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Evaluating Human & Computer for Expressway Lane Changing

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Abstract— **Google already showed the self-driving car can do stopping and accelerating more smoothly than the human drivers by doing extensive experiments. In this paper, we compare a human driver with computer generated motion for expressway lane changing. We did experiments at Nagoya ring route expressway and recorded all the detail motion information regarding lateral and longitudinal movement of a taxi driver. We developed an algorithm to generate and evaluate the alternative lane change motion sets considering both lateral and longitudinal trajectories. We defined a smoothness measure that integrates lateral and longitudinal motions to evaluate generated lane change motions. Evaluation results for 19 sets of lane change labeled data show the computer motion generator is able to generate close or better motion compared with a taxi driver using proposed evaluation function.**

I. Introduction

The past decade has witnessed ambitious researches in the area of automated driving and automated vehicles advance toward handling realistic road traffic in urban area. In August 2012, the Google team announced that they have completed over 300,000 automated-driving miles (500,000 km) accident-free at any given time and typically have a dozen cars on the road [1,2]. Currently four U.S. states have already passed laws permitting automated cars on the roads and there are more on waiting [3].

Gradually some questions are raising about automated driving such as how much we can trust the efficiency and safety of the self-driving cars compared to a human driver? According to the MIT Technology Review, Google's Chris Urmson made claims at the Santa Clara ROBO Business conference on Oct 2013 that Google's self-driving cars are better at driving than you, or me, or anyone else out on the road [4]. However how, exactly, can an automated car be a better driver than a human driver? A lot of its function would do with the safety features and advanced driver assistance systems such as ACC (Adaptive Cruise Control), FCW (Forward Collision Warning), CWS (Collision Warning System,) & LKA that we're already driving around with. Some of these systems (e.g. anti-lock brakes, traction control, automatic braking) are designed to remove human error and others (e.g. blind spot detection) include sensors that are capable of detecting vehicles and other objects that human may fails to detect.

What a self-driving car does is essentially replace the human factor with computer, just like Deep Blue did. On Feb, 1996, Deep Blue became the first machine to win a chess game against a reigning world champion (Garry Kasparov) under regular time controls [5]. After the loss, Kasparov said that he sometimes saw deep intelligence and creativity in the machine's moves. Deep Blue was capable of examining all of the relevant movement and determining the next appropriate move by using an evaluation function. Though, there's a huge difference between analyzing chess moves and making real-time decisions while moving through the flow of traffic. According to two studies that Urmson presented at ROBO Business, there really isn't much of a difference. The root of his claim owes more to human shortcomings than robotic advantages, since the studies compared data that was recorded during both human- and computer-operated driving sessions. The results of these studies showed that Google's self-driving cars were capable of stopping and accelerating more smoothly than the human drivers. The studies showed that the computer-controlled cars were better at maintaining constant following distances than human drivers in distance keeping [6,7].

In this paper, we are looking to compare human driver motion with computer motion generator during the expressway lane changing. Lane change at expressway is a challenging operation and many parameters such as operation time, lateral & longitudinal acceleration patterns should be carefully tuned for safe and smooth operation. For our experiments, we selected a skilled taxi driver whose driving skill is higher than the average and drove at Nagoya ring road expressway. We recorded all the detail motion information including lateral and longitudinal movement of taxi driver during lane change. We also recorded the environment information using lasers and cameras to check the safety of the motions generated by computer. Though, we mainly focus on analyzing smoothness and comfort of the human driver and computer motion regardless of safety. Like Deep Blue, computer generates alternative motion sets including different lateral and longitudinal acceleration patterns. Then, we evaluate motion sets using an evaluation function and compare them with taxi driver motion. Different from previous approaches [8], we integrate both lateral and longitudinal trajectories to generate lane change motion. Previous methods consider lateral and longitudinal trajectories independently to evaluate the comfort of the vehicle motion and simplify the strong relations between them. In this paper, we propose an evaluation function that integrate both lateral and longitudinal trajectories in a same function. Through experiments, we found the proposed evaluation function not only select close motion to human driver but also minimize the lateral jerk. The evaluation function is defined as integral over the square of arc-length derivative of curvature. It is a suitable evaluation

