A Dynamically-Concise Roadmap Framework for Guiding Connected and Automated Vehicles

Ricardo O. Jacome[1]
Midwest Roadside Safety Facility
University of Nebraska-Lincoln
Lincoln, Nebraska, USA
rjacome@huskers.unl.edu

Cody Stolle
Midwest Roadside Safety Facility
University of Nebraska-Lincoln
Lincoln, Nebraska, USA
cstolle2@unl.edu

Ronald K. Faller
Midwest Roadside Safety Facility
University of Nebraska-Lincoln
Lincoln, Nebraska, USA
rfaller1@unl.edu

George Grispos
School of Interdisciplinary Informatics
University of Nebraska-Omaha
Omaha, Nebraska, USA
ggrispos@unomaha.edu

***Abstract*— A new map framework is proposed to improve the guidance and trajectory prediction capabilities of connected and automated vehicles (CAVs), even in challenging conditions of low visibility and adverse environmental effects. Based on the fusion of vehicle dynamics and road design standards, the map framework provides a consolidated collection of critical reference points of roadways, such as centerlines and information about the shape of the roadway in the vicinity of a vehicle, including curvature and road alignment angle. Roads are discretized using reference points, and simple parameters are used to connect adjacent segments representing the road shape. Additional data can be appended to the map, including elevation and roadside slope data, variable speed limits, and lane controls.**

***Keywords*—Connected and Automated Vehicles, Curvature, Framework, Vehicle Dynamics, Street Design**

I. Introduction

Full vehicle autonomy is one of the most coveted achievements in contemporary transportation research. These "intelligent" vehicles fall under a broad class of Connected and Automated Vehicles (CAVs) with an ultimate goal of providing destination travel without any driver input other than starting and final locations. Ongoing efforts provide incremental improvements on safety and functionality until full autonomy is achieved. According to National Highway Traffic Safety Administration (NHTSA), on-vehicle Advanced Driver Assistance Systems (ADAS) contributed to reductions in annual crashes and prevention of serious injuries since their introduction in production vehicles [1], and existing technologies are often utilized in newer systems to further expand their benefits. For example, anti-lock brake systems (ABS) improved vehicle control by increasing the average tire-pavement friction coefficient during braking [2]. ABS systems became a significant component contributing to Electronic Stability Control, which resists out-of-control vehicle trajectories and the associated risk of rollovers [3], as well as lane departure warning and automated crash prediction and mitigation (pre-crash braking) systems [4][5].

Evolving from ADAS, CAVs added communications with the environment as part of an Internet-of-Things (IoT) approach. CAVs aim to be the state-of-the-art technology for the foreseeable future and could lead to a renaissance of transportation-related opportunities: Transportation-as-a-Service (TaaS), automated shipping; convenient carpooling or ride-shares; and automated tour industry. The United States Department of Transportation (DOT) has developed programs to promote traffic optimization with CAVs, with partnering agencies including NYCDOT, THEA, VDOT, the Connected Vehicle Pooled Fund, and WYDOT [6]. For example, the THEA project relies on providing CAVs with information such as Wrong Way Entries, or End of Ramp Deceleration Warnings [7]. This pilot system is currently restricted to urban areas and exclusively provides in-vehicle driver warnings. For highway projects, WYDOT utilizes Roadside Units (RSUs) to provide properly-equipped CAVs with information about the current weather (i.e. snow weather warnings), for primarily cargo vehicles and trucks [8][9].

Several approaches have resolved very difficult vehicle navigation challenges, including automated parking assistance [10][11] and lane navigation during passing maneuvers [12]. Multiple urban-navigation efforts have culminated in solutions; the Defense Advanced Research Projects Agency (DARPA) Grand Challenge for automated driving in 2004, 2006, and 2007 led to many of the principal concepts for automated vehicle guidance frameworks, some of which are still utilized today. For example, "Boss", the Chevrolet Tahoe vehicle which ultimately won the DARPA challenge, utilized fundamental vehicle dynamics principles, extracted lane curvature from optical measurements, estimated occupied space from moving and stationary objects, and adjusted the trajectory to follow routes in real time up to 48 km/h [13]. Numerous studies have been conducted evaluating improvements to similar computer vision-based feature navigation, most recently equipped with dynamic artificial intelligence and deep learning [12][14][15]. However, using the attributes and criteria described by the Society of Automotive Engineers (SAE) J3016 "Levels of Driving Automation" [16], few vehicles have been able to accomplish a fully "Level 4" automation [17]. Some are publicly questioning if it is still impractical with current technological limitations to achieve full vehicle autonomy [18]. If such a vehicle were to be developed, it may require a different operational framework than has currently been implemented.

Researchers at the University of Nebraska Lincoln (UNL) have proposed a new framework for CAV guidance based on a mathematically-compact and dynamically-consistent map formulation as an enhancement for existing road map and localization approaches. The proposed map formulation integrates preferred travel corridors, reference vector

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definitions for curvature and heading, and updatable fields including elevation, variable speed limit, and options for additional expansion fields. The map framework is intended to improve navigation information with remote management of some road parameters from DOT control locations and to complement existing technologies for a more robust vehicle guidance solution. The purpose of this paper is to review existing map frameworks and develop the foundations of the new proposed map framework.

