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What Preview Elements do Drivers Need?

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Abstract: Driving is a tracking task with preview as has been recognized since the 60s. Subsequent research to model human curve negotiation divides into two camps. One in which a limited number of points in the future (generally one or two) are used to guide lane keeping control on straight and curved roads and another that uses optimal preview control (OPC) to characterize human control behavior. The former is too simplistic as it cannot accurately handle curve entry and exit with a single preview and gain setting (i.e. non situation adaptive) and the latter is arguably too computationally intense for a human to adopt (but not unreasonable to converge to over time). This paper shows theoretically that by selecting two preview points strategically related to vehicle dynamics for near preview point and striking a balance between curve cutting on entry, curve overshoot on exit, and smooth control throughout for the far preview point, two-point-controllers approach the performance of a full optimal preview controller. The difference between the reference full OPC and two-point-controllers lies mainly in the fact that the three phases of curve negotiation (entry, within, and exit) require different previews and gains which only the OPC is capable of.

Keywords: Manual control, Optimal preview control, driver model, cybernetics, human performance.

1. INTRODUCTION

Driving is a preview control task where drivers perceive future constraints to arrive at control that primarily satisfies these constraints and secondarily smooths control. Many models have been presented since the 1960s that propose what information human drivers use to steer their vehicle within the lane boundaries (e.g. Sheridan, 1966; Tomizuka and Whitney, 1976; Sharp et al., 2000). The question is whether there are some guiding principles that aid us in better understanding what cues drivers use and what control strategy they employ. This information is not just of scientific value but also has implications for autonomous control that is maximally acceptable to humans. Here we examine the control strategy by exploring how close simply look ahead controllers can match full optimal preview controller (OPC).

Except when the road ahead presents obstacles, the lane boundaries are generally smooth. From sampling theory we know that a smooth signal only needs to be sampled as often as twice its highest frequency (Senders et al, 1968). This means that drivers may only need one or two points within the available preview to steer their vehicle. Some of the most often cited lane keeping and curve negotiation models do indeed have two preview points (e.g. Donges, 1978). From slalom skiers we know that it is no use looking many portals ahead because only the next two are needed to shape the approach through the upcoming portal. The equivalent of slalom skier portals in driving are tangent points (Boer, 1996; Lappi and Lehtonen, 2012).

With the two point models, a key question addressed in this paper is where the pair of preview points should be placed and whether this placement depends on the road shape and other factors. The tangent point has been proposed as a candidate for the far point in a two point model (Mars and Navarro, 2012). Here we purposefully do not include the tangent point to first gain a clear understanding of fixed preview two-point-controllers versus optimal preview controllers which have also been used to model human drivers (e.g. Sharp et al., 2000).

2. MODELS & CONTROLLERS

The adopted road model, vehicle model, optimal preview controller (OPC), two point optimal preview controller (OPC2) and look-ahead-controller (LAC2) are described.

2.1. Vehicle Model (1 of 2)

A purely kinematic model without any dynamics can be accurately controlled with simpler controllers than a model with dynamics. In order to show the differences between a simple two-point proportional look-ahead controller and a full optimal preview control model, the car is modelled with a bicycle model. Furthermore, the vehicle is driven at 20mps through tight curves that yield lateral accelerations in excess of 3m/s^2 so that the car slips a bit.

The continuous time state space model equations are as follows:

$$\begin{pmatrix}\dot{\beta}\\ \ddot{\psi}\end{pmatrix}=\begin{bmatrix}-\dfrac{C_{ar}+C_{af}}{mv_x} & \dfrac{L_rC_{ar}-L_fC_{af}}{mv_x^w}-1\\ \dfrac{L_rC_{ar}-L_fC_{af}}{I_z} & -\dfrac{L_r^2C_{ar}+L_f^2C_{af}}{I_zv_x}\end{bmatrix}\begin{pmatrix}\beta\\ \dot{\psi}\end{pmatrix}+\begin{bmatrix}\dfrac{C_{af}}{mv_x}\\ \dfrac{C_{af}L_f}{I_z}\end{bmatrix}\delta_f$$

The two dynamic states are side slip angle β and yaw-rate $\dot{\psi}$. Details about the meaning of each of the coefficients can

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be found in Lee (1990; Rajamani, 2006). The coefficients values are (Lee, 1990):

$$C_{af} = 42200, C_{ar} = 28567, L_f = 1.18, L_r = 1.52, m = 1582, I_z = 2430$$

In order for the vehicle to travel along a road, it is necessary to update the (xc,yc) location of the car in the world. Because the yaw angle or heading angle ψ is not maintain in a global sense in the state space model (see below for details on per time step coordinate transformations), heading is maintained globally separately based on the yaw-rate[1]. In discrete time the equations are:

$$\psi_n = \psi_{n-1} + T_s \dot{\psi}_{n-1}$$
$$xc_n = xc_{n-1} + v_x \, \mathrm{T}_s \cos(\psi_{n-1})$$
$$yc_n = yc_{n-1} + v_x \, \mathrm{T}_s \sin(\psi_{n-1})$$

These update equations are non-linear as they involve trigonometric functions and can thus not be used in linear optimal preview control computation (Lewis, 1986). Here we employ an approach that will enable usage of the linear vehicle dynamics model that resembles the approach adopted by Sharp et al., 2000. While it is possible to use model predictive control with non-linear state space equations (Maciejowski, 2002), linear models are used for clarity of understanding the benefits of full preview over two-point preview models.

