Assessing Eye Movement Patterns in the Context of Distracted Driving: The Influence of Cognitive, Emotional, and Texting Factors Using Statistical AI/ML Models

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ABSTRACT

Every day driving involves several types of distractions in modern times. Some of the distractions can hinder visual attention which might affect the driving perfor- mance. Visual distractions like texting are very evi- dent but there are no practical tools available to detect non-visual distractions automatically while driving. Eye tracking technology has promising capability to detect a persons state of mind and there is possibility to re- late the driving performance under mental distractions. Identification of eye movement patterns can reveal char- acteristics such as fixation and saccade under all kinds of distractions. Present study make use of I-DT algorithm to derive fixations and saccades for 26 participants for 4 driving conditions. Using eye tracking and driving re- sponse data, normal driving is compared with driving under three distractions i.e. cognitive, emotional, and texting. When compared to driving with no distrac- tions, results show a significant increase in fixation du- ration along with decrease in number of fixations while texting. For cognitive and emotional distractions, re- strictive eye movements were seen by utilizing visual- ization techniques. Statistical techniques were used to verify these results.

Author Keywords

Distractions; Visual attention; Eye movements, Fixa- tion, I-DT algorithm, Saccade; Eye-tracking

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INTRODUCTION

It is widely believed that both physical and mental dis- tractions behind the wheel are real and dangerous. Dis- tracted driving behaviors led to 3,477 deaths in 2015 alone in the United States [1]. While visual distractions are straightforward, when drivers look away from the road. Therefore, traffic regulations are adopted in many counties across the United States that forbid physical distractions such as texting/talking on cell phone while driving. At present, no rules can be formulated for men- tal distractions. One of the key reason being there are not enough clearly abstracted studies to determine men- tal distractions such as cognitive and emotional distrac- tions when drivers think about something which may impair his/her attention during driving.

Distraction is one form of inattention and it is a factor in over half of the crashes that involve some form of driver inattention which is estimated for at least 25% of po- lice reported crashes[2]. It has been noted that mental distractions processing capacity causes problems with driving performance [3]. For such distractions which are not observable, no simple measure can be implied. Currently, to assess secondary activities like cognitive and emotional distractions among which eye movements are the most promising [4]. Another advantage is that eye movements are an implicit measure of performance and do not necessarily involve conscious processes[5]. Results from this study can very well be used to de- velop algorithms to automatically detect effects of men- tal distractions and enhance safety on roads. Stud- ies have shown an established link between eye move- ments and cognitive distractions [6]. Glance analysis studies are done to evaluate physical distractions like radio-tuning, mirror checking, and texting showing dif- ferences in eye movement when compared with normal driving[7]. Additionally, the scientific community is not able to describe all forms of mental distractions dan- gerous. Against traditional thinking, a study done at University of Kansas concluded that some forms of dis- tractions actually helps drivers to pay more attention on the road while driving monotonously [8].

In this paper, the author will distinguish primarily two types of eye movements under distracted driving and compare them with normal driving. These movements are fixations and saccades. A fixation is aggregation of gaze points based on a specified area(~ 20-50 px) and minimum timespan (200 ms)[9]. Saccades describe a rapid eye movement (30-80 ms) from one fixation to the other[10].

Accelerating technological environment has made ad- vanced driving simulators available with real-time sim- ulations for variety of driving paths, traffic, and weather conditions in virtual reality based environment. Nowa- days driving simulators are being used for driver train-