II. Review of Transportation Guidance Frameworks

A. Machine-Driven Guidance Systems

Most existing ADAS guidance frameworks follow a data-processing scheme similar to Fig. 1 [19]. These strategies are a combination of five multi-layered sections, which for the purposes of this paper, will be assumed to occur in a sequential order: (1) *Sensors* receive data from the environment (e.g., image recognition, positional data) [15][20]; (2) *State estimation* identifies the location of the vehicle (and its parameters) in reference to the data obtained from sensors [21][22]; (3) *Local planning* identifies the geometrical and dynamic constraints on all possible vehicle actions (denoted in this paper as workable space, i.e., street) [23][24][25]; (4) *Trajectory Generation* predicts trajectory paths of the vehicle (e.g., clothoid paths, polynomials) based on vehicle controls and physics constraints (e.g., kinodynamic constraints). The name comes from determining which trajectories (inside of the workable space) are possible for the vehicle to perform, based on its current state [26][27]; (5) *Controllers* implement vehicle controls using data from the Trajectory Generation phase (e.g., throttling, braking, steering, or disengaging the automatic mode), which are decided by different control theory approaches that depend on the previously-established trajectories [28][29][30].

Each strategy has its own research field [31], but further exploration of the development of each component of the framework is beyond the scope of this paper. Examples of the different combinations available for the main five steps that are performed during autonomous driving are shown in Fig. 1.

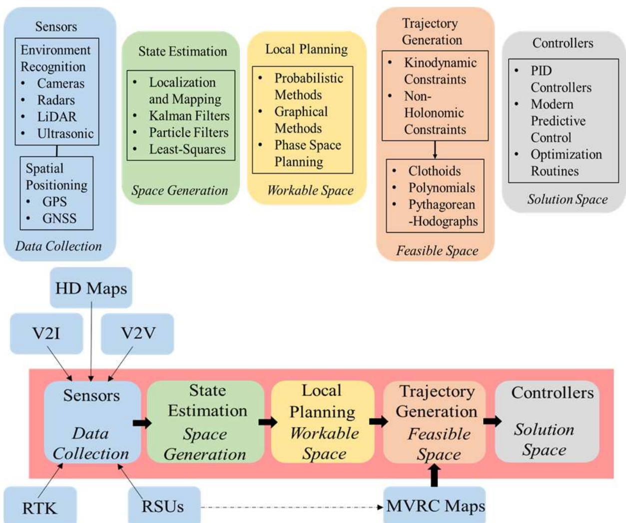

Fig. 1. Sample of Current CAV Guidance Framework

While these intelligent vehicle systems continue to improve in quality, no ADAS guidance systems have yet demonstrated the capability to perform according to SAE's "Level 4" autonomy; further, industry experts have predicted that a level 5 autonomy solution are still on a horizon beyond current capabilities [16][32]. In part, the difficulty of advancing to higher autonomy is that current solutions have shown a generally high reliability in only the most favorable conditions: adequate light; clear contrast for lane edge markings; good road maintenance with clear markings on pavement; and no visual obfuscations (precipitation, blowing smoke, dust, fog, or snow). Efforts to improve the existing automated guidance technologies are under evaluation; glass beads added to reflective pavement paint improve optical identification during precipitation and improve lidar reflectivity [33], and wider paint markings or adjusted markings, such as parallel marks, improve optical contrast and lane keeping systems [34]. Object recognition systems using artificial intelligence for feature identification rely on common sign geometries for both positioning and determining critical information [35][36][37][38][39]. However, even minor defects on signs have disrupted feature recognition algorithms [40][41].

Current CAVs adopted a new framework for data collection in which information from external sources establish communication channels for enhancement of previously-established ADAS technology. Multiple external sources are currently available for CAVs, including Vehicle-to-Infrastructure (V2I) communication, Vehicle-to-Vehicle (V2V) communication, Real-Time Kinematics (RTK) used with Global Navigation Satellite System (GNSS), RSUs, and high-definition (HD) maps, as shown in the bottom of Fig. 1 [42][43][44][45][46]. These sources aim to augment the data collection capabilities of CAVs, simultaneously increasing their hierarchal data processing. Simpler methods from RSUs can provide simple warning messages for the driver (e.g., weather alerts), whereas high-density operations aim to supply high-quality locations and identification data for processing (e.g. three-dimensional LiDAR imagining).

