Offline estimation of vehicular inertial parameters using onboard LIDAR

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1 Abstract

Inertial parameters of vehicles are important for safety as they affect handling and stability. The novel application of an onboard LIDAR sensor to the problem of inferring vehicle mass, center of mass in the plane, and moments of inertia in the roll and pitch axes is presented. The method relies on scan matching to accurately resolve vehicle pose while generating a detailed model of the terrain so as to determine suspension travel distance. Then, a batch optimization is used to determine the desired parameters.

2 Introduction

With the rise in proliferation of autonomous vehicles such as the Google Self-Driving Car [9], issues of safety are increasingly relevant and important. In particular, determining the vehicle inertial parameters is important for effective control and accurate motion simulation. These vehicles often contain a LIDAR sensor for localization and obstacle avoidance. As such, the LIDAR sensor is an obvious choice for determining said inertial parameters.

Numerous studies have addressed the problem of determining inertial parameters in both the online and offline settings by using a variety of different sensors and techniques. Rajamani and Hedrick proposed in 1995 a method for inferring vehicle mass by observing the suspension, for example by directly measuring suspension travel using LVDTs [1]. Several studies have investigated solving this problem in the online setting with accelerometers using various filtering techniques [2][3][4][5]. The present study uses *base excitation dynamics*, which has also been studied by Pence *et al* in 2009 [6] using acceleromaters and in the theoretical setting by Rozyn and Zhang 2010 [7] and Kolansky and Sandu [8]. My work is most similar to that of Rozyn and Zhang [7] in that it uses a known terrain profile and suspension parameters. However, to my best knowledge, there has been no study using the LIDAR sensor to provide such a terrain profile.

3 Model and implementation

The problem statement is: Given LIDAR sensor input as point clouds sampled at discrete time steps, the vehicle geometry (wheelbase L and track B), and suspension stiffness k and damping b, the output is the mass m, the roll moment of inertia J_r, the pitch moment of inertia J_p, and the center of gravity in the plane c_x, c_y.

The model used is a three degree of freedom base excitation model, with the state being pitch θ, roll ϕ, and bounce Z. It is assumed that the front and rear suspensions behave linearly and have identical parameters $k_f = k_r, b_f = b_r$, and that unsprung mass is negligible. Furthermore, it is assumed that the vehicle is travelling at a mostly constant velocity forwards, and that roll and pitch angles are small. No information about the yaw and lateral motion is obtained or inferred.

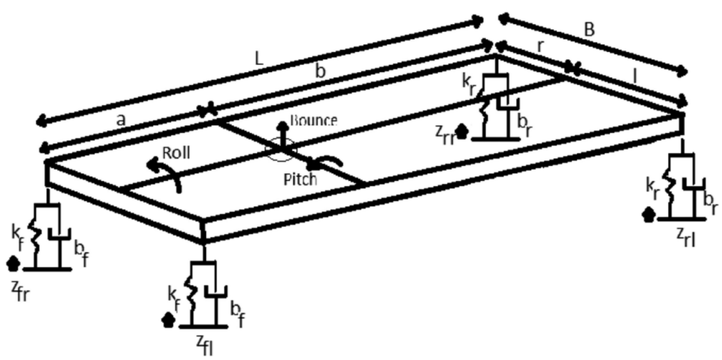

Figure 1: Three degree of freedom base excitation model.

The equations of motion are

$$m\ddot{Z} = \sum_{i \in \{fl, fr, rl, rr\}} F_i \tag{1}$$

$$J_p\ddot{\theta} = T_p = -c_x(F_{fl} + F_{fr}) + (L - c_x)(F_{rl} + F_{rr}) \tag{2}$$

$$J_r\ddot{\phi} = T_r = c_y(F_{fl} + F_{rl}) - (B - c_y)(F_{fr} + F_{rr}) \tag{3}$$

where the forces F_i are given by a parallel spring damper approximation:

$$\forall i \in \{fl, fr, rl, rr\} : F_i = -kZ_i - b\dot{Z}_i \quad (4)$$

The algorithm used can be summarized as such:

- The generalized iterative closest point algorithm (GICP) [10] is used to determine the relative transformation between synchronized and rectified point clouds produced by the LIDAR sensor.
- At each time step, the suspension travel is determined using a ray shooting method.
- Inertial parameters are inferred from the suspension travel as a function of time.

The implementation of the GICP algorithm used in this study is provided by the Point Cloud Library [11]. For ray shooting, the LIDAR sensor clearly cannot see directly beneath the vehicle. As such, the point cloud is aggregated over 100 time steps (50 before and 49 after the current timestep) of 0.1 s each for a total duration of 10 s. Vertical rays are computed from the known relative position from the wheels to the LIDAR sensor, and all points within 20 cm of each ray are obtained. The suspension travel distance is then determined by the median of those points.

For inertial parameter estimation, the cost function is defined as the Euclidean distance, for all time steps, between the left and right sides of Equations 1, 2, 3, where the left side is computed from twice numerical differentiation of the pose data and the right side is obtained from Equation 4 using the ray shooting method to determine Z_i, where $\dot{Z}_i$ is computed from central differences. A simplex method provided by MATLAB's `fminsearch` function is used to search over c_x, c_y to minimize this error while m, J_p, J_r are computed using least squares given c_x, c_y.

