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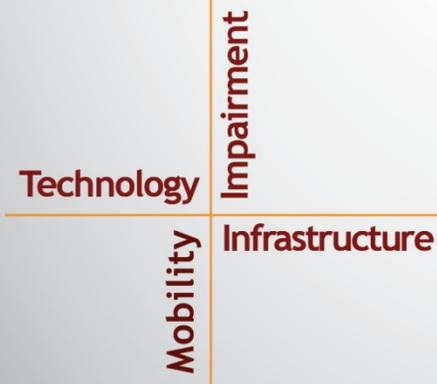
National Surface Transportation
Safety Center for Excellence

Identifying Distraction

**Kinematic Detection of Off-Road Eye
Glances**

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ABSTRACT

Visual attention is a key component of the driving task. Identifying times when the driver is not looking toward the forward views has been shown to be a successful indicator of distracted driving (Olson, Hanowski, Hickman, & Bocanegra, 2009). Previous technologies have successfully captured eye-glance location, but have come at great expense in terms of both cost and intrusiveness. This project explored the possibility of using a low cost and unobtrusive Inertial Measurement Unit (IMU). Through data collected from the IMU, the aim was to identify vehicle kinematic signatures associated with times the driver is looking away from the forward view. Two methods were utilized. The first of the two methods relied on yaw rate anomalies to detect steering corrections. The second utilized the detection of sharp lateral accelerations which occurred as a result of corrective steering maneuvers. These methods both showed promise, as the yaw rate anomalies method and the lateral acceleration anomalies method both showed improved detection rates over the baseline.

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LIST OF ABBREVIATIONS AND SYMBOLS

IIHS	Insurance Institute for Highway Safety
MEMS	Micro Electro Mechanical Systems
VTTI	Virginia Tech Transportation Institute

CHAPTER 1. INTRODUCTION

Distracted driving contributes to nearly 900,000 injury and/or fatality crashes annually in the United States (National Highway Transportation Safety Administration, 2013). Moreover, distracted driving has been a growing problem over the past decade as more sophisticated technology is literally at the fingertips of drivers. In the age of mobile communications and handheld computing, the potential for driver distraction from these technologies seems to grow every day. The Governors Highway Safety Association (Governors Highway Safety Association, n.d.) reports that 14 states have instituted bans on handheld cell phone use and 44 states ban texting while driving. Within this landscape, there is a strong need to be able to objectively identify distracted driving as it occurs and mitigate its potential impact on crash or near-crash risk. This report details efforts to use an algorithm relying on kinematic sensors to detect the visual attention (more specifically, the eyes-off-road behavior) associated with distracted driving.

Visual attention is a key component in the execution of the driving task. Navigation, path planning, hazard recognition and avoidance, and environmental awareness are all tasks that require visual attention to the roadway and its surroundings. Unfortunately, other non-driving tasks require drivers to allot visual attention to locations other than the forward roadway. Drivers often look away from the roadway to perform secondary tasks, such as adjusting the radio, reaching for an object, or operating a mobile device. Glances away from the forward roadway have been shown to increase the odds of a crash or near-crash, with the odds increasing by glance duration length (Olson, Hanowski, Hickman, & Bocanegra, 2009). These glances away from the roadway include glances related to the driving task as well as secondary tasks, which can result in driver distraction.

The Australian Road Safety Board comprehensively defines driver distraction as follows (Ranney, 2008; Trezise et al., 2006):

Driver distraction is the voluntary or involuntary diversion of attention from the primary driving tasks not related to impairment (from alcohol, drugs, fatigue, or a medical condition) where the diversion occurs because the driver is performing an additional task (or tasks) and temporarily focusing on an object, event, or person not related to the primary driving tasks. The diversion reduces a driver's situational awareness, decision making, and/or performance resulting, in some instances, in a collision or near-miss or corrective action by the driver and/or other road user.

In the driving context, attention is essential because the driver must provide appropriate control inputs to the vehicle. In general, most driver models represent the driver acting as a controller of the vehicle with only a limited number of inputs (to the vehicle). These outputs manifest themselves in most vehicles as acceleration, braking, and steering. Drivers, whether fully alert, distracted, or otherwise partially impaired, control the vehicle through these means. Gear selection can also be considered a selectable input. However, with manual transmissions representing less than 8% of new car sales and less than 2% of new truck sales, vehicles requiring manual gear selection represent a small portion of overall road traffic (Environmental Protection Agency, 2013) and will be ignored for this example. The objective of this project is to explore means by which acceleration, braking, and steering inputs can be used to identify driver distraction by examining the associated vehicle kinematic responses.

Attempts have been made to identify driver distraction through measures of steering angle entropy. Nakayama, Futami, Nakamura, and Boer (1999) proposed a method of measuring high-frequency steering corrections in steering angle data to monitor driver distraction. Their method proposed measuring the deviation from the expected steering angle using a second-order Taylor expansion for prediction of the future state of the steering wheel angle. As the workload of the driver increases, the distribution of the prediction error (the difference between the predicted steering angle estimates and the actual steering angles) widens. A steering entropy value is based on the distribution of this prediction error. As driver workload increases, the prediction error also increases, resulting in an increased steering entropy. Therefore, the widening of the distribution of entropy is used as an indicator of increased driver workload. Boer (2005) revisited this idea by utilizing different filtering techniques and an autoregressive model for calculating the prediction error. The work of Yekhshatyan and Lee (2013) further showed a small correlation between eye-glance scanning frequency and steering angle.