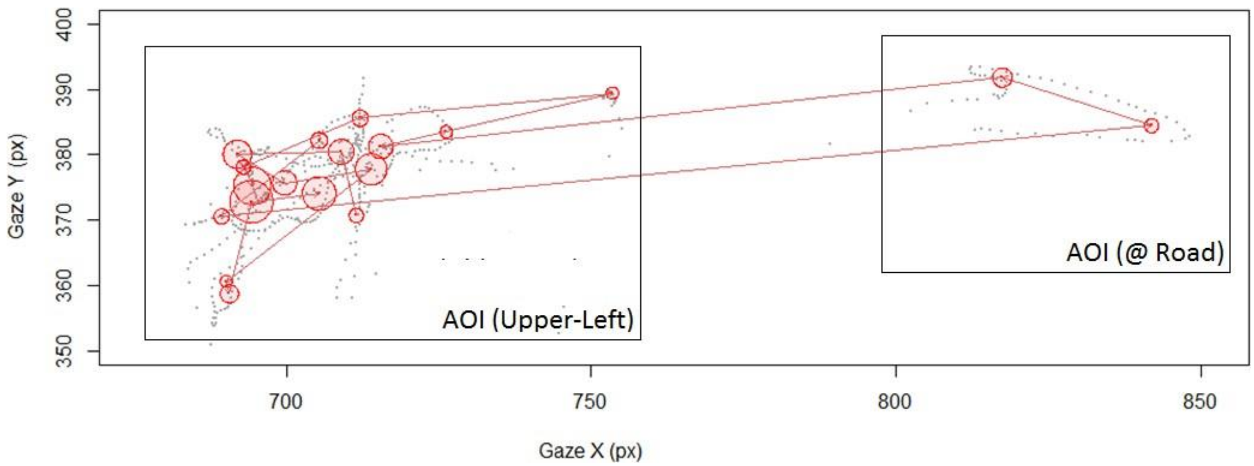

Figure 1: Fixations and Saccades (10 second span)

ing, race-car driver training, aircraft pilot training, video games halls etc. They offer various advantages over real vehicles such as controllable environment, ease of data collection, comparative studies and dangerous conditions without begin physically at risk[11]. Despite being some disadvantages, the potential role of driv- ing simulators will continue. This paper evaluates the results of eye movements on a driving simulator where participants operated under normal and distracted driv- ing conditions. Distracted conditions were of three types - cognitive, emotional and texting. Results from this paper could be used to develop algorithms to au- tomatically detect some kinds of distractions to further develop driver prediction models for real-time warning systems in case of expected dangerous situations due to distractions.

EXPERIMENTAL DESIGN

The participants were recruited from Bryan and College Station, TX communities. All the participants had at- least 1.5 year of driving experience and a valid driver's license and not on medications which might affect their ability to drive safely. Participants were in 2 age groups, young cohorts 18-27 years and old cohorts above 60 years of age. The personality type A/B using Jenkins Activity Survey[12] is scored for each participant. Addi- tionally, trait anxiety inventory (TAI) is also noted for each participant to see the effects of long term stress on driving behavior or eye movements.

The driving performance data is collected using a high-fidelity simulator manufactured by Realtime- Technologies, Inc. Eye tracking data was collected in unobstructed way using two components, a light source, and a camera. The experimental procedures were approved from Institutional Review Boards (IRB) of the University of Houston and Texas A & M University. The light source is directed towards the eye and the camera tracks the reflection of the light source along with ocular features such as the pupil.

Figure 2: Simulated driving setup

In simulated driving setup, each participant drove along 10.9 km long track with two lanes in each direction. The simulated environment was designed in daylight setting where there were no cars to follow, only oncoming traffic (>12 vehicles per km), no traffic lights or stop signs during each session (except at the beginning), posted speed limit of 45 mph on which participants drove for about 12-14 min per session with realistic highway view including construction zones, lane marks, construction cones etc. The simulator used 3 screens, one on each side and the middle screen which was about ~ 3.5 ft away from the participant. All screens were displayed at 1920 px × 1080 px resolution. The eye gaze locations were

Table 1: Participant profiles by age & gender

Category	Number of Participants	Age Range (Years)	Personality (Type A/B) Range	Trait Anxiety Inventory Range
Young Males	6	21 - 24	200 - 259	24 - 41
Young Females	9	22 - 27	176 - 282	30 - 49
Old Males	5	62 - 73	182 - 247	24 - 37
Old Females	6	61 - 72	184 - 232	20 - 31
Total	**26**	**21 - 73**	**176 - 282**	**20 - 49**

recorded at 60 Hz from top-right corner of the middle screen which approximates about 90° visual field for a participant on that screen. Driving parameters like speed, acceleration, steering angle, lane position and braking were recorded at 42 Hz.

