Objective Evaluation Method of Vehicle Ride Comfort Based on Small-Sample Statistics

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Abstract

Although ride comfort has been researched for many years, there is still no definite objective evaluation method which can match the subjective assessment feeling well. The mainly presented approaches are mostly based on ISO 2631, but the consistency and correlation between subjective evaluation and objective evaluation are inadequate in these studies. Taking the motion control as the study content, which is primary ride comfort. Different type components of vehicle have been combined in a tuning car to achieve various ride performance, such as springs, dampers, jounce bumpers and tires. Then corresponding subjective evaluation results and acceleration measurement data have been collected when driving the tuning car on a sine wave road. With correlation and clustering analysis, the most representative features of measurement data for subjective assessment were extracted. Based on the small-sample statics theory, a new objective evaluation method for ride motion control has been established using the features by the LASSO model. The cross validation and comparison results indicate that the new objective evaluation method has a good estimation for ride motion control and the method can be a complement for ISO 2631.

1. Introduction

With the development of automotive industry, more and more new technologies are applied on improving the vehicle performance, especially the ride comfort. Many surveys show that customers focus on the ride comfort due to the reason that the passengers can directly feel it when driving a car on different roads. Hence, the ride comfort is an important aspect of vehicle performance development. In the meantime, the perceptions of ride comfort are also the market segment and brand specific. However, in contrast to the abundant approaches and test techniques which exist for handling performance, methods to quantify ride comfort quality remain primarily subjective evaluation at most OEM's. Subjective approaches are usually influenced by the environment and evaluators' emotion and psychology. Even the subjective evaluation need experienced specialist and making at least one mule vehicle which lead to more cost and development cycle time. According to all these reasons, objective evaluation method for ride comfort is imperative and significative.

Ride comfort can be separated into five components: impact feel, shake, isolation, motion control and smoothness [1]. Many researches of objective ride comfort evaluation method for one or more components have been studied. For now there are mainly three standard on ride comfort prediction: ISO 2631 – 1997 [2], BS 6841 – 1987 [3] and VDI 2057 – 2002 [4]. The most widely accepted and referenced is ISO 2631-Evaluation of human exposure to whole-body vibration. In this standard, the basic evaluation method for vibration is using weighted root mean square (RMS) of acceleration. If underestimated, the additional methods are vibration dose value (VDV) and maximum transient vibration value (MTVV). Then other approaches for ride comfort evaluation are explored. Researchers from university of Windsor designed a frequency weighting filter and used the "estimated Vibration Dose Value" (eVDV) to quantify the ride comfort referred to ISO 2631-1 [5]. Gao Yinhan, et al. indicated that there are some flaws in the [illegible]d objective vibration given by the ISO2631, so they presented

an alternative approach based on neural network model to evaluate the vehicle ride comfort, which achieved good results [6]. Tang Chuanyin, et al. adopted random fuzzy evaluation model from people subjective response to vibration, and established an annoyance rate evaluation method which is the supplement of the traditional evaluation method [7]. Based on the regularities of the weighting factors from ISO 2631-1, Du Feng developed several vertical and horizontal weighting filters to assess the ride comfort, which are proved effective by comparing with traditional method [8]. Mohajer N, et al designed equivalent digital filters for ISO 2631 and 5349 weighting factors, and applied a 3D passive MBS-based Human Biomechanical Model (HBM) of a seated human for the objective assessment of ride comfort [9]. Xu Jin, et al. performed a driving tests based on natural driving behavior, and collected tri-axial acceleration data to analyze for determining the level of ride comfort [10].

Researches in past few years mainly focused on impact, shake and isolation, but there are few on the motion control. Additionally, though lots of approaches for ride comfort assessment are explored, most are based on ISO 2631. There are little studies considering the consistency and correlation between subjective evaluation and objective evaluation for ride comfort. Taking motion control as the study content, which is one component of ride comfort. This paper firstly collected the subjective evaluation results and corresponding measurement data. Then the correlation and clustering analysis were proceeded. Based on small-sample statistics theory, a new objective evaluation method using LASSO model for ride motion control has been presented. The cross validation and comparison results indicate that the new objective evaluation method has a good estimation for motion control and the method can be a complement for ISO 2631.

