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Investigating the Effect of Drivers' Body Motion on Traffic Safety

(Project #2013-051S)

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ABSTRACT

Although significant advances have been done with respect to vehicle technology and roadway construction, driver behaviour remains the number one contributing factor of traffic crashes worldwide. Studies show that one of the major causes of crashes is driver inattention. Driver inattention may occur when drivers are involved with secondary activities (e.g., texting, talking on the phone, or eating), and when they fail to follow the cues of the surrounding environment while driving. The latter is particularly important when drivers are negotiating maneuvres and are required to interact with other vehicles as in the case of changing lanes or merging onto the freeway. The main objective of this research is to investigate the relationship between driver behavior and safety, by looking at the actual body movements and posture, as well as the eye fixation of the drivers when they are performing lane changing and merging maneuvers under different traffic conditions. To accomplish this objective, a total of 35 drivers were recruited to participate in an instrumented vehicle field study, where each participant drove for approximately two hours along a pre-selected route. Participants' 3D body posture was recorded with the use of a low-cost infrared depth sensor (Microsoft Kinect). In addition, participants' eye gaze throughout the entire data collection effort was recorded with the help of eye-tracking equipment. Lastly, the vehicle was equipped with two cameras that faced the front and the rear which allowed for information about the traffic conditions during the data collection period to be obtained. A rich dataset of driver behavior was developed and analyzed as part of this research. The analysis findings relate the 3D sequence of driver motion and posture with the actual eye and head movement of drivers. Based on the analysis, head movements were the predominant type of movement when driving. The average duration of head movements was 4 seconds and 3.75 seconds for freeway merging and lane changing maneuvers respectively, and 2.3 seconds for arterial lane changing. Analysis of the magnitude of movements while driving showed that the right arm was more active than the left arm for the majority of the drivers, and differences between different driver groups were observed. However, given the small sample available in this study, the findings should be treated with caution. This report presents the research approach, summarizes findings, and provides recommendations accordingly. The research approach is useful for establishing guidelines for monitoring driver behavior as part of advanced driver assistance systems. The proposed framework has also potential in developing appropriate alert mechanisms for increasing driver alertness by monitoring driver body posture.

EXECUTIVE SUMMARY

This project examines a new research framework for examining the driver's movement and posture during merging and lane changing maneuvers, in order to investigate correlations between body motion patterns and unsafe driving conditions. One of the key contributions is that the proposed framework takes into account the driver's body position and movements, rather than considering solely the vehicle position relative to other vehicles on the road, which is an important factor as driver behavior remains the number one contributing factor of traffic crashes worldwide.

In addition to the commonly used head tracking technology, this framework introduces the use of a low-cost depth sensor, which was installed in the cabin of an instrumented vehicle and used to track the motion of the drivers who participated in this study. Two analytical frameworks (i.e., a quantitative and a qualitative framework) were developed to analyze the motion patterns of the drivers, correlate those patterns with potential unsafe driving conditions, and derive statistical patterns observed in various demographic groups.

The developed frameworks were applied to real data collected from 35 drivers who participated in this study and performed merges and lane changes while driving along a predetermined route in Ganesville, FL. The age of participants ranged from 16 to 60 and included 18 male and 17 female drivers. The participants drove an instrumented vehicle which was equipped with cameras, GPS, and the low-cost depth sensor. Eye-tracking glasses were also used to gather drivers' gaze.

The results of the proposed quantitative and qualitative analysis indicate differences in driving patterns (i.e., range of body motions and reactions in the presence of other vehicles during the maneuver) based on the gender or age of the driver. The results also indicate that the proposed algorithm is able to capture accurately the motion of drivers' head, left arm and right arm. Lastly, eyes-off-the-road and head movement analysis based on the maneuver type are offered.

The recorded data were organized in the form of an open source dataset of depth frame sequences which is now available on-line, along with a programing API, to facilitate the dissemination of the dataset and its systematic study in order to explore new research questions in the future.

CHAPTER 1: INTRODUCTION

Background

Significant amount of research has been recently performed in the overall area of connected vehicles and intelligent transportation systems as it is presented in detail in the literature review of this report (Chapter 2). However, there is limited prior work that takes into account the driver's body position and movements, rather than considering solely the vehicle position relative to other vehicles on the road, which is an important factor as driver behavior remains the number one contributing factor of traffic crashes worldwide.

To set the grounds for this project, the team of co-PIs developed a pilot study in 2013 to investigate the feasibility of use of low-cost depth sensors in passenger vehicles in order to monitor the driver's body motion. The results of this study were well received by the research community (received ICCVE'13 Merit Certificate and Best Paper Award Finalist) and demonstrated the efficacy of the proposed research framework in the article by Kondyli et al. (2013).

In the present project the pilot framework was extended and implemented as a medium-size study with a quantitative and a qualitative framework as it is presented in details in the next sections.

Project Objectives

The main objective of the research is to investigate the relationship between potentially unsafe driving events and the actual driver body posture and movements when performing a driving maneuver (e.g., lane changing, merging) under different traffic and geometric configurations and when engaging with a secondary task. The findings of this research can provide significant insights regarding which body movements may hide unsafe situations while performing a driving maneuver that requires the attention of the surrounding environment. A second objective is to identify typical behaviors of specific driver groups (e.g., younger vs. older drivers, aggressive vs. conservative drivers, men vs. women), in naturalistic settings. Such information can be used for enhancing current driver training methods for targeted driver groups such as novice or elderly drivers.

Project Impact and Products

A key product of this project is the development of an open-access scientific database of depth frame sequences that depict the body motion of drivers during merging and lane changing maneuvers. The database consists of 523 depth video sequences with more than 300,000 depth frames and 16 billion 3D points, and it is published on-line along with a 3D data viewer and a comprehensive programming framework for implementing and executing custom research experiments. To the best of our knowledge this is the first publicly available resource for such type of research and is expected to have significant impact on studies that investigate driver's behavior in the future.

Furthermore, the findings from the quantitative and qualitative analyses of the collected data are expected to assist in establishing monitoring guidelines for advanced driver assistance systems that take into account the driver's body position and movements, rather than considering solely the vehicle position relative to other vehicles on the road.

To enhance the impact of this project, the authors have presented parts of this work to major conference proceedings and journal publications such as the articles by Kondyli et al. (2013), Barmpoutis et al. (2015), and Kondyli et al. (2015). Finally, an international data challenge was organized at the 2015 3D Shape Retrieval Contest (SHREC) as part of the dissemination tasks of this project. Contestants from India, South Korea, and the United States competed in designing computer algorithms for processing the depth data sequences collected in this project and segment the body regions of the depicted drivers, which is an essential step in automated tracking of their body movement (Barmpoutis et al., 2015).

Report Organization

The next chapter presents the literature review summary related to identifying and predicting drivers' body posture. Chapter 3 summarizes the research approach undertaken in this project. Chapter 4 presents the data collection and reduction effort. Chapter 5 offers the research findings that pertain to the investigation of the 3D driver body posture while performing lane changing or merging maneuvers and its impact on safety. Chapter 6 provides the project conclusions and recommendations. The two questionnaires that were used as part of the field data collection are presented in Appendix A and B. Appendix C presents some results that pertain to the data analysis.

CHAPTER 2: LITERATURE REVIEW

Despite the advances in vehicle manufacturing technology and roadway construction and design, a large proportion of traffic crashes are still due to driver error (World Health Organization-WHO, 2004). According to WHO, annually there are over 1.2 million fatalities and over 20 million serious injuries worldwide. In the US, the 100-car naturalistic study sponsored by the National Highway Traffic Safety Administration (NHTSA) concluded that driver inattention is the cause of about 80 percent of crashes and 65 percent of near crashes (Dingus et al., 2006). Driver behaviors that lead to crashes need to be studied in greater detail in an effort to reduce the occurance and severity of such crashes in the future.

A lot of attention has been drawn lately to USDOT's connected-vehicle research program, which uses a mixture of technologies such as advanced wireless communications, on-board computer processing, advanced vehicle-sensors, GPS navigation, and smart infrastructure, to identify and warn the drivers on imminent road hazards (USDOT, 2011). The program includes vehicle-to-vehicle and vehicle-to-infrastructure communication research activities. The vehicle-to-vehicle communication involes the exchange of data (e.g., speed, acceleration, heading angle, etc.) over wireless network that provide information on surrounding vehicles status and allows for performing calculations and issue driver warnings to avoid crashes. The communication option is based on the Dedicated Short Range Communications (DSRC). Although the development of the communication component of this program is not complete to date, a number of crash avoidance systems have been established so far. These are:

- Emergency stop lamp warning: the host vehicle broadcasts an emergency braking event to surrounding vehicles to warn others of a possible hazard;
- Forward collision warning: the host vehicle is informed about an imminent rear-end collision with a vehicle ahead in traffic, traveling in the same lane and same direction;
- Intersection movement assistance: the host vehicle is warned when it is unsafe to enter an intersection, due to the possibility of colliding with another vehicle coming from the side;
- Blind spot and lane change warning: the driver is warned when a vehicle is in its blind sport or if the driver activates the turn signal and the corresponding blind spot has a vehicle present;
- Do not pass warning: The driver is warned when a slower vehicle cannot be passed safely because of a vehicle coming from the opposite direction; and,
- Control loss warning: The DSRC-equipped vehicle can broadcast a control loss event to its surrounding vehicles.

Additional advanced (or intelligent) driver assistance systems (ADAS) designed to provide added traffic safety are already in place (Shaout et al., 2011). These systems typically do not involve inter-vehicle communication, and are designed to provide assistance or warning to drivers by considering the longitudinal position of the vehicle or other vehicle-related components. Examples of ADAS applications include automatic parking, adaptive light control, night vision enhancement, lane change assistance, traffic sign recognition, collision avoidance system, lane departure warning system, and hill descent control. Apart from such systems that focus on the vehicle, there are limited systems currently in place that are designed to monitor the driver. Existing driver monitoring systems are capable of tracking driver's inattention and drowsiness using LED sensors to monitor eye movement.

In vision-based systems that involve understanding of driver intentions and actions (e.g., inattention or distraction states), research studies focus primarily on the head and face of the driver. For instance, Tijerina et al. (2005), Trivedi et al. (2007) and McCall et al. (2007) analyzed head pose and gaze for identifying and predicting driver's intent to change lanes. Tijerina et al. (2005) observed the eye glance of various drivers using a face camera at a 30Hz refresh rate, while executing lane changes with an instrumented passenger car and an instrumented van. The authors produced link diagrams showing the probabilities of a glance to a specific location (e.g., right/ left mirror, road ahead, center mirror, etc.) 10 seconds prior to the lane change event. Tijerina et al. (2005) concluded that drivers did not always check their mirrors or turned their heads during the 10 seconds before starting the lane change. Similarly, McCall et al. (2007) analyzed head movements and vehicle data in order to investigate driver's intent to change lanes using sparse Baysian learning. Their model was calibrated using real world data. Trivedi et al. (2007) attempted to develop a system that simultaneously looked inside and outside the vehicle, in an effort to correlate driver's physical monitoring activity with the surrounding roadway conditions, and capture driver's situational awareness. They used a combination of cameras, sensors, and radars. Their system was used to investigate and predict drivers' intention to change lanes, and also develop a predictive brake-assistance system.

Research has also studied the hand position and grasp in conjunction with head monitoring for lane change intent analysis and prediction. Cheng and Trivedi (2006) used driver body pose information and developed an algorithm that recognizes and predicts driver's left/right turn behaviors at intersections. The data were collected using a commercial motion-capture system with retroreflective markers placed on the driver. The retroreflective markers were placed on the driver's head and wrists, in order to obtain his/her body pose information. Four cameras around the driver were also installed in the test vehicle. Tran and Trivedi (2009) developed a vision-based system for analyzing driver activity by observing 3D movements of their hands and head. The authors first determined the basic movements of driver's upper body, such as head looking left/ right/ straight or hand in rest or moving. Then, they used a fusion process to develop a higher level of driver activity. This system was tested in a real-world driving environment and it was found that it captures drivers' movement well, however, it focuses only on the driver and does not consider the impact of the surrounding vehicle environment to the driver.

Recently, Tran and Travedi (2010) presented a system for tracking the 3D body movement combined with head pose tracking system. The authors tested their system in a simulation environment and obtained preliminary results related to body posture and lane changing activity. Although the experimental platform is promising, their results to date are limited and do not consider differences between various driver groups.

As part of this project, Kondyli et al. (2013) developed a 3D framework for exploring drivers' body activity using the Microsoft Kinect depth sensors. Using a small set of data from a pilot study the authors showed that the proposed approach captures significant differences between drivers' body movements while performing merging and lane changing maneuvers. The pilot study included data from four drivers (two male and two female) and the developed framework provided a proof of concept for continuing the experiments reported herein.

The use of depth sensors for monitoring 3D body activity improves significantly the tracking accuracy and addresses robustness issues that are common in traditional computer vision-based techniques that employ 2D image computer vision algorithms. The latter may lead to inaccuracies when computing 3D data due to lack of the depicted information. It has been shown that many traditional computer vision problems can be solved more efficiently and/or accurately using range cameras in conjunction with regular video, see examples by Han et al. (2013). When it comes to pose estimation such as the work by Shotton et al. (2011) or 3D reconstruction of the human body by Weiss et al. (2011) and Tong et al. (2012), it has been shown by Barmpoutis (2013) that depth sensors can estimate the shape characteristics of the human body in real-time, which has numerous applications in various research areas from human-computer interaction to rehabilitation and monitoring obesity, see Barmpoutis et al. (2014) and Barmpoutis (2013).

One popular area of application of human body tracking algorithms is electronic games. There are several examples in literature that report novel uses of body tracking technologies in games (see Lange et al. 2012), or the development of novel algorithms for custom-made interaction using special-purpose partial body tracking as shown by Oikonomidis et al. (2011). An interactive game-based rehabilitation system using Kinect was presented by Lange et al. (2012). For a comprehensive literature review regarding the use of virtual reality and interactive games for rehabilitation the reader is referred to the article by Adamovich et al. (2009).

In most of these applications it has been shown that the existing body-tracking algorithms pose significant limitations such as constraints on the environmental setup, requirements regarding the pose of the users, the number of users being recognized, the number of 3D points tracked, etc. For example Barmpoutis et al. (2014) have shown that generic game-based depth-camera tracking algorithms fail in complex environments, when the human body is in close proximity with other objects or subjects in the field of view. As we also demonstrate in this project, the same limitations apply to the case of vehicle's cabin as it was presented by Kondyli et al. (2013). To overcome these issues, as we discuss in detail in the presentation of our research methods, we developed a novel special-purpose body-tracking framework that focuses on detecting and tracking joints of the upper-body of the driver in a typical vehicle environment.