Control switching is also useful in describing the distraction behavior of drivers when splitting attention between the primary driving task and a secondary distracting task. When control focus is returned from the secondary task to driving, if path error has developed, a corrective steering input is required to return the vehicle to the driver's desired position and path of the vehicle. This can be viewed as a closed-loop feedback control system to effectively allow path maintenance, while eye-glance distraction creates open-loop vehicle operation (Sheridan, 2004).

Another degradation factor in control performance is proposed by Wierwille (1993) and reiterated by Sheridan (2004), which is centered on the reduction in sampling rate. As the sampling rate of a system is reduced, the performance of the controller is also compromised. Therefore, a task requiring visual attention would reduce the amount of glance time available to be allocated to general driving and path maintenance. Less-frequent glances with shorter glance durations will equate to a lower sampling rate, and thus decreased performance.

Most commercial driver distraction systems rely on vision systems for the monitoring of eye closure, glance direction, head orientation, percentage of eye closure (PERCLOS), and the tracking of facial features. However, prototypes have been developed for detecting impaired driving using vehicle-mounted hardware as well as modern smartphones to identify sloppy handling maneuvers, weaving, and swerving, which are signatures of extreme operator impairment or distraction.

With an increase in the odds of crash and near-crash events associated with glances away from the forward roadway (Olson, Hanowski, Hickman, & Bocanegra, 2009), detecting these glances could prove useful in identifying situations of elevated crash and near-crash risk. Glance identification has traditionally been performed using manual video reduction, eye trackers, and more recently advanced computer vision algorithms. However, there is significant financial and/or labor cost associated with these methods of glance detection. New alternatives are made possible by the recent progress in Micro Electro Mechanical Systems (MEMS) accelerometers and gyroscopes, which has led to an abundance of low-cost inertial sensors that can be installed with little modification of the vehicle.

Previous research work has examined correlations between distraction or impairment and driver inputs to the vehicle (Dai, Teng, Bai, Shen & Xuan, 2010; Futami, Nakamura, and Boer, 1999;

Lee, Li, Liu, & Chen, 2006). This research focused on kinematic signatures (i.e., measured from vehicle motion), as opposed to only considering measured direct driver input, to indicate when a driver is not looking at the roadway. A distracted driving detection system based on vehicle kinematics would be less expensive than current eye-tracking systems. It would also be less intrusive, given that kinematic sensors can be mounted anywhere within the vehicle. The purpose of this project is to identify if correlations exist between kinematic measures and eye-glance behavior. It is hypothesized that distractions, especially those that require glances off the forward roadway, lead to changes in driver inputs to the vehicle. If normal attentive driving performance can be quantified, then deviations from this normal performance can be identified. These deviations might be indicators of visual distraction. If such correlations are found to exist, the development and testing of an identification algorithm could provide a low-cost alternative to the visual reduction methods currently in use.

CHAPTER 2. METHODS

DATA DESCRIPTION

The data used in this analysis were collected as a part of the 100-Car Naturalistic Driving Study (Dingus et al., 2006). This study included 105 participants and several models of vehicles across a multi-year range. Additional eye-glance and distraction reduction were performed as a part of the Insurance Institute for Highway Safety (IIHS)–Virginia Tech Transportation Institute (VTTI) distraction study (Farmer, Klauer, McClafferty & Guo, 2014). Two trips per month were randomly selected for each of 105 driver participants from the 100-Car data set. Videos of these trips were reviewed and coded for various distractions. Trips were required to be a minimum of 7 minutes in length and were coded for a maximum of 30 minutes. Half of these files were then further coded for eye-glance location at a frame rate of approximately 7 frames per second. The 20 different glance locations that were coded can be seen in Table 1. These efforts resulted in the coding of 1,141 trips from 104 participants. The number of trips per participant ranged from 4 to 17, with a mean of 11 and a standard deviation of 2.9. The mean length of trip was 16.6 minutes with a standard deviation of 7.8 minutes. For this analysis, the 20 possible glance locations from the original analysis were further grouped into four zones: glances outside the car (Zone 1), all glances into the side or rearview mirrors (Zone 2), glances to the instrument cluster and center stack (Zone 3), and all other off-road glances (Zone 4). Most of the eye-glance locations in Zone 4 are limited to interior spaces; however, glance locations such as “No Eyes Visible” and “Over-the-Shoulder” may include external glances. An illustration of the zones can be seen in Figure 1.

Table 1. Driver eye-glance locations.

Zone 1	<ul style="list-style-type: none"> • Center Forward • Left Forward • Right Forward • Left Window • Right Window
Zone 2	<ul style="list-style-type: none"> • Right Mirror • Left Mirror • Rearview Mirror
Zone 3	<ul style="list-style-type: none"> • Center Stack • Instrument Cluster
Zone 4	<ul style="list-style-type: none"> • Passenger • Cell Phone • iPod • Other • Other Interior Object • Over-the-Shoulder • Eyes Closed • No Eyes Visible (off-road)
No Zone	<ul style="list-style-type: none"> • Unknown/No Video • No Eyes Visible (glance locations unknown)



Figure 1. Diagram. Zones used to group glance locations in the analysis.

YAW RATE ANOMALIES

The kinematic measures explored in this study were speed, lateral acceleration, and rotational velocity about the z -axis (i.e., yaw rate). Kinematic behavior occurring during both straight-line driving and turning was examined in relation to eye glance. Previous work on steering entropy suggests that it may be possible to predict driver distraction based on corrective maneuvers observed in the steering wheel angle signal. In this particular analysis, no such sensor measure was available; however, the kinematic corollary, the gyroscopic measurements about the z -axis (yaw rate) were examined for similar tendencies. While steering wheel angle and yaw rate are both related to vehicle steering, they are measurements of different quantities. Steering wheel angle is largely the direct measurement of driver input to the vehicle, while yaw rate is the measurement of the actual movement of the vehicle through space.

