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Creation of a Driver Preference Objective Metric to Evaluate Ground Vehicle Steering Systems

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***Abstract*: The evaluation of vehicle steering systems has typically been performed by engineers and consumer focus groups using in-vehicle and automotive simulator studies. In the latter case, driver preferences have been extensively gathered using written questionnaires. However, this delays the testing procedure and may introduce outside influences that may skew the results. In this paper, an objective steering preference metric has been created to gather steering preferences without directly communicating with the driver. Streaming vehicle data has been recorded, processed, and correlated with subjective response data to create a global steering preference metric. A combination of the vehicle's yaw rate, longitudinal acceleration, and lateral acceleration demonstrated an excellent correlation with survey responses regardless of the steering setting. Furthermore, changes in the steering ratio resulted in an even stronger correlation between the objective data (longitudinal acceleration, front tire angle, and throttle position) and test subject questionnaire responses. Overall, the proposed index offers a unique approach to evaluate steering system designs.**

I. Introduction

A re-occurring problem in ground vehicle steering system development is the identification of a steering setting (ratio and effort characteristics) that is favored by a majority of likely customers. The initial dealership drive tends to be critical to the vehicle purchase process. However, there are two inherent difficulties with steering system parameter selection. First, steering tuning has been typically performed by seasoned automotive engineers who may select a setting based on either personal preference or estimation of what the target customer may prefer. Although this may be partially remedied by customer feedback, the difficulty remains in selecting the design parameters given the subjective nature of the task. Second, drivers are different and each likely has a unique preference for their steering setting. This means that no matter how diligently an engineer tries to obtain an optimal setting, their selection will always be a compromise and hence, a non-optimal selection. However, the emerging trend toward customer personalization may lead to unique steering settings for future vehicles.

Previous research has been focused on finding an optimal steering setting using a driving simulator and questionnaires aimed at tapping into a driver's steering preference [1,2]. While successful, it still required the interaction of researchers with drivers to inquire about their preferences. Sugita *et al.* [3] attempted to establish design criteria for an optimal electric power steering system configuration. Their efforts focused on determining a target level of passivity that felt most comfortable to the driver. Andonian *et al.* [4] used an automotive simulator to study the steering performance of drivers using a joystick versus a steering wheel. Performance was judged objectively, paving the way for future objective judgements of steering systems. Català *et al.* [5] attempted to correlate objective steering torque data with kinematics and compliance test results. Jaksch [6] found that yaw velocity response time was a dominant factor in the subjective rating of a vehicle's handling characteristics during a lane change maneuver. Hearthershaw [7] developed a variable steering ratio strategy that maximized driver performance in multiple repeatable tests. Yamaguchi and Murakami [8] used an adaptive control steer-by-wire system to create virtual steering characteristics. In the future, such a system could be applied to create personalized steering preferences for drivers. The next step in steering preference research should be the development of an objective metric to identify preferences without significant driver interactions so that the process may be automated.

The link between objective vehicle response and driver steering preference was investigated. In essence, a hybrid metric of fused vehicle dynamics signals may be used to predict how much drivers enjoy their steering experience. It should be recognized that many implications associated with this topic exist that may merit further study. First, if questionnaires could be removed from the simulator (or in-vehicle) testing procedure, then the required participation time would decrease. More importantly, the accuracy should improve. For example, one challenge faced during human subject testing was requesting the participants to synthesize their steering experience as a separate entity from the rest of the vehicle environment. Simply asking participants about their steering experience likely tainted their response to the questions. Thus, an objective metric would eliminate this possible questionnaire bias.

The second issue concerns the development of an objective steering metric establishing the foundation for an automatically adjusting steering system. It has been assumed that each driver has a unique steering preference. Instead of forcing a driver to adapt to a non-optimal steering setting compromise, the steering setting could instead adapt to the driver. This innovative feature is the basic concept behind developing a steering feedback automatic tuning controller. Specifically, this system would systematically adjust

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steering settings while tracking and optimizing a prescribed objective preference metric. After a learning period, the steering system would be optimized for the given driver, eliminating the need to create a compromised steering design. Finally, an on-board self-tuning steering control system will eventually become a standard feature on future production vehicles.

