Eye Movement Analysis in Simulated Driving Scenarios

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Abstract

This study investigates eye movement behaviour during three conditions: Baseline, Ride (simulated drive under normal visibility), and Fog (simulated drive under reduced visibility). Eye tracking data are analyzed using 31 parameters, organized into three groups: (1) saccade features, (2) Bivariate Contour Ellipse Area (BCEA), and (3) blinking features. Specifically, the analysis includes 13 saccade, 13 BCEA, and 5 blinking variables. Across all feature groups, numerous statistically significant differences emerge between Baseline and the driving conditions, particularly between Baseline and Ride or Fog. Between Ride and Fog, saccade features show minimal changes (four out of 13), whereas BCEA (9 of 13) and blink features (four of 5) exhibit pronounced differences, highlighting the strong impact of reduced visibility on gaze stability and blinking behaviour. In addition to conventional measures such as Mean Squared Error (MSE) and entropy metrics, a new parameter, Guzik's Index (GI), is introduced to quantify fixation asymmetry along the major axis of the BCEA. This index utilizes eye tracking data to enhance the understanding of eye movement dynamics during driving conditions. Separately from GI, other parameters elicit the largest deviations compared to Ride (*e.g.,* number of saccades: Cliff's δ = 0.98, BCEA: Cohen's d = 0.89, and standard deviation of blink duration: Cliff's δ = 0.80), underscoring the influence of reduced visibility on visual attention. Overall, these findings demonstrate that combining BCEA with saccade and blink parameters provides a comprehensive understanding of visual attention and gaze stability, while GI offers additional insights into fixation asymmetry under varying visibility conditions.

Keywords: adaptive threshold; BCEA; blink; driving simulator; eye movements; saccade detection

1. Introduction

Driving represents a complex, multitasking activity that demands both mental acuity and physical coordination [1, 2]. Visual attention plays a critical role in safe driving, with eye movements serving as a key indicator of cognitive and perceptual processing [2-5]. Eye movements and fixations are crucial for decision-making and attention, especially while driving [6-8]. Rapid eye movements, or saccades, which can reach the speed of up to 500 degrees per second and typically last less than 100 ms [9], allow drivers to quickly acquire precise visual information [2]. Saccades are essential for scanning the environment, detecting hazards, and making decisions [10-14]. To properly perceive visual information during driving, saccades are accompanied by other eye movements, such as smooth pursuit [15, 16], optokinetic reflex [17], vestibulo-oculomotor reflex [17], and vergence movements [18]. Saccades can be accurately detected and analyzed using eye tracking technology, which provides detailed insight into visual attention and gaze behavior during driving [19, 20].

Eye trackers are devices that measure the position and movement of the eyes [21-23]. Modern systems offer remote tracking with high sampling rates and accuracy, making them suitable for studying human behaviour [21]. Recent advances in eye tracking technology have made it increasingly feasible to monitor and analyze drivers' eye movements [24], providing high-resolution gaze data that allow for detailed characterization of saccades, fixations, and blinks, even in dynamic and unpredictable driving environments. In driving research, eye trackers are used to examine drivers' behaviour, providing detailed information on gaze patterns, attention allocation, and visual scanning strategies [24, 25]. Eye trackers enable comparisons of eye movements during different driving conditions, such as active and passive tasks [7] and calculation of saccades and fixations [25-28], which are critical for understanding underlying cognitive and perceptual processes [29-31]. Beyond these analytical applications, eye trackers are also used to monitor driver state and detect signs of fatigue and drowsiness [26]. Eye tracking technology offers a powerful tool for analyzing drivers' visual strategies, providing critical insights into their attentional focus and potential distractions on the road [32]. By examining eye movement patterns, researchers gain insights into how drivers allocate attention, identifying behaviors that may compromise safety [24]. These findings can inform the design of targeted training programs to enhance driver performance and reduce the risk of accidents [7]. Integrating eye tracking data into driving studies can guide the development of evidence-based interventions, fostering safer driving habits and contributing to accident prevention [24, 25]. However, eye tracking data are inherently noisy and often show limited reproducibility, particularly in dynamic, real-world environments, such as driving [33]. The usefulness of eye trackers in such settings is therefore dependent on carefully selected analytical strategies, including the choice of metrics, filtering, and preprocessing steps, to ensure reliable results [34]. Limitations such as data loss, calibration drift, and sensitivity to head movements must be acknowledged. Consequently, while eye tracking technology offers potential insights into drivers' visual behaviour, its application in naturalistic driving scenarios requires careful consideration of methodological constraints and the inherent variability of the data [35, 36].

Driving simulators provide a controlled and replicable environment for studying visual attention under conditions that closely mimic real-world driving [37, 38]. In [4], a driving simulator was used to compare visual and cognitive distractions, showing that minimizing visual demands in in-vehicle systems is crucial for improving safety. In another study [26], a driving simulator was used for driving fatigue detection using electroencephalography (EEG) data and eye tracking. These studies indicate that a driving simulator in combination with eyetrackers can provide valuable insights into drivers' behavior and attention patterns. By analyzing drivers' gaze patterns across diverse driving scenarios, researchers can gain a deeper understanding of how visual distractions, road conditions, and other factors influence driving performance [24, 32]. This information can be crucial for developing Advanced Driver Assistance Systems (ADAS) and improving overall road safety [39]. Furthermore, integrating eye tracking with driving simulators enables controlled experiments, allowing researchers to isolate specific variables and evaluate their effects on driver behavior with high precision [40].

The central question guiding this work is: How do our eye movements differ during the resting phase and simulated driving and can we detect changes in three distinct measurement conditions by using eye tracker data? More specifically, we ask whether incorporating Bivariate Contour Ellipse Area (BCEA) alongside saccade and blink metrics provides additional information about visual attention and gaze stability across these conditions. For conducting measurements, we employ the Tobii [41] eye tracking system to gather high-quality gaze data under both resting (Baseline) and simulated driving conditions (Ride and Fog). To achieve precise event classification, an adaptive I-Velocity Threshold (IVT) algorithm is used to detect saccades, while blinks are identified to assess cognitive states such as fatigue or distraction. Moreover, the BCEA is computed to quantify fixation stability and spatial dispersion, supplementing traditional eye movement metrics with a measure of gaze precision.

1.1. Research Objectives

The main research question of this study is:

1. Does incorporating BCEA alongside saccade and blink measures enhance understanding about visual attention and gaze stability during Baseline and simulated driving tasks?
2. Can eye tracker data reveal distinct changes across three measurement conditions?
3. How does the presence of the fog affect visual attention and gaze stability in comparison to the Ride and Baseline conditions?
4. To what extent do newly introduced parameters, such as Guzik's Index (GI), provide additional insights into eye movement dynamics and visual attention during simulated driving?

Here, we present an analytical strategy for analyzing eye tracker data that integrates BCEA with widely used oculomotor measures, such as saccades and blinks, to better understand visual attention and gaze stability during simulated driving conditions and in relation to the simulation alterations. In total, three categories of parameters are analyzed, comprising 31 parameters overall: saccade-related parameters capturing rapid eye movements, BCEA parameters assessing gaze variability, and blink-related parameters reflecting eye closure patterns. The analysis includes both conventional metrics and newly derived parameters such as GI. The study aims to determine whether BCEA can serve as a complementary metric that enhances the interpretation of visual behavior beyond conventional eye movement parameters.

2. Materials and Methods

In this study, eye tracker data were collected, preprocessed, and relevant features were extracted. Based on the extracted parameters, statistical analysis was performed to examine differences and relationships between the three conditions - Baseline, Ride (simulated driving under normal visibility), and Fog (driving simulation with reduced visibility).

2.1. Measurement Setup

The study was conducted in a simulated driving environment (Fig. 1) using a motion-based driving simulator at the Faculty of Electrical Engineering (University of Ljubljana) equipped with authentic vehicle components (seat, steering wheel, and pedals) and a physical dashboard. The simulation visuals were shown on three curved screens with full High Definition (HD) resolution (1920 x 1080 pixels), providing a 145° field of view of the driving environment. The driving scenario was created in SCANeR Studio [42].

The protocol was designed and conducted in accordance with the Code of Ethics for researchers and the Guidelines for Ethical Conduct in Research Involving People issued by the University of Ljubljana (approval #049-2025). Prior to participation, written informed consent was obtained from all participants. Participation in the study was on a voluntary basis, and the participants could stop their participation at any point.

Participants first completed a demographic questionnaire, adjusted the drivers' seat, and mounted and calibrated the eye tracker. The entire measurement lasted approximately 30 minutes and consisted of three consecutive stages (baseline, normal driving conditions, and fog).