Steering wheel angle directly affects the steering angle of the tires. However, the yaw rate of the car is not directly related to the steering angle of the tire. The tire is the interface between the car and the ground and, for purposes of steering, is the primary method of changing the direction of the vehicle. As speed and/or steering angle increases, the tire slip angle also increases. This slip angle is the difference between the steering angle of the tires and the actual direction of travel. Tire slipping removes the direct relationship between the steering wheel angle and the actual steering angle by accounting for many vehicle dynamics and tire properties. The actual angle of travel (steering angle minus slip angle) is related to yaw.

When similar steering entropy methods, as described in Nakayama, Futami, Nakamura, and Boer (1999), were applied to the yaw rate signal in the present study, small correction signals were not observed. This is not surprising, as the high-frequency signal content from the steering angle that

the steering entropy approach relies on would not be expected to be detectable in the dynamic response of a high-mass vehicle with numerous intervening response functions between the steering input and whole-vehicle motion. This finding is supported by Gilland (2008), in which no statistically significant difference was found in yaw rate measurements from the gyroscope (as a surrogate for steering wheel angle) between distracted and non-distracted drivers.

Measures of yaw rate, lateral acceleration, and speed were examined to attempt identification of kinematic signatures associated with eye-glance distraction. Fourier analyses of the signals were carried out to isolate corrective motions in the yaw rate and acceleration signals. These steering maneuvers were anticipated corrections from the lane position observed upon returning eyes to the road versus the driver’s desired lane position. This follows with the idea of control switching between driving and a secondary task.

In the interest of beginning with more salient signals in the data, driving on curves was investigated in detail. The definition of a turn was defined as a sustained yaw rate greater than 2 degrees per second. These turns were further restricted by imposing a minimum 1-second duration requirement, and a minimum speed requirement of 5 mph through the duration of the turn. The categorized turns were further broken down into turns that contained any off-road glances (Zones 2, 3, and 4) and turns that contained non-mirror off-road glances (Zones 3 and 4). In this particular context, a turn containing a glance could contain any off-road glance of any duration. The total number of turns can be seen in Table 2.

Table 2. Description of turns in analysis.

Total turns	32,623
Total turns meeting duration and speed requirements	15,471
Turns containing off-road glances	4,591
Turns containing non-mirror glances	2,175

When a driver is not executing a turn smoothly, yaw rate will reflect this as rapid changes relative to surrounding yaw values. Yaw rates that seemingly fluctuate between different steady states can indicate distraction or inattention. This agrees with the idea of distraction and its effects on reduced sampling frequency (Wierwille, 1993). These steady states reflect either a smooth and continuous input based on attentive preview of the road ahead or an open-loop input, where the last forward glance and associated input are being maintained. When attention returns, a deviation from steady state will be present as the correction is made. Though not necessarily distracted, drivers often employ less-than-optimal control, such as when releasing the steering wheel to reposition hands while turning, or driving with their knees. Periods of open-loop operation are typically followed by a large angular acceleration followed by a very small change in angular velocity and then finally another sharp angular acceleration. These events often occur in succession. The exact durations of these open-loop periods vary and can be identified by sharp mid-turn yaw rate transitions. An example of these yaw rate anomalies can be seen in Figure 2. Periods of identified steady states can be seen as red lines. A turn with no turn rate anomalies can be seen in Figure 3.

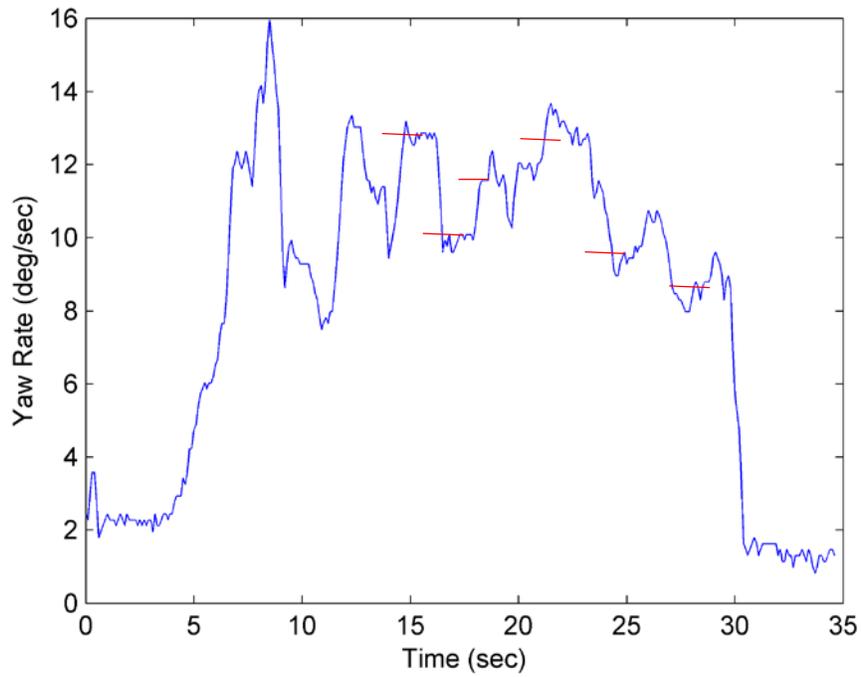


Figure 2. Graph. Yaw rate anomalies identified in a turn.

