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**STUDY OF TARGET VISIBILITY ON THE ROAD WITH
DRIVING AS WORKLOAD**

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STUDY OF TARGET VISIBILITY ON THE ROAD WITH DRIVING AS WORKLOAD

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Abstract

Existing models to predict night-time target visibility on a road are mainly based on psychophysical experiments conducted in laboratory environments, which may not be representative to predict target visibility during actual driving conditions. Target visibility, under mesopic conditions, with driving as workload is investigated in this paper by using a driving simulator. Results show that driving workload leads to a reduced detection rate and an increased reaction time, which means that target visibility is impaired during driving conditions. The corresponding target visibility levels (VL) are calculated for different workloads. The derived VL values with driving workload conditions are higher than the currently recommended VL value, which indeed suggests that the effect of driving workload is not included. We defined the mesopic visual performance (MVP) model as a combination of detection rate and reaction time which provides another way for describing the effect of driving workload on target visibility.

Keywords: Target visibility, driving workload, visibility level (VL), mesopic visual performance (MVP).

1 Introduction

A CIE report, published in 1992, includes a review of 62 studies on lighting and road traffic accidents from 15 countries, and suggested that new or improved lighting led to accident reductions after dark in the range of 13% to 75% (CIE, 1992). Using lighting can increase the likelihood of detecting a potential hazard and a reduced detection time leads to a more rapid braking response. (Fotios & Gibbons, 2018). Therefore, the appropriate-designed road lighting installation is an effective guarantee for night traffic safety.

Relative visual performance (RVP) model (Rea & Ouellette, 1991) and small target visibility (STV) model are two widely used visual performance models which take the contrast into consideration. Adrian's VL (visibility level) model (Adrian, 1987), based on the detection of a small object in the roadway, is the most popular theoretical model used to describe the STV. Research has been conducted to explore the value of VL needed for adequate visibility on real road conditions. Some studies suggest that when VL is greater than 7, targets could be detected. The French recommendations for road lighting (Association Francaise de l'Eclairage. 2002) use the VL>7 criterion.

Nevertheless, neither the RVP model nor the STV model takes the impact of driving workload into account or the driving workload has been greatly simplified in the laboratory environment, which cannot reflect the actual driving condition. It has been demonstrated that driving activity has a negative significant effect on target visibility in night driving environments (Brémond & Mayeur, 2011). Brémond et al. confirmed that the VL threshold (VL = 7) was only relevant for a very simple driving task (Brémond et al., 2013), which may not be suitable for the real driving condition. Therefore, the visual performance model used in the study of road lighting environment should be improved accordingly by considering the proper driving workload.

In this paper, the visibility of three different levels of workload has been studied by the driving simulator experiment with reference to the STV scenario, in addition the influence of target contrast and distance on visibility under night driving condition was also studied.

2 Experiment platform

A driving simulation experimental platform was designed to study the visibility under different workloads. It is the same platform as used in our previous study (Chen *et al.*, 2018), and is schematically represented in Figure 1.

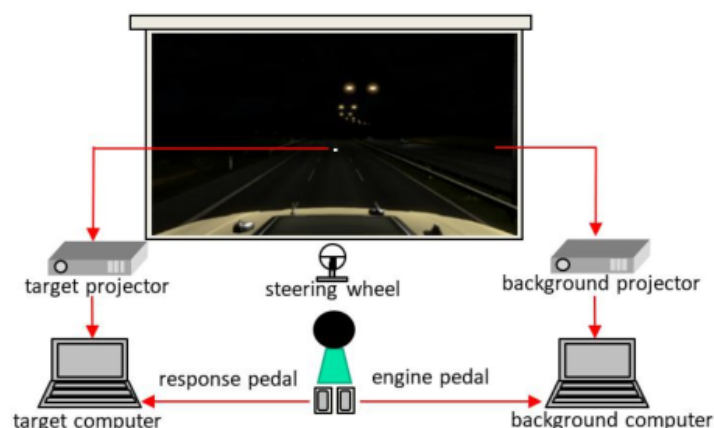


Figure 1 – Layout of experimental set-up

Two projectors were used to overlay the scenes and the visual targets. The projector (NEC:NP-M332XS+) resolution was 1024×768, with a refresh rate of 60 Hz. The positions of the two projectors are adjusted so that the projected images are almost completely overlapped. The screen size was 2.69m in width and 1.6m in height. The subjects were required to sit at 2.2 m from the screen and their eye position was at 1.1 m height. The steering wheel and engine pedal were used to control the driving direction and start the car. The response pedal, connected to target computer, was used to record target detection and reaction time data. The synchronization of the target module is controlled by an E-Prime program. The reaction time can be accurately calculated by the time of the targets' appearance and the time of the pedal responds.

