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Anti-Lock Brake System Acceleration Analysis with Wavelet Transforms

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Abstract

Abstract: Anti-Lock Braking Systems (ABS) serve to prevent vehicle locking by maintaining a proportional decrease in wheel speed to forward vehicle speed during braking events. Electronic Stability Control (ESC) systems take advantage of ABS to maintain a constant yaw direction to prevent spin out scenarios through applying different braking pressures to compensate for uneven surfaces. Extensive research has been performed evaluating models of ABS and ESC with successful implementations in vehicles [][][]. The performance of these systems rely entirely on the tire-road interaction that occurs while braking. For this reason, extensive research has been performed on determining appropriate coefficients of friction (COF), for multiple tire-surface interactions [][][]. However, there is minimum research on scenarios where the vehicle encounters two surfaces simultaneously or changes in friction surfaces. High speed scenarios where the vehicle is deviated from the highway road can force a driver to either maintain a split surface path or switching to a different road surface altogether.

Signal analysis is used to decompose a signal into elements such as noise or other elementary functions in order to filter or categorized the sampled information. Many methods for decomposition and filtering exists such as Fourier Series and Fast Fourier Transforms (FFT). This paper takes a more general method known as Wavelets with its corresponding Wavelet Transforms. A basic review of the method is provided along with some examples and applications of Wavelets in engineering applications such as acceleration analysis. The Wavelets are compared with the FFT method for filtering a noisy signal. The Wavelet method is performed with the MATLAB wavelet tool that permits decomposition and analysis of the accelerations experimented by a vehicle under harsh braking scenarios such as different surface roads.

Keywords: Acceleration Analysis, Signal Processing, Wavelet Transform, Anti-Lock Braking

Introduction

Motivation

Anti-Lock Braking Systems (ABS) serve to prevent vehicle locking by maintaining a proportional decrease in wheel speed to forward vehicle speed during braking events. Electronic Stability Control (ESC) systems take advantage of ABS to maintain a constant yaw direction to prevent spin out scenarios through applying different braking pressures to compensate for uneven surfaces. Extensive research has been performed evaluating models of ABS and ESC with successful implementations in vehicles [][][]. The performance of these systems rely entirely on the tire-road interaction that occurs while braking. For this reason, extensive research has been performed on determining appropriate coefficients of friction (COF), for multiple tire-surface interactions [][][]. However, there is minimum research on scenarios where the vehicle encounters two surfaces simultaneously or changes in friction surfaces. High speed scenarios where the vehicle is deviated from the highway road can force a driver to either maintain a split surface path or switching to a different road surface altogether. This lead to a study of split road surfaces conducted at the University of Nebraska – Lincoln (UNL).

Conventional methods for determining COF involve a full braking test in which the average acceleration (in g’s) of the braking event determines the COF for the corresponding tire-surface pair []. This method is expanded upon the introduction of wavelets transforms for the acceleration data. In signal analysis, decomposition methods are used to filter out noise and preserve the nature of the true signal that the system has. The most common technique for this is Fourier Signal Decomposition, in which the signal is modeled through sinusoids. For braking events, the ideal acceleration profile resembles a ramp function followed by a constant

Path Prediction in Autonomous Vehicles

In this paper, a path is defined a connection in between two points (i.e. Point A to Point B). Any curve which connects two points is therefore a possible path, as shown in Figure 1. The optimized path is identified as the path which closely follows the geometry of a lane centerline, is continuous and differentiable across segments, and minimizes mathematical instabilities or irregularities. Vehicle trajectory is defined as the path that the vehicle CG followed between two points (i.e., trace-line).



Figure 1. Different Trajectories in Path from Point A to Point B.

Human and autonomous drivers both operate the vehicle using Path Planning, which consists of the estimation of the vehicle’s future trajectory given the vehicle’s current position, velocity, acceleration, and operational constraints. Characteristically, optimal paths are selected based on evaluation of path intersections of traversable and non-traversable zones, as well as the evaluation of input controls required to produce the trajectory. Path planning for vehicles and robotics applications utilize physics models, geospatial curve modeling and estimation, and feedback controls [5].

Path planning applied to vehicle guidance may include sampling-based planning, which uses sampling from sensors to create a path based on limited data sets; probabilistic methods, which rely on approximating the free space available for navigation such as Probabilistic Road Maps and Rapidly Exploring Random Trees [5][6]; and Phase Space Planning which incorporates different sampling-based planning algorithms and compares them to extract the most optimal one [6].

All currently-implemented Path Planning algorithms for autonomous vehicle controls rely on narrow sample spacing to limit error. Path Planning formulations are either ad hoc (e.g., LIDAR, machine vision) or driven by low-speed, continuously-monitored GNSS triangulation with external ground-based monitoring compared to a highly-discretized road coordinate map. Vehicle sensors are also used generate navigational maps, for example discretizing areas of space from an image to determine if they are feasible for navigation.

