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Wider is better but sharper is not: optimizing the image of camera-monitor systems

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ABSTRACT
The replacement of rear-view mirrors with camera-monitor systems introduces new opportunities for design, such as altering the image quality and the rearward field-of-view. We investigated how the image quality and field-of-view might affect the distance and time-to-contact estimation of other vehicles. Eighty-six subjects estimated either their egocentric distance to a stationary vehicle (Experiment I) or the time-to-contact to an approaching vehicle (Experiment II). Throughout the experiments, the pixel density and either the field-of-view or the viewing condition varied. A larger field-of-view increased distance estimation accuracy and confidence. Reduced pixel density led to larger estimates. In contrast, reduced pixel density and simulated dirt shortened time-to-contact estimates. This is compatible with a safety strategy applied under conditions of impaired vision. Moreover, a limited benefit was observed for higher pixel densities. Therefore, camera-monitor systems with large field-of-view and a pixel density of around 300 ppi could ensure accurate TTC and distance estimation.

Practitioner summary: A camera's field-of-view and image quality are important parameters for camera-monitor systems. In two experiments, we investigated the effects of these two parameters on rearward distance and time-to-contact estimation. Whereas a larger field-of-view improved distance estimation accuracy, increasing the pixel density had a limited effect in the estimation of time-to-contact.

Abbreviations: CMS: camera-monitor systems; FOV: Field-of-view; PPI: pixels per inch; TTC: time-to-contact; lnError: natural logarithm of error ratios; lnError: natural logarithm of error ratios; rmANOVA: repeated-measures analyses of variance; M: Mean; SD: Standard deviation; CV: coefficient of variation; P25: 25% percentile; P75: 75% percentile; IQR: Interquartile range

1. Introduction

We are in the midst of a paradigm shift in rearward traffic perception: conventional side-mounted rear-view mirrors are being replaced by camera-monitor systems (CMS). In these systems, a camera mounted on the vehicle body transmits a video of the rearward scene to a monitor placed in the cockpit. CMS open up many possibilities to reframe rearward vision. For example, the camera's field-of-view (FOV) can be enlarged and adjusted flexibly, which could aid driving (Terzis 2016; van Erp and Padmos 2003). However, CMS also introduce potential risks, such as dirt on the camera or transmission latencies compromising image quality (Terzis 2016). But how do FOV and image quality affect rearward perception? So far, this question cannot be answered because CMS research has focussed on the comparison of mirrors and cameras (Flannagan, Sivak, and Mefford 2002; Flannagan and Mefford 2005; Flannagan and Sivak 2003; Schmidt et al. 2016), the placement of in-vehicle monitors (Beck, Lee, and Park 2017; Beck, Jung, and Park 2021; Large et al. 2016; Murata, Doi, and Karwowski 2018; Murata and Kohno 2018), and lately the placement of the exterior camera (Bernhard and Hecht 2021).

The research presented here set out to investigate how FOV and image quality of CMS affect drivers' rearward perception. Image quality in this context refers to the visibility of a target and its surroundings in the monitor, which could be impaired, for example, by low pixel density (low number of pixels per inch; ppi) or reduced target visibility due to external sources

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(e.g. dirt on the camera lens). Two experiments examined the effects of FOV and reduced image quality on egocentric distance estimation (Experiment I) as well as the effect of reduced image quality on the estimation of time-to-contact (Experiment II).

1.1. FOV, image quality, and the estimation of distances

The effect of FOV on distance estimation in virtual environments has been discussed controversially (Creem-Regehr et al. 2005; Kline and Witmer 1996; Knapp and Loomis 2004). No effect was found when head movements were possible (Creem-Regehr et al. 2005; Knapp and Loomis 2004). However, if head movements and FOV were restricted, Kline and Witmer (1996) observed reduced accuracy in verbal distance estimates. Likewise, Creem-Regehr et al. (2005) found a smaller FOV to reduce estimation accuracy in a blind walking task, in terms of distance underestimation. This effect had also been observed in other experiments (Hagen, Jones, and Reed 1978; Philbeck et al. 2018; Watt, Bradshaw, and Rushton 2000). The underestimation of distance in restricted viewing conditions could be explained by the loss of visual cues in a close environment. The importance of these cues was highlighted by the hypothesis of a sequential surface-integration process (He et al. 2004; Wu, Ooi, and He 2004). This hypothesis proposed that depth cues in the close environment form a ground-surface representation which is used as a gauge for the estimation of distances. If these cues are not available, the visual system has to rely on far ground surface information, which is less accurately represented, causing the far surface to be perceived as slanted towards the observer, which in turn produces distance underestimation (Gibson 1950; He et al. 2004; Wu, Ooi, and He 2004). In accordance with the hypothesis, the distance was underestimated when near-ground surface information was occluded (Dong et al. 2020; He et al. 2004; Wu, Ooi, and He 2004).

The relationship between environmental cues and distance estimation is also important with respect to image quality. As quality decreases, detailed information on environmental characteristics is likely to be lost, which could also lead to distance underestimation. Several experiments observed this effect in virtual environments (Kunz et al. 2009; Loyola 2018; Phillips et al. 2009; Thompson et al. 2004). Here, image quality was manipulated in terms of high- *vs.* low-fidelity rendering, comparable to our experiments. In contrast, other experiments failed to find changes in distance estimation when adding blur to pictures, which was more comparable to reduced visual acuity, such as when being near-sighed or far-sighed (Langbehn et al. 2016; Tarampi, Creem-Regehr, and Thompson 2010). Additionally, some experiments investigated the effect of fog on distance estimation in a more realistic driving context and found an overestimation of egocentric distance (e.g. Buchner et al. 2006; Cavallo, Colomb, and Doré 2001). Note that fog impairs visibility by decreasing the image contrast. Taken together, the effect of reduced image quality on distance estimation seems to depend on how quality is manipulated.

1.2. Image quality and the estimation of time-to-contact

Time-to-contact (TTC) can be conceptualised as the time a moving object would need to arrive at some point on its trajectory, typically the observer's position (Tresilian 1991). According to the so-called tau-approach (Lee 1976), TTC can be specified by the optical variable tau (τ) as follows: $\tau = \theta/\dot{\theta}$, where θ is the visual angle of an object and $\dot{\theta}$ the temporal derivative of this angle (Feldstein 2019; Landwehr et al. 2013; Lee 1976; Tresilian 1991). Accordingly, TTC estimation should remain unaffected by image quality as long as this ratio remains unchanged. However, it seems that TTC estimation is influenced by several cues other than τ, such as object size, perspective, or texture (DeLucia 1991; DeLucia et al. 2003; Hecht, Landwehr, and Both 2015; Landwehr et al. 2013; Landwehr, Hecht, and Both 2014; Oberfeld, Hecht, and Landwehr 2011) and heuristic information about size and distance is directly associated with TTC estimation (DeLucia, Preddy, and Oberfeld 2016; Keshavarz et al. 2017; Yan et al. 2011). Accordingly, low image quality could change or eliminate depth cues used to form an accurate ground surface representation, thus again leading to distance underestimation, as proposed in the sequential surface-integration process hypothesis (He et al. 2004; Wu, Ooi, and He 2004). As distance information seems to be integrated into TTC estimation (DeLucia, Tresilian, and Meyer 2000; Keshavarz et al. 2017; Landwehr et al. 2013), this could also make TTC appear shorter. An underestimation of TTC caused by redued image quality, in terms a blur, has been observed recently (Hecht et al., 2021). Alternatively, low image quality and the associated uncertainty of the stimulus outline could trigger an implicit safety strategy, leading to shorter TTC estimates. This was observed earlier with respect to threatening or very large objects (Brendel et al. 2012;

Caird and Hancock 1994; Schleinitz, Petzoldt, and Gehlert 2020).

