MODEL-BASED VEHICLE STATE ESTIMATION USING PREVIEWED ROAD GEOMETRY AND NOISY SENSORS

Alexander A. Brown
Department of Mechanical and Nuclear Engineering
The Pennsylvania State University
University Park, Pennsylvania 16802
Email: aab5009@psu.edu

Sean N. Brennan*
Department of Mechanical and Nuclear Engineering
The Pennsylvania State University
University Park, Pennsylvania, 16802
Email: sbrennan@psu.edu

ABSTRACT

This paper proposes a method for using previewed road geometry from a high-fidelity map to improve estimates of planar vehicle states in the presence of unmodeled sensor bias errors. Using well-established, linear models for representing human driver behavior and for planar vehicle states, a causal link between previewed road geometry and vehicle states can be derived. Cast as an augmented, closed-loop linear system, the total driver-vehicle-road system's states are estimated using a Kalman filter. Estimation results from this filter using simulated noisy measurements of vehicle states and map-based measurements of previewed road geometry are compared to standard Kalman filters with identical measurements of vehicle states alone. The effects of errors in driver modeling, vehicle nonlinearity, and measurement disturbances on the estimator's fidelity are also examined and discussed.

INTRODUCTION

As computing power has become increasingly affordable in smaller and smaller packages, so have the inertial and position sensors common to the automotive world. Unfortunately for the designers of vehicle driver assist systems, however, most low-cost sensors still suffer from debilitating noise characteristics that make their use for vehicle tracking difficult.

The outlook is less dire when absolute vehicle position is not required. For instance, commercial vehicle stability control algorithms have long relied on model-based estimation to make the most of available inertial sensing technology [1]. Model-based estimation with noisy sensors has essentially enabled the production and deployment of stability-control-equipped vehicles, but with growing interest in vehicle autonomy and driver assist technologies like high-speed collision avoidance, slip detection and control, great interest in gaining sufficient knowledge of vehicle states from low-cost sensors remains [2].

In the case of autonomous vehicle guidance or in modeling of driver response, it is generally assumed that maps are available of the road geometry. Map information has already shown to be a useful tool in improving vehicle localization accuracy [3]. The key insight of this paper is that the steering input, calculated from a previewed road geometry, can be considered yet another sensor input to estimate vehicle state. This is a particularly low-cost data source, especially in contrast to the costs associated with high-quality sensing equipment that makes direct measurements of vehicle states like sideslip, lateral position within a lane, and true vehicle yaw angle possible. The present study augments the typical Kalman filter for vehicle state estimation by using multiple map measurements per time step to aid in reliable, drift-free state estimation. This is achieved by coupling road geometry to vehicle dynamics through a representative driver model. Results are encouraging, even though the models used are linear, subject to error, and the actual inertial sensors used on the simulated vehicle are subject to large amounts of error. The use of road preview in the state estimation problem offers marked improvement over the use of inertial sensors and GPS alone.

The following pages outline an estimation paradigm that enables the use of high-fidelity geometric maps of roads as measurements in a model-based Kalman filter framework. The remainder of the paper is organized as follows: The following section gives a brief outline of the history and state of the art in driver modeling using linear models with preview and set the precedent for increased use of map information in vehicle state estimators. Then, a brief discussion outlines the driver-vehicle

*Address all correspondence to this author.

model used in the development of two model-based Kalman filters designed to estimate vehicle states with and without road preview information. The results of using these two types of estimators, both with a perfect vehicle model and in the presence of modeling error are discussed, and results from simulations of a vehicle traversing a 80kph (50 mph) double lane change maneuver follow.

Linear Models of Automobile Drivers using Preview

Vehicle driver modeling has been an important field of study for over 20 years. In fact, some modern, high-fidelity vehicle simulation software packages still make use of driver models that are over 30 years old [4]. In 1980, MacAdam applied an optimal fixed-point preview controller to vehicle lateral guidance in [5] and showed that the model agreed well with actual human driver behavior. A decade later, as a result of the PATH program at the beginning of the 1990s, researchers at U.C. Berkeley [6, 7] developed guidance laws for autonomous vehicle control. These control strategies also used feedforward control acting on previewed road curvature along with feedback to achieve vehicle path tracking. But instead of focusing on matching human driver behavior, the aim was to engineer solutions for autonomous vehicles that could be implemented on public highways. Researchers involved in this program, along with others, continued this vein of research through the 1990s [8–10]. This paper is not intended to be a comprehensive review of lateral vehicle control; the authors would like to refer readers to more comprehensive reviews on this topic in [11, 12].

Whether for driver modeling or for vehicle autonomy, nearly all of such research makes use of *previewed* information in one form or another. In other words, autonomous driving and driver models assume knowledge of what lies *ahead* of the driver in the vehicle steering task. Amongst the more or less successful linear driver models in the literature, at least two distinct schools of thought emerge. The first, consistent with [5], relies on a projection of the system states into the future. In a sense, even the applications of model-predictive control [13, 14] follow this thread. The other seems to have grown out of an interest in applying methods from optimal preview and LQR suspension control [15]. Sharp and Prokop used previewed *road geometry* to drive the actions of their optimal preview steering controller in [16], and the authors' work along these lines continued through the following decade in [17, 18]. While the controller proposed in [16] was probably not devised to model human behavior exactly, Pick and Cole were able to show that this type of controller approximates human behavior quite well [19], especially when neuromuscular dynamics are included. Pick and Cole also examined the mathematical relationship between predictive control theory and Linear Quadratic preview control theory in [12]. This is an enlightening read, and clearly shows how, under many circumstances, the two approaches can yield identical controllers. The authors also found that there are some instances where this is not possible, and the approaches give divergent results.