2. Subjective Evaluation And Measurements

Ride motion control is the ability of vehicle to constrain pitch/bounce motions, especially the resonant vibration of the sprung mass (1.0-1.5 Hz). Resonant vibration at these low frequencies can cause driver discomfort and in the extreme case can lead to sea sickness [1].

Subjectively, the ride motion control can be evaluated by experienced engineer on specific road, such as sine wave road in Guangde Proving Gound (GDPG) in China. When the subjective evaluation proceeded, the acceleration and pose angle data can also be collected at the same time by the sensors installed on the vehicle. To analyze the relationship between subjective evaluation and measurement data, different performance vehicle conditions were achieved by combining various tuning part on a vehicle.

2.1 Subjective Evaluation

The subjective evaluation is based on a tuning vehicle for convenience. By changing different suspension and tire parts, different motion control performance can be obtained. To avoid the coupling effect of different part and enlarge the performance difference, every evaluation loop is corresponding to one change point, such as springs, jounce bumpers, shock absorbers and tire dimensions, etc.

The subjective evaluation was proceeded in same environment by three experienced engineers in GDPG. The evaluation road condition is the sine wave road of ride loop, which has low frequency and large vertical amplitude, shown as Fig. 1.

Evaluation speed was maintained at $100 \pm 2kph$, which can bring enough vertical body motion to evaluate the motion control performance. In order to reduce the variance of subjective evaluation results, which is caused by the deviation of evaluate velocity, position driving through the road and personal preferences, the subjective evaluation of one same vehicle performance combination ran at least two times. In addition, the changing part combination evaluation ran with the original combination alternately for accuracy. The final estimation scores were the average values of three engineers' results.

The subjective evaluation results for every combination are listed with Table 1. The original combination is the base status and the corresponding subjective evaluation score is zero. Other combination scores are relative scores comparing with the base status, and the scoring interval is 0.125. Positive score means better than base status and negative score means worse than base. The larger the score is, the bigger the performance gap will be.

Table 1
Subjective Evaluation Results

Item	Combination Status	Subjective Evaluation Score	Samples
1	Base	0	9
2	Larger Stiffness Springs	+ 0.5	2
3	Smaller Stiffness Springs	-0.75	2
4	Lower Damping Shock Absorbers	-1.5	2
5	Longer Jounce Bumpers	+ 0.625	2
6	Shorter Jounce Bumpers	-0.25	2
7	Thicker Dimension Tires	-0.125	3
8	Lower Tire Pressures	-0.125	2
9	Suspension without Watt-Links	-0.125	4
10	Suspension without Watt-Links & Lower Tire Pressures	+ 0.125	2

2.2 Measurements and Data Collection

The measurements were proceeded with subjective evaluation at the same time for alignment. Main collected data are acceleration signals and angle signals in time domain on the specific road of every loop. The acceleration data were measured by piezoelectric sensors, which were installed on different eat bottom, seat back and foot floor, etc. The angle data were

obtained by gyroscope, which can monitor the vehicle pose in real time. The measurement equipment are shown as Fig. 2.

The mainly measurement channels are described as Table 2. Acceleration data have 7 sensors' record data with X (longitudinal), Y (lateral), Z (vertical) directions. Meanwhile, the angle data have roll (Rotation-X) and pitch (Rotation-Y) directions.

Table 2
Measurement Channels

Equipment	Fixture Location	Directions
Acceleration Sensor	Driver's Seat Bottom	X, Y, Z
	Driver's Seat Back	X, Y, Z
	Driver's Foot Floor	X, Y, Z
	Driver's Seat Track	X, Y, Z
	Co-driver's Foot Floor	X, Y, Z
	Co-driver's Seat Track	X, Y, Z
	Second Row Left Foot Floor	X, Y, Z
Gyroscope	Second Row Center	roll, pitch

3. Objective Evaluation Method Development

3.1 Feature Extraction

As described as Chap. 2, there are totally 30 sample data for the subjective evaluation, and every sample have 24 channels (include time channel). Due to the different start and end time of each measurement sample, the time domain data can not be used directly for comparing to analyze the relationship between subjective evaluation and objective evaluation. Hence, the feature of sample channel data need to be extracted.