During baseline, participants were asked to sit still and relax for 15 minutes. After baseline, participants familiarized themselves with the simulator setup, including vehicle controls and task execution. Then they started the driving sessions by driving on the highway during normal conditions. After 10 minutes weather conditions suddenly changed, and dense fog appeared along the highway, which lasted for around 2 minutes (Fig. 2). Participants' main task was only to drive safely and successfully reach the final destination.

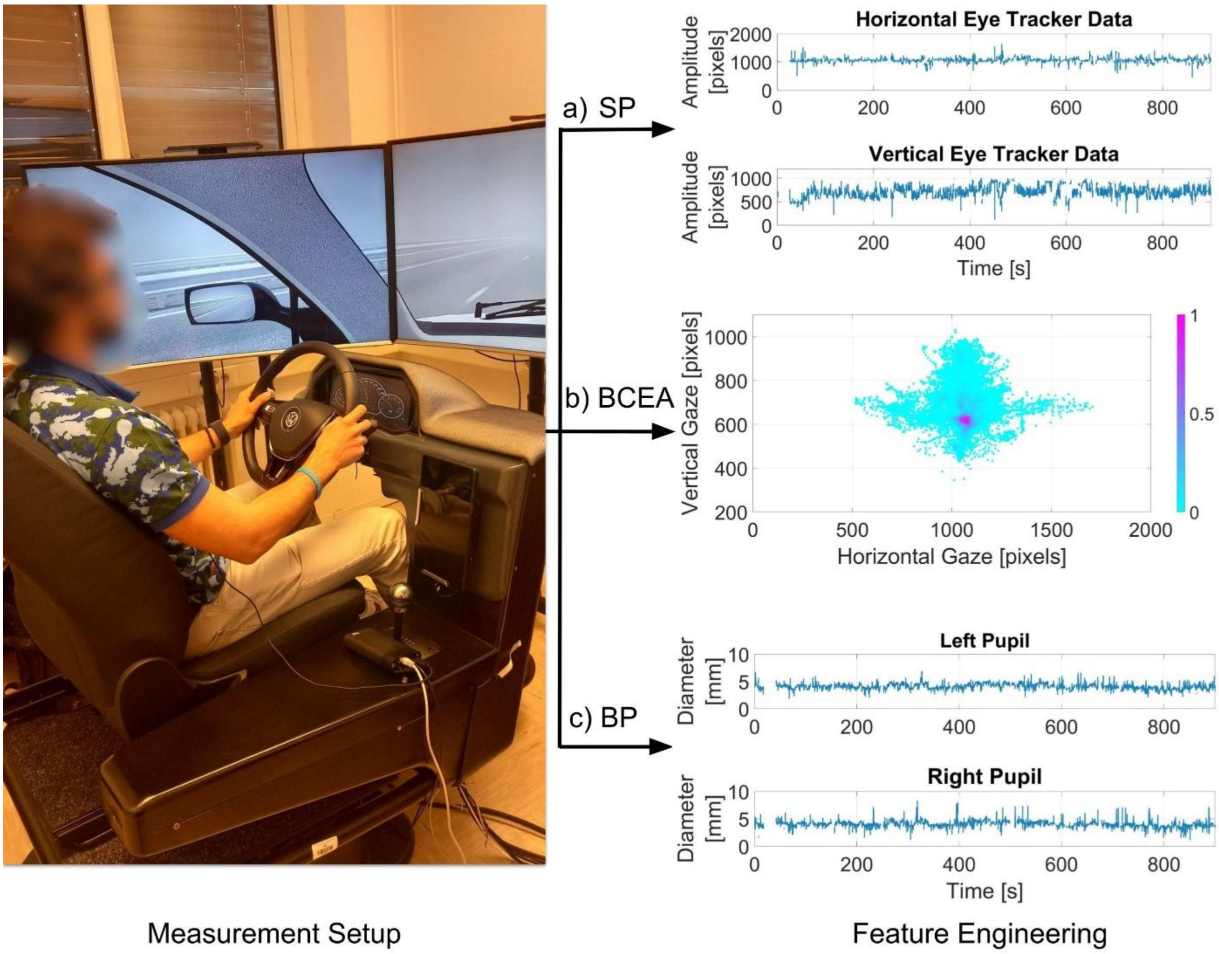

Fig. 1. Environment of a driving simulator and measured sample signals. a) Raw signals of the horizontal and vertical degree of visual angle. b) Scatter heat map of horizontal and vertical gaze point plots during the experiment. c) Diameter of the left and right pupils used for blink detection. SP - Saccade Parameters. BCEA - Bivariate Contour Ellipse Area. BP - Blinking Parameters.

2.2. Data Acquisition

Overall, 28 participants (17 males and 11 females) aged from 21 to 42 (average age = 25.64, SD = 5.76) with normal or corrected-to-normal vision, who held a drivers' license (average year = 6.9, SD = 5.96), completed a task in a driving simulator (with aural instructions provided by the system on how to complete the driving task). As described in the previous paragraph, the task included Baseline, driving under normal conditions (Ride), and driving during fog (which will be referred to as Fog throughout the manuscript). Participants' eye movements were recorded with the Tobii Pro Glasses 3 eye tracker [41], with a sampling frequency of 100 Hz and stored for further analysis.

a)

b)

Fig. 2. Sample snapshots from the simulator. a) Driving during normal visibility (Ride). b) Driving during lower visibility (Fog).

2.3. Preprocessing

All processing steps are performed in MATLAB R2021a (The Mathworks, Natick, USA). Due to the data loss (one participant had complete data loss, another had only baseline data, and two had partial recordings), the data of 4 participants are excluded, and the recordings obtained from 24 participants are analyzed. For further analysis, normalized coordinates that indicate the participants' gaze position as a proportion of the screen's width and height are used. These normalized coordinates are then converted into pixel-based resolution (1920 x 1080). To reduce inaccuracies and distortions inherent in the eye tracking data [43, 44], missing or invalid samples are removed from the dataset to ensure continuity [45]. The remaining data are then smoothed using a third-order Savitzky-Golay filter [46], with an 11-sample window corresponding to 110 ms at the sampling frequency of 100 Hz [47]. The window width was selected to reduce high-frequency noise while preserving the main signal features effectively, following approaches used in similar eye tracking studies [48]. After preprocessing, the data are analyzed using the Identification - Velocity Threshold (I-VT) algorithm to extract relevant eye movement parameters, blinks are identified based on signal loss in the pupil data, and BCEA parameters are calculated (Fig. 3).

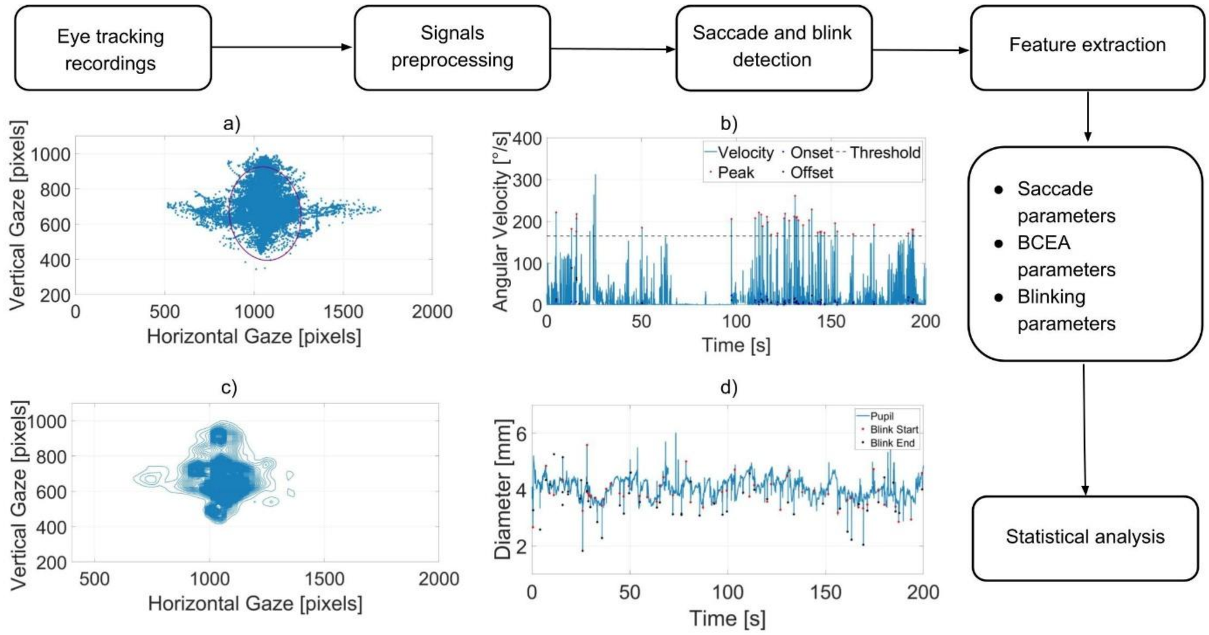

Fig. 3. Proposed methodological approach. a) Scatter plot of horizontal and vertical gaze point plots during the experiment with BCEA. b) Detected saccades on angular velocity profiles during the first 200 s of Baseline. c) Contour plots for detecting the number of Preferred Retina Locus (PRLs). d) Detected blinks on the left pupil diameter during the first 200 s of Baseline.