In summary, the literature review reveals that a significant amount of research has been involved with the development of advanced driver-assistance systems; however, most of these systems rely on the automobile position and do not necessarily consider the drivers' actions. Apart from that, the lane trajectory and position of the vehicle could potentially differ from the driver's intent to change lanes. In addition, safety research has focused on eye tracking as a means of capturing driver's attention, fatigue, or drowsiness; however, the entire body posture of drivers when performing a maneuver as well as different postures between various groups of drivers may also reveal behaviors that contribute to unsafe driving conditions, and thus is worth exploring.

CHAPTER 3: RESEARCH APPROACH

Introduction

In this chapter the research methodologies followed in this project are presented in detail. The research methods involve the study of different types of data collected during this project, such as questionnaires, video data, and depth data. Depending on the nature of the particular data modality a quantitative or qualitative approach was employed. The primary focus of the quantitative analysis was on processing the acquired depth frame sequences by tracking the motion of the drivers. The qualitative analysis was based on the systematic manual data reduction and annotation of the driving sessions in order to study the correlation of different factors during specific types of maneuvers.

Driver Questionnaires

For the purposes of this research, two driver questionnaires have been developed to facilitate the field data collection process. The first one is a pre-screening questionnaire that was designed for the selection of drivers to be invited to the field data collection. The pre-screening questionnaire gathered mostly demographics information. An example of the pre-screening questionnaire is presented in Appendix A. The study subjects before participating the in-vehicle study filled out a second questionnaire, which was designed to gather information on their driving habits. An example of the pre-driving questionnaire is presented in Appendix B. Further details on the two driving questionnaires are discussed in Chapter 4: Data Collection and Reduction.

In-Vehicle Driver Study

The goal of the in-vehicle driver study is to obtain information on driver body posture while performing lane-changing or merging maneuvers at various locations with different geometric and traffic conditions. For the purposes of this study, participants of the in-vehicle experiment were requested to drive the vehicle along pre-selected routes, while being accompanied by a researcher at all times. To avoid any bias while conducting the driving study, the communication between the driver and the researcher was limited. The targeted data collection conditions that were considered for this study include:

i. Discretionary lane changing while driving along a freeway and arterial segment under various conditions (congested vs. non-congested traffic conditions, availability of gaps in the adjacent lanes, urgency of the maneuver, presence of heavy vehicles in proximity),

ii. Mandatory lane changing in the presence of work zones/lane closures with varying traffic, signage and geometric characteristics, and

iii. Merging onto the freeway from on-ramps with varying acceleration lane length, merging angle and field of view.

Although it was initially desired to cover locations where all three types of maneuvers could be observed, no work zones or lane closures were identified in the vicinity of the freeway section; therefore, mandatory lane changes as described earlier were not observed. The final data collection conditions include discretionary lane changes along freeway and arterial segments, and merges onto the freeway.

Three video data collection methods were used to obtain data through the in-vehicle driver study, namely Kinect video, eye-tracking video, and in-vehicle cameras. More specifically:

i. Kinect video data captured body motion and depth sequence. These videos show the driver and what he/she is actually doing (e.g. rotating the steering wheel, looking in front/side view mirror and/or rear view mirror etc.)

ii. Eye-tracking video data captured eye gaze. These videos show the front view, occasional side view (while driver looks at the side view mirror) and occasional back view (while drivers look at the rear view mirror) of the drivers.

iii. In-vehicle cameras captured vehicle environment data. These videos show traffic conditions in front and at the back of the instrumented vehicle.

Since this research project looks at lane changes and merges, it was important to define the start and end times of these two maneuvers for both arterial and freeway conditions, in order to perform the analysis procedure. As such, the start and end of the lane changing maneuver was defined by considering the entire thinking process of the driver before the maneuver takes place, and the actual lane changing maneuver. Typically, when drivers start thinking about changing lanes they look at their side or rear-view mirrors, they activate the left/right indicator lights, and/or they move their body/ head in order to have a better view of traffic in the surrounding lanes. The actual lane changing maneuver starts when the vehicle moves laterally towards the target lane and finishes when it is entirely within the target lane. Lane changing maneuvers at both freeway and arterial segments were obtained using the eye-tracking videos and the in-vehicle videos.

The start and the end of the merging maneuver is set at predetermined locations along the ramp/freeway area. The start of the merging maneuver is located at a specific point along the on-ramp while the end is found at another point along the freeway. These points are different for each ramp junction investigated in this study. As discussed in the next section, the use of the same start/end points of the merging maneuvers allows us to evaluate the variability of the merging behavior across the different participants.

Apart from the video data, information on the vehicle position was collected and stored through the GPS. Further information on the data collection effort and the driving routes is presented in Chapter 4: Data Collection and Reduction. All data obtained through the field data collection were used for analyzing body posture and for investigating potentially unsafe driving conditions.

Analysis Approach of Body Posture Using the Kinect Depth Sensors

The depth sensor recorded the motion of the drivers as a sequence of depth frames. Each data frame captured by a digital depth sensor is a two dimensional array of depth values (i.e., distance between the sensor and objects). Similarly, a collection of frames is a three dimensional array that can be represented as $D \in \mathbb{R}^{W\times H\times N}$, where N denotes the total number of recorded frames, and W and H denote the number of pixels across the width and height of the depth frame respectively. The depth value in a particular pixel with coordinates (i, j) on frame i is denoted by $D_{i,j,t} \in \mathbb{R}^{+}$. In practice, each depth camera has a specific range of operation, which restricts accordingly the range of the recorded values (see depicted field of view in Figure 1). The depth frames can be equivalently expressed as quadratic meshes given by $X_{i,j,t} = (i - i_c)D_{i,j,t} f^{-1}$, $Y_{i,j,t} = (j - j_c)D_{i,j,t}f^{-1}$, and $Z_{i,j,t} = D_{i,j,t}$, where (i_c,j_c) denote the coordinates of the central pixel in the depth frame, and f is the focal length of the depth camera. One of the advantages of the quadratic mesh representation of the depth frames is that they can be easily visualized using virtual lighting, shading, perspective and point of view using standard computer graphics techniques. An example of the quadratic mesh of a captured depth frame is shown in Figure 1 using a color map. The color in this map is a function of the distance of a particular point from the plane of the camera. In our setup the majority of the 3D captured points from the body of the driver are located in the range between 50-150 cm (1.64-4.92 ft) from the sensor.

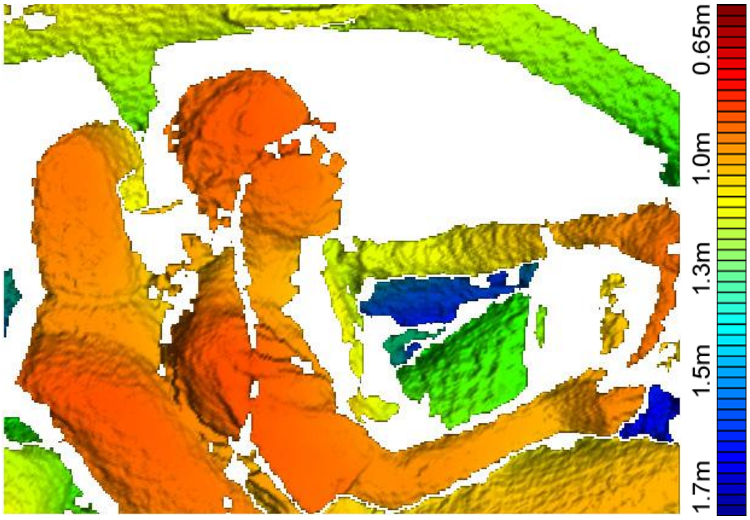

Figure 1: A depth frame from the captured sequence shown here as a 3D surface with colormap.

The segmentation of the depth frames is a necessary pre-processing step for analyzing the activities of the human body. The process of image segmentation is a well-studied computer vision problem, which may be inaccurate when adjacent regions have similar color patterns, and there is no clear boundary between them. For an in-depth presentation and comparison of image segmentation algorithms the reader is referred to the book by Forsyth and Ponce (2003), which dedicates a chapter in mid-vision problems including segmentation. In our proposed framework, the information captured in the depth frames is enough for estimating accurately the outlines or boundaries between critical regions in the field of view, such as the driver's arms, as follows: For each depth frame, a binary mask is computed by evaluating the following two conditions for every pixel *x*,*y* and frame *t*

- $\max_{x,y \in N(i,j)} |D_{i,j,t}-D_{x,y,t}|<threshold_{dz}$
- $\min_{s \in N(t)} D_{i,j,s}>float_{err}$,

where *N(t)* and *N(i,j)* denote 1D and 2D sets of integers in the neighbor of the input *t*, and *i*,*j* respectively, and $threshold_{dz}$, and $float_{err}$ are two predefined constants. Each pixel for which both conditions are true is considered part of the depicted object in contrast to the rest of the pixels that belong to the boundary between regions or to an empty space. The role of the first condition is to segment together pixels with similar depth values, while the second condition ignores pixels with: a) depth values in the range of a computer precision error and/or b) inconsistent depth estimation across neighboring frames. Figure 2 shows an example of a computed mask with clear outlines around the depicted objects.

Figure 2: Left: Visualization of a depth frame. Right: The corresponding mask with enhanced boundaries between objects, computed using our framework.

The masked depth frames are fed as input to a graph-based skeleton fitting algorithm that traces key body features, which is the primary goal of our data processing method. The body features of our interest include the X, Y, Z coordinates of the wrists, elbows, and shoulders as well as the orientation of the driver's torso. The values of these quantities can be estimated by fitting a human skeletal model to each of the depth frames in our datasets. The main challenge in the skeletal fitting process is that the human body in our particular field of view is very close to other objects such as the driver's seat, the steering wheel and the driver's door. Any generic skeletal fitting algorithm performs better when the human body is clearly visible and at a distance from nearby objects as discussed by Barmpoutis et al. (2014), and therefore will fail in our in-cabin setting. For instance, the skeleton tracking algorithm included in the Microsoft Kinect Software Development Kit (SDK) fails in detecting the driver's body as shown in Figure 3, which motivates the development and use of a special-purpose tracking algorithm for in-cabin environments.

Figure 3: Example of the skeleton model that was erroneously fit to an arbitrary frame of the depth sequence by the skeleton tracker provided with the Microsoft Kinect SDK.

In order to overcome the aforementioned skeleton fitting challenges we developed a novel graph-based algorithm that was designed to fit a 7-point skeletal model to the body of the driver using a sequence of depth frames. Our skeletal model included the line segments between the following joints: right wrist, right elbow, right shoulder, neck, left shoulder, left elbow, and left wrist.

The proposed skeleton fitting algorithm scans the depth frames in a diagonal fashion from upper right to lower left (see illustration in Figure 4), pixel strip by pixel strip until the entire image is covered and segmented into line strips that are smoothly-varing 1-pixel-wide regions defined as

$$L=\{(i_s,j-i_s),\ldots,(i_e,j-i_e):\ i_s<i_e,\ |\partial D_{i,j-i,t}/\partial i| < \varepsilon_1,\ |\partial^2 D_{i,j-i,t}/\partial i^2| < \varepsilon_2\ ;\ \forall\ i \in (i_s,i_e)\ \}$$

where i_s and i_e denote the start and end pixel coordinates of the line segment, which lies on the line strip *(i,j-i)*. The length of a line segment can be easily computed by $length(L)= (i_e-i_s+1)\sqrt{2}$.

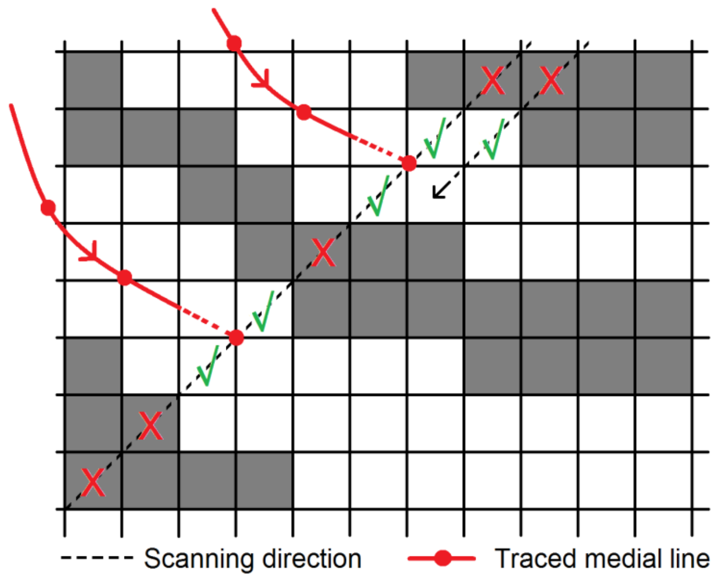

Figure 4: Illustration of the skeleton tracking algorithm.
Note: The pixels of the masked depth frames are scanned diagonally and the medial lines of the body regions are traced (shown in red) using a graph-based algorithm. The medial curves are then filtered in order to form the driver's skeleton.

The computed line segments are organized in the form of a directed graph, which is constructed simultaneously with the segmentation of the line segments. In such graph each line segment *L* can be connected with line segments in the previous row of pixels that form the set of *parents(L)* defined as

$$L'\in \mathrm{parents}(L)\ \leftrightarrow\ \exists\,(i,j-i) \in L,\ \exists\ (i,j-i-1) \in L':\ |\partial D_{i,j-i,t}/\partial j| < \varepsilon_1.$$

Equivalently, each line segment can be connected with line segments in the next row of pixels by defining the set *children(L)* as the inverse of the equation of parents as follows:

$$L' \in \mathrm{children}(L) \leftrightarrow L \in \mathrm{parents}(L').$$

The graph produced by the equations above may contain cycles. To enforce the creation of non-cyclic graphs we define the set *father(L)* as the subset of *parents(L)* that contains the largest line segment:

$$\mathrm{father}(L)=\mathrm{argmax}_{L' \in \mathrm{parents}(L)}\ \mathrm{length}(L').$$

The above process segments a given depth frame into several regions that are computed as independent disconnected graphs and typically correspond to different objects in the field of view. In most applications the subject of interest corresponds to the graph with the largest number of pixels, and in general can be easily isolated from the rest of the objects in the scene.

