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LINKS BETWEEN SUBJECTIVE ASSESSMENTS AND OBJECTIVE METRICS FOR STEERING AND DRIVER RATING EVALUATION

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Abstract

During development of new vehicles finding correlation links between subjective assessments and objective metrics is an important part in the vehicle evaluation process. Studying different correlation links is of importance in order to make use of the gained knowledge in the front end of development, during testing and for new systems. Both subjective assessments using the rating scale of 1-10 from expert drivers and objective metrics from different tests measured by a steering robot were collected by standard testing protocols at an automotive manufacturer. This paper evaluates driver ratings and analyse correlations by using Regression Analysis and Neural Networks through a case study approach. Links have been identified and are compared to related research.

1. INTRODUCTION

In time of writing, vehicle dynamics characteristics for the same class of vehicles could vary a lot even with similar components from same suppliers. It is the appropriate integration of these components and calibration that makes a product specific. To evaluate the dynamics of a vehicle the manufacturers usually use two approaches, subjective assessments (SA) using test drivers and objective metrics (OM) from simulations, steering robot tests or logged measurement data. Though some of the OM can be used to describe dynamic behaviour of a vehicle, they cannot indicate if the settings of the vehicle and its components lead to good interaction between a driver and the vehicle. Thus, the subjective perception of driving or riding a vehicle is an important measure to evaluate the vehicle. Subjective evaluation of a vehicle includes various different SA to rate the vehicle as a whole. So far many companies in the vehicle industry use SA in the tuning process of vehicle development and some of them develop their own evaluation standards. AVES (Alliance Vehicle Evaluation Standard) [1] defined by Renault-Nissan Alliance have been adopted as a major item to evaluate the vehicle quality. Approximately 350 criteria concerning static and dynamic characteristics are listed in this evaluation system. One of the most common subjective rating scale that has been widely applied since 1985 comes from SAE recommended practice J1441 [2], which is visualized in Table 1.

Table 1. Subjective rating scale for vehicle handling, SAE J1441.

Very Poor		Poor		Fair		Good		Excellent	
1	2	3	4	5	6	7	8	9	10
Undesirable			Borderline			Desirable			

One of the most challenging tasks for vehicle engineers is, under cost and time constraints, to satisfy every requirement regarding vehicle dynamics characteristics and the reliability and repeatability of SA. Still, vehicle tuning mainly relies on subjective evaluation from test drivers, due to a limited knowledge of links between SA and OM. Therefore, there is a strong need in the vehicle industry to further study the links between the SA and the OM in order to improve the efficiency of vehicle development and calibration.

One of the first attempts of correlation activity in the area of vehicle handling can be dated back to 1979 where Jaksch [3] studied driver-vehicle interaction with respect to steering controllability. On-centre handling or the steering feel during straight line driving with small sinusoidal steering inputs has been an interesting area and studied by many, [4-12], both with and without correlation of subjective and objective data. It is not so surprising that there has been a lot of activity around on-centre handling or the Weave Test ISO 13674-1 since the vehicles are driven most of the time with moderate steering corrections, e.g. highway driving.

There are only a few references from related work that have studied the nonlinear mapping between subjective and objective data concerning handling, i.e. using Neural Network [12] [13]. Others have utilised linear regression analysis [3] [4] [8] [9] [14-18] and some use other methods like paired comparison [11] and Fuzzy Logic and evidence theory [19], hence one aim of this paper is to further analyse the correlation between SA and OM and compare with findings from related research. This paper focuses on vehicle handling, mainly steering feel, i.e. events and manoeuvres where the vehicle has lateral motion.

2. METHOD

2.1 Data collection

The data used to acquire the results presented in this paper comes from an automotive manufacturer who gathered the data using its own test procedure, i.e. no specific pre-design of the data collection was made for the purpose of using the tools and methods presented in this paper. The SA was rated absolute and follows the rating system presented in Table 1, i.e. no specific vehicle was used as a reference when evaluating. The objective data set comes from the tests using a steering robot [20]. All data collected includes 12 SA and 27 OM gathered from 7-10 expert test drivers and 23 different vehicles spread over four classes. See Appendix A for a list of SA and OM used and section 3 for a list of vehicles used.

2.2 Case study approach

Chen [21] introduced a case study method for subjective-objective correlation analysis. This approach is also used in this work to describe and explain correlation findings for each driver. During the test process, each test driver does his or her SA on different vehicles. Thus, the number of SA of a given vehicle depends on how many test drivers are involved. For OM only one unique measurement set of objective data for a specific vehicle is available, which means that there are more data points for each SA than each OM since one vehicle is only measured once.

