

PEDESTRIAN BEHAVIOR ANALYSIS USING 110-CAR NATURALISTIC DRIVING DATA IN USA

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ABSTRACT

The research objective of this work was to understand pedestrians' behavior and interaction with vehicles during pre-crash scenarios that provides critical information on how to improve pedestrian safety.

In this study, we recruited 110 cars and their drivers in the greater Indianapolis area for a one year naturalistic driving study starting in March 2012. The drivers were selected based on their geographic, demographic, and driving route representativeness. We used off-the-shelf vehicle black boxes for data recording, which are installed at the front windshield behind the rear-view mirrors. It records high-resolution forward-view videos (recording driving views outside of front windshield), GPS information, and G-sensor information.

We developed category-based multi-stage pedestrian detection and behavior analysis tools to efficiently process this large scale driving dataset. To ensure the accuracy, we incorporated the human-in-loop process to verify the automatic pedestrian detection results. For each pedestrian event, we generate a 5-second video to further study potential conflicts between pedestrians and vehicle. For each detected potential conflict event, we generate a 15-second video to analyze pedestrian behavior.

We conduct in-depth analysis of pedestrian behavior in regular and near-miss scenarios using the naturalistic data. We observed pedestrian and vehicle interaction videos and studied what scenarios might be more dangerous and could more likely to result in potential conflicts.

We observed: 1) Children alone as pedestrians is an elevated risk; 2) three or more adults may be more likely to result in potential conflicts with vehicles than one or two adults; 3) parking lots, communities, school areas, shopping malls, etc. could have more potential conflicts than regular urban/rural driving environments; 4) when pedestrian is crossing road, there is much higher potential conflict than pedestrian walking along/against traffic; 5) There is an elevated risk for pedestrians walking in road (where vehicles can drive by); 6) when pedestrians are jogging, it is much more likely to have potential conflict than walking or standing.; and 7) it is more likely to have potential conflict at cross walk and junction than other road types.

Furthermore, we estimated the pedestrian appearance points of all potential conflict events and time to collision (TTC). Most potential conflict events have a TTC value ranging from 1 second to 6 seconds, with the range of 2 seconds to 4 seconds being associated with highest percentages of all the cases. The mean value of TTC is 3.84 seconds with standard deviation of 1.74 seconds.

To date, we have collected about 65TB of driving data with about 1.1 million miles. We have processed about 50% of the data. We are continuously working on the data collection and processing. There could be some changes in our observation results after including all data. But the existing analysis is based on a quite large-scale data and would provide a good estimation.

INTRODUCTION

In this project, the goal is to determine detailed pre-crash scenarios for vehicle-to-pedestrian collisions in the United States. With the support from Toyota Motor Corporation and Toyota Engineering & Manufacturing North America Inc., we recruited 110 cars and their drivers in the greater Indianapolis area for a one year naturalistic driving study starting in March 2012. The Transportation Active Safety Institute (TASI) at IUPUI is located in the heart of downtown Indianapolis. In addition, within the 30 mile radius around Indianapolis, where many people commuting daily, there is a variety of urban streets, highways, freeways, suburban areas, and rural areas. This makes it possible to collect driving and vehicle data from very diverse driving conditions. We used off-the-shelf vehicle black boxes for data recording, which are installed at the front windshield behind the rear-view mirrors, which record high-resolution forward-view videos (recording driving views outside of front windshield), GPS information, and G-sensor information.

We designed and developed a suite of tools to process the data, perform automatic pedestrian detection, and pedestrian behavior analysis. This paper describes our approach and highlights the findings of the pedestrian behavior analysis. This project involves human subjects and received approval from the Indiana University Institutional Review Boards (IRB).

RELATED NATURALISTIC DATA COLLECTION PROJECTS IN USA

In 2002, with the support from National Highway Traffic Safety Administration (NHTSA), Virginia Tech Transportation Institute (VTTI) performed 100-car naturalistic driving data collection [1]. The focus of VTTI's 100-car study was to obtain data on driver performance and behavior in the moments leading up to a crash. Recently, the National Academies of Science-Strategic Highway Research Program 2 sponsored the SHRP 2 Naturalistic Driving Study [2]. The objective of SHRP 2 is to address the role of driver performance and behavior in traffic safety. For both projects, the study focuses are on the driver's performance and behavior.

