus, the outcome is very promising.

    b) The validation of our advisory speed computation method shows that there is less than 5-MPH difference between our proposed method and current methods that commonly use REIKER devices. With the advisory speed typically rounded down to the nearest 5 MPH, the proposed method is acceptable and is very promising because it uses low-cost smartphones; it will be much more scalable and impactful in future implementation.

5) A preliminary case study was conducted using the proposed method; smartphone data was collected on 5 curves with 5 runs of data collection on Georgia State Route 17. Results demonstrate that implementation of the proposed method is feasible, and it is promising for collecting and extracting detailed in-service curve characteristics, acquiring BBI values, and computing advisory speeds. The computed advisory speed can be used to identify inadequate advisory speed by comparing it with an existing advisory speed. An inadequate advisory speed could potentially be caused by the sub-standard pavement conditions or by the change of curve characteristics due to new pavement resurfacings. It is, therefore, very efficient to compute curve characteristics information using typical smartphones. Using 5 runs of data collected in each driving direction, the results demonstrate the proposed method shows very little variability; in most cases, the 5 data collection runs resulted in the same advisory speed (after rounding down to the nearest 5 MPH); in a few cases, 4 out of 5 data runs had the same advisory speed. This suggests the advisory speed obtained from the proposed method is highly repeatable. If using the variability between multiple runs of data collection as an indication of the confidence level of the data, this would suggest the results computed from the proposed method have a high confidence level.

IDEA PRODUCT

A disproportionally high number of serious vehicle crashes (25% of fatal crashes) occur on horizontal curves, even though curves represent only a fraction of the roadway network (5% of highway miles) (*1*). When the friction is insufficient to compensate for the lateral force experienced by a vehicle being driven on a curve, the vehicle will slide and run off the road (ROR). This is a high priority problem that has the great interest among transportation agencies throughout the nation because the ultimate goal is to reduce serious vehicle crashes on curves. The problem is complicated because, based on our communication with state DOTs' engineers, the in-service curve characteristics, including superelevation, may change over time because of new pavement resurfacings. Therefore, understanding in-service curve characteristics is vital to improving the safety of curves. The in-service curve characteristics, including curve radius, superelevation, and BBI angles, are vitally important for setting up adequate curve advisory speeds and for performing curve safety assessment and analysis. A BBI measurement is one of the important curve safety indicators specified by the MUTCD (2009); it is a combined indicator that includes curvature, superelevation, side friction condition, and driving speed.

However, acquiring this detailed level roadway characteristics information on in-service curves at the network level is very difficult for transportation agencies. For example, state DOTs, like the Georgia Department of Transportation (GDOT) use an electronic device (manufactured by Rieker Inc.) to collect BBI measurements in the field. For the curves to be assessed, GDOT engineers make more than two runs on each curve at incremental speeds and measure the BBI in each run to determine a curve's adequate advisory speed. This operation typically requires two workers (one drives a vehicle while another records BBI) and is labor-intensive, time-consuming, and costly. Once a representative BBI value, along with an adequate advisory speed for each curve, has been determined, countermeasures (such as setting up an advisory speed at the beginning of the curve or applying a High Friction Surface Treatment (HFST) or some other treatment) can be applied based on an analysis of the potential safety improvement, completion of benefit-cost ratio analysis, and determination of funding availability. In summary, current transportation agencies' practices use dedicated devices operated by designated engineers to collect curve characteristics information at the network-level for curve safety condition assessment. The practices are typically labor-intensive, time-consuming, and costly.

Because the current practices and methods are time-consuming, labor-intensive, and costly, it typically takes one to two years to complete the curve safety assessment of 100% of their state-maintained roadways. For local transportation agencies (counties and cities) that have limited resources, the process of completing a network curve safety assessment can take longer. Thus, roadway curve sections that need safety improvement(s) are often not identified until accidents occur. Because of long intervals between curve safety assessments, it is difficult for DOTs to take proactive actions in terms of identifying problems or making timely curve safety improvements. The constraints of current practices and methods significantly hinder transportation agencies' capabilities to reduce the disproportionally high number of fatalities on curves. The problem of current practices significantly hinders transportation agencies' abilities to proactively apply safety improvements and reduce the number of crashes on roadway curves. Thus, there is an urgent need to develop enhanced methods that enable transportation agencies to perform network-level curve safety assessments in a timely, cost-effective, and safe manner. Because transportation agencies' funds/budgets are often limited and must be used wisely, an innovative and cost-effective method that enables transportation agencies to do more with less is required.

With the advancement of sensor technologies, low-cost mobile devices (such as smartphones, tablet PCs, GoPro cameras, etc.) that usually integrate various sensors (such as GPS sensors, accelerometers, magnetometer, and gyroscopes) are available to collect sensor data and vehicle's kinematic parameters, such as vehicle speed, lateral acceleration, rolling angle, etc. These sensor data and vehicle's kinematic parameters can be used to compute curve characteristics information, including radius, superelevation, and

BBI values for network-level curve safety assessment.

The objectives of this research project are 1) to develop an enhanced curve safety assessment method that uses low-cost mobile devices and proposed computation methods and 2) to critically assess the feasibility of the proposed method for network-level curve safety condition assessment. The project will use intra-agency, crowdsourced, low-cost mobile devices and multi-run data analysis to identify, in a timely manner, problematic roadway curves that need safety improvement. The research project's overall objective is to reduce the current disproportionally high number of fatalities on roadway curves. The use of intra-agency, crowdsourced, low-cost mobile devices to collect sensor data on the roadway while engineers are performing other tasks can reduce engineers' time on the road and minimize their exposure to hazardous curve sections.

Figure 1 illustrates the proposed methodology for timely curve safety assessment and improvement using low-cost mobile devices. As is currently done in Uber vehicles, low-cost devices, like smartphones, can be installed in state DOT vehicles. This method establishes a new intra-agency, crowdsourced data collection and computation framework by leveraging agencies' existing vehicles and transportation engineers. The framework uses low-cost mobile devices (e.g., smartphones and/or tablet PCs) for collecting data (including GPS data, accelerations, gyroscope data, and image data) from multiple runs; using the methodology, transportation engineers can collect data while performing other tasks.

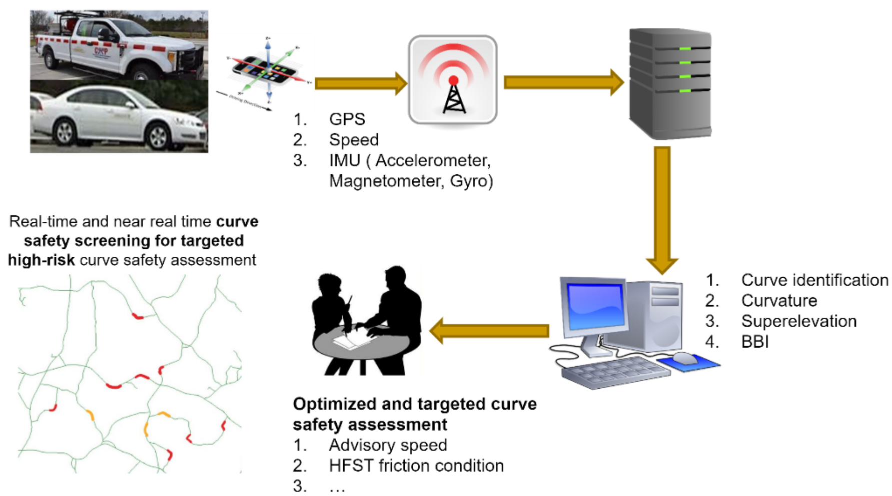

Figure 1. Diagram. The proposed low-cost smartphone-based methodology for an accelerated curve safety assessment and improvement.

CONCEPT AND INNOVATION

As indicated, it is difficult for transportation agencies to take proactive action to make curve safety improvements in a timely manner because of the long interval between curve safety inspections (they are usually accomplished annually or bi-annually). The proposed methodology provides a low-cost means for transportation agencies to perform a preliminary network-level curve safety screening on a daily or weekly schedule. Once roadway sections in need of curve safety improvement are identified, a detailed curve safety assessment can be conducted on the identified targeted sections. This enables transportation agencies to focus their time and attention on targeted roadway curve sections that need improvement, not those that do not need improvement. This will save significant time and cost for transportation agencies. This proactive and targeted attention, done on a daily, weekly, or monthly basis rather than an annual or biannual basis, will vastly improve the quality and timeliness of curve safety inspection and proactive improvements. The proposed methodology is aimed at enhancing the current network-level curve safety assessment method, which is costly, labor-intensive, time-consuming, and often dangerous. The proposed methodology provides a means for transportation agencies to proactively reduce fatalities in the most cost-effective and timeliest manner.

To optimize the data collection effort, the innovation of the proposed methodology is that it creatively utilizes intra-agency, crowdsourced, low-cost mobile devices. With the proposed method, roadway data can be collected using an agency's vehicles while its personnel are conducting other day-to-day operations. In this way, it is expected that the survey frequency can be increased from annually to, at least, weekly. Because an agency's vehicles traverse the same roads many times, multiple runs of data can be collected from different drivers at different times for a single curve section; the data can then be analyzed to eliminate biases that occur when data is collected only on a single run. Crowdsourcing data collected from the fleet and employees in a single transportation agency, i.e., intra-agency, can ensure data quality.

To the best of our knowledge, there are, currently, no crowdsourced, low-cost mobile applications that can productively and cost-effectively collect and analyze data (gathered from multiple runs by different drivers) for assessing roadway curve safety at the network level or that can perform BBI computation, super-elevation computation, and advisory speed determination**.** The proposed method, using a new intra-agency, crowdsourced data collection and computational framework, leverages a) existing, low-cost mobile devices, (e.g., smartphones, tablet PCs, GoPro cameras, etc.) to collect multiple runs of sensor data, including GPS data and IMU data, and b) agencies' existing vehicles and transportation engineers (who can collect data while simultaneously performing other tasks). The data collection and computation framework of the proposed method consists of six modules: 1) mobile data collection, 2) mobile data registration and processing, 3) driving kinematics calculation, 4) curve geometry calculation, 5) advisory speed calculation, and 6) curve warning sign design. The detailed data collection and computation framework is presented in the next section.

INVESTIGATION

Research Objectives and Scope

The objectives of this research project are 1) to develop an enhanced curve safety assessment method that uses low-cost mobile devices and new proposed computation methods and 2) to critically assess the feasibility of the proposed method for network-level curve safety condition assessment. This research critically assesses the feasibility of using low-cost mobile devices to compute BBI, computing super-elevation, and determining accurately and reliably the adequate advisory speed. In addition, the refined superelevation computation algorithms using smart phone data, with a new calibration procedure, taking into account vehicle body roll, must be developed and validated so they can be used with confidence on different vehicles and under more general field conditions. The following are the major tasks:

1) Review existing regulations and current practices on network-level curve safety assessment, analysis, and management.
2) Develop an enhanced method using low-cost mobile devices with a proposed data collection and computation framework.
3) Propose the network-level smartphone-based ball-bank indicator (BBI) and curve superelevation computation method with a new calibration procedure, taking into account body roll to improve the accuracy of superelevation computation.
4) Develop temporal and spatial inter-device data referencing and registration methods.
5) Validate the proposed method, using the data collected on 1.7 miles of the Nation Center Asphalt Technology (NCAT) test track.
6) Perform a field case study on Georgia State Route 11 and 17 to evaluate the proposed method.

Literature Review

The following sections present the review of the current practices for horizontal curve safety assessment and summarize the technical challenges of reducing the cost for supporting network-level safety assessment.

Required Specification for Curve Safety Management

This section presents the required specifications for curve and curve sign designs; it also presents the practices and methods used for a network-level curve safety assessment with a special focus on superelevation computation. In our study, we have focused on discussing regulations for curve and curve sign designs, curve sign condition assessment, and network-level curve safety assessment of in-service curves. There are still other curve safety-related roadway elements, including sight distance, guardrail, etc., that are not included in our literature review. In this section, we present the required curve geometry, including superelevation, curve radius and side friction for meeting the expected advisory speed, the required curve roadway characteristics for curve sign installation, and the requirements for sign condition assessment. Based on curve and curve sign design regulations, curve roadway characteristics (CRC) to be evaluated at the network level to ensure roadway safety can then be identified. As this CRC information is related to roadway safety, which is very important for transportation agencies to properly manage their roadways; it is essential to identify any deficiencies in a timely manner. In each subsection, the current methods to collect data and to perform design and assessment are also discussed. Finally, the challenges and needs for improvement are summarized.

Geometric Design of Horizontal Curves

Curve geometry design requirements can be found in the AASHTO Green Book (*2*). The main concept is to design the roadway geometry (e.g., superelevation, curve radius, and side friction) to meet the demand of the expected driving speed on a curve. The curve radius, superelevation, and friction are designed based on the design curve driving speed in the curve design stage. In our project, we assume we know curve radius, superelevation, and roadway side friction. Equation (1) illustrates the relationship between the expected driving speed on a curve, superelevation, curve radius, and side friction.

$$V^2 = 15(0.01e + f) * R \tag{1}$$

where R is the radius (ft), V is the vehicle speed (MPH), e is the average super-elevation, and f is the side friction factor.

Once the curves have been built and are in service, the actual CRC information, including superelevation, curve radius, and BBI, is often not available. This is because the as-built roadway characteristics information is typically different from the designed CRC information. In addition, the CRC information, like superelevation, changes with new pavement resurfacing. Based on our discussion with GDOT District engineers, the superelevation often changes with new pavement resurfacing, and sometimes, insufficient superelevation sections have caused accidents. In addition, due to the changes of curve design standards over time, substandard curves will need to be identified and corrected to ensure the safety of curves. Therefore, network-level curve safety assessment on in-service curves is very critical. However, current network-level curve safety assessment methods used on in-service curves are time-consuming, labor-intensive, and costly. Our research focuses on enhancing the current network-level curve safety assessment on in-service curves.

Curve Advisory Speed Determination

The curve advisory speed is unarguably the most important factor in terms of horizontal curve safety because the driving speed is the only thing that a driver can control when navigating a vehicle along a curve. It is emphasized that the curve advisory speed is not the safe speed for every type of vehicle under every condition; it is a speed obtained by a defined testing procedure that provides comfort and safety for most driving conditions. In other words, under extreme conditions, such as icy pavements, a driver should evaluate the situation and drive even at a lower speed to avoid danger, e.g., skidding.

It is critical to follow a consistent standard to calculate, design, and set the advisory speed, and through investigation, it is found that the "Ball Bank Indicator" (BBI) is the most important factor in establishing the appropriate curve advisory speed. According to the "FHWA method for establishing advisory speed," the "master" equation that computes the safe vehicle speed when negotiating a banked horizontal curve is defined in Equation (1).

This equation can be derived from the law of mechanics and is the foundation of how horizontal curve advisory speeds are set. Equation (1) requires that side friction be a known factor. In practice, the side friction is chosen among three empirical values (0.21, 0.18, 0.15) depending on the driving speed, pavement surface condition, and vehicle type, so the key variables that need to be assessed are the superelevation and the radius. In the following sections of the FHWA publication, six methods to establish the advisory speed are discussed. These methods are as follows:

- Direct Method
- Texas A&M Transportation Institute (TTI) Curve Speed Model – Compass Method
- TTI Curve Speed Model – GPS Method
- TTI Curve Speed Model – Design Method
- Ball-Bank Indicator Method
- Accelerometer Method

The direct method asks a tester to drive over a curve at various speeds and determine the appropriate curve advisory speed subjectively. Historically, the 85^{th}-percentile speed of free-flowing traffic is used as the advisory speed, which is no longer explicitly supported by the MUTCD 2009 guidelines. The compass method is used in combination with other methods (e.g., BBI) to determine the curve advisory speed. The purpose of the compass is to obtain the curve radius; therefore, we do not consider it as an individual method to obtain the curve advisory speed. Similarly, the GPS method is used merely to obtain the curve radius and should not be listed individually. The ball-bank indicator method and the accelerometer method are the two methods that are widely adopted and commercialized. They both utilize digital sensors mounted on a vehicle to indirectly calculate the curve safety-related characteristics. In addition to the six methods listed above, there is also a less commonly used Driver Comfort Speed Method, which is the oldest empirical method used to determine a curve advisory subjectively (not considered in this report).

Due to the inefficient and impractical nature of the 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 combined effects from super-elevation, unbalanced lateral acceleration (i.e., side friction), and vehicle body roll. For example, a vehicle equipped with an IMU is driven along a curve at a known speed; then, the curve radius can be indirectly calculated using vehicle kinematic equations.

A network-level BBI measurement is also relatively easier to accomplish than the other methods presented above. More recently, several studies have tried to estimate BBI using kinematic data acquired from vehicle-mounted cell phones. Notably, a mobile application, “CurveWare,” is available on both Android Play and at the Apple Store as of December 2019; the application seems to be only partially functioning, since the log feature is not working as expected. Also, there is no information on whether the BBI results of this app are validated. We provide the details on estimating the curve radius in the following subsection.

Curve Radius Estimation

A survey conducted by Carlson, et. al. (2005) summarized ten common methods to measure curve radius . They can be further classified into four categories: database lookup; field survey; indirect methods; and aerial photographic.