The vehicle angular acceleration can be calculated by the geometry of the sensor position, shown as Fig. 3, where, LF is driver's foot floor sensor data, RF is Co-driver's foot floor sensor data, LR is second row left foot floor sensor data, L1 is the lateral distance between LF and RF, and L2 is the longitudinal distance between LF and LR.

So additional roll and pitch acceleration channels were achieved by Eqs. (1) and (2).

$$roll\_acc = \frac{(RF\_Z - LF\_Z)}{L1}$$

1

$$pitch\_acc = \frac{(LR\_Z - LF\_Z)}{L2}$$

2

where, *roll_acc* is the roll accelertation channel data, *pitch_acc* is the pitch accelertation channel data, and *_*Z* is the acceleration data of Z direction in the specific sensor position.

Before extracting the features, all the channel data were filtered by a low frequency (0.05 ~ 5 Hz) band-pass Butterworth filter to remove the influence of the high frequency data. In consideration of the requirement of analysis accuracy and comprehensiveness, 433 features were extracted with engineering experience and general mathematics technique. Among them, there are 395 acceleration features and 38 angle features for each sample. The detailed acceleration and angle features are listed as Table 3, where PSD is the abbreviation of power spectral density, envelop is the absolute Hilbert transformation of the channel data, decentralization is removing the central trend of the channel data, and crossed hull is the 2-D convex hull of two selected channel data points.

Table 3
Sample Features

Features	Channel Types & Directions
Maximum	Acceleration: X, Y, Z, roll, pitch
	Angle: roll, pitch, roll-pitch
Minimum	Acceleration: X, Y, Z, roll, pitch, X-Z, roll-pitch
	Angle: roll, pitch, roll-pitch
Maximum of Derivative Data	Acceleration: X, Y, Z, roll, pitch, X-Z, roll-pitch
	Angle: roll, pitch, roll-pitch
Minimum of Derivative Data	Acceleration: X, Y, Z, roll, pitch, X-Z, roll-pitch
	Angle: roll, pitch, roll-pitch
Range	Acceleration: X, Y, Z, roll, pitch, X-Z, roll-pitch
	Angle: roll, pitch, roll-pitch
Variance	Acceleration: X, Y, Z, roll, pitch, X-Z, roll-pitch
	Angle: roll, pitch, roll-pitch
Root Mean Square	Acceleration: X, Y, Z, roll, pitch, X-Z, roll-pitch
	Angle: roll, pitch, roll-pitch
Range of Envelop	Acceleration: X, Y, Z, roll, pitch, X-Z, roll-pitch
	Angle: roll, pitch, roll-pitch
Area of Envelop	Acceleration: X, Y, Z, roll, pitch, X-Z, roll-pitch
	Angle: roll, pitch, roll-pitch
Maximum of PSD	Acceleration: X, Y, Z, roll, pitch, X-Z, roll-pitch
	Angle: roll, pitch, roll-pitch
Area of PSD	Acceleration: X, Y, Z, roll, pitch, X-Z, roll-pitch
	Angle: roll, pitch, roll-pitch
Range of Decentralization Data	Acceleration: X, Y, Z, roll, pitch
	Angle: roll, pitch
Variance of Decentralization Data	Acceleration: X, Y, Z, roll, pitch
	Angle: roll, pitch
	Acceleration: X-Z, roll-pitch

Features	Channel Types & Directions
	Angle: roll-pitch

3.2 Correlation and Cluster Analysis

All the extraction features are too much to be used for modeling. Therefore, a correlation analysis is needed to determine which features are important and correlative enough. Then we can screen out these features.

Through statistics method, the Pearson correlation coefficient [11–13] of the subjective evaluation scores and the extraction features were calculated. By setting an appropriate threshold of the correlation coefficient, features with low correlation can be eliminated. The Fig. 4 shows the relationship of the threshold and chosen features. Taking the features retention and the variation stability of feature-size into consideration, the threshold is selected as 0.7, and the relative number of chosen features are 87. With the correlation analysis, the size of features for modeling were reduced to 20%.

