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Characterization of the Lateral Control Performance by Human Drivers on Highways

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ABSTRACT

The characterization of human drivers' performance is of great significance for highway design, driver state monitoring, and the development of automotive active safety systems. Many earlier studies are restricted by experimental scope, the number and diversity of human subjects, and the accuracy and extent of measured variables. In this work, driver lateral control performance on limited-access highways is quantified by utilizing a comprehensive naturalistic driving database, with the emphasis on measures of vehicle lateral position and time to lane crossing (TLC). Normative values at various speed ranges are reported. The results represent a statistical view of baseline on-road naturalistic driving performance, and can be used for quantitative studies such as driver impairment and alertness monitoring, the triggering of lane departure warning systems, and highway design.

INTRODUCTION

The human driver is the most unpredictable link in the driver-vehicle-road system. When performing driving tasks, drivers can change their behavior significantly, for instance, due to physical conditions, emotions, or distractions. Studies of natural human driving performance can be used as baseline data for comparison with investigations on driver impairments, such as influences of alcohol or medications, driver fatigue, and distractions caused by the usage of in-vehicle systems. Better understanding of drivers' natural performance is also valuable in the improvement of highway design and the development of automotive active safety systems, such as adaptive collision warning system and lane departure warning system.

Characterizing driver states helps to evaluate the consequences of driver impairments and to quantify driver's control capability. Considerable effort has been spent on searching for effective metrics to represent drivers' mental workload. These measures can be broadly classified into three categories: subjective workload ratings, physiological measurements, and driving performance metrics.

Subjective workload assessments are usually conducted in post-experiment sessions, such as Driver Behaviour Questionnaire [1], NASA-Task Load Index [2]. Although the subjectivity of the reporting mechanism provides great insight into individual workload, it is prone to confusions and personal biases. Physiological measurements [3] include eye movement (glance frequency and duration, percentage of eye closure), heart rate, heart rate variability, electroencephalogram (EEG), electrocardiogram (ECG) activities, and so on. However, due to their intrusiveness and requirements on special instruments, they are not well suited for on-board experimental tests. In addition, the relationship between these measurements and driver states has not been conclusively established.

The focus of this study is on the third category. Naturalistic driver performance on limited-access highways is characterized by directly quantifying the inputs to and outputs from the vehicle. A variety of representative driver performance measures [4] are presented in Table 1. They are grouped into two categories, the "driver inputs" and the "vehicle outputs." Both driver control inputs and vehicle outputs are decoupled into longitudinal and lateral directions. The focus of this work is on natural baseline performance, rather than limit performance.

Table 1 Measures of Driver Performance

Category		Variables
Driver inputs	Lateral	SD of steering wheel angle (SDSW); Frequency analysis of SW angle; Steering wheel reversal rate (SRR); Steering entropy (SE)
	Longitudinal	Throttle position variation; Brake reaction time; Abrupt brake application
Vehicle outputs	Lateral	Mean lateral position (MLP); SD of lateral position (SDLP); Time to lane crossing (TLC); Frequency and duration of unplanned lane deviations
	Longitudinal	Time headway (T_h); Range & Range Rate; Time-to-collision (TTC)

Performance metrics have been used for a wide variety of applications, including the detection of driver drowsiness or impairment, the study on alcohol influence, and assessing the effects of mobile phone usage. These metrics offer unobtrusive and intuitive means to characterize driving performance and to detect performance degradation. Although many studies have reported on various metrics, their results vary considerably. For example, numerical values for the standard deviation of lateral position (SDLP) differ substantially as experimental context (road/simulator/test track), road type (freeway/local), and traffic condition (moderate/heavy) change [5]. Therefore, carefully defined test conditions are essential for this type of analysis. The distinctiveness of this study is that the blend of on-road driving, rich channels of signals, and a large number of participants makes it possible to gain insight into “real-world” driving behavior with high fidelity.

LATERAL CONTROL OUTPUT METRICS

Except during lane changes/merges, a driver controls the vehicle to stay inside current lane boundaries. Increased lane weaving or lane boundary encroachments are indicative of degraded directional control, which relates positively with increased accident risks. Drivers’ lateral control performance is often signified by distance-, and time-based measures. It should be emphasized that lane position measures are also influenced by driving conditions, such as road curvature and traffic density. Therefore, uniform experimental conditions are necessary for fair comparisons.

DISTANCE-BASED PERFORMANCE METRIC - Lateral lane position is measured as the distance between the vehicle center and the lane center. Although lateral position appears to be a straightforward measure, there are significant technological challenges to determine it accurately in real time. Devices performing “lane tracking” functions have to be installed to process road image information and provide estimates of vehicle state and lane geometry. Mean lateral position (MLP) and standard deviation of lateral position (SDLP) are frequently used to characterize driver’s lane-keeping capability. MLP refers to the average of lane positions for a vehicle staying in the same lane, whereas the variation in lateral positions is represented by SDLP. In real-world driving, the vehicle is constantly subject to external disturbances including road surface unevenness, cross wind, and road curvature excitations. These factors make the vehicle wander even if the driver is fully attentive and responsive. In addition, SDLP is known to be affected by trip duration, alcohol/drug influence, and driver’s mental workload [6, 7].