The remainder of the paper has been organized as follows. The custom steering simulator and testing procedure will be covered in Sections II and III. The analysis methodology for investigating the steering preference metric will be described in Section IV. The test results will be analyzed in Section V with a comprehensive discussion. Finally, the summary is contained in Section VI.

II. AUTOMOTIVE DRIVING SIMULATOR

The Clemson University steering simulator (refer to Fig. 1) was developed to accurately replicate an automobile's steering feel to investigate driver steering preferences [9]. Beyond realistic steering feel, the steering simulator had to be highly adjustable and provide environments that simulate typical driving situations. The front half of a Honda CRV vehicle body was used as the simulator cabin. The production steering shaft was removed and replaced with a motor-torque sensor system connected directly to the steering wheel. Pedal linkages were replaced with linear potentiometers and the stock dashboard was rewired to be controlled remotely.

Fig. 1: Steering simulator with immersive environment

A dSPACE 1103 rapid control prototyping board created the interface between the hardware components and the real-time simulated driving environment. Two computer workstations were added for control and display functions: the first offered run control, and the second generated the visual scenes that were projected using three short throw projectors. CarSim, a commercial vehicle dynamics software package from Mechanical Simulation Corporation, created the realistic vehicle response of a Honda CRV along with the visualization of the driving environment. The CarSim module was coupled with a steering model [10] in Matlab/Simulink. The dSPACE controller board handled real-time data acquisition and control tasks.

III. HUMAN SUBJECT TESTING

The first phase of this steering project was the development of an objective steering preference metric. Extensive simulated vehicle performance data was collected during human subject tests. Human subjects drove the simulator on a winding country road shown in Fig. 2. The course had no traffic and ended after approximately one minute of driving time. Subjects drove five steering configurations: baseline (C1), quick steering ratio (C2), slow steering ratio (C3), heavy effort (C4), and light effort (C5). These steering adjustments were large enough to be noticeable to an average driver while still being within a reasonable design range. After each steering configuration was driven through the complete course, the drivers completed a nine question survey to capture their steering preferences [11]. The vehicle behavior data was also recorded simultaneously for future off-line analysis.

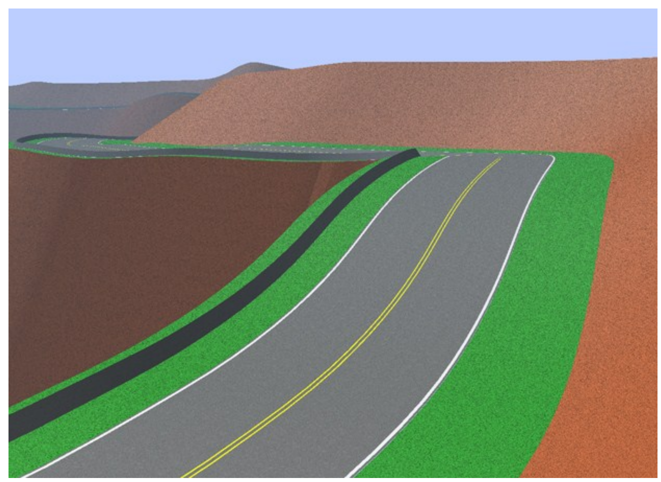

Fig. 2: Final turn of winding country road in simulator

The steering data for two different configurations has been displayed in Fig. 3. The solid line corresponds to a preferred steering setting while the dotted line denotes a low rated steering setting (and subsequent poor driver performance). Both traces were from a single driver, test subject 20 of 39, and the only difference between the runs was the steering setting (C2 and C3). While driving the less preferred setting, this driver had a tendency to overshoot their steering input by as much as 86%, often with a subsequent overcorrection as noted in the graph. This steering wheel "sawing" could be pulled out of the data stream through the application of basic statistics (e.g., mean, standard deviation).

