Changes in Attention Levels While Driving a Car Estimated Using Modelling Techniques with Features of Oculo-Motors

Minoru Nakayama[1][a], Qian (Chayn) Sun[2][b] and Jianhong (Cecilia) Xia[3][c]
[1]*Institute of Science Tokyo (Tokyo Tech.), O-okayama, Meguro-ku, Tokyo, 152–8552, Japan*
[2]*RMIT University, Melborune, VIC 3000, Australia*
[3]*Curtin University, Perth, WA 6102, Australia*

Keywords: Car Driving, Attention, Eye Movement, Pupil, Mental Workload, Modelling.

Abstract: Changes in attention levels while driving a car were estimated using a modelling technique involving pupillary changes and the frequency of saccades of 11 drivers. The driving route used in the experiment consisted of 19 sections of road divided into 5 groups: university campus, left turn, straight, right turn, and roundabout. The sections of road with posted speed limits were divided into 6 conditional states, and model parameters were estimated by assuming transitions across the states. The estimated model parameters were used to examine changes in the level of attention resources used during each section of driving. The results of a comparison of attention resources by section showed a significant decrease, in the following order: straight and roundabout, within campus, left turn and right turn. In addition, the relationship between NASA-TLX was evaluated after driving and attention resources were examined, and a significant correlation with the factor for "difficulty" was confirmed. The relationship between the confidence interval of the change in attention resources and the factor for "mental demand" was also confirmed.

1 INTRODUCTION

Eye movements of drivers and human visual acuity have been studied in order to improve the safety of motor vehicle operation (Kapitaniak et al., 2015; Paeglis et al., 2011; Schmitt et al., 2015; Yamani et al., 2016). A detailed analysis of images viewed during driving has also been developed in order to understand driving behaviour (Palazzi et al., 2019; Hu et al., 2022). Currently, safety aspects of various intelligent vehicles designs which use autonomous driving systems are frequent points of discussion (Deng et al., 2020). While human behavioural factors during motor vehicle operation may show possible problems, they can be used to better optimise safe driving practices, even when autonomous operating systems are employed. In particular, the driving behaviour of elderly motorists should be considered when addressing the issue of safe driving. The relationship between a driver's workload and their driving actions is often studied, and detailed analysis of the relationship is limited (Sun et al., 2016a; Sun et al., 2016b; Nakayama et al., 2022), however. Elderly motorists may possess significant individual differences in ability to recognise workload levels, so the relationship between their own impressions and behaviour-based attention levels should be extracted.

The authors have introduced modelling techniques in order to estimate the attention levels of drivers (Nakayama et al., 2024a; Nakayama et al., 2024b), though the notations used in the model should be updated to recognise some of the behavioural factors of some elderly motorists. In the previous study, factors of road conditions and overall temporal changes were still unclear. In order to emphasise these factors, the calculation model for attention levels should be improved.

This paper shows the features of some model parameters of the experimental driving conditions using an updated model and a state-space modelling technique.

The following topics are addressed in this paper.

1. Estimation of attention levels across segments of driving routes using a state-space model, which is based on measured saccade rates of eyes and pupil sizes of individuals while driving a car.

[a] https://orcid.org/0000-0001-5563-6901
[b] https://orcid.org/0000-0002-5421-5838
[c] https://orcid.org/0000-0002-2593-9423

Nakayama, M., Sun, Q. C. and Xia, J. C.
Changes in Attention Levels While Driving a Car Estimated Using Modelling Techniques with Features of Oculo-Motors.
DOI: 10.5220/0013101400003911

In *Proceedings of the 18th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2025) - Volume 1*, pages 846-852
ISBN: 978-989-758-731-3; ISSN: 2184-4305

2. The relationship between estimated attention levels and surveyed workload scores are analysed in order to provide an overall impression of participating drivers.