Using the driving environment as explained earlier, the participants were asked to drive Each participant drove for 4 different sessions, normal drive, cognitive drive, emotional drive and driving while texting. The order of these four driving sessions were randomized. The secondary activity was triggered in form of question- naires by an experimenter for cognitive and emotional distractions. A sensorimotor was utilized for texting by sending back words, sent to participants smart phones. There was a 2-minute break between each session of drive. Each session of drive (d ∈ [N, C, E, T]) was de- signed in following pattern[13].

- n_1: With no distraction for ∼ 80 s
- d_1: Engage in secondary activity ∼ 160 s (Section I)
- n_2: With no distraction for ∼ 240 s
- d_2: Engage in secondary activity ∼ 160 s (Section II), and
- n_3: With no distraction for ∼ 120 s where,

n → normal drive, and d → distracted drive N → No distraction
C → Cognitive distraction E → Emotional distraction T → Texting distraction

Same questionnaires for cognitive drive like analytical and mathematical questions were same for each partici- pant in same order. However, the Section I and Section II were randomly switched. In each session (including normal drive) the participant drive in right lane for 4.4 km, followed by guided path using constriction cones to change the lane to the left, drive straight for 1.2 km on left lane and then back to the right lane using similar guided path. The lane changes were in between sections of secondary activities, it was done to avoid monotonous driving.

DATA DESCRIPTION

Since average length of each session of drive is 760 s, and at 60 Hz frequency, an average of 760 × 60 = 45,600 eye gaze positions per session per participant. For all of the 26 participants ∼ 4.74M eye gaze positions. There is a limitation to the collected eye gaze data, the camera cannot obtain a position measurement when the eye is closed/blinking. These instances the eye tracker takes the gaze position at the origin or top-right corner of the middle screen. Before any in-depth analysis can be done the false data at origin must be replaced and treated as missing information. Some of these noise then can be removed by using smoothing techniques. Ordinarily lin- ear smoothing is not suitable for eye-tracking data[14]. Using non-linear interpolation techniques like Savitzky Golay filtering, the raw data can be best describes by avoiding noise and keep the overall shape of the eye gaze data.

The driving performance data is up-sampled from 42 Hz to 60 Hz using linear interpolation. The reason for not down-sampling the eye gaze data is the smoothed samples which might provide more sensitive data. Such a large amount of eye tracking data has to be down- sampled which not only reduces the size but also the complexity of the data. Commonly, the researchers use fixations and saccades to analyze the eye movements. The data was also clearly labeled to classify normal (N), cognitive (C), emotional (E) and texting (T) mode of driving.

METHODOLOGY

The analysis of fixations and saccades requires some form of *fixation identification* - that is, the translation from raw eye-movement data points to fixation locations (and implicitly the saccades between them) [15]. There are 5 popular algorithms based on *Dispersion Thresh- old* (I-DT), *Velocity Threshold* (I-VT), *Minimum Span- ning Trees* (I-MST), *Hidden Markov Model* (I-HMM) and *Area-of-Interest* (I-AOI). Fixation identification is a critical step in eye movement data analysis and one must be careful to select algorithm to ensure accuracy and reasonable number of fixations to not loose the im- portant characteristics of the eye movement data. The authors decided to discard I-MST, I-HMM and I-AOI algorithms either due to lower accuracy (in I-AOI) and complexities involved in I-MST and I-HMM algorithms. The authors compared I-VT and I-DT algorithms which are highly accurate and less complex for present analy- sis.

Velocity-Threshold Identification: In I-VT algorithm uses a single parameter called velocity threshold[16] (e.g. 100°/sec) determines the aggregation of gaze points i.e. fixation before moving to the next fixa- tion. For present analysis, a velocity threshold of 15 $\times$ σ_v (where, σ_v is standard deviation of velocity dis- tribution)[17]. The I-VT algorithm is able to take care of missing information and the noise in eye gaze data, which results in number of fixations with very few gaze points. Moreover, since most of the time the partic- ipants look at the road and velocities distribution is very steep, too few number of fixations ($\sim$ 79,000 for all 26 participants) were identified with too many gaze points in a single fixation and for much longer fixation timespans.