B. Attributes for an All-Purpose Navigation System

Considering the extensive developments conducted to date on CAVs and intelligent transportation systems, researchers identified attributes that were consistent with a successful transportation system for all-purpose implementation:

- Geographically unconstrained, system should accommodate navigation for all locations on earth
- Operational in range of common, realistic operating conditions:
    - Environmental: ice, snow, rain, cold, heat, dust, wind, hot and cold temperatures
    - Network: high radio frequency noise, low radio, satellite, or cellular connectivity
    - Road: paved, gravel, mud, dirt, wet, snow-covered, leaf-covered
    - Light: twilight, sunrise, daylight, sunset, dusk, darkness
- Updatable:
    - Closures of a lane or roadway as a result of feature loss (bridge collapse), emergency medical services, fire, or police activity
    - Lane geometry or speed adjustments in conjunction with work zones, detours, diversions, emergency

- evacuations, variable speed limit adjustments (e.g., icy or fog conditions), and school zones or political activities (e.g., presidential motorcade)
  - Road expansions, new construction, terrestrial shifts over time
- Accommodations to growth including new features or parameters

Human drivers and mobile vehicles are highly adaptable; drivers are generally able to handle many types of terrain and even navigate areas not explicitly defined as roadways (e.g., off-road or snow-covered roads with no obvious lane markers). Hundreds of millions of people will navigate slick, icy, and snow-covered roads each year. Drivers pass through work zones by navigating around traffic cones and barricades, and obeying traffic signs, and may adjust travel paths based on public service notifications of planned construction or road closures. Likewise, school zones frequently utilize reduced speed limits to promote safety for high pedestrian traffic, which are typically denoted with flashing lights, providing a form of variable speed limit enforcement. Roundabouts, vulnerable road user facilities, bike lanes, flashing turn signals, and changes to highway systems have been implemented to existing roads and intersections, and drivers adapted to these systems. Therefore, successful, complete, automated guidance frameworks should accommodate every one of these common travel conditions and adjust to future changes in transportation.

In the authors' observation, all existing and proposed guidance frameworks are derived from a need to adapt to an existing transportation framework. As such, guidance frameworks are limited to identifying the road geometries, connections, and directions, mapping an optimized local trajectory (tens of meters in front of the vehicle), modifying the vehicle trajectory to adapt to other vehicles, interruptions, or obstructions, and executing stable maneuvers. As CAVs continue to evolve and adapt, and particularly as new and novel transportation vehicles become available for use, it may be necessary to reimagine the guidance framework operation to implement desirable features and accommodate future growth.

III. Introduction to the MVRC Map Framework

To address the attributes from the previous section, a new paradigm is proposed, which utilizes critical vehicle dynamics properties to construct high-fidelity reference data. Authors of this research study deemed this map the Midwest Virtual Road Corridor, or MVRC. Its operating framework is intended to provide a low-memory yet mathematically consistent road representation that can be utilized by all current and proposed guidance methods. Thus, regardless of what navigational method and vehicle control scheme is utilized, consistent map data is available for defining the physical space that a CAV is intended to occupy. Moreover, when combined with vehicle-to-infrastructure communication, a new localization system and thus new guidance framework could be developed based on the data provided by the MVRC map.

The underlying principle of the MVRC map is to provide data, which is directly usable in the trajectory generation and local planning modules for CAVs, while providing a reference on dynamic-trajectory navigation which is independent of vehicle on-board sensors. Thus, the MVRC provides a more robust redundancy layer of data for aiding navigation. This bypass of information is demonstrated in Fig. 2, where external MVRC data (in this example, coming from RSUs) is inputted as part of the trajectory generation rather than following the typical information flow. With this bypass and after establishing a proper geospatial location, the vehicle has a dynamic reference on how to navigate the road without requiring image processing. This MVRC reference data can be compared with on-board CAV computed trajectories to increase travel safety.

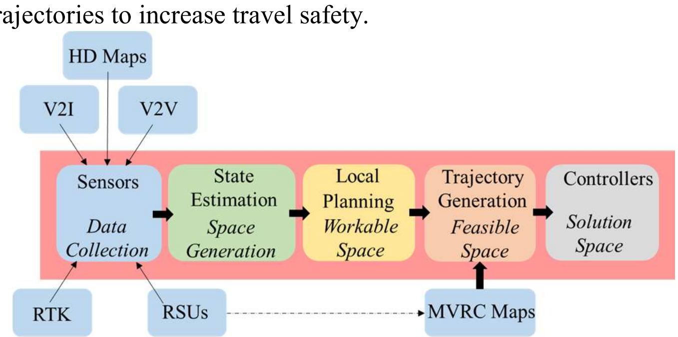

Fig. 2. Proposed MVRC Framework for CAV Guidance

The MVRC, in technical terms, consists of segmented roadways using high-precision GNSS reference points and consecutive connection anchor points. These points are prescribed with dynamic-attributes, such as curvature, turn direction, lateral angle change per segment, cardinal travel direction, lane width, lane elevation, and lane-specific speed limit data. The numerical values for these data points are derived from the link between vehicle dynamics and road design standards, as described next.

A. Relationship Between Road Design and Vehicle Dynamics

The principles of vehicle dynamics are well defined in literature: for conciseness, only elements critical to the application of the MVRC are discussed herein. For more complete discussions of vehicle dynamics, including evaluations of critical stability, readers are encouraged to review additional references [47][48].