1.3. Research scope and hypotheses

This research paper investigates how two important system parameters of CMS, namely FOV and image quality, affect the perception of rearward distances and TTC. Both parameters are of high relevance for traffic safety, as they determine the amount of information available to the driver to evaluate the safety of an intended action, such as a lane change. A beneficial effect of larger FOV on driving performance (i.e. lane deviation and curve navigation) has previously been shown for indirect viewing systems (van Erp and Padmos 2003). In contrast, the issue of image quality could be more heterogeneous. A higher pixel density provides more details, which should aid driving. However, as pixel density increases, so does the data volume transmitted from the camera to monitor. In real driving, this in turn could cause transmission latencies in low-end CMS and thus constitute a potential risk for traffic safety. Therefore, it is particularly important to identify the minimum pixel density needed to accurately judge distance and TTC.

In Experiment I, we investigated how different FOV and pixel densities affect egocentric distance estimation errors. A change of the camera's FOV in CMS usually changes the retinal size of the depicted objects, which has an independent effect on distance and TTC estimation (DeLucia 1991; Hahnel and Hecht 2012; Hecht and Brauer 2007). Note that we unconfounded these two quantities in Experiment I and changed only the amount of information presented, but not the retinal size of the target. We expected the smaller FOV to increase estimation errors in terms of distance underestimation, compared to larger FOV, as observed earlier and as proposed in the sequential surface-integration process hypothesis (Creem-Regehr et al. 2005; Hagen, Jones, and Reed 1978; He et al. 2004; Philbeck et al. 2018; Watt, Bradshaw, and Rushton 2000; Wu, Ooi, and He 2004).

Image quality was manipulated in two different ways. First, the pixel density—the number of pixels per inch used to depict an image on a given monitor—was varied. This changed the overall image acuity, but not the contrast. In addition, dirt on the camera lens was simulated in Experiment II by overlaying the stimuli with a grid of random greyscale pixels. In this case, the visibility of the target and environment was reduced non-uniformly. We hypothesised to find shorter distance (Experiment I) and TTC (Experiment II) estimates with low image quality compared to high quality, consistent with effects on the distance estimation (Kunz et al. 2009; Loyola 2018; Phillips et al. 2009; Thompson et al. 2004), recent findings Hecht et al. (2021) and an implicit safety strategy (Brendel et al. 2012; Caird and Hancock 1994; Schleinitz, Petzoldt, and Gehlert 2020). As low image quality could increase subjects' estimation uncertainty, we also examined the estimation confidence (Experiment I) and estimation variability (Experiment II).

2. Experiment I: distance estimation

2.1. Methods

2.1.1. Sample description

As the mixed evidence for the effect of image quality and FOV on distance estimation might indicate a small effect size, we collected a large sample to increase the statistical power. 51 volunteers (31 female) were recruited via an e-mail distribution list. Their age ranged between 19 and 32 years ($M = 23$ years, $SD = 3.48$ years). All subjects had normal or corrected-to-normal visual acuity and were naïve regarding the experimental hypotheses. This research complied with the tenets of the Declaration of Helsinki.

2.1.2. Experimental design

A within-subjects factorial design with three factors was employed. Four different egocentric distances (10, 30, 45, and 60 m) were fully crossed with three horizontal FOV sizes (33, 50, and 67°) and five-pixel densities (96.4, 48.2, 32.1, 24.1, and 19.3 ppi) resulting in a total of 60 experimental conditions. The three FOV levels were blocked and their order evenly distributed across subjects. In each block, 20 pictures (4 distances × 5 pixel densities) were presented in randomised orders. Finally, all pictures were repeated once, resulting in 120 trials and six blocks. In each trial, subjects verbally estimated their egocentric distance to the vehicle depicted in the picture in metres and subsequently rated their estimation confidence. The confidence rating was introduced by the question '*How certain are you about your estimation?*' and was assessed using a discrete scale ranging from 1 (*very uncertain*) to 7 (*very certain*).

2.1.3. Apparatus and stimuli

The experiment took place in a small lab chamber. Pictures were presented on a desktop monitor (Dell 1702FP, 17-inch diagonal size, resolution: 1280 × 1024 pixels, maximal pixel density: 96.4 ppi). The subject's

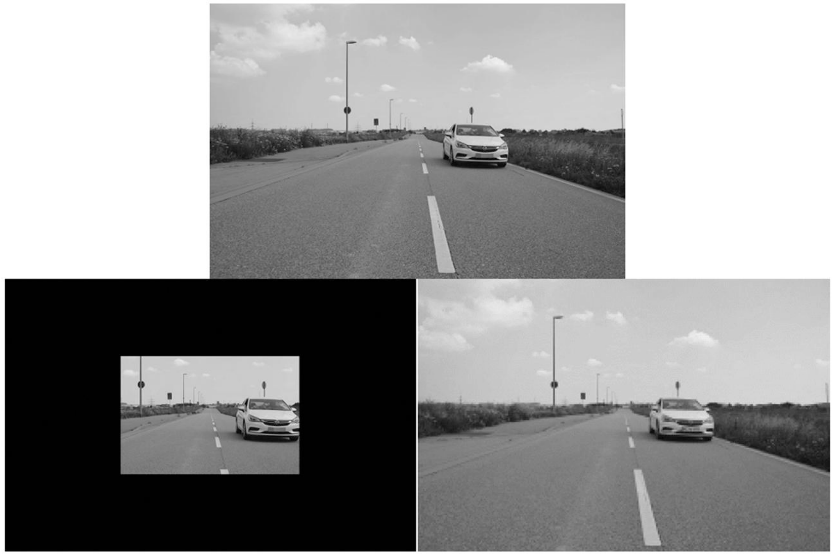

Figure 1. Example stimuli in Experiment I. All stimuli with a target distance of 10 m. The depicted environment and the image size of the vehicle are identical for all three stimuli. Top: 67° FOV, 96.4 ppi. Bottom left: 33° FOV, 96.4 ppi. Bottom right: 67° FOV, 19.3 ppi. The cropped images made the vehicle look nearer.

eye position was aligned with the monitor centre using a chin rest with an eye-monitor distance of 40 cm and at an eye height of 110 cm above the ground.

To create our stimuli, we photographed an actual car (white Opel Astra; H: 1.51 m, W: 2.01 m, L: 4.42 m) standing at four egocentric distances from the camera and on the left lane of a two-lane rural road. We determined the exact distances with a laser distance metre and took pictures with a Nikon D5100 (CMOS sensor, W: 23.6 mm, H: 15.6 mm) mounted on a tripod 110 cm above the ground. The camera was placed in the right lane, towards the median stripe, thus representing the side-mounted rear-view camera of a CMS. Pictures were taken with a horizontal angle of 67°, which represented one level of the FOV factor. To generate the other two FOV levels, these pictures were cropped to sizes identical to a FOV of 50° and 33°, respectively. The required horizontal size of the pictures was calculated beforehand using the camera and monitor specifications. The vertical size of the pictures was cropped to match the horizontal size, thus maintaining the original 16:9 aspect ratio. However, the stimuli were not scaled up to the size of the original pictures, as this would have changed the optical size of the target. To vary pixel density, two to five pixels were packed together using the mosaic filter in Adobe Photoshop 2020. This reduced the original resolution (1280×1024) to resolutions of 640×512, 320×256, 160×128, and 80×64 pixels. These resolutions were depicted in full size on the monitor, thus resulting in the pixel densities mentioned above. Figure 1 illustrates three example stimuli.

