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PD Controller for Car-Following Models Based on Real Data

Xiaopeng Fang[1], Hung A. Pham[1] and Minoru Kobayashi[2]
[1] Department of Mechanical Engineering
Iowa State University, Ames, IA 50010
[2] Honda R&D

The car following model is a key element in driver behavior modeling. A PD controller car-following model is a popular and realistic model. A big problem met in designing driver behavior models is the absence of reliable data from the real traffic. However, experiments using an instrumented vehicle driven in the real world supplied the radar tracking data. This paper first analyzes the desired distance for car-following. Then it presents the PD control gains obtained from the real data. A *Kp* and *Kd* fitting curve is presented and suggested to use in the microsimulation. Finally, the paper shows the simulation results comparing with the experimental results.

1. INTRODUCTION

Driver behavior modeling is a crucial issue in traffic microsimulation. Driver behaviors in the microsimulation typically consist of following behavior, lane change behavior, free driving behavior, and collision avoidance behavior. Car following models are key elements in modeling driver behavior and are included in almost every traffic microsimulation.

Two approaches are used by most of car-following models:
1. safety control strategy;
2. spacing control strategy

P. G. Gipps presented his car-following model for computer simulation in 1980. This model is derived by calculating a safe speed with respect to the preceding vehicle. It will make sure that the following car would stop should the vehicle ahead come to a sudden stop. D. Swaroop (et al. 1994) presented a spacing control strategy for car-following models. There are many other car-following models belonging to these approaches like NETSIM, INTRAS, FRESIM, CARSIM, and INTELSIM *(2)*.

PD-controller car following model is a spacing control strategy approach. It is based on the assumption that drivers try to keep the relative speed to the lead car zero and simultaneously attempt to keep the distance headway at a desired value *(3)*. It is easy to be implemented into the microsimulation, and the method is efficient and realistic.

To study driver behaviors, microscopic traffic data are needed. Till now, however, not many experiments were done to get the real traffic data. To evaluate behavior models, most researchers used the data from driver simulators. The main drawback of this method is the uncertainty about whether the driver behavior in the simulators are the same as the real world. Masroor Hasan (et al. 1997) showed that they extracted traffic data from video. Since the limitation of pixel size, it is hard to get an accurate measurement. Another problem of this method is that the data is static since cameras are installed in a fixed place.

An alternative method of gaining information on behavior, however, is the use of an instrumented vehicle. The instrumented vehicle is driven in the real traffic system and the behavior of adjacent drivers is recorded. This approach is realistic and accurate. It may be the only method that can produce a sufficient quality and quantity of data to allow the continued development and validation of simulation models *(4)*.

2. EXPERIMENT AND DATA

Experiment

The experiments are done with an instrumented truck, equipped with a radar tracking device, an optical speed sensor and two video cameras (as figure 1). The radar can track the relative distance and relative velocity between tracking vehicles and the instrumented truck. The optical speed sensor can record the velocity of the truck. And two video cameras are used to record the information of the environment so that the data can be categorized to different behaviors. Totally, the number of data sets is around 2000. It includes information of several behaviors, such as car-following, car-braking, and car-lanechanging, and experiments are done in different traffic environments, such as in highway and in town, and at different time. The drivers include both female and male. Their ages are from 25 to 75.

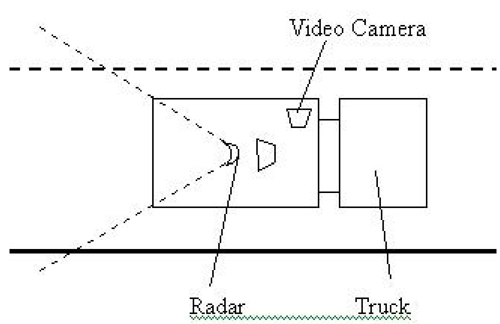

Figure 1 Experiment setup

Data

First, preprocessing must be performed for the radar can track eight different objects each time. Tracking angles of vehicles are used to distinguish between differing vehicles. Second, since the measurement data includes signal and noise, a one-dimension Kalman filter is used to estimate the relative distance as well as relative velocity to remove the measurement noise. Figure 2,3 shows the original data and the data after Kalman filtering.