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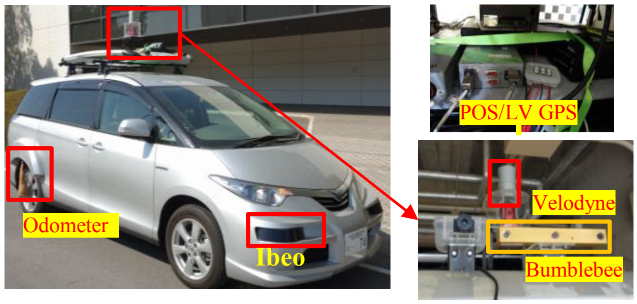

Figure 1. Vehicle platform for experiments

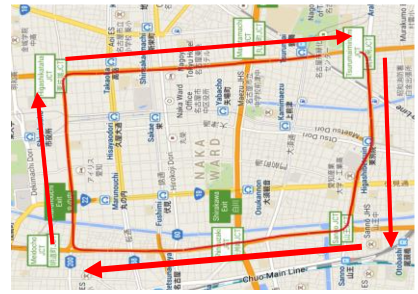

Figure 2. Experiment path in Nagoya ring route - marked by red line.

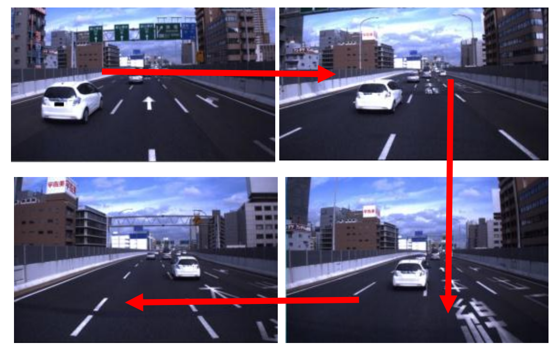

Figure 3. Lane change experiment at expressway

function to evaluate the lane change motions in expressway as we have to adjust both lateral and longitudinal velocity and acceleration at the same time.

We have evaluated the human driver motion and computer generated motion for 19 sets of labeled lane change data. The experiments shows the computer can generate close or even better motion than a human driver using proposed evaluation function. In the following, we discuss about experiment platform and expressway in section II, in section III, we discuss about the motion generation and evaluation function, finally we analysis the detail of 19 sets of lane change experiments.

II. Expressway Experiments

A. Experiment Platform

We enhanced a Hybrid ESTIMA car as shown in Fig. 1 with different sensors to do experiments. To record motion information, an Applanix POS LV 620 system is used to provide real-time integration of multiple dual-frequency GPS receivers with RTK mode, a high-performance Inertial Measurement Unit (IMU) and wheel odometry via a distance measurement unit (DMI). The real-time position and orientation errors of this system were typically below 100 cm and 0.1 degrees, respectively. For external sensing, our vehicle features a HDL-32E LIDAR sensor which is small, lightweight and features up to 32 lasers across a 40° vertical field of view. Additional range sensing is achieved through two IBEO Alasca XT sensors, mounted on the front bumper of the vehicle. Our vehicle uses a Bumblebee cameras, manufactured by PointGray.

We developed a flexible software architecture to fuse and synchronize all sensors data. Our system facilitates efficient communication between asynchronous software modules operating on the vehicle's computer. This architecture has enabled the rapid creation of a code base that incorporates data logging, replay recorded data, and 3-D visualization of all experimental data, coupled with an interface for labeling the experiments and sensor data.