2.4. Saccade Detection

Instead of using raw gaze coordinates, saccade detection is performed on angular velocity, calculated from the Cartesian gaze coordinates according to Eq. (1):

$$\dot{\theta} = \sqrt{(\phi_1 \dot{x})^2 + (\phi_2 \dot{y})^2} \quad (1)$$

where $\dot{x}$ and $\dot{y}$ represent Cartesian velocities (the first derivative of x and y), while ϕ_1 and ϕ_2 represent pixel-to-angle transformation factors, which are calculated based on the Tobii user manual [41] as 95°/1920 and 63°/1080, respectively. Velocities higher than 1000°/s are considered to be physiologically impossible, so they are omitted from the analysis, as well as values lower than the signal median [49].

The adaptive I-VT algorithm improves upon the original I-VT algorithm by determining the optimal value of the multiplier parameter n [50]. The calculation of the adaptive threshold is shown in :

$$AT_{i+1} = mean(vel < AT_i) + n * sd(vel < AT_i) \quad (2)$$

where AT_{i+1} represents the adaptive threshold in i^{th} iteration, sd standard deviation, n represents the multiplier parameter, and vel is the eye movement velocity profiles obtained by the central difference method [49, 50]. Optimization of the parameter n begins by defining a range between 2.5 and 6, using a step of 0.5 [50]. Afterwards, the optimal parameter n is determined by calculating the misdetections of the saccades. As a criterion for calculating the misdetections, the psychological duration of the saccades is used as proposed in [51]. Saccades with a duration shorter than 10 ms or longer than 100 ms are classified as misdetections [49, 50, 52]. In the Nyström-Holmqvist adaptive algorithm, the saccade peak velocity, θ_{PT} is set to an initial value within the range 100-300°/s. After setting to an initial value, a new threshold is calculated for all velocity samples lower than θ_{PT} as:

$$\theta_{PT} = \mu + \lambda\sigma \quad (3)$$

where μ is the mean, σ is the velocity standard deviation, and λ is a scale factor set to 6. This procedure is then repeated until the error between iterations is less than 1°/s. To determine saccade onsets, the algorithm looks back in time from the putative saccade until it reaches the first point that crosses the saccade onset threshold defined in Eq. (4):

$$\theta_{ST}^{onset} = \mu + 3\sigma \quad (4)$$

If the algorithm detects that a certain threshold has been crossed, it will go back in time to find the nearest local velocity minimum, which is considered the saccade onset. The process is similar for saccade offsets, except that the threshold for saccade offsets is defined differently:

$$\theta_{ST}^{offset} = 0.7\theta_{ST}^{onset} + 0.3LocalNoise \quad (5)$$

The velocity signal average and 3 times the standard deviation are calculated in the 40 ms before the saccade starts and represent $LocalNoise,$ as presented by Nyström and Holmqvist [49] with the initial value for the threshold set to 200°/s. The initial value is set to 200°/s using error and trials. After saccade detection, numerous parameters are calculated and described in Table 1, including saccade amplitude, saccade duration, peak velocity, and fixation duration. For each subject, the mean, SD, and median of each parameter across all saccades are computed.

Table 1. Description of calculated saccade parameters

Parameter	Explanation	Expectation	Reference(s)
Saccade amplitude [°]	The angle of eye movement from the beginning to the end of a saccade.	More complex driving situations, like navigating bends or tunnels, may lead to smaller saccade amplitudes as drivers focus on specific details.	[2, 53, 54]
Peak saccade velocity [°/s]	The maximum speed achieved during a saccade.	Peak velocities should be lower during mental attentional demand.	[55, 56]
Saccade duration [ms]	The duration of a saccade, measured from its initiation to its termination, typically ranges from 30 to 80 milliseconds.	Duration may be prolonged during driving and shorter than 200 ms.	[2]
Number of detected saccades [a. u.]	Quantification of detected saccadic eye movements.	An increased number of saccades is expected during driving and cognitive load.	[57]
Fixation duration [ms]	Duration spent on a single fixation point, approximately 200-300 ms	Fixations during Baseline are expected to be longer and more stable, while driving may elicit shorter fixations due to the need for rapid visual sampling.	[58-60]

2.5. BCEA

BCEA, Bivariate Contour Ellipse Area, is proposed in [61] as a means to assess PRL quantitatively, calculated using Eq. (6):

$$\text{BCEA} = 2\pi k \sigma_x \sigma_y \sqrt{1 - \rho^2} \quad (6)$$

where σ_x and σ_y are the standard deviations of the horizontal and vertical eye movements, and ρ is the Pearson product-moment correlation coefficient of the horizontal and vertical eye movements, with $k = 3$ corresponding to a probability value of 0.95 [61]. To assess fixation stability, we calculate the BCEA [61, 62]. Thus, a small BCEA corresponds to a high fixation stability, while a larger BCEA suggests more variability in fixation. Previously, the BCEA was used to determine how people look while watching a movie [63] or to calculate the Preferred Retinal Locus (PRL) for patients with eye diseases, such as glaucoma or macular degeneration [61-66]. In the context of driving, BCEA is valuable as it provides insights into visual attention and distraction. A smaller BCEA indicates more stable fixation and higher attention, while a higher BCEA represents increased wandering and potential distraction. The additional parameters shown in Table 2, including the mean and standard deviation of gaze points, correlation coefficient (ρ), and number of PRLs. GI, Mean Squared Error (MSE), and sample and approximate entropy, together, offer a comprehensive representation of fixation behavior and gaze stability.

Originally introduced in electrocardiography for analysis of heart rate variability, Guzik's index (GI) quantifies asymmetry in heart rate variability by comparing magnitudes of acceleration and deceleration in successive RR intervals [67]. Similarly, in this study, GI is calculated to quantify the anisotropy of gaze dispersion relative to the major axes of the BCEA ellipse. First, gaze coordinates are centered by subtracting the mean horizontal and vertical positions from each sample. These centered data points are projected on the major and minor axes of the BCEA ellipse to obtain the components of gaze variability parallel and perpendicular to the main direction of dispersion. GI is calculated as the ratio of the standard deviation along the major and along the minor axis, presented in Eq. (7):

$$GI = \frac{SD_{parallel}}{SD_{perpendicular}} \quad (7)$$

Table 2. List of parameters for BCEA analysis

Parameter	Explanation	Expectation	Reference(s)
Mean value of horizontal and vertical gaze data [°]	Average value of a participants' gaze along the horizontal and vertical axes	During Baseline, horizontal and vertical positions are expected to remain close to the display center, while during driving, they are expected to increase.	[60]
Standard deviation of horizontal and vertical gaze data [°]	Amount of variation in the horizontal and vertical position, indicating how much individual gaze positions deviate from the average position	Higher standard deviation is expected during driving, especially for the horizontal gaze position	Proposed here
ρ [a.u.]	Pearson product-moment correlation coefficient of the horizontal and vertical eye movements	ρ should potentially increase during driving, due to coordinated diagonal gaze movements when scanning the roadway	Proposed here

Parameter	Explanation	Expectation	Reference(s)
BCEA $[minarc^2]$	Bivariate Contour Ellipse Area	Higher BCEA is expected during Baseline, and lower BCEA during driving.	Proposed here and previously used in clinical research [61]
PRL [a.u.]	Preferred Retinal Locus	The number of PRLs is expected to be higher while driving.	[61]
Guzik's index (GI) [deg²]	Measurement of the asymmetry of BCEA	GI is expected to be higher during driving, reflecting more time spent above or below the major axis of the fixation ellipse.	Proposed here and previously used for Poincaré plot (Piskorski and Guzik, 2007) [67, 68]
MSE [deg²]	Mean Squared Error is used as a metric of the asymmetry of BCEA.	MSE is expected to be higher during driving, while fixations spread more around the ellipse major axis.	Proposed here
Sample entropy of horizontal and vertical gaze data [a. u.]	Measure of irregularity of gaze positions in horizontal and vertical data	Higher values indicate greater irregularity, while lower values indicate more regularity	Proposed here
Approximate entropy of horizontal and vertical gaze [a. u.]	Similar to sample entropy, but less robust	During driving, approximate entropy is expected to decrease.	Proposed here

2.6. Blink Detection

Besides saccades, blinking and precise frequency of blinking represent crucial parameters to determine the level of fatigue and attention [2, 69]. Blink duration is expected to be between 150 and 500 ms, with 50 milliseconds of fully closed eyes [70, 71]. For adults, the blink rate is between 16 and 20 blinks [71], while the amplitude is between 10 and 60° [72, 73]. Changes in blink rate, duration, or amplitude can signal shifts in cognitive state, with prolonged or more frequent blinks often associated with increased fatigue and drowsiness [69, 70]. Blink detection is performed on pupil diameter signals recorded at a sampling frequency of 100 Hz, following the procedure described in [73]. To reduce the impact of prolonged signal loss due to artifacts unrelated to blinks, missing intervals longer than 200 consecutive samples (equivalent to 2 s at a 100 Hz sampling rate) are excluded from the analysis [74, 75], while shorter gaps are preserved as potential blink candidates. Blink events are defined as continuous sequences of missing pupil samples that satisfy specific temporal criteria. A minimum blink duration of 100 ms and a maximum duration of 400 ms are applied to ensure physiological plausibility [76, 77]. For each blink, the onset, the offset, and the blink duration are computed, as well as the blink rate. Parameters calculated for blink detection are described in Table 3.