3 Experimental design

The purpose of this study was to evaluate the impact of driving workload on target detection performance under night driving conditions. Three levels of workloads: uniform black condition, static snapshot condition and dynamic driving condition are designed. The dependent variables in the study were reaction time and detection rate. They were collected in different workloads (three levels), target positions (three lanes), and luminance contrasts of the targets (six levels).

3.1 Driving scene

A schematic diagram of the scenarios in different workload conditions is shown in Figure 2. The uniform black condition has no driving workload and was used as a reference for target visibility under ideal conditions (no driving workload and a uniform background); the static snapshot condition is a static picture taken from the dynamic driving scene, which has a complicated background environment but the scene itself is stationary, and the participants needn't to control the simulator; the dynamic driving condition requires the participants control the simulator, which has a large driving workload and is closest to the actual driving situation. The dynamic driving scene is provided by the game-Euro Truck Simulator 2.



Figure 2 – Scenarios for three levels of workloads

3.2 Stimulus

The luminance contrast was defined as the Weber fraction:

$$C = (L_t - L_b) / L_b \quad (1)$$

where L_t is the target luminance and L_b is the background luminance. A cube with the side length of 20 cm was selected as the target, which is conform to the IES standard RP-08-00 (IESNA. 2000). The luminance contrast between the target and the near background were nearly the same in the three conditions. The luminance of the road on the screen was obtained by the average luminance of nine points within the target appearance range. The average luminance was 1.0 cd/m², with maximum luminance being 1.02 cd/m² and the minimum luminance being 0.94 cd/ m². Eight target contrasts (0.1, 0.2, 0.3, 0.4, 0.6, 0.8, 1.6, 3.2) were used in this study. Three positions (left, middle, right) were defined according to the three lanes in the driving scene and the target appearance distance was 30 m or 67.5 m. All stimuli were repeated 8 times.

A within-subject experiment was designed where each subject had to perform (3 (workloads) × 3 (lanes) × 2 (distances) × 8 (contrasts) × 8 (repetitions)) 1152 target detection tasks. Subjects were required to step on the response pedal as quickly as possible when they saw the target (on the road). Targets appeared randomly during experiment and disappeared immediately after the subject pressed the pedal. If the subject did not respond, the target would disappear automatically after 1.2 s. The interval between the stimuli was assigned randomly between 3 seconds and 5 seconds. The E-prime program was used to control the appearance of the target randomly and to record the signals from the response pedal.

3.3 Participants

In total 13 subjects participated in the experiment, including 9 males and 4 females from 23 to 25 years old, with an average age of 24.5 years (SD=1.1). Subjects were required to have (corrected-to) normal vision and no visual problems such as strabismus or color blindness. All subjects had a driver's license and some night driving experience.

3.4 Procedure

The experiment was divided into 3 sessions, corresponding to three different workload scenarios. Due to the large number of visual target detection tasks in the experiment, the experiment was divided into two sub-sessions according to the distance (30 m or 67.5 m). The schematic diagram of the experimental process is shown in Figure 3. There was a 5-minute adaptation phase before the experiment to adapt to the dark environment. The difference between the dynamic driving scene session and the other two sessions is that it required at least 5 minutes of driving training. To prevent the effects of fatigue, there was a 5-minute break between two sub-sessions. Considering the workload of the dynamic driving session was significantly larger than the other two conditions, an additional 5-minute break was included in each sub-session.