Green [5] reviewed 36 studies in which SDLPs were studied. In each case, information was extracted regarding the experiment context (public road, simulator, test track), road type, traffic density, test condition (baseline, task, alcohol influence), and speed driven. The data under baseline conditions for on-road driving were collected and the mean was found to be 0.18 m. UMTRI [8] conducted experimental studies with a test vehicle driven by eight drivers on level expressways at 65 mph (105 km/h) where drivers were instructed to "lightly" and "tightly" hold onto the wheel. Given the data from the driving on straight sections of expressways in light traffic, it was determined that an SDLP of 0.18-0.27 m can be expected from a human driver, with a typical value around 0.24 m.

TIME-BASED PERFORMANCE METRIC - Lateral position itself is inadequate to fully describe the lateral control performance in that it does not take longitudinal speed into account. Obviously driving close to the lane boundaries at high speeds is more hazardous than doing the same at low speeds. The concept of Time to Lane Crossing (or Time to Line Crossing, TLC) was initially proposed by Godthelp et al. [9, 10] to quantify the imminence of lane crossing. It is defined as the time left until the outer edge of a moving vehicle crosses either side of the lane boundaries, under the assumption that the vehicle proceeds along the projected trajectory if current steering angle and forward speed are kept unchanged. The essence of TLC is that it incorporates relevant longitudinal and lateral motions simultaneously, and provides an assessment of the lateral control safety margin.

Unlike SDLP, TLC is a synthetic variable and is dependent on several measurements. In [11] the predicted vehicle motion was based on the 2-DOF lateral dynamics model. Although dynamic models are suitable for numerical studies [12], there are practical challenges in experimental studies. For instance, accurate estimation of tire cornering stiffness is nontrivial. Therefore, few results are reported for TLC computation based on on-road tests. An alternative is to use simplified calculations, which are based on lateral position, lateral velocity, and sometimes lateral acceleration [13]. A first-order approximated TLC was suggested as the lateral distance from outer tire sidewall to the lane boundary divided by lateral velocity. This simplified algorithm is accurate only under limited circumstances, hence is not suitable for use in studies of driver lateral control behaviors [14].

NATURALISTIC EXPERIMENTAL DATA SOURCE

The experimental driving records used in this study are obtained from a comprehensive driving database, the Automotive Collision Avoidance System Field Operational Test (ACAS FOT) [15]. In the ACAS project, 96 drivers drove 11 instrumented test vehicles as their primary cars for three or four weeks. The vehicles were used for unrestricted daily commutes and general driving, with no researcher being present. The participants were selected from three age groups: 20’s, 40’s and 60’s, with equal number of men and women in each group. Over the 12-month period of the field operational test, the vehicle fleet covered 220,000 km in total. The drivers showed considerable differences, including assertiveness of driving style, traveled mileage, road types, and traffic conditions.

The resultant database of engineering variables is 164 GB in volume and contains around 400 variables sampled at 10 Hz. The most relevant data fields useful for human driving performance analysis include: host vehicle motion (velocity, acceleration, yaw rate, lane offset, heading in lane), preceding vehicle motion (range, range rate), driver actions (brake application, throttle opening, steering wheel angle), and road environment (road curvature, road class, lane width), among many others. The ACAS FOT also captured video clips from a forward-looking camera and a camera showing the driver's face; both video streams were synchronized with the numerical database, which makes it possible to replay any driving episode of interest. Compared with results reported in the literature, most of which were based on experiments conducted on closed-circuit test tracks or driving simulators, this database excels in terms of fidelity, channel richness, number of test subjects, and test duration.

Real-time lane tracking is challenging. In ACAS, the lane tracking functionality is performed by four complementary road geometry estimation subsystems: radar scene-tracking, yaw rate sensor, GPS/map, and forward machine vision sensor. Based on these channels, optimal estimates of upcoming road geometry parameters are synthesized by a data fusion module. Estimates of the vehicle lateral position and orientation angle are derived by a machine vision system developed by Delphi, which consists of a forward-looking video camera and an image-processing unit. The accuracy of lane position and heading angle information was deemed to meet the project requirements. Estimated system resolutions (3-σ values) for lateral position and heading angle are 0.07 m and 0.45 deg, respectively [15]. In addition, estimates of confidence level for the lateral position, the heading angle, and the road geometry are also provided. These estimates are based on sensor subsystems' capability, environmental conditions and road classifications, and are determined by heuristic rules in the data fusion module.

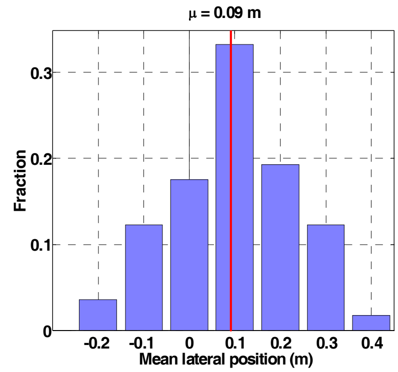
Since the objective of this study is to examine drivers' normal lateral control performance on straight limited-access highways, query conditions are defined to extract driving segments of interest from the database. These "controlled" conditions are structured as follows and implemented in the form of SQL commands.