Mean value of the SA is sometimes used for correlation analysis [14]. Monsma has studied subjective-objective correlations using both the mean rating and each set of SAs from individual drivers [22]. Taking the disturbances such as a small statistical sample of vehicle configurations in each segment, rating preferences of drivers and other external influences into account, only using mean ratings to carry out correlation analysis may cloud existing links and give unreliable results. Thus, a case study method will be used in this work. This means that if the same linear (Regression Analysis) or nonlinear (Neural Networks) correlation is found for several drivers the link will be considered confirmed.

2.3 Simple linear regression analysis

Simple linear regression fits a straight line to estimate a linear model with one single explanatory variable x_i (OM), seen in Equation 1, where y_i is the true value (SA), f_i is the regression value, μ is a random component, also called error or residual, β_0 is a constant and β_1 is the regression coefficient.

$$y_i = f_i + \mu = \beta_0 + \beta_1 x_i + \mu \tag{1}$$

The approach used to find the best fit is to minimize the sum of the squares of the difference between the data and a line, so-called least squares minimization. The correlation coefficient ($r \in [-1,1]$) is widely adopted as a measure of the strength of linear dependence between two variables. An $|r|$ value of 1 indicates the strongest correlation. If the $|r|$ value is smaller than 0.7, this is considered to be weak or even no correlation in this research.

2.4 Multiple linear regression analysis

Multiple linear regression basically follows the same procedure to achieve best fit. The only difference is that more than one explanatory variable are introduced as seen in Equation 2. The coefficient of determination ($R^2 \in [0,1]$) is a measure to study how well the true values are likely to be predicted by the model. R^2-value of less than 0.7 was considered as an uncertain correlation in this research.

$$Y_i = \beta_0 + \left[x_1 \cdots x_{np}\right]\begin{bmatrix}\beta_1 \\ \vdots \\ \beta_p\end{bmatrix} + \mu_i \tag{2}$$

- Y_i is the SA of a specific test group for $i=1,2,\dots n$ different vehicles/settings.
- There are p sets of OM for n different vehicles/settings.
- β_0 is the constant in the regression equation.
- $\beta_1 - \beta_p$ are the coefficients for the regressors x_{np}.
- μ_i is the residual.

For multiple linear regression models, F-statistics can be used to check the significance of the regression equation and of each regression coefficient in the equation. A confidence level of 75% was adopted for F-test in this research.

2.5 Neural network analysis

Linear correlation analysis can only show that some OM probably has monotonically positive or negative effect on the corresponding SA. If an optimal design target needs to be defined for an OM in order to produce an excellent subjective perception, a nonlinear method has to be used in order to find a maximum or minimum in the range of an OM. Neural network (NN) is basically a kind of mathematical structure composed of interconnected artificial neurons to imitate the way a biological neural system works (e.g. our brain). It has the ability to learn from data. A typical multi-layer NN consists of an input layer, one or several hidden layers and an output layer of neurons. A base NN structure to explore nonlinear subjective-objective links is shown in Figure 1.

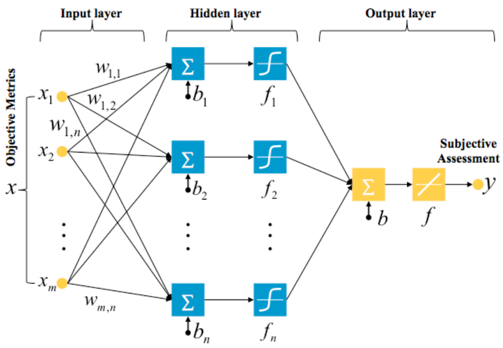

Figure 1. Structure of a three-layer static Neural Network.

The input metrics x_i (OM) is transmitted through the connections by first being multiplied by the scalar weight w_i to form a product ($w_i \times x_i$). Secondly, this product will be added with a scalar bias b_i and processed by a transfer function f_i. Three types of transfer functions are most commonly used, namely hard-limit, linear and tan-sigmoid. In this study, tan-sigmoid was adopted as the transfer function in the hidden layer to find nonlinear subjective-objective correlations. The calculated results from the hidden layer will then be added together and to a scalar bias in the output layer and then go through a linear transfer function where the output y is produced and can be compared with target value. The main principle of NN is that the scalar weights and bias can be adjusted in order to obtain desired results, like recognizing a pattern.