There is a strong correlation between these chosen features and subjective evaluation results, but these chosen features may also have strong relationship with each other, that is, these features may have the same nature. Hence, the chosen features should be clustered to make the similar features as one group. Then the most relevant feature in each group can be selected for modeling effectively.

Using the formula (3) to calculate the cluster distance of each two features,

$$D = 1 - abs(cc)$$

3

Where, D is the cluster distance, and abs(cc) is the absolute correlation coefficient between each two features.

The hierarchical clustering [13, 14] result with Ward method is shown as Fig. 5, all the 87 chosen features can be classified as 6 groups.

Taking out the most relevant element in each group as the modeling feature, which has strongest correlation with subjective evaluation in each group. It also ensures that the selected feature has low impact on other feature groups. The selected features in each group are listed as Table 4. It indicates that the lateral data has little relation with motion control performance assessment, and effective data are mainly come from driver's location sensors.

Table 4
Selected Features of Cluster Analysis

No.	Selected Feature	Channel	Direction
1	Crossed Hull Area	Driver's Seat Track Acceleration	X-Z
2	Range of Envelop	Driver's Seat Bottom Acceleration	X-Z
3	Minimum of Derivative Data	Second Row Left Foot Floor Acceleration	Z
4	Minimum	Geometry Complex Acceleration	roll-pitch
5	Maximum of Derivative Data	Driver's Foot Floor Acceleration	X
6	Maximum	Driver's Seat Bottom Acceleration	X

3.3 Objective Evaluation Modeling

With the selected features of sample data and subjective evaluation scores, regression method can be used for objective evaluation modeling. In consideration of the briefness and efficiency, given that sample size, a linear regression was applied. In comparison to the common least-squares regression, LASSO algorithm [15, 16] is more appropriate. Because the LASSO method can minimize the usual sum of squared errors with a bound on the sum of the absolute values of the coefficients. It is a shrinkage and selection method for linear regression, which can be expressed as Eq. (4).

$$\hat{\beta} = \operatorname{argmin} \| Y - X\beta \|^2 + \lambda |\beta|_1$$

4

Where, β is the regression coefficients, $\|.\|$ is Euclidean norm (L2 norm), λ is the penalty parameter, and $|.|_1$ is the sum of the absolute values of the vectors.

In order to ensure the generalization of the objective evaluation model and prevent overfitting, the LOOCV (Leave One Out Cross Validation) method was used to estimate the MSE (Mean Squared Error) with the sample features. The simulation result is shown as Fig. 6.

From the simulation result, optimal λ can be obtained. Then the objective evaluation LASSO model was established with the best penalty parameter. The model can be expressed as Eq. (5), and the regression coefficients are listed as Table 5, which is relative to the Table 4 features.

$$OES = SF_i \bullet coef_i + intercept$$

5

Where, OES is the objective evaluation score, SF is the selected feature, and $coef$ is the LASSO model regression coefficients.

Table 5
LASSO Model Regression Coefficients

Table 4 Relative No.	Item	Coefficient
1	Selected Feature1	11.389
2	Selected Feature2	9.788
3	Selected Feature3	478.221
4	Selected Feature4	-23.116
5	Selected Feature5	-459.556
6	Selected Feature6	-11.730
N/A	Intercept	1.577

3.4 Comparison

With the established cross validation LASSO model, the objective evaluation score of each sample can be obtained. The objective evaluation results are shown as Table 6. It shows that the objective evaluation scores fluctuate slightly of different samples with the same combination status. This is mainly due to the variance of measurement caused by the deviation of velocity, position driving through the road, etc al.