2.1.4. Procedure

At the beginning of the experiment, subjects gave their written informed consent. They received a standardised instruction for the task at hand and were told they would see pictures of a vehicle on a rural road and that their task would be to estimate their egocentric distance to this vehicle in metres. They also received an explanation of the confidence rating scale. In the following four training trials, subjects verbally estimated their egocentric distance to road signs placed at different locations in metres without receiving feedback on the accuracy of their estimates. This training block ensured that subjects had fully understood the task. After the training trials, the test trials started. Figure 2 depicts an exemplary test trial. We chose a viewing time of 2 s as this corresponds to the maximum time needed for a glance at the driver-side rear-view mirror (see Sodhi, Reimer, and Llamazares 2002), which is also sufficient to provide a verbal estimate of the perceived distance. After 120 trials, subjects received a debriefing about the experimental background. The whole experiment lasted between 25 and 35 min.

2.1.5. Data analysis strategy

Error ratios were calculated from the raw distance estimates by dividing each estimate by its physical distance. Using boxplots and quantile-quantile plots, no

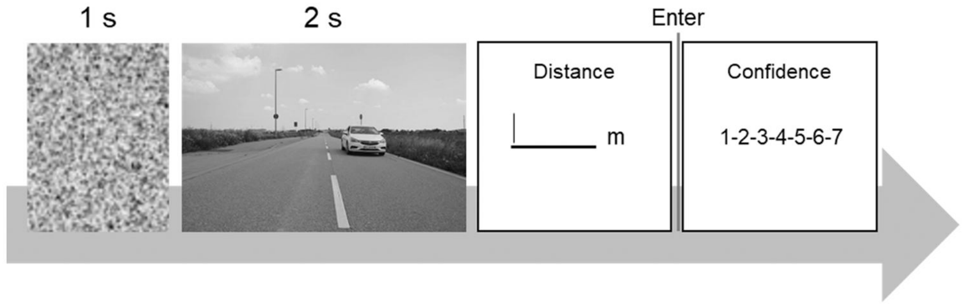

Figure 2. Procedure of an exemplary test trial in Experiment I. After a random dot mask had appeared for 1 s, the stimulus was presented for 2 s. Afterwards, the subjects estimated the egocentric distance in metres as well as confidence on a 7-point scale.

extreme values were observed for the confidence ratings, which approximated a normal distribution. However, one subject produced high error ratios with values of up to 80 (i.e. estimates were 80 times higher than the physical distance). Therefore, this subject was excluded from the analyses. As the residuals of the error ratios deviated from a normal distribution, we transformed the error ratios using the natural logarithm, which will be referred to as lnError in the following. The residuals of lnError approximated a normal distribution and were aggregated across the two measurement points.

Two 4 (distance) × 5 (pixel density) × 3 (FOV) repeated-measures analyses of variance (rmANOVA) were calculated separately for *lnError* and the *confidence ratings* using an univariate approach. For both analyses, Greenhouse-Geisser correction (Greenhouse and Geisser 1959) of the degrees of freedom was applied if sphericity was violated. Effect sizes (η^2_p) and the correction value $\hat{\varepsilon}$ will be reported. The main effects of pixel density and FOV were further analysed using repeated contrasts, where the levels of each factor are compared successively using one-tailed paired-sample *t*-tests. From these comparisons, *p*-values and, if significant, Cohen's d_z will be reported. For all other comparisons, Bonferroni-corrected *post-hoc* tests were calculated and *p*-values will be reported. Figures show 95% within-subjects confidence intervals, which were calculated following the approach of Cousineau (2005) and the corrections proposed by Morey (2008) and Baguley (2012). We performed the analyses in R 3.6.1 and interpreted all results using a significance level of $\alpha = .05$.

2.2. Results and discussion

Subjects underestimated the metric distance to the rearward vehicle in all conditions, by 19.6% on average ($M_{\text{estimated-real}} = -5.72$ m, $SD_{\text{estimated-real}} = 34.16$ m). A more detailed overview of the raw estimates and confidence ratings can be found in the Supplementary Material. The rmANOVA on *lnError* revealed a significant but small main effect of physical distance, $F_{(3,\ 147)} = 4.46$, $p = .034$, $\eta^2_p = .08$, $\hat{\varepsilon} = .38$. However, Bonferroni-adjusted *post-hoc* tests only revealed a trend towards larger distance underestimation for a 45 m distance than for a 60 m distance ($p = .064$). Moreover, the main effects of FOV, $F_{(2,\ 98)} = 44.48$, $p < .001$, $\eta^2_p = .48$, $\hat{\varepsilon} = .95$, and pixel density, $F_{(4,\ 196)} = 9.89$, $p < .001$, $\eta^2_p = .17$, $\hat{\varepsilon} = .68$, were significant. Figure 3 illustrates both main effects. Errors decreased linearly for larger FOV, as indicated by the significant differences between successive levels (33 *vs.* 50°: $p < .001$, $d_z = .85$; 50 *vs.* 67°: $p < .001$, $d_z = .51$). This corresponds to a mean difference of 3.22 m (50–33°) and 3.00 m (67–50°) in absolute terms. Since, contrary to our hypothesis, errors increased with increasing pixel density, two-tailed tests were applied. Errors significantly increased between the levels 24.1 and 32.1 ppi, $p < .001$, $d_z = .69$, while the other consecutive comparisons were not significant (all $p > 0.1$). However, as depicted in Figure 3, left panel, the differences between the pixel densities were rather small, with an absolute mean difference of up to 2.32 m.

Moreover, the interaction effects of physical distance with FOV, $F_{(6,\ 294)} = 13.89$, $p < .001$, $\eta^2_p = .22$, $\hat{\varepsilon} = .71$, and pixel density, $F_{(12,\ 588)} = 4.14$, $p < .001$, $\eta^2_p = .08$, $\hat{\varepsilon} = .78$, reached significance. Figure 4 illustrates both interaction effects. Apparently, the effect of FOV on estimated distance was maximal for smaller distances and decreased with larger distances. The effect of pixel densities on estimated distance increased with distance. This interaction effect can be considered as small, with a η^2_p of only 0.08. No significant effect was observed for the pixel density × FOV interaction, or the three-way interaction between physical distance, pixel density, and FOV.

Regarding the confidence ratings, the rmANOVA again revealed significant main effects of physical distance, $F_{(3,\ 150)} = 69.93$, $p < .001$, $\eta^2_p = .58$, $\hat{\varepsilon} = .47$,

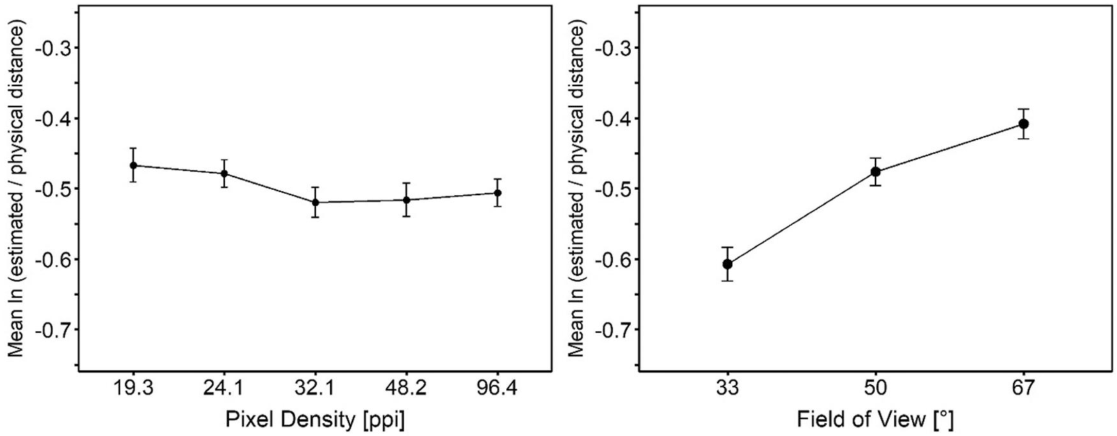

Figure 3. Mean lnError as a function of pixel density (left) and FOV (right). Y-axis is truncated to improve readability. Lower values on the ordinate indicate larger distance underestimation. A mean lnError of 0 would represent perfect accuracy. Error bars show adjusted 95% within-subjects confidence intervals. $N = 50$. Negative values indicate distance underestimation.