METHODS

Apparatus

In this project, we installed a DOD GS600 DVR in each vehicle to collect the naturalistic driving data that consists of the driving scene video, GPS information, and vehicle acceleration in X, Y, and Z directions. The DOD GS600 DVR can collect data continuously and save the data into a micro SD card. We used 32GB micro SD cards which can hold up to 10 hours of driving data. The SD card can be easily accessed and switched at the bottom of the camera. *Figure 1* shows the specification of the DOD GS600 DVR. It includes one 120° wide angle lens video camera, a GPS with internal antenna, and G sensor. We set the DOD

GS600 DVR to record video at 30 frames per second with 1280x720 resolution.



Figure 1 The specification of DOD GS600

Figure 2 shows the example installation to the subject's vehicle. It is installed behind the rear view mirror on the front windshield via its suction cup to record the driving scene. The power cable of the DVR is connected to the vehicle's cigarette charger. The camera will be turned on when vehicle is on; and will be off when the vehicle is off. (note: Due to this constrains, we only select the vehicles that their cigarette charger will be off when the vehicle is off.) To protect the subjects' privacy, we disabled the audio recording capability. To ensure the quality of data collection, we also disabled the "reset" and "format" buttons in the device.



Figure 2 An example installation

Figure 3 shows an example collected video frame, GPS and G sensor data. Video data in .mov format which is encoded using H.264. In the generated video, the GPS location and vehicle speed is displayed on the top left corner of the video. At the same time, it outputs a separate data file in text format with GPS location, speed, and G sensor information. Each second, it would output the GPS information along with calculated moving speed. Every 0.1 second, it would output the G sensor information.



Figure 3 Example collected data (video, GPS, and G sensor data).

Subjects

Subjects were recruited through a variety of outlets in the Greater Indianapolis area. 865 people responded to the ads and all were sent an electronic pre-screening form. 580 people returned the pre-screening form. Of those, 350 were eligible for the study. A second screening was done by phone and 270 people participated in the second screening. Of those, 116 people were chosen to participate in the study based on their demographic and geographic representation. Each subject has his/her own vehicle.

Of our 116 subjects, 78% are Caucasian, 10% are Asian, 6% are African American, 2% are Latino/Latin American, 1% are Middle Eastern, 1% are Indian and 2% are of unknown ethnicity. The high percentage of Caucasians compared to the other groups is representative of the population of Indiana where 78.1% of the population is Caucasian. 57 of our subject are female and 59 are male. 72% of our subjects are between the ages of 24-60, 20% are 18-24 and 8% are 60+.

Data Collection

In general, each subject is assigned 4 micro SD cards. For some subjects with high mileage driving, we assign 5 or more micro SD cards. At any given time, each subject had 2-3 micro SD cards available on hand to switch out the cards as needed. Subjects were instructed on how to put in and remove the micro SD cards without changing the angle of the camera. The subjects deliver the card(s) with data to our data collection coordinator via mail or direct drop-off. Our data collection coordinator would send empty cards to the subject upon receiving their data cards.

To manage this process, we designed the subject data management system (Figure 4). With this data management system and method, we can easily pinpoint to the status of any card at any given time. The management system automatically provides warning for the data collection coordinator in following two situations: requests the coordinator to send SD cards to a subject if he/she has only one card on hand; and requests the coordinator to contact a subject if he/she has not send any card in a 3-week period. To ensure the security of the data management system, we have three-level of access authorization to investigator of

this task, the data coordinator, data documentation specialist.

Car Number	Make	Model	Type	Year/Start/Date	Comments	Status
1	Cadillac	Dodge	Van	2008/12/2012		585
2	Honda	Santa Fe	SUV	2007/12/27/2012		585
3	Toyota	Prius	Compact	2008/12/27/2012		585
4	Toyota	Camry	Sedan	1999/12/18/2012		585
5	Mazda	3	Mid-size	2012/12/18/2012		585
6	Toyota	Corolla	Mid-size	2008/12/17/2012		585
7	Toyota	Prius	Compact	2008/12/17/2012		585
8	Mazda	3	Mid-size	2009/12/13/2012		585
9	Honda	Civic	Compact	2002/12/27/2012		585
10	Honda	Odyssey	Mini-van	2008/12/20/2012		585

Figure 4 The subject data management system

To assist the data documentation process, we designed the data documentation tool. Figure 5 shows the graphical user interface for data documentation, which can help to efficiently organize the data collected. The capabilities include: 1) copy and organize information, such as hard drive location, data type, process date, etc. 2) record, calculate and organize information related to each vehicle such as recorded mileage, recorded time, etc. 3) provide accurate information for subject management system. 4) create logs, such as mileage log, daily log, car log, overall log and etc. 5) automatically change the filename of each file while copying using our defined file name structure as shown in Figure 6. To minimize human errors during the card ID input process, the system would require double input of card ID and the ID number is also designed to help identify typos. This tool allows copying of multiple SD cards to two hard drives at the same time.