2 RELATED WORKS

Eye movement has often been analysed to assess driving behaviour in various environments, in order to support safe motor vehicle operation (Palazzi et al., 2019; Kübler et al., 2021). In particular, dynamic visual information processing ability depends on eye movement behaviour while driving (Kapitaniak et al., 2015; Paeglis et al., 2011). Driving ability and cognitive performance are sometimes influenced by ageing. Behavioural monitoring of aged drivers is necessary to ensure safe operation of motor vehicles (Schmitt et al., 2015; Yamani et al., 2016). Some studies have been conducted to measure the driving speed and deviations in position of cars on the road using a global positioning system (GPS) installed in cars, and measurement of eye movements while driving (Sun et al., 2015; Sun et al., 2018b). Also, route factors were discussed when considering elderly drivers, such as paying attention and perception of the situational environment (Sun et al., 2016b; Sun et al., 2018c). Cognitive performance is sometimes considered as a factor affecting individual drivers. For elderly drivers, visual perception performance and cognitive functions are often focused on through the use of eye tracking. Manoeuvre index, useful filed of view (UFOV) and mini-mental state examination (MMSE) of individual drivers was measured, and the contributions of these to driving performance has been discussed (Ball and Owsley, 1993; Wood and Owsley, 2014; Mombaugh and McIntyre, 1992; Adler et al., 2005). The factors affecting eye movement during driving have been discussed and some contributions to the evaluation of individual performance have been examined (Yamaguchi et al., 2019).

In driving situations, the cognitive workload or attention payment required by drivers for safe motor vehicle operation has also been measured and discussed. Most assessments were focused on aspects of viewing behaviour as mention above, as measurement of cognitive workload or attention level is not easy during driving, however. The cognitive workload is usually measured as overall assessment using NASA-TLX or other metrics (Hart, 2006). Change of the cognitive workload or attention may be recognised to affect behavioural reactions. Eye tracking has been used to assess and analyse attention and viewing behaviour (Underwood, 2005; Kübler et al., 2021; Hu et al., 2022). These contributions to driving actions were also extracted from the eye movements of drivers (Nakayama et al., 2022).

Table 1: Route segments.

No.	Route label	No.	Route label
1	Straight on campus	11	Pass RoundAbout
2	Pass RoundAbout	12	TurnRight3
3	TurnLeft1	13	Straight_two-lane2
4	Straight_four-lane1	14	Turn RoundAbout
5	TurnLeft2	15	Straight_two-lane3
6	TurnRight1	16	TurnLeft3
7	Straights	17	Straight_four-lane2
8	TurnRight2	18	TurnLeft4
9	Pass RoundAbout	19	TurnRight+campus
10	Straight_two-lane1		

Group 1 [On-campus]:1,2,11,19; $M_{dur.} = 35.8sec.$
Group 2 [Left-turn]:3,5,16,18; $M_{dur.} = 19.7sec.$
Group 3 [Straight]:4,7,9,10,13,15,17; $M_{dur.} = 51.5sec.$
Group 4 [Right-turn]:6,8,12; $M_{dur.} = 28.0sec.$
Group 5 [Turn Roundabout]:14; $M_{dur.} = 31.1sec.$

Some modelling techniques can extract latent activity such as attention level using a model hypothesised for laboratory-based experiments in order to conduct temporal change (Ueno and Nakayama, 2021; Dubiel et al., 2023). This technique can be applied to ocular metrics during driving by introducing a hypothesised model and restrictions (Nakayama et al., 2024a; Nakayama et al., 2024b). A more reasonable assessment of the change in attention levels during driving would require a detailed analyses using revised models since the model hypothesis was insufficient in the previous study.

3 METHOD

Both driving behaviour and oculo-motors of older drivers were measured while they drove their own cars along the assigned route around the university campus (Sun et al., 2016a; Sun et al., 2016b; Sun et al., 2018a).

3.1 Measurements Recorded During Driving Experiment

In order to measure the above metrics while driving (Sun et al., 2015; Sun et al., 2018b), 11 older participants (7 males and 4 females, aged 62 to 76, mean=67.3) drove the course under experimental conditions (Sun et al., 2016a). Informed consent was obtained from all participants prior to the experiment.