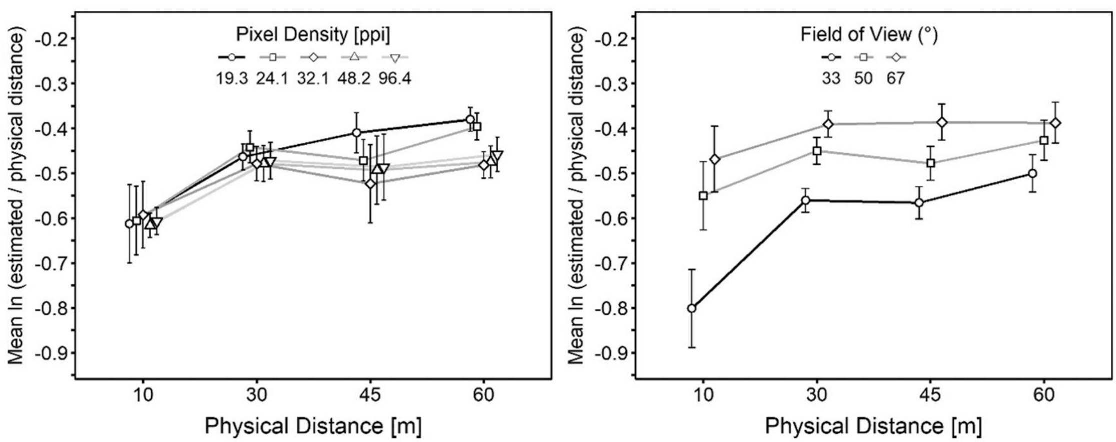

Figure 4. Mean lnErrors as a function of physical distance and pixel density (left), and as a function of physical distance and FOV (right). Y-axis is truncated to improve readability. Error bars show adjusted 95% within-subjects confidence intervals. $N = 50$. Negative values indicate distance underestimation.

pixel density, $F_{(4,\ 200)} = 19.21$, $p < .001$, $\eta^2_p = .28$, $\hat{\varepsilon} = .44$, and FOV, $F_{(2,\ 100)} = 6.17$, $p = .005$, $\eta^2_p = .11$, $\hat{\varepsilon} = .83$. Confidence ratings decreased as distance increased with all *post-hoc* comparisons being significant ($p < .05$), except between 45 and 60 m ($p = .59$). Figure 5 depicts the main effects of FOV (right panel) and pixel density (left panel). Confidence ratings increased slightly between 33° and 50° ($p = .002$, $d_z = .43$), but not between 50° and 67° ($p > .69$). However, the absolute differences between the three FOV levels can be considered as small. Furthermore, one-tailed *t*-tests confirmed the hypothesised linear increase of confidence ratings with increasing pixel density (19.3 *vs.* 24.1 ppi: $p = .040$, $d_z = .25$; 24.1 *vs.* 32.1 ppi: $p < .001$, $d_z = .54$; 32.1 *vs.* 48.2 ppi: $p = .008$, $d_z = .35$; 48.2 *vs.* 96.4 ppi: $p = .002$, $d_z = .43$).

Finally, the confidence ratings varied significantly as a function of physical distance and pixel density, $F_{(12,\ 600)} = 3.11$, $p = .003$, $\eta^2_p = .06$, $\hat{\varepsilon} = .64$. Again, this effect has to be considered negligible. According to Figure 6, the effect of pixel density on the mean confidence ratings increased with larger distances. No other effects were significant.

Overall, subjects underestimated the egocentric distance by 5.72 m on average. Distance underestimation with CMS has been observed earlier (Bernhard and Hecht 2021; Flannagan, Sivak, and Mefford 2002; Schmidt et al. 2016) and might be related to the compression of distance observed in virtual reality (e.g. Grechkin et al. 2010; Willemsen and Gooch 2002). Adding to this, subjects had no opportunity to adapt their judgements to the displays used, as they received no feedback on their estimation accuracy. This could have amplified the trend towards underestimation observed previously. Importantly, the effect of FOV was clear-cut and in line with prior

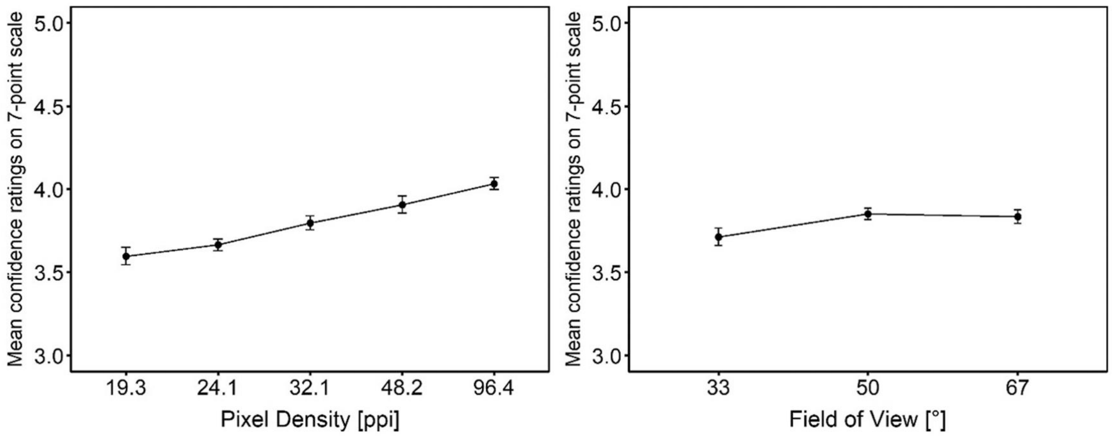

Figure 5. Mean confidence ratings as a function of pixel density (left) and FOV (right). End points were labelled very uncertain (1) and very certain (7). Y-axis is truncated to improve readability. Error bars show adjusted 95% within-subjects confidence intervals. $N = 50$.

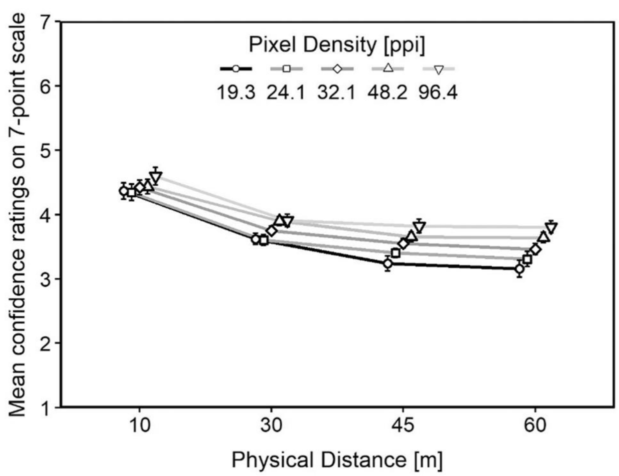

Figure 6. Mean confidence ratings as a function of physical distance and pixel density. End points were labelled very uncertain (1) and very certain (7). Error bars show adjusted 95% within-subjects confidence intervals. $N = 50$.

expectations – estimation errors decreased with the larger FOV. Subjects were also more confident about the distance judgements provided with the two larger FOVs, even if this effect was not as strong as the effect on the estimated distance. However, the effect of pixel density on distance estimation was small and contrary to our hypothesis. How can we explain the relative distance overestimation for low pixel densities? On one hand, this effect might be attributable to the use of aerial perspective as a crude heuristic for distance estimation, where distant objects appear grainy (Gibson and Flock 1962). On the other hand, some subjects noted that the lower pixel densities created an impression of a zoom-in into the pictures. This impression could have been taken into account and may have produced larger estimated distances. Therefore, the results of Experiment I could in part be an artefact of such stimulus interpretation. However, note also that the absolute distance estimation difference between the pixel density levels was only around 2 metres and the effect size η^2_p was comparatively small, challenging the practical importance of the observed effect. Nevertheless, if the observed relative distance overestimation was the result of a changed impression of depth and not of methodological shortcomings, reducing the image quality would represent a safety risk for driving. To evaluate this, we felt it important to investigate the effect of image quality in more detail and with respect to a task closer to actual driving.