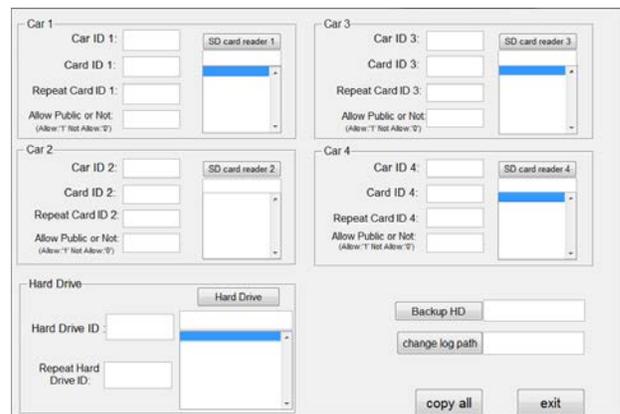


Figure 5 Data management tool



Figure 6 Filename structure

To collect one year data from over 110 subjects is not a trivial task. During the data collection process, we dealt with different kinds of incidents: SD card lost in mailing process, SD card damage, DVR damage, DVR drop off, DVR angle change, subject operation error, etc. We have a team of

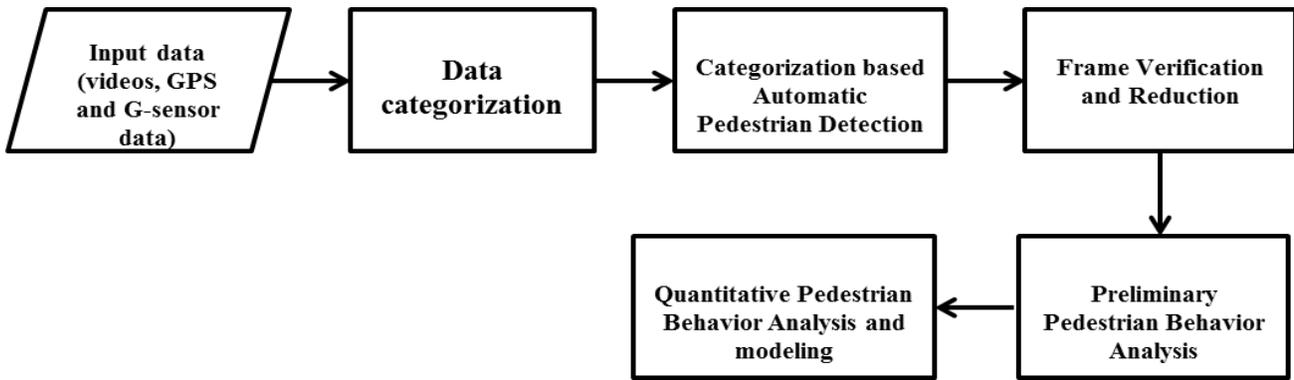


Figure 7 Overview of the process

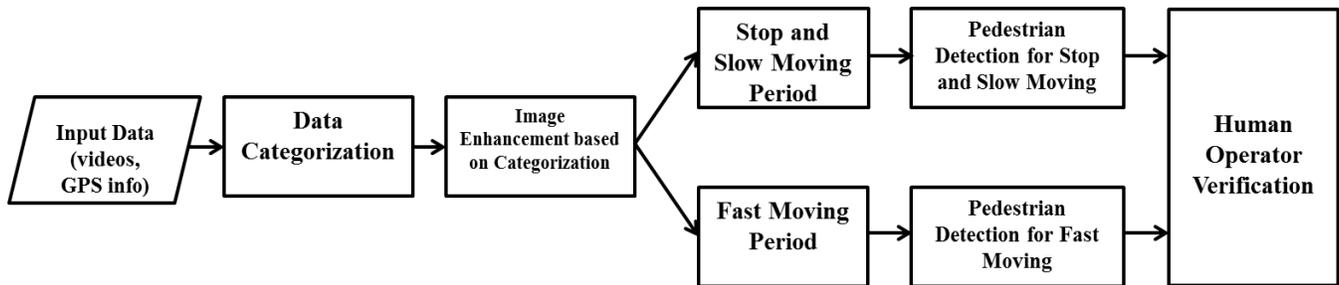


Figure 8 Overview of the categorization based pedestrian detection method

subject and data collection coordinators, data documentation specialists, technical support personnel, and researchers work together to streamline the collection process and develop various damage mitigation procedures.