The entire course was divided into 19 separate segment paths, which are called “routes”, as shown in Table 1, and these routes were classified into five groups according to driving actions. Simple duration of driving statistics are summarised in the table below.

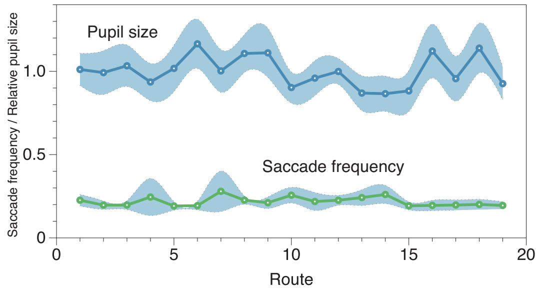

Figure 1: Changes in saccade rate and pupil size across 19 driving routes.

3.2 Experimental Measurements

The targeted data were eye movements including pupil sizes, and ratings for NASA-TLX as a measurement of cognitive workload, taken after all driving had been completed.

3.2.1 Oculo-Motor Measurement

Both eye movement and pupil size were measured using a wearable eye tracker (Arrington, 30Hz) (Sun et al., 2016a). This equipment can detect saccadic eye movements in a time-line (Arrington Research, 2016).

Mean temporal changes in the two measured metrics (saccade frequency and pupil size) over the 19 routes are summarised in Figure 1, with confidence intervals of 95%. While observing eye movements recorded while driving, it was noticed that drivers in turns or corners rotated their heads before moving their eyes. Therefore, these vestibulo-ocular reflexes (VOR) were recorded as saccades. Pupil size might be influenced by the luminance of the road. As a result, the averaged metrics remain almost constant over the entire route.

3.2.2 Cognitive Workload After Driving

A version of NASA-TLX [4] using six 21-point scales (0-20) was employed to measure the cognitive workload, which consists of Mental demand (MD), Physical demand (PD), Temporal demand (TD), Performance (OP), Effort (EF) and Frustration (FR).

Other metrics were also measured, though there were no significant differences between participants, as all participants were healthy individuals.

[4]https://humansystems.arc.nasa.gov/groups/tlx/downloads/TLXScale.pdf

4 MODELLING ATTENTION LEVELS

The estimated attention levels of drivers have been extracted using a state-space model based on both saccade rates and relative pupil sizes (Dubiel et al., 2023; Nakayama et al., 2024a; Nakayama et al., 2024b). A definition of attention level with minor revisions is as follows.

4.1 Model Description

Equation (1) introduces an inverse logit function (inv_logit) for six dimensional state changes in routes (S_level consists of 6 dimension) and individual factors (rID consists of 11 dimensions). However, route factor ($rRoute$ consists of 19 dimensions) could not be implemented in an inverse logit function since the range of the change was too large. This equation is revised by introducing an inverse logit function which normalises the factors of individual and temporal changes, in order to emphasise the differences in factors of the various routes.

The other conditions are the same as those in our previous reports (Nakayama et al., 2024a; Nakayama et al., 2024b). Changes in the index of the level of attention within routes is represented by the 6 states. Two measured metrics are simulated using base functions together with attention levels. Saccade rates ($Nsac_{times}$: 0$\sim$) are generated using Poisson distributions, and pupillary changes ($Pupil_{size}$) around overall mean sizes are generated using Gaussian (Normal) distributions (Dubiel et al., 2023). The validity of model may be examined by obtaining an optimised solution.

$$Attn = inv\_logit(S\_level + rPN + rID) + rRoute \tag{1}$$

State Model:

$$S\_level_i \sim Normal(S\_level_{i-1}, \sigma_s) \tag{2}$$

Observation Model:

$$\begin{aligned} \mu_{noise} &\sim Normal(Attn, \sigma_{noise}) \\ \lambda &= exp(\mu_{noise}) \\ NSac_{times} &\sim Poisson(\lambda) \\ Pupil_{size} &\sim Normal(Attn, \sigma_p) \end{aligned}$$

4.2 Parameter Estimation

Model parameters were estimated using sampling based on measured experimental data with the