Table 3. Description of calculated parameters for blink detection

Parameter	Explanation	Expectation	Reference(s)
Blink duration [ms]	The length of time during which the eyelids are closed during a blink	Longer blink durations are an indicator that a driver might be experiencing fatigue or increased workload.	[63, 78, 79]
Blink rate [a.u.]	Count of blinks detected during a specific period	Drowsiness can lead to a decreased blink rate.	[80]
Number of detected blinks per minute [a.u.]	Frequency of blinking in one minute.	The average adult blinks around 15 - 20 times during one minute.	[81]

2.7. Statistical analysis

A *post-hoc* power analysis is conducted using G*Power [82] for the repeated measures Analysis of Variance (ANOVA) with three conditions (Baseline, Ride, and Fog). Using the observed average effect size across variables (Cohen's $d = 0.33$) and within-subject correlation $\rho = 0.54$, G*Power estimated the statistical power to be 0.95, with an error probability $\alpha = 0.05$.

To assess differences in saccade detection parameters, BCEA parameters, and blink detection parameters across conditions, Baseline, Ride, and Fog, statistical analysis is performed. All steps of statistical analysis are conducted using the Python 3.12 programming language [83]. The following Python libraries are used for the realization of this research: NumPy [84], Pandas [85-87], SciPy [88], StatsModels [89], Seaborn [90], Matplotlib [91], Pingouin [92], Scikit-Posthocs [93], and IterTools [94]. During preprocessing, missing values are imputed using the median value [95]. For each eye tracking metric, data across Baseline, Ride, and Fog conditions are tested for normality using the Shapiro-Wilk test. Parametric variables are analyzed using repeated measures ANOVA, while non-parametric variables are analyzed using the Friedman test. *p*-values are corrected using Benjamini-Hochberg false discovery rate (FDR) correction. Significant effects are followed by pairwise comparisons using paired t-tests (Cohen's *d*) or Wilcoxon signed-rank tests (Cliff's δ).

3. Results

To get visual insight into the differences of Baseline, Ride, and Fog, boxplots are provided (Figs. 4-6) for all three groups of features: saccades, BCEA, and blinking parameters. In Figs. 4-6, separate colors are used to distinguish among three states: black for Baseline, blue for Ride, and purple for driving during Fog.

3.1. Saccade Detection

The results of the statistical analysis for saccade parameters are presented in Table 4, which includes only statistically significant *post-hoc* comparisons ($p < 0.05$). The Friedman test reveals significant effects of condition for most parameters, indicating that saccade behaviour differs across Baseline, Ride, and Fog conditions. *Post-hoc* pairwise comparisons show that the mean and median saccade amplitudes are significantly greater during Ride and Fog compared to Baseline ($p < 0.01$) with small to medium sizes (Cliff's δ = -0.19 to -0.34). Similarly, mean saccade duration is significantly greater in Baseline relative to Ride with a medium effect ($p < 0.01$; Cliff's $\delta = 0.38$).

Peak saccade velocity shows small differences between Ride and Fog ($p < 0.05$), suggesting that velocity dynamics remain relatively stable. However, fixation-related parameters demonstrate robust condition effects: mean and standard deviation of fixation duration are significantly higher during Baseline compared to Ride and Fog ($p < 0.001$) with a very large effect (Cliff's $\delta = 0.74$). The median fixation duration follows a similar trend ($p < 0.01$), with a large effect (Cliff's $\delta = 0.62 - 0.64$). The total number of saccades is reduced in Ride and Fog relative to Baseline ($p < 0.001$), indicating a very large effect size (Cliff's $\delta > 0.76$).

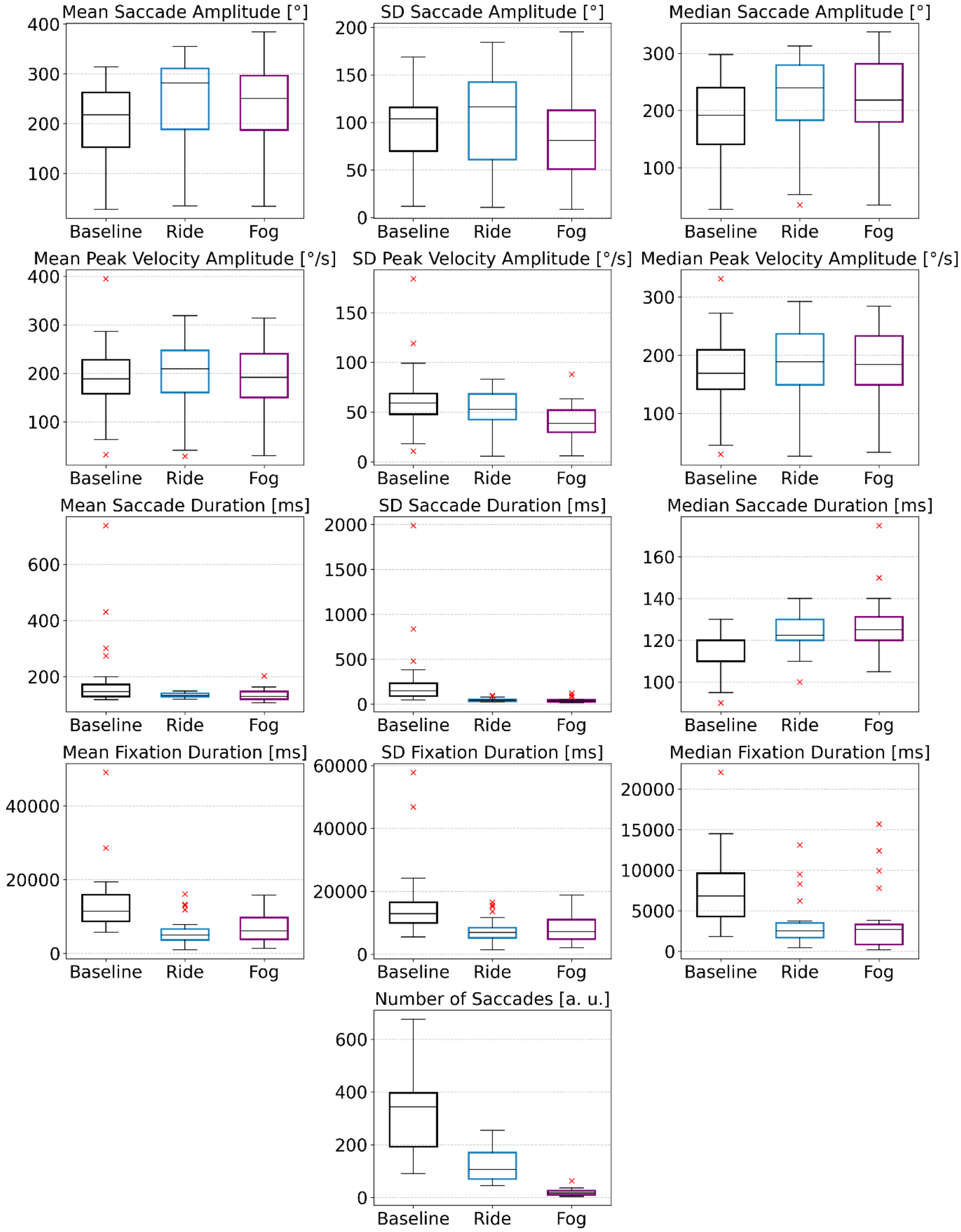

Fig. 4: Boxplots for saccade parameters. SD – Standard Deviation.

Table 4. Results of the statistical test for saccade parameters, significant difference *post-hoc* test (*p*-value > 0.05). SD – Standard Deviation. Statistically significant changes between Ride and Fog are marked in bold.