Data Processing

The flowchart of the entire process of the pedestrian detection and behavior analysis is shown in Figure 7. The collected data, including the recorded videos, GPS information and G sensor data, are first categorized based on the driving scenarios. We designed the categorization based automatic pedestrian detection algorithms [3] to class each video into different categories based on their driving scenario, location, time, and weather. We designed the category-specific algorithms to process each segment of the data based on its category. The automatic pedestrian detection results are verified and processed by reductionists. The tasks of reductionists include verifying the correctly detected pedestrians and eliminating the falsely detected frames and repeatedly detected pedestrian using our frame reduction tool. The rationale behind our human-in-loop process is illustrated in [3]. No automatic pedestrian system can achieve 100% accuracy, but on the other hand, pure manual selection and labeling is extremely expensive and time consuming given the fact that we have huge number of data to process. Therefore, the proposed human-in-loop strategy is a practical and effective trade-off between the accuracy and cost. The automatic algorithm can efficiently generate possible pedestrian frames while eliminating most non-pedestrian frames with high accuracy. The measured reduction rate is 99.92%, which means most of the non-pedestrian frames are eliminated by the automatic

algorithm. After frame reduction, only one frame for each pedestrian appearance event is kept. A five-second video is generated for each frame verified by reductionists. All the videos are preliminarily analyzed by our video analysts using our pedestrian behavior analysis tool. The potential conflict videos are selected and gone through quantitative analysis and modeling.

Automatic pedestrian detection process It is very challenging to design an algorithm that can work with all kinds of real-life driving scenarios. It would be reasonable to categorize the driving scenario first and apply a corresponding detection algorithm for different categories. The detailed flow chart of categorization based pedestrian detection is shown in Figure 8. The collected naturalistic driving data is first categorized into stop, slow moving, and fast moving periods based on the speed of the vehicles obtained from the GPS data. Categorization-specific algorithms will be applied to different categories of data respectively to achieve a well balance between accuracy and efficiency.

In the stop and slow moving periods, moving cars and pedestrians can be easily detected comparing to the relatively static background. We designed a simple background subtraction algorithm to generate possible binary foreground Regions of Interest (ROIs). By preprocessing the generated ROI, we can roughly get the following characteristics of the moving objects: object size, length-width ratio and orientation of the detected object. It would be very time-consuming and unnecessary to perform pedestrian detections in each frame since a pedestrian would show up in consecutive multiple frames. Therefore we can

process several frames per second. For highway or relatively low speed area, we use a bigger interval between frames and for local or higher speed area, we use smaller intervals. The potential pedestrians can be detected by matching the features we found.

For fast moving category, we designed a new pedestrian detection method based on multimodal histogram of gradient (HOG) and kernel based Extreme Learning Machine (ELM) [4-6] to improve the processing speed of the traditional HOG based method and at the same time it achieves a better detection rate. The pre-screening step can effectively reduce the number of the sliding windows and false positives. The lower body detector is additionally incorporated into the traditional whole body detector to effectively reduce the false positives. The naturalistic driving video is sampled and the generated video frame is first preprocessed and pre-screened to eliminate the non-pedestrian windows. Whole body and lower body HOG feature extractions are performed on the regions of interest using sliding window searching. The prescreening step dramatically reduced the number of slide windows. The kernel based ELM classification is then applied to each detection window. The classification results of the whole body and lower body are combined to generate the final decision.

Frame verification and reduction The goal of this step is to reduce the false alarm (the automatically detected frames that have no pedestrians) and reduce the same scenario frames. Our trained data reductionists look through each frame the computer filtered out to determine if there was a pedestrian. If there is a pedestrian in multiple frames, the data reductionist would only select one of the middle frames. Each data reductionist was specially trained by our data processing trainer and can only work after he/she passed our data reduction process test. To assist data reductionist, we developed a user friendly data reduction GUI to automatically log the results.