- The vehicle should travel on straight sections of limited-access highways ("interstate" or "other freeway" according to road functional classifications), with an estimated radius of curvature larger than 1250 m. Driving segments on curved sections are excluded because drivers tend to either cut the corners or drift towards the outside boundary, which complicates the comparison across different drivers.
- The longitudinal speed should fall into either one of three discrete intervals: 37~47, 52~62 and 67~77 mph (16.5~21.0, 23.2~27.7 and 30.0~34.5 m/s, respectively). These three treatments on speed are referred to as "low speed," "moderate speed," and "high speed" in later sections. The intervals are selected to create enough separation in between so the effect of forward speed might be detected. The "high speed" case roughly corresponds to free-flow driving on highways, whereas "moderate speed" and "low speed" cases occur on highways with different levels of congestion.
- The driver should remain in the same lane under the above circumstances for at least 30/40/60 s respectively, for the three speed ranges. In real-world drivings, as long as traffic conditions permit, drivers tend to travel as fast as possible. Preliminary query results showed that in many cases drivers decelerated or accelerated beyond the specified speed ranges, or changed lane, or the confidence in estimated lateral positions declined due to traffic conditions. Therefore, the length of low-speed driving segments included in this study is generally shorter than those of high-speed driving segments.
- During each episode, the lateral position is within $\pm$0.90 m from the lane center. Given the nominal vehicle width of 1.86 m and the prevailing highway lane width of 12 ft (3.65 m), this constraint ensures that no lane departure is included, namely, only "normal" lane-keeping cases are studied.
- Confidence levels of estimated lateral position, heading angle and lane width must be at the "high" level. This is imposed to ensure that only measurements with high quality will be used.

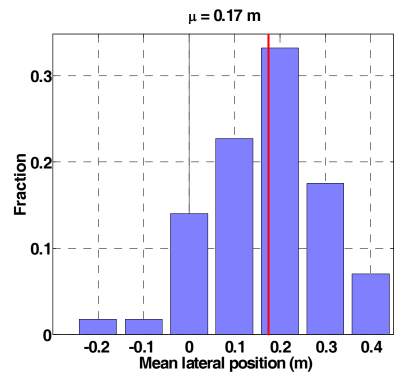
Out of the original 96 drivers, 57 satisfy the query criteria in all of the three treatments on speed, and each of them accumulates at least five valid segments per treatment. Demographically there are 28 women and 29 men; in terms of age group, there are 19 in their 20's, 16 in their 40's, and 22 in their 60's. Further studies can potentially be conducted by focusing on particular age groups or genders. For the three speed intervals (low, moderate, high), the median duration of segments is 38/58/120 s respectively (approximately 0.8/1.5/3.9 km in distance), and the median accumulated duration for each driver is around 540/660/1260 s, respectively.

STANDARD DEVIATION OF LATERAL POSITIONS

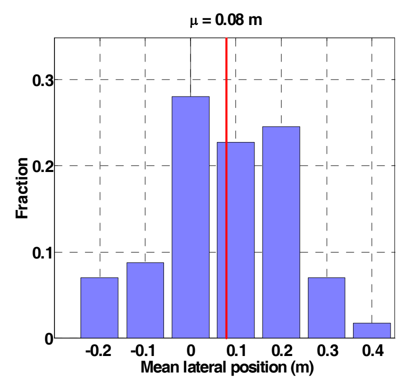
After all qualified driving segments were extracted, MLP and SDLP were computed for the 57 subjects. The distributions of MLP and SDLP among the drivers in ACAS FOT are presented in Figure 1 and Figure 2. In both figures, the vertical axis is the relative frequency of the number of drivers, and the average values are indicated by solid vertical lines for each treatment. As expected, most drivers stay close to the lane centerline. Substantially more drivers keep slightly to the right of the lane center than those keeping to the left. All three subplots in Figure 1 exhibit approximately inverted-bell shapes, although skewing is observed. On the whole, the mean lateral position preference of an "averaged" driver is located slightly to the right of the lane center, on the order of 0.10~0.20 m. As a side note, the distance between the driver seat center and the vehicle centerline is approximately 0.43 m. The dependence of MLP on velocity is not significant (p = 0.12). The range of SDLP values in Figure 2 is consistent with those reported in [8]. Almost all drivers' SDLPs fall into the interval between 0.10 and 0.27 m, and the typical value is approximately 0.20 m. One noteworthy trend of the three plots in Figure 2 is that overall the drivers show larger variations in lateral position at higher speeds. The effect of vehicle speed on SDLP is tested by analysis of variance (ANOVA). Three subsets (low, moderate, high speeds) were obtained, and each subset contained 57 values. The shifts in their mean values are statistically significant, with p-value less than 0.01.