In the United States, the prevailing standards for road design come from the American Association of State Highway and Transportation Officials (AASHTO), referred as the Green Book [49]. Road geometries, including lane geometries, are established using design speeds and number of lanes, curvature, and road "banking" (superelevation). Most roads designed to AASHTO specifications assume that the vehicle can successfully navigate, accelerate (including braking), and turn during wet or rainy conditions. The Green Book based its calculations for tire-pavement friction on empirical studies for "friction demand", the average amount of friction used by drivers when navigating curves [49]. Friction demand is derived from vehicle kinematics and dynamics (speed, acceleration, and turn radii), whereas friction supply between the tires and pavement varies based on inclement weather, road maintenance or smoothness, tire wear and quality, and incidentals (e.g., presence of gravel, sand).

Initially, a simple scenario is considered in which the vehicle is assumed to remain upright and oriented in a typical driving configuration, and vertical changes in the vehicle's center of gravity (c.g.) that are caused by the road are not considered. Under normal operating conditions, the vehicle remains far below critical stability and non-linearity thresholds; thus, the vehicle may be reasonably represented using a point mass representation, located at the vehicle's c.g. According to Newton's second law, the total force acting on the vehicle is the vector sum of all wheel forces, which are the only vehicle components interacting with the ground. An image of the sum of forces acting on the vehicle is shown in Fig. 3. Road design parameters include road friction, superelevation, and maximum width, while the vehicle parameters are velocity, acceleration, track width, and vehicle length. The resulting curve and superelevation relationship for road design is shown below, using small angle assumption for ϕ [49]:

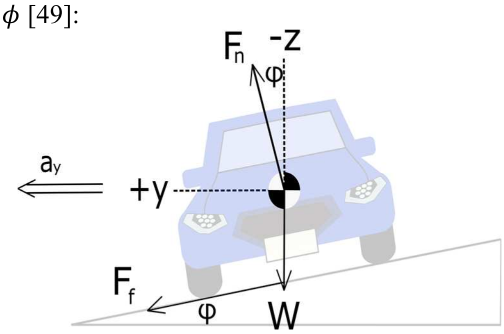

Fig. 3. Vehicle Dynamics on a Superelevated Curve

$$\frac{v^2}{g\rho} = \frac{\mu\cos(\phi) + \sin(\phi)}{\cos(\phi) - \mu\sin(\phi)} \approx \frac{\mu + 0.01e}{1 - 0.01\mu e} \tag{1}$$

v = Vehicle velocity (m/s)
g = Gravitational acceleration (9.81 m/s^2)
ρ = Radius of curvature (m)
μ = Coefficient of side road friction
ϕ = Superelevation angle (deg)
e = Superelevation: e = 100%*sin(ϕ) ≈ 100%*tan(ϕ)

In road design, both horizontal and vertical curves are considered. Horizontal curves focus on a top view of street (latitude and longitude), while vertical curves focus on a profile view of the street (altitude) [49][50]. When the road topology utilizes simultaneous horizontal and vertical curves, the limits on maximum allowable radii in both directions are affected. Horizontal curves are divided into 4 main categories shown in Fig. 4, where the main difference lies in the radius of curvatures per segment of road. For this discussion, only two-dimensional horizontal curves are shown.

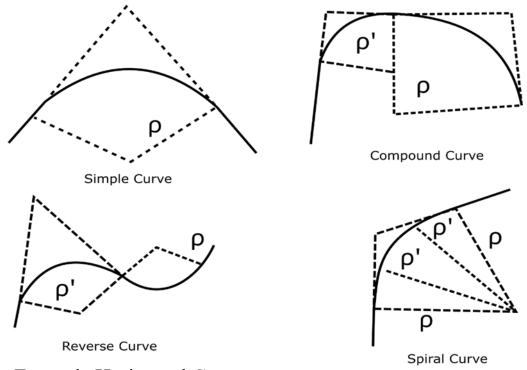

Fig. 4. Example Horizontal Curves

Where two road segments of different curvatures come together, a transition is usually designed, which allows vehicles to smoothly transition between curves. Curve transitions are typically designed according to AASHTO procedures, which utilize a clothoid or spiral construction [49]:

$$L = \frac{0.0214V^3}{\rho C} \tag{2}$$

where:

L = Minimum length of a transition (m)
V = Vehicle speed (km/h)
ρ = Radius of curvature (m)
C = Rate of increase of lateral acceleration $\left(\frac{m}{s^3}\right)$

The trajectory and dynamics of a moving vehicle utilize concepts from particle dynamics and are often described using a *Serret-Frenet* (or "Normal-Tangential") coordinate system [51]. This coordinate system definition is shown in Fig. 5, in which the principal longitudinal axis of the vehicle is parallel with the vector of rigid body velocity in what is referred to as a "tracking" orientation.