B. Lane Change Experiments

To evaluate the human driver motion during the lane change, we did experiments at Nagoya Expressway Ring Route with the length of 10.3 km. The experiment paths are shown in Fig. 2 and marked by red line. We selected a taxi driver for doing lane change experiments whose driving skills is generally higher than average people. We did lane change experiments from 8:45 to 10:15 AM just after morning rush hour and traffic was medium during recording. Nagoya ring route is one-way expressway and flows clockwise with 2 to 4 lanes of traffic. We frequently did lane change experiments between different driving lanes to cover most possible scenarios. After receiving the request for doing the lane change, the taxi driver adjusts longitudinal speed and finds safe space and time zone to start steering for lane change. Lane change in expressway is generally challenging task and the driver should adjust both the lateral and longitudinal acceleration to do safe and comfortable lane change. An example of lane change experiment is shown in Fig. 3.

III. Motion Generation

Vehicle basic movements include everyday driving maneuvers such as merging, lane change, lane keeping or avoiding other vehicles. This is where trajectory concepts come into play to provide suitable motion by the combined usage of steering and breaking/acceleration [9]. We generate different alternative patterns for lane change including alternatives for both lateral and longitudinal trajectories. We are able to fast generate the alternative trajectories by changing the operation time and/or end conditions.

A. Lateral Trajectory Generation

To model a geometric path during a lane change, literature show often approaches using 5th degree polynomials [10,11]. Polynomial function provides a geometric modelling of the vehicle trajectory that responds to the realistic demands of the maneuver. Quintic polynomials as following, used to generate alternative lateral trajectories

$$y(t) = a_5t^5 + a_4t^4 + a_3t^3 + a_2t^2 + a_1t + a_0 \quad (1).$$

The equation coefficients a_i are calculated considering dynamic constraints (boundary conditions for lateral acceleration) and values of the position, velocity and

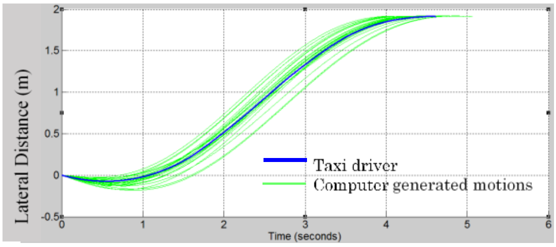

Figure 4. Alternative lateral trajectories for lane change

acceleration at initial and endpoint. We are able to get the initial velocity and acceleration of vehicle from the CAN and generate alternative lateral trajectories by changing operation time ($\Delta t = t_e - t_s$) and/or final value for lateral speed and acceleration ($v_y^{t_e}, a_y^{t_e}$). We sample ($\Delta t, v_y^{t_e}, a_y^{t_e}$) from valid range of operation time and end conditions to generate alternative lateral trajectories considering the boundary conditions for each sampling value (vehicle dynamic constraint and road limitations). Fig. 4 shows some alternative lateral trajectories. The blue curve shows the human driver lateral trajectory and green curves shows alternative lateral trajectories generated by sampling from operation time and end conditions.

B. Longitudinal Trajectory Generation

Lane change, distance keeping or lane keeping require longitudinal trajectories, to adjust velocity. Quartic polynomial can be found suitable for generating lateral movement of the vehicle as the following equation.

$$\mathrm{x(t)} = b_4 t^4 + b_3 t^3 + b_2 t^2 + b_1 t + b_0 \quad (2)$$

The equation coefficients b_i are calculated by considering dynamic constraints (boundary conditions) and longitudinal values of the velocity and acceleration at initial and endpoint. Same as lateral trajectory generation, we sample from operation time and end conditions ($\Delta t, v_x^{t_e}, a_x^{t_e}$) to generate alternative longitudinal trajectories. In Fig. 5, the blue curve shows the human driver longitudinal trajectory during the lane change and green curves shows alternative longitudinal trajectories.