Parameter	Condition	*p* – value	Effect	Effect Size	Interpretation
Mean Saccade Amplitude [°]	Baseline *vs* Ride	<0.001	Cliff's *δ*	-0.34	medium
	Baseline *vs* Fog	<0.01		-0.19	small
SD Saccade Amplitude [°]	**Ride *vs* Fog**	**<0.05**	**Cohen's *d***	**0.42**	**medium**
Median Saccade Amplitude [°]	Baseline *vs* Ride	<0.001	Cliff's *δ*	-0.29	small
	Baseline *vs* Fog	<0.001		-0.24	small
Mean Peak Velocity Amplitude [°/s]	**Ride *vs* Fog**	**<0.05**	**Cohen's *d***	**0.11**	**small**
SD Peak Velocity Amplitude [°/s]	Baseline *vs* Fog	<0.001	Cliff's *δ*	0.50	large
	Ride *vs* Fog	**<0.01**		**0.35**	**medium**
Mean Saccade Duration [ms]	Baseline *vs* Ride	<0.01	Cliff's *δ*	0.38	medium
SD Saccade Duration [ms]	Baseline *vs* Ride	<0.001	Cliff's *δ*	0.87	very large
	Baseline *vs* Fog	<0.001		0.89	very large
Median Saccade Duration [ms]	Baseline *vs* Ride	<0.01	Cliff's *δ*	-0.57	large
	Baseline *vs* Fog	<0.01		-0.55	large
Mean Fixation Duration [ms]	Baseline *vs* Ride	<0.001	Cliff's *δ*	0.74	very large
	Baseline *vs* Fog	<0.001		0.63	large
SD Fixation Duration [ms]	Baseline *vs* Ride	<0.001	Cliff's *δ*	0.66	large
	Baseline *vs* Fog	<0.001		0.57	large
Median Fixation Duration [ms]	Baseline *vs* Ride	<0.001	Cliff's *δ*	0.64	large
	Baseline *vs* Fog	<0.001		0.62	large
Number of Saccades [a. u.]	Baseline *vs* Ride	<0.001		0.76	very large
	Baseline *vs* Fog	<0.001	Cliff's *δ*	1.00	very large

Parameter	Condition	*p* – value	Effect	Effect Size	Interpretation
	Ride *vs* Fog	**<0.001**		**0.98**	**very large**

3.2. BCEA

Statistical results for BCEA parameters are presented in Table 5 with statistically significant *post-hoc* comparisons ($p < 0.05$). Mean horizontal gaze during Ride is higher than during Fog conditions ($p < 0.001$; negligible effect), while the mean value for vertical gaze has a medium effect comparing Baseline to Ride and Fog ($p < 0.001$; Cliff's $\delta = 0.44$). The SD of horizontal and vertical gaze is compared across Baseline, Ride, and Fog conditions. For horizontal gaze, significant differences are observed across all comparisons. The decrease from Baseline to Ride is statistically significant ($p < 0.001$), but has a small effect (Cliff's $\delta = 0.24$). In contrast, both Baseline *vs* Fog ($p < 0.001$; Cliff's $\delta = 0.59$) and Ride *vs* Fog ($p < 0.001$; Cliff's $\delta = 0.53$) show large effects, indicating that Fog decreases horizontal gaze variability.

For SD of vertical gaze, both Baseline *vs* Ride ($p < 0.001$; Cohen's $d = 1.34$) and Baseline *vs* Fog ($p < 0.001$; Cohen's $d = 1.70$) demonstrate significant and large effects, reflecting pronounced changes in vertical gaze variability under Ride and Fog conditions compared to Baseline. The difference between Ride and Fog is significant ($p < 0.001$), but has a medium effect, suggesting that vertical gaze variability changes moderately between these conditions.

The correlation coefficient, ρ, shows a huge effect for both Baseline *vs* Ride ($p < 0.001$; Cohen’s $d = 3.03$) and Baseline *vs* Fog ($p < 0.001$; Cohen’s $d = 2.55$), indicating a strong difference in gaze correlation between these conditions. For the BCEA, significant increases are observed across all comparisons ($p < 0.001$), indicating a substantial expansion of gaze dispersion during the Baseline. Significant differences are also found for the number of PRLs in all comparisons, with a large effect, indicating a reduced number of PRLs under Baseline and Ride conditions. GI is significantly higher in Baseline than in Ride and Fog ($p < 0.01$; Cohen's $d > 0.76$), while MSE is significantly higher in Baseline than in Ride ($p < 0.001$; Cliff's $\delta = 0.47$; medium effect), higher in Baseline than in Fog ($p < 0.001$; Cliff's $\delta = 0.74$; very large effect), and higher in Ride than in Fog ($p < 0.001$; Cliff's $\delta = 0.51$; large effect), suggesting that gaze variability is lowest under the Fog simulation conditions.

A small but statistically significant difference is observed in the calculated sample entropy of horizontal gaze between the Ride and Fog conditions, with a medium effect ($p < 0.001$; Cliff's $\delta = -0.46$), indicating a slightly lower horizontal gaze complexity during Ride compared to Fog conditions. In contrast, vertical gaze entropy shows larger and more consistent differences across conditions. Specifically, sample entropy in the vertical direction is significantly reduced during Baseline compared to Fog conditions ($p < 0.05$; Cliff’s $\delta = -0.24$; small effect) and lower during Ride compared to Fog conditions ($p < 0.05$; Cliff’s $\delta = -0.23$; small effect), reflecting an increase in vertical gaze complexity under Fog. Similarly, approximate entropy in the vertical direction is significantly higher during Ride compared to Fog ($p < 0.001$; Cliff’s $\delta = 0.41$; medium effect), reflecting increased irregularity and complexity of vertical gaze behavior in normal visibility compared to Fog conditions.

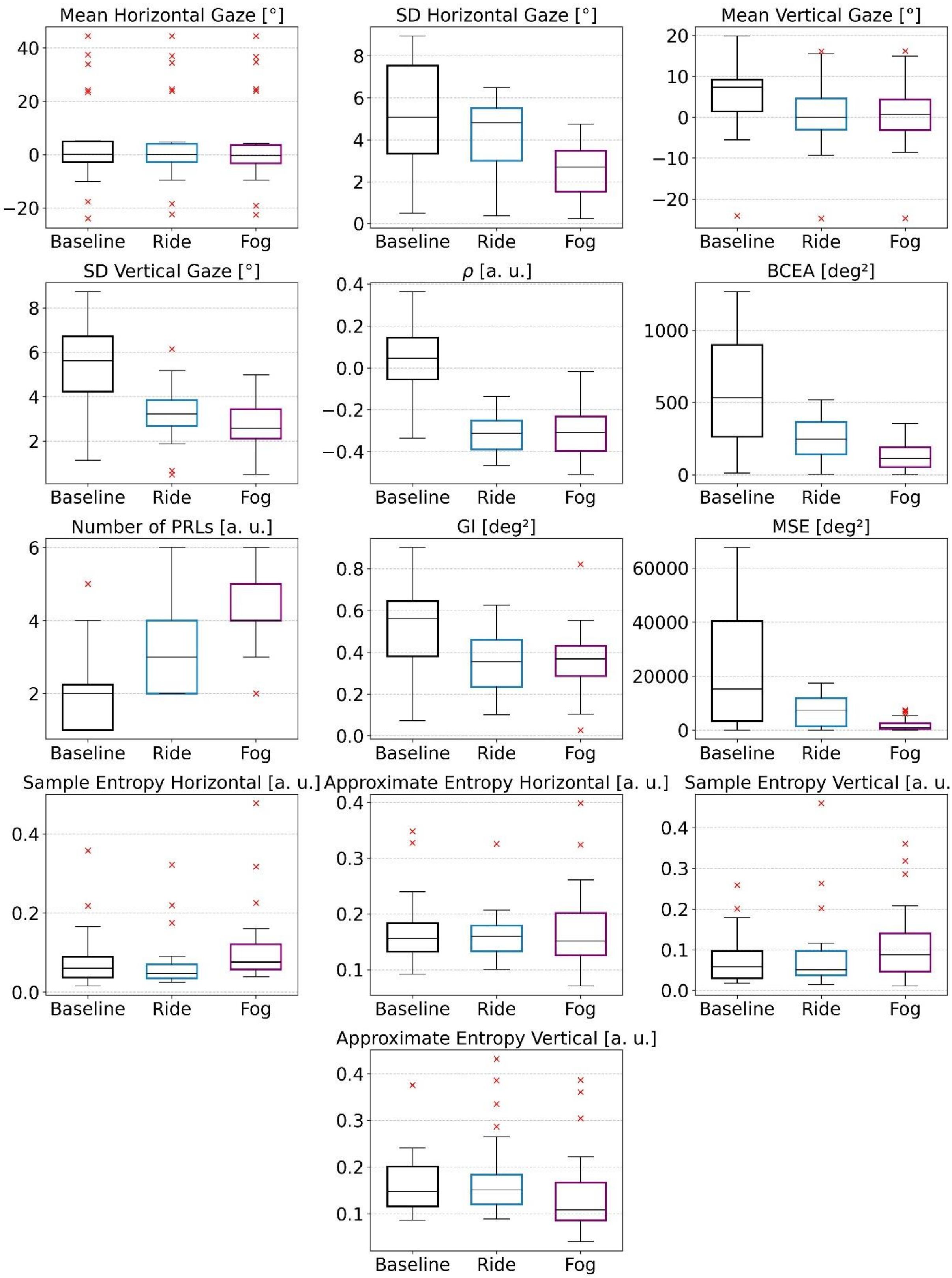

Fig. 5: Boxplots for BCEA parameters. SD – Standard Deviation, BCEA – Bivariate Contour Ellipse Area, PRL – Preferential Retinal Locus, GI - Guzik's Index, MSE - Mean Squared Error.