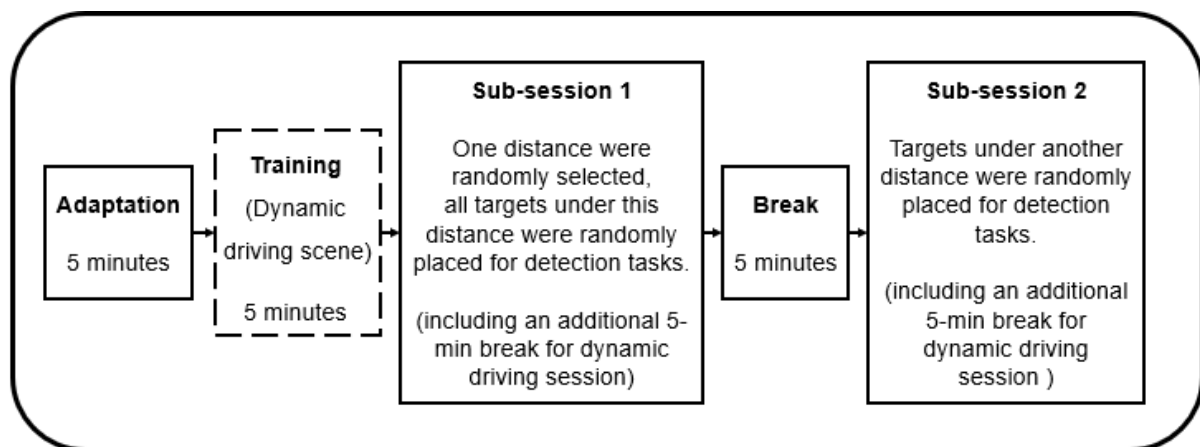


Figure 3 – The experimental process for one session

4 Result

4.1 Detection rate

A total of (13×1152) 14976 sets of data were obtained. The data were divided into three categories according to the reaction time (Jahn & Oehme & Krems *et al.*, 2005) required to detect the object: Mis-operation (reaction time ≤ 200 ms); Effective detection (200 ms < reaction time < 1000 ms); Missed detection (reaction time ≥ 1000 ms). The target detection rate is defined as the ratio of effective detection over all responses, which characterizes the subject's ability to detect the target. Figure 4 demonstrates the detection rate under different workloads (averaged over all contrasts, distances, positions, and repetitions). The detection rate decreases as the workload increases, and the average detection rate of the target decreases from 74.2% for the uniform black scene to 70.9% for the static snapshot scene, the mean target detection rate for the dynamic driving scene is only 42.8%.

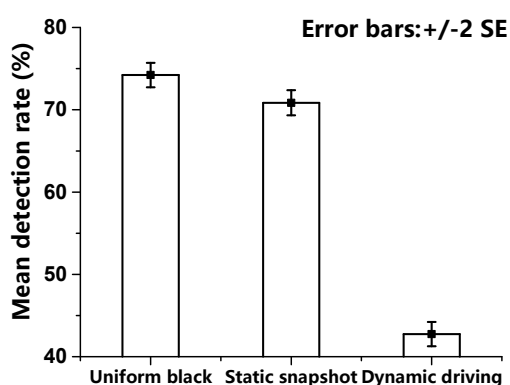


Figure 4 – Mean detection rate under different workloads

An analysis of variance (ANOVA) results for the dependent variable “detection rate” are given in Table 1. The fixed factors are workload, contrast, position and distance. Random factor is subject. A 2-way ANOVA, with main factors and their interactions, was performed. The significance of the impact is evaluated with the use of the Eta squared index (Cohen, 1973). The value of the partial η^2 reflects the size of the effect (partial $\eta^2 > 0.14$, large effect; 0.06-0.14, medium effect; 0.01-0.06, small effect; <0.01, insignificant effect (Cohen, 1988)). It can be seen that workload, contrast, distance and position all have a significant effect on the detection rate, workload and contrast have large effect sizes, distance has medium effect size and position has small effect size. There is a significant interaction between all the factors, while only the interaction between workload and contrast has a large effect size (see Figure 5). All other interactions have small or insignificant effects, and are therefore not included in Table 1.

Table 1 – ANOVA results of the detection rate

Factor	df	Sig.	partial η^2
Workload	2	<0.001	0.393
Contrast	7	<0.001	0.741
Distance	1	<0.001	0.085
Position	2	<0.001	0.040
Subject	12	<0.001	0.237
Workload * Contrast	14	<0.001	0.145

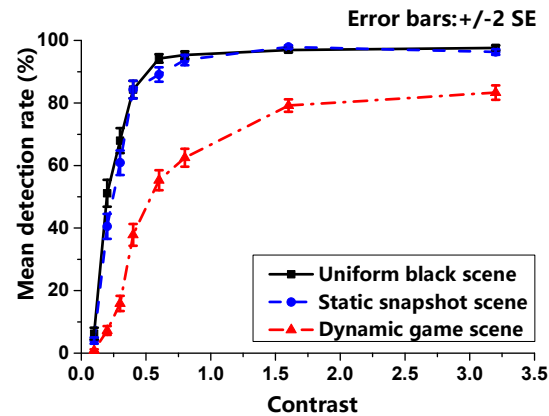


Figure 5 – The interaction between workload and contrast for mean detection rate

The interaction between contrast and workload is mainly caused by the lower detection rate and the slower increase in detection rate with increasing contrast level for the dynamic driving scene. A further Tukey's post-hoc test is shown in Table 2. The result of contrast in different workload is carried out separately due to the large effect size of the interaction.