Table 6
Objective Evaluation of Each Sample

Combination Status	Sample No.	Objective Evaluation
Base	1	0.068
	2	-0.033
	3	0.036
	4	0.159
	5	0.040
	6	-0.160
	7	0.178
	8	-0.200
	9	-0.058
Larger Stiffness Springs	10	0.168
	11	0.252
Smaller Stiffness Springs	12	-0.539
	13	-0.488
Lower Damping Shock Absorbers	14	-1.487
	15	-1.898
Longer Jounce Bumpers	16	0.103
	17	0.281
Shorter Jounce Bumpers	18	-0.085
	19	-0.238
Thicker Dimension Tires	20	-0.130
	21	-0.046
	22	0.022
Lower Tire Pressures	23	0.353
	24	-0.455
Suspension without Watt-Links	25	0.144
	26	-0.024
	27	0.123

Combination Status	Sample No.	Objective Evaluation
	28	0.079
Suspension without Watt-Links & Lower Tire Pressures	29	0.224
	30	-0.170

In order to reduce the influence of measurement error and measurement condition, the mean objective evaluation scores of same combination status samples are applied on the comparison with the subjective evaluation scores. For comparing conveniently and obviously, the column plot was adopted on comparison, shown as Fig. 7.

From the Fig. 7, we can find that though there is some gap of the two type scores in specific combination status, the variation trend of objective evaluation score can match the subjective score well, especially for the “4 - Lower Damping Shock Absorbers” combination status, which leads to the largest motion control performance change relative to the base. The differences of the two type scores may be mainly caused by that, the sample combinations can not make enough obvious distinction for motion control performance, and the sample size is not enough for accurate modeling. Generally, the overall analysis result is acceptable. The objective evaluation method can predict the ride motion control performance consistently with the subjective evaluation. The process is available and the method can be a complement for ISO 2631.

4. Conclusions

The acceleration data in X and Z directions, especially on the driver side, can be extracted as effective features for objective evaluation modeling of the ride motion control performance on sine wave road. Furthermore, the high correlation features relative to the subjective evaluation can be screened out by correlation and cluster analysis. Based on the small-sample statistics theory, the LASSO linear regression model is well adapted to the prediction of objective evaluation with the selected features. The cross validation and comparison results indicate that, though there are some differences, the consistency of objective evaluation and subjective evaluation is good and acceptable. The objective evaluation method is available to predict the ride motion control performance, which can be a complement for ISO 2631.

Declarations

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Not applicable.

Authors’ contributions

XL was in charge of the whole trial; WF assisted with problem analyses. All authors read and approved the final manuscript.

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Availability of Data and Materials

Not applicable.

Competing Interests

The authors declare that they have no competing interests.