Each graph can be further segmented into smoothly varying regions by constructing sets of connected line segments with coherent structural characteristics as follows:

$S=\{L_1,...,L_n : L_i = \text{father}(L_{i+1}), |\text{children}(L\_\{i\})|=1; \forall\ i \in [i,n-1]\}$.

The line segments L_i in the above equation form a sequence of descendants without siblings, which corresponds to a linear graph. The set of segments *S* can also be organized into a graph by defining the *father(S)* and *children(S)* using the connections defined in *father(L_1)* and *children(L_n)* respectively.

In our application, the regions of the arms of the depicted subjects can be found by performing simple graph searches. More specifically, the arms can be detected by searching for the two longest ancestor-child paths in the constructed graph with a common ancestor. The medial line curves of the corresponding segments along these two paths are shown in red in Figure 4. It should be noted that the medial curves are calculated in 3D and not in the 2D coordinates of the frames. After that, the detected medial curves are filtered with an 1-dimensional Gaussian filter so that potential noise caused by the depth sensor is removed. Finally, the points that correspond to the elbows, wrists, and shoulders are estimated using spatial constraints as well as geometrical constraints regarding the size, orientation and curvature of the arms. More specifically, the elbows are estimated as the points that belong to the medial lines and have the largest distance from the line segment formed by the end points of each medial line. Similarly, the location of the wrists and shoulders are estimated in relationship to the location of the corresponding elbow.

This process fits our 7-point skeletal model to the best matching medial curves. This graph-based algorithm has linear complexity, which allow us to perform the fitting of the skeleton in real time in less than 15 milliseconds per depth frame in the computer configuration described in Chapter 4.

After fitting the skeletal model to each depth frame, we used the location of the traced joints in order to segment the original mask into regions that correspond to the arms, forearms, head, and torso using the algorithm described by Barmpoutis et al. (2013), and the average X, Y, Z coordinates were computed from the pixels of each region. Figure 5 shows two examples of arm segmentation.

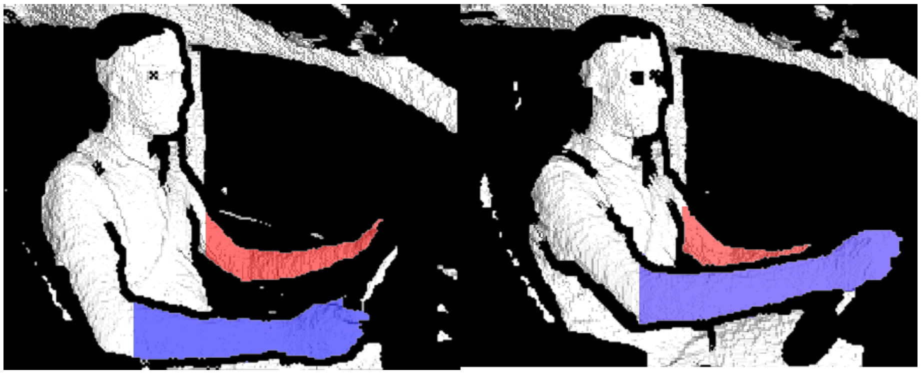

Figure 5: Two examples of the proposed arm segmentation.
Note: Both arms can be clearly segmented from the rest of the depth frame even when one arm is occluded or partially visible from the depth camera (right).

The goal of the segmentation step is to enhance the amount and quality of information that can be included in our quantitative analysis. For example, tracking one particular joint and analyzing its trajectory could highly depend on the quality and reliability of the coordinates of the tracked points. The robustness of such process could be significantly improved by taking into account additional contextual information such as the orientation of the forearm. In Chapter 5, we use the methods described in this section to analyze the motion statistics of the drivers who participated in this study as a high level quantitative descriptor of their driving behavior.

Qualitative Analysis Approach of Body Posture While Performing Maneuvers

Apart from the quantitative analysis described in the previous section, a qualitative assessment was performed. Such assessment was designed to investigate driver behavior and body posture during potentially unsafe situations in the merging or lane changing process, and examine possible correlations.

The qualitative analysis reduction and processing activities are focused on the following items:

1. Whether drivers succeed or fail to identify a potentially conflicting vehicle (side or rear) when performing a lane changing or a merging maneuver (scenario 1).
2. The time duration when drivers were not looking ahead while performing a lane changing maneuver (scenario 2).
3. Vehicle environment during lane changing and merging maneuvers.
4. Body movements during lane changing and merging maneuvers.
5. Correlation between vehicle environment and body movements, and
6. Correlation between scenario 1 and body movements.

The following sections present the respective methodologies for performing these aforementioned qualitative analyses.

Scenario 1: Drivers succeed or fail to identify a potentially conflicting vehicle when performing a maneuver

In this scenario, drivers either succeed or fail to identify the side or rear vehicle either by looking at the side mirror, the rear-view mirror or by turning their heads when performing a maneuver. Drivers look at the side view mirror in order to identify the back left or back right vehicle and look at the rear view mirror in order to identify the back vehicle. If such vehicle exists but the driver fails to identify it, then this is marked as “No”. If the driver identifies the potentially conflicting vehicle, then this is marked as “Yes”. This scenario was evaluated by examining the eye-tracking videos and the in-vehicle videos.

Scenario 2: Eyes off the road duration when performing a maneuver

In this scenario, we considered the time duration that drivers are not looking ahead while performing a lane change or a merging maneuver. During these situations, the driver may be looking towards the side mirror or the rear-view mirror, checking the blind spots or looking at something non-related to driving. This scenario was evaluated by analyzing data from the eye-tracking videos.

Vehicle environment during lane changing and merging

The traffic surrounding the instrumented vehicle was recorded during the lane changing and the merging maneuvers. The vehicle environment was evaluated by looking into the in-vehicle video that captures the presence of front/front right/front left, adjacent right/adjacent left and back/back right/back left vehicle(s). An example of a still image taken from the two cameras is shown in Figure 6.

Figure 6: Front and rear view image capturing vehicle environment while performing a lane changing maneuver

Body movement during lane changing and merging

A detailed qualitative analysis was conducted to identify the number of body movements for all driving maneuvers. The data collected for each of the three merging locations and lane changing maneuver on freeways and arterials were analyzed using the videos from the Kinect recorder and the eye-tracking equipment. The following body movements were recorded as a part of the analysis:

- Head movements,
- Upper body movements, and
- Non-driving-related arm movements (e.g., adjusting the glasses, drinking water, adjusting the seatbelt.)

The following assumptions were made for this data reduction:

- Head movements were recorded if the movement resulted in the driver completely losing sight of the road ahead. Primarily, a head movement to check the blind spot on either the left or right side of the driver was termed significant.
- Other short and multiple head movements during a maneuver were considered significant and recorded since they were believed to reduce the visibility of the road section ahead.
- Short and single head movements with duration of less than 0.15 seconds, involving checking the sideview mirror were ignored, since these were assumed to not cause significant reduction in the visibility of the road and in driver safety.
- Minor movements such as head nodding, adjusting driver's position on the seat that did not result in the driver losing the sight of the road were ignored.
- Turning of the upper body (i.e. shoulders) was termed significant and was recorded as a valid body movement. This movement usually supplemented the head movement of the participants, for example when checking their blind spot.

The start and end time of every movement were recorded along with the frequency of each movement during the corresponding time interval. The data were recorded for all available lane changing and merging maneuvers, as these were defined in the previous section.

Correlation between vehicle environment and body movements

This situation investigated how likely drivers were to change their body posture subject to presence of vehicles in the surrounding lanes. To accomplish this analysis, we calculated the Pearson correlation coefficient from the information related to the surrounding environment of the instrumented vehicle during the lane changing and the merging maneuver, and the body posture information described earlier. More specifically, the following correlations were investigated:

1. Correlation between head/upper body/arm movement presence, duration and frequency of a following vehicle at the target lane, when performing a lane change at the freeway segment.
2. Correlation between head/upper body/arm movement presence, duration and frequency of a following vehicle at the target lane, when performing a lane change at arterial segment.
3. Correlation between head/upper body/arm movement presence, duration and frequency of a following vehicle at the target lane, when performing a merging maneuver at the freeway segment.

As discussed in the previous section, changes to drivers' head position or head rotation and changes of the torso position were recorded separately. Arm movements were also recorded, but since lane changing and merging maneuvers cannot be executed without an arm movement, only these arm movements that are not related to driving (e.g., seatbelt adjustment, gestures while talking, reaching for an object inside the vehicle) were recorded.

Two-tailed statistical tests were performed to evaluate whether the correlation between the two values is statistically significant at a 0.05 level.

Correlation between scenario 1 and body movements

This investigation attempted to capture any relationship between potentially unsafe situations identified in scenario 1 discussed earlier, and body (head, torso and arms) movement. The qualitative assessment looked into whether drivers' body position and movements inside the vehicle are correlated with their ability to detect other conflicting vehicles during a lane change or a merging maneuver. Similarly to the previous case, statistical tests evaluate the significance of the correlations.

CHAPTER 4: DATA COLLECTION AND REDUCTION

Introduction

This chapter presents the data collection effort undertaken as part of this project.

Selection of Drivers and Driver Questionnaires

The study was advertised through local organizations in Gainesville, Florida, and candidates completed an eligibility-screening questionnaire. This questionnaire assembled information on candidates' demographics, such as age, gender, race, driver's license and car insurance information, experience driving in the U.S. as well as contact information. This information was used to select a diverse set of participants for the in-vehicle data collection. Appendix A presents the eligibility screening questionnaire developed and used in this study.

A total of 35 drivers were selected to participate in the field data collection experiment. Each of the selected drivers completed a pre-driving questionnaire before each session. The pre-driving questionnaire contained several multiple-choice questions related to their driving habits and culture. These questions solicited participants' driving frequency to work/school, total duration of driving on weekdays, desired speeds on urban streets, lane changing frequency, and frequency of involvement in secondary tasks while driving (texting, eating, etc.) Appendix B presents the pre-driving questionnaire. Table 1 summarizes the participants' information obtained through the pre-driving questionnaire.

In-Vehicle Data Collection

The data collection effort was conducted between February and March of 2014 and participants drove during morning (AM), midday and afternoon (PM) peak. All 35 participants drove for approximately 2 hours along a pre-selected route in Gainesville, FL. The route consisted of a 5.0 mi section along I-75 in the southbound (SB) and northbound (NB) directions, and a mile long arterial segment (Archer Road, EB and WB directions). The freeway segment along I-75 has three lanes per direction and the arterial segment has three through lanes per direction, several median openings, and four signalized intersections. A schematic of the data collection site is shown in **Error! Reference source not found.**. During the two-hour experiment, participants were asked to drive along the preselected route several times; hence multiple data samples were collected per driver.

The instrumented vehicle that participants used during the data collection was a Honda Pilot SUV, owned by the University of Florida-Transportation Research Center (TRC). The vehicle has a Honeywell Mobil Digital Recorder (HTDR400) system. This system has two digital cameras, which capture front and rear view video. The video is stored in the hard drive of the HTDR400 system. The instrumented vehicle is also equipped with a GPS where information of the vehicle position and speed is recorded on the system. Additional data such as left-right turn signal activation, video clips and audio recording are also recorded in the hard drive. A laptop is connected to the system and allows the display of the two cameras through the HTDR400 software. The videos from the cameras that capture the front and the rear of the subject vehicle were used to obtain information on the vehicle environment when performing lane changes and merging maneuvers. **Error! Reference source not found.** provides an internal view of the instrumented vehicle.

Table 1: Characteristics of Participants

ID	Gender/ Age	Q2 Driving experience	Q3 Driving duration	Q4 Drive frequency to work/ school	Q5 Time spent driving on a weekday	Q6 Drive:	Q7 Desired speed when speed limit is 40 mph	Q8 Desired speed when speed limit is 20 mph	Q9 Lane change frequency	Q10 Eat or drink while driving	Q11 Use GPS while driving	Q12 Use cellphone while driving	Q13 Text while driving	Q14 Reach for sth without taking eyes from road	Q15 Multitask while driving
125	M/21	Very experienced	3-9 yrs	Daily	< 30 min	With 1 or more passengers	40-45 mph	20-25 mph	Often	Occasionally	Occasionally	Often	Occasionally	Frequently	Frequently
106	M/16	Somewhat experienced	< 1 year	Daily	30-60 min	Alone	35-40 mph	20-25 mph	Seldom	Never	Occasionally	Occasionally	Never	Rarely	Rarely
134	F/17	Somewhat experienced	1-3 yrs	Daily	30-60 min	Alone	40-45 mph	25-30 mph	Often	Occasionally	Occasionally	Occasionally	Never	Frequently	Occasionally
108	F/19	experienced	3-9 yrs	Daily	30-60 min	Alone	40-45 mph	15-20 mph	Seldom	Occasionally	Occasionally	Occasionally	Never	Occasionally	Occasionally
120	M/20	Very experienced	3-9 yrs	1-2 times	< 30 min	Alone	40-45 mph	20-25 mph	Seldom	Occasionally	Occasionally	Never	Never	Rarely	Rarely
107	M/24	experienced	3-9 yrs	1-2 times	30-60 min	Alone	40-45 mph	20-25 mph	Often	Often	Occasionally	Occasionally	Never	Occasionally	Rarely
102	F/22	-	3-9 yrs	3-4 times	< 30 min	Alone	40-45 mph	15-20 mph	Often	Never	Never	Never	Never	Never	Rarely
135	M/57	Very experienced	>10 yrs	Daily	1-1.5 hrs	Alone	40-45 mph	20-25 mph	Seldom	Occasionally	Occasionally	Occasionally	Occasionally	Occasionally	Rarely
121	F/22	experienced	3-9 yrs	3-4 times	30-60 min	Alone	40-45 mph	20-25 mph	Often	Occasionally	Often	Occasionally	Occasionally	Rarely	Occasionally
136	F/19	experienced	3-9 yrs	Daily	1-1.5 hrs	Alone	35-40 mph	15-20 mph	Often	Occasionally	Occasionally	Never	Never	Occasionally	Never
137	F/60	Very experienced	>10 yrs	3-4 times	1-1.5 hrs	Alone	40-45 mph	20-25 mph	Seldom	Occasionally	Occasionally	Occasionally	Never	Occasionally	Occasionally
138	F/59	Very experienced	>10 yrs	Daily	30-60 min	Alone	40-45 mph	20-25 mph	Seldom	Occasionally	Occasionally	Never	Never	Never	Never
123	F/20	experienced	3-9 yrs	3-4 times	> 2 hrs	Alone	40-45 mph	20-25 mph	Seldom	Occasionally	Occasionally	Occasionally	Occasionally	Rarely	Rarely
129	M/34	Very experienced	>10 yrs	3-4 times	30-60 min	Alone	40-45 mph	15-20 mph	Whenever possible	Never	Occasionally	Occasionally	Never	Occasionally	Never
127	M/20	experienced	3-9 yrs	Daily	< 30 min	Alone	40-45 mph	15-20 mph	Seldom	Often	Occasionally	Never	Never	Occasionally	Rarely
110	F/58	Very experienced	>10 yrs	3-4 times	1-1.5 hrs	Alone	40-45 mph	20-25 mph	Often	Occasionally	Occasionally	Never	Never	Occasionally	Rarely
105	M/24	experienced	3-9 yrs	Never	< 30 min	Alone	35-40 mph	20-25 mph	Seldom	Occasionally	Never	Occasionally	Never	Rarely	Rarely
133	M/23	experienced	1-3 yrs	1-2 times	< 30 min	With 1 or more passengers	40-45 mph	20-25 mph	Whenever possible	Never	Often	Never	Never	Rarely	Never
104	F/21	experienced	3-9 yrs	3-4 times	1-1.5 hrs	With 1 or more passengers	40-45 mph	20-25 mph	Seldom	Occasionally	Occasionally	Occasionally	Never	Occasionally	Occasionally
126	F/25	Very experienced	3-9 yrs	3-4 times	> 2 hrs	With 1 or more passengers	35-40 mph	15-20 mph	Seldom	Occasionally	Occasionally	Never	Never	Rarely	Never