For the present study, Sharp's Optimal LQ steering controller will be used as the control model for the closed-loop driver-vehicle-road system. This structure is ideally suited to the current application, which seeks to utilize the control effort associated with the previewed map to better estimate current planar vehicle position, yaw rate, angular rate and lateral velocity.

Vehicle state estimation with and without map information

Estimating vehicle states using low-cost sensing equipment is hard, and forces many production driver assist systems to be quite conservative in anticipation of sensor error [2]. The relatively low signal-to-noise ratio of production sensors makes it challenging to measure vehicle states like sideslip, the angle between the the vehicle orientation and the vehicle's total velocity vector, because sideslip has extremely small magnitudes under normal driving conditions. Many low-cost sensors suffer from severe bias instability, quantization effects, poor resistance to temperature and other environmental variability. As a result, the use of common low-cost inertial sensors in traditional Kinematic Kalman Filters (KKFs) is often out of the question, although success with vehicle sideslip estimation without a model using GPS and yaw gyro measurements was shown in [20]. Some researchers in the vehicle dynamics community have turned towards model-based estimators that make use of known vehicle dynamics to improve estimator accuracy [21, 22]. Some have even found success using model-based estimation techniques to estimate vehicle parameters and/or tire-pavement friction in real time [2, 23, 24]. In the application most similar to the current study, Mudaliar used a model-based Kalman filter in the design of a lane departure warning system [4], and the match between the filter and the simulated CarSim vehicle was exceptional.

While model-based estimation can indeed improve state estimates using otherwise inferior sensors, relying on the model structure itself is a double-edged sword: the benefits are that the model dynamics constrain the estimator error to be consistent with expected behavior. The consequences are that modeling error, when left unchecked, can introduce artificially amplified errors in estimated states. One of the goals of the present study is to examine whether the detrimental effects of modeling error can be somewhat mitigated through the use of a map, which has the potential to offer nearly limitless measurements at any given time step, and with an extremely high degree of accuracy.

Using maps for vehicle localization and state estimation is not a new idea. Recent work by the authors [3, 25–27] makes use of extremely compact maps of roads to localize a vehicle by using a measurement of its pitch angle alone. Alas, most of these studies tend to bring map information into a filter once every time step. If multiple measurements are available from a map at each time step, each coupled to the model slated for state estimation, accuracy is likely to improve. The above discussion on preview control suggests benefits for including multiple map measurements at a given time step in an estimation algorithm; because preview control makes use of *future* as well as current information to exact a particular system trajectory, future and current information are both available (and useful) to a state estimator which employs a closed-loop model of the preview-controlled system.

Background on the Optimal Preview Controller

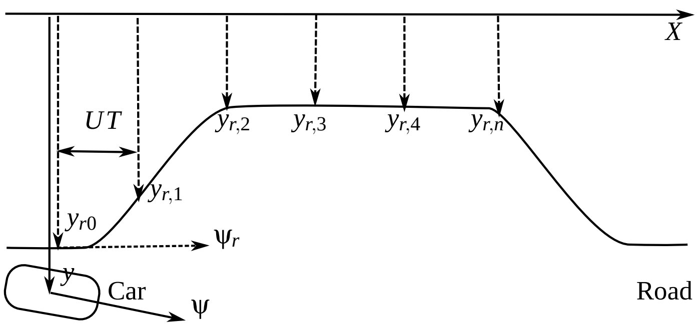

Figure 1. SETUP OF THE VEHICLE-ROAD SYSTEM VARIABLES

The controller used in this study is identical in structure and derivation to the one proposed in [16]. This background is intended to be brief, and the authors would like to refer the reader to [12, 16, 17, 19] for a more detailed discussion of its derivation. This model was chosen for its relative ease of implementation, and its explicit use of multiple preview points. These will be used later in the closed-loop estimation framework as extra measurements. The continuous time open loop vehicle dynamic model to be controlled is the planar "bicycle model" in its familiar, error-coordinate form:

$$\dot{\vec{x}} = A \cdot \vec{x} + B \cdot \delta \tag{1}$$

with the following state vector, state, and input matrices:

$$\vec{x} = \begin{bmatrix} y \; \dot{y} \; \psi \; \dot{\psi} \end{bmatrix}^T \tag{2}$$

$$A = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & \frac{-(C_f + Cr)}{mU} & \frac{(C_f + Cr)}{m} & \frac{(bC_r - aC_f)}{mU} \\ 0 & 0 & 0 & 1 \\ 0 & \frac{(bC_r - aC_f)}{I_z U} & \frac{(aC_f - bC_r)}{I_z} & \frac{-(a^2 C_f + b^2 C_r)}{I_z U} \end{bmatrix} B = \begin{bmatrix} 0 \\ \frac{C_f}{m} \\ 0 \\ \frac{aC_f}{I_z} \end{bmatrix} \tag{3}$$

where C_f, C_r are tire cornering stiffnesses, m, I_z are vehicle mass and yaw moment of inertia, a, b are the distances from the vehicle CG to the front and rear axles, respectively, U is the vehicle forward speed, and δ is the lone system input, the steering input (the vehicle's front road wheel angle).