(a) Low speed: [16.5~21.0]m/s



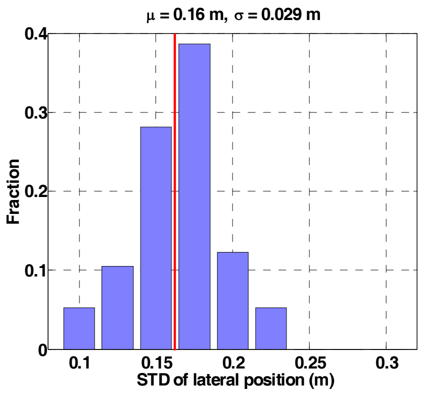
(b) Moderate speed: [23.2~27.7]m/s



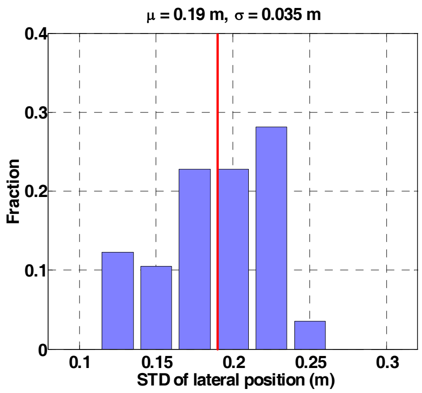
(c) High speed: [30.0~34.5]m/s

Figure 1. Distribution of MLP among 57 drivers in ACAS FOT (bin size: 0.1 m).

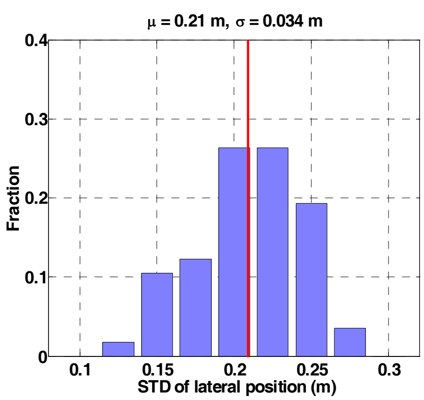
In general, vehicle lateral response is more sensitive at higher speeds than at lower speeds. Based on the standard 2-DOF lateral dynamics model, it can be demonstrated that the effective system damping decreases as the longitudinal speed increases. At higher speeds, the system poles shift towards the right-half plane, and in time domain larger transient responses will occur, even if the input (control input or disturbance) is of the same magnitude. Therefore, it is more challenging for drivers to maintain lateral control when the vehicle travels faster.



(a) Low speed: [16.5~21.0]m/s



(b) Moderate speed: [23.2~27.7]m/s



(c) High speed: [30.0~34.5]m/s

Figure 2. Distribution of SDLP among 57 drivers in ACAS FOT (bin size: 0.025 m).

Also the accuracy of the machine vision system may degrade at higher speeds because of more roll/pitch excitations, which partially contribute to greater variance of lateral position at higher speeds. Although Delphi employed compensation algorithm to mitigate pitch/roll effects, no specific information was provided regarding estimation confidence at different speeds. Given the estimated resolution of lateral position (3-σ = 0.07 m), the granularity was deemed adequate for this study though.

STATISTICAL ANALYSIS OF TLC

KINEMATIC COMPUTATION OF TLC - TLC provides a better assessment of the lateral control performance than SDLP, but requires more sensing capabilities. To determine the moment when a vehicle might cross the lane boundary, the vehicle path must be predicted and the upcoming road geometry needs to be estimated. Therefore, a suite of vehicle and road information is required: vehicle's forward speed u, steering wheel angle δ, yaw rate r, lateral offset y, heading angle relative to the lane centerline ψ, and parameterized upcoming road geometry.

The TLC calculation algorithm adopted in this work is based on kinematic assumptions. It predicts future vehicle path by fixing current forward speed and yaw rate; essentially the vehicle is assumed to travel in a circular arc. The arc is denoted *AB* in Figure 3, and the radius of curvature is ρ. The coordinates of right (Y_R) and left (Y_L) lane boundaries are known functions of longitudinal coordinate X, which are synthesized from the estimated clothoidal parameters, local curvature C_0 and curvature change rate C_1. In the simplest case when the vehicle is traveling on a straight road, they are just a half-lane width away from the road centerline.

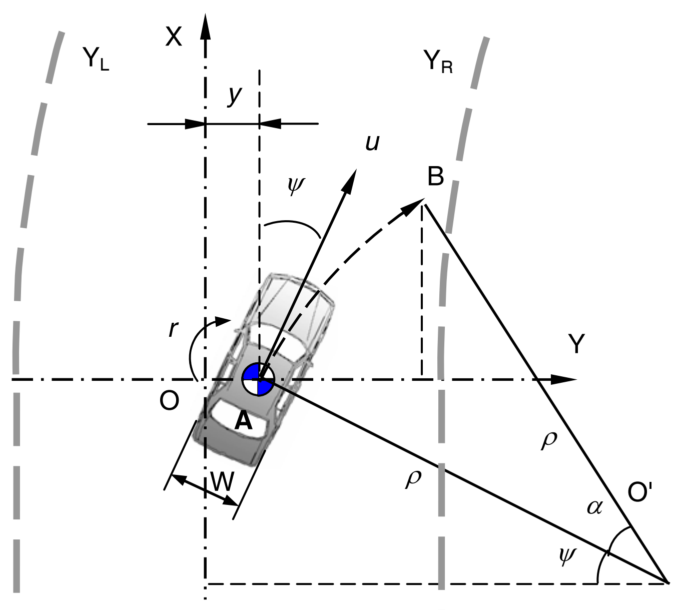


Figure 3. Coordinates and kinematic variables for TLC computation.