IV. MOTION EVALUATION

To integrate and evaluate both lateral and longitudinal trajectories in same function, we use the same smoothness measure as Kanayama and Hartman proposed [12]. Evaluation function C_s is defined as integral over the square of arc-length derivative of curvature along the path for a function $f(x)$ with curvature $\kappa(x), x \in [x_s, x_e]$. There is one-to-one relation $ds = (1 + \acute{f}(x)^2)^{1/2}$, between x and arc-length s. Therefore the smoothness C_s measure can be re-written as following;

$$C_s = \int_{s(x_s)}^{s(x_e)} \dot{\kappa}(s)^2 ds = \int_{x_s}^{x_e} \frac{\acute{\kappa}(x)^2}{(1 + \acute{f}(x)^2)^{1/2}} dx \quad (3)$$

For a lateral time based trajectory function $y(t)$ from (1) and longitudinal trajectory function $x(t)$ from (2) smoothness measure in (3) can be re-written based on time;

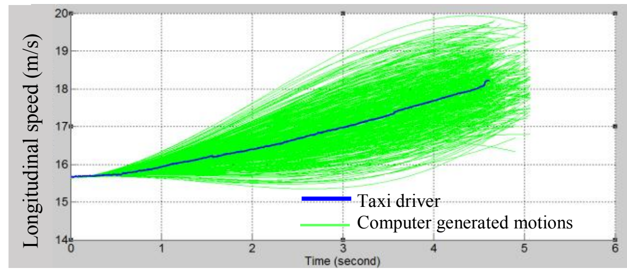

Figure 5. Alternative longitudinal trajectories for lane change

$$C_s = \int_{t_0}^{t_1} \frac{\acute{\kappa}(t)^2}{\sqrt{\dot{x}(t)^2 + \dot{y}(t)^2}} dt \,, \kappa(t) = \left| \frac{\dot{x}(t)\ddot{y}(t) - \ddot{x}(t)\dot{y}(t)}{(\dot{x}(t)^2 + \dot{y}(t)^2)^{3/2}} \right| \quad (4)$$

As you can see in (4) the evaluation function C_s considers both lateral and longitudinal trajectories $x(t), y(t)$. C_s makes a suitable evaluation function to evaluate the lane change motions in expressway.

Here, we are trying to minimize the C_s for all available motion sets including lateral and longitudinal trajectories in the following optimization problem;

$$\min C_s \qquad (5)$$
$$x(t), y(t) \in M$$

where M is set of all available motion sets for vehicle. There are other constraints that limit the available motion sets including vehicle dynamic constraints, safety and road limitations related to driving environment. There is direct method to solve the above problem using Lagrange multiplier and Gradient Descent [13]. Though finding the exact solution for optimization problem in (5) is difficult and time consuming. Here, we turn our attention to approximations of the minimizer through a simplification and sampling from search space. Instead of calculating the best trajectory explicitly and modifying the coefficients to get a valid alternative, we generate in a first step, such as in [8,14-16], alternative trajectories for both $x(t), y(t)$. Later we can pick the valid and safe motion which is safe and has the lowest value for C_s .

We start with extracting the taxi driver longitudinal and lateral trajectories information such as positions (x_t, y_t), velocities (v_x^t, v_y^t) and accelerations (a_x^t, a_y^t) from the labeled lane change data. Though, we use expensive GPS/IMU receiver, the lateral and longitudinal acceleration data (a_y^t, a_x^t) are still noisy as shown in Fig. 7, 10 by blue lines. In this paper, we use **polyfit** function from **Matlab** to smooth the lateral and longitudinal acceleration data of taxi driver as depicted in Fig. 7, 10 by red curve. After smoothing, we extract the operation time Δt, end condition for lateral trajectory $\left(y_{t_e}, v_y^{t_e}, a_y^{t_e}\right)$, and end condition for longitudinal trajectory $\left(v_x^{t_e}, a_x^{t_e}\right)$ from taxi driver lane change experiments.

In next step, we generate alternative lateral trajectory sets by sampling from operation time Δt and/or end condition of taxi driver lateral trajectory including $\left(y_{t_e}, v_y^{t_e}, a_y^{t_e}\right)$. For sampling, we use Gaussian distribution and standard deviations $\left[\delta_{\Delta t}, \delta_y, \delta_{v_y}, \delta_{a_y}\right]$ are considered to generate samples. In practice, we consider low value for $\delta_y, \delta_{v_y}, \delta_{a_y}$ as we are going to align the vehicle with the road curvature and center of the lane after the lane change. We also do not consider high value for $\delta_{\Delta t}$ as we are going to decrease the risk of collision with the surrounding objects. We generate $i = 1, \dots, N$ different lateral trajectories $y_i(t)$ with different end conditions $\left(\Delta t_i, , y_i^{t_e}, v_{y_i}^{t_e}, a_{y_i}^{t_e}\right)$.