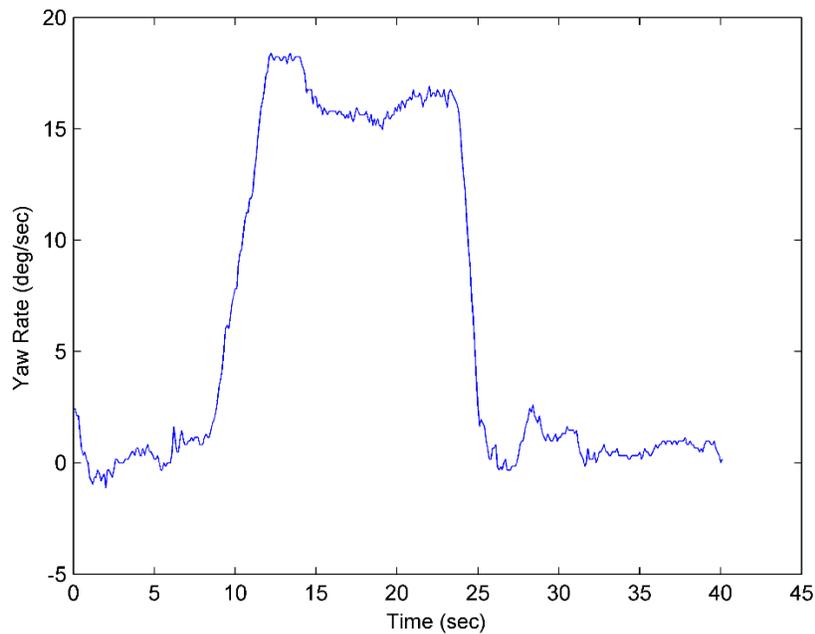


Figure 3. Graph. Yaw rate for turn with no yaw rate anomalies.

The epochs selected for analysis were turns from all trips that had undergone a full eye-glance reduction as part of the IIHS-VTTI distraction study. All evaluations based on eye-glance condition were made using the IIHS-VTTI coded eye-glance positions. Turns where eyes-off-

road events were detected were classified as “condition positive,” and turns where no eyes-off-road events occurred were classified as “condition negative.” The algorithm attempted to identify condition positive cases among the set of condition negatives.

Algorithm performance was based on the number of successfully identified eyes-off-road events (true positives), and also on the positive predictive value. These two metrics were contained in or derived from the confusion matrix. It is important that the algorithm correctly identify eyes-off-road events successfully while minimizing false alarms (i.e., misclassified eyes-on-road-events). The positive predictive value will give the percentage of the total classified eyes-off-road events that are correctly classified. Meanwhile, monitoring the number of true positives gives an idea of how many actual cases are being considered when calculating the positive predictive value.

A technique was developed to identify these yaw rate anomalies in the data for analysis relative to eye-glance data. The method used to isolate these anomalies begins with the identification of the turn. Turns in this context have been defined to have a yaw rate greater than 2 degrees per second with a duration of more than 1 second at a speed greater than 5 mph. Low-speed turns were excluded from the analysis based on the assumption that there will be significant speed changes at low speeds.

The yaw rate signal in the turn was subdivided into periods of low mean yaw rate change (where the differenced yaw rate signal was less than 3 deg/s^2) to identify locally stationary regions in the data. Periods where there was very little change in the yaw rate indicate a steady state of steering. When the yaw rate is repeatedly punctuated by sharp changes, short steady-state epochs exist between these sharp changes. This is clearly illustrated in Figure 4, where the individual steady-state regions are identified by red boxes. When the yaw rate is differenced, these sharp changes (seen as large rate changes in the differenced data) serve to separate the turning event into these short epochs of steady-state yaw rate. Changes in yaw rate less than the threshold of 3 deg/s^2 were considered part of the steady states, while changes in yaw rate greater than the threshold of 3 deg/s^2 were not. These steady-state epochs, or anomalies, are candidates for consideration because it is presumed that the driver is not attentive to controlling the vehicle. The epochs of the yaw rate signal where these criteria were met for 0.7 consecutive seconds or more were retained for consideration, while shorter epochs were ignored. This eliminated small periods of constant angular velocity, while leaving the more sustained instances. Ignoring the shortened signals did not compromise the analysis since the goal was to locate and count the number of sustained suspected inattentive periods, i.e., anomalies in the signal.

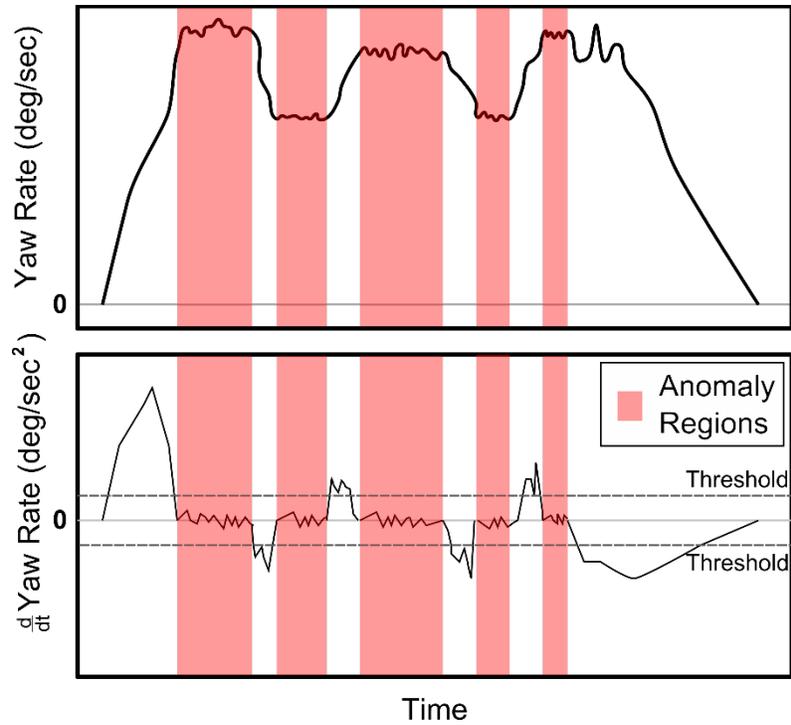


Figure 4. Graph. Example of anomaly regions in yaw rate as identified by differenced yaw rate.