Table 2 – Results of Tukey's post-hoc test of detection rate; items that are underlined together are not statistically significantly different

Factor		Detection rate (%yes)
Workload		Dynamic driving (42.8%) < Static snapshot (70.9%) < Uniform black (74.2%)
Contrast	Workload	Uniform black: C _{0.1} (6.3%) < C _{0.2} (51.1%) < C _{0.3} (68.0%) < C _{0.4} (84.3%) < <u>C_{0.6}(94.2%) < C_{0.8}(95.4%) < C_{1.6}(97.0%) < C_{3.2}(97.6%)</u>
		Static snapshot: C _{0.1} (4.0%) < C _{0.2} (40.5%) < C _{0.3} (60.9%) < <u>C_{0.4}(84.3%) < C_{0.6}(89.1%) < C_{0.8}(93.8%) < C_{3.2}(96.3%) < C_{1.6}(97.9%)</u>
		Dynamic driving: <u>C_{0.1}(0.8%) < C_{0.2}(7.2%) < C_{0.3}(15.9%) < C_{0.4}(37.8%) < C_{0.6}(55.3%) < C_{0.8}(62.5%) < C_{1.6}(79.2%) < C_{3.2}(83.3%)</u>
Distance		D _{67.5m} (57.3%) < D _{30m} (68.0%)
Position		Right (57.6%) < <u>Left (64.4%) < Middle (65.8%)</u>

Figure 5 illustrates that, in general, the increase of target contrast leads to an increase in detection rate, but finally saturates at a certain contrast. Fortunately, the smaller the target distance (the bigger the target size), the higher the target detection rate. The result for position (left, middle, right lane) shows that the middle lane has the highest detection rate but the detection rate of the right lane is lower than the other two lanes, which is inconsistent with our expectations. By asking the participants' opinion after the experiment, we think it is caused by the street lights on the right side of the road in static snapshot and dynamic driving scene (for uniform black scene, there is no difference in detection rate of the three lanes). Due to the influence of street lights, the right lane scene is more non-uniform and increases the difficulty of target search, which may result in the target detection rate of right lane is significantly lower than the other two lanes. However, it needs further verification in a follow-up study.

4.2 Reaction time

The reaction time is defined as the mean reaction time of the subject under effective detection, which can reflect how fast the target has been detected. The reaction time under different workloads is shown in Figure 6. The reaction time of uniform black scene and static snapshot scene is not much different. The reaction time of the static snapshot scene (606ms) is even slightly, but not statistically significantly, smaller than the uniform black scene (614ms). But once the driving workload is added, the reaction time increases to 713ms.

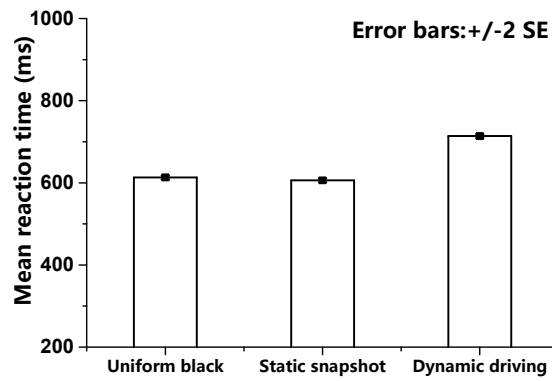


Figure 6 – Mean reaction time under different workloads

The ANOVA results for reaction time are given in Table 3. The dependent variable is the reaction time. The other variables are consistent with the analysis of detection rate. Different from the detection rate, since the target detection rate of $C=0.1$ (3.7%) is close to 0, the reliability of the reaction time data in this case is very low, therefore, we excluded the $C=0.1$ data in the analysis to ensure the overall data has a good reliability. All the interactions have small or insignificant effect size. Figure 7 shows the interaction between workload and contrast for reaction time (partial $\eta^2=0.55$). Different from the detection rate, the reaction time changes with contrast under three workloads are roughly consistent under three workloads. A further Tukey's post-hoc test is shown in Table 4.