In this paper the focus is only on a single-input NN model, i.e. only one OM vs. one SA criteria is studied. More data and further designed data collection is needed in order to train a reliable NN with more inputs.

3. ANALYSIS OF SUBJECTIVE ASSESSMENT DATA

In the SA data set all the 10 drivers did not drive all the vehicles from the four different vehicle classes, so the SA data set decides how much data is available for each vehicle class for analysis. The subjective data from test drivers that have only provided 3 or 4 ratings in each vehicle class will be disregarded when studying subjective-objective correlation. This leaves the following data set for the linear methods, for the non-linear method the data used will be explained in Section 4.3:

- Class C: 4 drivers tested 6 vehicles
- Class D: 7 drivers tested 5 vehicles
- Class E: 3 drivers tested 7 vehicles, and 1 driver tested 6 vehicles
- Class SUV: 6 drivers tested 5 vehicles

3.1 Analysis of driver ratings

To investigate the validity of ratings, the rating spread of drivers on a specific vehicle should be examined. This has been done for each of the different vehicle classes. The rating quality is high but some things could be seen, e.g. Driver 1 has a larger rating spread for each vehicle, meaning he uses a larger part of the scale, while Driver 6 has much narrower rating spread compared with other drivers, see Appendix B. This small rating tendency will however still be accepted for the continued analysis of the data in this work. One reason is that these drivers show consistent rating habit across all the vehicle models. If the rating spread of a driver fluctuates a lot with the given vehicles within the same segment, the ratings of him or her cannot be considered reliable.

3.2 Evaluation of rating tendency

Expert drivers may have their own rating tendencies. Some of them are likely to always rate higher or lower than other drivers, or in other cases some of the drivers possibly have wider or narrower rating range than the rest. There are five vehicles in D-class so each driver gave five ratings on each SA, based on this data a tool were developed to evaluate driver rating tendency. The maximum, minimum and mean values of SA for each driver were investigated. The approach to find out preferences is to compare the before mentioned values between different drivers. The results are graphically illustrated in Appendix B. Studying the figure in Appendix B, each of the 12 subplots presents a SA with ratings of seven drivers. By examining the drivers SA in the figure closely it is easy to find that some of the drivers show rating tendency. For example, Driver 4 rated most of the times lower for most of the SA. After close observation, four drivers show possible rating tendency and they are listed in Table 2. The results shown in Appendix B and in the table below will be used for analysis of the results, for future work and as a training tool for the automotive manufacturer during training of test drivers.

Table 2. Evaluation of driver rating on each subjective assessment.

Notation	H – highest average rating L – lowest average rating				W – widest rating spread N – narrowest rating spread		
	Driver 1	Driver 2	Driver 3	Driver 4	Driver 5	Driver 6	Driver 7
SA-1				L			H
SA-2	W						H
SA-3		N					H
SA-4	N H			L			
SA-5	H			L			
SA-6	W H			L			
SA-7	H			L			
SA-8	W						
SA-9	W			L			
SA-10	W			L			
SA-11	W	N		L			
SA-12							
Summary	6 W, 4 H	2 N		8 L			3 H

Mikael Nybacka 13-8-18 20:31
Comment [1]: Uppdatera tabell, driver 6?

4. RESULTS

This section will show examples on results from analysis, both from linear regression and non-linear NN.

4.1 Linear regression correlations

Simple linear regression is one of the simplest in statistics and attempts to explore the relationship between two variables using a straight line. But finding a link for only one driver is not enough for conclusive results which is why more findings of the same correlation in a vehicle class is required. Considering that the small sample size could increase the chance to reject a correlation, then no less than a half of all drivers should show the same correlation. In D-class, there are seven test drivers, out of which six drivers show correlation between SA-2 and OM-26, this indicates a strong correlation. Analysing the regression coefficients can help us to know if the relation between parking effort (SA-2) and steering wheel torque (OM-26) can be shown to be positive or negative, i.e. if the SA rating increase with increasing OM or vice versa. As seen in Table 3, using case study based on data of each driver in D-class the regression coefficients are all negative except for Driver 6 that have a low correlation coefficient. Therefore, a negative relation between SA-2 and OM-26 has been confirmed.

Table 3. Regression coefficients between parking effort and steering wheel torque.