Database lookup: Curve radius is the fundamental characteristic associated with horizontal curves. Since the curve radius remains constant over its lifetime, the most efficient way to acquire curve radius data is to look it up in an agency’s database. Unfortunately, few DOT agencies have created consolidated databases for horizontal curves. Such information is especially scarce for the county-level highway and roads.

Field survey: To measure the curve radius in the field, the starting point (PC) and the ending point (PT) of the curve must be determined first. Next, field operators place a survey rod at safe test points along the inner and outer edges of the curve. At least three test points should be chosen for reliable results. The average of the inner and outer radii will be used as the curve radius. The radius calculated using this method is considered as the ground truth radius and is used to validate other methods.

Measurement of the curve radius in the field can be time-consuming and puts investigators in a dangerous roadway scenario; therefore, there is an urgent need to establish an alternative method to systematically extract curve geometry information to reduce the number of field survey operations required for safety assessment.

Current Curve Safety Assessment Practices and Challenges

The following summarizes the discussion with GDOT engineers on the field assessment of curve safety conditions. District maintenance crews routinely drive over the roadways and make engineering judgments based on their knowledge of roadway guidelines (AASHTO, MUTCD, GDOT Signing, and Marking Guide, etc.) to proactively assess safety concerns on curves (such as insufficient sight distance, lack of signs, poor pavement condition, missing striping, insufficient super elevation, etc.). GDOT also responds to citizen concerns (for example, people report frequent crashes on specific curves), investigates the locations, and identifies unsafe curves. After the maintenance crews identify the safety concerns on the curves, they notify the GDOT Office of Traffic Operation. The Office of Traffic Operations investigates the reason/issue, evaluates the situation, and determines the suitability of signage to resolve the safety concerns. If new signs are required, the Office of Traffic Operations then approves new signage and the new signs are installed by the maintenance crews.

District maintenance crews routinely drive over the roadways and assess the existing signs. Because they are familiar with the roadways and their requirements for good, safe signage, most of the time, GDOT personnel recognize missing signs. They also assess the existing signs for damage and fading. In addition to physical sign conditions, they assess the retro-reflectivity condition of the signs by an annual nighttime visual inspection. Roadway maintenance crews are tasked with the upkeep of signage in their areas (including reflectivity); they are responsible for any signs that are damaged/removed. If a sign is knocked down/missing, damaged, or old/faded, the maintenance office will replace the sign.

The following current practices are challenges identified by GDOT engineers and Rieker representatives:

- The Curve Advisory Reporting System (CARS), a service provided by Rieker Inc., is commonly used by transportation agencies to determine advisory speeds.
    - However, the current practice of collecting data in the field for CARS requires dedicated Rieker devices operated by designated engineers. This field data collection practice is labor-intensive, time-consuming, and costly. In addition, different driver behaviors and driving speeds will negatively impact the accuracies of current super-elevation and advisory speed computation methods. Therefore, there is a need for an enhanced method that is robust against different driver behaviors and driving speeds.
    - The current data collection method requires a driver to drive very smoothly at a consistent speed (e.g., 40 MPH) because failing to do so may result in significant error in advisory speed determination.
    - To determine the appropriate curve advisory speed using CARS, detailed curve information, including radius, point of curve (PT), and point of Tangent (PT) have to be extracted manually one curve at a time. Because this method is a subjective, labor-intensive, and of a trial-and-error curve fitting nature, there is a need to develop an enhanced method that automatically extracts detailed curve information and determines appropriate curve advisory speeds.
- Other than using CARS, the current in-service curve safety assessment practices are, largely, manual operations based on visual inspection. However, the changes in roadway characteristics (like superelevation) caused by pavement resurfacings make visual assessments difficult. There is a need to have an automatic and cost-effective way to measure curve roadway characteristics (such as superelevation).
- Ball Bank Indicator (BBI) angles are important roadway safety indicators and are commonly used to assess curve safety conditions and to make recommendations for applying curve safety countermeasures such as the application of High Friction Surface Treatment (HFST). However, collecting BBI data requires dedicated vehicles and designated engineers. Consequently, there is a need to develop an enhanced and cost-effective method, such as one that uses smartphones, to collect BBI values.
- Currently, it is very time-consuming and difficult for field crews to thoroughly perform MUTCD compliance curve sign checking because crews must collect the required sign types, spacing, position for identifying missing signs, inadequate sign types, sign spacing, inadequate advisory speed limit, and inadequate super-elevation on each curve along a route.

In summary, the current practice of network-level curve safety assessment requires dedicated devices operated by designated engineers, which is costly, labor-intensive, and time-consuming (it may take years to complete a network-level curve safety assessment once). Therefore, there is a need to explore and develop a cost-effective method that uses low-cost mobile devices and leverage agency-owned vehicle fleets while engineers are undertaking their daily operations. This will require the proposed method to be robust and reliable, as different driving speeds and driving behaviors are expected when engineers collect data and simultaneously perform other daily tasks.

Enhanced Network Level Curve Safety Assessment Method Using Low-Cost Mobile Devices

A cost-effective method that uses low-cost mobile devices and leverages existing agency-owned vehicle fleets is proposed in this section. The method can accurately and robustly collect and compute in-service super-elevation, BBI values, and advisory speed limits. The proposed method needs to also resolve the current technical challenges in terms of different driving speeds and driving behaviours that are expected when engineers collect data and simultaneously perform other daily tasks. The proposed method is built upon a data collection and computation framework shown in Figure 2.

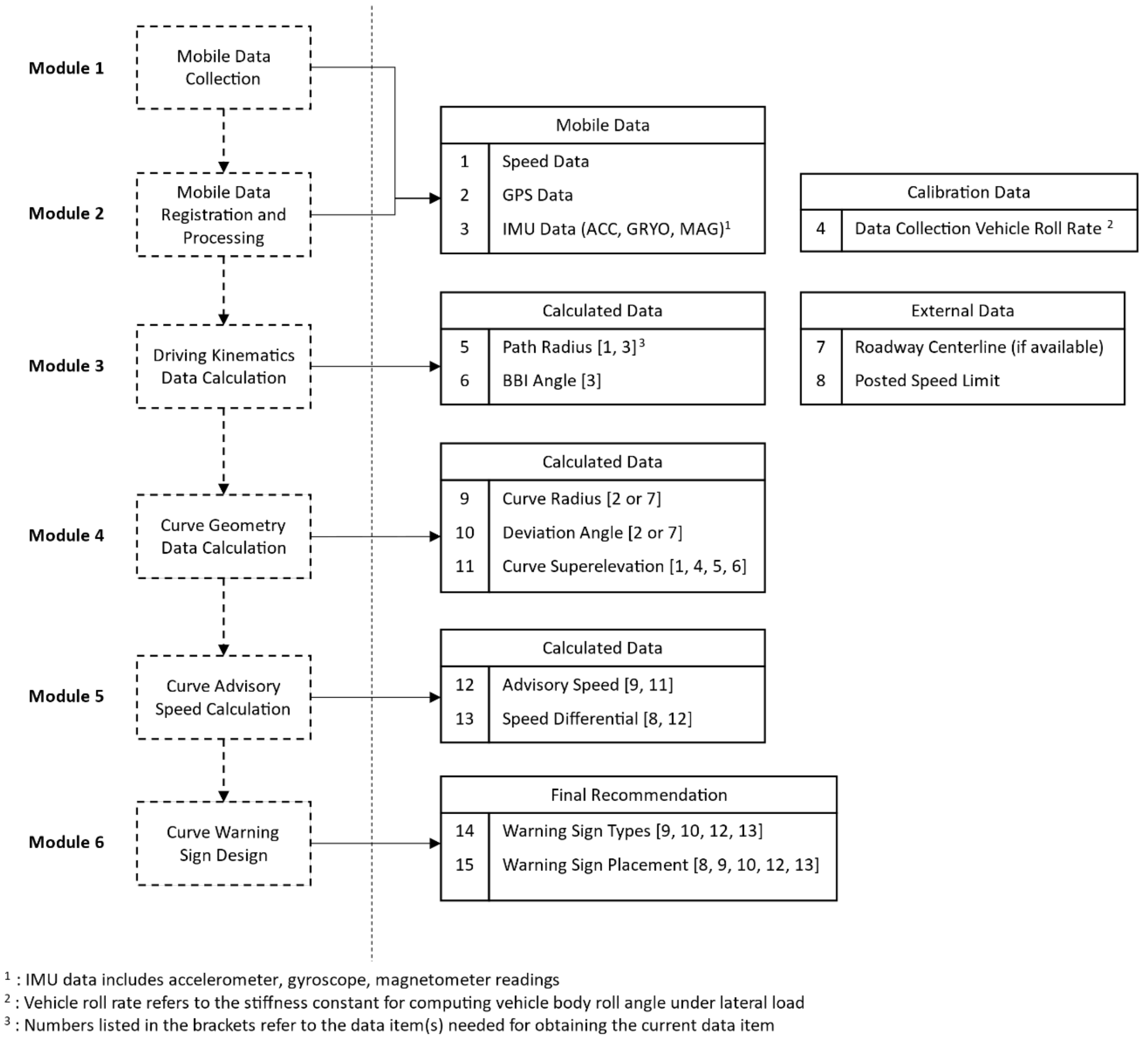

Figure 2. Flowchart. Data collection and computational framework and data items for network-level curve safety assessment using mobile devices.

There are six modules presented in this framework: mobile data collection, mobile data registration and processing, driving kinematics calculation, curve geometry calculation, advisory speed calculation, and curve warning sign design. In Module 1, mobile devices are used to collect vehicle speed, global positioning system (GPS), and inertial measurement unit (IMU) data. The collected data are registered and processed in Module 2. In Module 3, data items related to the driver inputs and the interactions between vehicle and roadway (driving kinematics data) are computed; this data includes the path radius of the driving trajectory and the BBI angle during the data collection. After driving kinematics data is processed, curve geometry data is computed in Module 4. While the data collected by the mobile device itself (without knowing vehicle’s roll rate) is enough to estimate roadway superelevation, better results can be obtained if the vehicle’s roll rate, a property related to the vehicle’s suspension, is available to calibrate the superelevation results. In addition, in order to obtain the curve radius and the curve deviation angle, it is recommended that the curve centerline be used as external data input for computing these data items. With curve geometry data obtained, the advisory speed and the speed differential can be computed (with posted speed limit as external data input) as shown in Module 5. Finally, in Module 6, the computed data outcome from previous modules can be used to provide a curve warning sign design that provides proper warning sign selection and placement. This section focuses on using the data collected by the mobile devices to compute the data items in Modules 1-5 to support MUTCD curve warning sign design. The section also proposes a new calibration method to estimate vehicle roll rate to compensate superelevation computation by considering the impact of vehicle body roll.

MODULE 1: Mobile DATA COLLECTION

A mobile application “AllGather” was developed by Georgia Tech for mobile data collection and storage of the GPS trajectory, vehicle speed, IMU data, and onboard camera view during the data collection.

The vehicle speed, GPS trajectory, and IMU data are stored in CSV format and used in the computational framework. The IMU data collected from the mobile devices includes three-axis (XYZ) readings of accelerometer, gyroscope, and magnetometer. This data can be used to describe the vehicle’s motion when driving; therefore, it is used to compute driving kinematics data, such as the driving path radius and the BBI angle. The three-axis readings of the IMU data use the mobile device’s local reference frame as the coordinate system, as shown in Figure 3. The vehicle speed, GPS, and IMU data are pulled and recorded using Android’s recommended library functions. The accelerometer and magnetometer measure the linear acceleration and magnetic field strength along each of the three axes, and the gyroscope measures the angular velocity around each axis. Since the axes use the mobile device’s local reference frames, they do not change with the smartphone’s orientation; therefore, to use the IMU data from the mobile device to describe the vehicle’s motion, the mobile device must be fixed to the vehicle to keep the local reference frames of the mobile device and the vehicle aligned.

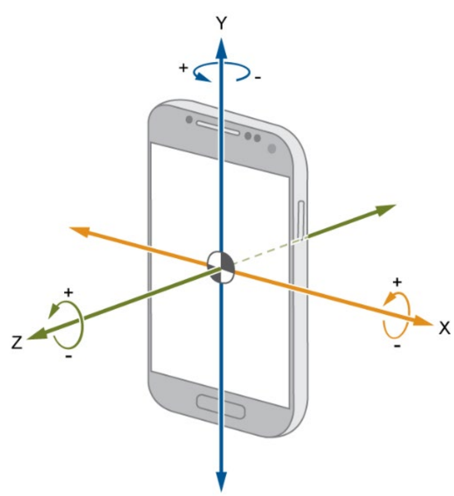

Figure 3. Diagram. Typical coordinate system for mobile device’s IMU.

The camera of the mobile device is used to record video during data collection of such data roadway image data that is useful for visualizing curve site conditions and data collection conditions; furthermore, the video log collected can also be used to detect and inventory traffic signs and other roadside assets, such as guard rails and retaining walls. Figure 4 shows an example setup of the mobile device using a windshield mount. The camera data collected using the AllGather application is stored in MPEG4 video format.

Figure 4. Picture. Example setup of AllGather application.

MODULE 2: MOBILE DATA REGISTRATION

Data registration is the procedure that aligns two or more data tables generated from different sensors or devices so that they share the same index column. For temporal data registration, the index column is the timestamp, and for spatial data registration, the index column can be GPS points or the linear referencing distance on a roadway centerline. This section presents the methods to temporally register data collected by different sensors in a single data collection run and spatially register the collected data in multiple data collection runs.

Temporal Data Registration

In single runs of data collection, the mobile data collection records readings from different sensors (GPS and IMU); even though the sensors share the same system clock, temporal data registration is still needed due to different sensors possibly having different sampling rates. For example, typical Android devices can report GPS data at a 1-Hz sampling frequency, while IMU data can be refreshed at higher frequency (e.g., 10 Hz). This will result in data tables that have different lengths for the same time period. Therefore, in order to have correlated IMU data at each GPS point, and vice versa, both data tables are resampled at a common timestamp with the same sampling frequency.

Figure 5 illustrates how two data tables are registered so that they share the same timestamps. The two data tables are first combined using the *outer join* operation, creating a super table that has one single timestamp column that contains the timestamps from both Raw Data from Device A and Raw Data from Device B. In the resulting Merged Data Table, the missing data (corresponding to the timestamp that only show up in one of the input tables) are created using linear interpolation. Finally, the Merged Data Table is resampled at a fixed frequency (e.g., 2 Hz) using averaged values to produce the registered data table.

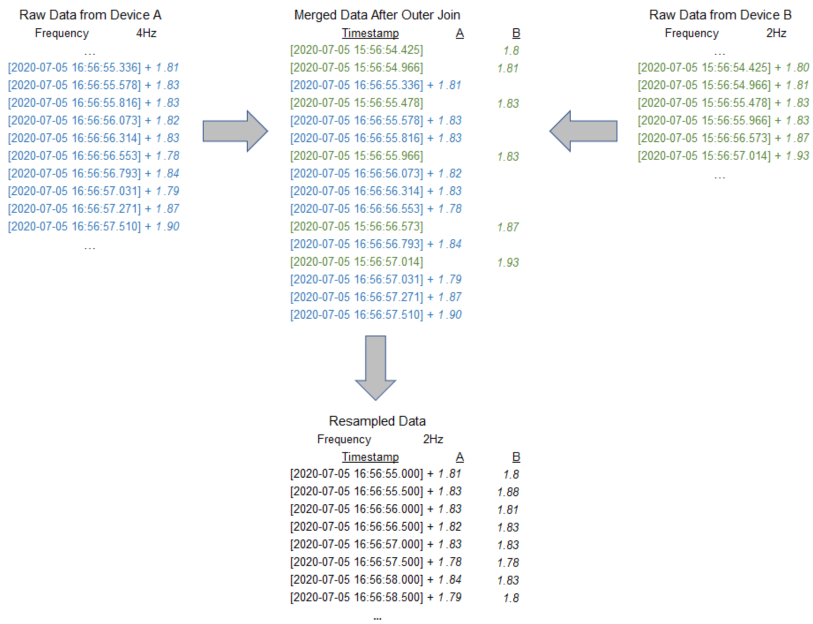

Figure 5: Illustration. Temporal data registration of data tables with different sampling frequencies.

Spatial Data Registration

In multi-run data collection, although the data collected in each individual run can be registered using temporal registration, the data from run to run do not share common timestamps. Therefore, to enable multi-run data aggregation, comparison, and analysis, spatial data registration is needed. The goal of spatial registration is to merge data tables so that the resulting table has a common GPS or spatial index column.

The process of spatial data registration is very similar to the temporal registration; the difference is that the spatial information is used as the common index. There are two types of spatial information that can be used as a spatial index: GPS and linear referenced distance. The benefit of using GPS as the spatial index is that GPS data are readily available from the collected data with no pre-processing needed; in order to get linear referencing distance, the GPS points need to be projected onto a roadway centerline before the linear referencing distance can be computed. However, since curve inventory data can define a curve segment using the linear referencing distance of the PC and PT points, using the linear referencing distance can be useful for querying data related to a specific curve. Other than the difference in what is being used as the common index, the spatial data registration procedure is essentially the same as the temporal data registration.