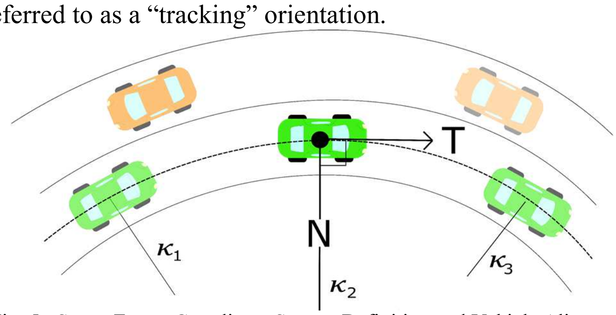

Fig. 5. Serret-Frenet Coordinate System Definition and Vehicle Alignment

The acceleration of the vehicle is defined by the time derivative of the velocity vector, which may have components in both the longitudinal direction (speeding up or slowing down) and lateral direction (centripetal acceleration). Noting that the curvature κ is defined as the inverse of the radius of curvature ρ per instantaneous road segment, the acceleration vector in Serret-Frenet coordinates can be simplified to:

$$a = \dot{v}\,T + \kappa v^2\,N \tag{3}$$

where:
a = Acceleration vector vehicle (m/s^2)
v = Vehicle speed (m/s)
κ = Curvature of vehicle path at an instantaneous point (m^{-1})
N = Normal unit vector
T = Tangential unit vector

Curvature is an advantageous parameter, because it is infinitely differentiable, whereas the radius of curvature is undefined (singularity) as a line becomes tangent. For the MVRC formulation, an adjusted SAE convention is adapted for a 2-dimensional planar problems where the vertical axis of the vehicle (SAE "Z" direction) is collinear with the binormal vector of the *Serret-Frenet* frame [52], implying that SAE (x,y,z) convention matches (T,N,B), as noted in Fig. 6.

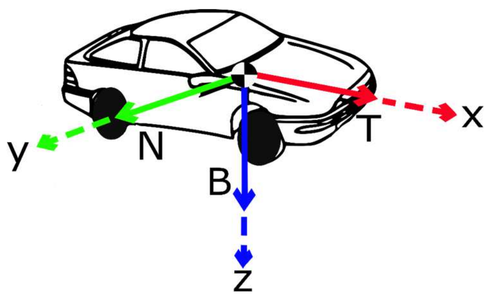

Fig. 6. Serret-Frenet Frame Imposed on SAE Orientation Convention

Although curvature is scalar in the Serret-Frenet equations, researchers redefined the product of the curvature and normal vectors as the curvature vector. The resulting mathematical relationships are:

$$K := \kappa\, N \tag{4}$$

$$a = \dot{v}\, T + v^2\, K \tag{5}$$

$$N \coloneqq \frac{K}{\kappa} y \tag{6}$$

where:
K = Curvature vector (m^{-1})
y = SAE pitch axis

The scalar representation of κ is therefore positive if the vehicle is performing a right-hand turn, and negative if the vehicle is performing a left-hand turn. For tangent road segments, the horizontal curvature is defined as zero.

B. Construction of MVRC Map

For most operating conditions, vehicle dynamics is based on particle dynamics relationships. All major lane-keeping or automated guidance systems rely on the curvature estimation to perform longitudinal and lateral vehicle control [29][30][53]. However, this data is rarely, if ever, provided in self-contained maps; therefore, it is either generated locally *ad hoc* or estimated using a sequence of GNSS waypoints. Hence, curvature was deemed an essential parameter to include in a high-fidelity map. Researchers generated methods of calculating the curvature based on positional data and augmenting position and curvature map data with additional informative reference data.

It was noted that curvature in road design standards, as shown in equations (1) and (2), can be used to formulate dynamic trajectories using equation (3). Geometrically, curvature can be defined as a property of curves that measures the amount of deviation from a straight line [54][55]. Numerically, this is expressed as the change of the angle made by the tangent of a curve with respect to segment length:

$$\kappa = \frac{d\theta}{ds} \tag{7}$$

which by integration implies the following is true:

$$\theta = \int_0^s \kappa(s)ds + \theta_0 \tag{8}$$

In trajectory generation, the well-known parametric representation of a curve $\alpha(s) = \big(x(s), y(s)\big)$ is used to represent vehicle trajectories in a local two-dimensional Cartesian map, such that:

$$x(s) = x_0 + \int_0^s \cos\left(\int_0^s \kappa(s)ds + \theta_0\right) ds \tag{9}$$

$$y(s) = y_0 + \int_0^s \sin\left(\int_0^s \kappa(s)ds + \theta_0\right) ds \tag{10}$$

Equations (9) and (10) when describing a trajectory are sometimes denoted as clothoids, Cornu spirals or Euler spirals. These are fundamental in both trajectory generation and street design. However, the difficulty of analytically defining these equations for on-board calculations has led to numerical approximations that can be used with spline interpolation or its alternatives [56]. Although these methods are reasonably accurate, current available data is not sufficient to provide guidance information for a vehicle under all driving conditions when dependent on vehicle on-board sensors only [57].