Table 5. Results of the statistical test for BCEA, significant difference *post-hoc* test (p-value > 0.05). SD – Standard Deviation, BCEA – Bivariate Contour Ellipse Area, PRL – Preferential Retinal Locus, GI - Guzik's Index, MSE - Mean Squared Error. Statistically significant changes between Ride and Fog are marked in bold.

Parameter	Condition	*p* – value	Effect	Effect Size	Interpretation
Mean Horizontal Gaze [°]	**Ride *vs* Fog**	**<0.001**	**Cliff's *δ***	**0.05**	**negligible**
SD Horizontal Gaze [°]	Baseline *vs* Ride	<0.001	Cliff's *δ*	0.24	small
	Baseline *vs* Fog	<0.001		0.59	large
	Ride *vs* Fog	**<0.001**		**0.53**	**large**
Mean Vertical Gaze [°]	Baseline *vs* Ride	<0.001	Cliff's *δ*	0.44	medium
	Baseline *vs* Fog	<0.001		0.44	medium
SD Vertical Gaze [°]	Baseline *vs* Ride	<0.001	Cohen's *d*	1.34	huge
	Baseline *vs* Fog	<0.001		1.70	huge
	Ride *vs* Fog	**<0.001**		**0.42**	**medium**
ρ [a. u.]	Baseline *vs* Ride	<0.001	Cohen's *d*	3.03	huge
	Baseline *vs* Fog	<0.001		2.55	huge
BCEA [minarc²]	Baseline *vs* Ride	<0.001	Cohen's *d*	1.06	very large
	Baseline *vs* Fog	<0.001		1.53	huge
	Ride *vs* Fog	**<0.001**		**0.89**	**very large**
Number of PRLs [a. u.]	Baseline *vs* Ride	<0.05	Cliff's *δ*	-0.49	large
	Baseline *vs* Fog	<0.01		-0.70	large
	Ride *vs* Fog	**<0.05**		**-0.49**	**large**
GI [deg²]	Baseline *vs* Ride	<0.01	Cohen's *d*	0.88	very large
	Baseline *vs* Fog	<0.01		0.76	large
MSE [deg²]	Baseline *vs* Ride	<0.001		0.47	medium

Parameter	Condition	*p* – value	Effect	Effect Size	Interpretation
	Baseline *vs* Fog	<0.001	Cliff's δ	0.74	very large
	Ride *vs* Fog	**<0.001**		**0.51**	**large**
Sample Entropy Horizontal [a. u.]	Baseline *vs* Fog	<0.05	Cliff's δ	-0.31	small
	Ride *vs* Fog	**<0.001**		**-0.46**	**medium**
Sample Entropy Vertical [a. u.]	Baseline *vs* Fog	<0.05	Cliff's δ	-0.24	small
	Ride *vs* Fog	**<0.05**		**-0.22**	**small**
Approximate Entropy Vertical [a. u.]	**Ride *vs* Fog**	**<0.001**	Cliff's δ	**0.41**	**medium**

3.3. Blink Detection

Blinking behaviour is analyzed to assess changes in ocular activity during Baseline, Ride, and Fog conditions (Table 6). Results reveal that both the mean ($p < 0.001$; Cliff's $\delta > 0.90$; very large effect) and median ($p < 0.05$; Cliff's $\delta > 0.70$; very large effect) blink durations are significantly reduced during Ride and Fog compared to Baseline, indicating that blinks become shorter under these conditions. Similarly, the Standard Deviation (SD) of blink duration decreases significantly in Ride and Fog relative to Baseline ($p < 0.01$; Cliff's $\delta > 0.80$; very large effect). Blink rate is significantly higher in Ride and Fog than Baseline ($p < 0.001$; Cliff's δ = 0.95-0.99; very large effect), and medium effect comparing Ride and Fog ($p < 0.001$, Cliff's δ =0.39). The number of detected blinks per minute is elevated in Ride and Fog *versus* Baseline ($p < 0.001$; Cliff's δ = 0.89-0.91; very large effect), with a small, but statistically significant difference between Ride and Fog ($p < 0.01$; Cliff's δ = 0.39).

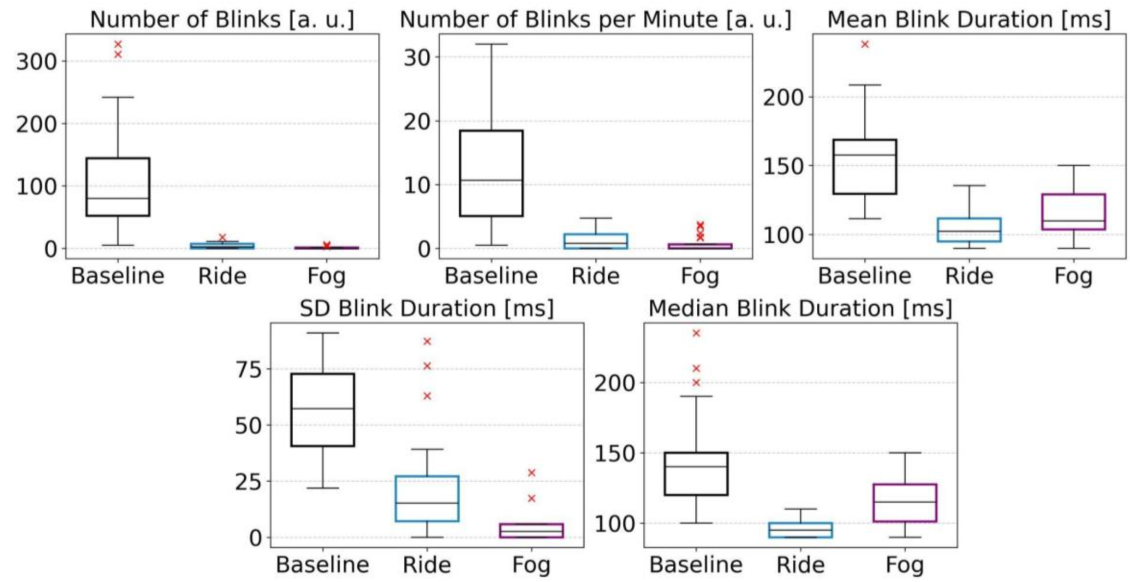

Fig. 6: Boxplots for blinking parameters. SD – Standard Deviation.

Table 6. Results of the statistical test for blinking parameters, significant difference *post-hoc* test (*p*-value > 0.05). SD – Standard Deviation. Statistically significant changes between Ride and Fog are marked in bold.

Parameter	Condition	*p* – value	Effect	Effect Size	Interpretation
Mean Bllink Duration [ms]	Baseline *vs* Ride	<0.01	Cliff's δ	0.95	very large
	Baseline *vs* Fog	<0.01		0.90	very large
SD Blink Duration [ms]	Baseline *vs* Fog	<0.01	Cliff's δ	1.00	very large
	Ride *vs* Fog	**<0.01**	Cliff's δ	**0.80**	**very large**
Median Blink Duration [ms]	Baseline *vs* Ride	<0.01	Cliff's δ	1.00	very large
	Baseline *vs* Fog	<0.01		0.70	large
	Ride *vs* Fog	**<0.05**		**-0.68**	**large**
Blink Rate [a.u.]	Baseline *vs* Ride	<0.001	Cliff's δ	0.95	very large
	Baseline *vs* Fog	<0.001		0.99	very large
	Ride *vs* Fog	**<0.001**		**0.39**	**medium**
Number of Detected Blinks per Minute [a.u.]	Baseline *vs* Ride	<0.001	Cliff's δ	0.88	very large
	Baseline *vs* Fog	<0.001		0.91	very large
	Ride *vs* Fog	**<0.01**		**0.32**	**small**

4. Discussion

The present study examined oculomotor behavior across different conditions by analyzing three groups of features obtained from eye movement measurements: saccade parameters, BCEA parameters, and blinking behavior. Comparing the obtained results, the mean and median saccade amplitudes significantly increased during Ride and Fog conditions, compared to Baseline, which is contrary to initial expectations that a more demanding visual environment leads to smaller gaze shifts [2, 53, 54].