Table 1. continued

ID	Gender/ Age	Q2 Driving experience	Q3 Driving duration	Q4 Drive frequency to work/ school	Q5 Time spent driving on a weekday	Q6 Drive:	Q7 Desired speed when speed limit is 40 mph	Q8 Desired speed when speed limit is 20 mph	Q9 Lane change frequency	Q10 Eat or drink while driving	Q11 Use GPS while driving	Q12 Use cellphone while driving	Q13 Text while driving	Q14 Reach for sth without taking eyes from road	Q15 Multitask while driving
130	F/35	Very experienced	>10 yrs	Daily	-	With 1 or more passengers	35-40 mph	20-25 mph	Often	Occasionally	Never	-	-	-	Never
139	F/21	experienced	3-9 yrs	Never	< 30 min	With 1 or more passengers	40-45 mph	20-25 mph	Seldom	Occasionally	Occasionally	Occasionally	Never	Rarely	Rarely
109	M/24	Very experienced	1 to 3 years	3-4 times	30-60 min	With 1 or more passengers	40-45 mph	20-25 mph	Often	Never	Often	Occasionally	Occasionally	Occasionally	Occasionally
140	F/20	Very experienced	3-9 yrs	Daily	< 30 min	Alone	40-45 mph	20-25 mph	Often	Occasionally	Occasionally	Occasionally	Occasionally	Rarely	Rarely
141	M/21	experienced	1-3 yrs	Daily	> 2 hrs	Alone	40-45 mph	20-25 mph	Often	Occasionally	Often	Occasionally	Never	Occasionally	Frequently
131	M/23	experienced	3-9 yrs	3-4 times	30-60 min	Alone	40-45 mph	20-25 mph	Whenever possible	Occasionally	Never	Occasionally	Never	Occasionally	Occasionally
118	M/20	Very experienced	3-9 yrs	3-4 times	< 30 min	Alone	35-40 mph	15-20 mph	Seldom	Never	Never	Never	Never	Never	Rarely
122	M/54	Very experienced	>10 yrs	Daily	> 2 hrs	Alone	40-45 mph	15-20 mph	Seldom	Never	Often	Occasionally	Never	Occasionally	Rarely
132	M/25	Very experienced	>10 yrs	Daily	> 2 hrs	With 1 or more passengers	40-45 mph	20-25 mph	Often	Occasionally	Occasionally	Occasionally	Occasionally	Occasionally	Occasionally
128	M/20	experienced	3-9 yrs	Daily	1-1.5 hrs	Alone	40-45 mph	20-25 mph	Often	Occasionally	Never	Occasionally	Never	Rarely	Rarely
124	M/21	experienced	3-9 yrs	3-4 times	2-1.5 hrs	Alone	40-45 mph	20-25 mph	Seldom	Occasionally	Occasionally	Occasionally	Never	Occasionally	Rarely
119	F/25	Somewhat experienced	< 1 year	3-4 times	< 30 min	With 1 or more passengers	40-45 mph	20-25 mph	Never	Never	Occasionally	Never	Never	Rarely	Rarely
103	F/35	Very experienced	>10 yrs	Daily	> 2 hrs	With 1 or more passengers	35-40 mph	15-20 mph	Often	Occasionally	Often	Often	Occasionally	Rarely	Occasionally
101	F/21	experienced	3-9 yrs	3-4 times	30-60 min	Alone	40-45 mph	15-20 mph	Seldom	Occasionally	Occasionally	Occasionally	Occasionally	Occasionally	Occasionally
111	M/30	experienced	3-9 yrs	1-2 times	< 30 min	Alone	40-45 mph	20-25 mph	Whenever possible	Never	Occasionally	Never	Never	Rarely	Never

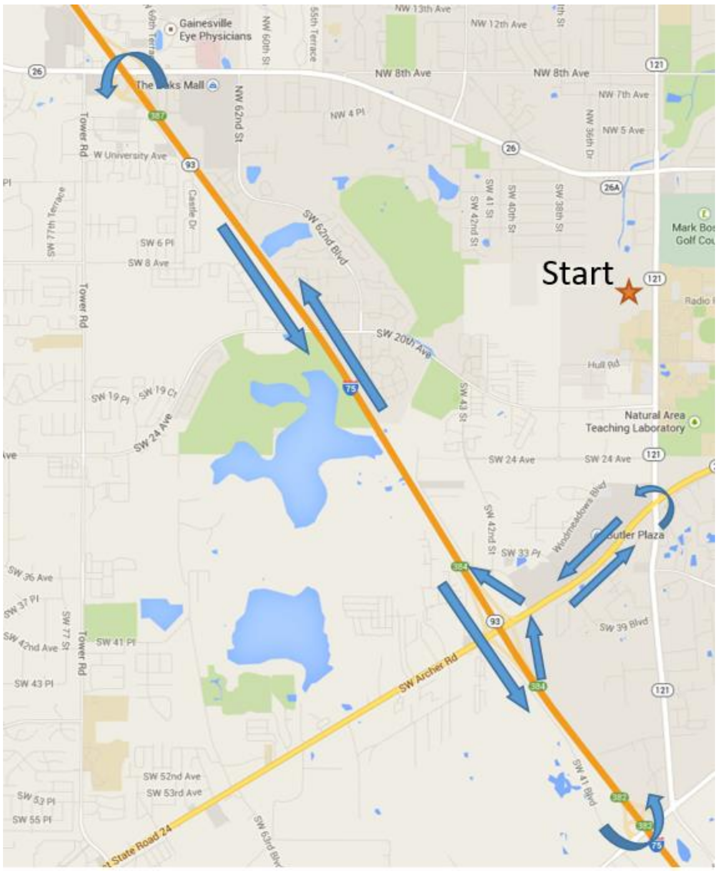

Figure 7: Data collection site

Figure 8: Inside view of the instrumented vehicle

The instumented vehicle was also equipped with a depth camera, which was the PrimeSense™ infrared structure-light sensor embedded in Microsoft's Kinect™ device. The depth sensor is shown in Figure 9. The sensor was connected to a laptop during the entire duration of the data collection effort. The device was connected (via a USB 2.0 port) to a 64-bit computer with Intel Core i5 (quad core) CPU at 2.53GHz and 4GB RAM. The computer and sensor were both powered using a 75-watt car power inverter.

Figure 9: Kinect™ by Microsoft

The resolution of the depth sensor was 320 * 240 pixels at ~25-30 frames per second and was calibrated so that it recorded depth in the range from 0.4m to 3.0m. This depth was adequate to capture the motion of the driver with the sensor mounted on the upper right side of the cabin. An example illustration of the collected depth frames is shown in Figure 10. The videos obtained from this equipment were used to perform the quantitative analysis discussed in the previous chapter. These videos were also used to identify and group body movements (head, upper body, arm movements) as part of the qualitative analysis.

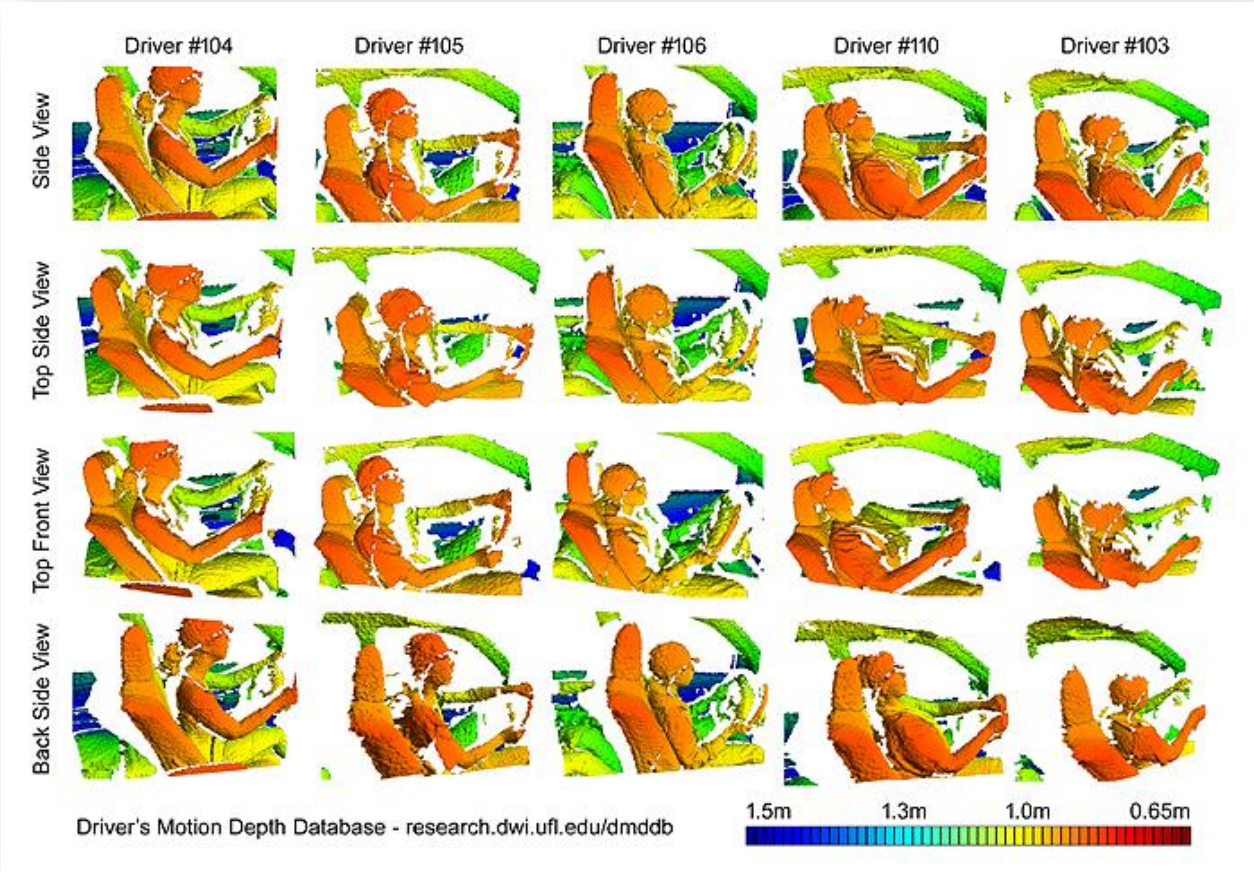

Figure 10: Example of a depth frames from the collected dataset, visualized as a 3D surfaces using computer graphics shading with color-mapped depth visualization (depth in meters).

The depth sequences captured during this study were manually segmented into several clips that corresponded to the merging and lane changing maneuvers that were performed as participants were driving along the freeway and the arterial segment. The segmentation of the depth frames is a necessary pre-processing step for scenario-based analysis of the human body activities. Depth sequence clips for each merging and lane-changing maneuver can be used to study the body posture for the entire duration of these maneuvers. The color video data from the vehicle cameras and the eye-tracking device were used to obtain information on the surrounding traffic and capture vehicle interactions when performing the maneuvers, and have been documented as part of the metadata of the dataset that was created, dubbed DMDDB, Driver's Motion Depth Database.

In total, the data reduction process produced 523 depth video sequences of 27 drivers performing 236 merges and 287 lane changes with more than 300,000 depth frames (305,333) and 16 billion 3D points (15,739,194,425). Representative examples of depth frames from our dataset are shown in Figure 10. The dataset can be browsed on-line using our on-line DMDDB 3D viewer, which is available at the following URL address: http://research.dwi.ufl.edu/dmddb/browser/.

Furthermore, a programming interface (API) was developed that allows researchers to get full access to the DMDDB database and easily build their own custom experiments in Java or JavaScript code. The DMDDB API documentation, which is also available at the aforementioned website, provides all the details regarding the functionality of the provided API, along with several source code examples for accessing the depth data and metadata of the database from custom written Java or Javascript programs. The developed API includes several high-level methods organized properly in object-oriented classes that allows programmers to get full access of the data in as few as 10 lines of Java code, as it is demonstrated in the source code examples provided in our website.

Eye-tracking equipment was also used in order to capture their gaze during the entire driving process. The eye-tracking equipment (Figure 11) consists of a pair of lightweight head-mounted glasses, a portable wireless Data Transmit Unit (DTU), the EyeVision software and a laptop. The glasses have two high-resolution digital cameras; one that records the field of view and the other records the driver's eye. The two images are integrated into a single video that includes a superimposed gaze crosshair (Figure 12).