Preliminary pedestrian behavior analysis For each selected frame by the data reductionist, we generate a 5-second video to perform preliminary pedestrian behavior analysis. We have developed the preliminary pedestrian behavior video analysis tool (Figure 9). It has four main functions: mark potential confliction cases; mark the main pedestrian(s) of interests in the video; label the video based our video analyst's tag to provide searching index and categorizing statistics; and record the pedestrian step frequency.

Our video data analysts are trained specialists in providing preliminary analysis of pedestrian behavior. Each video data analysis can only work on this task after passing the video data analysis test.

Potential conflict scenarios analysis graphical user interface For each selected potential conflict scenario, a 15-second video will be segmented for further analysis. Figure 10 shows our GUI for the behavior analysis which is

designed to analyze the selected potential conflict cases. In this step, the analyst will provide more detailed information about the scenario. We will count pedestrian step frequencies to further study pedestrian walking behavior; and calculate the time to collision (TTC) value when applicable.

RESULTS AND DISCUSSION

To date, we have collected 65TB driving data with about 1 million miles. And we have processed about 54% of data for data analysis. About 15,000 hours driving data has been processed by our pedestrian detection system with about 1.7 billion frames. After automatic pedestrian detection, about 2 million frames were detected with possible pedestrians. After verification and data reduction (remove the frames from same events), 9097 videos of interests were analyzed. From these videos, our video analysts detected about 773 potential conflict scenarios for our behavior analysts for further detailed behavior analysis. Here is the statistical information from our processed naturalistic driving data. We label 9097 videos as pedestrian videos which include both normal and potential conflict case. And calculate the potential conflict's rate by dividing the potential conflicts with the pedestrian videos.

Pedestrian behavior data statistics for potential conflict scenarios

Table 1 shows the statistical result of videos of potential conflict with all pedestrian videos (including both normal and potential conflict cases), and the potential conflict's rate. Of all pedestrian videos, we can see that within over 50% cases, only one adult pedestrian is present. Second most cases are two adults present (23.72%). Very few cases (0.76%) that only children were present.

Overall, for the potential conflict rate: when only children as pedestrians (no adult present), there is 23.19% potential conflict rate, which is 177% more likely than the cases with adult pedestrians present. This shows that there is elevated risk to let children walk alone. When only one adult is present, there are about 7.56 % cases that have potential conflict. When two adults are present, there are about 8.71% cases that have potential conflict. When three or more adults are present, there is about 10.26% chances to have potential conflict. This shows that it is more likely to have potential conflicts when more pedestrians are present. Moreover the case with only children as pedestrians has 175% more likelihood to have a potential conflict than the average of the other three cases, which is quite a relatively dangerous case.

Table 2 shows the statistical results of potential conflict rate at different driving environments. We can see that most of the potential conflicts happen in urban area (74.43%), and only 9.18% are encountered from rural area, the rest part (14.47%) are from other areas, such as parking lot, community, school area, etc. However, when comparing with the potential conflicts rate,