In this paper, the preferred corridor is assumed to be the centerline of a lane. Several methods for identifying lane boundary lines are applicable, such as utilizing satellite and aerial photography with "ground truth" corrections, using survey data, or collecting traces of vehicle routes in individual lanes [58]. The convergence of the vehicle SAE coordinate frame with a modified *Serret-Frenet* frame means that a vehicle's trajectory curvature, and by extension road centerline curvature, is orthogonal to the desired vector of velocity (tangent to the lane centerline) at any reference position. Therefore, the lane centerline is the geometric center between lane boundaries lines along *isocurvature* lines (lines of constant curvature, orthogonal to the lane). In other words, adjacent lanes form a family of lane boundary lines consistent with Bertrand Curves [55].

To simplify curvature estimation, spatial coordinate transformations are used to convert spherical data to a localized 2D overhead map in the vicinity of each discrete reference point [59][60]. Discrete reference points on the lane centerlines are converted to *(X,Y)* pairs. Three consecutive reference points are collected as a data triad, and the approximate curvature at the center of a data triad is estimated using the MDC procedure [61]. This process can be completed per road segment or per lane. Visually, this is denoted in Fig. 7 where a dynamic trajectory is mapped into the static road data for vehicle reference.

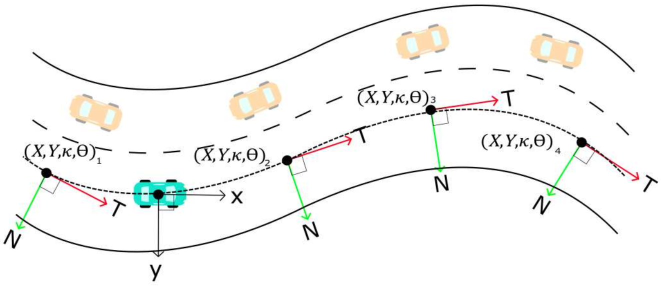

Fig. 7. MVRC Reference Data on Static Sample Map

Even though not shown in the previous picture, outcomes of the MVRC are stored in an adjustable matrix for any $i \in [1, n]$ where n denotes the number of data points for a given road:

$$ID_i \ = [Px_i, Py_i, s_i, \kappa_i, \theta_i] \tag{11}$$

where:
ID_i = Road segment identification

Px_i = Latitudinal position
Py_i = Longitudinal position
s_i = Segment length (m)
κ_i = Curvature at segment length (m^{-1})
θ_i = Road tangent angle (degrees)

C. Example Construction of MVRC Map

As a practical example, a simple curve on a road highway in Lincoln, Nebraska (USA) from Google Earth is shown on the top of Fig. 8. The map UTM coordinates are transformed, and the discrete curvature of the road was found, as shown on the bottom of Fig. 8. Note that a dense point discretization was utilized, leading to numerical noise in curvature calculations; likewise larger road segment lengths generate less numerical noise.

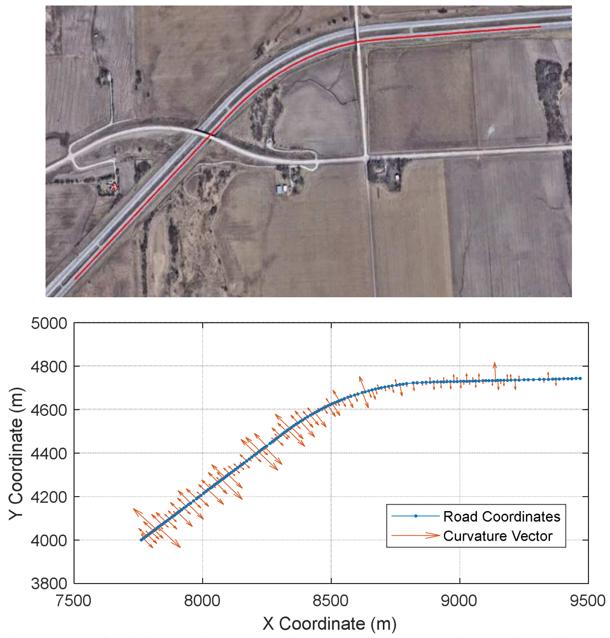

Fig. 8. Road Highway from Satellite Images (top) and Road Profile with MDC Curvature Vectors (bottom)

Using orthogonality of the curvature data, the road angle was identified through vector rotations. The angle was smoothed through a locally-weighted, quadratic-fit regression as shown in Fig. 9[62][63].

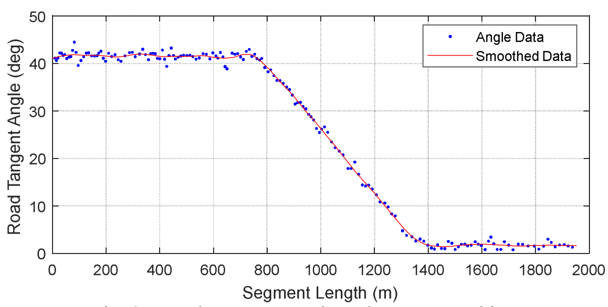

Fig. 9. Road Tangent Angle and Data Smoothing

The smoothed angle is used to assign a local heading angle reference for the vehicle to use during simple curve maneuvering, as shown in Fig. 10. Subsequently, a smoothed-curvature calculation was developed, and a simplified, piecewise-linear curvature relationship was used to condense road reference data into a compact segmentation scheme.