For each lateral trajectory $y_i(t)$ with operation time Δt_i, we generate M alternative longitudinal trajectories shown by $x_{i,j}(t)$ with same operation time Δt_i, $i = 1, \dots, N$, $j = 1, \dots, M$. Motion set $m_{i,j} = \left[y_i(t), x_{i,j}(t)\right]$ is defined by combining the lateral and longitudinal trajectory and we calculate the smoothness cost $C_s^{m_{i,j}}$ for each motion set $m_{i,j}$ using (4). Before evaluation, we validate generated lateral and longitudinal motion using maximum curvature formula from [17]. We remove the motions that exceeds the maximum curvature to avoid slip or fishtailing. We also check the collision of generated motion using sensor data. We used the Inevitable Collision States (ICS) method proposed in [18,19] to find collision free computer generated motion. First, using LADAR we estimate position, size, speed of surrounding moving objects. We use the method explained in detail in [19] to check collision of generated trajectories with all moving objects. There are many other parameters concerning the safety of lane change motion including the distances to surrounding objects that we donot consider in this paper.

We generate 40 alternative lateral trajectories ($N = 40$) and for each lateral trajectory, we generate 30 ($M = 30$) alternative longitudinal trajectories (totally 1200 motion sets). The detail information about the taxi driver motion and computer generated motions such as trajectories, accelerations, and curvature are shown in Fig 6-11. Red curve shows the taxi driver motion and green curve shows the computer selected motion using (4). As shown in Fig. 6, computer selects lateral trajectory which is close to taxi driver. In Fig. 9, computer generated motion considers higher longitudinal velocity and acceleration compared to the taxi driver. Though it considers higher value for longitudinal acceleration the motion curvature of computer motion generated is lower than the taxi driver as shown in Fig. 11. In Fig. 11, the black line shows the maximum curvature and calculated based on formula in [17]. The results of comparison between taxi driver action and computer motion generation are summarized in Table I. As shown in Table I, the operation time of computer motion generation Δt is increased about 0.275 s compared to the taxi driver. We have also lower value for maximum and minimum lateral acceleration and lateral jerk compared to the taxi driver.

V. Lane Change Comparison Results

Same as previous example, computer has generated motion for all remaining 18 sets of labeled lane change information. The results of comparison between taxi driver and computer motion generation are shown in Table II. In most cases the computer can generate close or even better motion sets compared to human driver as shown in Fig. 12 & 13. Human lane change behavior is very complicated with many parameters. We donot have the idea about the exact evaluation p that human consider to generate suitable motion for lane changing. Though experiments shows that the proposed

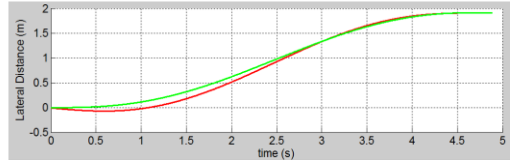

Figure 6. driver (red) and computer (green)lateral trajectory

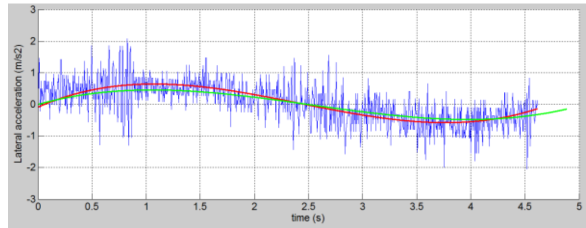

Figure 7. driver and computer lateral accleration for lane change- Blue lines shows the original data from IMU, red curve shows smoothed IMU data and green curve shows the compter lateral accleration.