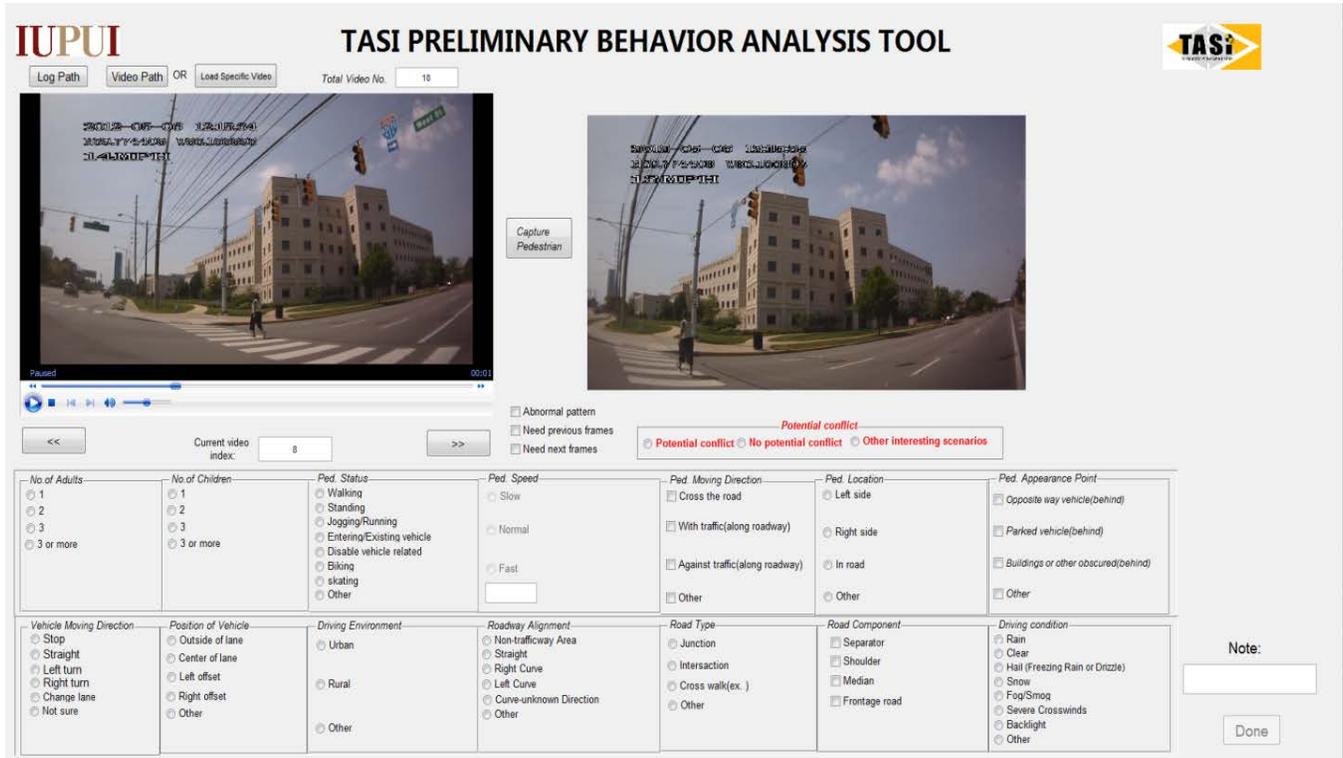


Figure 9 Pedestrian preliminary behavior analysis tool

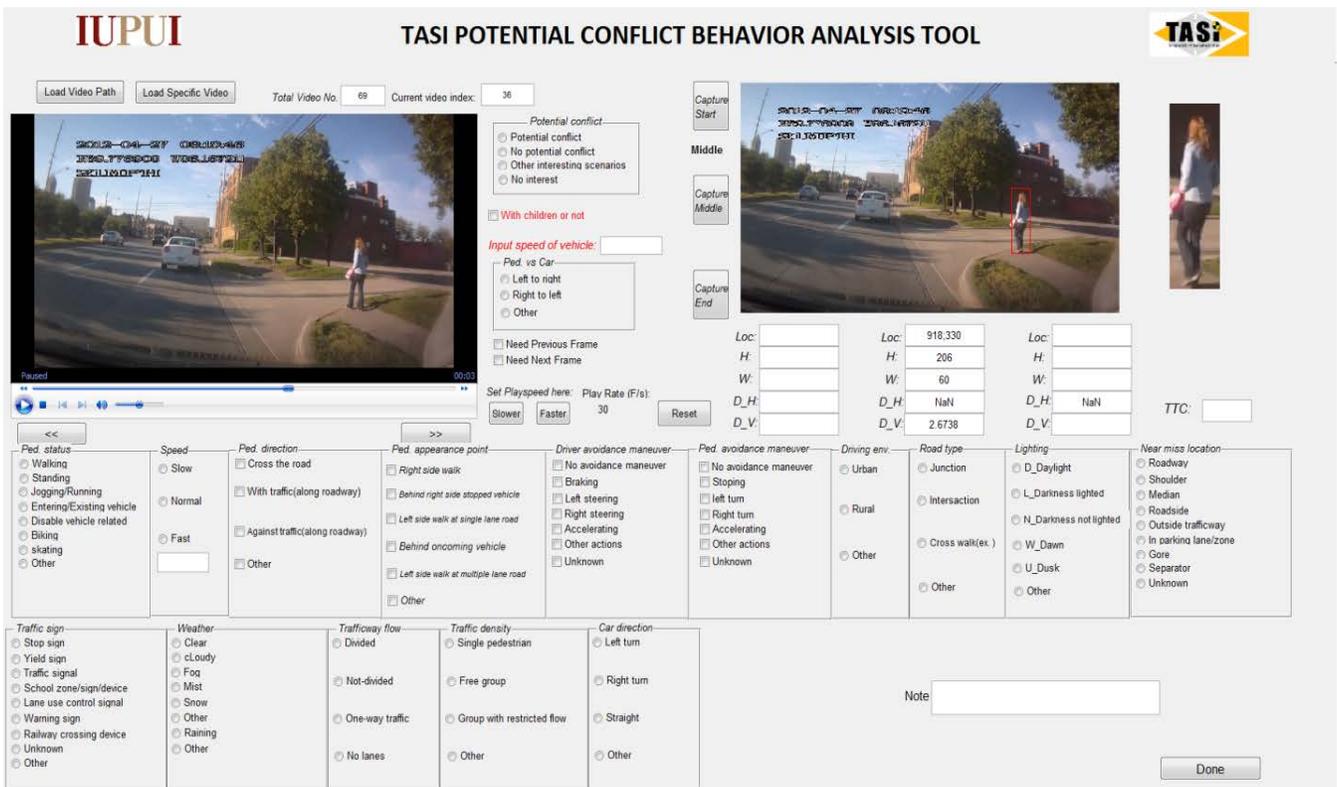


Figure 10 Potential conflict scenarios analysis

Table 1 Number of Adults Presented in the Scene

	Zero adult		One adult		Two adults		Three or more adults	
	No.	%	No.	%	No.	%	No.	%
Pedestrian videos	69	0.76%	5028	55.27%	2158	23.72%	1842	20.25%
Potential conflicts	16	2.07%	380	49.16%	188	24.32%	189	24.45%
Potential conflict rate	23.19%		7.56%		8.71%		10.26%	

Table 2 Potential Conflict Rate at Different Driving Environments

	Rural		Urban		Other	
	No.	%	No.	%	No.	%
Pedestrian videos	1158	12.73%	6771	74.43%	1168	12.84%
Potential conflicts	71	9.18%	533	68.95%	169	21.86%
Potential conflict rate	6.13%		7.87%		14.47%	

Table 3 Potential Conflict Rate at Different Pedestrian Moving Directions

	Against traffic		With traffic		Cross the road		Other	
	No.	%	No.	%	No.	%	No.	%
Pedestrian videos	1723	18.94%	1831	20.13%	2154	23.68%	3389	37.25%
Potential conflicts	50	6.47%	83	10.74%	423	54.72%	217	28.07%
Potential conflict rate	2.90%		4.53%		19.64%		6.40%	

Table 4 Potential Conflict Rate when Pedestrians Show up at Different Locations

	In road		Left side		Right side		Other	
	No.	%	No.	%	No.	%	No.	%
Pedestrian videos	1337	14.70%	2229	24.50%	4346	47.77%	1185	13.03%
Potential conflicts	270	34.93%	173	22.38%	233	30.14%	97	12.55%
Potential conflict rate	20.19%		7.76%		5.36%		8.19%	

Table 5 Potential Conflict Rate at Different Pedestrian Statuses