To compute TLC kinematically, the coordinates of the predicted path's end point *B* need to be updated at each future time step. Figure 3 depicts the situation when both heading angle ψ and yaw rate r are positive. The lane width is exaggerated to highlight the trigonometric relationship among variables. It is straightforward to show that the lateral coordinate of the end point *B* is given by

$$Y_B = y + \rho\cos\psi - \rho\cos(\psi + \alpha) \tag{1}$$

where $\rho = u/r$ and the central angle $\alpha = AB/\rho$. Similar relationships can be drawn for the remaining three ψ–r combination scenarios. Within the prediction time horizon, it will be checked whether $Y_L + W/2 < Y_B < Y_R - W/2$ is satisfied, where W is the vehicle width. The prediction proceeds until either the predicted path intersects the lane boundary or the end of the prediction horizon is reached. The moment when Y_B goes beyond either lane boundary is registered as the TLC. If there is no lane crossing within the prediction horizon, the upper limit of TLC will be used. The flow chart for this computation procedure is summarized in Figure 4. Thus at each sampling instant of a trip, TLC is calculated by iteratively comparing future vehicle path with lane edge geometry estimation.

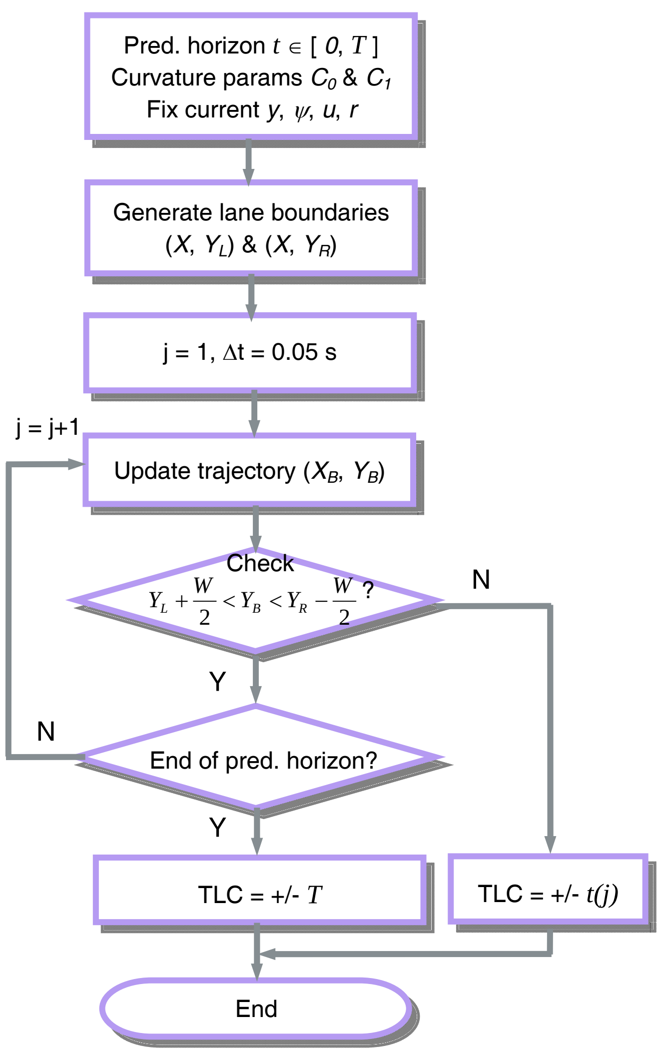


Figure 4. Flow chart of TLC computation.