For simulation purposes, this linear vehicle representation is converted to discrete time using a zero-order hold with sampling time T such that the A and B matrices become discrete-time state and input transition matrices A_d and B_d. Next, a shift register representing global road positions ahead of the vehicle is constructed for the vehicle-road system shown in Fig. 1. The road position at the preview distance is brought into this system, which lags the previewed measurement backwards through the state space at each time step until it corresponds with the global road position at the current time step k.

$$D = \begin{bmatrix} 0 & 1 & 0 & 0 \cdots & 0 \\ 0 & 0 & 1 & 0 \cdots & 0 \\ 0 & 0 & 0 & 1 \cdots & 0 \\ 0 & \vdots & \ddots & \vdots & \vdots \\ 0 & \cdots & \cdots & 0 & 1 \\ 0 & \cdots & \cdots & \cdots & 0 \end{bmatrix} E = \begin{bmatrix} 0 \\ 0 \\ 0 \\ \vdots \\ 1 \end{bmatrix} \tag{4}$$

Upon augmenting the vehicle state vector by adding the road position shift register dynamics into the discrete-time vehicle dynamic equations, the following open-loop system is obtained, where $\vec{x}_k$ is the state vector and $\vec{y}_{r,k}$ is the road's lateral position at time k.

$$[\vec{z}_k] = \begin{bmatrix} \vec{x}_k \\ \vec{y}_{r,k} \end{bmatrix} = \begin{bmatrix} A_d & 0 \\ 0 & D \end{bmatrix} \begin{bmatrix} \vec{x}_{k-1} \\ \vec{y}_{r,k-1} \end{bmatrix} + \begin{bmatrix} B_d \\ 0 \end{bmatrix} \delta + \begin{bmatrix} 0 \\ E \end{bmatrix} y_{r,i} \tag{5}$$

Where $y_{r,i}$ is an input equal to the road offset at the preview distance. Notice that the augmented state transition matrix is purely diagonal. Thus, there is no coupling here between the road dynamics and the vehicle dynamics, and the two systems essentially act independently of one another. In order to couple the systems, a discrete-time linear quadratic regulator (LQR) is employed that acts on all of the augmented states. The states are coupled through the quadratic cost function R_1 shown in Eq. 6, again exactly as in [16].

$$J = \lim_{n \to +\infty} \sum_{k=0}^{n} \left[\vec{z}^T(k) R_1 \vec{z}(k) + \delta(k) R_2 \delta(k) \right] \tag{6}$$

with R_1 defined as follows:

$$R_1 = C^T Q C \text{ where } C = \begin{bmatrix} 1 & 0 & 0 & 0 & -1 & 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 1 & 0 & \frac{1}{UT} & \frac{-1}{UT} & 0 & 0 & \cdots & 0 \end{bmatrix} \tag{7}$$

and R_2 is chosen as unity. This configuration penalizes vehicle yaw and lateral position error in the LQR design through the diagonal matrix Q.

$$Q = \begin{bmatrix} q_y & 0 \\ 0 & q_\psi \end{bmatrix} \tag{8}$$

Acceptable preview lengths and cost function weights q_y and q_ψ are not the topic of the present study– choosing these is a task tackled extensively in [12, 16, 19].

The key point here is that through the use of the cost function in Eq. 6, an optimal preview gain vector can be obtained for the augmented system using MATLAB's DLQR function, which solves the Discrete Algebraic Riccati Equation (DARE) automatically. The augmented system is fed into this function with the previewed road information as the only input. Note that, because there is no way for the controller to influence the road, there is a substantial subspace of this system which is uncontrollable. The coupling between the road geometry and the vehicle states is through the optimal state feedback control gain K. Once the control loop is closed, its discrete-time dynamics are given by the difference equation, Eq. 9

$$z_k = \left[\begin{bmatrix} A_d & 0 \\ 0 & D \end{bmatrix} - \begin{bmatrix} B_d \\ 0 \end{bmatrix} \begin{bmatrix} K_1 & K_2 \end{bmatrix} \right] z_{k-1} + \begin{bmatrix} 0 \\ E \end{bmatrix} y_{ri} \quad \text{and } K = \begin{bmatrix} K_1 & K_2 \end{bmatrix} \tag{9}$$

Consistent with common sense, the controller is unable to influence the road position, as confirmed by the structure of the input matrix through which the optimal controller influences the state vector. Notice, however, that closing the loop with a driver *does* in fact allow the road's absolute geometry to influence vehicle states through the $B_d \begin{bmatrix} K_1 & K_2 \end{bmatrix}$ term. This coupling of environment and physical system, through a model of a human driver, is the key to using high-fidelity maps of road geometry to improve vehicle state estimates.

Development of The Estimation Framework

The optimal preview steering controller outlined previously is one mechanism that can create a causal link between observed road geometry and the vehicle state vector. Therefore, a Kalman filter designed around the closed-loop, augmented system, armed with measurements of roadway geometry ahead of the vehicle (from a high-fidelity map) is developed below in hopes that the additional "measurements" offered by the road geometry will improve estimates of the system's states. For computational simplicity and in the interest of clarity, the system is, at present, designed with a steady-state Kalman observer gain. The vehicle velocity is assumed constant, as are the optimal preview and state feedback control gains of Eq. 9. The consequences of these assumptions are discussed in detail in the following sections.

Table 1. REPRESENTATIVE VEHICLE PARAMETERS.