Once the number of sustained anomalies were counted, the algorithm output the anomaly score. A flowchart of this algorithm can be seen in Figure 5. Simplified MATLAB code to perform this operation can be seen in Appendix A.

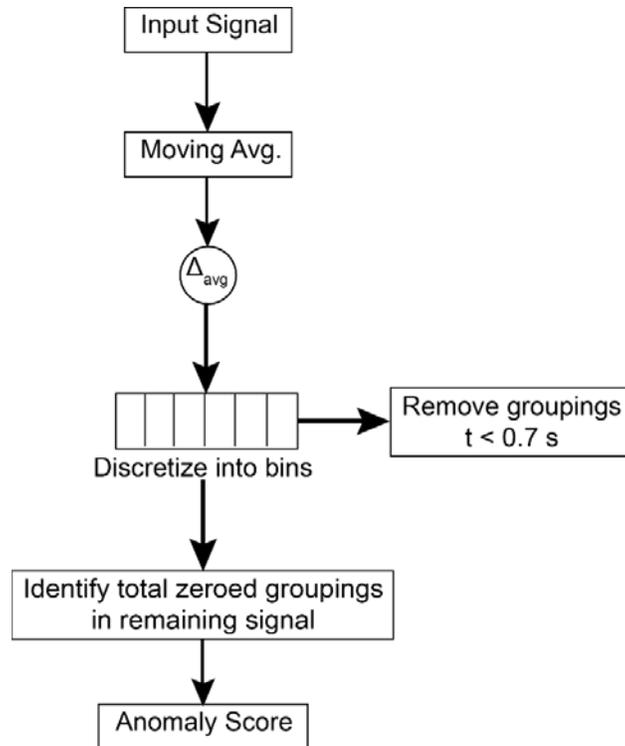


Figure 5. Flowchart. Steering anomaly detection.

SHARP STEERING CORRECTIONS

Based on the implementation of the reduced sample rate model proposed by Wierwille, another approach to identifying distraction is to monitor lateral acceleration that results from steering correction as a surrogate for steering wheel angle. This method is applicable to entire trips, not just in turns. By observing these lateral accelerations, it should be possible to quantify the control effort required to bring the vehicle back into alignment along the desired path. These sharp and sudden realignments may be indicators of a reduced sample rate by the driver, and in periods of distraction could be expected to increase in regularity and severity.

The corrective hypothesized maneuvers observed would exhibit higher-than-expected levels of lateral acceleration, and have the potential for high jerk as well. These characteristics should be especially noticeable when compared to the surrounding lateral accelerations. Note that vibration from road input and lateral acceleration associated with steering are both measured through the same accelerometer. However, sharp and unplanned lateral accelerations can be detected to indicate sudden recovery movements. These momentary spikes in lateral acceleration typically have an overall duration of less than a second, and their peak persists for only a few hundred milliseconds. An example of this behavior can be seen in Figure 6.

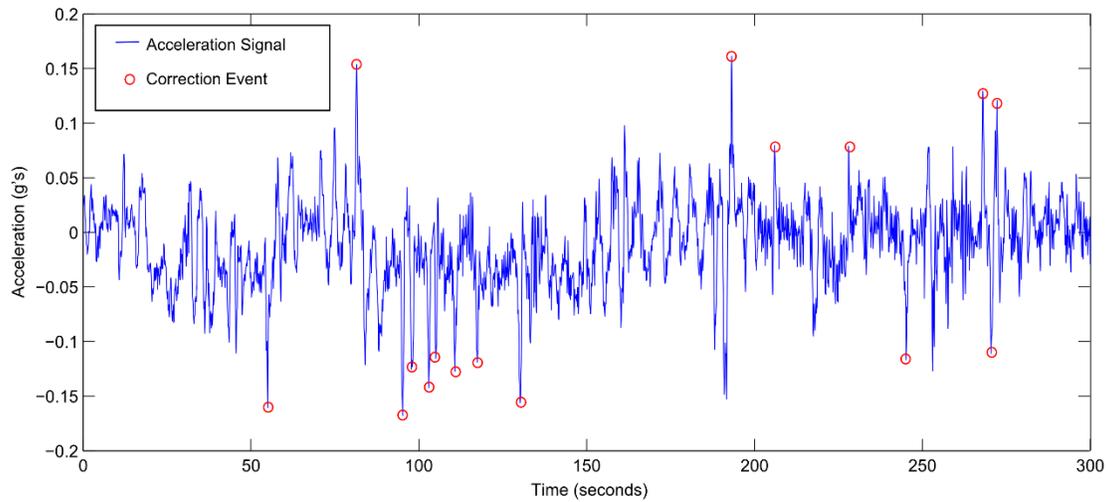


Figure 6. Graph. Steering corrections in the lateral acceleration signal.

This detection technique can be implemented by using a rudimentary high-pass filter. A one-hundred-point moving average filter is applied to the signal and then subtracted from the original signal. The result isolates the high-frequency deviations from the low-frequency signal. Local extrema are then identified from this filtered data. A set of logic criteria is then applied to locate the high-frequency spikes. A correction counter can be implemented to count the number of correction events in a given time period. This serves as an indicator of the level of attention of the driver to the roadway.