3. Experiment II: TTC estimation

Experiment II solely focusses on the effect of image quality. This was deemed reasonable as the effect of pixel density in Experiment I was rather small and contrary to our expectations. If the observed relative distance overestimation for small pixel densities were also present in more driving-related judgements, it could present a safety concern for CMS. To evaluate the effect of reduced image quality in a setting and task more related to driving, we had to adapt several aspects of our experimental regime. Most importantly, we used dynamic instead of static stimuli. Time-to-contact (TTC) estimates were collected in the prediction-motion paradigm. Moreover, photo-realistic renderings were used in Experiment II, for better control of the depth cues available to the subjects. As the range of pixel densities in Experiment I was not representative for state-of-the-art systems, we additionally

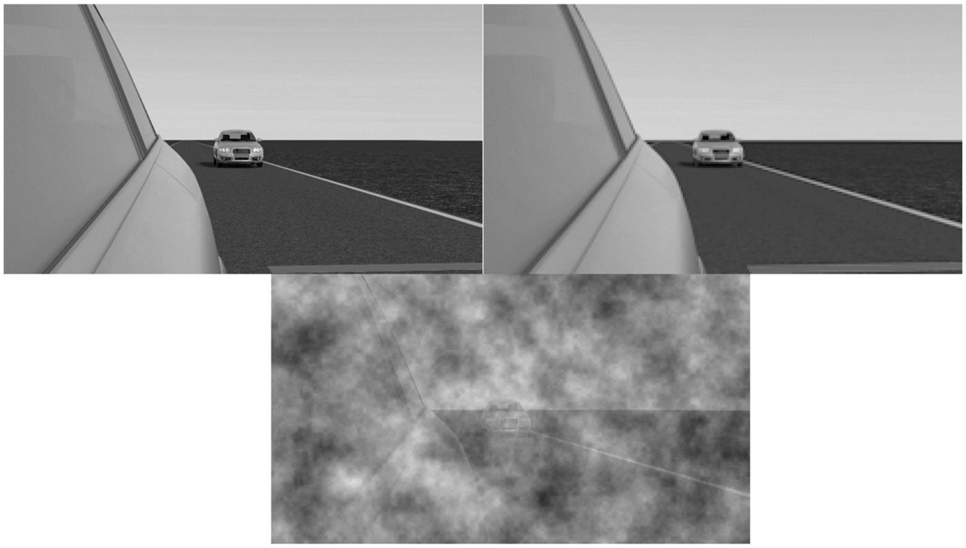

Figure 7. Exemplary rendered scenes used in Experiment II. The target line for TTC estimation was depicted in the lower right part of the stimuli. All stimuli with a TTC of 1 s. Top left: 314.7 ppi, without noise. Top right: 19.7 ppi, without noise. Bottom: 314.7 ppi, with noise. Note that the videos with noise appeared less obscured than implied by the still.

increased the pixel densities, with a maximum of 314.7 ppi. Finally, we added an image quality manipulation by overlaying the videos with fractal noise (see Figure 7). This manipulation simulated dirt on the camera and decreased the visibility of the target and environment non-uniformly. We hypothesised TTC estimates to decrease when image quality was reduced by the low pixel density or noise. Moreover, we examined whether the reduced image quality affects the variation of TTC estimates.

3.1. Methods

3.1.1. Sample description

In this experiment, the required sample size was determined using an *a-priori* power analysis. We used the metrics of the pixel density main effect from Experiment 1 ($\eta^2_p = .17$, $\hat{\varepsilon} = .684$) as the basis for our analysis and aimed at a power of 1-β = .95. The power analysis conducted in G*Power (Faul et al. 2007) recommended minimum sample size of $N = 33$ subjects. In total, $N = 35$ subjects ($n = 17$ female) volunteered in our experiment. Their age varied between 20 and 59 years ($M = 27.23$ years, $SD = 9.60$ years). All participants had owned a valid driving licence for a time period between 1 and 36 years ($M = 9.26$ years, $SD = 8.77$ years). The majority stated they would drive up to 10,000 kilometres per year. Seven subjects reported driving between 10,000 and 15,000 and only six subjects more than 15,000 kilometres per year. Subjects had a normal or corrected-to-normal vision, as confirmed by a Landolt ring optotype chart. They had not participated in the first experiment.

3.1.2. Experimental design

As in Experiment I, a within-subjects design was employed. The pixel density was varied in five steps (314.7, 157.4, 78.7, 39.3, and 19.7 ppi). Moreover, in some videos noise was added to decrease the image quality, whereas other videos were presented with clear vision. The time after disappearance until the target vehicle reached the target location (TTC) varied in five steps and the velocity as well as the start and end distances of the approaching target varied within each level of TTC (see Table 1). In the analyses, these end distances were split into two groups, similar to the approach employed in DeLucia, Preddy, and Oberfeld (2016). This manipulation increased the variability of our stimuli and minimised the risk of stereotyped responses. The four experimental factors were fully crossed, resulting in 5 (pixel density) × 2 (noise) × 5 (TTC) × 2 (distance condition) = 100 experimental conditions, which were presented five times each. The 500 experimental trials were presented in 10 blocks in randomised orders. As a dependent variable, we recorded the estimated TTC, which was defined as the time difference between the disappearance of the target and the button press of the subjects.

3.1.3. Apparatus and stimuli

The subjects sat in a small lab chamber in front of a 7-inch monitor with a resolution of 1920 × 1080 pixels (maximal pixel density: 314.7 ppi). The subject's bridge

Table 1. Start and end distances of the approaching target as function of TTC and velocity.

Distance condition	Close					Far				
Velocity (ms^{-1})	12	11	10	9	8	20	19	18	17	16
TTC (s)	0.5	1.0	1.5	2.0	2.5	0.5	1.0	1.5	2.0	2.5
Distance (m)										
Start	24	27.5	30	31.5	32	40	47.5	54	59.5	64
End	6	11	15	18	20	10	19	27	34	40

of the nose was aligned to the centre of the display using a chin rest. Both eyes and the display centre were at a height of 110 cm, with 60 cm between eye and display. A picture of the set-up can be found in the Supplementary Material. We employed a prediction-motion paradigm. The stimuli consisted of short video clips depicting a yellow target vehicle (L: 4.939 m, W: 1.886 m, H: 1.467 m) that approached the subjects' vehicle on the left lane of a two-lane road. The target vehicle disappeared after 1.5 s and subjects estimated the time until the vehicle would have arrived at a predefined location behind the subjects' vehicle. This location was marked by a frontoparallel red stripe on the left lane. Additionally, the scene consisted of a grassy landscape extending to the visible horizon. The 3-dimensional scene is depicted as exemplified in Figure 7.