2.2. Optimal Preview Controller (OPC)

The discrete time linear optimal preview model equations from Lewis, 1986 (Discrete Linear Quadratic Tracker in Table 4.4-1) are copied here for ease of reference. Note that this optimal preview controller (OPC) requires a linear state space system model.

System Model:

$$x_{k+1} = Ax_k + Bu_k$$
$$y_k = Cx_k$$

Performance Index:

$$J_n = \frac{1}{2}(y_N - r_N)^T P_N (y_N - r_N) + \frac{1}{2}\sum_{k=n}^{N-1}(y_k - r_k)^T Q_k (y_k - r_k) + u_k^T R_k u_k$$

Assumptions:

$P_k \geq 0, Q_k \geq 0, \mathrm{R}_k > 0,$ with all three symmetric

Optimal Affine Control:

$$K_k = \left(B^T S_{k+1} B + R\right)^{-1} B^T S_{k+1} A, \qquad S_N = C^T P C$$
$$S_k = A^T S_{k+1}\left(A - BK_k\right) + C^T Q C$$
$$v_k = \left(A - BK_k\right)^T v_{k+1}, v_N = C^T P r_N$$
$$K_k^v = \left(B^T S_{k+1} B + R\right)^{-1} B^T$$
$$u_k = -K_k x_k + K_k^v v_{k+1}$$

[1] In actuality, the heading angle and position updates are a bit more complicated as they also require side slip angle β or equivalently lateral velocity in car coordinates. Details for such slightly more accurate update equations can be found in Rajamani, 2006: Table 2.1 on page 27.

Note that the target reference is r and the system output is y in these equations. It is very important to recognize that the cost function weights can be different for every time step (i.e. depend on k). This is used below to select only two points in the preview for which Q will be nonzero; normally Q is held constant but mathematically it can take on any time profile as long as it remains symmetric and positive semi-definite.

Control is computed for the entire interval from time step n to N, where N is the maximum preview ahead of the vehicle which we denote with K (i.e. $K=N-n$). Only the control for the current time step is computed, the car state is updated and a new reference is computed and the OPC is rerun to get the next control action. This way it is similar to a simple look-ahead controller, where a new control action is also computed each time step.

The question is now, what is the reference profile r_k? Note that the reference needs to be defined in a car coordinate frame. To achieve this, each time step we define a new car centred coordinate frame that aligns its x-axis with the heading direction of the vehicle (i.e. ψ). It is then assumed that the vehicle travels each time step with a uniform increment along the new x-axis. The target reference is obtained by computing the distance to the road centre perpendicular to x-axis at uniform distance steps. The distance steps are equal to the distance the car travels in one time step (i.e. $v_x T_s$). We assume that the vehicle speed remains constant; in the simulations detailed below we set it at 20mps. Fig. 1 shows how the reference profile r_k is created each time step. The discrete reference points from r_0 to r_K at equidistant points $\{kT_s v_x, k \in [0,K]\}$ along the vehicle heading vector are obtained through interpolation of the reference line which is obtained by rotating the road centre line around the origin ($-cx_n$,$-cy_n$) and by $-\psi_n$. This assures that the model can be applied to any road shape.

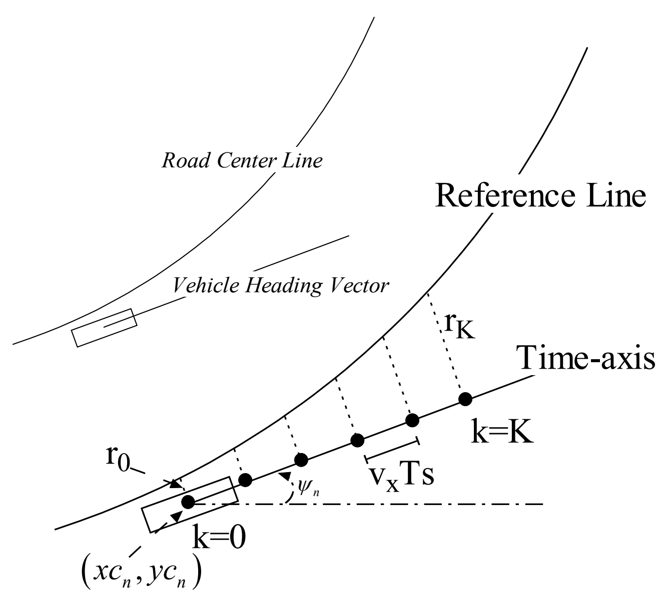

Fig. 1. Mapping from global world coordinates to local vehicle coordinates at each time step so that OPC (as well as OPC2 and LAC2 discussed in Sec. 2.4-5) can be applied.