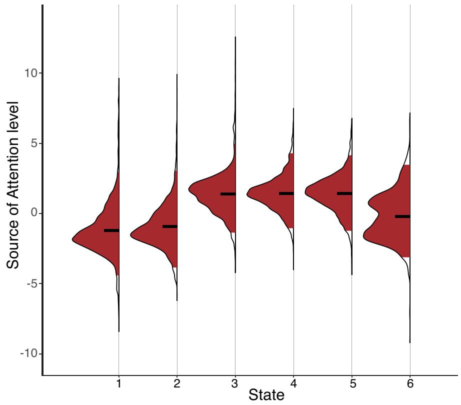

Figure 2: Estimated distributions of latent attention in 6 states (*S_level*).

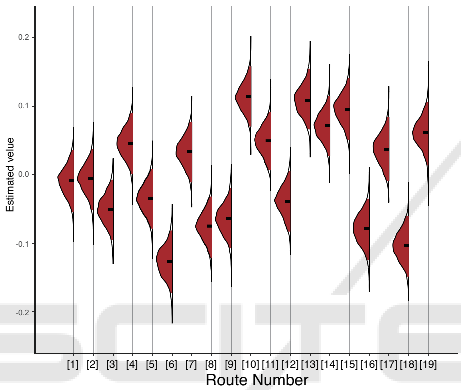

Figure 3: Estimated distributions of route parameter (*rRoute*).

Markov Chain Monte Carlo (MCMC) method. If the hypothesised model is appropriate, all parameters can be estimated to fit with the experimental data. In order to compensate for the data insufficiency of 11 participants, 7 sets of data of observations were generated by shifting the observed period by ± 1 second in increments of 0.33 seconds in order to obtain averaged metrics of the 6 states (Nakayama et al., 2024b). This data extension technique provides 7 times the data of the original measurements. A sampling using the Markov Chain Monte Carlo (MCMC) method was conducted as 4 chains and 6,000 iterations (including 2,000 burn-ins) using the converged condition $\hat{R} < 1.1$ for all parameters.

Distributions of estimated parameters for common latent activity levels (*S_level*) are illustrated in Figure 2, for route parameters (*rRoute*) in Figure 3 and for individual factor parameters (*rID*) in Figure 4. Using equation (1), attention levels (*Attn*) for each of the routes are summarised in Figure 5. Changes in attention levels may depend on the parameters of the route (*rRoute*), and the 5 route groups are indicated in Figure 6 using coloured lines. As the figure shows, the

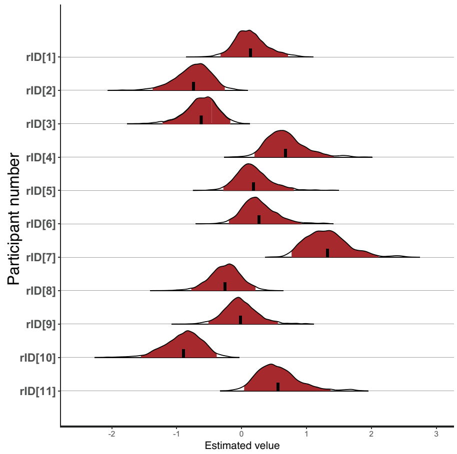

Figure 4: Estimated distributions of individual parameter (*rID*).

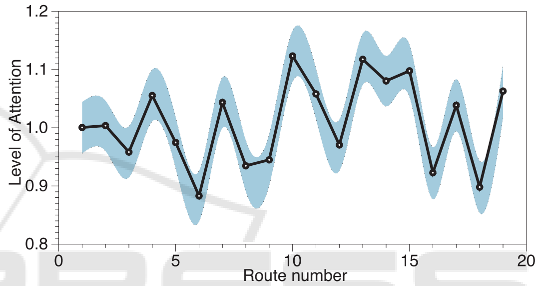

Figure 5: Mean attention levels (*Attn*) over routes with confidence intervals of 95%.

levels for [3] Straight and [5] Turn RoundAbout are higher than the others, and the levels for [2] Left-turn and [4] Right-turn are lower than the others. This suggests that the level of attention for turns made while driving is the lowest in order to devote these resources to overall operation of the motor vehicle. In this scenario, the results show that the level of attention decreases with the amount of the cognitive workload.