MODULE 3: DRIVING KINEMATICS DATA CALCULATION

The kinematics data items included in the computational framework include the path radius and BBI angle. It is worth noting that, in the proposed computational framework (Figure 2), there are two types of radius data: path radius and curve radius. Radius estimation is a crucial step of the computational framework, and it is important to understand the difference between the two types of radius data, as the path radius and curve radius should not be used interchangeably for computing curve superelevation and determining an appropriate curve advisory. During cornering, as the vehicle wanders laterally within the lane, the curvature of the vehicle path can be different from the geometry radius of the curve. As illustrated in Figure 6, an experienced driver may use lateral movement within the lane to "flatten" the curve so the path's curvature, the inverse of radius, is smaller than the curve centerline's curvature. Similarly, an inexperienced driver or a driver who makes a poorly executed turns by "jerking" the steering wheel may cause the path curvature to be temporarily larger than the curve centerline's curvature. Therefore, in the computational framework, we propose to use the path radius to reflect the driving trajectory and the curve radius to reflect the curved roadway geometry. The technical challenge is that the current practice of using curve radius is not a good representation of the actual path radius of the vehicle trajectory and it leads to error in superelevation calculation and increases sensitivity to driving behavior. There is a need to compute path radius based on the actual vehicle trajectory to obtain a more accurate super-elevation computation.

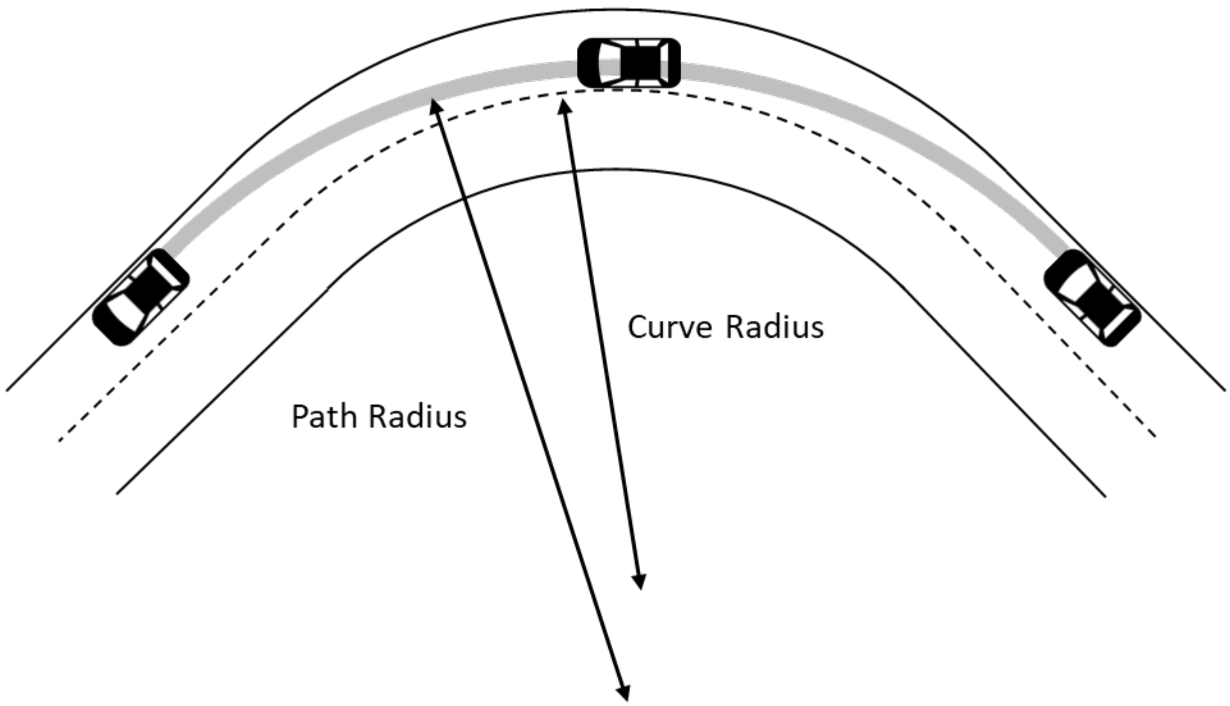

Figure 6. Illustration. Difference between path radius and curve radius due to lateral movement within the lane.

Path Radius Estimation Using Vehicle Speed and Angular Velocity

As illustrated in Figure 6, path radius is largely dependent on the steering input from the driver, and the path radius can easily change from one moment to another. Therefore, the measurement of the path radius should reflect the vehicle's movement at a particular instant. The GPS trajectory does reflect the general movement of the vehicle to certain degree for estimating path radius. However, given the fact that at least three GPS points are mathematically required for estimating the trajectory radius, meaning the result is not based on an instance but a period, and GPS accuracy may cause numerical instability in radius results when too few points are used, making GPS points sub-optimal data for the path radius estimation. However, the IMU sensor of the smartphone should be able to capture the dynamics of the vehicle. Assuming the vehicle is not spinning (oversteering) on the roadway, we propose a computational method to obtain the path radius at any given time of the vehicle's motion using the IMU and GPS data collected by the mobile device.

Curve Driving Kinematics

This section briefly describes the kinematics of curve driving to lay the foundation for BBI computation and superelevation computation using the BBI angle. To illustrate the kinematics of curve driving, this section largely references the Appendix A of the "Development of Guidelines for Establishing Effective

Curve Advisory Speed" (*7*).

The Ball-Bank Indicator angle (BBI angle) refers to "the movement of the ball is measured in degrees of deflection, and this reading is indicative of the combined effect of superelevation, lateral (centripetal) acceleration, and vehicle body roll" (*8*). Figure 7 illustrates the relationship between the BBI angle (**α**), the lateral acceleration ($\boldsymbol{m\frac{V^2}{R}}$), superelevation angle (**ϕ**) and a vehicle's body roll (**ρ**).

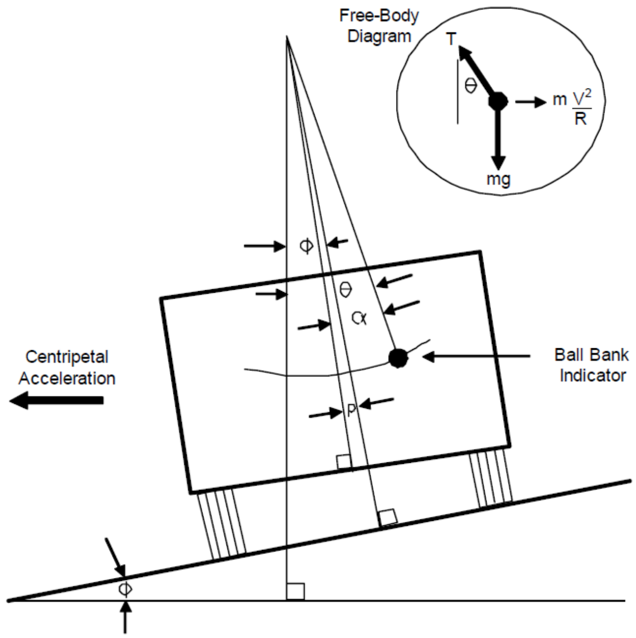

Figure 7. Diagram. Interaction between BBI and superelevation, lateral acceleration, and vehicle body roll. (*7*)

The relationship shown in Figure 7 is valid at any timestamp when a vehicle is on a curve, and this can be expressed as Equation (2).

$$\frac{\left(1.47 * V(t_i)\right)^2}{gR_p(t_i)} = \tan\left(\alpha(t_i) + \Phi(t_i) - \rho(t_i)\right) \tag{2}$$

Where,

$\alpha(t_i)$ = ball-bank indicator angle at $t = t_i$, radians;
$\Phi(t_i)$ = superelevation angle at $t = t_i$, equitant to atan($\frac{e}{100}$), radians;
$\rho(t_i)$ = body roll angle at $t = t_i$, radians;
$V(t_i)$ = vehicle travel speed at $t = t_i$, MPH;
$R_p(t_i)$ = vehicle path radius at $t = t_i$, ft;

From Figure 7, we can see that the angle **θ** is caused by the centripetal acceleration, while the superelevation supplies a portion of the acceleration; the remaining portion is supplied by the tire-pavement side-friction. As the angle **ϕ** represents the superelevation angle, we can define a side-friction angle ($\boldsymbol{f_r}$) as the difference between the lateral acceleration angle and the superelevation angle (**θ – ϕ**). Therefore, the relationship in Equation (3) can also be derived.

$$f_r = \text{atan}\left(\frac{\left(1.47 * V(t_i)\right)^2}{gR_p(t_i)}\right) - \text{atan}\left(\frac{e(t_i)}{100}\right) \tag{3}$$

We can also see in Figure 7 that the BBI angle ($\boldsymbol{\alpha}$) is closely related to the side-friction angle ($\boldsymbol{f_r}$) with the inclusion of the vehicle body roll angle ($\boldsymbol{\rho}$).

$$\alpha(t_i) = f_r(t_i) + \rho(t_i) \tag{4}$$

The vehicle body roll is caused by the lateral load acting on the vehicle; the amount of body roll under the same lateral load is heavily dependent on the vehicle's suspension properties. Research by Moyer and Berry (1940) revealed a constant roll rate can be found between side-friction angle and body roll angle. This relationship is shown in Equation (5), where k = roll-rate of the vehicle (rad/rad).

$$\rho(t_i) = k * f_r(t_i) \tag{5}$$

Subsequently, the relationship between the BBI angle and the side-friction angle can be expressed as Equation (6)

$$\alpha = f_r(t_i) * (1 + k) \tag{6}$$

And substitute side-friction angle in Equation (6) with Equation (3), Equation (7) can be derived.

$$\alpha(t_i) = \left(\text{atan}\left(\frac{\left(1.47 * V(t_i)\right)^2}{gR_p(t_i)}\right) - \text{atan}\left(\frac{e(t_i)}{100}\right)\right) * (1 + k) \tag{7}$$

It is worth noting that when a vehicle's roll rate is not available, assuming the vehicle roll rate equals to zero is equivalent to assuming no body roll when the vehicle is turning and using this assumption to estimate the side-friction angle from the BBI angle will exaggerate the side-friction angle. The amount of error from this assumption will increase as the BBI angle increases because the amount of error and the BBI angle have a positive linear relationship.

It is also worth noting that what Equation (7) represents is that when a vehicle's speed, path radius, and superelevation are known, the side-friction angle can be computed; it should have a (1+k) relationship to the BBI angle, and when the vehicle roll rate is also known, the expected BBI angle can be computed to validate the BBI angle as computed from the mobile device's BBI angle.

BBI Angle Computation

After understanding the curve driving kinematics, we can see the BBI angle is the angle between the vehicle chassis' vertical direction and the net acceleration (including gravity) experienced by the vehicle. Therefore, the two items needed for computing the BBI angle from mobile data are vehicle chassis' vertical direction vector ($\vec{\boldsymbol{G}}$) and the net acceleration vector ($\vec{\boldsymbol{A}}(\boldsymbol{t_i})$). The chassis' vertical direction vector represents the direction of the net acceleration vector and if they are parallel, it would result in a "zero" BBI reading; thus, this vector will be referred to as the "zero vector" in the rest of this report.

To obtain the "zero vector", the data collection device must be first fixed to the vehicle's chassis (e.g., mounted to the windshield using a suction cup holder), with the camera facing forward. The vehicle must remain stationary on level ground for the first few seconds of a data collection run. During the stationary phase, the direction of the gravity is being measured by the accelerometers and used as the "zero vector".

After the “zero vector” is obtained, the accelerometers continuously measure the acceleration experienced by the vehicle, and the acceleration component perpendicular to the vehicle’s driving direction is used for computing the BBI angle.

MODULE 4: CURVE GEOMETRY DATA COMPUTATION

This section presents the computational procedure for calculating curve geometry data. The curve radius and deviation angle are computed from the roadway’s centerline or GPS data; the curve superelevation is computed from IMU data.

Curve Radius and Deviation Angle Estimation

The curve radius and curve deviation angle of the roadway can be estimated by fitting a circle on the geometric shape of the road centerline or GPS trajectory. Typically, three major steps are involved:

Step 1: Centerline or trajectory data smoothing,

Step 2: PC and PT identification, and deviation angle estimation.

Step 3: Radius estimation.

Step 1 is to remove the outliers from the raw centerline and GPS data because the PC and PT identification is highly relying on the change of heading, which is computed by consecutive points rolling along the data. The polynomial approximation with exponential kernel (PAEK) method is a smoothing algorithm developed by ESRI ArcGIS software that provides a stable line-smoothing function. This function is developed based on the algorithm defined by Bodansky, et al, (*9*).

Step 2 is to identify the PC and PT based on the change of heading. A vehicle’s heading starts changing at PC and stops at PT. The change of heading can be computed as the difference of the bearing angle between consecutive points. Figure 8 shows the centerline data with extracted curves on State Route 2 (SR-2), and Figure 9 shows the bearing angle with extracted curves correspondingly.

Step 3 is to fit the circle between PC and PT to estimate the radius for each extracted curve. The Kasa method is a widely used least-squares circle geometric fitting method that is based on finding the minimum distances from the given points to the geometric feature to be fitted (*10*).

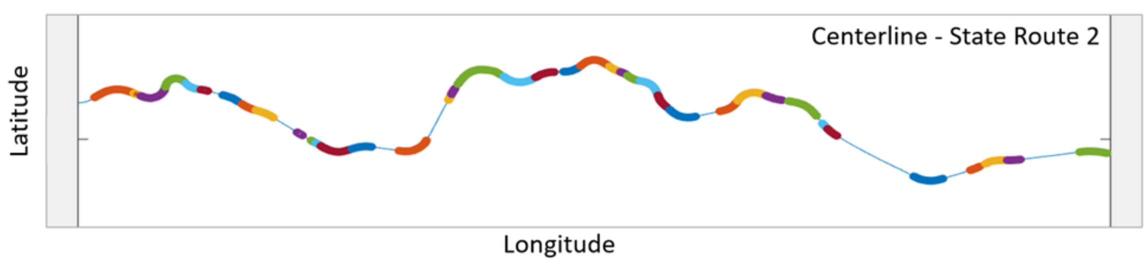

Figure 8. Plot. Roadway centerline with extracted curves on part of State Route 2.

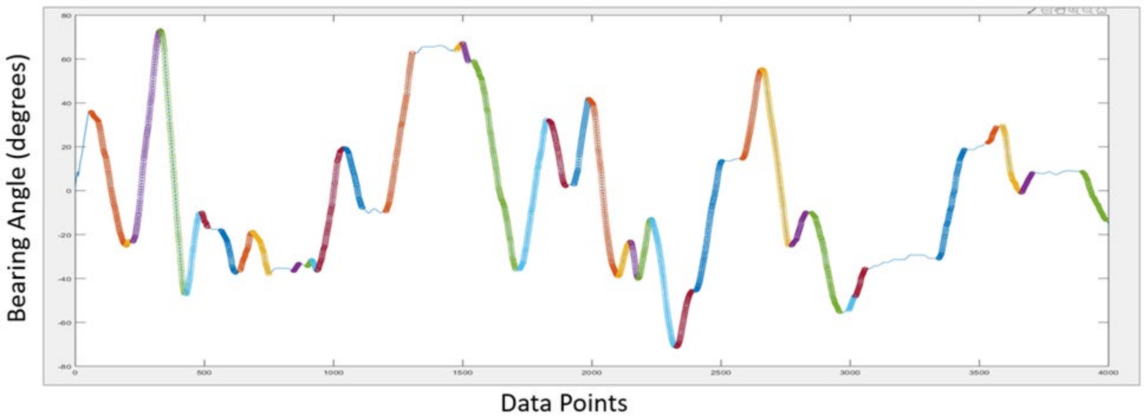

Figure 9. Plot. Bearing angle with extracted curves on part of State Route 2.

Curve Superelevation Computation

From Equation (7), the computation for superelevation can be derived as Equation (8). Note that the relationship in Equation (8) is based on any arbitrary instance of the vehicle's motion state; therefore, the path radius at a timestamp ($\boldsymbol{R_p(t_i)}$) is used to represent the vehicle's motions state.

$$e(t_i) = 100 * \tan\left(\operatorname{atan}\left(\frac{\left(1.47 * V(t_i)\right)^2}{gR_p(t_i)}\right) - \frac{\alpha(t_i)}{(1+k)}\right) \tag{8}$$

Note that a positive BBI angle should have a positive sign when the BBI reading indicates the "steel ball" is swinging towards the outside of the curve, and a negative sign should be used when the "steel ball" swings toward the inside of the curve.

CALIBRATION METHOD FOR VEHICLE ROLL RATE ESTIMATION

As shown in Equation (8), the vehicle speed, path radius, BBI angle, and vehicle roll rate are needed for superelevation computation. The vehicle speed, path radius, and BBI angle can either be directly obtained or computed from the collected mobile data. The vehicle roll rate ($\boldsymbol{k}$) cannot be directly measured by the mobile device. As discussed in the Curve Driving Kinematics section, assuming $\boldsymbol{k} = 0$, reasonable superelevation results may still be obtained, but the error in superelevation will continuously grow with higher and higher side-friction angles. Therefore, the current technical challenge is as the driving speed increases, the superelevation results will be more and more underestimated. This technical challenge will hinder the use of low-cost smart mobile devices and the leveraging of existing fleets (while engineers are undertaking their daily operations) because driving speeds and trajectories may not be consistently smooth.