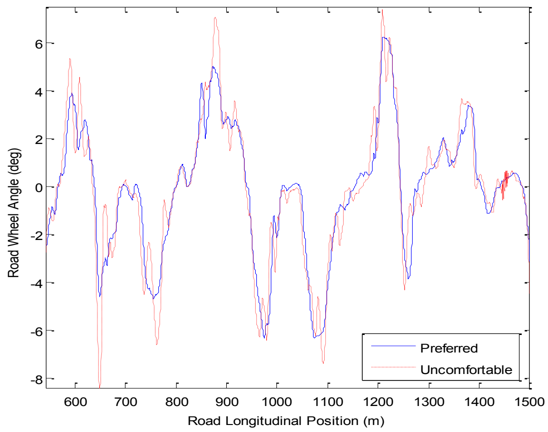

Fig. 3: Steering angle for test subject #20 (driving steering configurations C2 and C3 on a winding course) versus vehicle longitudinal position; the solid line (C3) was identified through questionnaire feedback as the preferred setting while dotted line (C2) was not preferred

IV. Analysis Methodology

An inspection of the available recorded simulator data reveals that drivers behaved differently depending on the steering configuration. A question was formulated – "Does a metric exists that can predict a driver's satisfaction with the vehicle's steering behavior using a normalized numeric value captured from the vehicle operating data?" A combination of vehicle operating variables may be used to create a robust metric. In this manner, the metric may be protected from changing road conditions that may skew a single element. Ideally, the evaluation index would not use impractical vehicle information such as lateral road position or tire slip angles so that the final entity would be valid in both simulator and vehicle applications.

In human-subject testing conducted using the steering simulator, thirteen data signals were collected via CarSim output (refer to Table 1). All driver inputs and the basic vehicle outputs were selected along with the two variables unique to a simulator environment: lateral offset from centerline and tire slip angles. Even though the goal was to use practical vehicle data streaming, it was important to be thorough in case an exceptional correlation emerged in this project. In other words, an objective metric can be created using the recorded vehicle variables based on the automotive engineer's preferences. In this study, a country road driving scenario was considered for the development of the steering preference metric. This decision was based on the consistent driving profile with a fixed route exhibited by the country road. City and highway driving environments allow too much creativity from the driver in terms of path selection and traffic demands, which may lead to unreliable data.

No.	Variable	Symbol	r_c	w_c	$w_{c_{ratio}}$	$w_{c_{effort}}$
1	Lateral offset	d	-0.22	0	0	0
2	Left front tire slip angle	α_{lf}	-0.28	0	0	0
3	Left rear tire slip angle	α_{lr}	-0.24	0	0	0
4	Right front tire slip angle	α_{rf}	-0.27	0	0	0
5	Right rear tire slip angle	α_{rr}	-0.25	0	0	0
6	Yaw rate	$\dot{\psi}$	-0.32	5	0	0
7	Longitudinal acceleration	a_x	-0.30	6	3	10
8	Lateral acceleration	a_y	-0.31	8	0	0
9	Brake position	BP	-0.15	0	0	0
10	Left front tire angle	δ_{lf}	-0.28	0	1	5
11	Right front tire angle	δ_{rf}	-0.27	0	0	0
12	Throttle position	TPS	-0.31	0	5	0
13	Longitudinal velocity	v_x	-0.18	0	0	9

Table 1: Chassis variables, single variable correlations, r_c, and weighting factors producing optimal steering preference metrics for global, w_c, ratio, $w_{c_{ratio}}$, and effort, $w_{c_{effort}}$

