Effects of motion cueing and adaptive procedure on acceleration JND estimation

Erik Gustaf Lilljebjörn[1,2], Sogol Kharrazi[1,2], Jan Åslund[2]

(1) Swedish National Road and Transport Research Institute (VTI), e-mail: {erik.gustaf.lilljebjorn, sogol.kharrazi}@vti.se
(2) Linköping University, Sweden, e-mail: jan.aslund@liu.se

Abstract - *To assess driveability in a driving simulator, it is important that test participants can notice subtle differences in acceleration in the simulator. In a moving-base driving simulator, the just-noticeable differences (JNDs) in longitudinal acceleration were estimated for nine professional truck test drivers using three variants of the classical motion-cueing algorithm (MCA). No statistically significant differences in JNDs were observed across MCA variants, possibly due to the low statistical power of the study. The mean JND across all participants and MCA variants was 5.4%.*
Motivated by the low statistical power of the driving simulator study, standard deviations and biases of JND estimators were subsequently estimated using Monte Carlo simulations of three adaptive procedures. The stationary distributions of the procedures provide an explanation for why JND estimates obtained with some procedures are asymptotically biased. The results further show that good statistical power can be achieved with the proposed procedures.

Keywords: *Driveability, motion-cueing algorithm, acceleration perception, just-noticeable difference (JND), Monte Carlo simulation*

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Introduction

Early in the product development of a new driveline, when physical prototypes are not available, the driveability cannot be evaluated using conventional methods. Testing the driveability using a virtual prototype of the driveline in a moving-base driving simulator could therefore be an attractive alternative. Driveline-related driveability has been tested in moving-base driving simulators in several previous studies (e.g. Baumgartner, et al., 2019b; Erler, et al., 2018; Kraft, et al., 2021).

Because the workspace of a moving-base driving simulator is limited, a motion-cueing algorithm (MCA) maps the motions of the vehicle model to feasible simulator motions. The classical MCA recreates transient accelerations using translational acceleration and recreates sustained accelerations by tilting the cabin – commonly known as *tilt coordination* (Reid and Nahon, 1985). The classical MCA typically scales down accelerations, and as a result, they may be less noticeable in the simulator. To assess driveability in a driving simulator, it is important that test participants can notice subtle differences in acceleration. One goal of the present study is therefore to investigate if small differences in longitudinal acceleration are more noticeable with a classical MCA tuned specifically for drive-off tests than with a general one.

The just-noticeable differences (JNDs) in acceleration across motion-cueing variants can be estimated using psychophysical methods. Psychophysics is a branch of experimental psychology that studies the relationship between stimuli and sensations (Gescheider, 2013).

Adaptive test procedures, where the stimulus intensity is adjusted based on participant responses in previous trials, are commonly used to estimate JNDs in driving simulator studies (e.g. Baumgartner, et al., 2019a; 2019b; Jamson, 2010; Menig, 2025; Nesti, et al., 2012; 2016). Several adaptive procedures have been proposed (Leek, 2001), and the choice of procedure may have a considerable effect on the variability and biases of JND estimators (García-Pérez, 1998), but this is rarely discussed in previous studies. Therefore, this paper also investigates how the rules and settings of adaptive test procedures influence the mean and variability of JND estimates in psychophysical experiments.

Estimating JNDs

To estimate a test participant's JND in acceleration, pairs of accelerations are presented to the participant successively. One stimulus is always the same and is called the *standard stimulus*, whereas the *compar-*

ison stimulus is varied from trial to trial. Rather than asking participants if they perceived a difference or not, the two alternative forced-choice (2AFC) method is commonly used in JND experiments (Gescheider, 2013). In a 2AFC task, participants are forced to choose which of two stimuli that they perceived as being more intense.

A staircase procedure is an adaptive method in which the stimulus intensity (or stimulus difference) is decreased after one or more correct responses and increased after an incorrect response. A reversal in a staircase procedure is a trial in which the direction of the staircase changes (i.e., the stimulus intensity is increased after a number of trials with decreasing stimulus intensity or vice versa). A sequence of trials between two reversals is referred to as a *run*. When a staircase procedure is used to estimate absolute or differential sensitivity, a threshold is usually estimated as the mean of the reversals, as shown in the top subplot of Figure 1. This method is equivalent to taking the average of the mid-points of every second run (Levitt, 1971), and these estimates are therefore referred to as *mid-run estimates*.

In this work, a hybrid method (Hall, 1981) for estimating the JND from staircase data is compared to the standard mid-run estimates. In a 2AFC task, the *psychometric function* describes the relationship between stimulus difference and the probability of responding that the comparison is higher. In the hybrid method, the participant's unknown psychometric function is approximated by fitting a sigmoid (e.g., logistic) function to the binary responses. The fitted model is then used to calculate the JND.

Figure 1 illustrates how the JND is estimated using the hybrid method. Responses of a hypothetical participant in the top subplot were generated using an assumed true logistic psychometric function shown in the bottom subplot. The fitted psychometric function, also shown in the bottom subplot, was obtained by fitting a logistic model to the responses using maximum-likelihood estimation. The circles represent the proportion of trials in which the participant judged the comparison as higher.