Driver	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Coefficient (β_1)	-3.19	-1.23	-1.69	-1.49	-2.48	/	-0.68

By employing the same method stated above, subjective-objective correlation with $|r| > 0.7$ has also been found in other vehicle segments. A subjective-objective correlation is supported only when data from no less than half of drivers demonstrate this correlation. Subjective-objective correlations found from simple linear regression analysis are summarized in Table 4. Only four strong correlations can be found, between SA 10 and OM 22 and 23, and for SA 2 and 26 and 27. One of the correlation to SA can be seen in every vehicle segment OM 26 and one in all but SUV OM 26.

Table 4. Summary of subjective objective correlations (negative shaded)

SA		**2**		**3**		**4**		**7**			**10**			**12**
C	**OM**	26	27					1	2	4	21		23	
D		26										22	23	23
E		26				2	4			4	19	22	23	22
SUV		26	27	26	27									15

4.2 Multiple linear regression correlations

All the assessments where at least one correlation is found include SA-2, 3, 4, 6, 7, 8, 10, 11 and 12. On the contrary, nothing is revealed regarding to SA-1, 5 and 9. A summary of which OM that have the best correlation to SA for the multi linear regression analysis are shown in Table 5. What needs to be noted here is that in C- and E-class not all drivers tested every available vehicle and hence those classes will naturally have less confirmed correlations.

Table 5. OM that correlates to SA (negative regression coefficient shaded grey, correlations where both positive and negative correlation coefficients have been found are marked with (--)).

Vehicle Class	**SA**	**OM 1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**
C-class	6									X	X																	
	7				X	X	X		X		X																	
	8											X						X										
	10																			X		X	--	X				
	12											X		X										X				
D-class	6									X	X																	
	7	X		X	X	--	X	X																				
	8												X	X	X	X	X											
	10																			X	X		X	X				
	11																			X	X	--	X	X				
	12											X	X		X	X	X					X	X	X				
E-class	6									X	X																	
	7		X			X			X	X																		
	11																				X	X	X					
SUV	6								X	X	X																	
	7						X		X																			
	8											X		X														
	10																				--		X					
	11																				X		X					
	12											X	X			X												

It can be seen that OM-22 *off centre hysteresis* has positive correlation to SA-10 *torque feedback* for D- and E-class, also seen in Table 4, but not for SUV-class. One way to explain this is that the measured OM is above the preferred range for SUV-class and below for D- and E-class.

4.3 Non-linear correlations

The data set in each vehicle class cannot reach enough sample size unless different but somehow similar testing groups are merged. Thus, D-class, E-class and some C-class vehicles (compact SUVs are excluded) will be combined since they share some similar properties. However, what need to be considered is that the driver's expectation from various vehicle classes likely varies. Only three of the expert drivers did all tests with 15 vehicles. That means that only their subjective ratings are valid for NN training. By using case study method each of the three drivers will have a result table that is used for further analysis. Here, a regression coefficient (*r*-value) larger than 0.7 and mean squared error less than 0.5 will be used to select the results for further studies. Each of the three drivers results plots are analysed and the range of the OM that give higher grade than 7 are listed in Table 6.

Table 6. Overview of OM range leading to high rating, including results from related research.

No.	Objective metrics	Preferred range	Related research [13]
2	Response gain straight [°/s/100°SWA]	25~30	Yaw velocity gain: 20~25
6	Response time delay [ms]	>95	
8	Torque deadband [°]	<2.2	
11	Yaw response gain [°/s/100°SWA]	28~32	
20	Torque build-up cornering [Nm/g]	4~6	
22	Off centre hysteresis [Nm]	1.5~2.2	
23	Effort level [Nm]	3.6~4.5	Steering torque at 0.3g: <6.5
26	Parking efforts standstill [Nm]	<3.3	
27	Parking efforts rolling [Nm]	>1.5	

When the *response gain at straight path* is between 25-30 °/s/100°SWA the SA rating will be above 7. Compared with the similar OM in another research by King et al. [13] the preferred yaw gain at 0.7 Hz is within the range of 20~25. The result of this metric seems to map well when taking the difference of testing settings into account. The optimal range for *effort level* during cornering starts from 3.6 Nm. This result fits with the positive correlation in the linear regression analysis. Based on current data the upper boundary of this range cannot be specified since there is no metrics larger than 4.5 Nm. In the research presented in [13] it is defined that the OM steering torque at 0.3 g should not exceed 6.5 Nm, which could be seen as the upper boundary of the *effort level*.