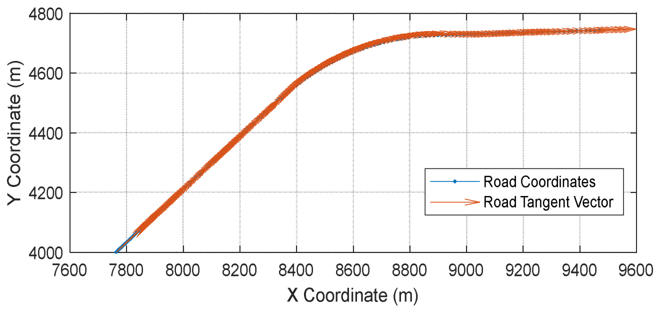

Fig. 10. High Discretization for Simple Curve with Heading Angle Reference

As a result, the filtered road angular data is used to identify smoothly varying curvatures with a piecewise-linear curvature function. It has been demonstrated that this piecewise-linear curvature fit produces pristine, smooth road centerlines and can be used in an optimization routine to map a condensed, segmented, high-precision and adjustable lane location spatial map and augmented curvature and angle data [64].

The dense discretization was shown to illustrate the robustness of the MVRC method. Sparse segmentation of the same road profile was mapped using the MVRC method, which produced very smoothly-varying road heading and curvature vector data without additional smoothing or realignment processing, as shown in Fig. 11. However, low-density spatial segmentation may require careful selection of road reference points, to accurately identify the transitions in curvature between consecutive road segments.

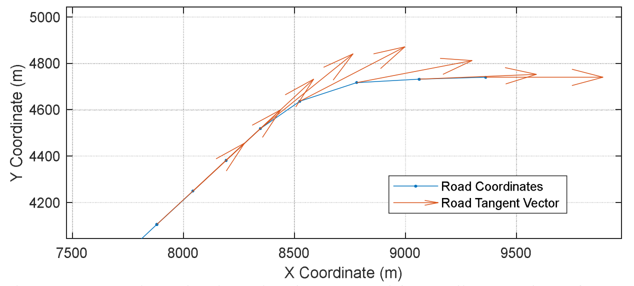

Fig. 11. Low Discretization Simple Curve with Heading Angle Reference

Furthermore, calculations performed on a single lane can be extrapolated to adjacent, parallel (non-intersecting) lanes along lines of *isocurvature* using the lane width. All roadways with multiple concurrent lanes in the same travel direction have strictly reinforced parallel lane tangencies relative to the road cross-section. In other words, roads with multiple lanes in a given travel direction will have parallel heading angles along the curvature vector lines, which are orthogonal to the roadway. As a result, once a single-lane geometry is identified, adjacent lanes may be easily and consistently described by adjusting the local lane curvature magnitude and offsetting lane reference point data by an equivalent amount to the lane centerline separation distance (i.e., lane widths). In addition, branching structures, which conjoin or separate from roads, are currently very difficult to implement into robust map frameworks. Branching structures, such as entrance or off-ramps, lane mergers, etc., may utilize identical data as lanes from a determined starting location, and preliminary research indicates this framework remains functional even for these unique cases. Lane offsets are discussed in detail by Jacome et al[64]. Lastly, rural and largely unmarked roads may not utilize discrete lanes but rather a shared multi-directional lane space. Integrating unmarked roads may require completely novel guidance approaches, as typical trajectories on unmarked roads trend to the center of the roadway, whereas opposite-direction passing on unmarked roads is accomplished when both vehicles shift laterally within the defined road width. Further research is being developed for the MVRC road data set. For further information on the extensions of the MVRC map, readers are referred to [64].

Recall that existing guidance frameworks use either predefined waypoint follower, *ad hoc*, or high-resolution maps with extracted lane boundary data to estimate curvature, which is essential for automated vehicles to estimate steering angle and safe operating speeds when navigating curves. The MVRC map produces this data *a priori* and provides it to the vehicle with road reference marker location for lane centerline, representing the preferred location of the vehicle. The computational efficiency of the MVRC map is easy to identify: the densely-discretized data for the 2 km length of road mapped in this paper was only 8 kB, before compacting and optimizing the road segmentation. Assuming a typical highway speed limit of 25 m/s, the approximate amount of data processed by LiDAR for high-definition maps with the same distance is 80 GB, a ~10^7 order of magnitude difference for describing the same road [65].

D. *Augmented Road Data*

The MVRC map framework is intended to provide dynamically consistent, spatially-discretized data, which can be implemented into kinematic and kinetic trajectory estimations in relationship, to speed and acceleration. Although details of the road data augmentation are beyond the scope of this paper and are addressed in additional papers submitted by the authors, the composition of the augmented data are described here.

First, vertical deviations in the road may affect both road segment lengths between reference points and vehicle stability. MVRC map data is augmented with a lane elevation values (relative to sea level) and dynamic rotations capturing the lateral slope of the road, which may include lane crowning, superelevation, road twist, and road pitch at multiple reference points.