Parameter	Value	Units
m	1592	kg
I_z	2488	$kg \cdot m^2$
a	1.18	m
b	1.77	m
C_f	2*75000	$\frac{N}{rad}$
C_r	2*55000	$\frac{N}{rad}$
U	22.2	$\frac{m}{s}$

In the interest of providing a somewhat realistic picture of how this estimator might be used, first consider a model-based Kalman filter design for a traditional open-loop bicycle model vehicle as described in Eq 3. To represent sensors typically available to measure vehicle dynamics, a yaw rate gyro, accelerometer, and a GPS are all represented in the measurement vector y_{bm}, which is presented for the continuous-time bicycle model dynamics below.

$$y_{bm} = H_{bm} x + D_{H,bm} \delta$$
$$y_{bm} = \begin{bmatrix} 0 & 0 & 0 & 1 \\ A_{21} & A_{22} & A_{23} & A_{24} \\ 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} y \\ \dot{y} \\ \psi \\ \dot{\psi} \end{bmatrix} + \begin{bmatrix} 0 \\ B_2 \\ 0 \end{bmatrix} \delta \tag{10}$$

This measurement vector can be used to generate a steady-state Kalman observer for the discrete-time bicycle model dynamics of the vehicle represented by Tab. 1. This observer, henceforth referred to as the "preview-free" Kalman filter, embodies the type of model-based vehicle state estimator that might be employed in a cost-sensitive or strap-on driver warning or assist system. Tab. 2 gives representative values of the sensor variances used in the simulations that follow. Note that since an extended or unscented framework was not used, sensor variance may seem higher than normal, since sensor noise was inflated to deal with unmodeled bias instability and/or other sensor error sources. These vehicle and sensor noise parameters will be used in the discussion that follows as a starting point for a Kalman filter acting on the closed-loop vehicle dynamics of Eq. 9.

To implement a preview controller, the optimal preview control problem of Sharp et al [16] is solved for the open-loop car-road system. While [16] and those that have followed this line of work have conceded that the most realistic application of this controller is realized by transforming the global coordinate system of Fig. 1 to one that is driver-referenced and local to the

Table 2. REPRESENTATIVE FILTER PARAMETERS.

Parameter	Value	Units
σ^2_{gyro}	0.066	$\frac{rad^2}{s^2}$
σ^2_{accel}	0.050	$\frac{m^2}{s^4}$
σ^2_{GPS}	1.5	m^2

vehicle, the goal of using global road map information in the estimation framework makes this transformation impractical and somewhat unnecessary.

In order to devise a Kalman filter that makes use of the previewed road points, an augmented measurement vector y_z is devised, and consists of the three measurements from the "preview-free" filter described above, the road wheel steering wheel angle resulting from the control action ($\delta = -Kz$), and a measurement of each previewed road geometry point in the shift register D. These "measurements" of global road position would, in practice, be products of a lookup table of road geometry in front of the vehicle's current position. This map could have many different sources; because of its compactness, it could be stored within the vehicle, or streamed in real-time through cellular or other communication technology. Because the map generation only has to be performed one time, high-accuracy sensors could be used in its creation, so any errors in the road position measurements would likely arise from the map registration procedure. In anticipation of this error, a substantial variance is assumed for each map measurement. The results of changing this variance are discussed in the following sections. The augmented measurement vector described above is presented below in compact form:

$$\begin{aligned} y_{CL} &= H_{CL} z \\ &= \begin{bmatrix} H11_{3x4} & H12_{3xn} \\ -K_1 & -K_2 \\ 0_{nx4} & I_{nxn} \end{bmatrix} \begin{bmatrix} x \\ z \end{bmatrix} = \begin{bmatrix} r \\ a_y \\ y \\ \delta \\ y_{r0} \\ \vdots \\ y_{rn} \end{bmatrix} \end{aligned} \tag{11}$$

Where the matrices $H11$ and $H12$ are given by

$$\begin{aligned} H11 &= H_{bm} - \begin{bmatrix} 0 \\ D_{H,2} \\ 0 \end{bmatrix} K_1 \\ H12 &= - \begin{bmatrix} 0 \\ D_{H,2} \\ 0 \end{bmatrix} K_2 \end{aligned} \tag{12}$$

which preserves the original state measurements from the "preview-free" filter while adding n map preview measurements associated with the control inputs to the modeled controller. It is important as well to mention that since the preview shift register exists only in the discrete domain, the H_{bm} and D_H matrices mentioned above must be the *discretized* versions.

For the filter design, the variance of each map measurement is considered to be a constant σ^2_{map} value, to be tuned based on map fidelity, and trust in the driver model, which will be discussed in the next section. With the augmented measurement vector and variances for each measurement, the design of the steady-state Kalman estimator is straightforward. System states are propagated forward using the farthest road preview point y_{ri} as an input, and when available, measurement updates are made based on the n road preview samples available from the map, along with measurements from a steering angle sensor and each of the inertial sensors on the vehicle. For all simulations that follow, the closed-loop and open-loop systems were discretized with a time step of $T = 0.025s$, and measurements (were made available at 10HZ for map geometry measurements, inertial measurements, and GPS measurements. States are propagated using measured steering input between Kalman updates.

Comparison of standard and preview-inclusive estimation

The remainder of this manuscript deals with simulations of a single maneuver. The vehicle described in Tab. 1 is subjected to a reference path describing a standard double lane change maneuver at 80kph. The reference geometry from the lane change maneuver was taken from the commercial multibody vehicle simulation package CarSim, but all linear model simulations, simulated measurements, and Kalman filtering were accomplished in MATLAB / Simulink.

First, a closed-loop model of the vehicle-driver system was run through the above double lane change maneuver with a preview controller examining the road 0.5s in front of the vehicle. To establish the general output behavior of the closed loop system, refer to Fig. 2.