A total of $i = 39$ human subjects evaluated $k = 5$ steering configurations for a total of 195 data sets. Each combination of driver and steering configuration had a matching questionnaire ($j = 9$) result, q_{ik}, with the test subject's opinion on "fun-to-drive", "controllability", and "ease of driving" for each setting (note: questionnaires were completed during an extensive demographics study) [11]. The results were averaged, $\bar{q}_i$, and normalized into a single global steering preference, Q_{ik}, for each steering configuration and test subject as $\bar{q}_i = \frac{1}{5}\frac{1}{9}\sum_{k=1}^{5}\sum_{j=1}^{9} q_{ijk}$ and $Q_{ik} = \frac{1}{9}\sum_{j=1}^{9} q_{ijk} \Big/ \bar{q}_i$ for $(i = 1, 2, ..., 39)$ and $(k = 1, 2, ..., 5)$. In the expressions, the symbol q denotes the question response on a given questionnaire, and Q is the normalized response for a given driver and steering configuration. The variables i, j, and k represent the human subject number, survey question number, and steering configuration, respectively.

The thirteen variables from Table 1 – column 3, placed in vector $H_c = \left[d, \ \alpha_{lf}, \ ..., \ v_x\right]$ where $(c = 1, 2, ..., 13)$ were processed with future applications in mind. Potential control strategies may require a metric to be positive and reliable after a fixed time period. The variables, H_c, were converted into a metric, J_{ick}, with a single value for each combination of test subject, data signal, and steering configuration for the country road using the expression

$$J_{ick} = \int_0^{40s} H_{ick}^2 dt \quad (i=1,...,39), (c=1,...,13), (k=1,...,5) \quad (1)$$

where c denotes the number corresponding to the respective data signal. Note that a $t = 40s$ period was selected using a sampling time of $\Delta t = 0.025s$.

The metric, J_{ick}, was then normalized for each driver. This action permitted comparisons with the subject pool by computing the average of the given metric for all steering configurations, $\bar{J}_{ic}$. The result was applied to the individual metrics, J_{ick}, such that a normalized value, J_{norm}, becomes $\bar{J}_{ic} = \frac{1}{5}\sum_{k=1}^{5} J_{ick}$ and $J_{norm_{ick}} = \frac{J_{ick}}{\bar{J}_{ic}}$ for $(i=1,...,39)$, $(c=1,...,13)$, and $(k=1,...,5)$.

The normalized metrics were then correlated with the normalized questionnaire data for a given human subject and steering configuration. The correlations were calculated as

$$r_c = \frac{\sum_{i=1}^{39}\sum_{k=1}^{5}(J_{norm_{ick}} - \bar{J}_{norm_c})(Q_{ik} - \bar{Q})}{\sqrt{\sum_{i=1}^{39}\sum_{k=1}^{5}(J_{norm_{ick}} - \bar{J}_{norm_c})^2}\sqrt{\sum_{i=1}^{39}\sum_{k=1}^{5}(Q_{ik} - \bar{Q})^2}} \quad (2)$$

where $\bar{Q} = \frac{1}{39}\frac{1}{5}\sum_{i=1}^{39}\sum_{k=1}^{5} Q_{ik}$ and $\bar{J}_{norm_c} = \frac{1}{39}\frac{1}{5}\sum_{i=1}^{39}\sum_{k=1}^{5} J_{norm_{ick}}$ for $(c=1,2,...,13)$.

Once the strongest (i.e., largest absolute value of r_c) correlations were discovered, a computer-based optimization algorithm was applied to create a robust metric, $J_{w_{ik}}$, based on both the combination and weighting of individual metric elements. The weighted metric was formulated as

$$J_{w_{ik}} = \sum_{c=1}^{13} w_c \cdot J_{norm_{ick}} \quad (i=1,2,...,39), (k=1,2,...,5) \quad (3)$$

where $w_c = \{w_1, w_2, ..., w_{13}\}$ is a vector of scaling factors. The weighting factors, w_c, were allowed any integer value between 0 and 10 with the goal of maximizing the absolute value of the correlation coefficient.