Video frames were rendered using Autodesk 3ds Max 2018, with a virtual camera placed at the position of the conventional rear-view mirror of a sedan, 110 cm above the ground. After rendering the frames for each TTC × distance combination, noise and pixel density were manipulated. The noise was created by overlaying each video frame with a static grid of six layers in which random greyscale pixels were assigned to blocks of pixels. Differences were linearly interpolated to create a smooth transition between each pixel. The grid's opacity was set to 80%. Finally, the videos were rendered with resolutions of 1920 × 1080 pixels, 960 × 540 pixels, 480 × 270 pixels, 240 × 135 pixels, and 120 × 68 pixels and presented on the 7-inch monitor in full size. This resulted in the five-pixel densities described above. Both manipulations were applied using Adobe After Effects 2020. Figure 7 depicts single video frames with low pixel density (top right) and noise (bottom). Example videos and detailed settings for noise manipulation are available in the Supplementary Material.

3.1.4. Procedure

At the beginning of the experiment, subjects received detailed information about the procedure and gave their written informed consent. They were told that they would watch short video clips of 1.5 s length showing a target vehicle approaching their own vehicle on a two-lane road. After the 1.5 s, the target car disappeared while the rest of the scene remained visible. Subjects were instructed to press the space bar on a keyboard in front of them at the time they thought the target would have reached the red stripe on the ground. To familiarise the subjects with the experimental scene, eight training trials were conducted without feedback about the estimation accuracy. In these trials, subjects observed the targets approaching at velocities of 7 or 21 ms^{-1}. It would disappear either at TTCs of 0.5 (in case of the lower velocity) or 2.5 s (in case of the higher velocity). These two videos were shown with pixel densities of 314.7 and 19.7 ppi as well as with and without noise. Afterwards, 500 test trials followed. Figure 8 depicts an exemplary trial. At the end of the experiment, a short manipulation check was applied. Subjects saw all 100 stimuli again and rated how well the targets could be recognised (7-point scale, end points: *very poorly*, *very well*). Finally, subjects filled out a short questionnaire on demographic information and received a debriefing. The whole experiment lasted approximately 90 min.

3.1.5. Data analysis strategy

The raw TTC estimates were first inspected descriptively. Moreover, an outlier analysis for each combination of subject and experimental conditions was performed using the Tukey heuristic (Jones 2019). We defined data points as outliers if $x_i < (P_{25} - 3 \times IQR)$ or $x_i > (P_{75} + 3 \times IQR)$, with x_i representing each individual data point, P_{25} and P_{75} the 25 and 75% percentiles, and IQR the interquartile range, respectively. In total, 688 data points (3.93%) were classified as outliers and excluded from the analyses. We then aggregated the estimates across presentation times. To analyse the variation of the TTC estimates, the coefficient of variation (CV) was used. We calculated this metric by dividing the TTC variable error—the standard deviation of TTC estimates across presentation times—by the mean TTC estimate (SD_{TTC} / M_{TTC}). This metric was used instead of the variable error to unconfound differences in the variable error from differences in the mean TTC estimates (DeLucia, Preddy, and Oberfeld 2016). The residuals for both dependent variables approximated a normal distribution. Therefore, the further analysis strategy was adapted from Experiment 1.

3.2. Results and discussion

Before analysing the TTC estimates and their variation, the visibility ratings provided by the subjects at the

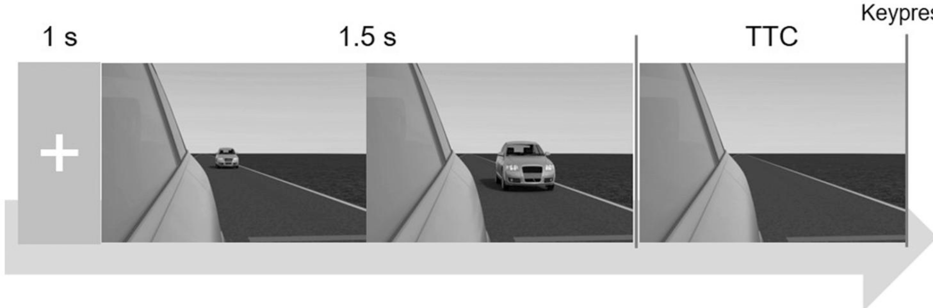

Figure 8. Procedure of an exemplary test trial in Experiment II. After a fixation cross had been presented for 1 s, the yellow vehicle appeared at various distances from the observer and approached with different velocities. It disappeared after 1.5 s. Subjects then estimated the time until it would have reached the red target line depicted in the lower right part.

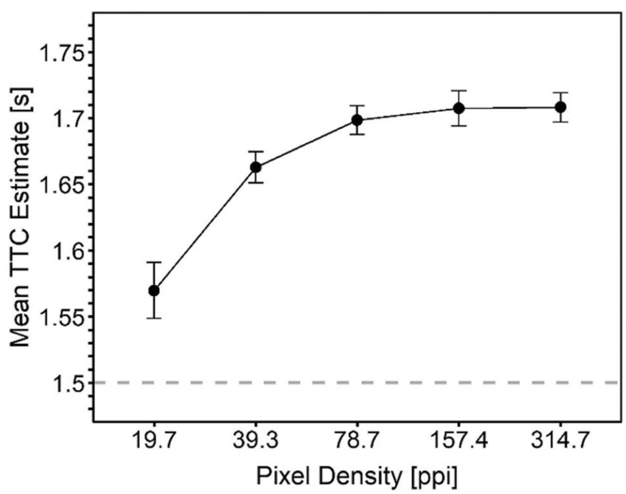

Figure 9. Mean TTC estimates as a function of pixel density. The dashed line indicates perfect estimation accuracy. Y-axis is truncated to improve readability. Errors bars show 95% within-subjects confidence intervals. $N = 35$.

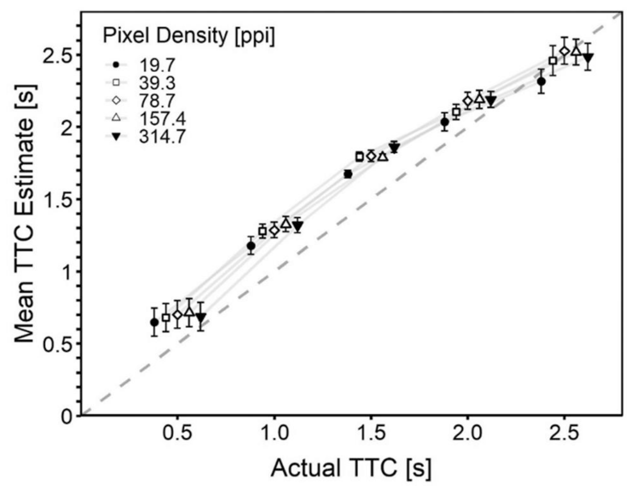

Figure 10. Mean TTC estimates as a function of pixel density and actual TTC. The smallest and largest pixel densities are highlighted by black symbols to facilitate the comparison. The dashed line indicates perfect estimation accuracy. Errors bars show 95% within-subjects confidence intervals. $N = 35$.

end of the experiment were analysed with a univariate rmANOVA. According to this analysis, the experimental manipulation had been successful—visibility ratings increased with pixel density and decreased with noise. A more detailed description can be found in the Supplementary Material.