Figure 11: Eye-tracking equipment (Mobile Eye-XG) provided by Applied Science Laboratories


(a)

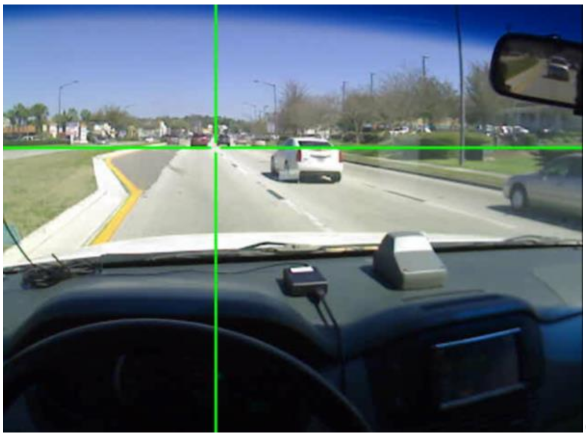
(b)

Figure 12: Field of view from the eye-tracking camera and gaze crosshair capturing (a) following vehicle through the rear-view mirror and (b) leading vehicles.

The eye-tracking videos were used to obtain information related to the duration of the lane changing maneuver, the duration of the merging maneuver, the vehicle environment, whether drivers succeed or fail to identify a potentially conflicting vehicle (side or rear) when performing a lane changing or a merging maneuver (scenario 1), and the time duration when drivers were not looking ahead while performing a lane changing or a merging maneuver (scenario 2).

Data Collection Technical Issues and Limitations

Due to technical issues that arose during the data collection process, some study limitations were identified. Concerning the quantitative analysis, the raw Kinect depth frames were occasionally contaminated with visual artifacts due to the limitations of the employed depth sensing technology. More specifically, infrared structured light was projected to the field of view and was observed and processed by an infrared camera in order to reconstruct in real-time the depth frame as described by Sali and Avraham (2014). The projection of the infrared light pattern failed in the following two cases: 1) surfaces of irregular or complex reflectance, such as specular and transparent, and 2) presence of intense direct light from external sources, such as the sun. Data that correspond to these two cases were not analyzed.

Furthermore, the position and orientation of the camera is slightly different each time due to reinstallation of the sensor before each recording session. The driver's seat was also adjusted differently by each driver, which introduced a natural variability of content in the depth sequences. Both of these factors pose additional challenges in quantitative data processing and need to be considered in order to develop robust algorithms for quantitative analysis of driver movements.

Several limitations were also identified for the qualitative part of this study. Although it was initially planned to collect eye-tracking data for all drivers participated in the study, several drivers were not able to drive wearing the eye-tracking glasses, as they already wore other glasses, or because they found the glasses to hinder their vision. Although the specific eye-tracking glasses can be worn on top of other glasses, some drivers were not willing or were not comfortable doing so. As such, useful data regarding their driver behavior were not collected in this case, and it was not possible to complete the qualitative assessment for those drivers.

The calculation of the entire lane changing maneuver duration requires going back before the actual lane changing and observe when drivers have actually thought of and decided to perform the maneuver. This thought process was difficult to track without checking whether the driver actually looked through the mirror in the eye-tracking video. When this operation was not visible from the eye-tracking videos, then approximations have been used.

Another challenge that was encountered during the data reduction phase involved the synchronization of the various types of video data, in order to check all in-vehicle/ driver-related and vehicle environment-related information. The Kinect videos and the eye-tracking videos would start almost at the same time, so these were more or less aligned. However, the in-vehicle videos would start as soon as the car ignition was on, so a significant effort was made to synchronize these videos with the rest.

CHAPTER 5: RESULTS

Introduction

This chapter presents the results of both the quantitative and the qualitative analyses performed. The chapter is organized into two sections that describe the details of each respective type of analysis and discuss the obtained results.

Quantitative Analysis Results

The quantitative analysis was performed in the depth sequences recorded from the Kinect sensor. Each depth frame sequence was processed using the body tracking and segmentation method described in Chapter 3. The segmentation results were tracked across frames by computing the magnitude of the motion observed in each respective body region. More specifically, the magnitude of the motion of the arms was computed by calculating $\Delta x^2+\Delta y^2+\Delta z^2$ of the 10 right-most pixels of each segmented region. The choice of these pixels approximated well the regions of the corresponding wrists, hence their tracking was considered a good descriptor of the arm activity during maneuvers. In order to enhance the robustness of the calculations a region of 10 pixels was used, and the average location (x,y,z) was computed from these pixels. Similarly, the average location was computed from the pixels of the entire head region computed from the classifier.

The total magnitude of the motion was computed individually for the left arm, right arm, and head for each of the 523 depth video sequences. The average and standard deviation of the magnitude of motion of each driver was calculated and plotted in Figure 13.

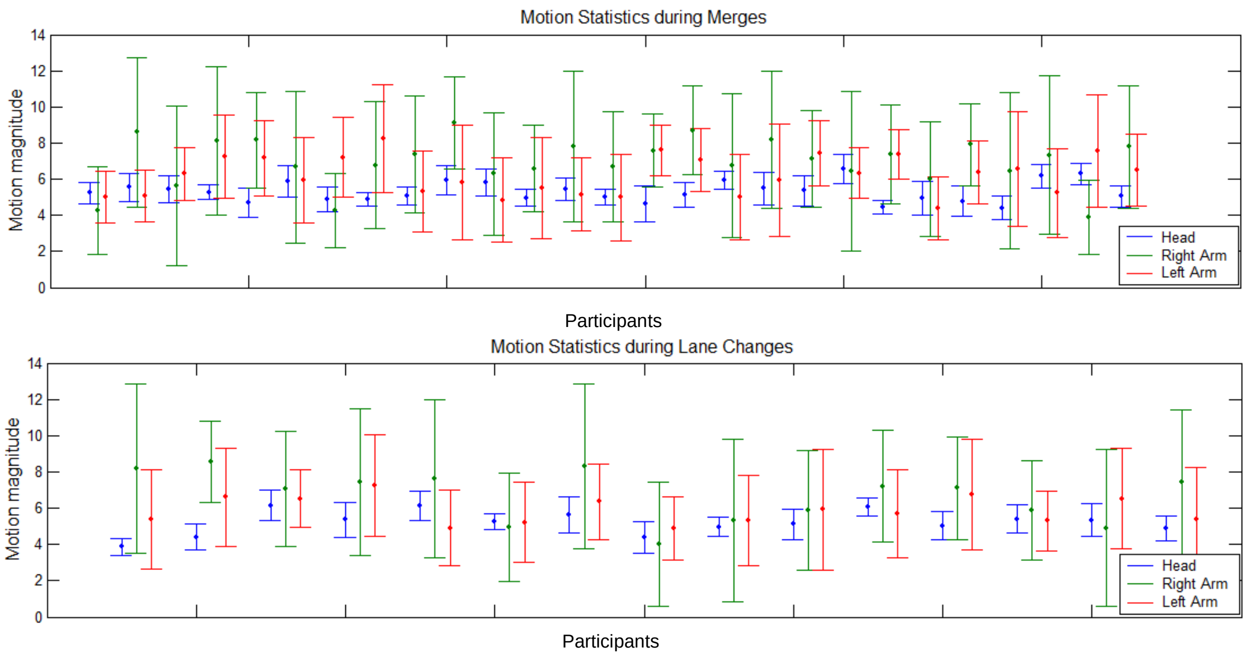

Figure 13: Plot of the statistics (average and standard deviation) of the magnitude of the motion observed in the regions of the left and right arms and head of each driver. The results are separately reported for merging and lane changing maneuvers.

In Figure 13, the x-axis corresponds to different drivers in the dataset, and the y-axis corresponds to the calculated magnitude of motion. The average and standard deviation are shown as color-coded bar plots in blue, green, and red, for the head, right arm, and left arm respectively. By observing the plots, it is evident that the calculated motion of the region of the head was significantly smaller than the magnitude of motion observed in the arm regions, which was expected.

Another observation is that the right arm is more active than the left arm in the majority of the drivers, because the average magnitude (shown in dots) is slightly higher in the case of right arm (green dot) compared to the left arm (red dot). This result was also anticipated as there is more physical space for right arm movements. However, it should be noted that right arm movement could correspond to non-driving related action, which was not separated from the statistical calculation. The standard deviation of the magnitude of motion was also notably larger for the region of the right arm that indicates inconsistent pattern across video sequences.

Similar analysis can be performed across various groups of drivers in our dataset. Figure 14 shows the statistics (average and standard deviation) of the motion magnitude of female drivers (11 subjects), male drivers (16 subjects), 20 year old drivers or younger (7 subjects), drivers between 20 and 30 years of age (13 subjects), and 30 year old drivers or older (6 subjects). In general, minor variations were observed across the different groups of drivers. For instance, the average motion of the head was smaller in the female subjects compared to the male drivers; that could indicate either that more male subjects moved their head during maneuvers or that in general head motions were more frequent in the male drivers. On the other hand the subject in the middle age group had slightly more intense arm motions compared to the younger or older subject; that could either indicate that their driving pattern was more intense or that, in general, they moved their arms and especially the right one more frequently during the maneuvers.

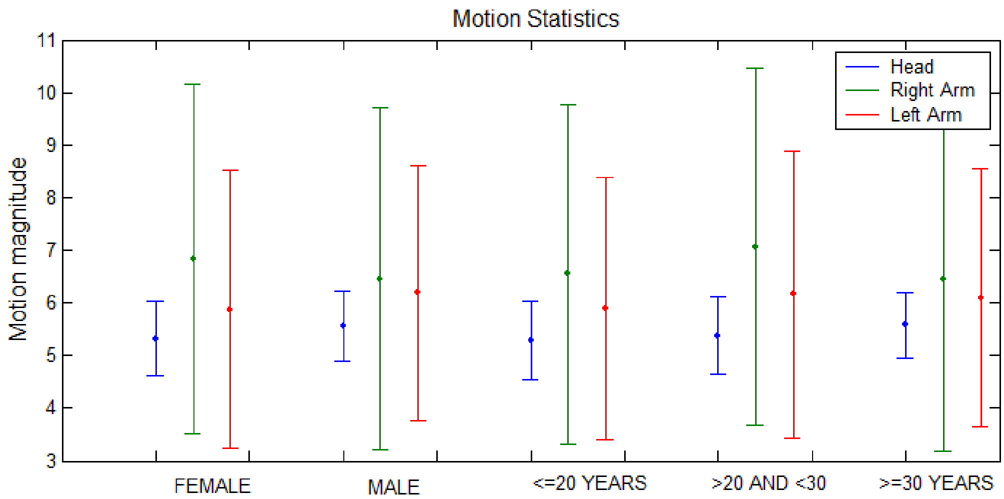

Figure 14: Plot of the statistics of the magnitude of the motion from various groups of drivers based on gender or age.

Qualitative Analysis Results

As detailed in the Methodology section (Chapter 3), the qualitative analysis performed in this study focused on the effect of body posture and body movement into drivers' potential conflict with other vehicles when changing lanes or merging onto the freeway. The main findings are summarized next.

Scenario 1

This scenario examined whether drivers fail or succeed in identifying a side vehicle either by looking at the side mirror, the in-vehicle mirror or by turning their heads/body when performing a lane changing or a merging maneuver. Table 2 presents the summary of the data reduction for this scenario when performing a lane changing maneuver. The table shows the total number of instances when a vehicle was present in the study vehicle’s environment (back left or back right). Subsequent columns indicate the total number of instances when the driver of the study vehicle either identified or failed to identify the presence of vehicles in his/her environment. The total number of instances may be differed from the overall instances because a single lane-changing maneuver could have had vehicles present on either side of the study vehicle i.e. in the vehicle environment. Therefore, the overall results from the table indicate the number of lane-changes and the corresponding number of instances when the drivers identified and/or failed to identify the vehicles in their environment.

Table 2. Summary of Data Reduction for Scenario 1 when Performing Lane Changes

Driver ID	Instances when vehicle was present at the back			Instances when vehicle at the back was identified			Instances when vehicle at the back was not identified		
	Left	Right	Total	Left	Right	Total	Left	Right	Total
103	3	3	6	3	1	4	0	2	2
104	1	1	2	1	1	2	0	0	0
106	0	1	1	0	1	1	0	0	0
109	-	-	-	-	-	-	-	-	-
111	7	5	12	5	3	8	2	2	4
118	2	4	6	2	3	5	0	1	1
119	0	0	0	0	0	0	0	0	0
120	2	5	7	2	3	5	0	2	2
121	1	3	4	1	1	2	0	2	2
121	2	3	5	2	2	4	0	1	1
122	0	7	7	0	4	4	0	3	3
122	4	7	11	4	5	9	0	2	2
124	6	9	15	6	7	13	0	2	2
125	3	3	6	3	3	6	0	0	0
126	1	6	7	1	4	5	0	2	2
# of instances	32	57	89	30	38	68	2	19	21
# of LC	77			57			20		

Note: “-” Not Applicable

Table 3 shows the type of lane changes (right- or left-side) performed by a specific driver (Driver ID 103) and whether this driver identified or not the following vehicle at the target lane. Similar tables were generated for all participants and all 77 lane changes performed. These tables are provided in Appendix C.

Table 3. Sample Data Reduction for Scenario 1 for Lane Changing Maneuvers of Driver ID 103

Driver ID	Type of Lane Change	Vehicle Present		Vehicle Identified		Vehicle Not Identified	
		Left	Right	Left	Right	Left	Right
103	R	-	Y	-	Y	-	-
	L	Y	-	Y	-	-	-
	L	Y	-	Y	-	-	-
	L	Y	Y	Y	Y	-	-
	L	-	Y	-	-	-	Y

Note: "-" Not Applicable

Generally, although drivers sometimes failed to identify the presence of another vehicle in their environment, this event would not constitute unsafe conditions, because that vehicle was not at the target lane. That is, all the instances when the driver failed to identify the presence of a vehicle were when the driver was performing a lane changing maneuver for the opposite side and the presence of a vehicle did not impact the maneuver in any way. For example, if the driver failed to identify the presence of a vehicle at the back right it was because the driver was performing a lane-changing maneuver on the left side. The presence of a vehicle on the back right side did not alter the driver's intentions nor resulted in the driver abandoning the maneuver.

Similar analysis was performed for the merging maneuvers.

Table 4 summarizes the number of instances that drivers identified (or not) the following vehicle at the shoulder lane (on their left) while they were merging on the freeway. Appendix C also includes the scenario 1 data reduction for all participants that performed merging maneuvers.