While the vehicle roll rate can be measured mechanically, it is impractical to require all data collection vehicles' roll rates be mechanically measured. Therefore, this section proposes two calibration procedures that estimate vehicle roll rate using only mobile data collection without any mechanical tests. The first method requires the superelevation to be measured; the second method does not require a known superelevation, but it does require multi-run data collection on the same curve at different driving speeds.

Calibration Using Curves with Known Superelevation

As shown in Equations (3) and (6), the side-friction angle ($\boldsymbol{f_r}$) can be determined with the known vehicle speed, path radius, and superelevation. The resulting side-friction angle ($\boldsymbol{f_r}$) would also have a $(1 + \boldsymbol{k})$ relationship with the measured BBI angle. Therefore, when the superelevation is known, the side-friction angle can be calculated using the known superelevation for locations where BBI angle data was measured, the side-friction angle and BBI angle would show a linear relationship with the slope equal to $(1 + \boldsymbol{k})$.

Figure 10 shows an example outcome from tests performed by the research team on the National Center of Asphalt Technology (NCAT) test track. The superelevation was manually measured at 100-ft-stations on spiral sections and 200-ft stations on constant radius sections. The measured superelevation was combined with collected mobile data to compute the side friction angle and showed a good linear relationship with the computed BBI with a slope equal to 1.093, indicating the data collection vehicle had a roll rate of 0.093 rad/rad. Detailed results of using this calibration method are presented in the validation section.

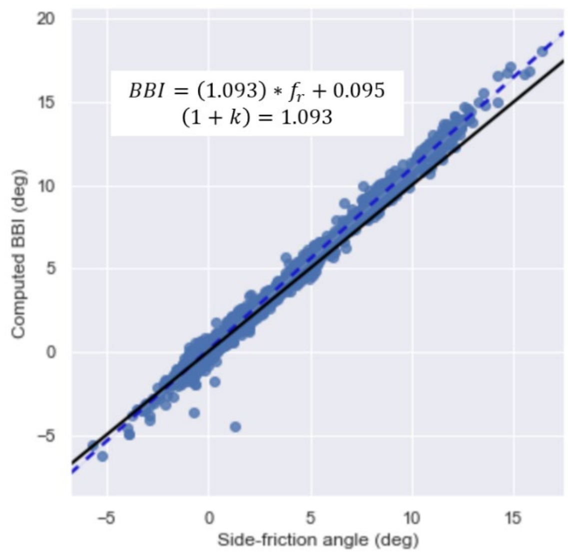

Figure 10. Chart. Example relationship between computed BBI and side-friction angle on NCAT test track with manually measured superelevation.

Calibration Using Curves with Unknown Superelevation

Considering that manually measuring curve superelevation might be impractical for agencies without access to a closed facility, another calibration method can be used. Multiple runs of data can be collected at different speeds on the same curve with unknown superelevation. This method works because the superelevation does not change for the same curve between multiple passes**.** Although the true superelevation is unknown, if vehicle roll rate is estimated correctly, the computed superelevation should be similar between runs at different speeds.

The data presented in Figure 10 were collected at five different speeds in 5 MPH increments. Using the same data, but without using the measured superelevation, this calibration method finds a best-fit vehicle roll-rate equal to 0.095 rad/rad, similar to the roll-rate found in using the “Known Superelevation” method of 0.093. Detailed analysis of this calibration method is presented in the validation section.

MODULE 5: ADVISORY SPEED DETERMINATION

Advisory Speed Determination from Single-Run Data Collection

Accurate computation of the curve advisory speed is critical to driver safety because it determines the type and placement of warning signs. If the computed advisory speed is too high, drivers may be unprepared for the sharpness of a curve. If the computed advisory speed is too low, drivers will lose their trust in the curve warning signs and begin disregarding them, ultimately putting themselves in danger. Equation (9) shows the calculation for determining the curve advisory speed. Note that curve radius ($\boldsymbol{R_c}$), not path radius

($\boldsymbol{R_p}$), is used in this calculation, as the advisory speed is dependent on the curve geometry, not a particular driver during a particular data collection run.

$$V_{adv} = \sqrt{15 * \left(\frac{e}{100} + f_{max}\right) * R_c} \quad (9)$$

Where,
f_{max} = maximum allowed side friction factor by the advisory speed criteria;
R_c = curve radius, ft;
V_{adv} = advisory speed limit, MPH.

The MUTCD 2009 edition defines the advisory speed criteria as follows:

- 16 degrees of ball-bank for speeds of 20 MPH or less,
- 14 degrees of ball-bank for speeds of 25 to 30 MPH, and
- 12 degrees of ball-bank for speeds of 35 MPH and higher.

This corresponds to the maximum allowed side friction factors as follows:

- 0.287 for speeds of 20 MPH or less,
- 0.249 for speeds of 25 to 30 MPH, and
- 0.212 for speeds of 35 MPH and higher.

For single-run collected data, the advisory speed can be calculated for each data point along a curve, and the lowest advisory speed result will be reported as the advisory speed of the curve.

Advisory Speed Determination from Multiple-Run Data Collection

For multi-run collected data, each individual data collection run will be processed using the proposed computational framework. Since an advisory speed is determined based on the minimum advisory speed results along the curve, any noise or unreliable data will almost always lower the overall advisory speed for the curve; therefore, for multi-run data processing, the highest advisory speed from the individual single runs should be used as the advisory speed of the curve. In addition, variations between individual runs can be used as indicators for flagging unreliable results that are recommended for data re-collection. The outcome of the final advisory speed is determined by comparing the advisory speeds derived from the multi-run data. Besides choosing the highest computed advisory speed among the multi-run data as the final design advisory speed, a confidence level (L, M, and H) of the computed advisory speed is recommended based on the variability among the computed single-run advisory speeds. This confidence level is a qualitative indicator. For a low confidence level (L), it means that there is a high variability among different runs of data. In some cases, re-collecting the data in the field is recommended because of high data variability. A high confidence level indicates that there is a high consistency on different runs of measurements. A case study on multi-run analysis using data collected on Georgia State Route 17 is presented in the later section. In the current computational framework, the multiple-run data being used is based on the advisory speed outcome. The rich data collected in the multi-run mobile data collection still has a huge potential to be used for other analyses that can be used to determine data quality and driver behavior.

Validation of Proposed Computational Framework Using Mobile Data Collection Devices

This section presents the validation tests and results of the proposed computational framework for curve safety assessment using mobile data collection devices. Two tests are presented in this section, a repeatability test to perform a preliminary evaluation of the mobile sensor's repeatability across different devices, and a validation test to comprehensively evaluate the performance using mobile devices in the proposed computational framework. The validation test was performed at National Center for Asphalt Technology (NCAT) closed test track, with the goal of validating the proposed method using different driving speeds and driver inputs. This section will evaluate the computed results of the radius, BBI angle, superelevation, and advisory speed. Using the proposed method to evaluate the feasibility of estimating superelevation with low-cost smartphones, the validation test was centered around comparing the computed superelevation results with the manually measured track superelevation. The logic behind this design is two-fold. First, superelevation is an important element in curve geometry information needed to determine appropriate curve advisory speed. Its accuracy is dependent on other computed elements, such as path radius and BBI angle; therefore, an accurate superelevation estimation would require accurate estimation of both the path radius and the BBI angle. Second, superelevation, as part of the curve geometry, can be physically measured and does not change during the test with different travel speeds or different driver inputs. This makes the evaluation of the proposed method straightforward, as data collected from different data collection runs can be compared to the same ground reference superelevation values.

Repeatability Test of The Mobile Sensors

The reliability and repeatability of mobile sensors are fundamental to the use of mobile devices for curve safety assessment data collection. In this test, the goal is to evaluate the repeatability of the IMU data collected by multiple mobile devices in the same data collection environment. The test was designed to place a number of mobile devices in the same orientation within the data collection vehicle and record the IMU data as the vehicle was driven. The test was set up, as shown in Figure 11, by placing three smartphones on the dashboard. Three different smartphones were used: the Xiaomi Redmi Note 4 White (Xiaomi 1), Google Pixel 3a (Pixel), Xiaomi Redmi Note 4 Black (Xiaomi 2).

Figure 11. Picture. Device setup for multi-device sensor repeatability test.

Since these smartphones were all placed in the same vehicle during the same data collection, the data collection environment is identical for all the devices. In other words, if the data collected by different devices was perfectly repeatable, the IMU data collected by the different devices should have a perfect correlation among the devices.

The IMU data in each device reports the linear acceleration, angular velocity, and magnetic fields in all XYZ directions. However, the proposed computational framework only requires linear acceleration and angular velocity data from the IMU. For each of the sensor readings, the normalized cross-correlation was compared for each pair of devices. Normalized cross-correlation measures the similarity between two signals and is bounded between -1 and 1; a correlation of 1 indicates the signals have a perfect similarity. Table 1 shows the normalized cross-correlation of different sensor data between different pairs of devices.

Table 1. Correlation of collected sensor data between different devices.

	Normalized Cross-Correlation		
Collected Data	**Xiaomi1 & Xiaomi2**	**Xiaomi1 & Pixel**	**Xiaomi2 & Pixel**
Linear acceleration X	0.9805	0.9638	0.9961
Linear acceleration Y	0.8431	0.9225	0.9845
Linear acceleration Z	0.9998	0.9997	0.9997
Angular velocity X	0.9921	0.9436	0.9516
Angular velocity Y	0.9948	0.8000	0.8036
Angular velocity Z	0.9999	0.9996	0.9997

From the results, we can see that the majority of the sensor data has a high (more than 0.98) correlation, indicating results computed from the data collected by one mobile device can be repeated by another mobile device. Among different sensors, the angular velocity in the Y direction showed the lowest normalized cross-correlation value. This is likely due to the way the devices were set up in Figure 11; the Y-axis of the devices was aligned with the driving direction, and in typical driving conditions, the vehicle does not rotate significantly around this axis. Therefore, there was no significant rotation signal for the sensor to collect and the correlation score was largely impacted by the random noise of the sensor. Given that the sensor qualities within the same device are generally similar, the repeatability of the angular velocity Y should be similar to other axes if the device was orientated differently in the vehicle.

Validation Test of The Proposed Method

The purpose of the validation test was to evaluate the feasibility of the proposed method which uses mobile devices for curve safety assessment data collection and analysis.

This test focused on validating the superelevation estimation accuracy. Superelevation is an important data item for determining the appropriate curve advisory speed, and superelevation is part of the curve geometry that can be physically measured to evaluate the superelevation estimation accuracy. Evaluation of other computed data items, such as the BBI angles and advisory speed limit, was expanded from the superelevation by using manually measured superelevation to back-calculate the expected values.

Validation Test Location National Center for Asphalt Technology (NCAT)

The National Center for Asphalt Technology (NCAT), located in Auburn, Alabama, has a closed facility with a 1.7-mile oval test track for accelerated pavement tests (shown in Figure 12). NCAT's test track is an ideal site for performing the validation test, as the superelevation can be manually measured without the need for traffic control, since the test track is not on public roads. In addition, horizontal alignment and cross-section drawings are available to provide curve geometry information. However, since the test track has been repaved multiple times after its initial construction, the superelevation values were manually measured throughout the curve to obtain the current superelevation on the test track.

Figure 12: NCAT Test Track (Google Earth).

Validation Test Design and Test Procedure

As stated previously, while the purpose of the test was to validate the computed data items in the proposed computational framework, the design of the validation was focused on using superelevation as the physically measurable curve geometry to validate the superelevation computation; the validation also used the measured superelevation to back-calculate the expected values for validating the BBI angle and advisory speed computation. In addition, the validation of the curve radius estimation was done by comparing the estimated curve radius to the radius documented in the track design drawing.

Manual Superelevation Measurements

To obtain detailed superelevation data on the NCAT test track, superelevation was measured throughout the curves. The curves on the NCAT test track are composed of one constant radius portion in the middle of the curve with a radius of 476 feet, and two spiral proportions at the beginning and the end of the curve to transition to the tangent parts of the track. The superelevation data was measured every 200 feet on the constant radius section and every 100 feet on the spiral sections; additional measurements were made at transition points between tangent and spiral sections and between spiral and circle sections. Figure 13 shows the locations on the NCAT test track where superelevation was manually measured.

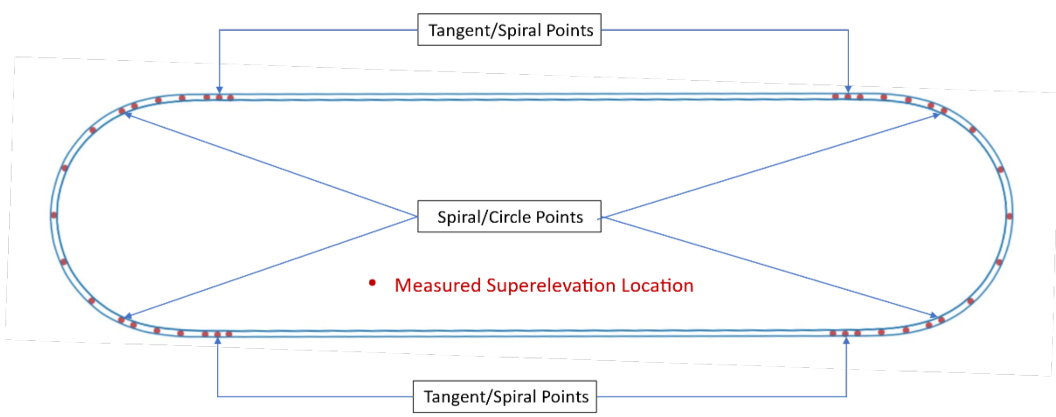

Figure 13. Diagram. Locations on the NCAT test track where superelevation is manually measured.

At each location shown in Figure 13, superelevation measurements were manually taken using an 8-ft straightedge and a digital level; three measurements were taken at each location with 1 ft between each location. Averages of the three measurements were used to represent the track superelevation. The equipment used to measure superelevation is shown in Figure 14; the digital level used can provide slope readings down to 0.1 % slope.

Figure 14. Picture. Straightedge and digital level used for superelevation measurements.

The manually measured superelevation results can be found in Appendix A. According to the design drawings, the test track was designed to have a 15 % slope on fully superelevated sections of the curves; the manually measured results showed the current test track has a 14-16 % slope on fully superelevated sections.

Driving Speed and Driving Behavior

The validation test was performed by making multiple runs of data collection at different driving speeds and with different driving behaviors. Different driving speeds were performed using the vehicle's cruise control system. The test was performed at five different speeds, ranging from 30 MPH to 50 MPH in 5 MPH increments. At each speed, five laps were driven to evaluate the repeatability of the calculation. Different driving behaviors were introduced. For example, the driver drove as smoothly as possible through the curve to represent "good/optimal" driving behavior; on the last lap, the driver made sudden steering adjustments, which made the vehicle wander over the lane, to mimic "bad/undesired" driving behaviors.

Data Collection Devices and Setup

Figure 15. Picture. Mobile devices used in the validation test and their setup.

Three mobile devices were used during the validation test, two Android smartphones and a GoPro camera that has internal GPS and IMU sensors. Two smartphones were equipped to evaluate the impact of different mounting methods as Smartphone 1 was mounted with a clamp mount to the dashboard, and Smartphone 2 was mounted with a suction cup that has an extension arm to secure the device. The inclusion of the GoPro camera was to evaluate the impact of the different sensors, as the GPS and IMU sensors in the GoPro camera have a higher sampling frequency than the smartphones; also, the quality of the sensors might be different in the GoPro. In addition, the Rieker inclinometer was included in the test to represent commercial solutions for BBI angle measurement.

Test Procedure

The following procedure was followed to validate the test at NCAT.

Task 1: Survey the superelevation on the NCAT test track

1. Using a measuring wheel, locate key reference points (spiral-tangent point and circle-spiral point).
2. Starting from the mid-point of each curve, measure the superelevation at the following distance away from the mid-point.
    a. Distance to mid-point where superelevation is measured:
    0 ft, 200 ft, 400 ft, 543.7 ft, 600 ft, 700 ft, 800 ft, 900 ft, 951.7 ft, 1000 ft, and 1100 ft.
3. At each location, measure superelevation three times with each measurement spaced 1 ft apart. Report the average of the three measurements.

Task 2: Collect mobile data (in motion)

1. Set up the data collection devices in the vehicle (Chevy Tahoe SUV).

2. Before the start of each data collection, park the vehicle on the tangent section, preferably riding the centerline to balance the cross-slope.
3. All test devices will start the recording at the same time.
4. After recording starts, stand by for at least 10 seconds for zeroing the BBI measurements.
5. Proceed with the following data collection runs in Table 2. Restart the recording after each run.

Table 2. Description of the data collection runs.