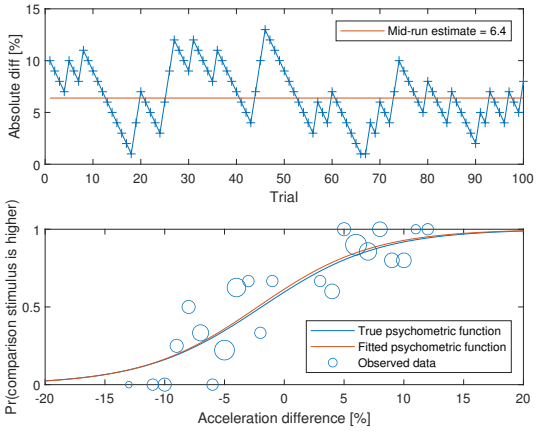


Figure 1: Example of an adaptive staircase procedure. Circle size reflects the total number of trials at each acceleration difference.

The point of subjective equality (PSE) is defined as the stimulus difference at which the probability of responding "comparison stimulus is higher" equals 0.5. A high JND estimate can be calculated as the difference between $X_{0.75}$, i.e., the difference where $p = 0.75$, and the PSE. Similarly, a low JND estimate is the difference between the PSE and $X_{0.25}$ (Gescheider, 2013). A single JND estimate is obtained by calculating the mean of the low and high JND estimates.



Figure 2: Driving simulator used in the study.

Driving simulator study

To investigate the effects of the MCA variants on the JNDs in acceleration, a driving simulator study was conducted with nine professional drivers that routinely assess driveability of heavy truck drivelines.

A moving-base driving simulator with a seven-meter-long translational workspace, shown in Figure 2, was used in the study. The simulator can recreate accelerations of up to 8.0 m/s^2 using translational motion and can simulate sustained longitudinal accelerations of up to approximately 1.5 m/s^2 by tilting the cabin.

Two variants of the classical MCA that are tuned specifically for short drive-off tests and one more general variant were considered. The Unscaled Tip-In (UTI) MCA variant does not scale down the acceleration, whereas the Downscaled Tip-In (DTI) and Downscaled Generic (DG) variants use a scale factor of 0.7. The UTI and DTI variants can recreate a 1.4 m/s^2 step input for three and five seconds, respectively, before the simulator reaches the end of its linear rail. Therefore, the maneouvre must be stopped automatically after three seconds, and the simulator is returned to the starting position. The Downscaled Generic (DG) variant is the most general and can reproduce a 1.4 m/s^2 step input indefinitely by using cabin tilt more than the other variants.

The simulator is pre-positioned before the maneouvre so that the variants that are tuned specifically for the drive-off maneouvre can take full advantage of the long linear rail. Some of the most important parameters of the MCAs are shown in Table 1 and the outputs of the MCAs are shown in Figure 3.

The simulator study used a within-subjects design, i.e., all participants tested all MCA variants, which was the only factor of the study.

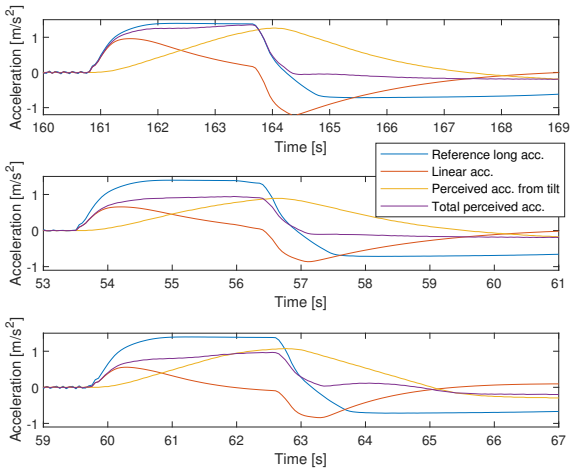


Figure 3: Outputs of UTI (top subplot), DTI (middle subplot) and DG (bottom subplot).

Motion cueing	Scale factor	Cut-off frequency [rad/s]	Max tilt speed [deg/s]
UTI	1	0.3	3
DTI	0.7	0.32	3
DG	0.7	0.55	3

Table 1: Summary of the motion cueing variants.

The participants were asked if a modified acceleration was lower or higher than a 1.4 m/s^2 reference acceleration in a 2AFC task. Stimulus intensities around participants' JNDs in acceleration were obtained by using an adaptive up/down staircase with an up-step twice the size of the down-step, as shown in Figure 4. A test with an MCA variant ended after 20 trials, and the signs of the acceleration differences were randomized.

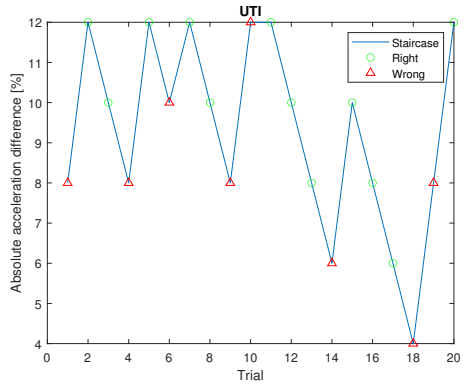


Figure 4: Example staircase of one of the participants in the simulator study.