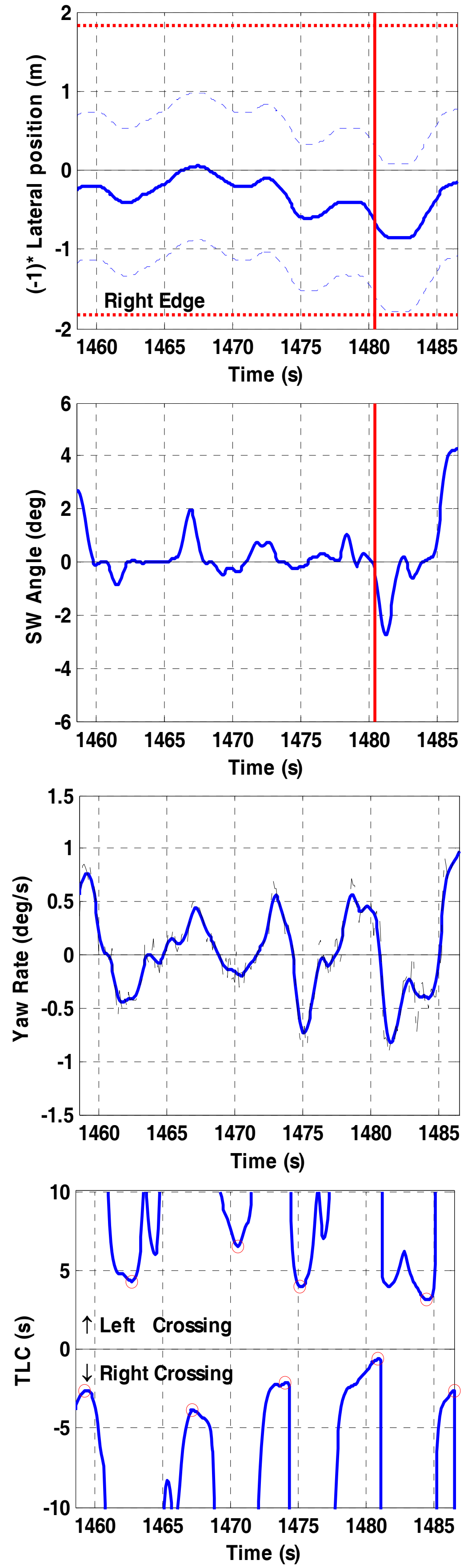


Figure 5. A sample lane-keeping record and the derived TLC.

A sample plot for a lane-keeping record on a straight highway is shown in Figure 5, which contains subplots for TLC, lateral position, steering wheel angle, and yaw rate. To differentiate the side of potential lane crossings, negative sign is associated with a lane crossing at the right boundary. Typically TLC behaves in a wavy pattern, reflecting the fact that the vehicle heads towards left and right lane boundaries alternately, due to external disturbances and imperfect driver control.

The sign change of TLC at 1481 s helps to better appreciate its usefulness. TLC declines as the vehicle approaches the right lane boundary. By examining the lateral position after 1480 s, obviously the vehicle is on the verge of encroaching on the right edge. At this moment the driver intervenes by steering quickly to the left. As a result, the vehicle heads towards the opposite side and an instantaneous sign change of TLC results. Hence the driver's lateral control behavior is reflected in the computed TLC.

DISTRIBUTION OF TLC - A variety of TLC-based lateral control performance metrics were suggested in the literature:

- The proportion of TLC values less than a certain threshold
- The median and the 15th percentile values [9]
- The minimum TLC value in a relevant trip segment

As for the numerical value of threshold TLCs, Brookhuis [7] suggested tentative TLC criteria for impaired driving behaviour: minTLC < 1.4s (right) and < 1.7s (left), and median TLC < 3.1s (right) and < 4.0s (left). The road-departure prevention system designed by UMTRI [16] used TLC = 2.0s as the warning threshold and TLC = 1.0s as the intervention threshold. In another prototype road departure warning system designed by Carnegie Mellon University [17], 1.0s is set as the TLC threshold to trigger an alarm.

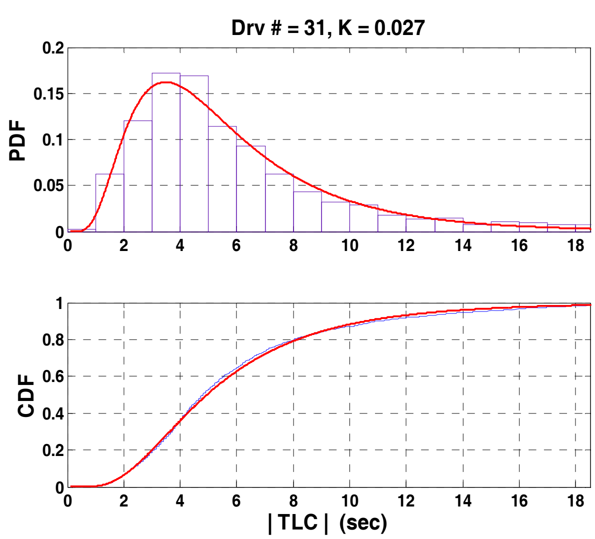


Figure 6. An empirical TLC distribution and the fitted lognormal distribution function.

While focusing on extreme TLC values might be appropriate for driver impairment detection, it is not appropriate for general driver performance characterization. In addition, choosing only two values (median along with the 15th percentile) to represent a distribution seems somewhat rough and arbitrary. Therefore, we propose to examine and represent the overall distribution of TLCs. Figure 6 shows the probability density function (PDF) and empirical cumulative distribution function (CDF) of the TLC (in absolute values) for subject #31 using the "high speed" data set. By and large the histogram is uni-modal and has a skewed inverted-bell shape. The left tail is restricted to be positive whereas the right tail is considerably longer. Since it is tedious to fully specify a histogram, attempts were made to fit observed data with statistical distributions. The pattern and the positive definiteness of its values suggest a few candidate basis functions, such as lognormal, gamma and log-logistic functions. By balancing the complexity of the distribution function and the goodness of fit, we decided on the lognormal distribution. The PDF of a 2-parameter lognormal function is defined by

$$f(x \mid \mu,\sigma) = \frac{1}{x\sigma\sqrt{2\pi}} e^{-(\log x-\mu)^2/2\sigma^2} \qquad (2)$$

where μ and σ are the mean and standard deviation of log(x). The PDF starts from zero, increases to its peak, and declines thereafter. Figure 6 contrasts the computed CDF of the TLC with the theoretical lognormal CDF. The goodness of fit is assessed by the maximum absolute difference *K* between the two curves:

$$K = \max_x \left| S(x) - P(x) \right| \qquad (3)$$

where $S(x)$ is the computed CDF based on the sampled data, and $P(x)$ is the theoretical lognormal CDF. The two curves match quite well, with the largest discrepancy lower than 3%.