Second, vehicle-control optimization schemes have been identified to obtain velocity profiles based on properly extracting curvature data [64]. These velocity profiles are dependent on the limits of local tire-roadway friction, horizontal and vertical curvature, horizontal wind shear, and lateral road slope. Although the initial concept for the optimization approach was intended for dynamic CAV vehicle planning, an extension of this technique will allow remote road controllers (e.g., state Departments of Transportation or DOTs) or reference datasets, such as the precipitation and temperature map from the National Oceanographic and Atmospheric Administration (NOAA), to temporarily modify the limiting road friction in a region, achieving a remotely-controlled variable speed limit.

It is possible that augmentation of data provided on [64] can further adjust local parameters such as friction to assess traffic flow in CAVs under multiple scenarios. DOT administrators can manually adjust lane-specific speed limits to accommodate for work zone construction, weather changes (affecting the maximum allowable friction by either ice or snow), lane closings, lane merging, or reducing speed limits not available from signs.

Third, vehicle-to-infrastructure communication may also be conducive to real-time traffic congestion and route planning maps. Using third-party or passive observer (e.g., cellular communication) techniques and vehicle-reported average travel speed through road segments, congestion and travel times may be predictable. Data augmentation may improve end-to-end destination planning and route optimization for enhanced automated vehicle travel.

An example of MVRC road data input is shown in Table 1 and an ArcGIS map is show in Fig. 12 to illustrate the curvature of the road per segment length available to the vehicle.

TABLE 1
MVRC ROAD DATA SAMPLE

Latitude	Longitude	Curvature (10^{-3} m^{-1})	Segment Length (m)
40.89054275	-96.67512273	0	0
40.89169123	-96.67331671	0.0107	198.59
40.89301687	-96.67124164	0.0155	228.60
40.89414874	-96.66945791	0.013	195.96
40.89506415	-96.66800844	0.888205	158.93
40.89592139	-96.66612935	1.164702	184.77
40.89655836	-96.66329365	1.039262	249.23
40.89663343	-96.66050674	0.129552	235.01
40.89664038	-96.65733051	0.0107	267.67
40.89664966	-96.65503712	0	193.27
40.89054275	-96.67512273	0	0
40.89169123	-96.67331671	0.0107	198.59

Fig. 12. ArcGIS Road Data Example

IV. DISCUSSION AND IMPLEMENTATION OF MAP FRAMEWORK

The MVRC road database was constructed to complement current CAV efforts by making a road dynamic reference output as concise and simplified as possible. Currently, multiple data exchange methods exist for CAVs including: conventional GPS applications in phones, RSUs vehicle On-Board Units with Dedicated Short-Range Communications, and simultaneous communication with vehicle's On-Board Units. The MVRC map can provide current CAVs and controller technologies, a sensor-independent driving reference constructed from external sources.

The fidelity of the method is dependent on the initial data map extraction, which can be complemented by multiple road-data extraction techniques such as LiDAR, or satellite imaging as previously shown. Current work in progress is focused on the extraction of lane edge coordinates, and trajectory generations based on differential geometry principles, and supplementary vehicle positioning research. Investigators are encouraged to use the provided findings to implement the MVRC data into their own research. This can be achieved by exploring multiple sources of data map and evaluate the performance of the method. Implementation of the MVRC map data into automated systems may require some adaptation but was intended for smooth, convenient integration.

V. Conclusions

The presented work aimed to provide the reader with a complete and through overview of CAV technology frameworks available. Multiple efforts to arrive at a level five autonomous vehicle were described, and an alternative framework was constructed based on the characteristics wherein other methods were not designed to operate. The method provided reasonable road-tangent angle profiles to aid autonomous navigation from satellite imaging and GPS coordinates. Roads were segmented into curved and straight segments for continuous roads.

Further augmentation of the MVRC map data is possible to better synergize with other existing technologies and guidance frameworks. Researchers encourage the broad collaboration and expansion of the data to bridge gaps between multiple contributors and end-users of the data. Once the vehicle's position can be established, the map provides an outlook beyond what sensors are capable of estimating. As a result, even rural, unpaved, unmarked low-traffic roads could be reasonably mapped with enough accuracy to permit automated navigation; however, new reaction and control methods may need to be developed to address opposite-direction vehicle navigation on these roads that are frequently narrow. When coupled with a wireless vehicle communication system, the value of the detailed MVRC map increases with rapid road network updates, vehicle data feedback about current travel speeds, road conditions (including friction), crash events, disruptions, road congestion, and a potential for arbitrary point-to-point navigation.

It is worth noting that the proposed framework is intended to complement the guidance and trajectory prediction techniques utilized by CAVs. Data provided by the MVRC system could compliment systems such as machine vision and waypoint follower techniques, offering an extra layer of redundancy for normal driving operations and for critical information when sensor-extracted data is poor (e.g., snow). Further investigation, testing, and augmentation on the proposed MVRC method could pose a vehicle reference independent of environmental sensors that limit current CAV navigation. Thus, providing the ability to navigate under impairing conditions such as harsh weather and considerably improve the performance of CAVs.

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