Attention levels paid while driving along each route are compared using one-way ANOVA with a factor of the 5 route groups. This route group factor is statistically significant (F(4,1219)=112.6, $p < 0.01$). In order to extract the relationship between the groups of routes, the sub-effect test in Tukey method is applied. In the results, there are significant differences between [1] On-campus and others, [2] Left-turn and others except [4] Right-turn, and [4] Right-turn and [5] Turn RoundAbout. This suggests that the attention level for turns made while driving is the lowest in order to devote these resources to overall operation of the motor vehicle.

However, the results and discussions depend on the hypothesised model, which is defined as behavioural processing, and the validity assessment is

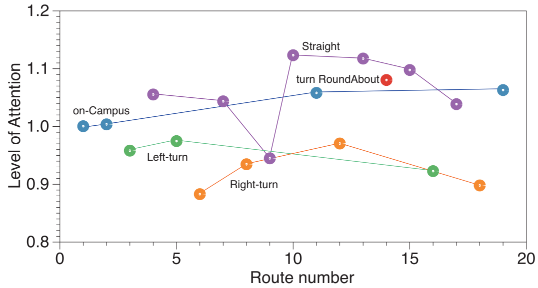

Figure 6: Mean attention levels (*Attn*) across route groups.

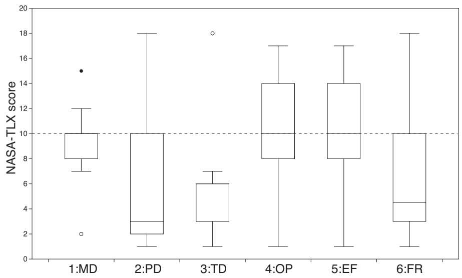

Figure 7: NASA-TLX score measurements.

not easy to evaluate. Therefore, the results may have some limitations in explaining the change in workload under actual driving conditions.

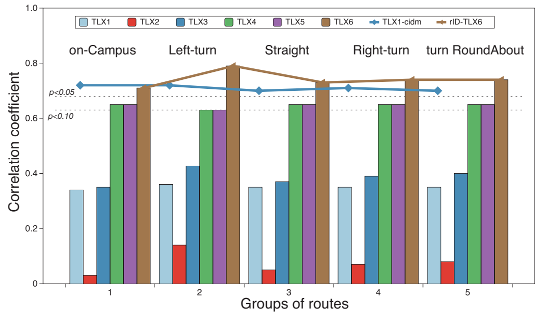

Figure 8: Correlation coefficients between attention levels and NASA-TLX scores.

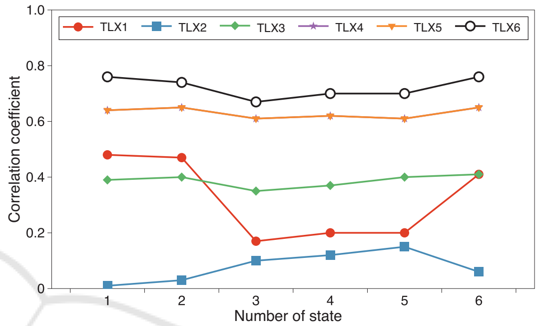

Figure 9: Correlation coefficients between attention levels during routes and NASA-TLX scores.

5 MENTAL WORKLOAD EVALUATION

The results of the assessment of the measurement of cognitive workload are summarised in a box-plot, as shown in Figure 7. Individual ratings correlate with metrics of oculo-motors (Nakayama et al., 2022).

In this section, the contribution of the attention level to the ratings (Nakayama et al., 2024b), and the dependency of the estimation models examined. Correlation coefficients between the ratings and mean attention levels across all participants in the 5 route groups are summarised in Figure 8 as a bar graph. The levels of significance ($p < 0.05$, $p < 0.10$) are illustrated in the figure using dotted lines.