Dispersion-Threshold Identification: In I-DT algorithm, 2 parameters namely dispersion threshold and dura- tion threshold. After careful consideration a dispersion threshold of 20 px[9] and duration threshold of 200 ms [11] is used. The authors used 'emov'[18] package in R to identify fixations. I-DT algorithm uses a moving window that starts with first point and cover the du- ration threshold as far as *dispersion of the gaze points* $\leq$ *dispersion threshold*. From the fixation start and end durations, saccades were calculated as anything between fixations using end time of a fixation as starting point for the saccade and start time for next fixation as end time for the same saccade. After using I-DT algorithm on the given eye gaze data and removing noisy data, total number of fixations for all 26 participants were 128,926 fixations averaging about 1.6 fixations per seconds.

The fixation identifications from I-DT algorithm are chosen mainly because of reasonable amount of data Special precaution is taken to calculate saccades by re- moving the saccades which might be calculated from a range of missing eye gaze information. Fixations last- ing longer than 2.4 sec and saccades lasting longer than 800 ms were also removed from the data as noise. The driving responses were re-calculated by averaging the driving performance from the fixation duration window.

The down-sampled eye tracking data for n = 26 partic- ipants, is labeled as normal, cognitive, emotional and texting based on the stimuli onset timing for start and end times for each section of distractions (Section I and Section II). Initially, eye tracking data was available for n = 31 participants. After careful consideration for each participants, 5 participants were removed due to exces- sive amount (> 2 min) of missing information for eye gaze data (for 3 participants) or unexplained eye gaze data (for 2 participants).

To compare the normal vs distracted driving in terms of eye movement parameters, features like fixation du- ration, saccade duration, fixation counts, and saccadic movements were compared. Both visual and statisti- cal analyses were performed by comparing sections of distracted drive to the sections of normal drive by com- paring the results between same tracks. It was done to have an comparable size of data to compare against nor- mal driving. This will allow the authors to compare the said eye movement parameters within each participant and participants as a group as well.

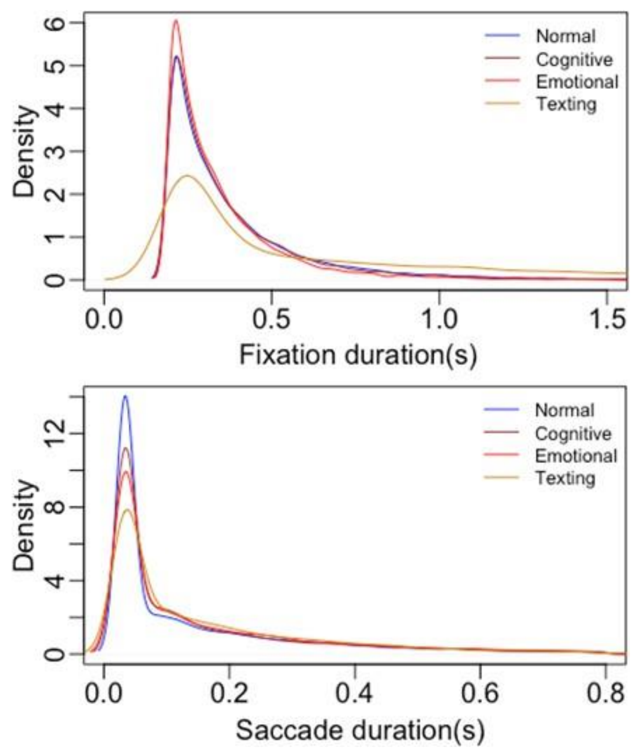

Figure 3: Density plot for fixation & saccade du- ration for normal, cognitive, emotional and driv- ing while texting for all participants together

Fixation/Saccade Duration: Initial look at the fixa- tion duration density plots (Figure 3) reflects a right skewed data and for within participant analysis, the distributions either need to be transformed using log- arithmic or square-root transformations or implement non-parametric statistical tests. Some of the statistical test like Kolmogorov-Smirnov test can also be imple- mented to compare the distributions.