On average, subjects overestimated TTC by 11.29% ($M_{TTC\_est\text{-}TTC\_real} = 0.17$ s, $SD_{TTC\_est\text{-}TTC\_real} = 0.72$ s). The TTC estimates were analysed by means of a rmANOVA using an univariate approach with the factors pixel density (five levels), noise (two levels), TTC (five levels), and distance (two levels). The rmANOVA resulted in a significant main effect of pixel density, $F_{(4,\ 136)} = 35.24$, $p < .001$, $\eta^2_p = .51$, $\hat{\varepsilon} = .60$. Figure 9 illustrates this main effect. Lower densities resulted in shorter estimated TTC, compared to higher densities. Repeated contrasts resulted in significant differences between the pixel densities 19.7 and 39.3 ppi ($p < .001$, $d_z = .99$) as well as between 39.3 and 78.7 ppi ($p = .001$, $d_z = .55$), but not between higher pixel densities ($p > .05$). Similarly, noise added to the stimuli resulted in slightly shorter TTC estimates ($M = 1.65$ s, $SD = 0.94$ s), compared to conditions without noise ($M = 1.69$ s, $SD = 0.95$ s), $F_{(1,\ 34)} = 5.24$, $p = .029$, $\eta^2_p = .13$. This effect can be considered as small. Furthermore, the main effects of distance, $F_{(1,\ 34)} = 155.62$, $p < .001$, $\eta^2_p = .82$, and TTC, $F_{(4,\ 136)} = 192.63$, $p < .001$, $\eta^2_p = .85$, $\hat{\varepsilon} = .28$, were significant. Smaller final distances ($M = 1.55$ s, $SD = 0.88$ s) resulted in shorter TTC estimates than larger distances ($M = 1.79$ s, $SD = 1.00$ s). The TTC estimates increased with longer actual TTC, as indicated by Figure 10. The differences between consecutive TTC values were all significant ($p < .001$). Subjects were able to make largely correct TTC estimates.

The rmANOVA also resulted in a small but significant interaction effect of pixel density and TTC, $F_{(16,}$

$_{544)} = 2.63$, $p = .009$, $\eta^2_p = .07$, $\hat{\varepsilon} = .49$, as well as an interaction effect of TTC and distance, $F_{(4,\ 136)} = 43.77$, $p < .001$, $\eta^2_p = .56$, $\hat{\varepsilon} = .58$. As indicated in Figure 10, the differences in TTC estimates between the smallest and larger pixel densities increased with longer actual TTC. However, the effect is small, as indicated by its effect size. The TTC × distance interaction is illustrated in Figure 11. The effect of distance also increased with longer actual TTC. Finally, a three-way interaction between pixel density, TTC, and distance reached significance, $F_{(16,\ 544)} = 2.47$, $p = .016$, $\eta^2_p = .07$, $\hat{\varepsilon} = .46$. This effect indicated that the interaction effect between pixel density and actual TTC described above was larger in the closer distances.

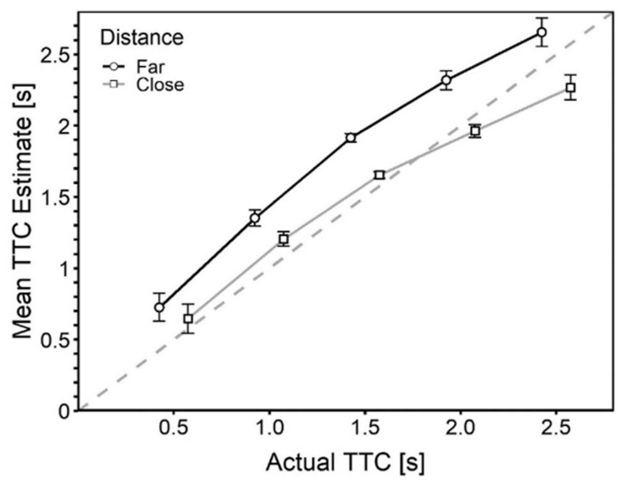

Figure 11. Mean TTC estimates as a function of distance and actual TTC. The dashed line indicates perfect estimation accuracy. Errors bars show 95% within-subjects confidence intervals. $N = 35$.

Similar to the TTC estimates, a univariate rmANOVA was employed to analyse CV. CV was not affected by pixel density, $F_{(4,\ 136)} = .90$, $p = .452$, $\eta^2_p = .03$, $\hat{\varepsilon} = .86$, by noise, $F_{(2,\ 34)} = .83$, $p = .370$, $\eta^2_p = .02$, nor by distance, $F_{(2,\ 34)} = .18$, $p = .671$, $\eta^2_p = .01$. The main effect of TTC was significant, $F_{(4,\ 136)} = 27.40$, $p < .001$, $\eta^2_p = .45$, $\hat{\varepsilon} = .68$. This effect is shown in Figure 12, left panel. Relative to their mean estimates, the variability of the estimates monotonically decreased with longer TTC, with TTC values of 0.5 and 1 s being significantly different from each other and all other TTC values ($p < .05$). Moreover, a small pixel density × noise interaction was found, $F_{(4,\ 136)} = 3.15$, $p < .022$, $\eta^2_p = .08$, $\hat{\varepsilon} = .88$. As illustrated in Figure 12, right panel, CV decreased in the highest density without noise. However, when noise was added, the CV was lowest for the medium density and increased again for higher densities. Finally, the noise × TTC interaction, $F_{(4,\ 136)} = 2.99$, $p = .029$, $\eta^2_p = .08$, $\hat{\varepsilon} = .83$, and noise × TTC × distance interaction, $F_{(4,\ 136)} = 3.22$, $p = .018$, $\eta^2_p = .09$, $\hat{\varepsilon} = .92$ reached significance. These interactions indicated that the estimation variation relative to the mean estimate was smaller for conditions with noise than without for TTC values of 1 s (close distance) or 0.5 s (far distance). However, all these interactions should be considered as small, with effect sizes $\eta^2_p \leq .09$.

Overall, subjects overestimated TTC. Most likely, this result was caused by the small size of our monocular display (Hahnel and Hecht 2012; Hecht and Brauer 2007). Note that the display was also substantially smaller than the one used in Experiment I, which could explain why the distance underestimation was not reflected in the TTC estimates. However, as the sample, stimuli, and apparatuses were different, we warn against comparing absolute judgements

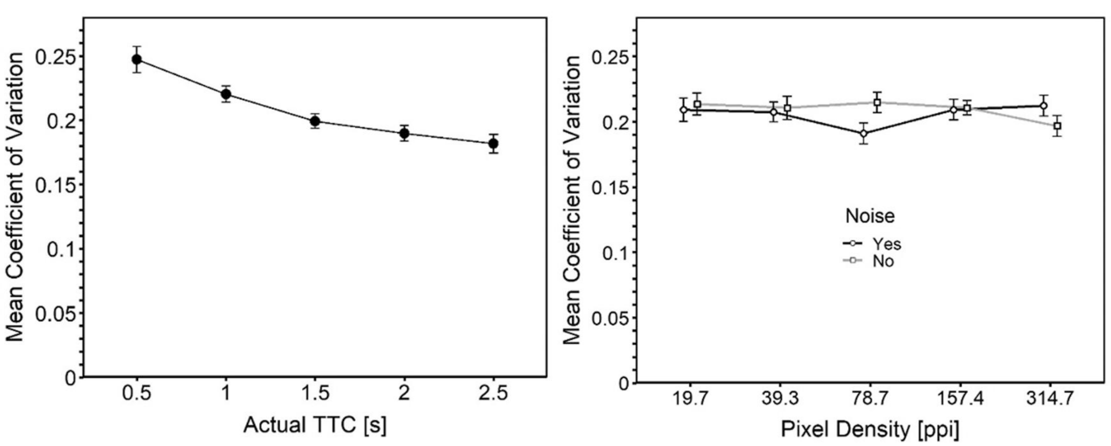

Figure 12. Mean CV as function of actual TTC (left) and as function of noise and pixel density (right). Errors bars show 95% within-subjects confidence intervals. $N = 35$.

between the two experiments. Moreover, we replicated the common observation of relative underestimation of TTC for larger time distances (Hecht, Landwehr, and Both 2015; Keshavarz et al. 2017; Petzoldt 2014). TTC was also estimated shorter for the closer distances, which is in line with previous findings (DeLucia, Preddy, and Oberfeld 2016; Petzoldt 2014). Most importantly, our results suggest that image quality does affect TTC estimation. If image quality was decreased, either by random noise or by low pixel density, subjects underestimated TTC, as compared to clear or well-resolved stimuli. This is in line with our previous expectations. In contrast and other than expected, the image quality manipulations did not affect the variation of the TTC estimates.