To identify short-duration corrective maneuvers, an extreme value threshold was identified. This was set to be 2.5 standard deviations of the high-pass filtered lateral acceleration signal. There must also be a definition of what can be defined as a normal acceleration extrema. For this, the normal value threshold was set to be 1.5 standard deviations of the high-pass filtered lateral acceleration signal. The local extrema that exceeded the bounds of the extreme value threshold were labeled as “extreme,” while those that were within the normal threshold boundaries were labeled as “normal.” In order to be counted as a candidate for a correction, the two preceding extrema, the current extrema, and the two following extrema must be normal, so that the pattern appears [Normal, Normal, Extreme, Normal, Normal]. An example of a qualifying signal can be seen in Figure 7. It is important to remember that the signal being analyzed is the extrema of the high-pass filtered lateral acceleration. Having multiple simultaneous points which exceed the extreme value threshold would indicate a maneuver that is more sustained in nature and not a sharp corrective action. Extrema points falling between the normal value threshold and the extreme value threshold also indicate the maneuver is more sustained, and therefore not a sharp corrective action.

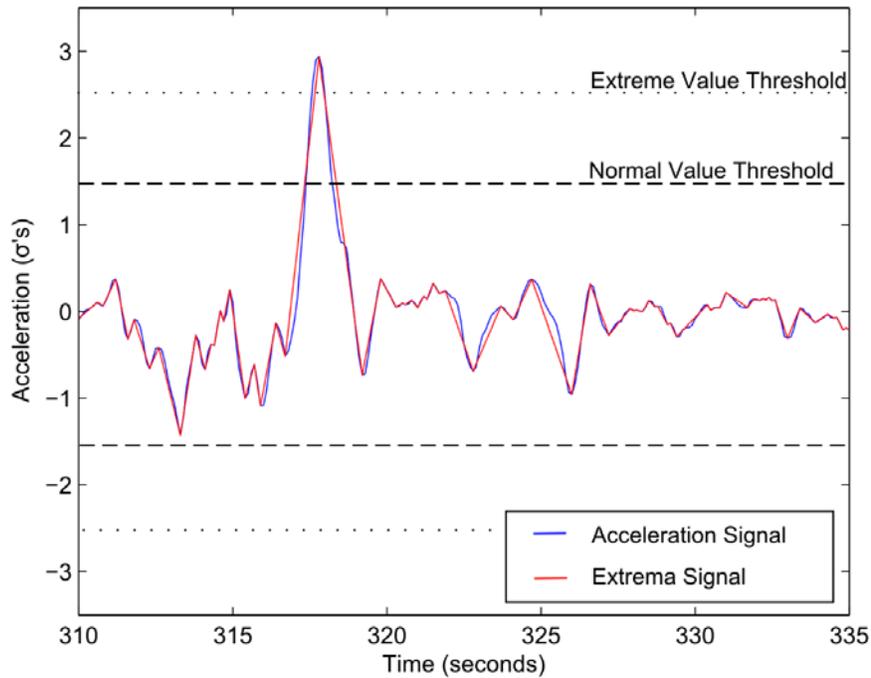


Figure 7. Graph. Example of a steering correction exceeding the threshold conditions.

An additional iteration of this method was evaluated using a local difference method. A slope was found between the point preceding the current point and the point following it. The distance between this sloped line and the current point was found. This distance was normalized by standard deviation and then evaluated using the same extreme value threshold method described previously to identify corrective maneuvers.

To evaluate the effectiveness of the algorithm, a baseline group was selected and then compared to the results identified by the algorithm. To determine a baseline, 10 random points in time were selected from each file in the VTTI-IIHS data set. From each of these points, the eye-glance data were analyzed to see if there were any off-road glances in the previous 1 second, 2 seconds, or 5 seconds, in the same way that was done for actual identified corrections. The baseline served to show the algorithm's effectiveness when compared with random chance.

CHAPTER 3. RESULTS

YAW RATE ANOMALIES

Testing the effectiveness of the algorithm relied on the total number of events correctly identified and the true positive rate. The true condition for looking away from the road was defined as any turn with any eye glance off-road time (Zones 2, 3 and 4). For each turn, the number of yaw anomalies was counted and recorded. This was used as a threshold to classify the turns as either containing exterior glances (Zone 1) or not containing exterior glances (Zones 2, 3, and 4). If the number of observed yaw anomalies was equal to or greater than the current threshold, then it was considered positive by the algorithm. The results of this algorithm can be seen in Figure 8, with the true positive percentage increasing as the yaw anomalies threshold is increased, while the raw number of turns being identified as containing off-road eye glances (both true positive and false positive) decreased as the strictness of the yaw anomaly threshold was increased. The Receiver Operating Characteristic (ROC) curve of the model is provided in Figure 9, with an area under the curve of 0.603. A more detailed summary of these results is provided in Table 3, located in Appendix B.