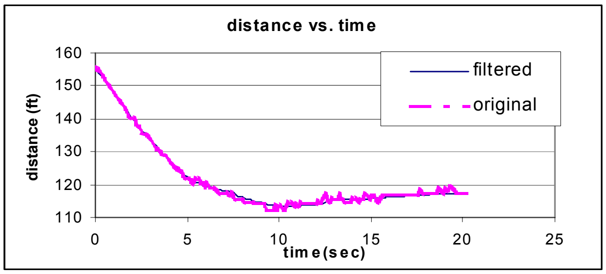

Figure 2 Relative distance vs. time

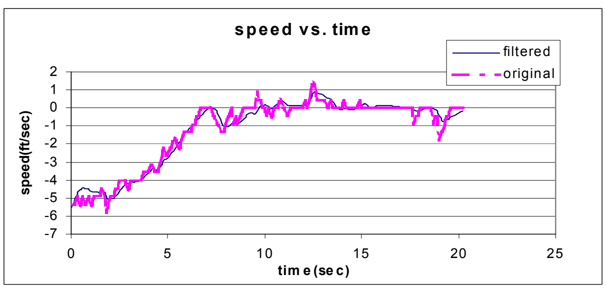

Figure 3 Relative velocity vs. time

3. PD CAR-FOLLOWING MODEL

PD Controller Concept

PD controller assumes the driver adjusts his or her speed with respect to the leading vehicle. It assumes the acceleration of the following vehicle is a function of relative distance and relative velocity between following and leading vehicles:

$$a(t+1) = Kp*\left[D_r(t) - D_d(t)\right] + Kd*V_r(t)$$

Where:

$a(t+1)$ is the acceleration at time t+1

$D_r(t)$ is the relative distance at time t

$D_d(t)$ is the desired distance at time t

$V_r(t)$ is the relative velocity at time t

Kp, Kd are gains for relative distance and velocity

Desired Distance

In the equation of PD controller for car-following models, there is a desired distance. A study by Michanels and Solomon *(5)* indicated that a driver reacts to changes in the speed of the leader by equalizing his or her speed with the leader's speed in order to maintain spacing. When the steady state reaches, the distance between the following vehicle and the leader's vehicle is considered as the desired distance. It is typically a function of the speed of the leading vehicle. There existed two kinds of models for the desired distance. The linear model assumes a constant time headway and the desired distance can be expressed as:

$$\text{Desired distance} = \text{speed} \times \text{preferred time headway} + \text{offset}$$

Another model is using a quadratic function to describe the desired distance as a function of speed. This model is used in MIXIC microsimulation.

Figure 4 shows the data of desired distances in different speeds got from the experiments. It is found that the linear model is good to describe the relation between the desired distance and the leader's speed. Even though the quadratic model has more freedom and is thought better than the linear model, it is really no need to use a complex model. Not only these experiments show the desired distance is close to a linear function of the leader's speed, but also experiment results in *(4)* show this kind of relation. It is interesting to find that the preferred time headway in the regressive form of the data is 1.18 second. It shows the time headway for most of drivers is near 1.18 second.

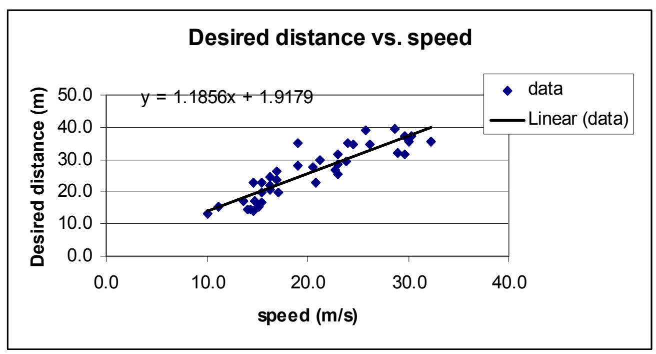

Figure 4 Desired distance vs. leader's speed

Figure 5 shows the density function of the preferred time headway got from the experiment results. It shows for different drivers the preferred time headway may be not the same. The range for car-following preferred headway time is from 0.9 second to 1.5 seconds. The probability density function for the preferred headway time is kind of similar to normal distribution. This information is very useful to generate different driver's behaviors in traffic microsimulation.