4.1. Saccade Detection: Eye Movement Dynamics

Specifically, values obtained during Baseline are lower than during Ride and Fog conditions, with small and medium effects (Cliff's δ = -0.24 to -0.34). These results suggest that under increased visual and cognitive load, participants perform larger gaze shifts to extract more information from the environment. Similar findings were reported in previous studies, where saccade amplitude decreased in congested traffic due to environmental complexity, but increased during distracted or multitasking states, such as hands-free, video call, and texting messages [96, 97]. Mean saccade duration decreases during the Ride, which does not align with the prediction that saccades would become slightly longer under higher visual and cognitive load [97]. However, some previous research also showed that introducing central greenery landscapes increases the cognitive demands on drivers as they navigate a visually more complex environment, leading to more extensive saccades, which is in line with our results [98].

Earlier findings showed that peak saccade velocity decreased during mental fatigue [56, 99, 100]. In particular, Bachurina and Arsalidou (2022) reported a significant main effect of mental attention demand on peak saccade velocity, indicating a moderate reduction in saccade speed with increased cognitive load [55]. In the present study, peak saccade velocity showed only small effects ($p < 0.05$, Cliff's $\delta = 0.11$), suggesting that velocity changes, but not overly dramatic. This discrepancy may reflect differences in task design, as the simulated driving environment likely elicited more naturalistic gaze behaviour and smaller variations in visual demand compared to the structured attention task.

Fixation time typically decreases when a driver is familiar with the road environment [101], suggesting that experience and expectation of the scene allow for faster extraction of relevant information. Based on expectations, fixations during Baseline are anticipated to be longer and more stable, whereas driving tasks are expected to elicit shorter fixations. In line with this, fixation durations significantly decrease under both Ride and Fog conditions, indicating shorter and more frequent fixations. Mean fixation duration is lower during Ride (very large effect, Cliff's $\delta = 0.74$, $p < 0.001$) and Fog (large effect, Cliff's $\delta = 0.63$, $p < 0.01$). Variability, precisely a standard deviation of fixation duration, is reduced in both driving conditions (Ride: large effect, Cliff's $\delta = 0.66$, $p < 0.001$, Fog: large effect, Cliff's $\delta = 0.57$, $p < 0.001$). Median fixation durations followed the same trend, showing shorter fixations under Ride state (large effect, Cliff's $\delta = 0.64$, $p < 0.001$) and Fog (large effect, Cliff's $\delta = 0.62$, $p < 0.001$).

The number of detected saccades decreased across driving conditions, especially during Fog. The observed decrease in the number of detected saccades under Ride and Fog conditions is consistent with findings from tunnel driving studies [102]. Wang *et. al.* reported that drivers' number of saccades and saccade amplitude initially decreased upon entering the tunnel, and then gradually increased under reaching a stable value inside the tunnel. Experienced drivers in daytime conditions reduced their mean saccades from 3.79 times per second at 250 m before the tunnel entrance to 3.40 times per second at 30 m inside the tunnel, later stabilizing at 3.62 times per second. Novice drivers showed a decrease reaching minima of 3.25-3.33 times per second before gradually increasing to stable values around 3.45-3.51 times per second [102]. In our study, saccade number decreased significantly under Ride and Fog conditions (Baseline *vs*. Ride: very large effect, Cliff's $\delta = 0.76$, $p < 0.001$, Baseline *vs* Fog: very large effect, Cliff's $\delta = 1$, $p < 0.001$, Ride *vs* Fog: very large effect, Cliff's $\delta = 0.98$, $p < 0.001$).

4.2. BCEA: Is Gaze Variability a Reliable Indicator of Visual Attention?

To further characterize gaze behaviour, calculation of BCEA parameters is presented during Baseline and driving conditions in Table 5, providing additional insight into the spatial dispersion of eye movements. Parameters such as mean vertical gaze and SD of horizontal and vertical gaze decreased during driving conditions, indicating a larger, wider dispersion across the visual field during Baseline. In contrast, during driving, both horizontal and vertical gaze values typically increase as drivers scan the environment and monitor peripheral areas [103]. This broader distribution of gaze reflects active visual exploration and engagement with the driving environment, particularly under conditions of reduced visibility or increased task demand [103, 104].

Previous studies have reported a significant main effect of screen manipulation on horizontal gaze dispersion, with *post-hoc* analyses showing differences between no Fog and heavy Fog + secondary task conditions ($p < 0.05$) [103]. Horizontal scanning remained similar when drivers experienced full visibility and complete occlusion ($p = 0.66$), indicating consistent horizontal scanning patterns across conditions [103]. Engagement of Adaptive Cruise Control (ACC) showed that horizontal gaze dispersion was significantly reduced when ACC was engaged ($p < 0.001$), indicating that cognitive distraction and environmental complexity had no significant effect on horizontal scanning ($p = 0.88$; $p = 0.79$). Vertical gaze dispersion increased under cognitive distraction ($p < 0.01$) and with higher environmental complexity ($p < 0.05$), indicating that vertical gaze was more sensitive to task and environmental demands [105]. Our results align with these findings. In our study, the mean horizontal gaze during Ride is higher than during Fog ($p < 0.001$; negligible effect), while the mean vertical gaze shows a medium effect comparing Baseline to Ride and Fog ($p < 0.001$; Cliff's $\delta = 0.44$). The SD of horizontal gaze decreases from Baseline to Ride ($p < 0.001$; Cliff's $\delta = 0.24$) but shows a large effect when comparing Baseline *vs* Fog ($p < 0.001$; Cliff's $\delta = 0.59$) and Ride *vs* Fog ($p < 0.001$; Cliff's $\delta = 0.53$), indicating that Fog strongly reduces horizontal gaze variability. For vertical gaze, large effects are observed for Baseline *vs* Ride ($p < 0.001$; Cohen's $d = 1.34$) and Baseline *vs* Fog ($p < 0.001$; Cohen's $d = 1.70$), with a medium effect for Ride vs Fog, reflecting that vertical gaze variability is highly sensitive to changes in visual conditions. Time-of-day effects also modulated gaze behavior. Previous studies have shown that drivers fixate closer to the vehicle during nighttime driving compared to daytime conditions [106, 107]. Our results under Fog conditions show a similar pattern, with vertical gaze becoming more focused when visual information is limited, suggesting that drivers adaptively narrow their gaze under challenging conditions.

The correlation coefficient, ρ, and BCEA indicate a significant effect between conditions, with a decrease during driving conditions, reflecting a more focused visual strategy when participants faced higher task demands. BCEA decreases from Baseline to Ride ($p < 0.001$, Cohen's $d = 1.06$; very large) and from Baseline to Fog ($p < 0.001$, Cohen's $d = 1.53$; huge), while the difference between Ride and Fog is also significant ($p < 0.001$, Cohen's $d = 0.89$, very large). Such a difference in BCEA aligns with prior findings showing reduced eye movements when focusing on a target [61, 108]. These results confirm that during driving, participants maintained more stable fixations compared to Baseline, consistent with the expected effect of increased task engagement on gaze stability.

The number of PRLs increases during driving conditions, while participants focus on the road, rearview mirrors, and dashboard. Specifically, the number of PRLs increases from Baseline to Ride ($p < 0.05$, Cliff's $\delta = -0.49$; large) and from Baseline to Fog ($p < 0.01$, Cliff's $\delta = -0.70$; large), with a significant difference between Ride and Fog ($p < 0.05$, Cliff's $\delta = -0.49$; large). These findings are consistent with the literature on PRL usage, which showed that more distributed fixation points are associated with maintaining functional gaze strategies under challenging visual conditions, such as during central vision loss or increased task demands [109]. This confirms that during driving, participants engaged in more active visual exploration, consistent with the expectation for increased task demand and environmental monitoring.