The weighted metric was correlated with the normalized questionnaire responses, Q_{ik}, to create the weighted correlation, r_w, as

$$r_w = \frac{\sum_{i=1}^{39}\sum_{k=1}^{5}(J_{w_{ik}} - \bar{J}_w)(Q_{ik} - \bar{Q})}{\sqrt{\sum_{i=1}^{39}\sum_{k=1}^{5}(J_{w_{ik}} - \bar{J}_w)^2}\sqrt{\sum_{i=1}^{39}\sum_{k=1}^{5}(Q_{ik} - \bar{Q})^2}} \quad (4)$$

where $\bar{J}_w = \frac{1}{39}\frac{1}{5}\sum_{i=1}^{39}\sum_{k=1}^{5} J_{w_{ik}}$. The optimization problem was formulated as $\max_{w_c \in \{0:10\}} |r_w|$ and solved by calculating all combinations of the thirteen weighting factors.

The analysis method has been displayed in Fig. 4 as a flowchart. In summary, both objective and subjective data was collected from the human test subjects who drove five steering configurations on a winding road course. The objective data was formulated into positive metrics, and then both the metrics and subjective data were normalized for consistency. Correlations between the metric elements and the subjective data were calculated for preliminary review. The metric elements were then combined into a single robust metric that was weighted to maximize the correlation with the subjective data. The full results of this analysis will be presented in the next section.

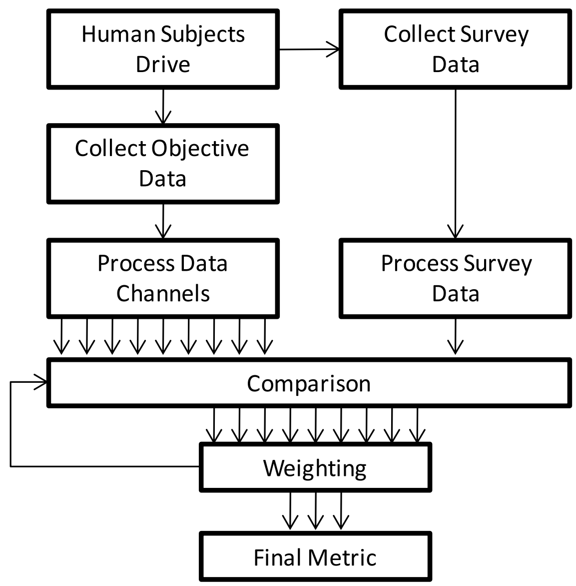

Fig. 4: Analysis methodology to create a weighted objective metric to predict driver steering preference

V. Discussion of Results

All correlations were evaluated using the standard scale. Specifically, values between $0.1 < |r| < 0.3$, $0.3 < |r| < 0.5$, and $|r| > 0.5$ can be considered small, moderate, and large correlations. The metrics were correlated with the global normalized questionnaire data. Initially, the important connection was between the physical survey and the collected data signals, while the steering setting was ignored.

The objective metrics were calculated for each data signal, human subject, and steering configuration using equation (1) for a total of 2,535 data points. These metrics were normalized and correlated with the global normalized questionnaire data. A single correlation coefficient, r_c, was calculated for each data variable for a total of thirteen correlation coefficients which have been displayed in Table

1. Note that all correlations were negative, which implied that a smaller metric value corresponded to a more favorable steering setting. The best correlation, $r = -0.32$, occurred with the yaw rate, $\dot{\psi}$. This correlation, along with three of the remaining correlations, fit in the moderate correlation category. The normalized yaw rate metric has been plotted against the normalized questionnaire data in Fig. 5 to visualize the strength of the correlation. For the horizontal axis, $0 < Q \leq 1$ and $1 < Q < 2$ corresponds to "do not like" and "favorable" responses by the subjects, respectively. The vertical axis can be split into $0 < J_{norm_6} \leq 1$ and $1 < J_{norm_6} < 2$ as smooth and aggressive yaw rate responses. Using a standard four quadrant approach, quadrants II and IV support the negative correlation which reflects that drivers have been recorded to drive more smoothly when they prefer a steering setting, and more aggressively when they dislike a setting. In contrast, quadrants I and III are less populated, but support a positive correlation implying that drivers drive more aggressively when they prefer a steering setting, and more smoothly when they do not like it.