The results of scenario 1 for the merging maneuvers indicate that, in total, there were 47 cases when a vehicle was present at the back left and the driver identified the vehicle either by checking the sideview mirrors or by turning his/her head. There were no cases when a driver failed to identify the vehicle at its back left. Also, in a total of 95 cases analyzed there was no vehicle present at the back left of the study vehicle but in 93 of those cases the drivers still had head movements to identify vehicle presence.

Table 4. Summary of Data Reduction for Scenario 1 when Performing Merging Maneuvers

Driver ID	Total merging maneuvers	Instances when vehicle was present at the back left	Instances when vehicle at the back left was identified	Instances when vehicle at the back left was not identified
101	9	5	5	0
103	9	4	4	0
105	9	1	1	0
109	8	3	3	0
110	9	3	3	0
111	9	1	1	0
118	5	0	0	0
119	5	2	2	0
121	9	6	6	0
122	8	2	2	0
124	9	1	1	0
126	12	4	4	0
127	11	4	4	0
130	3	2	2	0
131	9	2	2	0
132	9	1	1	0
133	9	6	6	0
Total	**142**	**47**	**47**	**0**

Scenario 2

During each lane changing maneuver performed, we investigated the amount of time that drivers' eyes were off the road when they performed the maneuver. This assessment concerns primarily lane changing events, because in these situations the relationship with the lead vehicle is more prominent. In merging maneuvers a leading vehicle was typically absent from our database; thus, the need to evaluate the duration of time that the participants' eyes were off the road was minimal.

Data from thirteen participants were used for this analysis. Each lane changing maneuver performed by the participants was looked thoroughly by the researchers, and the times where the drivers were not looking at the leading vehicle were recorded.

Table 5 presents the results of the analysis, along with some demographic information (gender, age) of these 13 participants.

Based on

Table 5, it was observed that the average duration was similar for all participants; however, the maximum duration where drivers' eyes were not looking at the vehicle in front of them, differs significantly. Such situations could hide unsafe conditions during the lane changing maneuver. While the findings are valuable, given the small variation between the ages of the participants and the limited sample, we cannot assume that different age groups are more likely to take their eyes off the road for longer periods of time than others.

Table 5. Summary of Scenario 2 (eyes off the road) when Performing Lane Changing Maneuvers

Driver ID	Average Duration	Median Duration	Min Duration	Max Duration	Gender	Age
103	0:00:04	0:00:04	0:00:01	0:00:07	F	35
104	0:00:04	0:00:03	0:00:01	0:00:07	F	21
106	0:00:03	0:00:02	0:00:01	0:00:07	M	16
109	0:00:03	0:00:03	0:00:01	0:00:08	M	24
111	0:00:04	0:00:03	0:00:01	0:00:15	M	30
118	0:00:02	0:00:02	0:00:01	0:00:03	M	20
119	0:00:04	0:00:03	0:00:01	0:00:07	F	25
120	0:00:04	0:00:03	0:00:01	0:00:08	M	20
121	0:00:03	0:00:02	0:00:01	0:00:08	F	22
122	0:00:03	0:00:03	0:00:01	0:00:09	M	54
124	0:00:03	0:00:03	0:00:01	0:00:10	M	21
125	0:00:03	0:00:02	0:00:01	0:00:09	M	21
126	0:00:03	0:00:03	0:00:01	0:00:06	F	25

Vehicle environment during lane changing and merging

For all lane changing and merging maneuvers in our database, we obtained information on the vehicle environment. More specifically, the following information was obtained:

- Vehicle in the adjacent lane;
- Vehicle in the front of the subject vehicle;
- Vehicle in the front left/right of the subject vehicle;
- Vehicle at the back of the subject vehicle; and
- Vehicle at the back left/right of the subject vehicle.

The observations of the vehicle environment concern the entire duration of the lane changing and the merging events, as these were defined in Chapter 3. The results of this analysis were used for completing the qualitative analysis and more specifically, for assessing the relationship between vehicle environment and body movements, and for investigating scenario 1 as discussed earlier.

Body movement during lane changing and merging

As it was discussed in Chapter 3, the following drivers' body movements were obtained and analyzed when drivers performed lane changing and merging maneuvers, i.e.,:

- Head movements,
- Upper body movements, and
- Non-driving-related arm movements (e.g., adjusting the glasses, drinking water, adjusting the seatbelt.)

The results of this analysis were used to investigate correlations between body movements and vehicle environment and scenario 1. Video data for 27 drivers were analyzed for the merging maneuvers at the three locations: Archer Road NB, Newberry Road SB, and Williston NB. Similarly, data for 11 drivers were analyzed for the lane changing maneuvers on the freeway and the arterial segment.

The analysis showed that head movements account for the most predominant type of body movements while driving. All the drivers had a tendency to look over their shoulders, check the rearview/sideview mirrors to ensure whether it was safe to complete the merging and/or lane changing maneuvers. Also, most of the drivers used a substantial portion of their upper body (shoulders) when making the driving maneuvers especially at the very instance of merging and lane changing. Non-driving related maneuvers included every instance when the driver released his/her hand from the steering to perform non-driving related tasks such as: adjusting the glasses, drinking water, adjusting the seatbelt, hand gesturing when talking to other passengers in the vehicle, and scratching their nose/hand. The non-driving movements are not associated with distracted driving instances unlike talking on the cellphone, adjusting the radio, etc.; therefore, these movements did not result in drivers taking their eyes off the road.

The start and end of every movement was recorded along with the frequency of each movement during the corresponding time interval. Table 6 shows a sample for the qualitative analysis for merging maneuvers on SB Newberry Road for Driver ID 110. The data were recorded for every round completed by the driver. The start and the end of the maneuver correspond to the frame on the Kinect player. To determine the total duration of the maneuver in seconds, the difference between the start and end frame was divided by 25 (25 frames per second). The frequency denoted the number of relevant body movements the driver made during the corresponding time interval.

Table 6. Sample Qualitative Data Analysis for Merging Maneuvers Performed by Driver ID 110 on SB Newberry Rd.

Driver ID	Round	Type of Body Movement											
		Head				Upper Body				Non-Driving			
		Start time	End time	Duration (s)	Frequency	Start time	End time	Duration (s)	Frequency	Start time	End time	Duration (s)	Frequency
110	1	422	440	0.72	1								
		500	515	0.60	1								
		639	852	8.52	3	639	688	1.96	1				
	2	34	53	0.76	1								
		461	490	1.16	1								
		514	819	12.2	5	539	591	2.08	1				
	3	365	397	1.28	1					793	835	1.68	1
		500	525	1.00	1								
		598	752	6.16	4								
		793	835	1.68	1								
		932	953	0.84	1								

After analyzing a total of 235 videos of merging maneuvers and 335 videos of lane changing maneuvers, the following generalized conclusions can be drawn:

- Head movements were the most predominant type of body movement when driving. In the majority of the cases drivers preferred turning around to check the blind spot when performing the required maneuvers.
- The average duration of a head movement was about **4 seconds** for the merging maneuvers with a frequency of 2 movements, consistent for all three merging sites.
- Interestingly, the average duration of head movement for a lane changing maneuver on the freeway was approximately **3.75 seconds** with a frequency of 1.8 and the average duration of head movement for a lane changing maneuver on the arterial was approximately **2.3 seconds** with a frequency of 1.1, consistent for both the locations. Therefore, drivers were more careful when making the lane changing maneuvers on the freeways than the arterials.
- Upper-body movements were observed only when a driver required checking the blind spot. Although, it was observed that the upper body movements were relative to each driver and varied from driver to driver, it cannot be concluded from the qualitative analysis that checking the blind spot involved the use of upper body movements for all the drivers. At the three merge locations, the average duration of an upper body movement was **4.5 seconds** while during lane changes, the average duration of an upper body movement was **3.5 seconds**.
- Non-driving related movements did not necessarily impact the drivers' safety. The most common non-driving related movement was the drivers' tendency to use their hands for gesturing when talking to the researcher that was sitting on the back seat. Coincidentally the average duration of the non-driving related movements at the three merge locations and at the two lane changing locations was **3.12 seconds**. Thus, it could be suggested that non-driving related body movements are not correlated to the type of the driving maneuvers involved and were performed by the drivers irrespective of the two maneuvers, i.e. merging and lane-changing.

Correlation between vehicle environment and body movements

The objective of this analysis was to investigate how likely drivers are to change their body posture subject to the presence of vehicles in the surrounding lanes. More specifically, for both merging and lane changing maneuvers, we were primarily interested in the correlation with vehicles located in the target lane (either left or right side lane) that will become followers after the maneuver is complete.

Several different correlation tests were performed. For example, freeway merging, freeway lane changing and arterial lane changing maneuvers were examined separately. In addition, the relationship between the vehicle environment and the duration or frequency of head, upper body, or arm movement was also investigated separately.

Table 7 presents the correlation results between the frequency of movements, the actual movement event, and the total duration of the movement with the event that vehicles are present at the rear-left/ rear-tight side, or that there is a follower in the target lane. This table concerns only lane changing events along the arterial road. Table 8 presents similar correlation results but for freeway lane changing maneuvers. Lastly,

Table 9 shows the correlation between the follower in the freeway shoulder lane (left of the instrumented vehicle) and the body movements (actual movement, frequency, duration) of the driver.

Table 7. Correlation between vehicle environment and body movement during arterial lane changing maneuvers.

Movement	Criteria	Variable	Correlation	Reject Null
Head	Frequency	Vehicle Presence (all sides)	0.0876	No
		Vehicle - Follower	0.2065	Yes
	Movement	Vehicle Presence (all sides)	0.0100	No
		Vehicle - Follower	0.1810	No
	Duration	Vehicle Presence (all sides)	0.0629	No
		Vehicle - Follower	0.1729	No
Upper Body	Frequency	Vehicle Presence (all sides)	0.0760	No
		Vehicle - Follower	0.1695	No
	Movement	Vehicle Presence (all sides)	0.0825	No
		Vehicle - Follower	0.1358	No
	Duration	Vehicle Presence (all sides)	0.1167	No
		Vehicle - Follower	0.2146	Yes
Arms (Non-Driving Related)	Frequency	Vehicle Presence (all sides)	0.0178	No
		Vehicle - Follower	-0.0085	No
	Movement	Vehicle Presence (all sides)	0.0163	No
		Vehicle - Follower	-0.0075	No
	Duration	Vehicle Presence (all sides)	-0.0284	No
		Vehicle - Follower	-0.0184	No

To evaluate the correlation coefficient a two-tailed statistical test was performed in all cases where the null hypothesis states the following:

H_o: there is no linear relationship between frequency, movement, or duration of movement and vehicle environment when performing lane changes or merging maneuvers at the arterial and freeway segment.

The sample size for the arterial lane changes $N_{Art\text{-}LC}$ was 196, whereas, the sample size for the freeway lane changes $N_{Free\text{-}LC}$ was 116. The sample size for the freeway merges $N_{Free\text{-}M}$ was 141.

Considering a 0.05 significance level, it can be concluded that in almost all cases the Null hypothesis cannot be rejected. Actually, it is found that there is a positive linear relationship between the frequency of head movements and the presence of a follower in the target lane in the case of arterial lane changes. It was also found that, for the same maneuvers, a positive linear relationship exists between the total duration of the upper body movement and the presence of a follower in the target lane.

Correlation between scenario 1 and body movements

This correlation was not further investigated since scenario 1 did not reveal any instance where drivers failed to identify potentially conflicting vehicles when performing a merging or a lane changing maneuver.

Table 8. Correlation between vehicle environment and body movement during freeway lane changing maneuvers.

Movement	Criteria	Variable	Correlation	Reject Null
Head	Frequency	Vehicle Presence (all sides)	0.1949	No
		Vehicle - Follower	0.1340	No
	Movement	Vehicle Presence (all sides)	-0.0219	No
		Vehicle - Follower	-0.0630	No
	Duration	Vehicle Presence (all sides)	0.2102	No
		Vehicle - Follower	0.1788	No
Upper Body	Frequency	Vehicle Presence (all sides)	-0.1247	No
		Vehicle - Follower	-0.0365	No
	Movement	Vehicle Presence (all sides)	-0.1247	No
		Vehicle - Follower	-0.0365	No
	Duration	Vehicle Presence (all sides)	-0.1446	No
		Vehicle - Follower	-0.0648	No
Arms (Non-Driving Related)	Frequency	Vehicle Presence (all sides)	-0.0572	No
		Vehicle - Follower	-0.0835	No
	Movement	Vehicle Presence (all sides)	-0.0572	No
		Vehicle - Follower	-0.0835	No
	Duration	Vehicle Presence (all sides)	-0.0569	No
		Vehicle - Follower	-0.0808	No

Table 9. Correlation between vehicle environment (vehicle presence at the back left) and body movement during freeway merging maneuvers.

Movement	Criteria	Correlation	Reject Null
Head	Movement	0.0841	No
	Frequency	-0.0278	No
	Duration	0.0381	No
Upper-Body	Movement	-0.1078	No
	Frequency	-0.1053	No
	Duration	-0.1029	No
Arms (Non-Driving Related)	Movement	0.0141	No
	Frequency	-0.0443	No
	Duration	-0.0600	No

CHAPTER 6: CONCLUSIONS AND RECOMMENDATIONS

Conclusions

This project examined a new research framework for investigating the driver's movement and posture during merging and lane changing maneuvers. In addition to the commonly used head tracking technology, this framework introduced the use of a low-cost depth sensor, which was installed in the vehicle cabin and tracked the motion of the drivers. Two analytical frameworks (i.e., a quantitative and a qualitative) were developed to study the motion patterns of the drivers, correlate them with potential unsafe driving conditions, and derive statistical patterns observed in various demographic groups.

The developed frameworks were applied to real data from 35 driver subjects who participated in this study and performed merges and lane changes in a specific route in Ganesville, FL. The results of our quantitative and qualitative analyses indicate differences in driving patterns (range of body motions and reactions in the presence of other vehicles during the maneuver) based on the experience or age of the driver.

Finally, the recorded data were organized in the form of an open source dataset of depth frame sequences which is available on-line along with a programing API to facilitate the dissemination of the dataset and its systematic study in order to explore new research questions in the future.

Project Deliverables

In addition to the present report and the papers published by our team as a result of our collaboration through this project, a key project deliverable is the database of depth frame sequences that was created during this project. The database is published on-line as an open-access resource that is available to the research community in order to facilitate other future studies on analyzing the driving behavior based on the body movements and posture of the drivers. The data can be accessed from the main website of the database at: http://research.dwi.ufl.edu/dmddb. There are five types of deliverables associated with this database: 1) the raw depth frame data, 2) the on-line 3D data viewer, 3) the application programming interface (API) developed for accessing the data through programming environments, 4) the API documentation, and 5) the source code examples. Each type of deliverables is discussed in detail in Appendix D.