Analysis of GI, a novel parameter proposed in this study, and MSE reveals significant changes in fixation asymmetry. Both GI and MSE are higher during Baseline compared to Ride and Fog, indicating that fixations are more unevenly distributed and more widely dispersed under resting or low-demand conditions. Specifically, GI is significantly greater in Baseline *vs* Ride ($p < 0.01$, Cohen's $d = 0.88$; very large) and Baseline *vs* Fog ($p < 0.01$, Cohen's $d = 0.76$; large). MSE shows significant differences between Baseline and Ride ($p < 0.001$, Cliff's $\delta = 0.47$; medium), Baseline *vs* Fog ($p < 0.001$, Cliff's $\delta = 0.74$; very large), and importantly, between Ride and Fog ($p < 0.001$, Cliff's $\delta = 0.51$; large), suggesting that gaze dispersion is sensitive not only to Baseline *versus* driving, but also to differences between driving conditions. In contrast with our initial expectations, where higher GI and MSE are predicted during driving due to more dispersed fixations, results suggest that participants' gaze is more focused and symmetric under task conditions, while Baseline allows more wandering and uneven fixations.

Entropy analyses further indicate that gaze patterns become less predictable under increased task demands. Sample entropy in the horizontal axis shows medium differences between Ride and Fog ($p < 0.001$, Cliff's $\delta = -0.46$), whereas vertical gaze entropy is significantly higher in the Fog condition, relative to both Baseline ($p < 0.05$, Cliff's $\delta = -0.24$; small) and Ride ($p < 0.05$, Cliff's $\delta = -0.23$; small). The comparison between Ride and Fog is important, as it demonstrates changes in driving conditions, such as reduced visibility. Approximate entropy decreases from Ride to Fog ($p < 0.001$, Cliff's $\delta = 0.41$; medium), reflecting that eye movements become less variable under limited visibility. In contrast, Virtual Reality (VR) tasks showed increased eye movement complexity, indicating continuous gaze adaptation under dynamic conditions, highlighting the sensitivity of entropy-based measures to cognitive load and visual attention across varying environments [47].

4.3. Blink Detection: What do our Blinks Really Reveal?

Studies have shown that blink duration can be a more reliable indicator of visual workload than blink rate, particularly in situations like driving [78]. Previous studies have shown that visual or cognitive distractions during driving significantly affect oculomotor behavior. In particular, cognitive and combined task loads have been associated with an increased blink rate and altered gaze dynamics [4], suggesting that blink parameters can serve as reliable indicators of driver workload and attentional state. Mean and median values of blink duration decreased during driving conditions compared to Baseline, as well as SD. The number of blinks and the number of blinks per minute also decrease during driving conditions, indicating that environmental challenges such as motion and reduced visibility lead to shorter, more consistent, and less frequent blinks, suggesting a reduction in blinking activity, possibly to maintain visual stability under demanding conditions.

Published findings support this blink suppression pattern, showing that increased visual workload is associated with shorter blinks (71 - 100 ms; $p < 0.05$) while longer blinks (171-300 ms; $p < 0.05$) tend to occur more frequently as time-on-task increases, reflecting fatigue-related changes in oculomotor control [78]. Schmidt *et. al.*, 2017, reported a significant decrease in correct detection rates from manual to automated driving ($p < 0.001$) [110]. In line with this, Bachurina and Arsalidou (2022) found a significant main effect of mental attentional demand on spontaneous blink rate, with *post-hoc* analyses showing reduced blinking for higher demand levels, supporting the sensitivity of blink measures to cognitive load [55]. Video game studies provided additional evidence for blink suppression under dynamic visual conditions [111]. In the study [111], participants playing adventure and action video games showed a significant reduction in blink rate compared to baseline ($p < 0.001$), while sport games showed less pronounced changes. Viewing pre-recorded gameplay also reduced blink rate ($p < 0.02$), indicating that even passive observation of a dynamic visual scene demands attentional resources [111]. Previous work by Cardona *et. al.*, 2011, demonstrated that during highly dynamic visual display terminal tasks, blink rate is significantly reduced relative to baseline ($p < 0.001$), with blink rate during fast-paced tasks dropping to nearly one-third of baseline [112]. This supports the interpretation that blink parameters act as reliable indicators of visual workload and scene dynamism,

Overall, the present findings indicate that drivers adapt their oculomotor behavior to cope with increased visual and cognitive demands. Under Ride and Fog conditions, saccade amplitude increases, while saccade number decreases, reflecting more targeted gaze shifts to extract critical information from the environment. BCEA measures show reduced gaze dispersion, particularly vertically, suggesting a more focused and efficient visual strategy. Such adaptation likely reflects an effort to maintain stability and optimise visual processing under challenging sensory conditions when maintaining situational awareness is critical. Blink parameters further support this adaptive behaviour, with shorter, less frequent, and more consistent blinks under higher workload conditions, highlighting the sensitivity of blink measures to cognitive load. These results suggest that drivers dynamically modulate saccadic and fixation behavior, gaze distribution, and blinking patterns to maintain visual stability and task performance when facing environmental complexity.

4.4. Limitations and Future Research

This study is not without limitations. We recognize the following limitations and suggest the following improvements:

1. Sampling frequency influences the accuracy of eye movement detection [52, 113]. Systems with higher frequencies (>250 Hz) are recommended to ensure precise measurement. For a frequency of 100 Hz, preprocessing, interpolation, or filtering can help improve data quality [50, 114,115]
2. Using an eye tracker is also a notable limitation [116]. Despite their widespread usage, previous studies have identified several disadvantages of mobile eye tracker usage: data loss [117], slippage [119], scene instability [120], and gaze accuracy issues [117].
3. Although driving simulators offer a safe driving [120, 121], controlled environment for training and research [121, 122], there is always a lack of realistic physical sensation, weather [123], and potential for simulator sickness [124, 125], and they may not fully assess real-world driving behaviours like tendency to speed or drive, while distracted.
4. A direct comparison of the exact metric values across more diverse driving simulations is not recommended, as variations in the driving routes - road type, environmental complexity, and conditions can strongly influence gaze behavior.
5. Machine learning can be used for saccade detection and classification by using algorithms like Random Forest (RF), Support Vector Machines (SVM), and Convolutional Neural Networks (CNN) to classify eye tracking data into saccade or fixation [126-130]. Machine learning models like SVM and deep neural networks are used for high-accuracy saccade detection and analysis, enabling real-time application in driver safety and saccade-based traffic sign detection [130, 131].
6. Cognitive and combined task loads have been associated with greater blink rates and altered gaze patterns [4]. Integrating such conditions into experimental designs could provide deeper insight into driver attention, workload, and safety mechanisms.
7. Future directions could include analysis of the eye openness signal to improve blink and fatigue detection [73, 132, 133]. Blink detection using the eye openness signal gave more robust blink detection, as well as more parameters than using pupil diameter [73].
8. Implementing additional algorithms for saccade detection, such as the MAD algorithm [134] or dispersion-based algorithms [51], may enhance the robustness of saccade identification.

5. Conclusion

In this study, eye tracking data are used to investigate visual attention and gaze stability during Baseline and simulated driving conditions with varying visibility demands. Together with saccade and blinking parameters, the BCEA measures provided complementary insights into gaze dispersion and visual focus. The results demonstrate that reduced visibility, as in the Fog conditions, induces pronounced changes in oculomotor behavior, including fewer but larger saccades, decreased gaze dispersion, and altered blinking patterns, reflecting adaptive visual strategies under increased perceptual load. The inclusion of the novel parameter, GI, further enhanced the sensitivity of eye movement analysis, capturing fixation asymmetry not reflected in conventional metrics. Overall, these findings underscore the value of combining saccade, BCEA, and blink parameters for comprehensive assessment of visual attention and workload, offering potential applications for driving safety evaluation and human-machine interface design.

CRediT Authorship Contribution Statement:

Smilja Stokanović: Writing - original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. Jaka Sodnik: Writing – review & editing, Methodology, Formal analysis, Data curation, Nadica Miljković: Writing - review & editing, Validation, Methodology, Investigation, Conceptualization.

Acknowledgment:

We express our deep gratitude to Jelena Medarević, from the Faculty of Electrical Engineering, University of Ljubljana and Đorđe D. Nešković, from the School of Electrical Engineering, University of Belgrade and Vinča Institute of Nuclear Sciences—National Institute of the Republic of Serbia, University of Belgrade.
N. M. kindly acknowledges the support from the Grant No. 451-03-137/2025-03/2001 funded by the Ministry of Science, Technological Development, and Innovation of the Republic of Serbia.
This work has been financially supported also by the European Union's Horizon Europe research and innovation program for the project FRODDO, grant agreement no. 101147819 and by the Slovenian Research and Innovation Agency within the program ICT4QL, grant no. P2-0246.

Declaration of Competing Interest:

The Authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data and Code Availability:

Eye tracker data and code can be obtained from the first Author upon reasonable request, as they are part of an ongoing study and will be shared subsequently.

Statement:

During the writing process, the Authors used GPT4o (ChatGPT) and Grok (model 4) to enhance readability and refine language. The Authors subsequently reviewed and revised the content as needed and take full responsibility for the content of the publication.

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