Run Number	Speed (MPH)	Number of Laps (Good Driving + Bad Driving)
Run 1	30	4 + 1
Run 2	35	4 + 1
Run 3	40	4 + 1
Run 4	45	4 + 1
Run 5	50	4 + 1
Total		20 + 5

Validation Test Results – Curve Radius Calculation

The NCAT test track has two main curves (West Curve and East Curve) that have the same curve radius. To validate the proposed method for computing curve radius, the estimated curve radius is compared to the curve radius in the design drawings.

The proposed method recommends the use of the roadway centerline for extracting the curve radius. For this test, Google Earth was used to extract the centerline of the test track. Using the "add path" tool, the centerline of the test track was manually traced on the satellite map (using the pavement marking as reference). Figure 16 shows the manually traced centerline overlaid on the satellite map.

Figure 16. Map. Manually traced centerline (green) on Google Earth.

After obtaining the centerline, the curve radius was computed by using the curve sections on the roadway centerline and using the Kasafit method to estimate the least square fit circle for radius estimation. The estimated curve radius using the proposed method showed a circular radius of 478.1 ft for the West Curve and 481.4 ft for the East Curve. The curve radius documented in the design drawing has a radius of 476 ft for the circular section of the curves. This shows that using the proposed method can very reasonably estimate the curve radius using the roadway centerline.

Validation Test Results – Superelevation Calculation without Body Roll Calibration

As shown in Equation (8), the superelevation calculations use the driving speed, path radius, and vehicle roll rate. However, the roll rate of the vehicle may not be readily available. In the case of unavailable roll rate information, the superelevation can be approximated by assuming the body roll is small enough that the roll rate constant is equal to zero. This assumption may be reasonable for low travel speeds; however, as/if a vehicle travels faster on curves, the amount of body roll increases; this could cause the assumption to be less accurate than the actual condition. This section presents the accuracy level of superelevation calculation at different driving speeds; it assumes there is no vehicle body roll.

Superelevation Results at Different Driving Speeds

Figure 17 shows the error of uncalibrated superelevation results that were calculated from the three data collection devices. As shown in the charts, at any given speed, the variation in the error (amount of vertical spread) remained similar for all devices, while the results from the GoPro showed the random error is lower in GoPro than in the smartphones. In addition, the bias of the superelevation error has a downward trend with increasing speed. This indicates that, without calibration, the calculation tends to underestimate the superelevation of the roadway when the vehicle is traveling at high speed. The amount of underestimation has a positive relationship to the travel speed. This behavior is expected and can be explained by Equation (8). When assuming no vehicle body roll, the large BBI angle (typically from higher driving speed) will cause the superelevation results to be lowered.

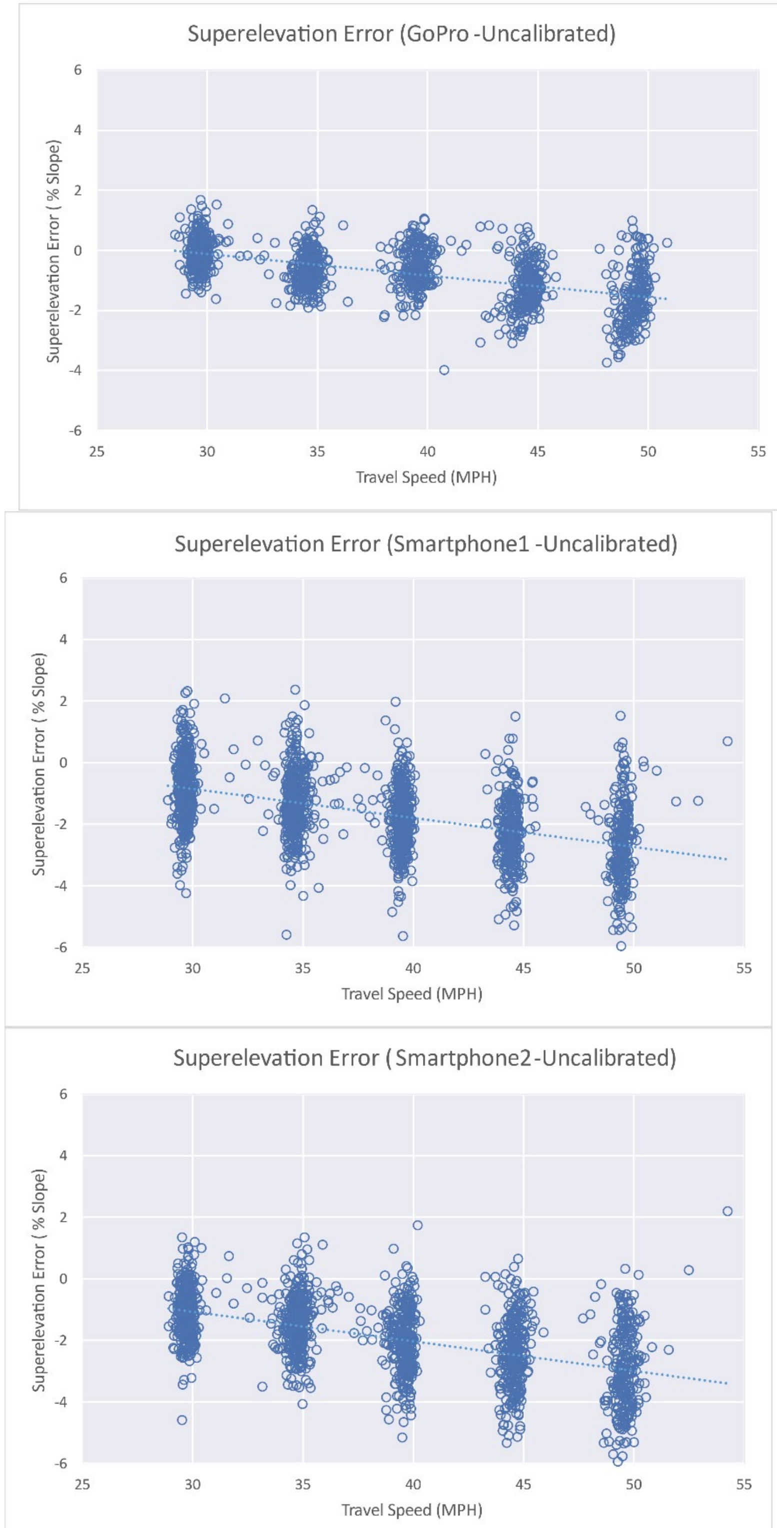

Figure 17. Charts. Uncalibrated superelevation error at different speeds.

Table 3 summarizes the root-mean-square error (RMSE) of the uncalibrated superelevation results categorized by vehicle speed, mobile device, and driving behavior. The superelevation RMSE is plotted in Figure 18. The results show that the GoPro data will produce more accurate results than those from smartphones. Smartphone 1 is slightly more accurate than Smartphone 2, which shows that the mounting mechanism for Smartphone 1 (mounted with dashboard clamp) may improve the accuracy but only slightly. Finally, poor curve driving (shown in Figure 19) does reduce the accuracy of the superelevation calculation. However, with the proposed method, the superelevation error level will only increase by less than 0.5 % slope.

Table 3. RMSE of uncalibrated superelevation results.

	RMSE of Superelevation (GoPro)		RMSE of Superelevation (Smartphone 1)		RMSE of Superelevation (Smartphone 2)	
Driving Style	Good	Bad	Good	Bad	Good	Bad
30 MPH	0.525	0.872	1.216	1.401	1.255	1.524
35 MPH	0.808	1.244	1.611	1.929	1.578	1.850
40 MPH	0.839	1.205	1.999	2.334	2.189	2.575
45 MPH	1.476	1.683	2.423	2.590	2.695	2.668
50 MPH	1.817	2.474	2.965	3.372	3.266	3.948
Overall	**1.093**	**1.496**	**2.043**	**2.325**	**2.197**	**2.513**

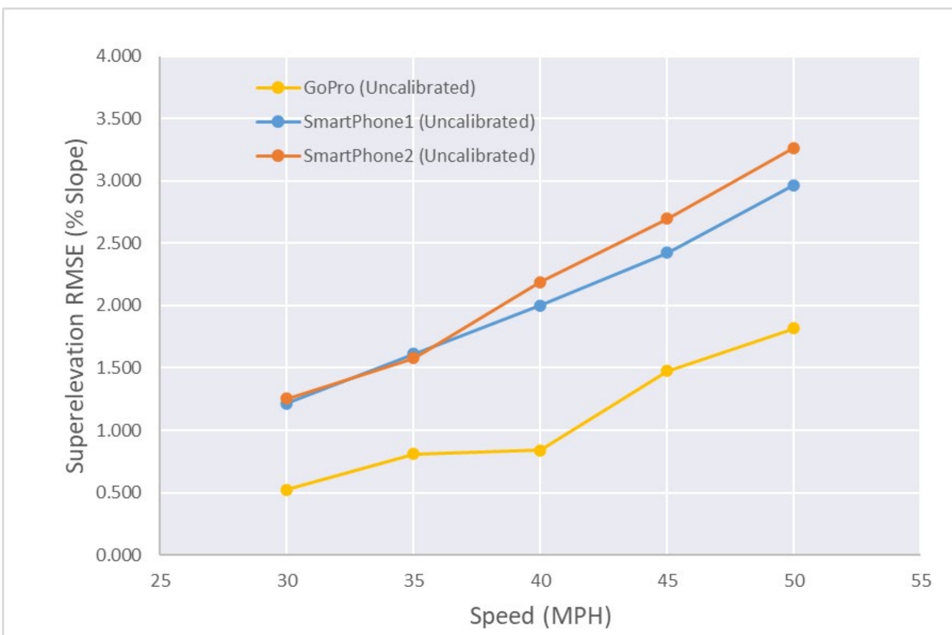

Figure 18. Chart. RMSE of uncalibrated superelevation.

Importance of Using Path Radius for Superelevation Calculation

As discussed in the validation test design, the validation test also introduced different driving behaviors to evaluate the robustness of the proposed method. Figure 19 illustrates the different driving behaviors used during the validation test.

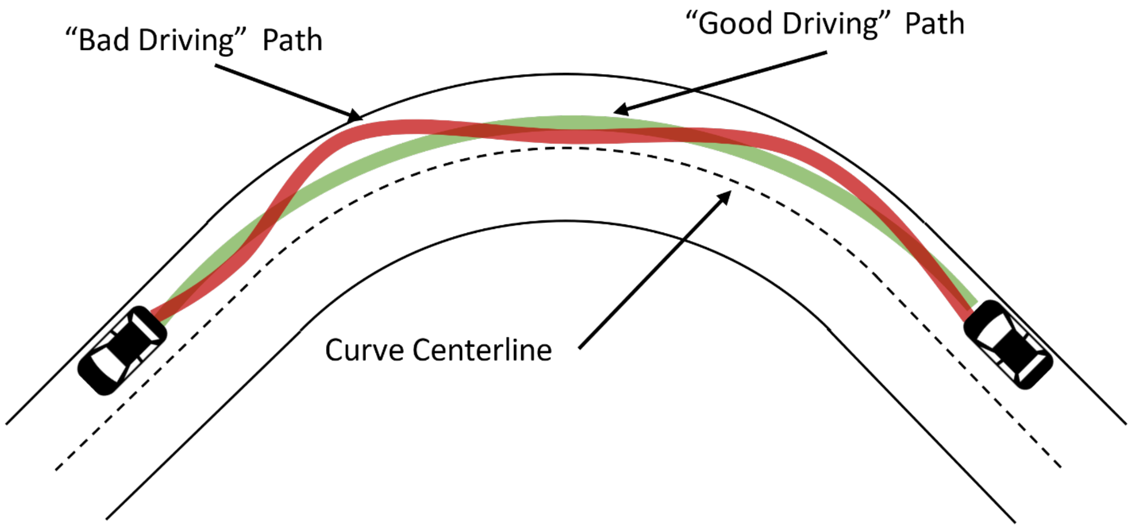

Figure 19. Diagram. Driving path of different driving behaviors.

For superelevation calculation, the radius of the vehicle's path is needed, and, generally, the curve's centerline radius is a good approximation of the path radius. As shown in Figure 19, the curvature of the "good driving" path is, generally, similar to the curvature of the centerline. However, some driving behaviors, such as frequent wandering within the lane and "jerking" the wheel when turning, may cause the curvature of the driving path to be drastically different from the centerline. Therefore, at any point during cornering, the superelevation calculation at that point should use the speed, BBI angle, and path radius corresponding to the vehicle at that moment.

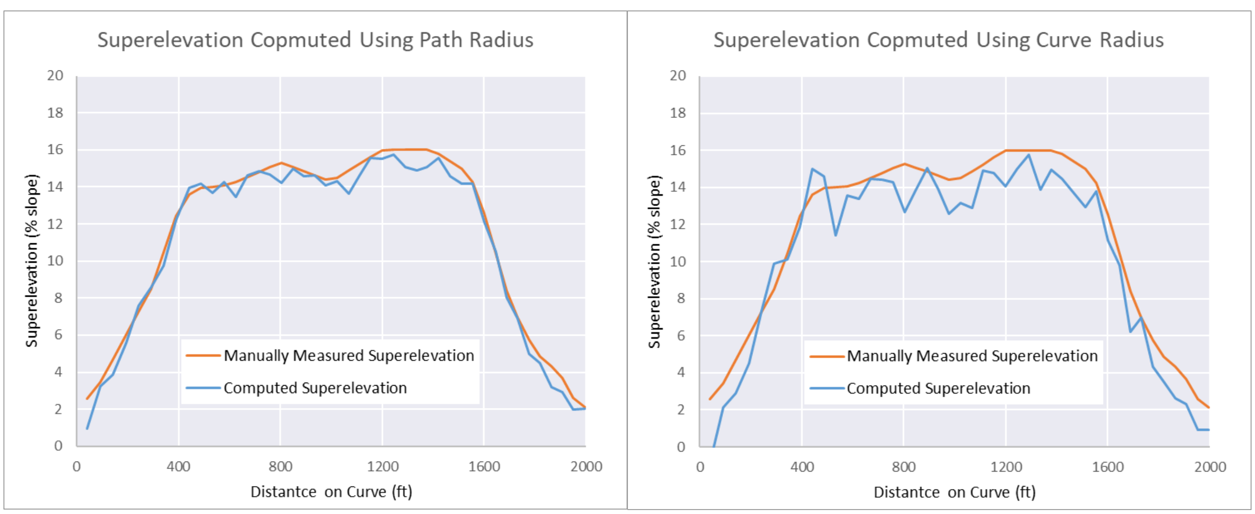

Figure 20. Charts. Computed superelevation using path radius vs. curve radius in "good driving" cases.

The example in Figure 20 shows that in "good driving" cases, using the curve radius to approximate the path radius can still result in acceptable superelevation estimation. However, when "bad driving," such as wheel jerking and wandering occurs, the curve radius can no longer describe the vehicle's driving path, leading to significant error in superelevation estimation (shown in Figure 21).

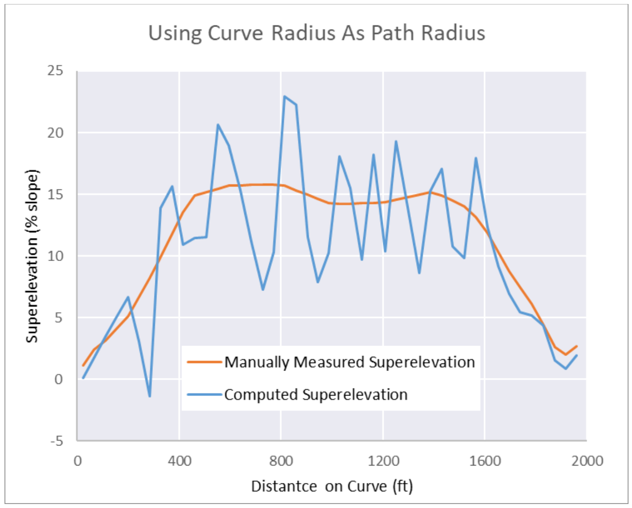

Figure 21. Chart. Using curve radius as path radius in "bad driving" cases

Performance Comparison of Different Path Radius Calculation Methods

It would be logical for the GPS that captures the vehicle's trajectory to be used to compute the path radius. However, given the GPS sampling rate in smartphones (typically 1 Hz) and the accuracy of GPS (typically about 15 ft), the subtle movement caused by steering input may not be able to be captured. In order to get the path radius at a particular GPS point, the neighboring points are also needed for the least square fitting; therefore, the path radius computed from the GPS cannot represent the curvature of the path at an instant, but the averaged curvature over a small period.

With this in mind, the proposed method measures the path radius from the angular velocity and vehicle speed. Figure 22 shows an example of a "bad driving" case in which the difference in superelevation measurement performance between using the path radius estimated from GPS and using the path radius estimated from the gyroscope.