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Figures

Figure 1

Comparison Plot of Subjective Evaluation and Objective Evaluation

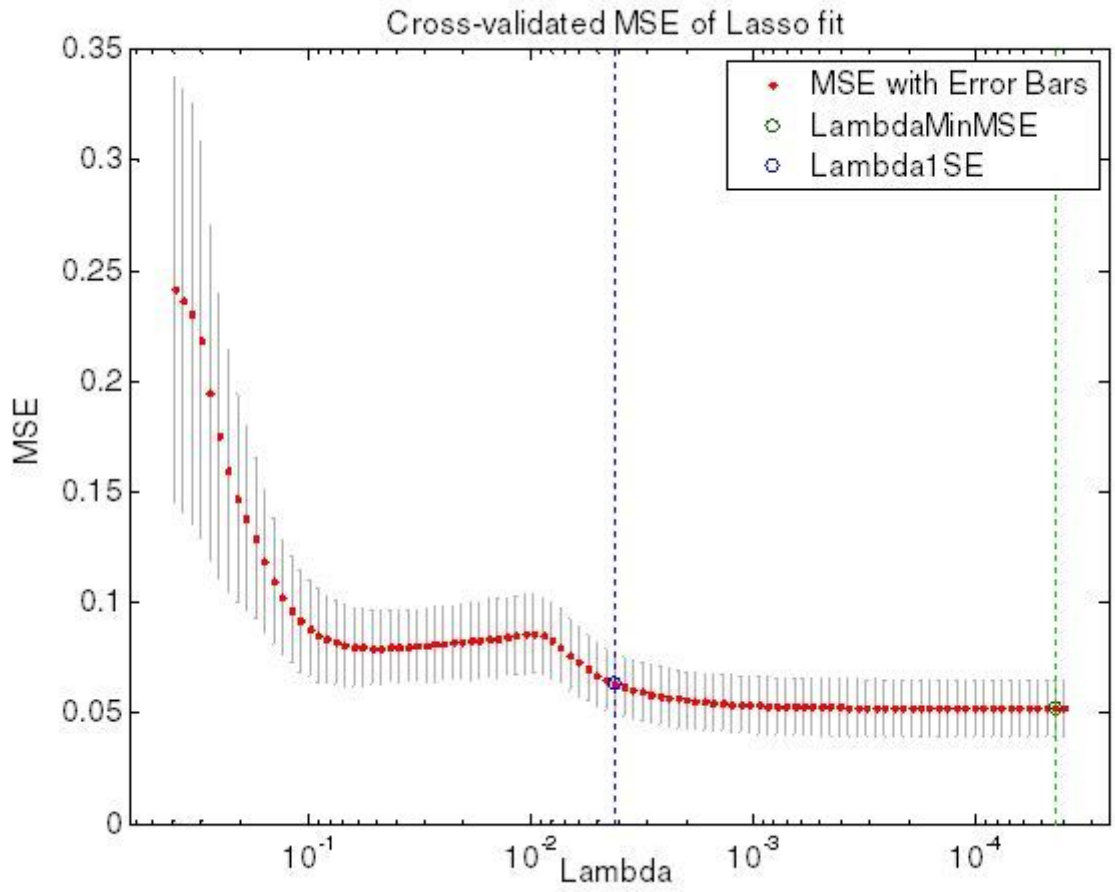

Figure 2

MSE Simulation of LASSO Model

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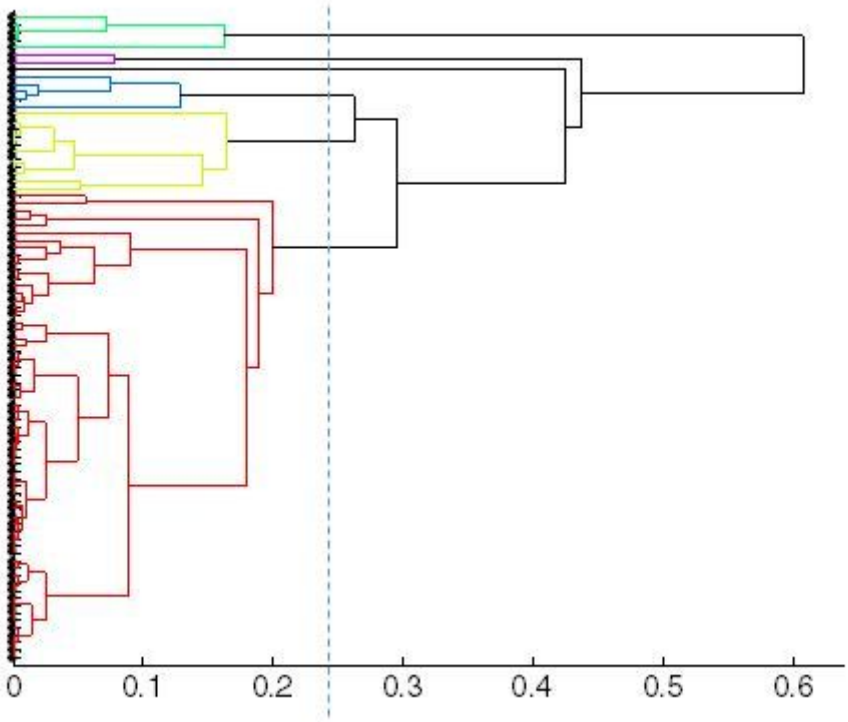