Implications for Practice

The qualitative and quantitative methods for investigating the driver's behavior (posture, movement, and gaze) during merging and lane changing maneuvers constitute a framework that considers the driver as a factor that needs to be tracked and taken under consideration along with other out-of-cabin information when assessing the status of the vehicle with regards to its safe movement. This study can also be viewed as an analytical tool for assessing the adoption of low-cost sensing technologies that track the motion of the driver in a minimally intrusive way, i.e. without introducing any markers or wearable devices.

The results indicate that there is a potential benefit by introducing depth sensors in vehicle's cabin for tracking the driver's activity. In research setting, the adoption of such technologies in instrumented vehicles will enhance the recorded data by including an additional data modality, which is rich in information and can be used in research as it was demonstrated in this project. In everyday real life settings, the adoption of such technologies in personal vehicles will add to the existing driver-assistance systems a new channel of information that could warn the driver if an unsafe condition is detected in-cabin, such as detecting driver's inattention based on body posture. A key issue would be to move to on-line and real-time analysis and prediction of the body movements.

Finally, the results from our quantitative and qualitative study indicate differences in driving patterns based on the gender or age of the driver. Although the results are not conclusive due to the limited range of the study, they suggest that different reactions and range of motions are expected during various types of maneuvers based on the profile of the driver.

Study Limitations

The limited scope of the population of study participants in terms of age and geographic distribution was one of the obvious limitations in this study. Another limitation was that, older drivers (older than 60 years old) did not participate in our study due to the fact that a large proportion of these drivers wear glasses and that would prevent them from wearing the portable eye-tracking equipment. In addition, as it holds for most naturalistic type of data collection efforts, there is the possibility of a bias in the current study, given that the drivers were not driving their own vehicle and also that they were observed, since a researcher was accompanying them at all times.

Although a significant amount of data was collected as part of this study, data that focus primarily on distracted driving (e.g., texting, talking on the phone, etc.) were not obtained due to the naturalistic setting of the data collection experiment and the safety risks involved. A more controlled driving setting would allow for such type of data collection and analysis in the future.

There were some technical limitations as expected due to the nature of the employed sensors. One of the key issues was the fact that the raw depth frames were occasionally contaminated with visual artifacts due to the limitations of the employed depth sensing technology. More specifically, structured light in the infrared range was projected to the field of view and was observed and processed by an infrared camera in order to reconstruct in real-time the depth frame as described in the patent by Sali and Avraham (2014). The projection of the light fails in the cases of: 1) surfaces of irregular or complex reflectance, such as specular and transparent, and 2) presence of intense direct light from external sources, such as the sun. As expected, the depth values of pixels that correspond to either of the above cases were not reconstructed and an undefined status was assigned to them.

One of the key limitations in the sensing technology was the limited spatial resolution of the recorded depth frames (320x240 pixels). Although the resolution was enough to capture the overall body shape and track the most obvious and well visible joints, several other details could not be captured such as the orientation of the head. This hindered significantly the job of the tracking algorithms and as a result the computer-based quantitative analysis could not be as detailed as the qualitative analysis that was based on manual observation.

Another limitation was the minimum distance of operation of the depth sensor which was 40 cm (1.31 ft). Therefore, the sensor should be installed at least 40 cm far from the closest point on the driver's body. This distance was marginally acceptable considering that the device itself has volume that adds at least 5 more centimeters (0.16 ft) to the above limit. The upper right corner in the vehicle was identified as the most suitable location for installing the depth sensor. However, even in that case, smaller vehicles with narrow cabin may not have large enough space to account for the minimum distance of operatic of the sensor.

Furthermore, the position and orientation of the camera is slightly different in each depth sequence due to reinstallation of the sensor before each recording session. As expected the driver's seat was also adjusted differently by each driver, which introduced a natural variability of content in the depth sequences. Both of these factors pose additional challenges in data processing and need to be considered in order to develop robust algorithms for quantitative analysis of driver movements.

Finally, experiments that involve multi-modal data collection, may face the problem of synchronization between the different sensors or the equivalent problem of data registration. Commonly visible landmarks were used to manually register the video data from the eye tracker, the video data from the in-vehicle sensor, and the data streams of the kinect sensor.

Future Research

Although a significant amount of data were collected in this research, additional data could be obtained to enrich the dataset with observations that focus on investigating the relationship between body movements and distracted driving such as texting, talking on the phone, etc.

One of the goals of this project was to set the basis for other future projects that will either a) use the experimental setup that was created in this project, or b) use the open-access database as test bed for investigating other research questions or for evaluating other 3D data processing algorithms.

In the first category, the use of low-cost depth sensors for monitoring the drivers' behavior could be adopted in other types of vehicles, such as service vehicles (for instance to study the body motion patterns of driver of ambulance or fire truck), special purpose vehicles (such as tractors), or even other transportation means (such as the cockpit of an airplane) to track the body activity of the driver/pilot, co-pilot, and study their interaction. Furthermore, the use of higher resolution depth cameras such as the new Kinect sensor that is based on the 'time-of-flight' depth sensing technology will allow more detailed data to be captured. This will improve significantly the quality and robustness of the tracking results and allow more body motion descriptors to be computed such as those currently estimated qualitatively after manual observation.

Regarding the future use of the open-access DMDDB dataset, there are various areas in engineering that could use the database as benchmark for performing quantitative comparisons between different algorithms. For example algorithms for automated classification of human activity into driving related or non-driving related activity (such as eating, scratching, repositioning arm in the armrest etc.) could be tested in this dataset. Furthermore, generic machine learning algorithms, body tracking methods, and 3D shape retrieval techniques could be quantitatively tested in the dataset. Alos, new research questions could be explored in our dataset such as the relative synchronization of the motion of the head with the motion of the arm during a particular maneuver.

Finally, the advances in sensing technology are expected improve the resolution of the depth data as well as the signal to noise ratio. As as result, future data processing algorithms will be able to generate more robust results and will manage to track and detect additional information similar to what was currently presented in the qualitative analysis section. In such case, the manual analysis could serve as the "ground truth" in order to evaluate the results obtained by the computer algorithms in the future.

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APPENDIX A – PRESCREENING QUESTIONNAIRE

Pre-Screening Questionnaire

Participant ID#:________________ Date: ________________

To Participants:

Note: Information collected in this questionnaire will be used for traffic engineering research only. All responses will be held confidential and exempt from public disclosure by law. In accordance with the Confidential Information Protection and Statistical Efficiency Act of 2002 (Title 5 of Public Law 107-347) and other applicable Federal laws, your responses will not be disclosed in identifiable form without your consent. By law, every interviewer, as well as every agent, is subject to a jail term, a fine, or both if he or she makes public ANY identifiable information you reported.

Name: ______________________________________ **Gender:** __________

Date of Birth (mm/dd/yyyy): ____________________ **Age:** __________

Eligible Age? ☐ Yes (continue below) ☐ No (not eligible)

Race:

☐ White/Caucasian	☐ Hispanic	☐ Bi-Racial
☐ Black/African American	☐ Asian	☐ Other

Do you have a valid US driver's license?

☐ Yes (continue below) ☐ No (not eligible)

Driver's License Number and State: ____

Do you have a valid car insurance?

☐ Yes (continue below) ☐ No (not eligible)

This study will require that you drive a vehicle. **Do you have any physical disabilities that might prohibit your full participation in the experiment?**

- ☐ No (continue below)
- ☐ Yes (not eligible)

How long have you been driving in the U.S.?

- ☐ < 1 year
- ☐ 1 to 3 years
- ☐ 3 to 9 years
- ☐ ≥ 10 years

In the past 7 days (not counting today), how many days did you drive?

- ☐ 0 (not eligible)
- ☐ 1 (not eligible)
- ☐ 2 (not eligible)
- ☐ 3 (continue below)
- ☐ 4 (continue below)
- ☐ 5 (continue below)
- ☐ 6 (continue below)
- ☐ 7 (continue below)

Contact Information:

Home address ____

____

Phone number Home __________________ Cell _________________

Email ___________________________________

APPENDIX B – PRE-DRIVING QUESTIONNAIRE

Driver Questionnaire

Participant ID#:_______________ Date:_______________

Note: Information collected in this questionnaire will be used for traffic engineering research only. All responses will be held confidential and exempt from public disclosure by law. In accordance with the Confidential Information Protection and Statistical Efficiency Act of 2002 (Title 5 of Public Law 107-347) and other applicable Federal laws, your responses will not be disclosed in identifiable form without your consent. By law, every interviewer, as well as every agent, is subject to a jail term, a fine, or both if he or she makes public ANY identifiable information you reported.

---

1. Do you have a valid driver's license?

☐ Yes ☐ No

2. How experienced are you at driving?

☐ Somewhat experienced ☐ Experienced ☐ Very Experienced

3. How long have you been driving in the US?

☐ Less than 1 year ☐ 1 to 3 years

☐ 3-9 years ☐ 10 or more years

4. How often do you drive to work/school?

☐ Every day ☐ 3-4 times a week

☐ 1-2 times a week ☐ Never

5. How much time do you spend driving on an average weekday?

☐ Less than 30 minutes ☐ 30-60 minutes

☐ 1 to 1.5 hours ☐ 1.5 to 2 hours

☐ More than 2 hours

6. I usually drive:

☐ Alone ☐ With 1 or more adult passengers

- ☐ With 1 or more child passengers

7. When the speed limit along an urban street is 40 mph, what speed are you likely to drive at (assuming good visibility and good weather conditions)?

- ☐ Less than 35 mph
- ☐ Between 35-40 mph
- ☐ Between 40-45 mph
- ☐ More than 45 mph

8. When driving on campus or neighborhood where the posted speed limit is 20 mph, what speed are you likely to drive at (assuming good visibility and good weather conditions)?

- ☐ Less than 15 mph
- ☐ Between 15-20 mph
- ☐ Between 20-25 mph
- ☐ Between 25-30 mph
- ☐ More than 30 mph

9. How often do you change lanes to gain speed or queue advantage?

- ☐ Whenever Possible
- ☐ Often
- ☐ Seldom
- ☐ Never

10. How often do you eat or drink while driving?

- ☐ Often
- ☐ Occasionally
- ☐ Never

11. How often do you use a GPS/navigation system while driving?

- ☐ Often
- ☐ Occasionally
- ☐ Never

12. How often do you use your cellphone while driving?

- ☐ Often
- ☐ Occasionally
- ☐ Never

13. How often do you text while driving?

- ☐ Often
- ☐ Occasionally
- ☐ Never

14. How often do you reach for something while driving without taking your eyes from the road?

- ☐ Frequently
- ☐ Occasionally
- ☐ Rarely
- ☐ Never

15. How often do you multitask while driving?

- ☐ Frequently
- ☐ Rarely
- ☐ Occasionally
- ☐ Never

APPENDIX C – SCENARIO 1 RESULTS

Scenario 1 – Lane Changes

Driver ID	Type of Lane Change	Vehicle present		Vehicle Identified		Vehicle Unidentified	
		Left	Right	Left	Right	Left	Right
104	L	Y	-	Y	-	-	-
	L	-	Y	-	Y	-	-

Note: "-" Not Applicable

Driver ID	Type of Lane Change	Vehicle present		Vehicle Identified		Vehicle Unidentified	
		Left	Right	Left	Right	Left	Right
106	L	-	Y	-	Y	-	-

Note: "-" Not Applicable

Driver ID	Type of Lane Change	Vehicle present		Vehicle Identified		Vehicle Unidentified	
		Left	Right	Left	Right	Left	Right
111	L	Y	-	Y	-	-	-
	R	Y	-	Y	-	-	-
	L	-	Y	-	-	-	Y
	L	Y	-	Y	-	-	-
	R	-	Y	-	Y	-	-
	L	Y	-	Y	-	-	-
	R	Y	-	-	-	Y	-
	R	Y	-	-	-	Y	-
	L	-	Y		-	-	Y
	L	Y	-	Y	-	-	-
	R	-	Y	-	Y	-	-
	R	-	Y	-	Y	-	-

Note: "-" Not Applicable

Driver ID	Type of Lane Change	Vehicle present		Vehicle Identified		Vehicle Unidentified	
		Left	Right	Left	Right	Left	Right
118	L	-	Y	-	-	-	Y
	R	Y	Y	-	Y	Y	-
	L	-	Y	-	Y	-	-
	R	-	Y	-	Y	-	-
	L	Y	-	Y	-	-	-

Note: "-" Not Applicable

Driver ID	Type of Lane Change	Vehicle present		Vehicle Identified		Vehicle Unidentified	
		Left	Right	Left	Right	Left	Right
120	R	-	Y	-	Y	-	-
	L	-	Y	-	-	-	Y
	R	Y	-	Y	-	-	-
	L	Y	-	Y	-	-	-
	R	-	Y	Y	-	-	-
	L	-	Y	-	-	-	Y
	R	-	Y	-	Y	-	-

Note: "-" Not Applicable

Driver ID	Type of Lane Change	Vehicle present		Vehicle Identified		Vehicle Unidentified	
		Left	Right	Left	Right	Left	Right
121	R	Y	Y	-	Y	Y	-
	L	-	Y	-	-	-	Y
	L	-	Y	-	-	-	Y
	L	Y	-	Y	-	-	-
	R	-	Y	-	Y	-	-
	R	-	Y	-	Y	-	-
	L	Y	-	Y	-	-	-
	L	-	Y	-	-	-	Y

Note: "-" Not Applicable

Driver ID	Type of Lane Change	Vehicle present		Vehicle Identified		Vehicle Unidentified	
		Left	Right	Left	Right	Left	Right
122	R	-	Y	-	Y	-	-
	L	-	Y	-	-	-	Y
	R	-	Y	-	Y	-	-
	R	-	Y	-	Y	-	-
	L	-	Y	-	-	-	Y
	R	-	Y	-	Y	-	-
	L	-	Y	-	-	-	Y
	L	Y	Y	Y	-	-	Y
	L	-	Y	-	-	-	Y
	R	Y	Y	Y	Y	-	-
	L	Y	-	Y	-	-	-
	R	-	Y	-	Y	-	-
	R	-	Y	-	Y	-	-
	L	Y	Y	Y	Y	-	-
	L	-	Y	-	-	-	Y