Table 3 – ANOVA results of the reaction time

Factor	df	Sig.	partial η^2
Workload	2	<0.001	0.314
Contrast	6	<0.001	0.420
Distance	1	0.001	0.040
Position	2	<0.001	0.032
Subject	12	<0.001	0.332

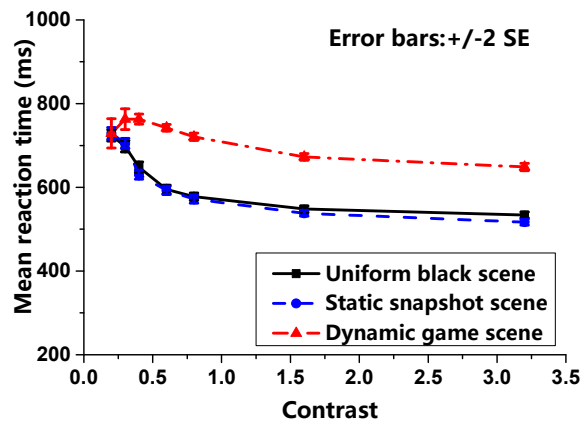


Figure 7 – The interaction between workload and contrast for reaction time

Table 4 – Results of Tukey's post-hoc test of reaction time; items that are underlined together are not statistically significantly different

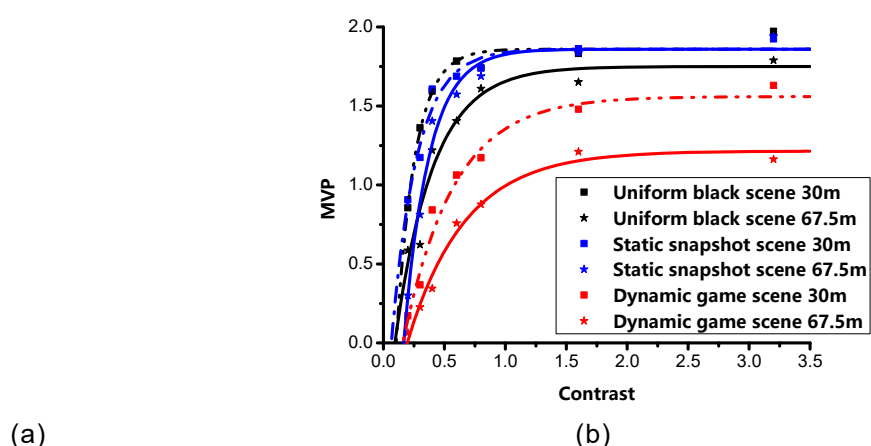
Factor	Reaction time (ms)
Workload	<u>Static snapshot (606) < Uniform black (614) < Dynamic driving (713)</u>
Contrast	<u>C_{3.2}(566) < C_{1.6}(586)</u> < C _{0.8} (623) < <u>C_{0.6}(641) < C_{0.4}(675) < C_{0.3}(715)</u> <u>< C_{0.2}(727)</u>
Distance	D _{30m} (628) < D _{67.5m} (653)
Position	Middle (629) < <u>Left (641) < Right (651)</u>

Figure 7 reveals that, a higher target contrast, and a shorter distance lead to a shorter reaction time. The reaction time of the middle lane is generally smaller than the left and right lanes, but different from detection rate, there is no difference between the reaction time of left and right lanes.

4.3 VL model verification and MVP value

The corresponding VL values were calculated according to the background luminance, target contrast, target size, exposure time and age factor in various conditions. Since the three lanes vary in the performance of detection rate and reaction time, here we only give the VL of the middle lane for analysis ($C=0.1$ is not included). However, there is no parameter in VL model to reflect the workload, which means that the VL values for the three workload conditions are located on a straight line, as shown in Figure 8 (a).

The VL model is the most widely used visibility model, but it cannot describe the real driving condition due to lack of workload. Therefore, we define a parameter mesopic visual performance (MVP) as the product of detection rate (DR) and the reciprocal of the reaction time (RT), $MVP = DR/RT$, according to the method defined by Weston (Weston, 1945). It means that high detection rate and low reaction time lead to large MVP value, and vice versa.