Significant coefficients with a factor for Frustration (FR) are confirmed across the 5 groups of routes. Both coefficients of factors for Performance (OP) and Effort (EF) show significant tendencies ($p < 0.10$). Therefore, most participants perceived some of the cognitive workload during the driving experiment. In particular, individual factor (*rID*) also correlates significantly with the factor rating for Frustration (FR). Since the attention level is estimated using equation(1), which consists of a function for individual factor (*rID*), the distribution of estimated individual factors may affect the ratings.

In addition, the range of the confidence interval for attention level (*Attn*) correlates with ratings for Mental demand (MD). The mean of MD does not correlate directly with attention level. The confidence interval may deviate along the driving route, so it is interesting that the range of the interval correlates with the ratings for MD.

Regarding changes in correlation coefficients along with segments of the routes, most coefficients are maximised slightly during the final route driven (No.19). Once again, these coefficients are almost completely dependent on the first term in equation(1) including individual factor (*rID*).

Dependency of change in the 6 states while driving the routes is examined by comparing the correlation coefficients. The changes in coefficients for attention level and ratings of cognitive workload are summarised in Figure 9. As mentioned above, only one rating for FR is a significant coefficient. For other factors, coefficients change from route to route, though these coefficients are not significant. More detailed analyses including the revision of the model, will be a subject of our further study.

6 SUMMARY

A procedure for estimating driver's attention levels over a driven course was developed using a state-space modelling technique with saccade rates and pupillary changes. In order to consider the interaction of the model's parameters, the attention estimation model was revised. The estimated attention levels are assessed along the routes driven. As a result, the estimated attention level decreased during routes with turns, such as Left-turn and Right-turn, in comparison with the straight route.

Also, driver's ratings for cognitive workload, such as the Frustration factor, correlate with mean attention levels over all 5 route groups when surveyed after driving as been completed. Some statistical information regarding changes in levels of attention correlate with some of the ratings for cognitive workload factors.

Examination of the contribution of route factors to attention levels will be a subject of our further study.

REFERENCES

Adler, G., Rottunda, S., and Dysken, M. (2005). The older driver with dementia: an updated literature review. *Journal of safety research*, 36(4):399–407.

Arrington Research (2016). ViewPoint EyeTracker User-Guide.

Ball, K. and Owsley, C. (1993). The useful field of view test: A new technique for evaluating age-related declines in visual function. *Journal of the American Optometric Association*, 64(1):71–79.

Deng, T., Yan, H., Qin, L., Ngo, T., and Manjunath, B. S. (2020). How do drivers allocate their potential attention? driving fixation prediction via convolutional neural networks. *IEEE Trans. ITS*, 21(5):2146–2154.

Dubiel, M., Nakayama, M., and Wang, X. (2023). Modelling attention levels with ocular responses in a speech-in-noise recall task. In *Proc. ETRA 2023*, pages 89:1–89:7. ACM.

Hart, S. G. (2006). NASA-task load index (NASA-TLX); 20 years later. In *Proceedings of the human factors and Ergonomics Society 50th Annual meeting*, pages 904–908.

Hu, Z., Lv, C., Hang, P., Huang, C., and Xing, Y. (2022). Data-driven estimation of driver attention using calibration-free eye gaze and scene features. *IEEE Trans. Industorial Electronics*, 69(2):1800–1808.

Kapitaniak, B., Walczak, M., Kosobudzki, M., Jóźwiak, Z., and Bortkiewicz, A. (2015). Application of eye-tracking in drivers testing: a review of research. *International Journals of Occupational Medicine and Environmental Health*, 28(6):941–954.

Kübler, T. C., Fuhl, W., Wagner, E., and Kasneci, E. (2021). 55 rides: Attention annotated head and gaze data during naturalistic driving. In Spencer, S. N., editor, *Proceedings of ACM Symposium on Eye-Tracking Research & Applications (ETRA 2021)*, pages 17(1–8), New York, USA. ACM.

Mombaugh, T. N. and McIntyre, N. J. (1992). The mini-mental state examination: A comprehensive review. *Journal of the American Geriatrics Society*, 40(9):922–935.