Figure 3

Hierarchical Cluster of Chosen Features

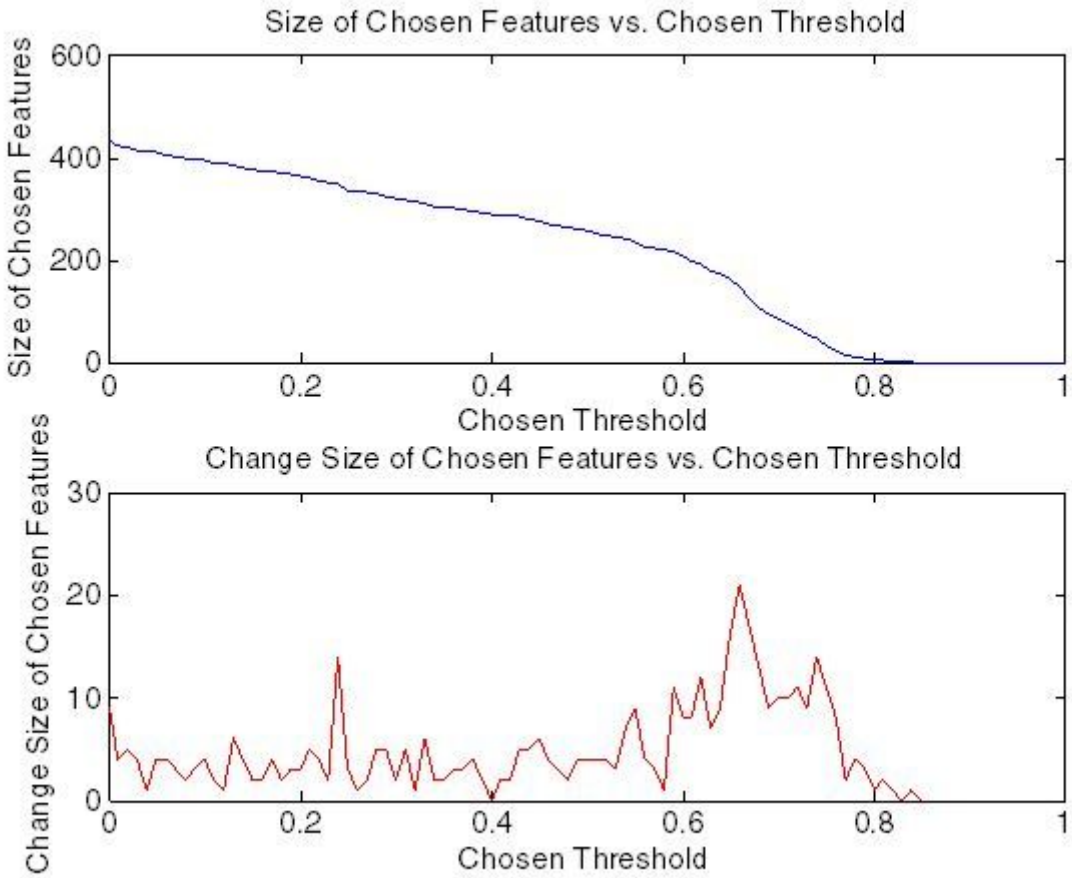

Figure 4

Threshold Selection

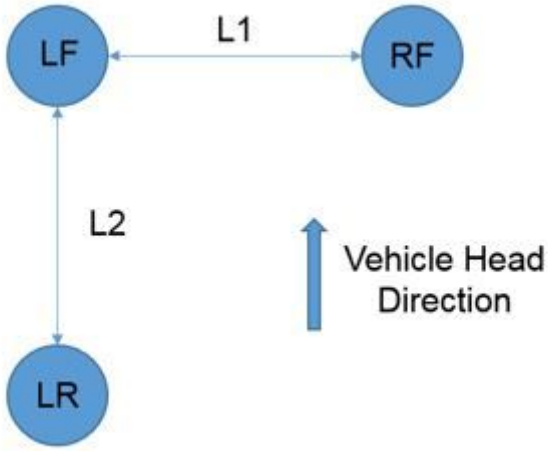

Figure 5

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(a) Seat Bottom Sensor (b) Seat Back Sensor (c) Foot Floor Sensor (d) Seat Track Sensor (e)Gyroscope

Figure 6

Measurement Equipment

Figure 7

Sine Wave Road in GDPG