Next, simulated "measurements" were derived from the system states by corrupting them with noise according to the variances in Tab. 2. These simulated measurements were fed into the "preview-free" Kalman filter, and then through the Kalman filter incorporating map measurements, which were also corrupted with Gaussian white noise. The map registration was accomplished assuming that an independent odometry (x-position) measurement was available to the filter at the sampling frequency, 40hz, with a variance equal to that of the GPS system. The authors believe that this is conservative enough to represent a realistic Kalman-filtered estimate of x-position at each time step derived from GPS velocity and position updates. Once the x-position of the vehicle is registered in the map, the y-locations of the road in front of the vehicle are known without additional noise, since these are obtained from a map representing the road

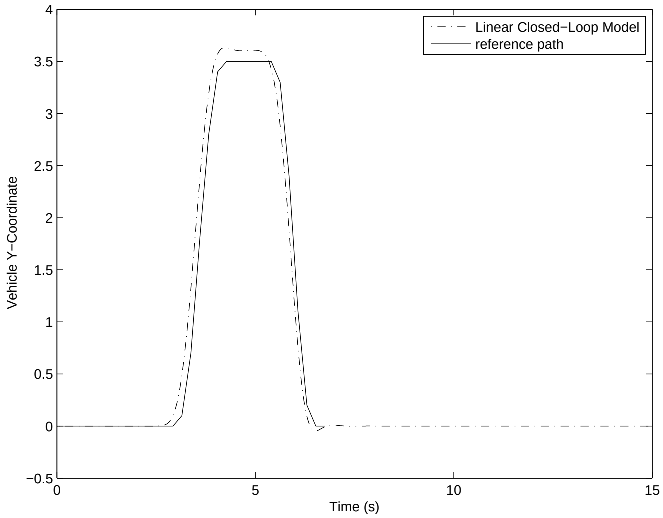

Figure 2. LINEAR CLOSED-LOOP VEHICLE MODEL LATERAL POSITION VS. REFERENCE PATH

centerline.

Comparisons of vehicle lateral position and heading estimates from each filter to the "clean" linear simulation are shown in Figs. 3-6.

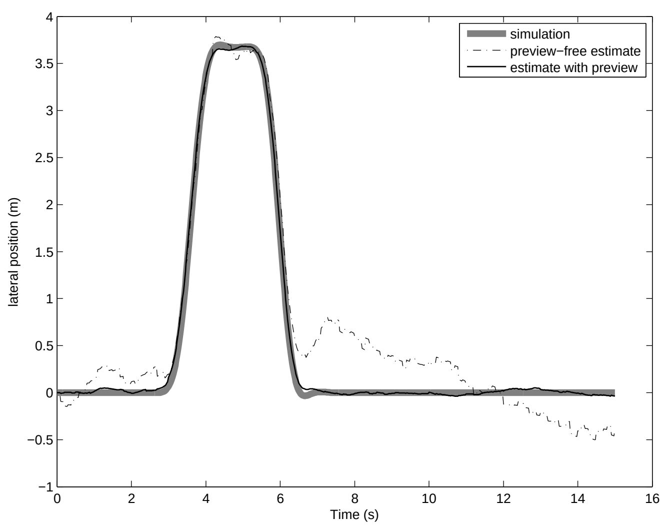

Figure 3. ESTIMATES OF LINEAR CLOSED-LOOP VEHICLE MODEL LATERAL POSITION

The inclusion of the map measurements leads to significant estimate improvement over the "preview-free" estimator for lateral position and yaw angle, but improvements in the derivative

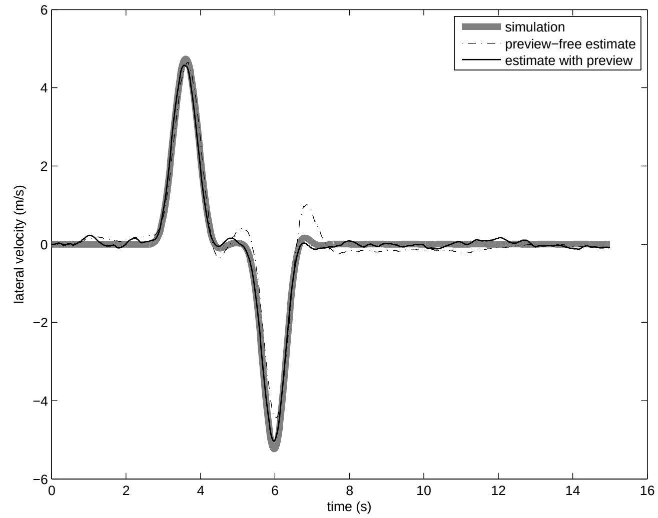

Figure 4. ESTIMATES OF LINEAR CLOSED-LOOP VEHICLE MODEL LATERAL VELOCITY

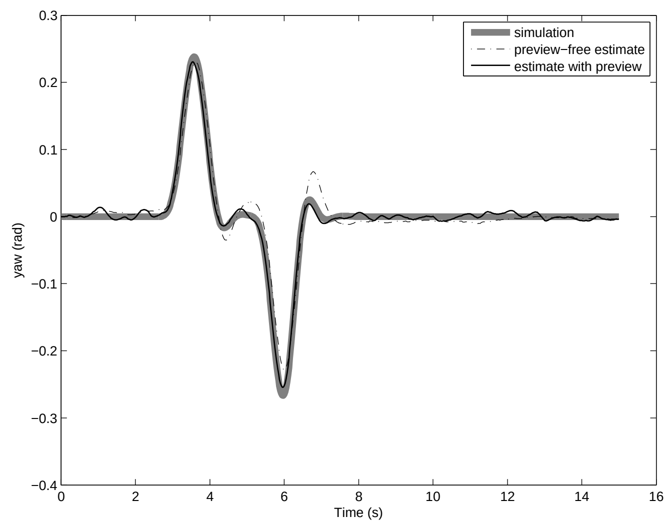

Figure 5. ESTIMATES OF LINEAR CLOSED-LOOP VEHICLE MODEL YAW ANGLE

states are less obvious. One important result of this exercise is the recognition that this filter, through heavy weighting of the road geometry relative to the inertial sensors actually on board the vehicle, does indeed tend to predict *modeled dynamics* almost exactly. Remembering that the discrete-time Kalman estimator is essentially a weighted average of measurements, it is apparent that the introduction of model error, either in the controller or in the open-loop vehicle model itself, is much more likely to corrupt the estimate than erroneous road preview measurements, for