Nakayama, M., Sun, Q. C., and Xia, J. C. (2022). Estimation of older driver's cognitive performance and workload using features of eye movement and pupil response on test routes. In *Proc. IV 2022*, pages 155–160. IEEE.

Nakayama, M., Sun, Q. C., and Xia, J. C. (2024a). Car driving temporal cognitive workload estimation using features of eye tracking. In *Proc. Eye Tracking Research & Applications (ETRA) 2024*, pages 35:1–3. ACM.

Nakayama, M., Sun, Q. C., and Xia, J. C. (2024b). Using oculo-motor features to estimate cognitive workload while driving a test route. *The Transactions of Human Interface Society*, 26(3):273–276.

Paeglis, R., Bluss, K., and Atvars, A. (2011). Driving experience and special skills reflected in eye movements. In *Proceedings of SPIE*, pages 1–7.

Palazzi, A., Abati, D., Calderara, S., Solera, F., and Cucchiara, R. (2019). Predicting the driver's focus of attention: The DR(eye)VE project. *IEEE Trans. PAMI*, 41(7):1720–1733.

Schmitt, K.-U., Seeger, R., Fischer, H., Lanz, C., Muser, M., Walz, F., and Schwarz, U. (2015). Saccadic eye movement performance as an indicator of driving ability in elderly drivers. *Swiss Medical Weekly*, 145:1–10.

Sun, Q. C., Xia, J. C., Falkmer, T., and Lee, H. (2016a). Investigating the spatial pattern of older drivers' eye fixation behaviour and associations with their visual capacity. *Journal of Eye Movement Research*, 9(6):2:1–16.

Sun, Q. C., Xia, J. C., Foster, J., Falkmer, T., and Lee, H. (2018a). Driving manoeuvre during lane maintenance in older adults: Associations with neuropsychological scores. *Transportation Research Part F*, 53:117–129.

Sun, Q. C., Xia, J. C., Foster, J., Falkmer, T., and Lee, H. (2018b). A psycho-Geoinformatics approach for investigating older adults' driving behaviours and underlying cognitive mechanisms. *European Transport Research Review*, 10(2)(36):1–11.

Sun, Q. C., Xia, J. C., He, J., Foster, J., Falkmer, T., and Lee, H. (2018c). Towards unpacking older drivers' visual-motor coodination: A gaze-based integrated driving assessment. *Accident Analysis & Prevention*, 113:85–96.

Sun, Q. C., Xia, J. C., Nadarajah, N., Falkmer, T., and Lee, H. (2016b). Assessing drivers' visual-motor coordination using eye tracking, GNSS and GIS: a spatial turn in driving psychology. *Journal of Spatial Science*, 61(2):299–316.

Sun, Q. C., Xia, J. C., Nadarajah, N., Foster, J., and Lee, H. (2015). Positioning eye fixation and vehicle movement: Visual-motor coordination assessment in naturalistic driving. In Veenendaal, B. and Kealy, A., editors, *Research@Locate15*, pages 90–99. CEUR Workshop Proceedings. http://ceur-ws.org.

Ueno, T. and Nakayama, M. (2021). Estimation of visual attention using microsaccades in response to vibrations in the peripheral field of vision. In *Proceedings of ETRA2021*, pages 1–6. ACM.

Underwood, G. (2005). *Cognitive Processes in Eye Gudidance*. Oxford University Press, New York, USA.

Wood, J. M. and Owsley, C. (2014). Gerontology viewpoint: Useful field of view test. *Gerontology*, 60(4):315–318.

Yamaguchi, K., Nakayama, M., Sun, Q., and Xia, J. (2019). Prediction of cognitive performance of drivers using eye fixation behaviours. In *Proceedings of 23rd International Conference Information Visualisation*, pages 186–190, London, UK.

Yamani, Y., Horrey, W. J., Liang, Y., and Fisher, D. L. (2016). Age-related differences in vehicle control and eye movement patterns at intersections: older and middle-aged drivers. *PLOS ONE*, 11:1–17.