All thirteen data signals produced small and moderate correlations with the questionnaire data; however, some variables may have contained similar vehicle response data. For instance, the left and right front tire angles, δ_{lf} and δ_{rf}, should have only differed slightly based on steering linkage compliance and suspension geometry effects. The weighting optimization aimed to eliminate data signals with duplicate information, while retaining those offering unique information that correlated with the questionnaire results. The weighted metric, J_w, was created and optimized while maximizing the absolute value of the correlation, r_w.

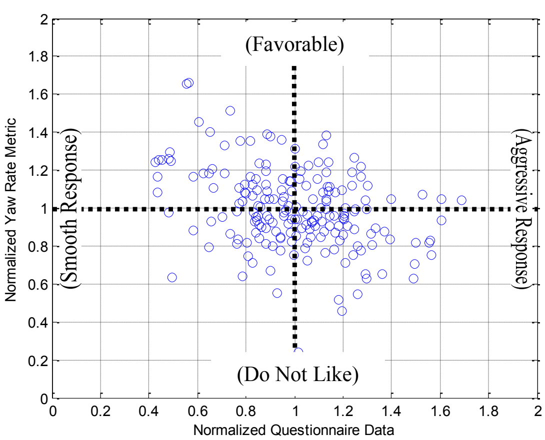

Fig. 5: Normalized questionnaire data, Q, vs normalized yaw rate metric, J_{norm_6}, to visualize $r = -0.32$ correlation

The optimization resulted in a maximum correlation of $r = -0.39$ for all five steering configurations (global weight) with the scaling factors listed in Table 1 – column 5 (yaw rate, longitudinal acceleration, lateral acceleration). Although still a moderate correlation, it nearly fell in the excellent correlation range, and was significantly stronger than any single metric. Fig. 6a shows the plot of the correlated data to visually demonstrate the strength of the correlation. In this plot, the vertical axis zones $0 < J_w \leq 19$ and $19 < J_w < 35$ correspond to smooth and aggressive command of the entire vehicle, respectively. The value $J_w = 19$ was selected as the cutoff point representing the mean of the data points. The horizontal axis was partitioned the same as Fig. 5 with $0 < Q \leq 1$ and $1 < Q < 2$ corresponding to "do not like" and "favorable" responses, respectively. Note that smoother driving habits corresponded with preferred steering settings (quadrant IV).

To further investigate the weighted metric, the same weighted optimization process was performed while isolating the cases where either the steering ratio ($k = 2,3$) or steering effort (k=4,5) was changed. The steering ratio (effort) corresponded to configurations C2 and C3 (C4 and C5). The results offered an interesting conclusion. The maximum correlation for steering ratio changes was $r = -0.55$; however, the maximum correlation for steering effort changes was $r = -0.15$. This result demonstrated that the objective metric may be reliable for discovering an optimal steering ratio, but insignificant for tuning steering effort settings. The best weighting factors for these two approaches have been summarized in Table 1.

The ratio weighting factors were largely longitudinal dynamics, which may indicate that the drivers misjudge safe cornering speeds when they are unhappy with the steering ratio (safety issue). The plots of the correlated data for the steering ratio and steering effort, independent of each other, have been presented in Fig. 6b and 6c versus the normalized questionnaire data. The significance of a $r = -0.55$ correlation can be clearly seen in Fig. 6b with a strong linear grouping. In contrast, Fig. 6c shows how ambiguous a correlation of $r = -0.15$ appears.