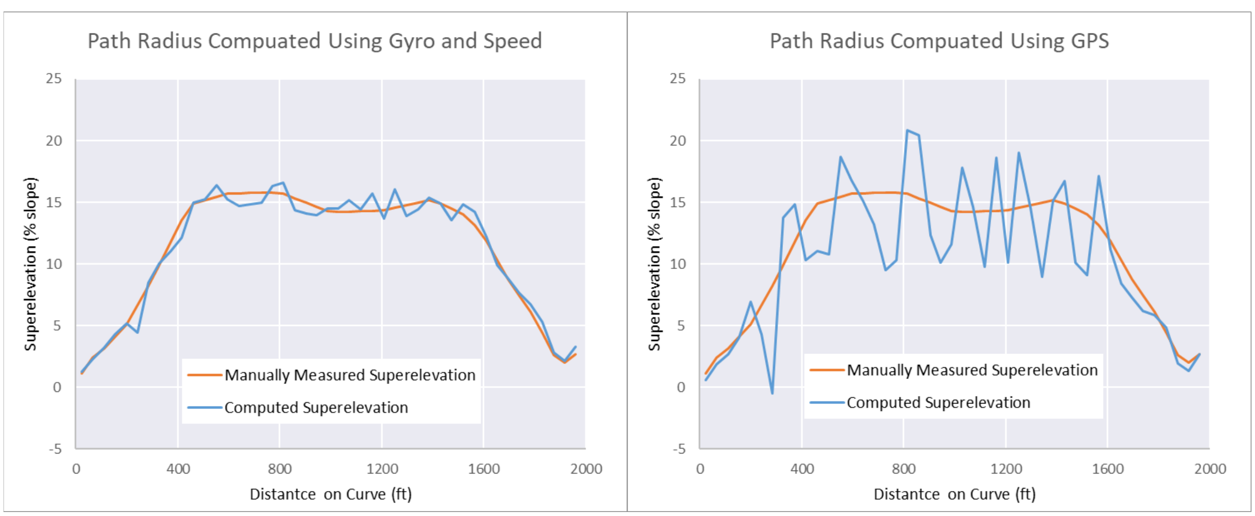

Figure 22. Charts. The performance difference between different methods of path radius estimation

From the results, we can see that there is still a significant amount of error in the GPS method. In the case of calculating the path radius from the gyroscope and vehicle speed, the curvature at every point of the cornering process, the radius was captured accurately, leading to no significant performance difference compared to the "good driving" cases.

Validation Test Results – Vehicle Roll Rate Estimation

As seen in the uncalibrated superelevation results, the vehicle speed has an impact on the accuracy results, as higher speed will introduce more vehicle body roll thus making the results less accurate. The errors introduced may be minimized if the vehicle roll rate is available. However, most vehicle owners do not know their vehicle's roll rate; the roll rate needs to be measured in order to calibrate the superelevation results.

As the proposed methods to estimate vehicle roll rate from collected mobile data are presented previously, this section presents the results of the proposed methods using data collected during the NCAT test.

Table 4. Roll-rate estimation of the data collection vehicle

	Estimated Vehicle Roll Rate (rad/rad)				
Estimation Method	**GoPro**	**Smartphone 1**	**Smartphone 2**	**Average Roll Rate**	**Standard Deviation**
With Known Superelevation	0.0918	0.0958	0.1089	0.0988	0.0073
With Unknown Superelevation	0.0938	0.1019	0.1202	0.1053	0.0110

Roll Rate Estimation with Known Superelevation

As mentioned in the previous section, this method uses the measured superelevation to compute the side-friction angle during data collection, and by comparing the relationship between the side-friction angle (calculated using Equation (3)) and the measured BBI angle (shown in Figure 23) to estimate the roll rate of the vehicle.

Figure 23. Charts. Relationship between measured BBI angle and side-friction angle.

Roll Rate Estimation with Unknown Superelevation

While the benefit of the roll rate estimation with the known superelevation is simple in its computation, detailed superelevation measurements might not be available in most circumstances. Therefore, as mentioned in the previous section, when the superelevation is not available, an alternative approach is to use the vehicle to collect mobile data on the same curve with different speeds. Using the data collected at NCAT with five different speeds (30 MPH – 50 MPH), and with two out of five laps, the vehicle's roll rate was estimated without using the measured superelevation. The results of the estimations are shown in Table 4, and we can see the estimations are also similar between different devices, there is a slight increase in the standard deviation compared to the "known superelevation" method.

Although this approach for estimating the vehicle roll rate requires multiple runs of data collection at different speeds, this approach might be more practical to implement since it does not require any knowledge of the curve geometry, and the repeatability of this method is similar to the "known superelevation" method.

Table 5. Estimated roll rate with different data collection strategies.

	Number of Runs at each speed	Total Number of Runs	Estimated Roll Rate		
			GoPro	Smartphone 1	Smartphone 2
Two speeds @ 5 MPH increment	2	4	0.1059	0.1802	0.1593
Two speeds @ 10 MPH increment	2	4	0.0984	0.1064	0.1202
Two speeds @ 15 MPH increment	**2**	**4**	**0.1042**	**0.0995**	**0.1085**
Two speeds @ 5 MPH increment	3	6	0.0858	0.1776	0.1662
Two speeds @ 10 MPH increment	3	6	0.0912	0.1170	0.1328
Two speeds @ 15 MPH increment	**3**	**6**	**0.0946**	**0.1080**	**0.1146**
Three speeds @ 5 MPH increment	2	6	0.0890	0.1186	0.1129
Four speeds @ 5 MPH increment	**2**	**8**	**0.0925**	**0.1069**	**0.1189**

To investigate the recommended speed difference between runs and the number of runs at each speed for this roll rate estimation method, Table 5 shows the estimated roll rate using different data collection strategies. We can see that while more runs generally improve the method's repeatability, the speed difference between the highest and lowest data collection speed plays a more important role in the result's repeatability. Therefore, if the method is to be formalized as a calibration method, performing the calibration test at two different speeds and repeating each speed two times should be enough to produce a reasonable roll rate estimation; repeating each speed three times would produce an estimation with higher confidence.

Validation Test Results – Superelevation Calculation with Body Roll Calibration

Using the vehicle roll rate estimated by the proposed method, the superelevation results can be calibrated to compensate for the impact of vehicle body roll. Figure 24 shows the comparison of the superelevation error before and after calibration using the estimated vehicle roll rate. Table 6 summarizes the RMSE of the uncalibrated superelevation results and is separated based on vehicle speed, mobile device, and driving behavior. The superelevation RMSE is plotted in Figure 25. The results show, after calibration, the superelevation measurement accuracy is no longer impacted by the travel speed. It is worth noting the device's random noise level (vertical spread at each speed) is unaffected by the calibration.

The validation results show that after calibration, the GoPro camera is able to measure superelevation with 0.598 % slope accuracy, and the smartphones can achieve a measurement accuracy between 1.4 -1.5 % slope.

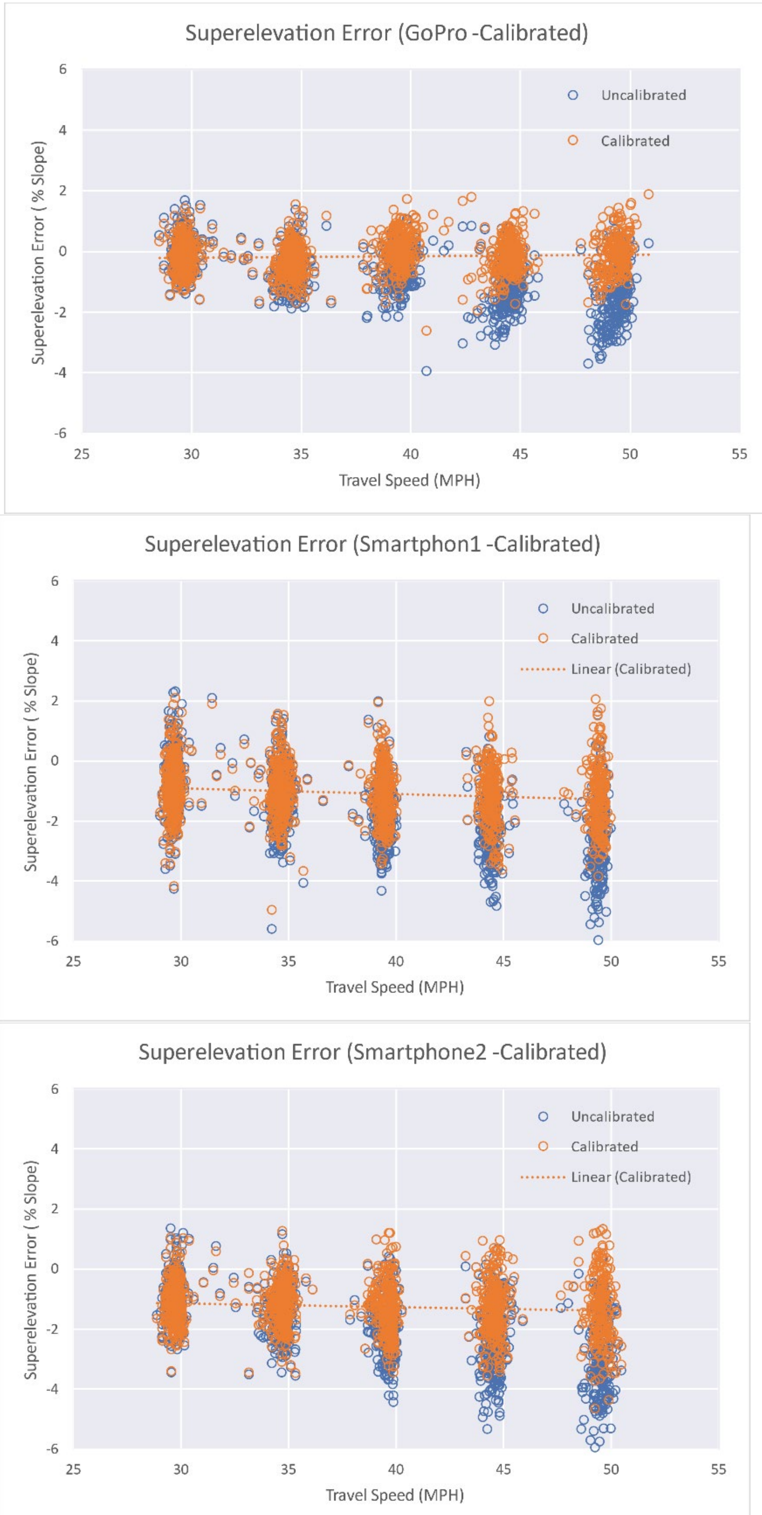

Figure 24. Charts. Calibrated superelevation error at different speeds.

Table 6. RMSE of Calibrated superelevation results.

	RMSE of Superelevation (GoPro)		RMSE of Superelevation (Smartphone 1)		RMSE of Superelevation (Smartphone 2)	
Driving Style	Good	Bad	Good	Bad	Good	Bad
30 MPH	0.522	0.695	1.226	1.366	1.318	1.501
35 MPH	0.622	0.820	1.368	1.629	1.322	1.441
40 MPH	0.576	0.638	1.434	1.615	1.532	1.808
45 MPH	0.619	0.758	1.473	1.590	1.599	1.524
50 MPH	0.652	1.509	1.556	2.181	1.729	2.490
Overall	**0.598**	**0.884**	**1.411**	**1.676**	**1.500**	**1.753**

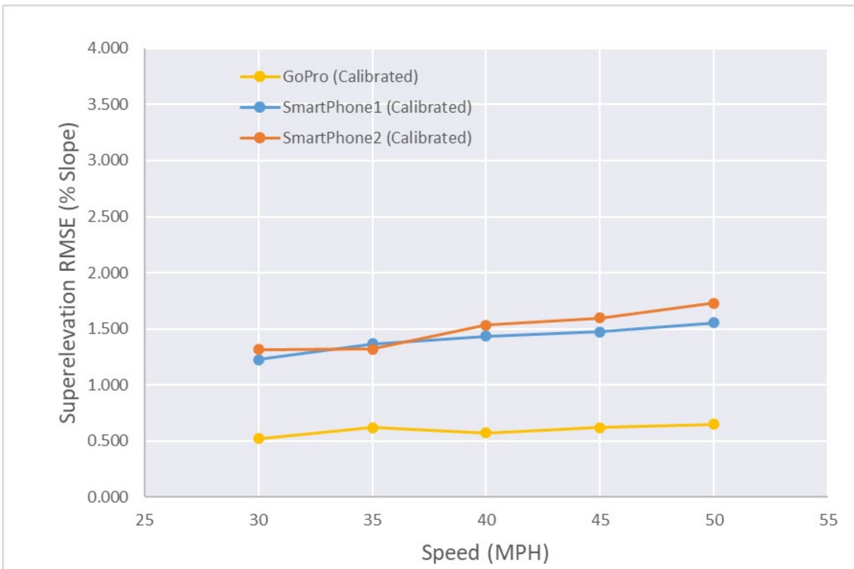

Figure 25. Chart. RMSE of Calibrated superelevation.

Validation Test Results – BBI Angle Computation

In order to assess the BBI angle measurement accuracy, the manually measured superelevation values were used to back-calculate the expected BBI angle based on the side-frication angle and the vehicle's body roll. Table 7 shows the RMSE of the BBI angle measured by each device. And the linear regression between measured and expected BBI angle is shown in Figure 26.

Table 7. RMSE of measured BBI angles compares to expected BBI angle computed from side-friction angles and vehicle body roll.

	GoPro	Smartphone 1	Smartphone 2	[1]Rieker Inclinometer
BBI RMSE (degree)	0.390	0.901	0.964	0.519

[1]Rieker inclinometer data collected at 30 and 50 MPH was not included due to data corruption.

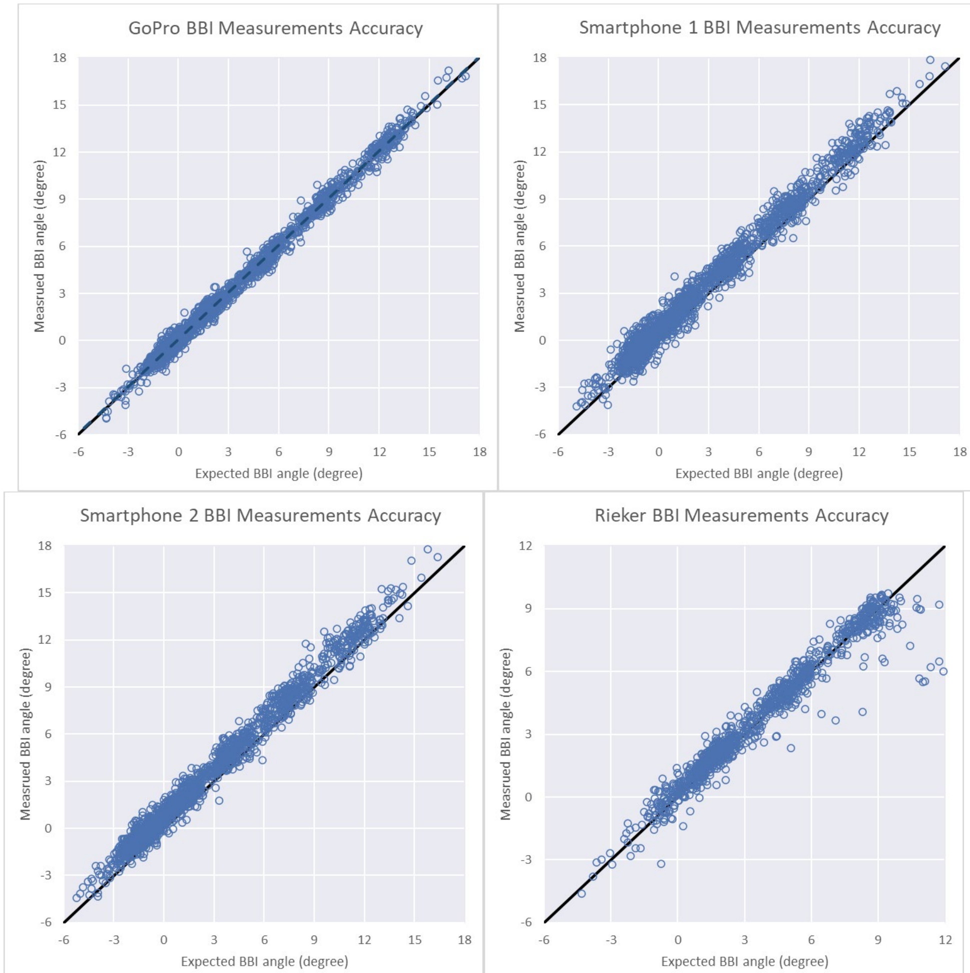

Figure 26. Charts. Linear regression between BBI angles measured using different devices and expected BBI angles.

It is worth noting that since the expected BBI angle is back-calculated from side-friction angles, the accuracy of the side-friction angle, which is dependent on the measured superelevation, vehicle speed, and path radius estimation, will affect the expected BBI angle. Therefore, the RMSE values presented in the table do not represent the BBI measurement error by itself. However, since the true BBI angle at every moment of data collection is difficult to obtain, the RMSE values presented are a good general indication of the BBI measurement accuracy.

Validation Test Results – Advisory Speed Computation

Table 8 shows the advisory speed results using the proposed method. From the manually measured superelevation, the exact advisory speed on the test track curves should be 49.7 MPH. The validation results show that, without calibration, as the superelevation is underestimated, the determined advisory speed decreases as data collection speed increases; however, the advisory speed difference between the lowest data collection speed and the highest data collection is less than 2 MPH.