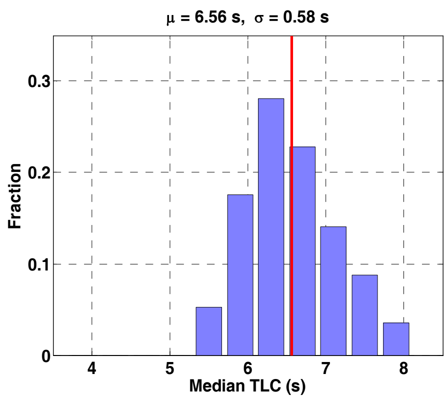
The distribution pattern of TLC in Figure 6 is not coincidental. On a larger scale, TLCs are computed for all 57 drivers contained in the three data sets (low, moderate, and high speeds) as discussed above. The closeness between the empirical CDF and the fitted lognormal theoretical CDF is measured by the largest deviation *K* of the two curves, as shown in Table 2. On average, the maximum deviation is less than 4%. Even in the extreme case, the deviation is reasonably small.

Table 2 CDF Deviation Measure *K* for All 57 Drivers

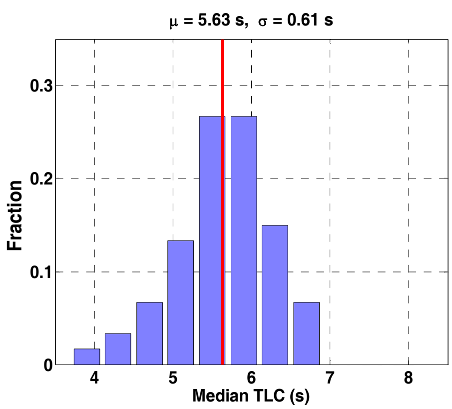
K	Low speed	Moderate speed	High speed
Mean	4.0%	3.9%	3.6%
STD	1.2%	1.3%	1.2%
Min	1.2%	1.3%	1.2%
Max	7.0%	6.7%	6.5%

STATISTICAL DESCRIPTION OF TLC - Since the lognormal function was found to be a valid indicator of

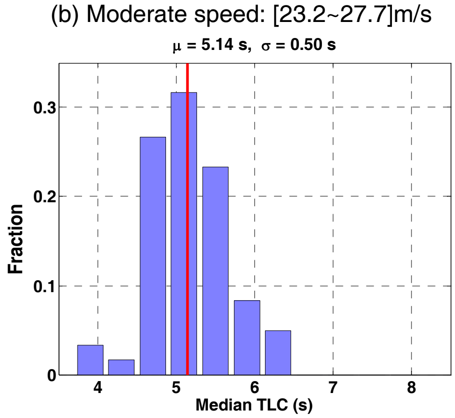
TLC distribution, attempts were made to seek performance metrics from the distribution parameters. Although a lognormal function can be fully specified by the two parameters μ and σ, they do not afford much intuitive appeal, because μ and σ are referred to only after the logarithm is taken. Instead, in this work the median e^{μ} and the mode $e^{\mu-\sigma^2}$ are proposed to represent the distribution, because (1) the median can be readily obtained from CDF graph and the mode can be identified easily from PDF curve, and (2) they have direct physical connotations (median and mode of TLC). Figure 7 shows the normative values for the TLC medians on straight road for the three speed intervals. It is evident that as speed goes up, the center of the distribution shifts to the left. Mean values are also calculated for the three treatments. The analysis is repeated for the distribution of TLC modes (Figure 8), and a similar trend is observed.