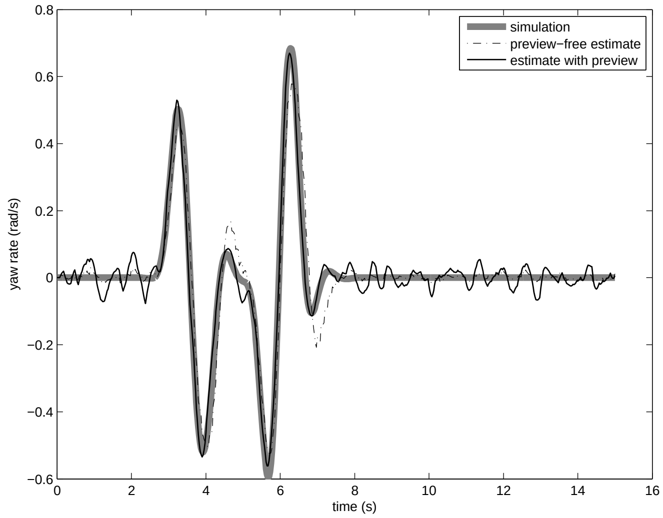

Figure 6. ESTIMATES OF LINEAR CLOSED-LOOP VEHICLE MODEL YAW RATE

instance. Thus, even with an extremely accurate road map, it is prudent to use restraint when choosing a variance σ^2_{map} for the preview filter design. Humans exhibit considerable variability in behavior from minute to minute, so it is only natural to assume that even with perfect knowledge of a vehicle model, error in the driver model itself is likely to add error to an estimate formulated with this method.

Results of application to a high-fidelity model of a vehicle-driver system

The next key question, then, is which is most important: driver model, map, vehicle model, or vehicle state sensor accuracy? What effects do errors in each have on the overall quality of the closed-loop state estimate?

To begin to investigate these questions in a controlled environment, a high-fidelity simulation of the exact same lane-change maneuver described in the preceding section was performed using CarSim, where sources of error and sensor noise can be controlled. CarSim's closed-loop path-following behavior mimics the model proposed by MacAdam in [5]. This means that the "driver" of the simulated vehicle in CarSim uses a single-point preview controller and an inverse model of the vehicle dynamics to guide its motion. This is a significantly different control structure from the one employed by the closed-loop state estimator outlined above. While some effort was expended to achieve *similar* controller performance between CarSim and the linear closed-loop model, some error was left intentionally in both the open-loop and closed-loop system dynamics for illustration purposes, and to try to make the simulation more representative of a real experiment. A comparison of the closed-loop responses of the CarSim (ground truth) vehicle and the linear model are shown in Fig. 7.

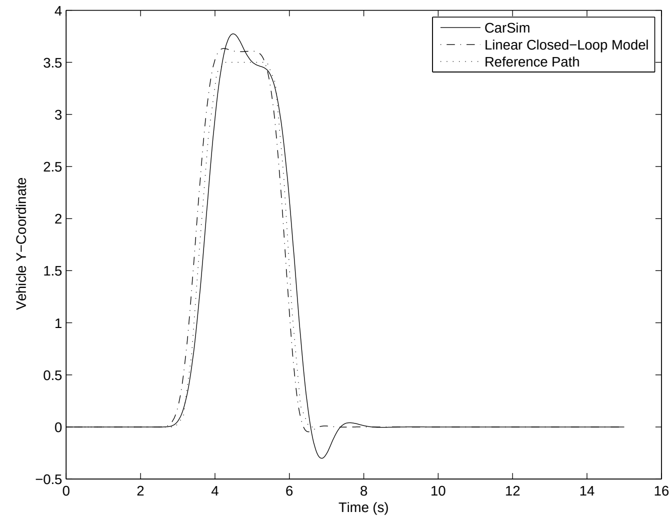

Figure 7. LATERAL POSITION VS. REFERENCE PATH FOR LINEAR AND HIGH FIDELITY VEHICLE

The vehicle dynamics with parameters summarized in Tab. 2 matched with CarSim's "E-Class Large SUV" responses reasonably well. But these results also show modeling error, as seen in the comparisons between CarSim and the open-loop linear bicycle model of Eq.3 in Fig. 8 and Fig. 9. These modeling errors are representative of the differences that could occur between linear model representations of vehicle dynamics, and actual vehicle states.

Both the "preview-free" estimator and the full closed-loop estimator for the CarSim simulation were compared. To obtain "measured" data, both the map information and CarSim data were corrupted with noise approximately represented by the noise accounted for in the Kalman Filter. These simulated measurements were used in the preview-inclusive and preview-free estimators. Additionally, for this experiment, the Gaussian noise added to each measurement available to each filter was complemented by a small $0.25\frac{m}{s^2}$ constant bias added to the accelerometer measurement at each time step, which represents an approximate 1.5° lateral accelerometer misalignment. This is a realistic scenario for an actual implementation, and shows the advantage of using previewed information, even in the presence of modeling error and unmodeled sensor noise. This small amount of accelerometer bias could result from an error in mounting the IMU, or even from a traveled road's cross-slope.