Simulator study results

Psychometric functions fitted to the data, such as those shown in Figure 5, were used to estimate participants' JNDs using the hybrid method.

The median values, 25th and 75th percentiles and extreme values of the JND estimates across MCA variants are shown in Figure 6. The median JND estimate with the DTI variant is higher than that of the UTI and DG variants, but the distributions of the UTI and DG variants are right-skewed and the mean value of all three variants are very similar.

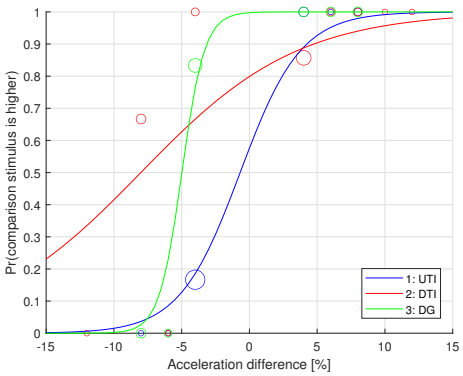


Figure 5: Fitted psychometric functions for each MCA variant for one participant.

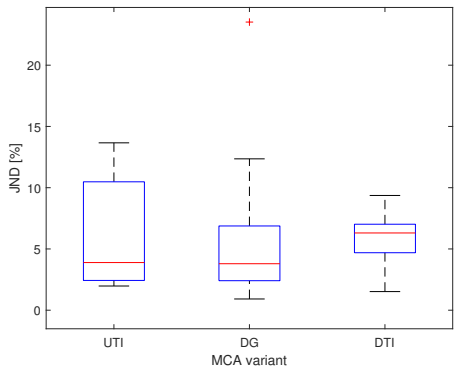


Figure 6: Medians, 25th and 75th percentiles and extreme values of the JND estimates. Estimates judged to be outliers are shown as red crosses.

Although the variability between participants is high in Figure 6, the within-subjects design allowed paired t-tests to be used to compare mean JNDs. Specifically, we compared the mean JNDs of the MCA variants that scale down accelerations – which are expected to yield higher JND estimates – to the UTI variant, based on within-participant differences.

Using a one-tailed paired t-test with significance level $\alpha = 0.05$, we tested the hypothesis that the mean JND of the DTI variant is higher than that of the UTI variant. The null hypothesis is that the mean JNDs are equal. The resulting p-value was 0.55, which exceeds α, and the null hypothesis can therefore not be rejected. Similarly, the hypothesis that the mean JND of the DG variant is higher than that of the UTI variant was tested using a one-tailed paired t-test. The p-value was 0.44, which is also greater than α, and the null hypothesis cannot be rejected. In other words, no statistically significant differences in the mean JNDs of the tested MCA variants were observed.

The participants only did 20 trials with each motion cueing variant and as a consequence, the standard deviations of the JND estimates are high. Baumgart-

ner et al. (Baumgartner, et al., 2019a) reported that the JND in acceleration is related to the reference acceleration according to the model

$$a_{JND} = 0.02 + 0.0275 a_{ref}.$$

Using this model, the predicted JND at a 1.4 m/s^2 reference acceleration is 4.2%. If the reference acceleration is scaled down to 0.7, the predicted JND, using the same model, is 4.8%. The 0.7 scale factor is thus expected to have a relatively small effect on the mean JND. Because of the high standard deviations, small expected differences across motion cueing variants, and the small number of participants in the study, the tests have low statistical power. This could explain why we did not see the expected difference in mean JND between variants.

Because the mean JNDs were found to not differ significantly across MCA variants, and to avoid overfitting, the responses with all MCA variants were used to estimate a single JND for each participant. In Figure 7, a more reliable fit – compared to the models shown in Figure 5 – is obtained by fitting a single psychometric function to all responses. The circles represent the proportion of trials in which the participant answered that the comparison stimulus was higher, at different acceleration differences. The solid curve is the fitted psychometric function. As shown in Figure 8, the variability in the responses of some participants is high.

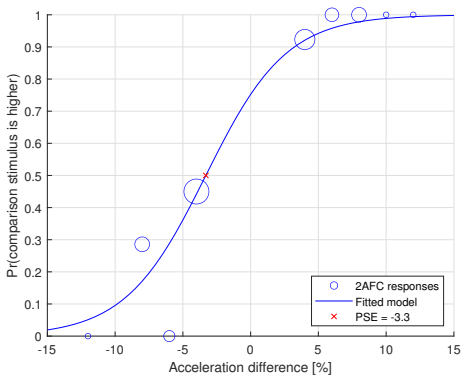


Figure 7: Fitted psychometric function of one of the participants.

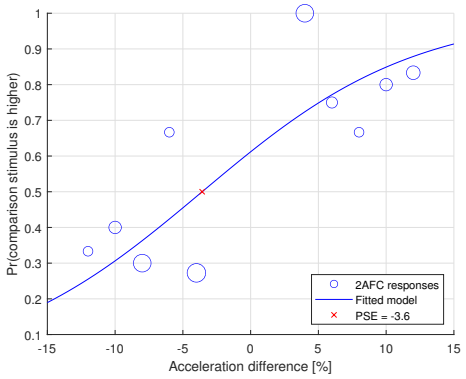


Figure 8: Fitted psychometric function of one participant with high variability in responses.