Statistical tests: It was noted that either type of trans- formation (logarithmic or square-root) failed to trans- form the data similar to normal distributions. Since no suggested transformation methods worked, authors decided to use non-parametric tests like Wilcoxon test which is an alternative to student t-test. To compare frequencies of fixations, the authors chose Chi-square goodness of fit test to check the statistical significance in number of fixations in normal drive vs distracted drive.

Visual Representation: For visual representation of the results, Tableau software is used. Comparable features like fixation duration for normal vs distracted drive for each participant. Saccadic amplitude and Velocities are represented by binning fixation durations with bins of 200 ms to represent how these motions are affected as fixation duration increases. Authors also visualize how the saccadic movements changed by showing *1 Standard Deviation* between normal drive and distracted drive in both vertical and horizontal directions. Box-plots were used to effectively represent changes in fixation & sac- cade duration as well as for the counts of fixations. Some visual representations are shown based on age, gender or both to see how participants behave as a group.

RESULTS

Fixation Counts: Fixation counts for normal vs dis- tracted driving (i.e. cognitive, emotional and texting) were plotted for each participants using a line graph. A boxplot for each drive type is superimposed on top of the changes in fixation counts as shown in Figure 4.

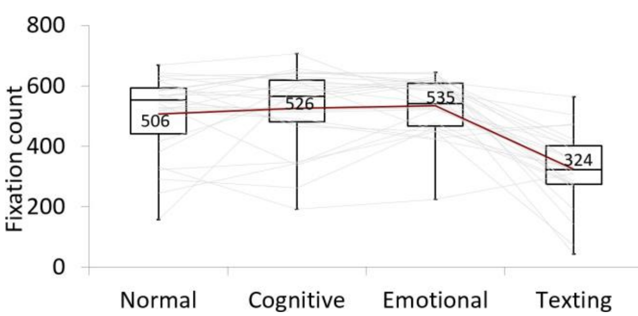

Figure 4: Fixation counts, all participants, nor- mal vs distracted drive

The figure shows the number of fixations reduces by ~36% under texting distraction. However, the num- bers of fixations see insignificant increase under cogni- tive and emotional distractions. Using chi-square good- ness of fit test, it can be determined that the changes in fixation counts while texting are statistically significant (p-value ≤ 0.05). Only texting reflects statistically sig- nificant fixation counts in comparison to normal drive. It was also noted that, in general older males the fixa- tion counts under cognitive and emotional distractions increases significantly (over 40%) as illustrated in Fig- ure 5 below. Fixation counts under texting distraction decreases among all groups in general.

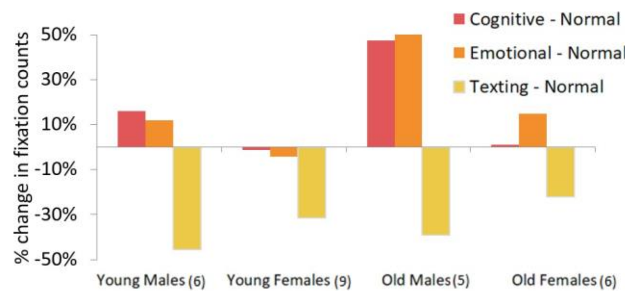

Figure 5: % change in Fixation counts, normal vs distracted drive, grouped by age & gender

In texting lower number of fixations are expected as the participant tend to look away from screen often to accommodate the said distraction. However, a relation can be visualize to see how the fixation counts behave under distractions when plotted against their duration by binning in steps of 200 ms as shown in figure 6 below:

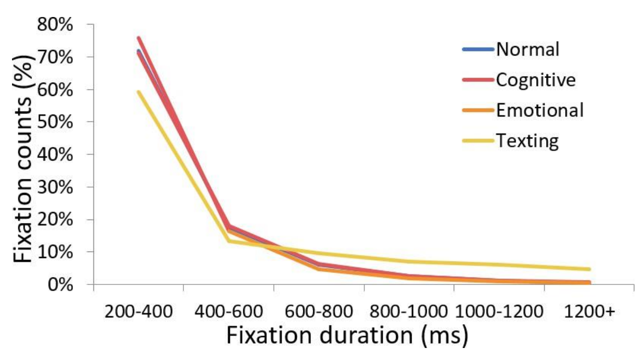

Figure 6: % of fixation counts vs fixation dura- tion bins, for all participants

It can be seen that in texing though the number of fix- ations reduces but the fixations tend to be longer. The changes in fixation durations under texting is presented in figure 7 below. It can be noted that the saccade du- rations do not change much under texting.