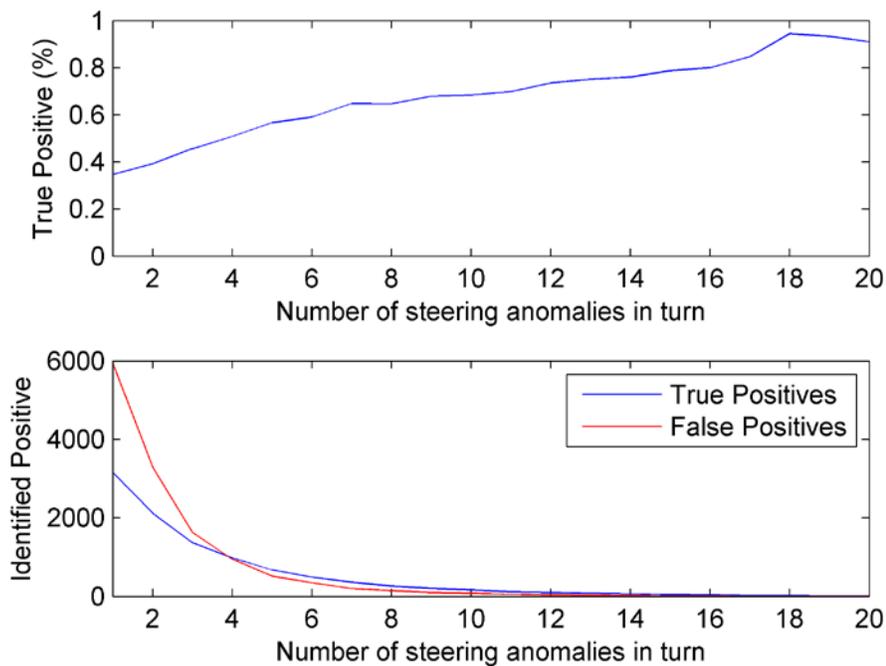


Figure 8. Graph. True positive percentage and total positives identified vs. the number of yaw anomalies in a turning sequence.

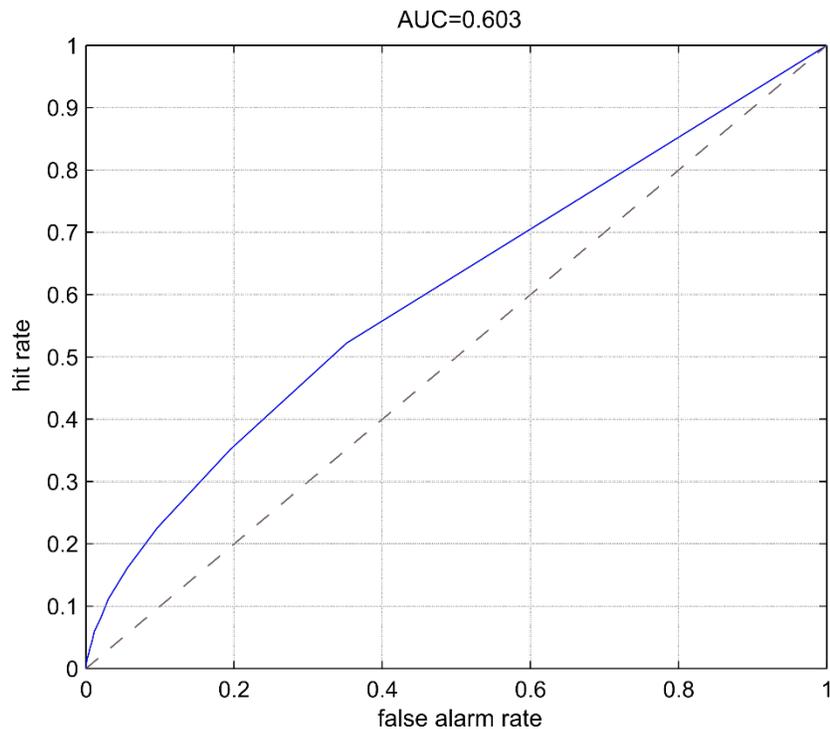


Figure 9. Graph. ROC curve for yaw rate anomalies algorithm.

It can be seen from these results that increases in performance can be achieved when the yaw anomalies threshold is increased. If very high true positive rates are desired, then the number of detected turns with eyes-off-road events will be so small that the algorithm will not be useful. However, if an acceptable (dependent on need) percentage of false positive will be allowed, then this identification method will prove to be of use in identifying the presence of off-road glances during driving. The algorithm tends to have very low sensitivity levels. However the specificity of the algorithm rapidly increases as the as the anomaly score threshold is increased.

SHARP STEERING CORRECTIONS

The developed algorithm for measuring sharp steering corrections relied on the assumption that an off-road glance is defined as any eye glance focusing on Zones 2, 3, or 4. The eye-glance signal was examined for any off-road glances 5 seconds prior to the correction event to determine if there was any relationship between the sudden correction and an off-road eye glance. These corrections were then classified and marked as having glances within 1 second of the identified correction, within 2 seconds of the identified correction, and within 5 seconds of the identified correction. A single identified correction could be found to have a glance occurrence in any of the time periods (1 second, 2 seconds, or 5 seconds).

Algorithm effectiveness was measured by comparing the algorithm hit rate and the hit rate of a random baseline. A successful algorithm would have a hit rate that was statistically different from the hit rate of the random baseline data and the analysis results. The ratio of these positive eye glances to the total number of identified events was calculated for each participant. These

same ratios were also calculated for the output of the algorithm. The distributions of these ratios for each of the two groups (baseline and algorithm results) were then compared using a one-way analysis of variance (ANOVA) for the 2-second window. A statistical difference between the two distributions was found, $F(1, 186) = 7.66, p = 0.0062$. The algorithm was found to successfully identify distraction over the baseline, although only by a 5% increase in the mean. The mean of the baseline set was 0.264, while the mean of the algorithm set was 0.316. The result is a small improvement, but the kinematic identification of off-road eye glances requires additional testing for the development of a robust algorithm. The distributions of the two sets can be seen in Figure 10.