After calibration, the superelevation is no longer being underestimated at high speed. The advisory speed results are very consistent at different speeds. The variation of the advisory speed across all data collection speeds is less than 1 MPH. Compared to the advisory speed computed from manually measured superelevation, the advisory speed results from the GoPro showed less than 0.5 MPH difference (underestimation), and the smartphones showed less than 1.3 MPH difference (underestimation).

Table 8. Advisory speed results before and after calibration.

Before Calibration						
	GoPro		**Smartphone 1**		**Smartphone 2**	
Driving Speed	**Average Adv. Speed**	**Standard Deviation**	**Average Adv. Speed**	**Standard Deviation**	**Average Adv. Speed**	**Standard Deviation**
30 MPH	49.618	0.197	48.545	0.285	48.791	0.323
35 MPH	49.266	0.231	47.986	0.748	48.692	0.181
40 MPH	49.066	0.333	47.870	0.070	47.890	0.237
45 MPH	48.339	0.404	47.674	0.320	47.591	0.408
50 MPH	48.095	0.408	46.892	0.431	46.690	0.393
Overall	**48.877**	**0.670**	**47.794**	**0.643**	**47.931**	**0.830**
After Calibration						
	GoPro		**Smartphone 1**		**Smartphone 2**	
Driving Speed	**Average Adv. Speed**	**Standard Deviation**	**Average Adv. Speed**	**Standard Deviation**	**Average Adv. Speed**	**Standard Deviation**
30 MPH	49.635	0.177	48.588	0.278	48.852	0.300
35 MPH	49.616	0.220	48.405	0.679	49.077	0.196
40 MPH	49.782	0.319	48.692	0.066	48.749	0.262
45 MPH	49.466	0.435	48.862	0.256	48.866	0.373
50 MPH	49.621	0.373	48.620	0.396	48.412	0.380
Overall	**49.624**	**0.324**	**48.633**	**0.412**	**48.791**	**0.340**

Sensitivity of Advisory Speed Results and Tolerance for Computation Error

Because the curves at the NCAT test track only have one curve geometry, a mathematical sensitivity study was conducted to determine the tolerance for error for curves with different geometry. Since the advisory speeds are typically rounded down to the closest 5 MPH, the error tolerances presented in Table 9 show the amount of error allowed in each factor that will not change the final computed advisory speed.

Table 9. Error tolerance for the computed data items

Factor	**Most Sensitive When…**	**Error Tolerance**	**Least Sensitive When…**	**Error Tolerance**
BBI angle	Large Radius, Low Speed	1 degree	Small Radius, High Speed	6 degrees
Superelevation	Large Radius	3%	Small Radius	8%
Curve Radius	Low BBI, Low Speed	150 ft	High BBI, High Speed	350 ft

As shown in the table, the sensitivity of each factor depends on the curve geometry and data collection characteristics. For accurate results in all cases, the BBI should be precise within 1 degree, the superelevation should be precise within 3%, and the curve radius should be precise within 150 ft. From the validation results presented in this section, we can conclude that the accuracy of the computed BBI angle, superelevation, and curve radius is within the error tolerance.

Validation Summary

The validation test presented in this section showed that using vehicle roll rate in superelevation calculation can dramatically reduce the error caused by different data collection speeds. It also shows that the proposed calibration method can estimate the vehicle's roll rate to compensate in superelevation calculation. The superelevation results before calibration showed an overall RMSE of about 1.0 % slope for the GoPro camera, and about 2.0 – 2.2 % slope for the smartphones. The superelevation error before calibration increases as driving speed increases, the superelevation RMSE at 50 MPH for the GoPro camera is about 1.8 % slope, and 3.2 % slope for the smartphones. After calibration, the superelevation error introduced by the driving speed is almost completely eliminated, resulting in an overall RMSE of about 0.6 % slope for the GoPro camera, and about 1.4 – 1.5 % slope for the smartphones. The BBI angle validation showed the GoPro camera (RMSE = 0.39 degrees) can estimate the BBI angle accurately enough to be comparable to commercial BBI devices (RMSE = 0.52 degrees), while the smartphones have an RMSE of 0.9 – 0.96 degrees, slightly worse than commercial devices but accurate enough for advisory speed determination. Finally, the advisory speed results show that the determined advisory speeds are very close to the advisory speed computed using measured superelevation, having a difference of less than 3 MPH before calibration and about 1 MPH after calibration.

Case Study

This section presents a preliminary case study using five runs of smartphone data collected on Georgia State Route 17 in September 2020, November 2020, and March 2021. The case study demonstrates the use of the proposed method using smartphones to perform curve safety assessments. The purpose of this case study is to demonstrate the feasibility of using the proposed method to derive the curve radius, BBI, superelevation, and advisory speed using smartphones. Furthermore, the case study provides an assessment of the confidence level of the outcomes. In addition, the smartphone and Rieker device were both mounted in the same vehicle, simultaneously to collect data for comparison. This is to compare the outcomes derived using the proposed method to those of the current, commonly used current assessment method, which uses dedicated Rieker devices.

Feasibility Study of The Proposed Method Using Smart Phone Data Collected on Georgia State Route 17

The purpose of this case study is to assess and demonstrate the feasibility of using the proposed method to derive the curve radius, BBI, superelevation, and advisory speed using smartphones and the smartphone data collected on Georgia State Route (SR) 17.

Data Collection

After discussing the best locations to test the proposed method with traffic engineers in the Georgia Department of Transportation (GDOT), SR 17 was chosen as the best location on which to perform this feasibility study because of the curvy nature of SR 17 and the frequency of crashes on the road. Figure 27 shows a map of the SR 17 test sites chosen for data collection with a close view of five curve sections that were used for the detailed data processing and analysis in our feasibility study. The selected portion of SR 17 is a two-lane, undivided rural minor arterial road with occasional painted/striped medians. This portion of SR 17 is mountainous and has many curves.

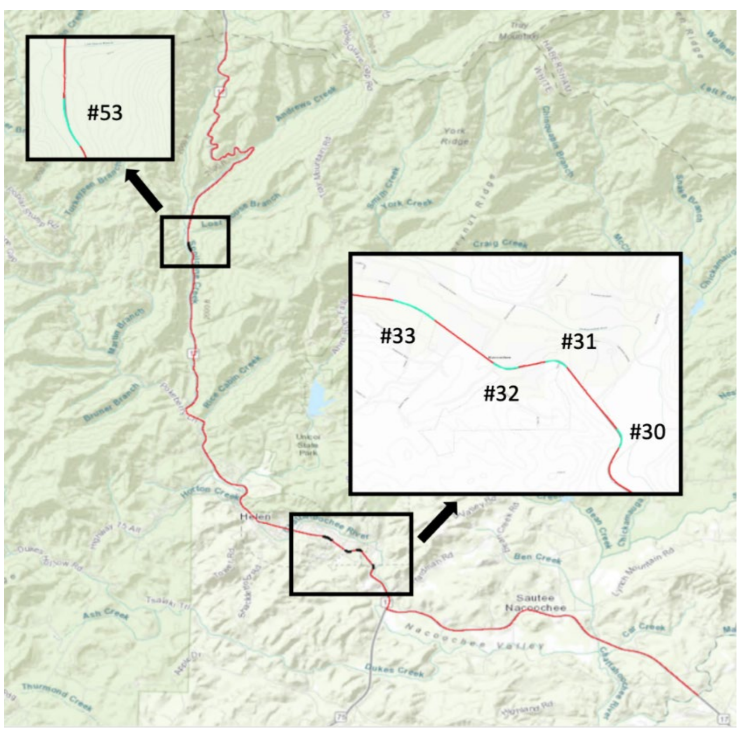

Figure 27. Map. State Route 17 in Georgia (mountain area) and selected curves.

The field data collection using smartphones was conducted with five runs in each direction. Data collection was carried out September 23, 2020, with GDOT Ford F150; November 11, 2020, with a Ford Fusion; November 4, 2020, with a GDOT Ford F150; November 6, 2020, using a GDOT Ford F150; and March 25, 2021, with GDOT Ford F150. Five runs in each direction were made in sunny weather conditions on each date. Each vehicle was equipped with one smartphone for data collection. Figure 28(a) shows the GDOT truck. Figure 28(b) shows a smartphone used for testing. The phone is a regular Android smartphone and the same smartphone is used in all field data collection. The smartphone data collected includes 1) timestamp, 2) speed, 3) GPS data, and 4) IMU data.

A. Subfigure showing the GDOT truck used for data collection

B. Subfigure showing the smart phone used for data collection

Figure 28. Photos. GDOT truck and smartphone used for field data collection.

Data Processing

The collected smartphone data, including timestamp, speed, GPS data, and IMU data, were processed for each of the five single runs, respectively. Since the detailed description of the data processing is provided in the proposed method and validation sections, it will not be duplicated in this section. The subsequent section presents the data analysis.

Data Analysis

The data collected using smartphones were processed to find the curve radius, BBI, superelevation, and advisory speed at each point. Using the five runs of data, it is possible to also assess the inherent variability of the outcomes using smartphone data. Table 10 presents the location and geometry of the five curves tested. Table 11 shows the range of radius, BBI, superelevation, and computed advisory speed for each curve. The BBI and superelevation values refer to those at the point of minimum computed advisory speed.

Table 10. Characteristics of the five curves tested on SR 17.

Curve ID	Latitude	Longitude	Radius (ft)	Length (ft)
30	34.69346272	-83.71341549	287	386
31	34.69683579	-83.71588127	222	320
32	34.69679324	-83.71802552	350	430
33	34.69904781	-83.72191988	1135	733
53	34.75750134	-83.75033975	921	575

Table 11. Variability of curve characteristics estimated using smartphone.

Northbound						
Curve ID	**Radius (ft)**	**BBI (degrees)**	**Superelevation (%)**	**Advisory Speed (MPH)**	**Posted Speed Limit (MPH)**	**Final Advisory Speed (MPH)**
30	192 – 239	0.10 – 5.70	2.72 – 5.49	32.13 – 33.94	55	30
31	181 – 192	0.16 – 1.68	4.79 – 7.52	29.44 – 30.94	55	30
32	255 – 280	2.86 – 12.98	0.05 – 1.55	33.46 – 33.75	55	30
33	844 – 981	0.23 – 1.45	3.73 – 5.52	65.22 – 66.64	55	None
53	563 – 780	0.23 – 3.97	0.15 – 4.74	54.40 – 59.95	55	None
Southbound						
Curve ID	**Radius (ft)**	**BBI (degrees)**	**Superelevation (%)**	**Advisory Speed (MPH)**	**Posted Speed Limit (MPH)**	**Final Advisory Speed (MPH)**
30	192 – 229	3.51 – 7.14	0.57 – 2.47	30.66 – 31.96	55	30
31	154 – 199	1.81 – 5.84	1.92 – 6.78	27.77 – 30.54	55	30
32	280 – 317	0.71 – 4.56	0.01 – 11.10	33.42 – 35.03	55	35
33	812 – 975	0.32 – 1.61	2.57 – 5.72	62.16 – 67.76	55	None
53	650 – 826	2.76 – 6.88	0.17 – 0.80	54.42 – 55.22	55	None

Using five sample curves on SR 17, it was found that the average variability of measurements between runs of the data collection is approximately 49 feet for the radius, 8 degrees for the BBI, 5% for the superelevation, and 2 MPH for the computed advisory speed. Table 11 and Table 12 list the range of the estimated radius, measured BBI, estimated superelevation, and computed advisory speed values of the five runs of data for the five selected curves in the Northbound and Southbound directions, respectively. The results show that there is a high level of consistency in the advisory speed computation among the five runs of smart phone data, which means there is a high confidence in the outcomes.

For the advisory speed computation, the standard practice is to add 1 MPH and then round down the raw computed result to the nearest multiple of 5 MPH for advisory speed plaque design. If all runs of the data collection yield the same rounded computed advisory speed, it indicates a very high confidence in that result. For the five sample curves studied on SR 17, each curve had ten total passes of smart phone data collection, five in each direction. The number of passes from each curve yielding the same advisory speed are shown in Table 12.

Table 12. Consistency of computed advisory speed from multiple runs.

Curve ID	Direction	Design Advisory Speed	Runs in Agreement
30	Northbound	30 MPH	5/5
	Southbound	30 MPH	5/5
31	Northbound	30 MPH	5/5
	Southbound	30 MPH	4/5
32	Northbound	30 MPH	5/5
	Southbound	30 MPH	4/5
33	Northbound	65 MPH	5/5
	Southbound	65 MPH	4/5
53	Northbound	55 MPH	4/5
	Southbound	55 MPH	5/5

This demonstrates a high level of repeatability in the outcomes of the proposed method using smart phones. It should be noted that due to the nature of the advisory speed rounding, two computations that are very close could give different advisory speeds (e.g., 29 would be rounded to 30 MPH while 28 would be rounded to 25 MPH). So, some variation in the final computed advisory speed is acceptable. If a curve has more than 5 MPH of variation between the computed advisory speeds from different runs, the result is significantly different enough that the data should be re-collected. In choosing the appropriate advisory speed for a curve, the highest computed advisory speed from the multiple runs should be selected because the highest computed advisory speed will be the closest to the true roadway conditions. The computation can be skewed unnaturally low through erratic driver behavior (changing speeds, jerking the wheel, failing to follow the road trajectory, etc.). On the contrary, there is no way to unnaturally increase the computed advisory speed through human error, so the highest result should most closely estimate the true value. The analysis of five curves on SR 17 demonstrates that the proposed method using smartphones is feasible to compute the curve radius, BBI, superelevation, and advisory speed.

Comparison of Outcomes Using the Proposed Method Using Smart Phones and The Method Using Rieker Devices

As most transportation agencies are currently using the method that uses dedicated Rieker devices, the research project compares the outcomes of the proposed method (that uses smartphones) and the current commonly used method (that uses dedicated Rieker devices). One vehicle, equipped with both a smartphone and a RIEKER device, collected data on March 11, 2021, for comparing the performance between the proposed method and the method with RIEKER devices.

Table 13 below compare the computed advisory speed output from each method. As shown, for these five sample curves, the proposed method and the Rieker method produce results within 6 MPH of one another. Thus, these two methods are comparable.

Table 13. Computed advisory speed comparison.

Northbound			
Curve ID	**Source**	**Advisory Speed (MPH)**	**Posted Speed Limit (MPH)**
30	Smart Phone	32.7	55
	Rieker	30.4	55
31	Smart Phone	30.5	55
	Rieker	25.9	55
32	Smart Phone	33.5	55
	Rieker	34.5	55
33	Smart Phone	65.7	55
	Rieker	60.1	55
53	Smart Phone	55.3	55
	Rieker	56.9	55
Southbound			
Curve ID	**Source**	**Advisory Speed (MPH)**	**Posted Speed Limit (MPH)**
30	Smart Phone	32.0	55
	Rieker	30.8	55
31	Smart Phone	30.5	55
	Rieker	29.2	55
32	Smart Phone	33.9	55
	Rieker	34.0	55
33	Smart Phone	67.8	55
	Rieker	64.1	55
53	Smart Phone	54.4	55
	Rieker	50.2	55

The smartphone data and Rieker data can also be compared in terms of repeatability. The repeatability of the computed advisory speed is important because it determines the overall confidence in the outcome. For the aforementioned five sample curves, the standard deviation of the computed advisory speed between the multiple runs of data collection was computed. It was found that the standard deviation of the computed advisory speed derived from the smartphone data is 0.89 MPH, and the standard deviation of the computed advisory speed derived from the Rieker data is 1.59 MPH. Thus, the advisory speed computation using the proposed method is more consistent.

Case Study Summary

This section demonstrates the feasibility of implementing the proposed method, which uses smartphone data to perform curve safety assessments. This is demonstrated through a case study of 5 curves on State Route 17 with 5 runs of data collection performed on each curve. The results are compared to the outcomes from the commonly used RIEKER data. The preliminary case study shows that the proposed method, which uses smartphones, has promising results and outcomes comparable to the RIEKER method. A large dataset with diverse curve characteristics is recommended for future research. It should also be noted that since the new calibration procedure cannot be applied in the RIEKER processing method, the new calibration procedure was not applied to the smartphone data used in this case study in order to keep the comparison fair.

PLAN FOR IMPLEMENTATION

The validation and preliminary study results of the developed proposed method have shown promising outcomes. The developed method will enable state DOTs to cost-effectively identify safety issues and target curves in days and weeks instead of years to save lives. The proposed method and technology will save significant costs and time for transportation agencies. These achievements highlight the interest in this technology expressed by both state and local transportation agencies (such as the Georgia DOT, Mississippi DOT, and the city of Nashville, Tennessee). Georgia DOT, a key stakeholder, is the first tester of the developed method, potentially leading a nationwide pre-standardization effort. After the successful development of the proposed method and technology, the next step is the implementation of the proposed method. Three phases are needed in the implementation plan.

The first phase is to continually evaluate and refine the proposed method. In addition to the validation test performed on the NCAT test track, the research team will collaborate with transportation agencies to further evaluate the accuracy of superelevation measurement and the feasibility of performing calibration procedures in the field on selected real-world roadways that have diverse in-service curve characteristics, including radius, superelevation, etc. The results from the evaluation will be used to refine the proposed method and to compare with the results from the current, commonly used method, which uses Rieker devices. A Rieker device is a commercial device used by many DOTs to collect curve BBI values and determine curve advisory speed.