Mean	Median	Min value	25th percentile	75th percentile	Max value
5.4	5.4	1.7	3.1	7.9	8.6

Table 2: Summary statistics for the JNDs (rounded to one decimal).

Mean	Median	Min value	25th percentile	75th percentile	Max value
-1.9	-2.1	-3.6	-3.4	-0.8	1.4

Table 3: Summary statistics for the PSEs (rounded to one decimal).

Summary statistics for the JNDs and PSEs are shown in Tables 2 and 3, respectively. Notably, the mean PSE was -1.9%. To test the hypothesis that the mean PSE is not equal to zero, a two-tailed one-sample t-test with significance level $\alpha = 0.05$ was used. The null hypothesis is that the mean PSE is equal to zero. The resulting p-value is 0.009, which is less than α, and the null hypothesis is rejected. In the performed simulator study, the comparison stimulus always preceded the standard stimulus, and the negative mean PSE may be the result of a so-called *time error*. It has been reported before that when pairs of stimuli are presented to test participants successively, the memory image of the first stimulus may fade rapidly and participants may therefore perceive the second stimulus as being stronger than the first (Gescheider, 2013).

More detailed information on the statistical analysis of the simulator study results can be found in (Lilljebjörn, et al., 2026).

Effects of the adaptive procedure on JND estimates

The low statistical power of the simulator study highlights the need for an adaptive procedure with low variability for estimating JNDs. To determine how different adaptive procedures affect the variability and bias of JND estimators, a separate Monte Carlo simulation study was conducted. This analysis is independent of the simulator study and is not intended to validate its results, but rather to investigate general properties of the considered procedures. Typical psychometric functions, informed by the simulator study results, were used in the simulations.

Three adaptive test procedures were compared, each targeting difference thresholds at a correct response probability of 75-79%. The first procedure is a weighted up/down staircase (Kaernbach, 1991) in which the up-step is three times the size of the down-step, as shown in Figure 9. The second procedure is a transformed up/down staircase (Levitt, 1971) requiring three consecutive correct answers to take a step down, as shown in Figure 10. The third procedure is a combination of a transformed and weighted up/down staircase in which two consecutive correct answers are required. To target the 75% threshold with this procedure, the up-step is – perhaps somewhat unconventionally – 1.286 times larger than the down-step, as shown in Figure 11.

An adaptive procedure oscillates around a target

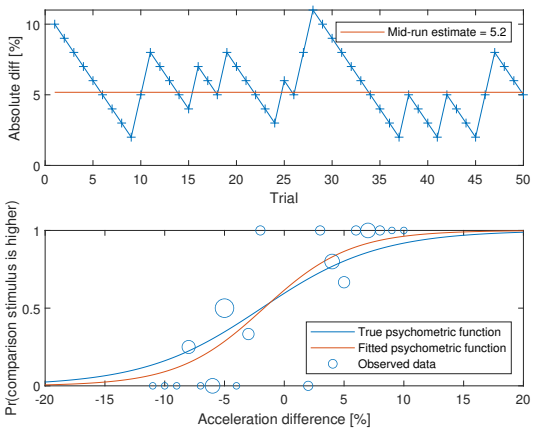


Figure 9: Example simulation of a JND experiment with procedure 1 and a logistic PF with JND = 5.4 and PSE = -1.9.

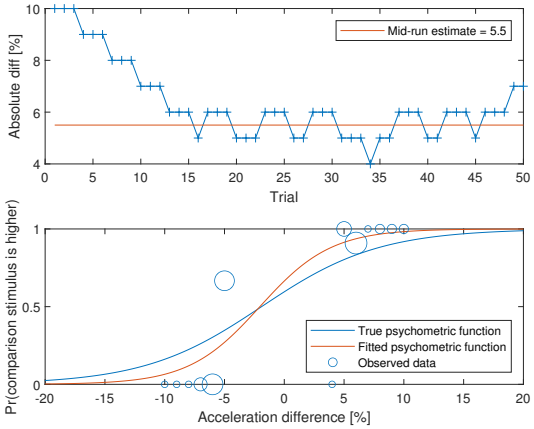


Figure 10: Example simulation of a JND experiment with procedure 2 and a logistic PF with JND = 5.4 and PSE = -1.9.

threshold because the step size and the number of correct responses required to take a step down are chosen so that the expected value of the step, $E(\Delta)$, after a trial with the stimulus intensity corresponding to the target threshold is zero.

$$E(\Delta) = \Delta^+(1 - p_{down}) - \Delta^- p_{down} = 0, \qquad (1)$$

where Δ^+ is the size of the up-step, Δ^- is the size of the down-step and p_{down} is the probability of a down-step. It follow from equation 1 that

$$\frac{\Delta^+}{\Delta^-} = \frac{p_{down}}{1 - p_{down}}. \qquad (2)$$

With procedure 1, only one right answer is required to take a step down, so $p_{down} = p_{right}$. To target the stimulus intensity where the probability of a right answer is 75%, $X(p_{right} = 0.75) = X_{0.75}$, it follows from equation 2 that

$$\frac{\Delta^+}{\Delta^-} = \frac{p_{right}}{1 - p_{right}} = \frac{0.75}{0.25} = 3.$$