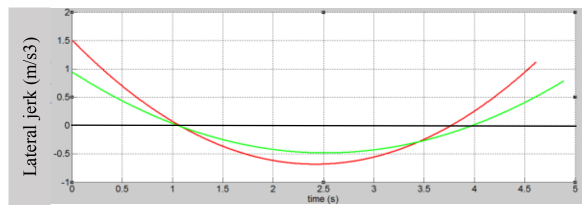

Figure 8. driver (red) and computer (green) lateral jerk

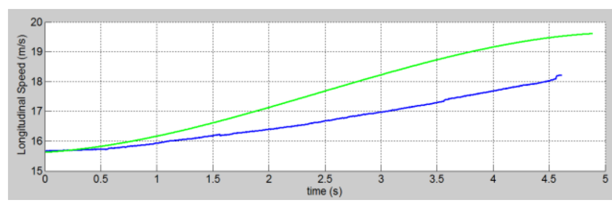

Figure 9. driver (blue) and computer (green) longitudinal speed

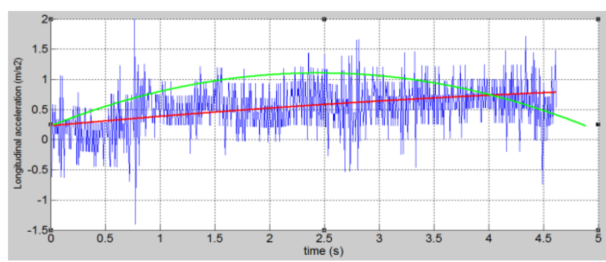

Figure 10. driver and computer longitudinal accleration for lane change- Blue lines shows the original data from IMU, red curve shows smoothed IMU data and green curve shows the compter longitudinal accleration.

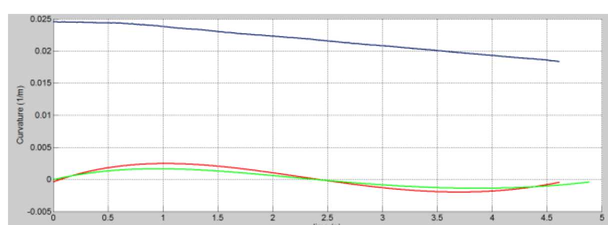

Figure 11. driver and computer curvature for lane change- red curve shows smoothed IMU data from driver, green curve shows the compter and the black line shows the maximum curvature during the lane change.

TABLE I. COMPUTER AND HUMAN DRIVER ANALYSIS

Motion Parameters	Taxi Driver	Computer
Operation time	4.615	4.890
Lateral Acceleration		
Max lateral acceleration (m/s2)	0.643	0.454
Min lateral acceleration (m/s2)	-0.579	-0.480
Jerk		
Maximum lateral jerk (m/s3)	1.506	0.946
Minimum lateral jerk (m/s3)	-0.680	-0.481
Evaluation		
Lateral jerk cost	1.681	0.803
Smoothness cost	1.43E-06	5.48E-07
Traveled distance	76.874	86.189