4 Results

The algorithm is tested on the KITTI data set [12][13][14], namely Sequence 00 of the Odometry data. The LIDAR point clouds are provided at a rate of 10 Hz, with about 1.3×10^5 points per timestep. The sensor is a Velodyne HDL-64E mounted atop a Volkswagen Passat B6 station wagon. It is known that for this vehicle, $L = 2.71$ m and $B = 1.60$ m.

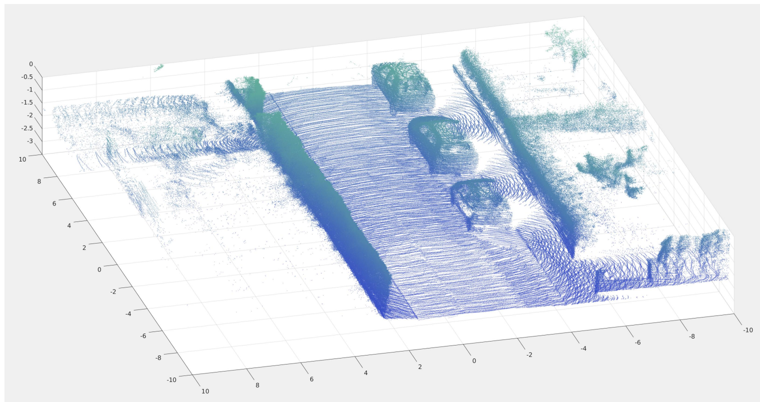

Figure 2: LIDAR point cloud accumulated over 2 seconds. Note that 10 seconds are used in actual experimentation (but it is not possible to plot 10 seconds of data due to memory limitations).

Assuming that $k \approx 5 \times 10^4$ N/m and $b \approx 2 \times 10^3$ kg/s, and using $(c_x, c_y) = (1.3, 0.8)$ m as an initial guess, then the output of the program is:

$$J_p = 3.8 \times 10^3 \text{ kg m} \tag{5}$$

$$J_r = 3.4 \times 10^3 \text{ kg m} \tag{6}$$

$$m = 1.7 \times 10^3 \text{ kg} \tag{7}$$

$$c_x = 1.1 \text{ m} \tag{8}$$

$$c_y = 0.9 \text{ m} \tag{9}$$

These look like reasonable values since the mass is expected to be over 1400 kg [15] and the moment of inertia in the pitch axis is clearly much higher than the one in the roll axis. The center of mass is close to the center of the vehicle and is closer to the front than the rear, which is expected since the car is front-engined.

5 Discussion

From Figure 4, it is clear that the data is extremely noisy. This could significantly affect the performance of the algorithm. The noise may arise from the fact that the assumptions in the model might not hold if the vehicle is being driven aggressively, or if there are nonlinear or hysteresis behaviour in the suspension. The KITTI dataset's data rate of 10 Hz is too low to capture high frequency behaviour in the suspension. Using an inertial measurement unit or a high fram-

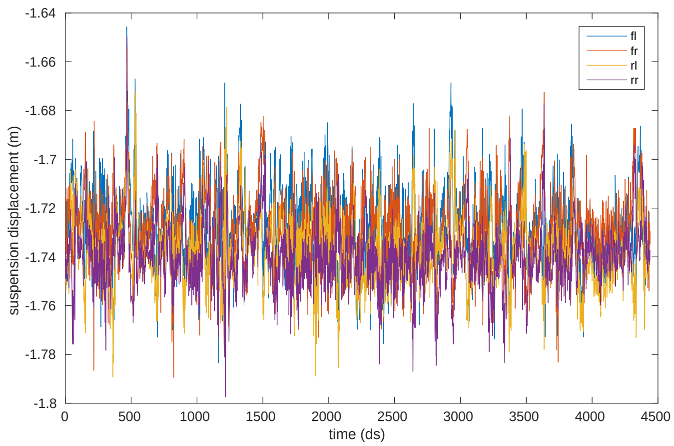

Figure 3: Vertical suspension travel over 444 seconds for all four wheels.

erate camera, the pose of the vehicle can be more accurately determined with finer temporal resolution, allowing for better estimates of acceleration.

6 Conclusion

An algorithm is presented for the novel application of an onboard LIDAR sensor to the problem of determining the mass, center of mass in the plane, and moments of inertia in the roll and pitch axes. Testing on data on a Volkswagen Passat B6 equipped with a Velodyne HDL-64E sensor resulted in values close to expectations, despite the noisy nature of the data.

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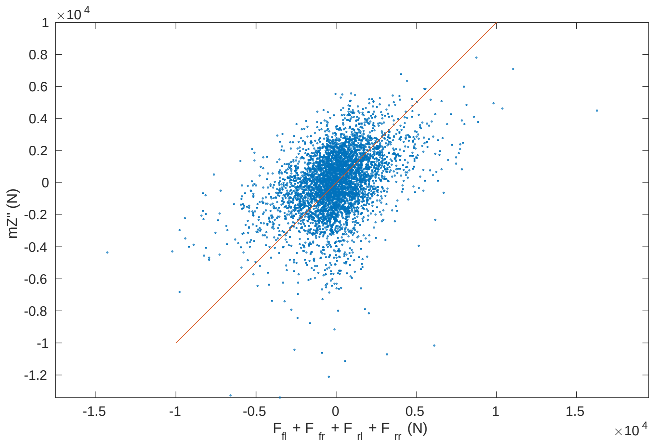

Figure 4: Left and right hand sides of Equation 3 over 4440 data points.

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