The second phase is to perform a pilot study to explore the optimal and implementable data management plan, which includes data transfer, data management, and data storage, to ensure the proposed method is scalable. Although the data is manageable for days using an individual smartphone, an optimal and implementable data management plan, including a data reduction strategy, is essential to manage the large quantity of data that will be collected daily or weekly for months from multiple users. Data and its management could, potentially, be an issue holding back state DOTs' implementation of the proposed method and technology.

The third phase is to perform a pilot study to explore the procedures to fit into agencies' routine business operations. Selected transportation agencies, including GDOT (one state DOT) and Nashville, Tennessee (one local transportation agency), will participate in the pilot study, as they have expressed strong interest in implementing the developed method and technology. The adaptation of the proposed method and technology will enable transportation agencies to identify roadway sections in need of safety improvement in a timely manner (days and weeks instead of years). However, coordination among different offices is required, and new business operations involve crowdsourcing field data collection, data transfer, development of a centralized database and data management system, and data analysis and decision-making among different offices. This could be an issue holding back state DOTs. Thus, it is required to explore and streamline current state DOT business operations that will need to be seamlessly aligned with the proposed method and technology. During this phase, the research team will work closely with transportation agencies' engineers to develop operating procedures that incorporate the proposed method into transportation agencies' day-to-day business operations, leveraging the state-owned vehicle fleet. In addition, the research team will be working with state agencies to produce a data management plan for the proposed method. The data management plan would include technologies for organizing and transferring field collected data and developing a centralized database and data hub. The development of the centralized hub would include optimized data storage that only stores data that will impact decision-making and safety assessment data analysis. This data would provide the entry point for state agencies to tap into all of the rich data collected at the network level, identify hotspots for curve safety improvements, and better support curve safety-related decision making.

Finally, for the proposed method to be integrated with current transportation business operations and implemented effectively, it is essential that the research team work with the selected transportation agencies to establish a safety-conscious culture and practices, recognizing that the proposed method is an enhanced method for time-sensitive safety assessment and improvement.

CONCLUSIONS

The objectives of this research project are to develop an enhanced curve safety assessment method that uses low-cost mobile devices and new computation methods to critically assess the feasibility of the proposed method for network-level curve safety condition assessment. The following are the conclusions for this research project:

1) A cost-effective method using low-cost mobile devices and an enhanced intra-agency, crowdsourced data collection, and computational framework has been developed to assist network-level curve safety condition assessment. The proposed data collection and computational framework consist of six modules: 1) mobile data collection, 2) mobile data registration and processing, 3) driving kinematics calculation, 4) curve geometry calculation, 5) advisory speed calculation, and 6) curve warning sign design. Key data items computed and acquired using the proposed method in this research project include BBI angles, curve radius, superelevation, and advisory speed. It can be extended to extract other data items in the future with this framework.
2) The proposed method achieves more accurate superelevation estimation by incorporating the vehicle's body roll angle, which is estimated from the vehicle's roll rate, in the calculation of superelevation. In addition, two calibration procedures are proposed to estimate the vehicle's roll rate and enhance superelevation computation accuracy.
3) A data collection application, "AllGather," was built for Android smartphones. "AllGather" is an advanced dashcam-like application that collects a driving video log, GPS data, IMU data, and driving speed.
4) The proposed method has been validated using the data collected on 1.7 miles of roadway at the NCAT test track. Using the data collected by mobile devices, this validation evaluated the feasibility of using the proposed method to compute curve safety assessment-related data items. Results show that the proposed method can achieve accurate results for computing superelevation, curve radius, BBI angle, and curve advisory speed.
    a) With the application of the proposed, enhanced superelevation computation method, the superelevation results from smartphones can consistently achieve an RMSE of 1.4 – 1.5 % slope at different data collection speeds. Without applying the enhanced super-elevation computation method, the RMSE value is 3.2 % slope at high speed. The advisory speed result is about 1 MPH off from the advisory determined from the manually measured superelevation (our ground reference). Thus, the outcome is very promising.
    b) The validation of our advisory speed computation method shows that there is less than a 5-MPH difference between our proposed method and current methods that commonly use Rieker devices. With the advisory speed typically rounded down to the nearest 5 MPH, the proposed method is acceptable and is very promising because it uses low-cost smartphones; it will be much more scalable and impactful in future implementation.
5) With the application of the proposed, enhanced superelevation computation method, the superelevation results from smartphones can consistently achieve an RMSE of 1.4 – 1.5 % slope at different data collection speeds. Without applying the enhanced super-elevation computation method, the RMSE value is 3.2 % slope at high speed. The advisory speed result is about 1 MPH off from the advisory determined from the manually measured superelevation (our ground reference). Thus, the outcome is very promising.

The proposed method has been developed, and the preliminary study has shown the outcomes are promising. The technology method, which uses enhanced computation methods, will enable state DOTs to identify safety issues and target curves in days and weeks instead of years.

1) **Further test and refine the proposed method on roadways with diverse in-service curve characteristic.** It is recommended to further evaluate the accuracy of superelevation measurement and the feasibility of performing calibration procedures in the field on selected real-world roadways that have diverse in-service curve characteristics, including radius, superelevation, etc. The results from the proposed method will also be compared with the results from the current, commonly used method, which uses Rieker devices. A Rieker device is a commercial device used by many DOTs to collect curve BBI values and determine curve advisory speed.

2) **Perform a pilot study that includes both state and local transportation agencies**. It is recommended to include both state and local transportation agencies (one state and one local transportation agency) in a pilot study that implements the proposed technology, gathers feedback, and streamlines the operation. The feedback will be used to produce a comprehensive package that focuses on the usability and scalability of the proposed technology. Since local transportation agencies typically have limited resources, the proposed technology would be very beneficial because it effectively improves roadway safety assessment by using low-cost data collection devices.

3) **Develop an implementable data management plan.** It is recommended to develop an optimal and implementable data management plan. Because the amount of data collected will grow with the scale of implementation, a data management plan and system should be in place to handle data collection, data transfer, data processing, and data storage. This would ensure the scalability of the proposed technology and enable large-scale implementation. The data management plan includes but is not limited to the following:

    a) **Field data collection**. Record and organize data collected in the field by state DOT owned vehicles during day-to-day business operation.

    b) **Data transfer**. Provide infrastructure and procedures for handling data transfer from data collection vehicles to transportation agency offices.

    c) **Data storage**. Provide a centralized hub for data storage, support data transfer from data collection vehicles, and provide data access for analysts or analysis software.

    d) **Data reduction plan**. Provide a plan for data reduction to save data storage space; for example, keep only the data collected on curves that show safety concerns, and remove other raw data collected.

4) **Streamline operation procedures to fit into agencies' routine business operations.** It is recommended to work closely with transportation agencies to explore ways to implement the proposed method and technology in transportation agencies' daily business operations. This involves the business operations among different offices, including the following:
    (a) field data collection (including what data to collect, who collects the data, like maintenance or traffic operation engineers, and a data collection mechanism and tools),
    (b) data transfer (using 5G real-time upload or using the local office for data transfer, and data transfer functions and tools),
    (c) data storage (including the database design and the data to be stored; only the roadway sections with safety improvement needs should be stored; managed by IT and transportation data offices),

(d) analysis and decision-making (store only the analyzed data with inadequate advisory speed; remove the remaining data; provide output reporting with tables and mapping so users can use the outcomes to make a decision; managed by traffic operations offices);
(e) leverage existing business operations, including transportation agencies' existing fleets and routine field surveys to collect data.

5) **Explore mobile devices for large-scale implementation.** It is recommended to further evaluate the cost, performance, and practicality of other types of mobile devices for data collection. Cost, performance, and practicality may hinder the successful implementation of any new technology. Sensor technology is advancing very quickly, so to maximize the potential for implementing the proposed method on a large, it is recommended that hardware alternatives to smartphones be explored.

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APPENDIX A. RESEARCH RESULTS

An Enhanced Network-Level Curve Safety Assessment and Monitoring Using Mobile Devices

This project proposed an enhanced method for performing network-level curve safety analysis and assessment using low-cost mobile devices.

Program Steering Committee:
NCHRP IDEA Program Committee
Project Number: NCHRP-IDEA/207
Start Date: November, 15, 2018
Completion Date: November, 14, 2021
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WHAT WAS THE NEED?

A disproportionally high number of serious vehicle crashes (25% of fatal crashes) occur on horizontal curves, even though curves represent only a fraction of the roadway network (5% of highway miles). This is a high-priority problem that has great interest among transportation agencies. The in-service curve characteristics information, including curve radius, superelevation, and Ball Bank Indicator (BBI) angles are extremely important for setting up adequate advisory speeds and for performing curve safety assessment and analysis. However, current transportation agencies' practices (using dedicated devices operated by designated engineers) are labor-intensive, time-consuming, and costly. Thus, there is an urgent need for developing a cost-effective method to identify the curves at the network level that need to reassess existing advisory speeds or apply surface treatments, e.g., HFST.

WHAT WAS OUR GOAL?

The objectives of this research project are 1) to develop an enhanced network curve safety assessment method that uses low-cost mobile devices and new computation methods and 2) to critically assess the feasibility of the proposed method for network-level curve safety condition assessment. The proposed method enables transportation agencies to perform preliminary screening for cost-effectively identifying targeted sites for detailed safety investigation and improvement.

WHAT DID WE DO?

An Android application, AllGather, was developed for data collection using low-cost mobile devices. The data collected includes Global Position System (GPS) trajectory, vehicle speed, Initial Measurement Unit (IMU) data, and on-board video recording. This data is used in the computational framework. The proposed data collection and computation framework consists of the following six modules: 1) mobile data collection, 2) mobile data registration and processing, 3) driving kinematics calculation, 4) curve geometry calculation, 5) advisory speed calculation, and 6) curve warning sign design.

Figure 1: Developed AllGather app for low-cost data collection.

The calculations of the required data items for curve safety assessment are based on the kinematic relationship between the vehicle's cornering behavior and curve geometry. This project proposes an improved method to measure superelevation using smartphone data by accounting for the vehicle's body roll angle in the superelevation calculation. The calibration methods are proposed to calculate the vehicle's body roll angle using the collected data.

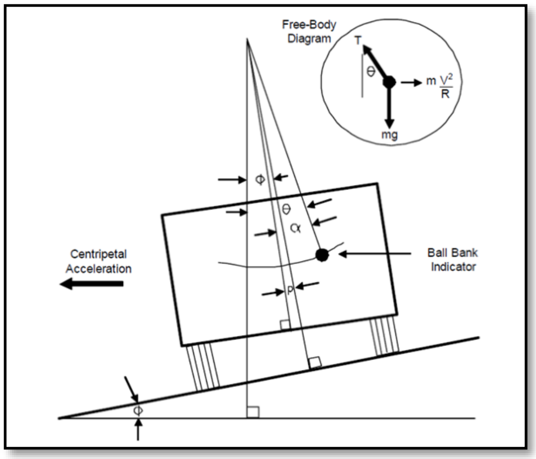

Figure 2: Interaction between BBI and superelevation, lateral acceleration, and vehicle body roll.

WHAT WAS THE OUTCOME?

To validate the proposed data collection and computational framework, a validation test was performed at the National Center for Asphalt Technology (NCAT) test track to evaluate the performance of the framework. NCAT is an ideal test location since it is a controlled site, and the true curve geometry can be measured or obtained from design drawings. Multiple superelevation measurements were taken from the NCAT test track to use as ground references. The test results show that, without using the calibration methods to estimate the vehicle's roll rate, superelevation measurement accuracy continuously decreases with increasing speed, up to an RMSE of 3.2 % slope at high speed. The results after calibration show that using the proposed method, the superelevation results from smartphones can consistently achieve an RMSE of 1.4 – 1.5 % slope at different data collection speeds. The validation test also shows that with a good quality centerline, the estimated curve radius is very close to the curve radius from the curve design drawings. In summary, the advisory speed computed for the NCAT test track using the proposed method, with calibration, is only 1 MPH off from the advisory speed determined from the manually measured superelevation.

Figure 3: Validation test performed at NCAT.

A preliminary case study was conducted using five runs of smartphone data collected on Georgia SR 17 (5 curves) to demonstrate the use of the proposed method for curve safety assessment. Based on the results, the proposed method shows very little variability between multiple runs of data collection, indicating a high degree of repeatability. In most cases, the five runs of data collection result in the same final computed advisory speed. The proposed method also yields results that are comparable to those found using the commonly-used Rieker device, further demonstrating the feasibility of this approach.

WHAT IS THE BENEFIT?

This project developed and validated an enhanced method that can productively and cost-effectively collect and analyze data for assessing roadway curve safety at the network level or that can perform BBI computation, super-elevation computation, and advisory speed determination. The outcome of this project could help address the high-priority need for state highway agencies to reduce the number of crashes on curves and enhance the current network-level curve safety assessment practice.

LEARN MORE

To learn more, find the final project report at: http://www.trb.org/Publications/PubsIDEAHighwayFinalReports.aspx.

APPENDIX B. MANUAL SUPERELEVATION MEASUREMENTS ON THE NCAT TEST TRACK

East Curve – North Part						
Location	**Distance from Mid-point (ft)**	**Track Station (ft)**	**Superelevation Measurement #1**	**Superelevation Measurement #2**	**Superelevation Measurement #3**	**Average Measurement**
Mid-Point	**0**	**110+00.00**	14.2	14.4	14.1	14.2
	200	**112+00.00**	14.2	14.6	14.2	14.3
	400	**114+00.00**	15.6	14.9	15.1	15.2
CS Point	**543.7**	**115+43.70**	13.8	13.8	13.8	13.8
	600	**116+00.00**	12.0	12.4	12.2	12.2
	700	**117+00.00**	8.6	8.6	8.6	8.6
	800	**118+00.00**	5.7	5.6	5.6	5.6
	900	**119+00.00**	1.7	1.7	1.5	1.6
ST Point	**951.7**	**119+51.70**	2.8	2.7	2.7	2.7
Tangent	**1000**	**120+00.00**	2.8	2.5	2.7	2.7
Tangent	**1100**	**121+00.00**	2.2	2.0	2.0	2.1

East Curve – South Part						
Location	**Distance from Mid-point (ft)**	**Track Station (ft)**	**Superelevation Measurement #1**	**Superelevation Measurement #2**	**Superelevation Measurement #3**	**Average Measurement**
	200	**12+00.00**	15.8	15.7	15.9	15.8
	400	**14+00.00**	15.6	15.6	15.8	15.7
CS Point	**543.7**	**15+43.70**	14.7	15.0	14.9	14.9
	600	**16+00.00**	13.1	13.0	12.9	13.0
	700	**17+00.00**	8.6	8.8	8.7	8.7
	800	**18+00.00**	5.1	5.1	5.1	5.1
	900	**19+00.00**	3.0	2.6	3.0	2.9
ST Point	**951.7**	**19+51.70**	2.1	2.3	1.9	2.1
Tangent	**1000**	**20+00.00**	0.0	0.0	0.1	0.0
Tangent	**1100**	**21+00.00**	2.6	2.6	2.7	2.6

West Curve – North Part						
Location	**Distance from Mid-point (ft)**	**Track Station (ft)**	**Superelevation Measurement #1**	**Superelevation Measurement #2**	**Superelevation Measurement #3**	**Average Measurement**
Mid-Point	**0**	**155+03.41**	14.3	14.4	14.2	14.3
	200	**153+03.41**	15.1	15.4	15.3	15.3
	400	**151+03.41**	14.1	14.1	14.2	14.1
CS Point	**543.7**	**149+59.71**	13.9	13.9	13.8	13.9
	600	**149+03.41**	12.7	12.9	12.7	12.8
	700	**148+03.41**	8.7	8.7	8.8	8.7
	800	**147+03.41**	6.2	6.2	6.2	6.2
	900	**146+03.41**	3.4	3.6	3.8	3.6
ST Point	**951.7**	**145+51.71**	2.8	2.7	2.7	2.7
Tangent	**1000**	**145+03.41**	1.8	1.9	1.8	2.0
Tangent	**1100**	**144+03.41**	2.2	2.3	2.1	2.2

West Curve – South Part						
Location	**Distance from Mid-point (ft)**	**Track Station (ft)**	**Superelevation Measurement #1**	**Superelevation Measurement #2**	**Superelevation Measurement #3**	**Average Measurement**
	200	**53+03.41**	16.0	15.9	16.1	16.0
	400	**51+03.41**	15.8	16.1	16.1	16.0
CS Point	**543.7**	**49+59.71**	14.8	14.7	14.5	14.7
	600	**49+03.41**	12.6	12.6	12.7	12.6
	700	**48+03.41**	8.0	7.9	7.9	7.9
	800	**47+03.41**	5.1	5.1	5.0	5.1
	900	**46+03.41**	3.8	4.0	4.0	3.9
ST Point	**951.7**	**45+51.71**	2.7	2.3	2.9	2.6
Tangent	**1000**	**45+03.41**	2.0	2.1	2.1	2.1
Tangent	**1100**	**44+03.41**	2.0	2.0	2.1	2.0

CS = **Curve to Spiral**
ST = **Spiral to Tangent**