VI. SUMMARY

Vehicle steering system setting targets (i.e., selection of design parameters such as ratio, damping, and power assist) remain an ongoing challenge for engineers. As society moves into an age of product personalization, automotive companies must adapt to "win" the next generation of car buyers who seek a custom ground vehicle. One area of adaptation resides in the creation of an automatic tuning steering control system that can customize the driving experience for each operator. Accordingly, the first step must be the identification of a performance index which captures a driver's steering system preferences.

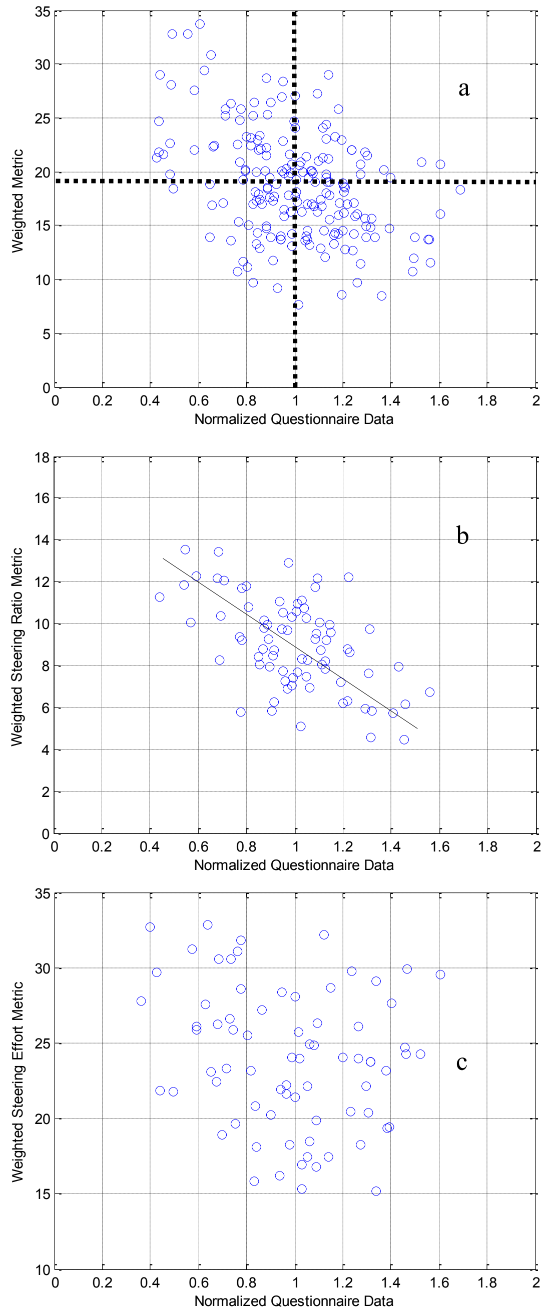

Fig. 6: Weighted metric, J_w, vs. normalized questionnaire data, Q: (a) $(k = 1,2,...,5)$ with $r = -0.39$; (b) $(k = 2,3)$ with $r = -0.55$; and (c) $(k = 4,5)$ with $r = -0.15$

This study has investigated an objective steering preference metric through the use of a steering simulator. Objective data recorded from vehicle sensor signals was correlated with questionnaire data completed by human test subjects. A global weighted objective metric was formulated which combined the yaw rate, lateral acceleration, and longitudinal acceleration variables. The resulting weighted objective metric produced a correlation with questionnaire data of $r = -0.39$. When steering ratio setting changes were isolated, an even stronger correlation of $r = -0.55$ was encountered using longitudinal acceleration, a_x, left front tire steer angle, δ_{lf}, and throttle position, TPS. The findings suggest that an objective steering preference metric may be able to predict a driver's steering ratio preference, while steering effort preferences may be transparent to an objective metric. Further research is recommended to investigate the application to vehicle steering system designs.

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