5. CONCLUSIONS

The aim of this work was to evaluate driver ratings and analyse correlations through a case study approach. It is shown that simple and multiple linear analysis are useful to detect if positive or negative correlation exists while NN is an more precise tool to specify preferred range of OM and to find nonlinear links that are not easily described by linear correlations. Both of the two analysing approaches lead to the findings concerning almost the same OM.

To conclude, correlation links have been identified using the proposed methodology. A preferred range for *yaw response gain* is found and presented. Meaning for the purpose of good driving response neither nervous nor too lazy steering character will be praised. Three additional ranges has been found apart from the two that relates to other research, *yaw response gain*, *torque build-up cornering* and *off centre hysteresis*. *Torque build-up cornering* should not exceed a certain upper boundary of 6 Nm and not go below 4 Nm. The *steering torque at parking* condition definitely has a maximum limit if studying the data and the steering torque below this critical value will give a better perception of *parking effort* during standstill. However the lower boundary is difficult to define because the steering systems in this investigation did not reach infinitely small parking torque.

The proposed methods and findings that are presented in this paper give the basis for future studies to find stronger and more reliable links between subjective assessments and objective metrics. The methods will be important to find an efficient vehicle evaluation process but the findings in this paper need to be further validated with a new data set involving more data.

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APPENDIX A

Table 7. Subjective assessment levels.

Level 2	Level 3	Level 4	Assessment
Steering feel	First impression	First impression	SA-1
	Parking/Manoeuvring	Effort	SA-2
		Returnability	SA-3
	Straight ahead controllability	Response	SA-4
		Roll control	SA-5
		Torque feedback	SA-6
		Modulation	SA-7
	Cornering controllability	Response	SA-8
		Roll control	SA-9
		Torque feedback	SA-10
		Returnability	SA-11
		Modulation	SA-12

Table 8. Objective metrics and corresponding levels.

Level 2	Level 3	Level 4	Metric
Straight ahead controllability	Response	Window	OM-1
		SWA at 0.05 g	
		Response gain straight path	OM-2
		On centre yaw gain straight	
		Lateral acc. resp. gain	OM-3
		Overall steering sensitivity	
		Lateral acc. resp. gain	OM-4
		Overall steering sensitivity	
		Gain linearity	OM-5
		Steering sensitivity ratio	
		Response time delay	OM-6
	Roll control	Roll control straight path	OM-7
		Total rollrate gradient @ 1 Hz	
	Torque feedback	Torque deadband	OM-8
		SWA at 1.3 Nm	
		Torque build up	OM-9
		Torsional rate	
		Friction feel	OM-10
		Torque at 0 g	
Cornering Controllability	Response	Yaw response gain	OM-11
		Off centre yaw gain	
		Response gain understeer	OM-12
		Linear range understeer Gradient	
		Response gain linearity	OM-13
		Yaw gain linearity	
		Rel. yaw gain@max lat. acc.	OM-14
		Yaw gain@max lat acc/max yaw gain	
		Sine time lag	OM-15
		Yaw - SWA phase time lag @ 4m/s2	
		Sine Time lag	OM-16
		Ay - SWA phase time lag @ 4m/s2	
		Sine time lag	OM-17
		Ay - Yaw phase time lag @ 4m/s2	
	Roll control	Roll control cornering	OM-18
		Total roll gain	
	Torque feedback	Torque buildup into the corner	OM-19
		Torsional rate cornering	
		Torque buildup cornering	OM-20
		Off centre torque gradient	
		On centre hysteresis	OM-21
		Torque deadband in degrees	
		Off centre hysteresis	OM-22
		Torque hysteresis @ 0.3 g	
		Effort level	OM-23
		Torque @ 0.3 g	
First impression		Low speed response gain	OM-24
		On centre yaw gain	
		Low speed torque buildup	OM-25
		Max. torsional rate	
		Parking efforts standstill	OM-26
		Parking efforts near centre	
		Parking efforts rolling	OM-27
		Parking efforts just off centre	

APPENDIX B

The first seven bars shaded in yellow show the rating ranges of seven drivers. The upper and bottom lines represent the maximum ratings and minimum ratings respectively. The dot-dash lines represent the mean values of ratings. The upper line of the *m* bar means the mean value of the maximum ratings of all the drivers, while the bottom line of *m* is the mean value of the minimum ratings of all the drivers. The mean value of *m* marked with a cross is average of the mean ratings of all the drivers.