With procedure 2, $\Delta^- = \Delta^+$, so it follows from equation 1 that

$$E(\Delta) = \Delta^+(1 - 2p_{down}) = 0 \Leftrightarrow p_{down} = 0.5.$$

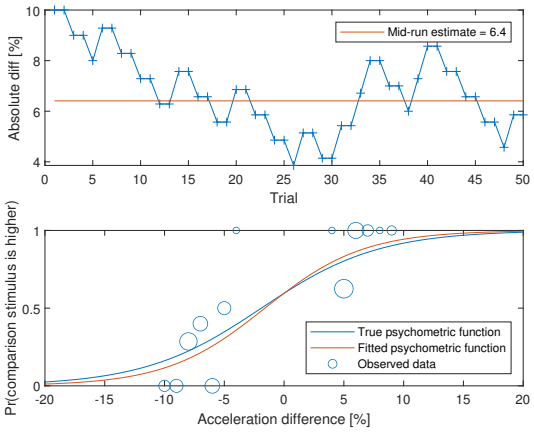


Figure 11: Example simulation of a JND experiment with procedure 3 and a logistic PF with JND = 5.4 and PSE = -1.9.

If three consecutive right answers are required to take a step down, then

$$p_{right} = p_{down}^{1/3} = 0.5^{1/3} = 0.79.$$

With procedure 3, $p_{right} = 0.75$ and two right answers are required to take a step down. With $p_{down} = 0.75^2 = 0.5625$, it follows from equation 2 that

$$\frac{\Delta^+}{\Delta^-} = \frac{p_{down}}{1 - p_{down}} = 1.2857.$$

Monte Carlo simulations in which an adaptive procedure is simulated 10000 times are done to calculate the mean and standard deviation of the JND estimators resulting from each procedure. One main result is that, with many (100+) trials, the hybrid method is hard to beat. As seen in Figure 12, the standard deviation of the hybrid estimators matches that of the mid-run estimators for 100 or more trials, while the bias is virtually zero in Figure 13. However, with fewer trials, the hybrid estimators show substantially higher variability than the mid-run estimators.

The bias of a JND estimator is defined as the difference between the expected value and the theoretical JND of the estimator, i.e., $Bias(\widehat{JND}) = E[\widehat{JND}] - JND$. The theoretical JND of mid-run estimators resulting from procedures 1 and 3 is the acceleration difference corresponding to a 75% correct response rate, while it is the 79% point for procedure 2.

In Figure 13, the bias of the first procedure stands out. When the starting stimulus in an adaptive procedure is far from the true threshold, the mid-run estimate is typically biased toward the starting value. However, here the procedure starts at an acceleration difference of 5.4%, i.e., the true 75% JND. The large bias of procedure 1 can therefore not be explained by a poor starting value, but rather by the estimator being asymptotically biased. This will be discussed further in the section on the asymptotic properties of the procedures below.

Note that since procedure 2 targets the 79% threshold, it goes from having a negative bias after 30 trials to a slightly positive bias after 200 trials in Figure 13.

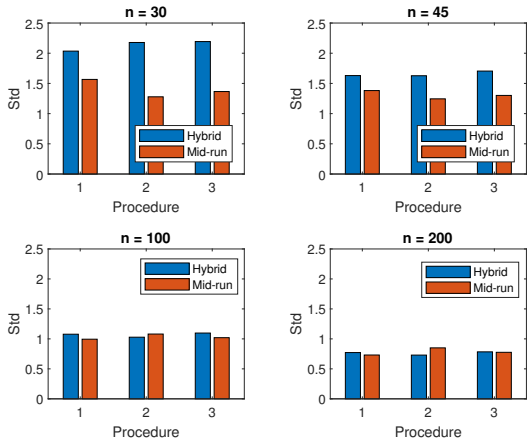


Figure 12: Standard deviations of JND estimators with 30, 45, 100 and 200 trials. The Starting acceleration difference is 5.4%.

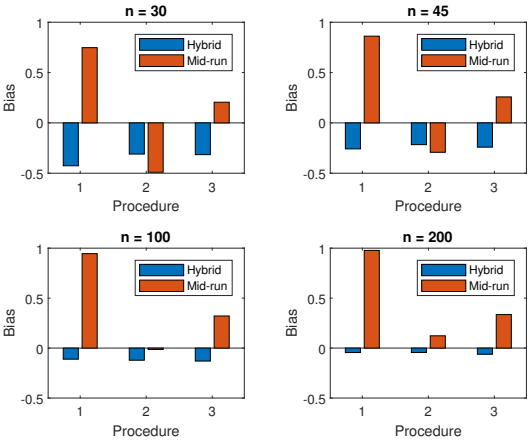


Figure 13: Biases of JND estimators with 30, 45, 100 and 200 trials. The starting acceleration difference is 5.4%.