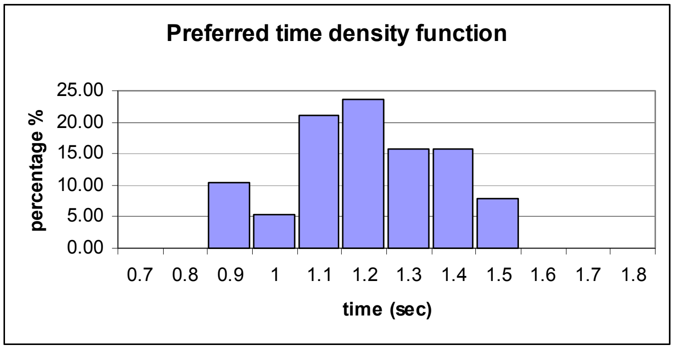

Figure 5 Preferred time density function

_Kp_ and _Kd_ gains

To design *Kp* and *Kd* control gains for PD controller, the first questions needed to think about are whether these gains are time-invariant, not dependent on current leader's speed or the desired distance. In the paper *(4)*, it is said that the parameters *Kp* and *Kd* are constant and they have been verified by the data from driver simulators. The following analysis is based on this assumption and the assumption is verified by comparing the simulation results and experiment results.

System analysis

In control areas, the PD controller is a simple but very useful controller. It can change the poles of the system so that the system can change from unstable to stable and attain certain response property. Car-following problems can be viewed as a feedback control problem. It can be thought that there is a spring with damping connecting the following car and the leading car. To design *Kp* and *Kd* gains means choosing the suitable spring and damping properties. Figure 6 shows the system diagram for the car-following model with PD controller. The following car updates its acceleration based on the PD controller at each time step. Then it updates its current velocity and position.

If the leading vehicle is driven in a constant speed, the whole system can be represented in the following control diagram (figure 7).

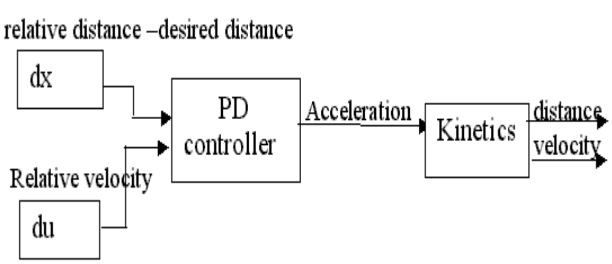

Figure 6 System diagram

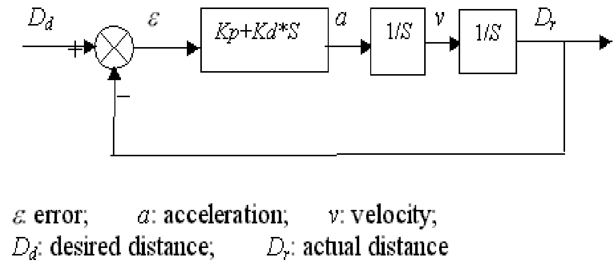

Figure 7 Transfer function diagram

The input is the desired distance (D_d). The output of the system is the actual relative distance (D_r). The feedback system's transfer function is shown in Equation 3.1.

$$\frac{D_r(s)}{D_d(s)} = \frac{Kp + Kd * S}{S^2 + Kd * S + Kp}$$

In the view of state space, the car-following model can be viewed as a two-dimension control problem. The state space form is always written in $\dot{x} = Ax + Bu$ format, where x is system state vector, u is the input, and *A, B* are system matrixes. The state space representation of car-following models with PD controller is shown as equation 3.2.

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -Kp & -Kd \end{bmatrix} * \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} * D_d$$

where:

x_1 is the relative distance;
x_2 is the relative velocity;

The eigenvalues of A matrix are the roots of equation $\lambda^2 + Kd\lambda + Kp = 0$. The system is internal stable if and only if all eigenvalues of A have negative real parts. To satisfy this condition, the *Kp* and *Kd* must be larger than zero. In another word, as long as *Kp* and *Kd* are positive, the system is internal stable.

Parameters Identification

From the above analysis, it seems control gains have a lot of choices if only considering stability. It is why the real traffic data is necessary that it is hard to choose control gains for PD controller without analyzing drivers' behavior in the real world. To analyze each set of car-following data, the steady following distance, i.e. the desired distance, is got from the data first. Then *Kp* and *Kd* control gains are computed with acceleration data, relative distance, and relative velocity. It is an overdetermined linear system and a least square method is used to solve control gains. Figure 8 shows the control gains got from experimental data.