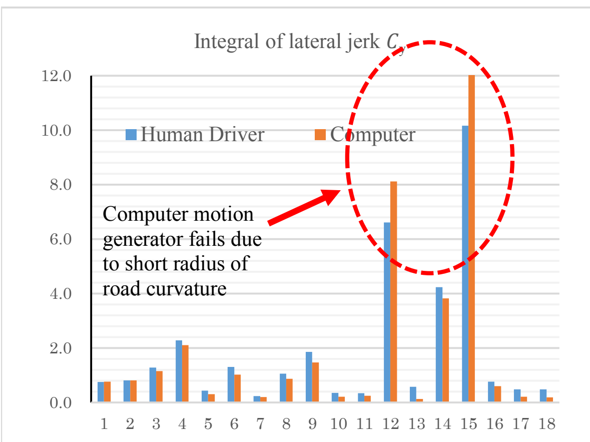

Figure 12. lateral jerk cost of taxi driver against computer motion generation

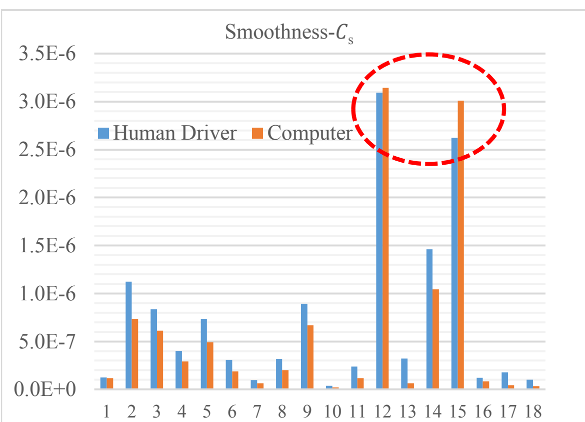

Figure 13. smoothness of taxi driver against computer motion generation

evaluation function in (4) can generate close lateral and longitudinal motion to the taxi driver.

In cases 12 & 15, the computer fails to generate better motion set. The reasons comes from road shape and road curvature for cases 12, 15. In these cases, the radius of road curvature is short (high curvature road) along the lane change (as we did experiments in rotary ring route- refer to Fig. 2) and the lateral trajectory generator fails to generate suitable lateral trajectory. The detail results of taxi driver motion and computer generated motion for case 15 is depicted in Fig. 14.

TABLE II. COMPUTER AND TAXI DRIVER ANALYSIS FOR ALL LANE CHANGE DATA

Case	Taxi Driver			Computer		
	Operation Time -Δt (s)	Smoothness (C_s)	Lateral Jerk Cost (C_y)	Operation Time -Δt (s)	Smoothness (C_s)	Lateral Jerk Cost (C_y)
1	4.92	1.23E-07	0.746	5.075	1.19E-07	0.761
2	7.135	1.12E-06	0.810	7.175	7.35E-07	0.802
3	4.195	8.35E-07	1.280	4.06	6.12E-07	1.145
4	4.265	4.00E-07	2.275	4.22	2.93E-07	2.102
5	4.15	7.34E-07	0.432	4.17	4.91E-07	0.303
6	3.66	3.10E-07	1.306	3.705	1.89E-07	1.022
7	3.02	9.70E-08	0.229	3.075	6.48E-08	0.199
8	3.995	3.19E-07	1.049	4.04	2.02E-07	0.863
9	5.605	8.94E-07	1.859	5.6	6.69E-07	1.463
10	4.285	3.94E-08	0.351	4.315	2.09E-08	0.205
11	3.195	2.37E-07	0.334	3.18	1.18E-07	0.242
12	3.025	3.09E-06	6.611	3.02	3.14E-06	8.112
13	4.83	3.22E-07	0.573	4.965	6.32E-08	0.130
14	3.85	1.46E-06	4.226	4.1	1.04E-06	3.823
15	4.585	2.62E-06	10.156	4.665	3.01E-06	12.169
16	5.155	1.23E-07	0.760	4.96	8.44E-08	0.597
17	4.335	1.79E-07	0.473	4.545	4.50E-08	0.205
18	4.425	1.01E-07	0.475	4.375	3.61E-08	0.186

As shown in these figures the computer generated motion is close to taxi driver though it fails to generate better motions. It is because of the simple & fast algorithm that we used to generate samples from lateral trajectories space. For these cases, it is necessary to develop more complicated algorithm to sample from the available motion sets and adjust the coefficient of the lateral trajectory function by considering the road curvature and shape. The detail information of case 3 is shown in Fig. 15. The results show that computer generated motion is close and even more smooth compared to taxi driver.

VI. CONCLUSION

We have developed a method to evaluate human driver with computer generated motion for expressway lane changing. The proposed evaluation function integrate both lateral and longitudinal trajectories in a same function. The results of experiments and evaluation function shows the computer is able to generate close or even better motions compared to a taxi driver. We did experiments with only one taxi driver and in future we extend experiments with more human drivers at different driving skill.

Finally, we didnot discuss about the surrounding environment and its impact on human generated motion. It is complicated model and there are many parameters that are not well known. We will consider it for future research.