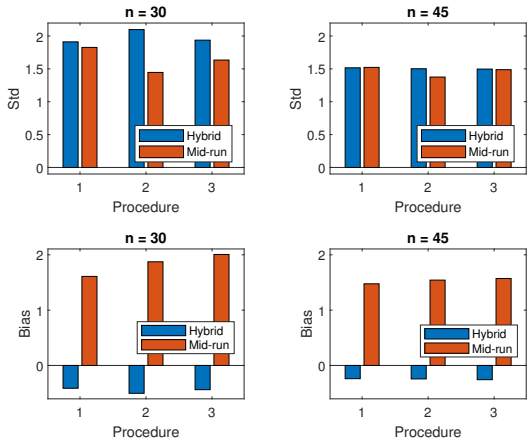


Figure 14: Standard deviations and biases of JND estimators with 10% starting acceleration difference and 1% base step size.

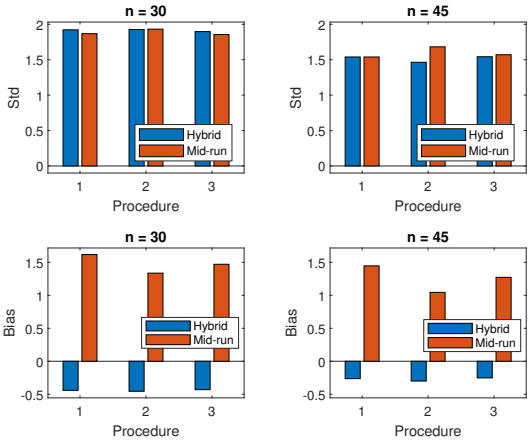


Figure 15: Standard deviations and biases of JND estimators with 10% starting acceleration difference. The base step size is 1% for procedure 1 and 2% for procedures 2 and 3.

Effects of starting stimulus and step size

In the previous section, the procedure started at the target JND. In a real experiment, this would rarely happen. In Figure 14, the starting acceleration difference is 10% instead of 5.4%, and the biases of procedures 2 and 3 are more affected by the starting stimulus than that of procedure 1. The reason for this is that procedures 2 and 3 require more trials than procedure 1 to reach the target threshold when starting from a high stimulus level. As shown in Figure 15, this can be mitigated to an extent by increasing the step size. The bias of procedure 1 is not improved by increasing the base step size, so it is kept at 1%.

Effects of the psychometric function

Procedure 2, which requires three consecutive correct responses to take a step down, has emerged as the best procedure based on simulations using a psychometric function whose JND and PSE were set to the mean JND and PSE obtained in the simulator study. Procedure 2 is nearly asymptotically unbiased, and its variability is comparable to that of procedure 1. In the previous section, the starting acceleration difference was shown to affect the bias of procedure 2 considerably. However, this effect can be mitigated to an extent by increasing the step size. Procedure 2 is also more practical than procedure 3 with its unconventional up-step/down-step ratio of 1.286.

To verify that these conclusions also hold for participants with JNDs below and above the average value of 5.4%, simulations were done with the psychometric functions shown in Figure 16. The red curve represents a participant with a below-average JND of 4%, and the yellow curve a participant with an above-average JND of 8%. The effect of the point of subjective equality is also examined in this section by using a PSE of 0%, instead of the average PSE of -1.9% used previously.

In Figure 17, a psychometric function with a 75% JND of 4% and a PSE of 0% was used, and procedure 2 is considerably less biased than procedure 1. Figure 18 shows results obtained using a psychometric function with a 75% JND of 8% and a PSE of 0%. Under these conditions, the bias of procedure 2 is comparable to, although somewhat larger than, that of procedure 1. The reason that procedure 2 is neg-

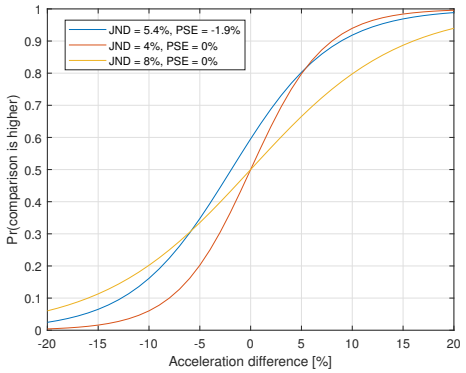


Figure 16: Three different psychometric functions used in simulations.

atively biased with 30 trials under these conditions is that it targets $X_{0.79}$, whereas the starting acceleration difference in the simulation is $X_{0.75} = 8\%$.

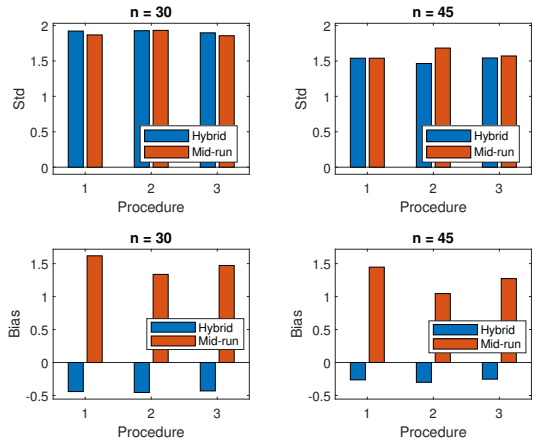


Figure 17: Standard deviation and bias of JND estimators. JND = 4% and PSE = 0%.