Note: "-" Not Applicable

Driver ID	Type of Lane Change	Vehicle present		Vehicle Identified		Vehicle Unidentified	
		Left	Right	Left	Right	Left	Right
124	L	Y	-	Y	-	-	-
	R	-	Y	-	Y	-	-
	L	Y	-	Y	-	-	-
	L	Y	-	Y	-	-	-
	R	Y	Y	Y	-	-	-
	R	-	Y	-	Y	-	-
	R	-	Y	-	Y	-	-
	L	Y	Y	Y	Y	-	-
	R	-	Y	-	Y	-	-
	L	-	Y	-	-	-	Y
	R	-	Y	-	Y	-	-
	L	-	Y	-	-	-	Y
	L	Y	-	Y	-	-	-

Note: "-" Not Applicable

Driver ID	Type of Lane Change	Vehicle present		Vehicle Identified		Vehicle Unidentified	
		Left	Right	Left	Right	Left	Right
125	R	-	Y	-	Y	-	-
	L	Y	-	Y	-	-	-
	L	Y	-	Y	-	-	-
	R	-	Y	-	Y	-	-
	L	Y	-	Y	-	-	-
	R	-	Y	-	Y	-	-

Note: "-" Not Applicable

Driver ID	Type of Lane Change	Vehicle present		Vehicle Identified		Vehicle Unidentified	
		Left	Right	Left	Right	Left	Right
126	L	Y	-	Y	-	-	-
	L	-	Y	-	Y	-	-
	R	-	Y	-	Y	-	-
	L	-	Y	-	-	-	Y
	R	-	Y	-	Y	-	-
	L	-	Y	-	-	-	Y
	R	-	Y	-	Y	-	-

Note: "-" Not Applicable

Scenario 1 – Merges

Driver ID	Round #	Merge Location	Vehicle at Back Left	Head Movement	Scenario 1
101	1	Archer	Y	Y	Y
		Newberry	Y	Y	Y
		Williston	-	Y	-
	2	Archer	-	Y	-
		Newberry	Y	Y	Y
		Williston	-	Y	-
	3	Archer	Y	Y	Y
		Newberry	-	Y	-
		Williston	Y	Y	Y

Note: "-" No Vehicle Present at the back left

Driver ID	Round #	Merge Location	Vehicle at Back Left	Head Movement	Scenario 1
103	1	Archer	-	Y	-
		Newberry	Y	Y	Y
		Williston	-	Y	-
	2	Archer	-	Y	-
		Newberry	Y	Y	Y
		Williston	-	Y	-
	3	Archer	Y	Y	Y
		Newberry	-	Y	-
		Williston	Y	Y	Y

Note: "-" No Vehicle Present at the back left

Driver ID	Round #	Merge Location	Vehicle at Back Left	Head Movement	Scenario 1
105	1	Archer	-	Y	-
		Newberry	-	Y	-
		Williston	-	Y	-
	2	Archer	-	Y	-
		Newberry	-	Y	-
		Williston	-	Y	-
	3	Archer	Y	Y	Y
		Newberry	-	Y	-
		Williston	-	Y	-

Note: "-" No Vehicle Present at the back left

Driver ID	Round #	Merge Location	Vehicle at Back Left	Head Movement	Scenario 1
109	1	Archer	Y	Y	Y
		Newberry	-	Y	-
		Williston	-	Y	-
	2	Archer	-	Y	-
		Newberry	Y	Y	Y
	3	Archer	-	Y	-
		Newberry	-	Y	-
		Williston	Y	Y	Y

Note: "-" No Vehicle Present at the back left

Driver ID	Round #	Merge Location	Vehicle at Back Left	Head Movement	Scenario 1
110	1	Archer	Y	Y	Y
		Newberry	-	Y	-
		Williston	-	Y	-
	2	Archer	Y	Y	Y
		Newberry	-	Y	-
		Williston	-	Y	-
	3	Archer	-	Y	-
		Newberry	Y	Y	Y
		Williston	-	Y	-

Note: "-" No Vehicle Present at the back left

Driver ID	Round #	Merge Location	Vehicle at Back Left	Head Movement	Scenario 1
111	1	Archer	Y	Y	Y
		Newberry	-	Y	-
		Williston	-	Y	-
	2	Archer	-	Y	-
		Newberry	-	Y	-
		Williston	-	Y	-
	3	Archer	-	Y	-
		Newberry	-	Y	-
		Williston	-	Y	-

Note: "-" No Vehicle Present at the back left

Driver ID	Round #	Merge Location	Vehicle at Back Left	Head Movement	Scenario 1
118	1	Archer	-	Y	-
		Newberry	-	Y	-
	2	Archer	-	Y	-
		Newberry	-	Y	-
		Williston	-	Y	-

Note: "-" No Vehicle Present at the back left

Driver ID	Round #	Merge Location	Vehicle at Back Left	Head Movement	Scenario 1
119	1	Archer	-	-	-
		Newberry	-	Y	-
	2	Newberry	-	Y	-
	3	Archer	Y	Y	Y
		Newberry	Y	Y	Y

Note: "-" No Vehicle Present at the back left

Driver ID	Round #	Merge Location	Vehicle at Back Left	Head Movement	Scenario 1
121	1	Archer	-	Y	-
		Newberry	Y	Y	Y
		Williston	Y	Y	Y
	2	Archer	Y	Y	Y
		Newberry	-	Y	-
		Williston	Y	Y	Y
	3	Archer	Y	Y	Y
		Newberry	-	Y	-
		Williston	Y	Y	Y

Note: "-" No Vehicle Present at the back left

Driver ID	Round #	Merge Location	Vehicle at Back Left	Head Movement	Scenario 1
122	1	Archer	-	Y	-
		Newberry	Y	Y	Y
		Williston	-	Y	-
	2	Archer	-	Y	-
		Newberry	-	Y	-
		Williston	-	Y	-
	3	Archer	-	Y	-
		Newberry	Y	Y	Y

Note: "-" No Vehicle Present at the back left

Driver ID	Round #	Merge Location	Vehicle at Back Left	Head Movement	Scenario 1
124	1	Archer	-	Y	-
		Newberry	-	Y	-
		Williston	-	Y	-
	2	Archer	-	Y	-
		Newberry	Y	Y	Y
		Williston	-	Y	-
	3	Archer	-	Y	-
		Newberry	-	Y	-
		Williston	-	Y	-

Note: "-" No Vehicle Present at the back left

Driver ID	Round #	Merge Location	Vehicle at Back Left	Head Movement	Scenario 1
126	1	Archer	-	-	-
		Newberry	-	Y	-
		Williston	Y	Y	Y
	2	Archer	-	Y	-
		Newberry	-	Y	-
		Williston	-	Y	-
	3	Archer	-	Y	-
		Newberry	-	Y	-
		Williston	Y	Y	Y
	4	Archer	Y	Y	Y
		Newberry	-	Y	-
		Williston	Y	Y	Y

Note: "-" No Vehicle Present at the back left

Driver ID	Round #	Merge Location	Vehicle at Back Left	Head Movement	Scenario 1
131	1	Archer	-	Y	-
		Newberry	-	Y	-
		Williston	-	Y	-
	2	Archer	-	Y	-
		Newberry	Y	Y	Y
		Williston	-	Y	-
	3	Archer	-	Y	-
		Newberry	-	Y	-
		Williston	Y	Y	Y

Note: "-" No Vehicle Present at the back left

Driver ID	Round #	Merge Location	Vehicle at Back Left	Head Movement	Scenario 1
127	1	Archer	-	Y	-
		Newberry	-	Y	-
		Williston	-	Y	-
	2	Archer	-	Y	-
		Newberry	-	Y	-
		Williston	Y	Y	Y
	3	Archer	-	Y	-
		Newberry	Y	Y	Y
	4	Archer	Y	Y	Y
		Newberry	Y	Y	Y
		Williston	-	Y	-

Note: "-" No Vehicle Present at the back left

Driver ID	Round #	Merge Location	Vehicle at Back Left	Head Movement	Scenario 1
132	1	Archer	-	Y	-
		Newberry	-	Y	-
		Williston	-	Y	-
	2	Archer	-	Y	-
		Newberry	-	Y	-
		Williston	-	Y	-
	3	Archer	Y	Y	Y
		Newberry	-	Y	-
		Williston	-	Y	-

Note: "-" No Vehicle Present at the back left

Driver ID	Round #	Merge Location	Vehicle at Back Left	Head Movement	Scenario 1
133	1	Archer	Y	Y	Y
		Newberry	Y	Y	Y
		Williston	Y	Y	Y
	2	Archer	-	Y	-
		Newberry	Y	Y	Y
		Williston	Y	Y	Y
	3	Archer	Y	Y	Y
		Newberry	-	Y	-
		Williston	-	Y	-

Note: "-" No Vehicle Present at the back left

Driver ID	Round #	Merge Location	Vehicle at Back Left	Head Movement	Scenario 1
130	1	Archer	-	Y	-
		Newberry	Y	Y	Y
		Williston	Y	Y	Y

Note: "-" No Vehicle Present at the back left

APPENDIX D – ON-LINE DATABASE COMPONENTS

Raw Depth Frame Data

The database is organized into merges and lane changes. Each merge or lane change depth frame sequence is packaged separately into a zip file, with the following file name convention: http://research.dwi.ufl.edu/dmddb/merges/DR104ArcherNBR1.zip, where DR104 is the unique ID of the driver and is followed by the location of the merge (in this example Archer NB) and the round number (here R1 denotes the first round). The zip file contains a header xml file with the total number of frames, width, height etc, and several depth frame files in increasing order: 1.depth, 2.depth, 3.depth, ... Each depth frame is a binary file. To read the raw depth data of a frame, the user should skip the first 28 bytes of the file, which is a fixed-size header, and parse the rest of the file, which is an array of 320*240 integers in unsigned short format. The total size of this array is 320*240*2 bytes because each depth frame has 320 x 240 pixels and each short integer is stored in 2 bytes. The depth in each pixel is the short number you read divided by 8, and is given in millimeters. For example if the short number in a pixel is 12000 then the depth is 12000/8=1500 millimeters = 1.5 meters from the camera.

On-line 3D Data Viewer

In order to facilitate quick access to the database and easy navigation through the 3D data points that can be used by the general audience, a browser-based 3D data viewer was developed and can be accessed at the URL address: http://research.dwi.ufl.edu/dmddb/browser/ . The viewer is based on the new canvas capabilities of HTML5 and webGL, which can render 3D content on websites. There is no need to download additional plugins to use these technologies, since they are already included in the majority of the popular desktop and mobile web-browsers. In Windows operating system the viewer is compatible with The following browsers: Mozilla Firefox, Chrome, Opera, and Internet Explorer (v.11+). In Mac OS the viewer is compatible with Mozilla Firefox, Chrome, Opera, and Safari. In Safari for OSx it can be enabled from the Preferences menu > Advanced tab > Show Develop menu in menu bar, and then from the Develop menu > Enable WebGL. In Linux, the viewer is compatible with: Mozilla Firefox, Chrome, and Opera. In mobile and tablet computers the viewer is supported by the majority of web-browsers for iOS, Android or Microsoft Windows 8.1+ devices.

The on-line viewer displays the 3D data as a 3D shaded surface with color-coded depth map using GPU-rendered computer graphics. The viewer offers several features such as interactive 3D rotation of the virtual camera using touch gestures or conventional mouse click and drag, time domain controls such as play, pause, rewind, fast forward, fast rewind, browse by driver, by type of maneuver (merge or lane change), by location, and by round number. The browser also allows you to download the raw data of the current depth sequence in the player.

Application Programing Interface (API)

In order to facilitate the future development of experiments in the dataset an application programming interface was created. The developed DMDDB API can be used in Java or Javascript. The API consists of six classes for connecting to the database, streaming the depth frame sequences, accessing and processing the depth values and metadata of the database. The main classes and their role are summarized below.

1) DMDDBTerminal: The main class for accessing the DMDDB database through Java or JavaScrip, 2) DMDDBWebPlayer: A simple implementation of the abstract class DMDDBTerminal for the J4K (Java for Kinect) library, 3) DMDDB: This class loads the index of the depth files in the DMDDB database, 4) DMDDBDriver: A simple data structure that holds the information of a driver in

the database, 5) DMDDBLocation: A simple data structure that holds the information of a location in the database, 6) DMDDBFile: A simple data structure that holds the information of a file in the database.

The DMDDB API was used during the 2015 Shape Retrieval Contest (SHREC) in a dedicated track that challenged contestants to segment and identify the regions of the arms of the drivers in our database. The details of this data contest can be found in the technical report by Barmpoutis et al. (2015).

API Documentation

A detailed documentation was created that describes the properties and methods of each class in the API, and the details of the interface of each class (input/output arguments, visibility, purpose, etc.). The documentation is in the form of a web-site and is structured as a JavaDoc, which is a popular way to document class structures in Java libraries. Since our DMDDB API was developed in both Java and JavaScript programming languages, the JavaDoc format was extended to accommodate both versions of the API. The root of the documentation is at the address: http://research.dwi.ufl.edu/dmddb/doc/ .

Source Code Examples

Finally, three fully functioning source code examples were created using the DMDDB API in order to assist the researchers understand better the functionality of the API. The examples cover three simple programming scenarios: 1) connecting to the database and parsing a particular depth sequence, 2) visualizing the depth data using 3D computer graphics, and 3) setting up an experiment that executes the same algorithm to a set of depth sequences specified by the researcher. The three source code examples can be downloaded from the main website of the database and are outlined below.

Simple Example: A simple example that opens a particular depth sequence from the DMDDB database, the one that corresponds to the Driver 101, merging onto I-75 from Archer road, round 1. This example parses one by one all the depth frames in this dataset, and computes the average depth value per frame and prints the result in the system console.

DMDDB Player: This example uses an external library for 3D graphics (JogAmp's JOGL Java library) to visualize the depth data as 3D surfaces in openGL. This example also offers a simple graphical user interface for playing/pausing the depth stream, rotating in 3D the depth frames by mouse drag and drop, and skipping frames by interacting with the time slider.

Simple Experiment: This example shows a simple experimental setup that opens multiple depth sequences from the DMDDB database and parses one by one all the depth frames in the selected datasets. This example gives you the option to process the depth data using your own algorithms and write the results in simple text files that are automatically exported during the execution of this experiment.