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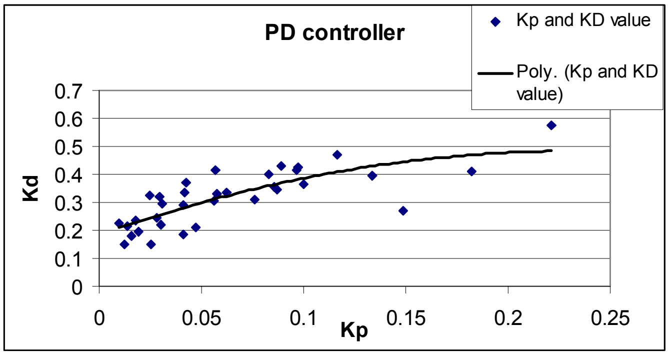

Figure 8 *Kp* and *Kd* control gains

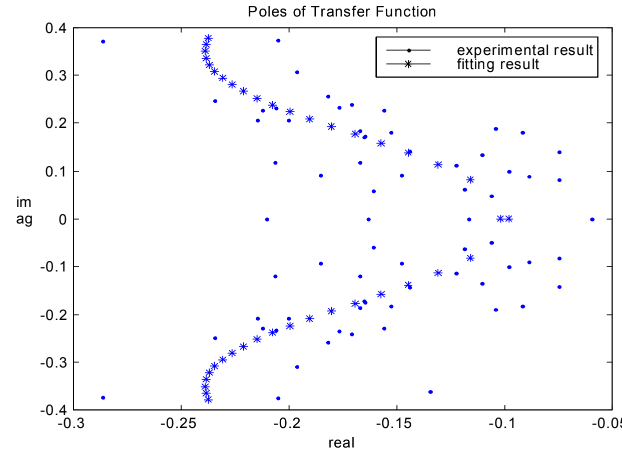

Figure 10 Root Locus of system

It is interesting to note that *Kp* and *Kd* control gains are not random distributed. They are kind of related each other and around a certain region. A second order polynomial was found to simulate *Kp* and *Kd* relation. It is found that *Kd* will increase slowly with increasing *Kp*. From the figure 9, it is known that most *Kp* and *Kd* locate in the region with small values. The density function of *Kp* has a decreasing trend. This information is useful to generate *Kp* and *Kd* values in microsimulation so that different following behaviors are simulated.

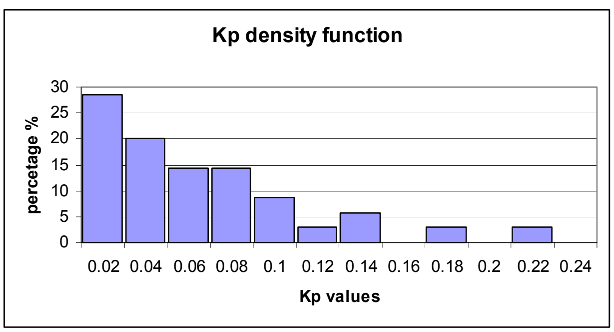

Figure 9 *Kp* density function

Analysis of control gains

The eigenvalues of *A* matrix are the poles of the closed-loop transfer function. The poles' distribution is shown as figure 10. Comparing with the poles got from above fitting cures, the experiment results are oscillating along the fitting results. . The fitting results are good representatives of PD control gains' distribution and are suggested to use in the traffic microsimulation to generate different PD controller car-following models. And, experiment results shows the damping ratio for car-following system ranges from 0.3 to 1.0 and nature frequency range is 0.06~0.4. Note that the setting time for step response is more than twenty seconds. This means the response of drivers is very slow.

Simulation Results

The simulation was run using *simulink*. Figure 11 shows the simulation results and experiment results. The simulation is run with the same condition as the experiment at the beginning. Hence, the simulation begins the same relative distance and same relative velocity between the following car and the leading car as in the experiment. The simulation is using the PD control gains which are got from the experiment using the least square method. The simulation results show that the PD controller is a good method in that its results are very close to the original ones. And it proves the PD controller gains can be considered as time-invariant too. The control gains used here are Kp=0.056 and Kd=0.30.

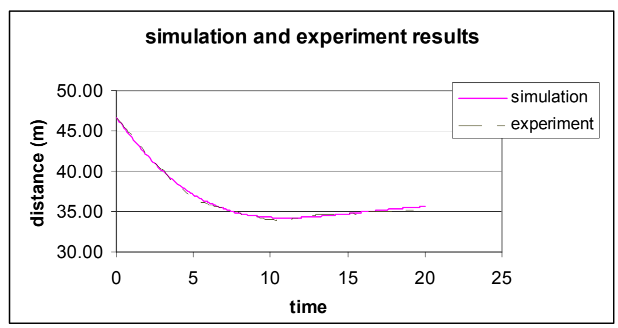

Figure 11 Simulation results and experiment results

For the same data in figure 11, different PD control gains were chosen to compare effects of control gains (figure 12). Differing drivers would choose different paths to attain the desired distance even in the same conditions. The PD controller car-following model simulates differing drivers following behavior through changing control gains. In designing PD controller, the damping ratio will affect the rising time and overshoot of the response. The nature frequency will affect the setting time.