Fig. 10 and Fig. 11 show estimates of the two states found in the last section to benefit most from the inclusion of preview. For this simulation, the CarSim-generated vehicle states for the double lane change trajectory are considered ground truth. It does appear from the plots that the preview-inclusive Kalman

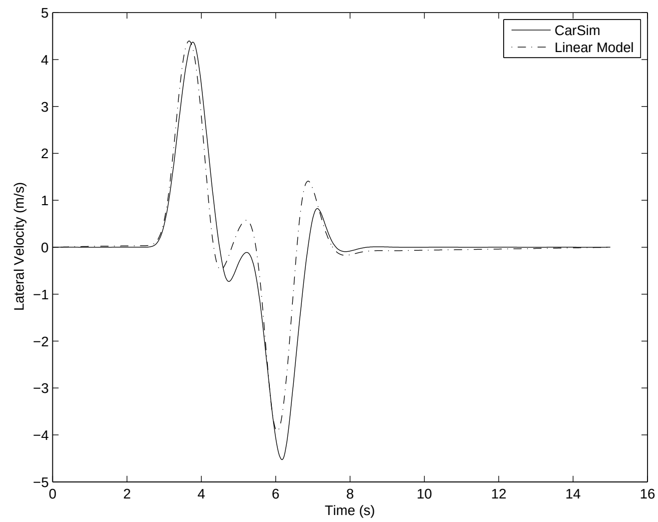

Figure 8. OPEN LOOP COMPARISON OF CARSIM AND LINEAR MODEL LATERAL VELOCITY FOR DOUBLE LANE CHANGE

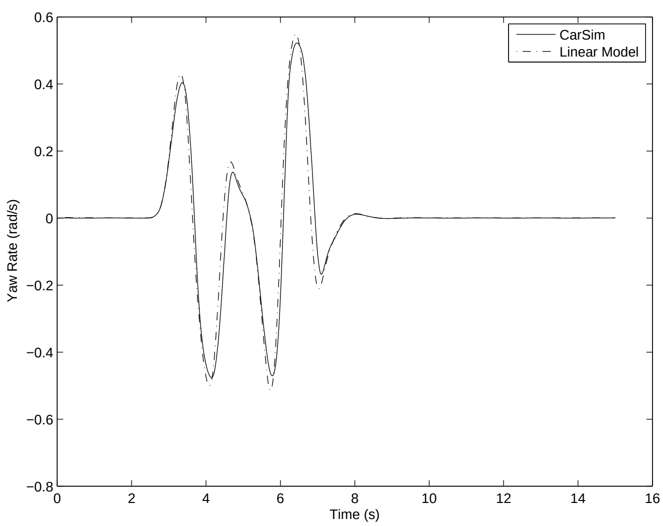

Figure 9. OPEN LOOP COMPARISON OF CARSIM AND LINEAR MODEL YAW RATE FOR DOUBLE LANE CHANGE

filter shows a smaller error magnitude over the trajectory than the “preview-free” estimator, although bias is obvious at certain points along the trajectory due to modeling error. Even so, the large-scale drift present in the y and ψ state estimates from the “preview-free” estimator is not present in the closed-loop filter. At the very minimum, this is a good result when sub-lane position accuracy is needed. This suggests that the addition of preview to the estimator helps to mitigate the effects of modeling error and unmodeled sensor biases to a degree. While the lateral position error is clearly smaller with the inclusion of preview (see Fig. 12), the differences in error for the vehicle yaw angle are less clear. Examining Fig. 13 shows that modeling error leads to bias in both filter schemes when the system dynamics are excited for the vehicle yaw state, but that the preview-inclusive estimator shows a smaller RMS error over the system trajectory, and has markedly better resistance to drift than its lower-order counterpart.

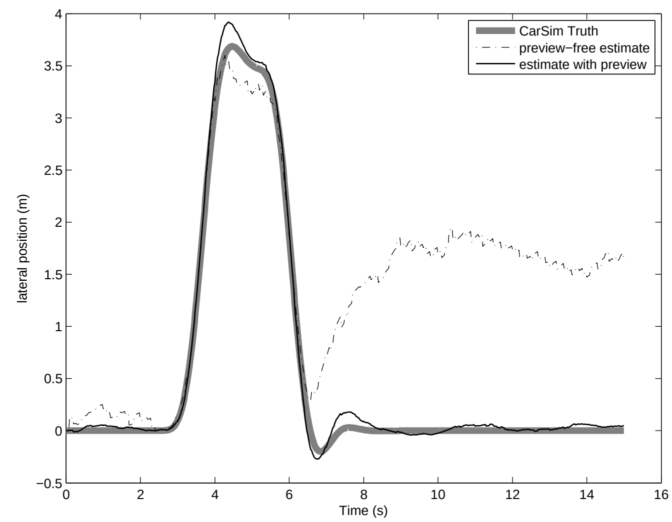

Figure 10. COMPARISON OF LATERAL POSITION ESTIMATES, GROUND TRUTH, AND LINEAR MODEL PREDICTION

One important point is that it is clear from the state traces from the linear model simulation in Fig. 10 and Fig. 11 that the closed-loop estimate appears to be “pulled” towards the linear model dynamics, which are known to be at least partially erroneous. The balancing act, then, is

1. striving for the best possible driver-vehicle model fit for a given driver-vehicle combination
2. weighting the previewed states from the map with an expectation of at least some modeling error

With respect for items 1 and 2 above, the inclusion of preview in a model-based vehicle state estimator has promise for improving accuracy with low-cost sensors to a point suitable for driver warning and assist technologies. Notice that in Fig. 10 the vehicle’s lateral position was corrupted significantly by the end of the maneuver. This could, at the very best, lead to false positives when used in conjunction with a lane departure warning system, and at worst, lead to a premature activation of a driver assist/intervention technology. The assistance of map-based estimation could help alleviate such errors.