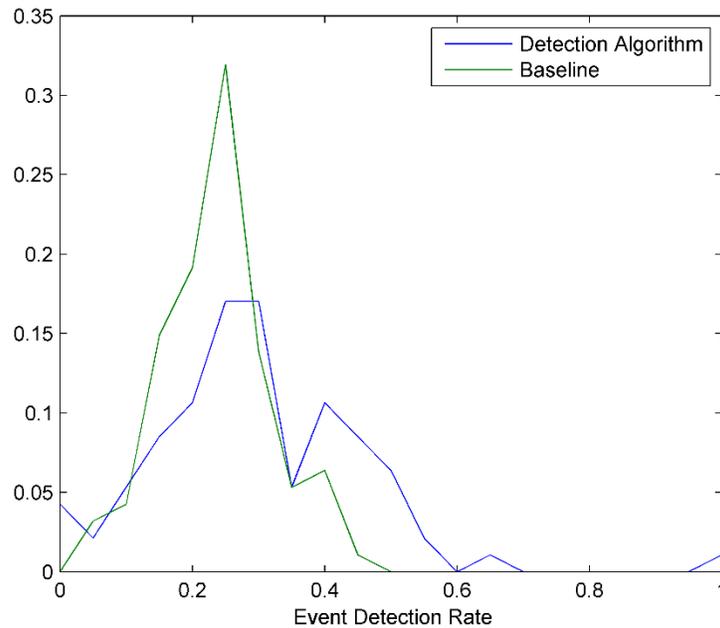


Figure 10. Graph. Distribution of baseline and algorithm event detection rate (2-s window).

CHAPTER 4. CONCLUSIONS

The kinematic measures available in the 100-Car data set are longitudinal and lateral acceleration, rotational acceleration around the vertical axis of the vehicle, and speed. The choice to use lateral acceleration and gyroscope measurements was made because these kinematic measures represented the best **available** estimators of lateral driver inputs into the system. Previous work in the area of driver distraction also provided some evidence for entropy in steering corrections as an indicator of distracted driving, but a steering signal was not available in the data set employed for this investigation.

The curve-specific detection resulted in an algorithm to identify yaw rate anomalies when driving through a curve. The algorithm developed showed a high number of false negatives; however, as the sensitivity threshold was increased, the true positive rate also increased. The resulting algorithm can be used to identify turns where eyes-off-road events occur. It showed that there may be some relationship between yaw rate anomalies during turning behavior and eyes-off-road events.

Steering corrections visible in lateral acceleration showed a statistically significant improvement over the baseline selection; however, the improvement was only a 5% increase in identification. This shows that some information on corrective maneuvers is associated with eye-glance behavior, but a more refined algorithm is needed to achieve the desired performance requirements.

The yaw rate anomalies that occur during curve negotiation indicate that there is more information to be gained from exploring this method of eyes-off-road identification. Knowledge of the driver environment might provide more context with which to understand these yaw rate anomalies. These kinematic measures contain information regarding drivers' repeated or prolonged off-road glances, and these may be identifiable with more focused data analysis.

The results of the methods proposed in this report do not demonstrate a robust solution to the problem of predicting eye-glance behavior based on kinematic measures. However, they do serve as insights to develop more in-depth strategies and studies on eye glance that could be revisited in future work. Drivers alter the way that they drive when they are engaged in visually distracting activities for periods of time. Finding faster, cheaper, and more reliable ways to identify these periods of visual distraction will serve not only researchers but also the driving public as a whole. Future work into this area should focus on improving algorithm robustness and sensitivity.

APPENDIX A. MATLAB CODE FOR ANOMALY SCORE

```
function anomaly_score= find_shifts2(input_data)

% Set the discretization threshold. This threshold will be used to
% discretize the differenced input signal, and thus its units will be in
% degrees/sec^2
discretization_threshold = 0.3;

smooth_win_size = 5;
group_size = 7;

% Smooth the input signal with a window size of 5, then take the difference
% of the signal.
smooth_diff = diff(smooth(input_data),smooth_win_size);

% Discretize the data bins as selected by the discretisation_threshold
% variable
diff_data = round(smooth_diff/discretization_threshold) * discretization_threshold;

% Identify groupings of 7 or more points where the input signal is constant
% (the difference of the smoothed input signal is 0)
[~,bools1] = find_contiguous_bool(diff_data == 0, group_size);

% Identify all points where the difference of the smoothed input is 0
bools2 = diff_data == 0;

% Using XOR, remove all non-grouped (of size 7 or larger) zero points.
% This operation is performed to eliminate small anomaly groupings while
% maintaining the more significant ones.
diff_data(xor(bools1,bools2)) = [];

% Identify the total number of these anomaly groupings
[~,bools] = find_contiguous_bool(diff_data == 0,group_size);

% Calculate the anomaly score
anomaly_score = sum(diff(bools) == 1);
```


APPENDIX B. YAW RATE ANOMALIES RESULTS

Table 3. True positives of yaw anomalies.

Steering Anomalies	True Positives (False Positives)	Positive Predictive Value	Steering Anomalies	True Positives (False Positives)	Positive Predictive Value
0	6,038 (16,861)	0.26	11	116 (50)	0.70
1	3,154 (5,937)	0.35	12	97 (35)	0.73
2	2,121 (3,293)	0.39	13	81 (27)	0.75
3	1,362 (1,628)	0.46	14	63 (20)	0.76
4	975 (944)	0.51	15	48 (13)	0.79
5	672 (515)	0.57	16	36 (9)	0.80
6	491 (341)	0.59	17	22 (4)	0.85
7	358 (195)	0.65	18	17 (1)	0.94
8	260 (142)	0.65	19	14 (1)	0.93
9	203 (96)	0.68	20	10 (1)	0.91
10	162 (75)	0.68			

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