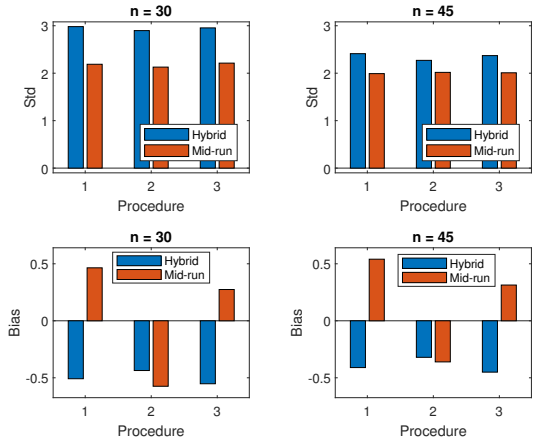


Figure 18: Standard deviation and bias of JND estimators. JND = 8% and PSE = 0%.

Asymptotic properties of the adaptive procedures

In a fixed-step size adaptive procedure, the probability of transitioning to any other state depends only on the current state, so it is, by definition, a Markov chain. The states of an adaptive procedure are the stimulus intensities. The state probabilities after the i'th transition is

$$\pi_i = \pi_{i-1} P,$$

where π_{i-1} are the state probabilities before the i'th transition and P is the state transition matrix. As the number of transitions tends to infinity, the vector of state probabilities tends to the stationary distribution of the Markov chain

$$\pi = \pi P.$$

The stationary distribution, π, is thus an eigenvector to the state transition matrix with eigenvalue 1.

The stationary distributions of the first and second adaptive procedures with a psychometric function with $JND = 5\%$ and $PSE = 0\%$ are shown in Figure 19 and in Figure 20, respectively. It is easy to see why the mid-run JND estimator that uses procedure 1 is biased high. In Figure 19, the variability of the stimulus intensities is high, and the distribution is right-skewed. The histogram is the distribution of the stimulus intensities of a Monte Carlo simulation of the procedure and the solid red line is the theoretical stationary distribution of the procedure.

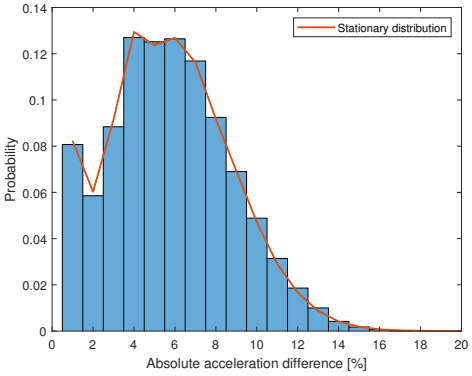


Figure 19: Stationary distribution of procedure 1.

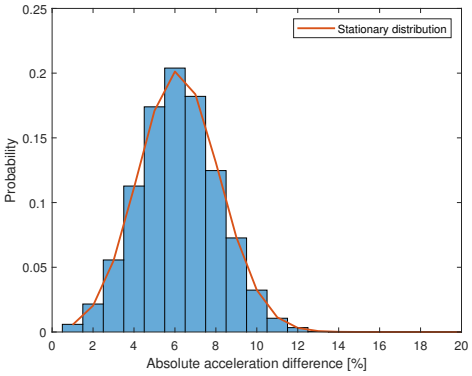


Figure 20: Stationary distribution of procedure 2.

Statistical power

To compare whether 30 or 45 trials per condition yield sufficiently low variability, we estimated the statistical power of the best JND estimators in a hypothetical study.

For practical reasons, each participant can perform around 90 trials. Thus, participants can either test three conditions with 30 trials each, or two conditions with 45 trails each. Mean JNDs (in %) are compared using paired t-tests.

Assuming equal variance of single JND estimates across conditions, the variance of within-participant differences is $\sigma_d^2 = 2\sigma_{JND}^2$, and the variance of the mean of all differences in a sample of N differences is σ_d^2/N.

Expected effect size was set to 1.2% (absolute) based on (Baumgartner, et al., 2019a). With 40 participants, the resulting sample sizes are $N = 40$ for 30 trials and $N = 20$ for 45 trials. Using a one-tailed paired t-test with $\alpha = 0.025$, statistical power of the best JND estimators with 30 and 45 trials was computed and is shown in Table 4. Under these assumptions, statistical power was consistently higher for 30 trials than for 45 trials across all JND estimators.

Table 4: Statistical power (%) of the best JND estimators

	Procedure 1		Procedure 2	
Trials	Staircase	Hybrid	Staircase	Hybrid
30	93	75	91	79
45	79	64	69	68

Conclusions

In a study with nine professional truck test drivers in a moving-base driving simulator, we compared the mean JNDs with three variants of the classical motion cueing algorithm. The mean JND of the generic variants with a scale factor of 0.7 did not differ significantly from that of the MCA variant tuned specifically for tip-in tests. The uncertainty of the JND estimates was high, and the sample size was low. As a result, the power of the statistical tests was low, and we believe this to be the reason why we did not see the expected effect of the scale factor on the JNDs.