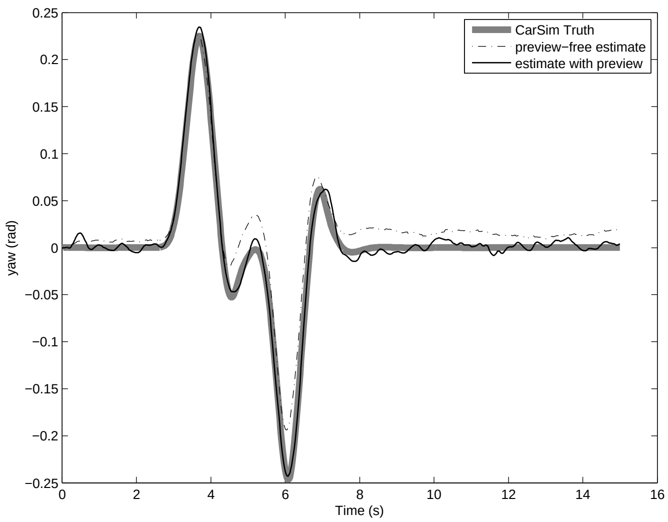

Figure 11. COMPARISON OF YAW ANGLE ESTIMATES, GROUND TRUTH, AND LINEAR MODEL PREDICTION

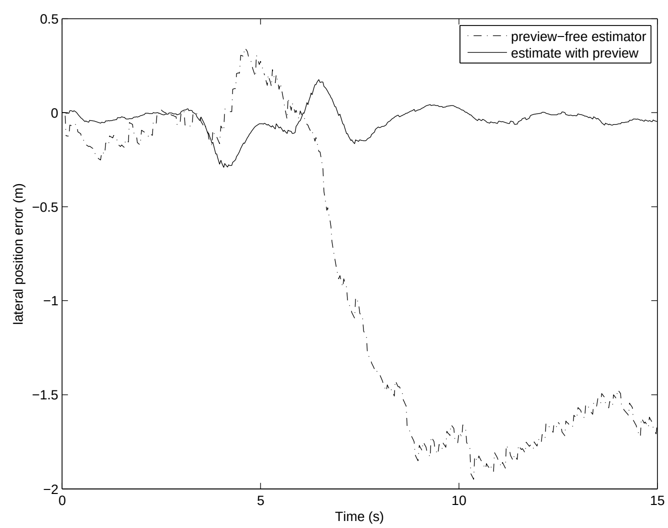

Figure 12. COMPARISON OF LATERAL POSITION ERROR BETWEEN PREVIEW-FREE AND PREVIEW-INCLUSIVE FILTERS

Conclusions

This work presents a simulation-based evaluation of a novel application of preview and map information for improvement of model-based state estimation in vehicle dynamics. The unique relationship of a vehicle to the global geometry of the road on which it travels hinges upon the behavior of the vehicle's driver. Humans, in pursuit of the steering task, use previewed information to aid in lane tracking. By including a driver model with preview in a model-based Kalman filter, and treating mapped preview samples as measurements in the filter, estimates of vehicle states were improved for a representative vehicle performing a double lane change maneuver at 80kph. Then, the technique was extended to test the estimator's performance in the face of considerable modeling error in both the vehicle and driver models, as well as an unmodeled sensor bias error.

While it is clear that the inclusion of preview information is extremely helpful when the closed-loop vehicle dynamics are known, the waters are more treacherous when parametric modeling error is introduced. This must be expected if this technique is to be applied to real vehicles, since human drivers exhibit considerable variability in behavior. However, through intelligent and careful modeling and selection of filter gains, the results suggest that the inclusion of preview in a model-based estimator can indeed increase accuracy to a degree which renders the filter useful for high-speed lateral control, driver warning, and driver intervention systems, even with commonly available, noisy vehicle state sensors.

Future work in this area is necessary to explore this type of estimator's ultimate utility for road vehicles. Physical experiments are planned to investigate whether the closed-loop model used is sufficiently predictive of human behavior to improve state estimates on a real vehicle driven by a human, and whether keeping track of the estimator's predicted system covariance could lead to a reliable predictor of driver inattention and/or an emergency maneuver.

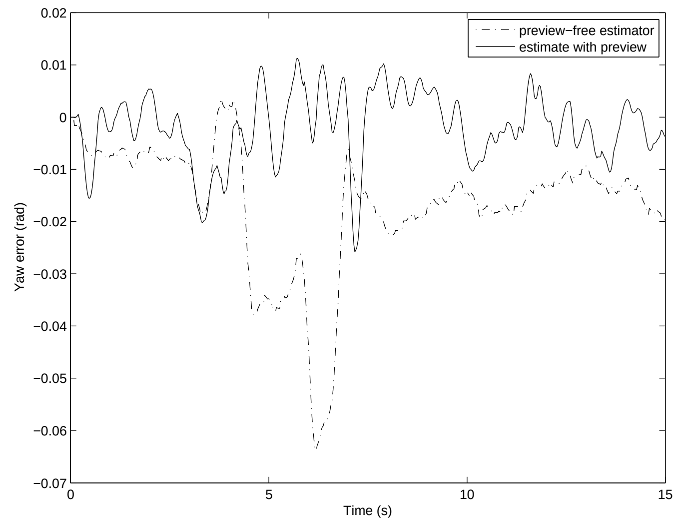

Figure 13. COMPARISON OF YAW ERROR BETWEEN PREVIEW-FREE AND PREVIEW-INCLUSIVE FILTERS

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