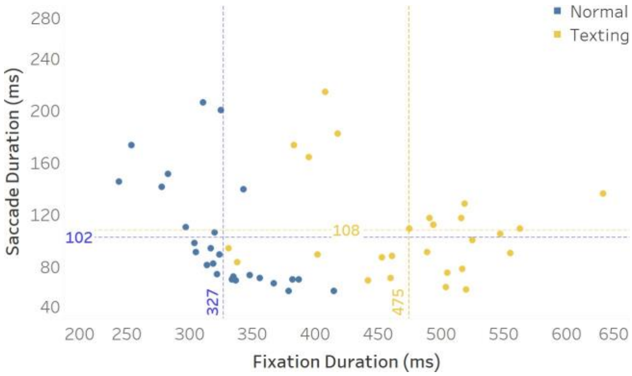

Figure 7: fixation and saccade duration from 26 participant, normal vs texting drive

Table 2: p-values, Kolmogorov-Smirnov test, fix- ation duration, normal vs distracted drive

	Participant	Normal vs Congnitive	Normal vs Emotional	Normal vs Texting
Young	1	0.000	0.001	0.000
	5	0.034	0.434	0.000
	9	0.000	0.043	0.000
	13	0.000	0.000	0.000
	19	0.000	0.351	0.000
	21	0.004	0.000	0.000
	4	0.379	0.266	0.000
	6	0.000	0.001	0.000
	10	0.829	0.480	0.601
	12	0.038	0.000	0.000
	14	0.000	0.006	0.000
	16	0.112	0.593	0.000
	20	0.058	0.000	0.000
	22	0.000	0.292	0.000
	24	0.449	0.081	0.000
Old	44	0.082	0.021	0.000
	46	0.979	0.141	0.000
	50	0.000	0.000	0.000
	51	0.000	0.000	0.000
	54	0.000	0.000	0.000
	25	0.028	0.387	0.000
	33	0.000	0.000	0.004
	35	0.103	0.073	0.000
	39	0.000	0.243	0.000
	41	0.894	0.640	0.000
	43	0.000	0.007	0.000
	Summary	19/26	16/26	25/26

Male
Female

p-value ≤ 0.01
0.01 < p-value ≤ 0.05
0.05 < p-value ≤ 0.10

It was also noted that both fixation and saccade du- rations for cognitive and emotional distractions do not change significantly. Under cognitive and emotional dis- tractions, the author tried to looked at other parameters like saccadic movements. Saccadic amplitude showed a significant reduction under cognitive and emotional distractions. Since saccadic durations do not change significantly, similar trend is expected for the saccadic velocities as well

Statistical tests like Kolmogorov-Smirnov test (to com- pare distributions) and Wilcoxon test (to compare me- dian) on the fixation durations resulted in statistically significant differences in many participants specially for texting distractions. The statistical results in form of p-values from both tests are shown in Table 2 above.

It is evident that texting distractions are statistically much different with over 99˚ confidence when compared to normal driving. Cognitive and emotional distractions also shows significant difference in majority of the par- ticipants. These results also suggests that males tend to have more significantly different fixation duration distri- butions for cognitive distractions when compared with emotional distractions.