During on-road driving, parameters such as velocity, acceleration dictate which possible paths may result in feasible trajectories. Path descriptions have been described using variational methods, clothoids, and velocity profiles [7] [8] [9]. Variational methods arise from optimizing functionals with non-holonomic constraints (i.e. constraints on the velocity and acceleration) [10]. These methods yield polynomial solutions of high order that are treated as boundary value problems (BVP) during vehicle navigation [11] [12]. Clothoid functions (Cornu Spirals or Euler Spiral), and spline functions are also studied in autonomous research because of their effectiveness to connect a straight line with a constant radius curve [13] [14] [15].

These trajectory estimates are then combined with optimization theory to be implemented into controllers for navigation purposes [16]. In general, these trajectories focus on providing a continuous function (up to the third derivative) while being smooth (i.e. minimizing the jerk ) [17] [18]. Alternative trajectory estimates

Method Formulation

Vehicle Dynamics and Road Design

Researchers utilized principles of vehicle dynamics in order to generate a road mapping technique which would automatically resolve limitations on vehicle stability and control. It was noted that all vehicle-road interactions are governed by the force generated at the wheels, and all vehicle controls are dictated by the direction and magnitude of friction force [19] [20]. Using Newton’s 2nd Law, those forces can be related to the fundamental kinematic constraints of path motion.

A Frenet-Serret reference frame is used along with unit vectors of N (normal), T (tangential), and B (binormal, out of plane) as shown in Figure 2. For this paper, it is assumed that the vehicle navigates on a 2D Euclidean Space.



Figure 2. Normal-Tangential Coordinates Example in Vehicle’s Center of Mass.

The net acceleration acting on the vehicle at an instant in time is described

*Discussion*

Road sampling data is critical for the use of the MDC method for identifying non-holonomic boundary constraints on target road paths. Aerial data and LIDAR or survey data are two methods discussed herein.

Aerial or Satellite Photography

Similar to Google Earth, this method requires identification (either manually or through software) of the lane. This method may be easily integrated into machine learning applications to preselect estimated road geometries without manual selection. The principal disadvantage from this method is susceptibility to error around unclear lane markings, such as adjacent to heavy tree foliage, road segments under construction, or roads affected by environmental effects. Furthermore, care must be taken to identify changes to the road network caused by road construction including additional lanes or closed lanes.

Survey, LIDAR, or Photogrammetry Point Clouds

If road geometries are surveyed using conventional survey equipment or through LIDAR sampling, very high-precision lane geometries may be identified. Nonetheless the process of point selection and the narrow spacing between consecutive lane edge points may introduce considerable numerical noise. This noise may be augmented by other vehicles or visual obstructions which interfere with clear lane edge identification.

Discussion/Recommendations

The study presented has the potential to be implemented in a distributed model of vehicle automization, but is not limited solely to passenger vehicles. Examples of other vehicle types which could utilize the target path formulation for positional error estimation and corrections include agricultural vehicles, transport vehicles (e.g., autonomous trucks), unmanned aerial systems, or mobile robots.

To achieve this goal, the following scheme is proposed for an implementation of the discrete road decomposition as shown Figure 25. The first step involves collection of road data through any convenient means: GPS Data, Surveying, or Aerial Scanning. This road data contains a representation of the road centerlines which can be exported in different formats. These road centerlines are decomposed with the proposed method, stored in a road target path matrix, and transmitted wirelessly to a vehicle in motion. The infrastructure may also assist with precise vehicle localization to improve error estimation, allowing the vehicle onboard systems to have excellent real-time observation of potential deviations from the target path. Finally, a controller is developed to consider the heading based from the discrete road decomposition and navigate safely through the road.



Figure 25. Implementation Scheme for Road Curvature Decomposition

Because the system does not rely on local ad hoc determination of lane boundaries, and does not utilize machine vision or de facto external tracking systems, the system is well-positioned to provide guidance system for autonomous vehicles even in adverse weather conditions, poor visibility, and even for temporary road or lane closures. The dynamic road network relay to autonomous vehicles may allow for alternative route selection in the event of congestion or crash events, and external guidance information such as tire-pavement friction reductions reported by other vehicles or estimated from weather reports may also be broadcast to the vehicle in targeted geospatial areas. As such, this technique for vehicle guidance systems could be complimentary to existing lane keeping and ADAS systems for crash avoidance or mitigation.

Research is ongoing at the University of Nebraska-Lincoln confirm the accuracy of this technique and the applicability to autonomous vehicle guidance systems. More research including empirical testing and simulation are recommended to integrate the MDC method into a broader vehicle guidance paradigm.

Summary/Conclusions

In conclusion, a method was proposed to calculate trajectories based on discrete curvature and road tangent calculations. The proposed method is consistent with AASHTO design guidelines and can be made to be compatible with vehicle performance limits by controlling allowable speed based on geospatial road curvature. Additional research was recommended to consider smoothing techniques such as Akima interpolation to provide the highest level of reliability for onboard driving, and should be verified using empirical testing and computer simulation. Successful implementation of this method could offer a new key piece to solve the autonomous vehicle paradigm under weather disruptions and/or other navigation technologies.

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