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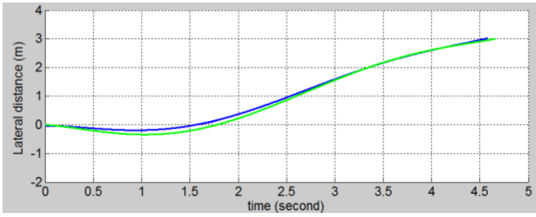
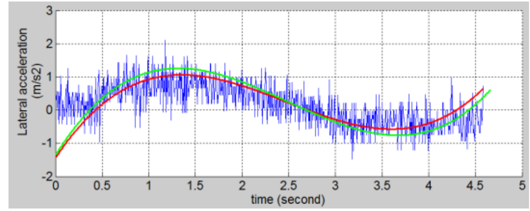
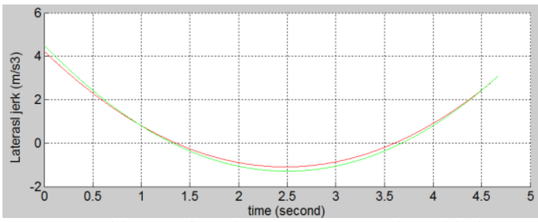


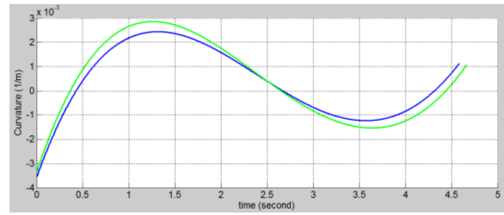
(a) driver (blue) and computer (green)lateral trajectory



(b) driver and computer lateral accleration -Blue lines (original) red curve (smoothed) ,green curve shows the compter



(c) driver (red) and computer (green) lateral jerk



(d) driver (blue) and computer (green) curvature

Figure 14. taxi driver motion and computer generated motion for lane change case 15 (computer fails to generate better motion)

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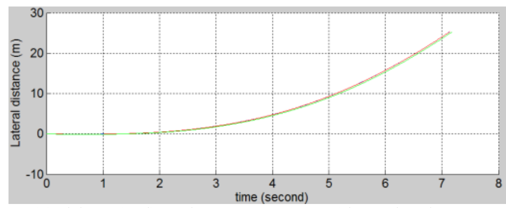
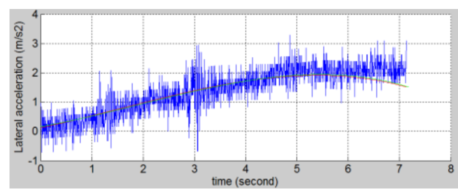
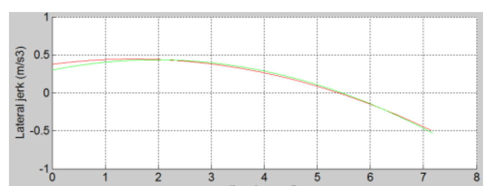


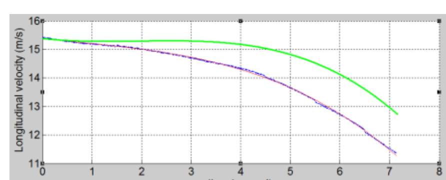
(a) driver (red) and computer (green)lateral trajectory



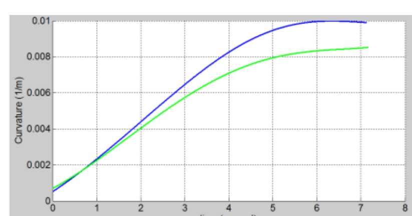
(b) driver and computer lateral acceleration -Blue lines (original) red curve (smoothed) ,green curve shows the computer



(c) driver (red) and computer (green) lateral jerk



(d) driver and computer longitudinal speed -Blue lines (original) red curve (smoothed) ,green curve shows the computer



(d) driver (blue) and computer (green) curvature

Figure 15. taxi driver motion and computer motion for case 3