(a) Low speed: [16.5~21.0]m/s

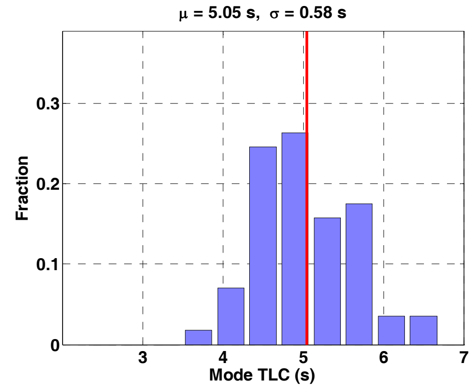


(b) Moderate speed: [23.2~27.7]m/s

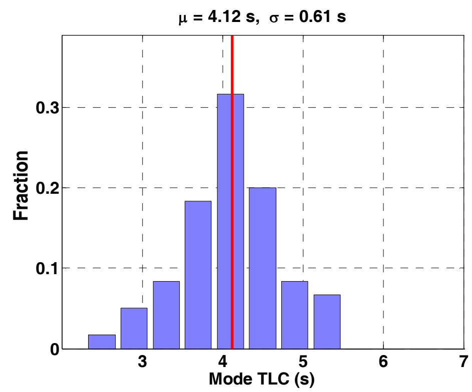


(c) High speed: [30.0~34.5]m/s

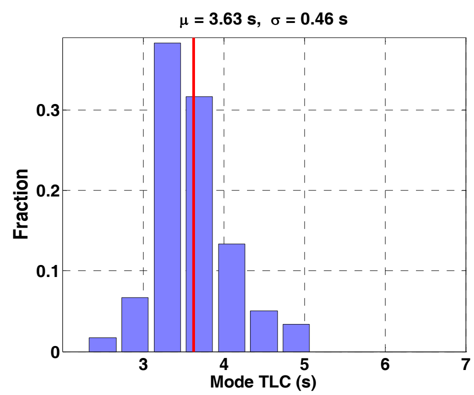
Figure 7. Distribution of TLC medians for driving on straight highways (bin size: 0.4 s).



(a) Low speed: [16.5~21.0]m/s



(b) Moderate speed: [23.2~27.7]m/s



(c) High speed: [30.0~34.5]m/s

Figure 8. Distribution of TLC modes for driving on straight highways (bin size: 0.4 s).

A comparison between this work and a frequently cited study by Godthelp [9] is shown in Figure 9, in which the median and 15th percentile TLC versus vehicle speed are reported. In [9] six male subjects were instructed to drive on a straight section of an unused highway. Longitudinal speed was automatically servo-regulated. To compute TLC, heading angle was derived from the lateral speed signal, which in turn was derived from the differentiated lateral position signal. In Figure 9 the error bars associated with the ACAS results represent 95% confidence intervals. Although the two experiments are quite different with regard to sensor capability, subject diversity, presence of neighboring traffic, sample size, and the computation of TLC, the results show quite consistent trends. Statistical tests by ANOVA conclude that the speed-dependence is highly significant ($p < 0.01$), which quantitatively justifies the intuition that a higher speed leads to a lower TLC, thus less lateral safety margin.

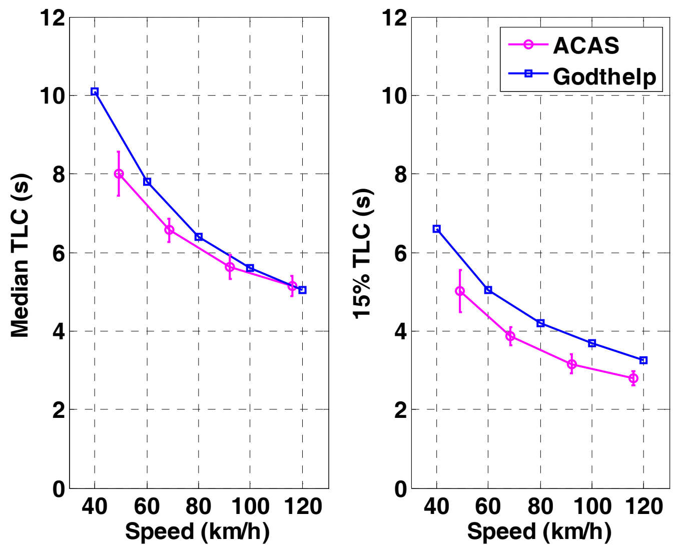


Figure 9. Average values of median and 15th percentile TLC at various speeds.

In summary, by analyzing the aggregate pattern of TLCs and approximating them with lognormal distributions, we have identified a method to describe drivers' macroscopic normal lateral control performance on straight highways, without being restricted to a single value like median TLC or an arbitrary level such as the 15th percentile TLC. The proportion of TLC less than any threshold can also be estimated if the distribution median and mode are available. Therefore, as metrics for lateral control performance, TLC median and mode are straightforward to obtain, but also general enough to describe the overall behavior. For potential application on TLC-based road departure warning systems, the speed dependency and inter-subject variation of TLC can be exploited to reduce nuisance alarms. Instead of applying fixed threshold values, the road departure assistance system may be more adaptive to changing travel speed as well as individual driver's traits. In the mean time, since real-world driving inevitably involves curve negotiation as well as lane change/merge, the applicability of TLC distribution throughout the entire driving scenario requires further exploration.

CONCLUSIONS

In this study, driver performance is characterized by using a recently constructed comprehensive driving database — the ACAS FOT database. This database presents a unique resource for driver performance study on account of its naturalistic driving conditions, high-fidelity measurements, channel richness, large number of test subjects, and long test durations. We focused on the driver lateral control capability and determined normative values for lateral position and TLC at various speed ranges on straight highways. The lognormal function was proposed to describe statistically the derived TLC, and the metrics TLC median and TLC mode were suggested as alternatives to existing measures. The validity was verified, and their typical values and variation ranges were provided in the form of histograms. All the values given in this work are meant to represent normal (or baseline) real-world driving conditions. They afford a basis to compare quantitatively with studies addressing driver distraction and impairment. A better understanding of TLC distribution also helps to improve the design of TLC-based road departure warning algorithms, to make them adaptive and reduce the rate of false alarms.

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