Motivated by the low statistical power of the driving simulator study, Monte Carlo simulations were done to compare the standard deviations and biases of JND estimators using different adaptive procedures. We demonstrated that a target threshold around 75-79% can be estimated using a weighted or a transformed adaptive staircase procedure, or by combining ideas from both procedures, as we did in procedure 3. We also demonstrated that the JND can be estimated by either calculating the mean of the reversals in the staircase, which is the standard method, or with a hybrid method in which the JND is estimated using a fitted logistic psychometric function. With less than 50 trials, the standard deviation of the mid-run estimators is considerably lower than that of the hybrid estimators, but the hybrid estimators are generally less biased.

In our next study, we plan to use either procedure 1 with a base step size of 1%, or procedure 2 with a base step size of 2%, as both yield low standard deviations, which is desirable when studying effect on JNDs. To reduce bias from the starting stimulus difference, the experiment should begin near the expected mean JND. The negative mean PSE in the simulator study indicates that participants detect smaller differences when the higher stimulus is presented last. We therefore recommend using comparison stimuli only below or only above the standard stimulus, with the comparison presented last in half of the trials and first in the other half. Finally, a within-subject design is preferred to maximize statistical power. Learning and fatigue effects will be managed through frequent breaks and a balanced order of conditions.

References

Baumgartner, E., Ronellenfitsch, A., Reuss, H.-C., and Schramm, D., 2019a. A perceptual approach for evaluating vehicle drivability in a dynamic driving simulator. *Transportation research part F: traffic psychology and behaviour*, 63, pp. 83–92.

— Feb. 2019b. Using a dynamic driving simulator for perception-based powertrain development. *Transportation Research Part F: Traffic Psychology and Behaviour*, 61, pp. 281–290. ISSN: 13698478. https://doi.org/10.1016/j.trf.2017.08.012.

Erler, P., Menig, A., Uphaus, F., Makosi, C. A. M., Rinderknecht, S., and Vogt, J., July 2018. Investigating the perception of powertrain shuffle with a longitudinal dynamic driving simulator. In: IEEE, pp. 1427–1431. ISBN: 978-1-5386-1854-7. https://doi.org/10.1109/AIM.2018.8452255.

García-Pérez, M. A., June 1998. Forced-choice staircases with fixed step sizes: asymptotic and small-sample properties. *Vision Research*, 38, 12, pp. 1861–1881. ISSN: 00426989. https://doi.org/10.1016/S0042-6989(97)00340-4.

Gescheider, G. A., 2013. *Psychophysics: the fundamentals*. Psychology Press.

Hall, J. L., 1981. Hybrid adaptive procedure for estimation of psychometric functions. *The Journal of the Acoustical Society of America*, 69, 6, pp. 1763–1769.

Jamson, A. H. J., 2010. *Motion cueing in driving simulators for research applications*. University of Leeds.

Kaernbach, C., May 1991. Simple adaptive testing with the weighted up-down method. *Perception & Psychophysics*, 49, 3, pp. 227–229. ISSN: 0031-5117. https://doi.org/10.3758/BF03214307.

Kraft, E., Viehmann, A., Erler, P., and Rinderknecht, S., 2021. Virtual Driving Tests of Powertrain Systems in the Driving Simulator. *ATZ worldwide*, 123(3), pp. 40–45.

Leek, M. R., Nov. 2001. Adaptive procedures in psychophysical research. *Perception & Psychophysics*, 63, 8, pp. 1279–1292. ISSN: 0031-5117. https://doi.org/10.3758/BF03194543.

Levitt, H., Feb. 1971. Transformed Up-Down Methods in Psychoacoustics. *The Journal of the Acoustical Society of America*, 49, 2B, pp. 467–477. ISSN: 0001-4966. https://doi.org/10.1121/1.1912375.

Lilljebjörn, E. G., Kharrazi, S., Åslund, J., and Singull, M., 2026. *Effects of motion cueing on longitudinal acceleration perception in a driving simulator*. https://doi.org/10.48550/arXiv.2606.28055. arXiv: 2606.28055 [eess.SY].

Menig, A., 2025. Der eben merkliche Unterschied von Längsbeschleunigung im Fahrsimulator–Experimentelle Analysen unter Berücksichtigung verschiedener Einflussfaktoren. PhD.

Nesti, A., Masone, C., Barnett-Cowan, M., Giordano, P. R., Bülthoff, H. H., and Pretto, P., 2012. Roll rate thresholds and perceived realism in driving simulation. In: *Driving Simulation Conference Europe (DSC 2012)*, pp. 23–31.

Nesti, A., Nooij, S., Losert, M., Bülthoff, H. H., and Pretto, P., May 2016. Roll rate perceptual thresholds in active and passive curve driving simulation. *SIMULATION*, 92, 5, pp. 417–426. ISSN: 0037-5497. https://doi.org/10.1177/0037549716637135.

Reid, L. D. and Nahon, M. A., 1985. *Flight simulation motion-base drive algorithms: Part 1 - Developing and testing the equations*.