**Figure 8 – The plots of VL & MVP versus contrast under three workloads**

The relationship between MVP and contrast under three workloads with two distances is shown in Figure 8 (b). The MVP values for the uniform black scene and the static snapshot scene are similar, but once the driving activity is added, the MVP value is significantly reduced. It means that the complexity of the static background has less impact on visual performance than the dynamic background while driving. Reducing the contrast and increasing the distance result in the decrease of MVP value. Compared with VL, the MVP value can better reflect the impact of driving workload on visual performance.

Moreover, because there is a linear relationship between contrast and VL, we consider to compare the detection rate and MVP to the VL more intuitively, as shown in Figure 9. It shows an exponential relationship between VL and detection rate & MVP, and MVP and VL are positively correlated. Since the results of detection rate and MVP for the uniform black scene and the static snapshot scene are close, they are merged as the static scene when predicting the detection rate (DR) and MVP from the VL. The relationship between detection rate and MVP and VL in static and dynamic background is shown in equations (2) ~ (5).

$$DR_{Static} = 97.28 - 166.83 \times e^{-VL/4.03}, R^2 = 0.89 \quad (2)$$

$$DR_{Dynamic} = 89.48 - 125.78 \times e^{-VL/11.15}, R^2 = 0.91 \quad (3)$$

$$MVP_{Static} = 1.84 - 2.41 \times e^{-VL/6.82}, R^2 = 0.91 \quad (4)$$

$$MVP_{Dynamic} = 1.47 - 1.80 \times e^{-VL/16.35}, R^2 = 0.92 \quad (5)$$

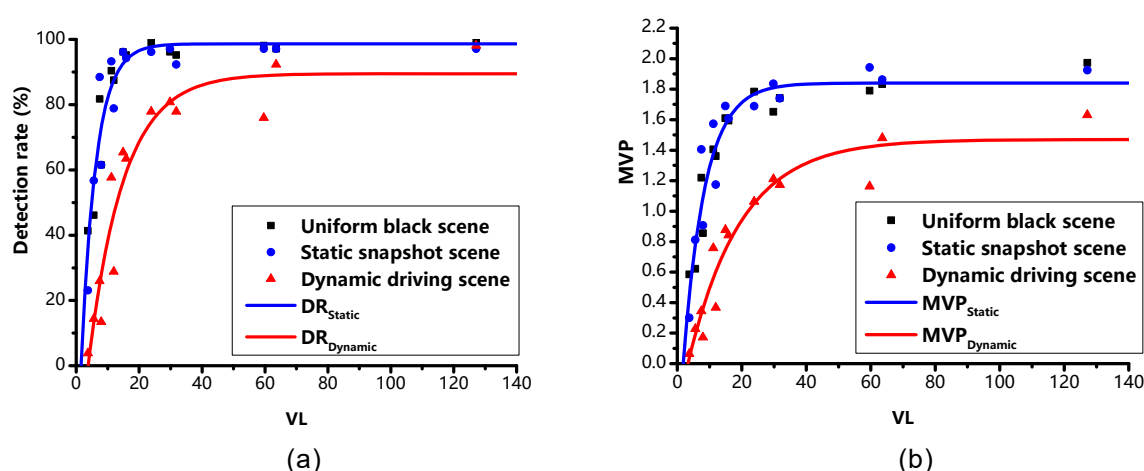


Figure 9 – Detection rate & MVP versus VL under static and dynamic conditions

VL = 7 is the currently recognized threshold for road lighting conditions. According to our experimental results, the predicted detection rate corresponding to VL = 7 for static and dynamic driving scene is 67.9% and 22.3%. It already is questionable if a detection rate of 68% is sufficient for night driving conditions, but for the dynamic driving scene, the detection rate at VL = 7 (only 22%) is much too low to meet the needs of the car drivers for effective detection.

According to the suggestion of Gallagher and Meguire, road lighting needs to enable drivers to obtain a detection rate of at least 85% (Gallagher & Meguire, 1975). Based on this detection requirement, the thresholds of VL for static and dynamic driving scene are about 11 and 38 respectively, while the VL value for dynamic driving scene is significantly larger than obtained with other studies.