Table 3: p-values, Wilcoxon test, fixation dura- tion, normal vs distracted drive

	Participant	Normal vs Congnitive	Normal vs Emotional	Normal vs Texting
Young	1	0.000	0.000	0.000
	5	0.002	0.421	0.000
	9	0.000	0.125	0.000
	13	0.000	0.000	0.000
	19	0.000	0.342	0.000
	21	0.014	0.000	0.000
	4	0.224	0.773	0.000
	6	0.000	0.001	0.000
	10	0.618	0.258	0.744
	12	0.016	0.000	0.000
	14	0.000	0.000	0.000
	16	0.129	0.577	0.000
	20	0.016	0.000	0.040
	22	0.000	0.108	0.000
	24	0.097	0.016	0.000
Old	44	0.172	0.173	0.001
	46	0.989	0.740	0.000
	50	0.000	0.000	0.001
	51	0.000	0.000	0.014
	54	0.000	0.000	0.000
	25	0.162	0.658	0.000
	33	0.000	0.000	0.064
	35	0.371	0.175	0.000
	39	0.000	0.558	0.000
	41	0.786	0.380	0.000
	43	0.000	0.005	0.000
	Summary	18/26	13/26	25/26

Saccadic Amplitude: Saccadic amplitude for cognitive and emotional distractions were lower for majority of fixations and significantly higher for texting distractions as seen in figure 8 below:

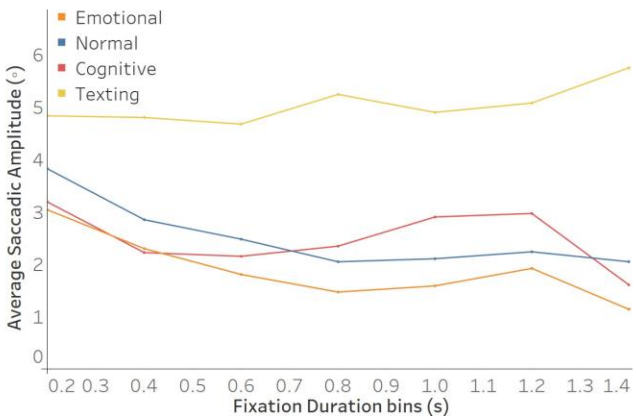

Figure 8: Saccadic amplitude for normal, cogni- tive, emotional & texting distractions vs fixation duration

For cognitive distractions, about 86% of fixations (≤ 600 ms) were found to have lower saccadic amplitudes in comparison to normal drive. For emotional distrac- tions all the fixations were found to have lower saccadic amplitudes and for texting distractions, the saccadic amplitudes were significantly higher when compared to the normal driving. Above figure signals that the eye movements might be very well restricted under cogni- tive and emotional distractions with emotional distrac- tion resulting in more restrictive movement than the cognitive distractions.

A scatter-plots is shown in figure 9 through figure 11 to see the 1 *Standard Deviation* range shown by grayed background in normal, cognitive and emotional distrac- tion drive. The scatter-plot also suggest that the hori- zontal saccadic movement ranges reduces by ∼18% un- der cognitive distractions and reduces by ∼46% when compared to normal drive under emotional distractions.

The differences in vertical movements are insignificant as seen from the figures below:

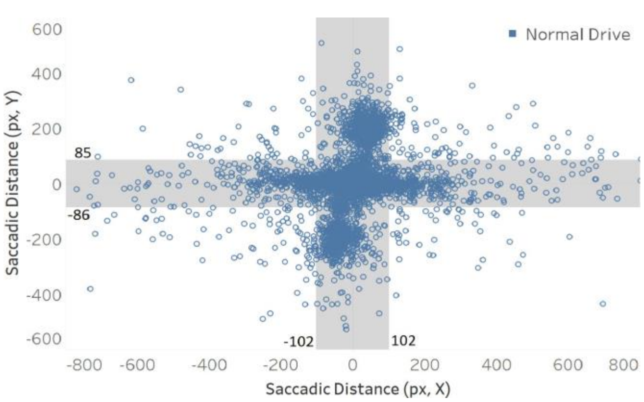

Figure 9: Saccadic ranges for driving under nor- mal conditions

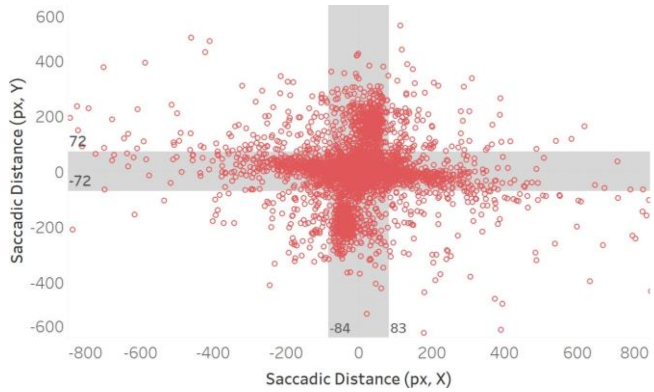

Figure 10: Saccadic ranges for driving under cognitive distractions

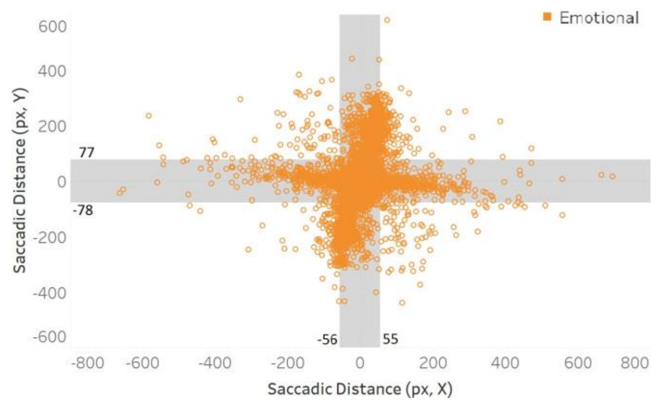

Figure 11: Saccadic ranges for driving under emotional distractions

These restriction in horizontal eye movement do not necessary convey that the person is not seeing on sides as fixations are not representation of the peripheral vi- sion[19]. Just because saccadic range is reduced, that does not mean that the participants are not paying at- tention to the visual field or understand it. More de- tailed analysis and much careful interpretation is needed to comprehend these results. However, one observation can be made which is participants are paying less at- tention to their sides like incoming traffic, construction zones etc or not viewing them in detail which might be a dangerous driving behavior. The results suggests that there are significant differences in eye movements (i.e. fixation duration, saccadic movement) under cognitive, amotional and texting distractions.

CONCLUSION

To summarize the above exploratory analysis, we found that frequency of fixations, fixation duration and spa- tial distribution of fixations (i.e. saccadic movements) are correlated with distractions. Following key observa- tions are seen for each type of driving distraction when compared against normal driving.

Texting Distractions: Under texting distractions, the drivers look away from the screen often[20] but still the fixation durations are higher in comparison to nor- mal driving which is counter-intuitive. Longer fixa- tion durations are linked with improved driving per- formance[21]. It can be concluded that even under tex- ting, when driver is looking at the screen his/her per- formance is considered safe. Only when a driver look away from the screen which the present analysis do not address, a dangerous behavior can be noticed. Texting distractions clearly distinguish from normal driving be- havior, from above analysis an average duration of ≥393 ms can detect the texting distraction with accuracy of ~88%. Texting distractions causes excessive lane depar- ture which might be a dangerous driving behavior[13].

Cognitive Distractions: Under cognitive distractions, the drivers have some reduction in saccadic movement in horizontal direction. The visual attention under cog- nitive distractions are restrictive even-though the par- ticipants face naturalistic driving conditions but since fixations do not represent peripheral view in totality. It is impossible to say that it results in unsafe driving behavior.

Emotional Distractions: Under emotional distractions, saccadic movements in horizontal direction reduces sig- nificantly (as much as by ~46%). A further analysis to restrictive attention shifts is needed to check how safe driving behavior may be affected.

Restrictive spatial distribution of fixations does not nec- essary suggest unsafe driving behavior. Some research in past noted that cognitive overload represented as a single glance at the roadway, it may be interpreted as an unsafe driving practice[7]. A further analysis to see how the cognitive and emotional distractions affect driving performance is needed to identify the level of risk from these distractions. Texing distractions surely represents higher saccadic movements and loss of attention which is unsafe driving behavior. Using the same driving pa- rameters, it was found that under any type of distrac- tions absolute steering control increases when compared to normal driving in all types of distractions[13].

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