4. General discussion

In two experiments, we have examined the effects of two CMS-specific parameters, FOV and image quality, on the estimation of rear-view distance and TTC. In Experiment I, distance underestimation was observed in all conditions. This is a common observation, especially in the case of digital displays and mirrors (Creem-Regehr et al. 2005; Daum and Hecht 2009; Geuss et al. 2012; Hecht and Brauer 2007; Higashiyama and Shimono 2004; Schmidt et al. 2016), in particular when the target objects are at distances beyond the immediate action space of about 10 m (Grüsser 1983).

When reducing the **field-of-view**, the distance was underestimated more strongly and errors increased. This matches the expectations derived from literature and theory, suggesting that as information is removed from the environment, it becomes more difficult to judge egocentric distance, possibly resulting in a biased integration of the ground surface and thus in an illusory slant, leading to distance underestimation (see e.g. He et al. 2004; Wu, Ooi, and He 2004). Moreover, the confidence of our subjects increased with larger FOV. Mind that our results only apply to situations where the FOV changes, but not the object size. In cases of zoom lenses or convex mirrors, however, the FOV and retinal size of the object are yoked. Thus, the effect of distance underestimation with reduced FOV might not be representative of these conditions.

With respect to **image quality**, the results were more inconsistent. In Experiment I, relative distance overestimation was observed for lower pixel densities. This could be attributable to the use of aerial perspective as a distance cue (Gibson and Flock 1962) or it could represent an artefact of a misleading stimulus interpretation as a result of the static stimuli used. To examine whether the relative overestimation also transfers to dynamic stimuli, we employed a TTC estimation task in Experiment II, which is more similar to a real driving task. This time, both image quality manipulations—a decrease in pixel density and simulated dirt on the camera lens—resulted in relatively shorter TTC estimates in Experiment II. Therefore, the discrepancy between the two experiments could be attributable to the differences in the experimental regimes, that is the different pixel density ranges, the different environmental cues provided in the stimuli, or the different presentation modes (static *vs.* dynamic). However, it could also hint at different strategies used to estimate distance and TTC (see below). Importantly, Experiment II indicated that larger pixel densities only affect TTC estimation until 78.7 ppi. Therefore, medium pixel densities might already provide enough detail to accurately estimate TTC.

How can we explain the shorter TTC estimates as a consequence of decreased image quality? The variation of TTC estimates was not affected, indicating that the smaller mean TTC estimates were not merely the result of increased estimation uncertainty. Instead, the change in the mean TTC estimates could represent a change in subjects' estimation strategy. For example, they could employ an implicit safety strategy, similar to effects observed with respect to threatening or very large objects (Brendel et al. 2012; Caird and Hancock 1994; Schleinitz, Petzoldt, and Gehlert 2020). This would also explain why we observed shorter TTC estimates independently of the exact type of impairment—as soon as vision deteriorates, subjects might employ a safety strategy. This has also been hypothesized recently (Hecht et al., 2021). Thus, our findings replicate the results of Hecht et al. (2021). Note that such a safety strategy may not be deliberate but merely reflect a smart change in the integration of optical information. Moreover, as hypothesised earlier, the observed underestimation could be attributable in part to a size-arrival effect (DeLucia 1991). As outlined in the introduction, subjects might replace or supplement τ-like variables to estimate TTC (Lee 1976; Tresilian 1991; Yan et al. 2011) with a heuristic. For instance, subjects could rely less on τ and more on the final visual angle subtended by the target (θ), which is easier to extract and does not require calculation (DeLucia 1991; DeLucia et al. 2003; DeLucia, Preddy, and Oberfeld 2016; Keshavarz et al. 2017). To explore this assumption, we have extracted the number of pixels used to depict the target in the stimuli and calculated the final visual angle (θ) subtended by the vehicle before occlusion for each pixel density and final distance. Indeed, the final angle increased by between 0.12 and 0.27°— or 13.36% on average — in the lowest pixel density condition as compared to the highest density. However, this assumption is highly speculative and should be viewed with caution, as the absolute size of the visual angles in the scene and the absolute changes in θ were rather small. Therefore, we cannot be sure if subjects actually relied on these angles to estimate TTC.

4.1. Limitations

Our results have to be understood in the context of the concrete experimental setting. At first, the subject had to perform metric (Experiment I) or time-based (Experiment II) estimations, which in the latter case might have involved cognitive extrapolation (DeLucia and Liddell 1998; Tresilian 1995). This makes it difficult to directly compare the size and direction of effects between the two experiments. Moreover, such estimations may not be representative of actual driving, even if research indicates that TTC is directly related to other important variables, such as gap acceptance (for a discussion, see Petzoldt 2014 and Beggiato, Witzlack, and Krems 2017). In actual driving, drivers often perform several tasks at the same time and kinaesthetic, haptic, or auditory cues are present, which might compromise visual perception. Therefore, our findings might not generalise to actual driving. It seems highly plausible that reduced image quality will promote a safety strategy in actual driving, which should lead to shorter perceived TTC, as observed in Experiment II. Nevertheless, the observed effects have to be replicated in a dynamic driving task. Moreover, effects could be different for other types of image quality degradations. Even if we are confident that our manipulations of image quality were realistic and ecologically valid for CMS, the effects of other degradations should be investigated in future experiments.

4.2. Practical implications

Our research provides important implications for the specification of CMS. First of all, increasing the FOV of the exterior camera could be beneficial, not only to decrease the size of the driver's blind spot but also to improve distance estimation accuracy. However, a larger FOV would also lead to decreased retinal object size, which has been associated with distance and TTC overestimation (Hahnel and Hecht 2012; Hecht and Brauer 2007). A solution would be to increase monitor size together with FOV. This could have negative side-effects, such as increased visual distraction when looking at the forward road or occlusion of objects on the road. Designers should be aware of these concerns before determining the size and/or FOV of in-vehicle monitors.

An important result of Experiment II was that the mean TTC estimates were not largely different for pixel densities higher than 78.7 ppi, even in situations where vision was additionally impaired by dirt on the camera lens. This limited benefit of increased pixel density is remarkable, especially since our subjects seem to have noticed changes in the visibility of the target in lower pixel densities, as indicated by the manipulation check (see the Supplementary Material). Likewise, increasing the exterior camera's resolution should be of surprisingly little benefit. A pixel density of 78.7 ppi equals a resolution of 480×270 pixels in our 7-inch monitor. Please note that not even the highest resolution tested here, 1920×1080 pixels, comes close to the resolutions possible in state-of-the-art cameras. However, as human users do not seem to benefit from higher image sharpness, monitors providing pixel densities of up to 300 ppi and a respective camera resolution could provide enough detail to ensure the accurate perception of distance and TTC. This assumption finds further support in the TTC estimation variability, which was largely unaffected by pixel density. Lower resolutions additionally have an important practical benefit, since they decrease the data volume transmitted between camera and monitor and thus the risk of latencies and transmission failures. However, note that the results observed here first need to be replicated in more realistic driving scenarios and for other driving tasks to provide specific recommendations on the resolution of cameras and monitors.

In summary, whereas a larger FOV of CMS could improve perception accuracy, the same might not apply to the resolution and pixel density of CMS. A pixel density around 300 ppi could provide enough detail to accurately perceive rearward distances and TTC.

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In accordance with Taylor & Francis policy and our ethical obligation as researchers, we report that there are no potential competing interests to declare.

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Data availability statement

The authors confirm that summary statistics supporting the findings of this study are available within the article's supplementary material. The raw data that support the findings of this study are available from the corresponding author, CB, upon reasonable request.

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