When VL=7, MVP=0.98 for the static scene and MVP=0.30 for the dynamic driving scene. Using the 85th percentile as the detection threshold, the corresponding MVP thresholds can be obtained: MVP=1.36 for the static scene (VL=11) and MVP=1.29 for the dynamic driving scene (VL=38). Or in other words, when the minimum MVP value would be fixed to 1.3, the corresponding VL values for static scenes would be 11 and 39 for dynamic scenes, the latter being more representative for actual driving conditions.

5 Conclusion

This study investigated the impact of driving workload on visual performance under night driving conditions using a driving simulator. One dynamic driving scene and two static scenes (different in complexity of background scene) represent three levels of workloads and were designed according to the small-target visibility (STV) scenario.

The result shows that workload has significant effect on both detection rate and reaction time ($p < 0.001$) with a large effect size (detection rate: partial $\eta^2 = 0.393$; reaction time: partial $\eta^2 = 0.314$). The detection rate for a dynamic driving scene with actual driving activity is significantly lower than the other two static scenes, and the reaction time is significantly higher than the other two static scenes. The difference of detection rate and response time between two static scenes is small, indicating the complexity of the static background scene has little effect on target visibility. The results also show that target contrast has a significant effect on detection rate and reaction time with a large effect size. On the other hand, the distance (target size) and position (left, middle and right lane) also both have a significant effect on detection rate and reaction time, but with a small effect size. Increase in contrast and decrease in distance leads to an increase of detection rate and a reduction of reaction time. For the complex background and dynamic scenes, the middle lane has higher detection rate and shorter reaction time than the left and right lanes. Only the interaction between workload and contrast of detection rate has large effect size, other interactions are small or insignificant.

The VL values for the static and dynamic driving scenes have been calculated. The results show that for an 85% detection rate, the VL value for dynamic driving scene with actual driving activity (VL=38) is much higher than currently used (VL=7). The mesopic visual performance (MVP) is defined as the multiplication of the detection rate and the reciprocal of the reaction time, and better represents the driving workload. The MVP threshold should be set to a minimum of 1.3 to obtain a VL value of 11 for static scenes (no driving workload) and VL=39 for dynamic scenes (with actual driving workload).

References

- ADRIAN, W. 1987. Visibility levels under night-time driving conditions. *Journal of the illuminating engineering society*, 16(2), 3-12.
- ASSOCIATION FRANCAISE DE L'ECLAIRAGE. 2002. *Recommendations Relatives à l'Eclairage des Voies Publiques*. Lux éditions.
- BREMOND, R. MAYEUR, A. 2011. Some drawbacks of the visibility level as an index of visual performance while driving: *Proceedings of the 27th Session of the CIE*. Sun City, South Africa, Vienna: CIE, 1140–1143.
- BREMOND, R. BODARD, V. DUMONT, E. et al. 2013. Target visibility level and detection distance on a driving simulator. *Lighting Research and Technology*, 45(1), 76-89.
- CHEN, Z.Y. et al. 2018. Target visibility under mesopic vision using a driving simulator. *Lighting Res. Technol.*, 0, 1-17.
- CIE 1992. *Road Lighting as an Accident Countermeasure*. Vienna: CIE.
- COHEN, J. 1973. Eta-squared and partial eta-squared in fixed factor ANOVA designs. *Educational and Psychological Measurement*, 33(1), 107-112.
- COHEN, J. 1988. Statistical power analysis for the behavioural sciences. *Journal of the American Statistical Association*, 2nd (334), 19–74.
- FOTIOS, S. GIBBONS, R. 2018. Road lighting research for drivers and pedestrians: The basis of luminance and illuminance recommendations. *Lighting Res. Technol.*, 50, 154–186.
- GALLAGHER, V.P. MEGUIRE, P.G. 1975. Driver Visual Needs in Night Driving. *Transportation Research Board Special Report*, 156.
- IESNA. 2000. *ANSI/IESNA RP-8-00 American National Standard for Roadway Lighting*. New York: IESNA.
- JAHN G. OEHME A. KREMS J. F. et al. 2005. Peripheral detection as a workload measure in driving: Effects of traffic complexity and route guidance system use in a driving study. *Transportation Research Part F Psychology & Behaviour*, 8(3), 255-275.
- REA, M.S. OUELLETTE, M.J. 1991. Relative visual performance: A basis for application. *Lighting Research and Technology*, 23(3), 135-144.
- WESTON, H.C. 1945. The Relation between Illumination and Visual Efficiency-The Effect of Brightness Contrast. *Industrial Health Research Board Report*, 87.