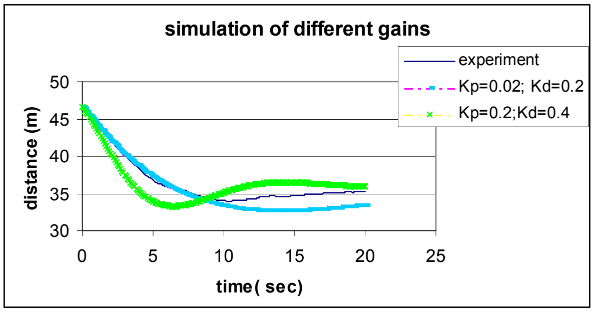

Figure 12 Simulation of different control gains

To compare PD controller with other following models, a simulation experiment has been set up to get average velocity and traffic density information. The following models chosen in this experiment is GIPPS, NETSIM, and PD controller. The GIPPS following model is used in MITSIM and considered a reliable but not realistic model. It does a complicated calculation to get the maximum acceleration for the following car so that it wouldn't collide with the lead car. NETSIM also gets the acceleration from the safe distance but add another parameter to simulate different drivers. The experiment used 13 simulating cars (including one leading car). The simulation's initial conditions are totally the same for three following models. The leading car is predefined to keep a constant speed 20 m/s for 5 seconds, then brake to zero (20 seconds), accelerate to 20 m/s (20 seconds), and keep at the current speed until the simulation is over.

Figure 13 shows the average traffic speed for three following models. The PD controller following model is better than NETSIM in most of the simulation time. Comparing with GIPPS, the PD controller get higher average speed in some situations, but worse mainly in acceleration areas. It is because that GIPPS use the maximum acceleration when it is calculatedly safe.

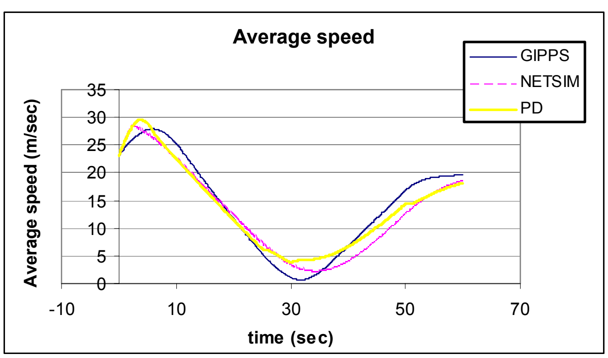

Figure 13 Comparison of average speed

Figure 14 shows the traffic density information. The density is the maximum vehicles per kilometer and is got from the following equation:

$$Density = 1000 \times 13 \times (X_d - X_e - L \times 12)$$

where X_d is the position of the leading car, X_e is the position of the last following car, and L is the car's length.

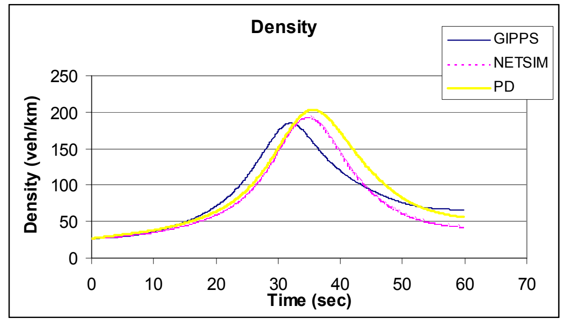

Figure 14 Comparison of Density

The simulation results show that the PD controller improves the traffic density. No matter what situations are, the PD controller is better than NETSIM models. Even though GIPPS gets higher density in some areas, the PD controller is much better in the whole simulation.

4. CONCLUSION

Real traffic data is very useful to analyze and design driver behavior models. The PD control gains got from the real data are used in traffic microsimulation. The simulation shows the PD controller car-following model is a realistic and efficient model. It can be applied to car-braking status, but needed to consider reaction time.

The experiments done are almost in high velocity (30mph-65mph). In the low velocity range, cars are close each other. The overshoot in the PD controller may result in collision with the leading car. The safety issue must be considered in this case.

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