	Walking		Standing		Jogging		Entering/exiting vehicle		Skating		Other	
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%
Pedestrian videos	601	66.12%	1636	17.98%	226	2.48%	206	2.26%	8	0.09%	1006	11.06%
Potential conflicts	558	72.19%	47	6.08%	37	4.79%	23	2.98%	1	0.13%	107	13.84%
Potential conflict rate	9.28%		2.87%		16.37%		11.17%		12.50%		10.63%	

Table 6 Potential Conflict Rate when Different Road Types Presented

	Cross walk		Intersection		Junction		other	
	No.	%	No.	%	No.	%	No.	%
Pedestrian videos	177	1.95%	2612	28.71%	146	1.60%	6162	67.74%
Potential conflicts	31	4.01%	193	78.14%	23	2.98%	526	68.05%
Potential conflict rate	17.51%		7.39%		15.75%		8.54%	

we can see that 14.47% cases from other driving environments are potential conflicts, which is almost 100% more likelihood than the other two cases.

Table 3 shows the statistical results of potential conflict rate categorized by different pedestrian moving directions. We collected almost evenly distributed pedestrian videos from four pedestrian moving directions: 18.94% are against traffic, 20.13% are with traffic, 23.68% are crossing the road and 37.25% from other moving scenarios. Over half of the potential conflicts (54.72%) are observed from pedestrian crossing the road, and the second most are from other moving directions (28.07%), 6.47% are from against traffic, 10.74% are from with traffic. The statistical results suggest that potential conflicts are more likely to happen in pedestrian crossing scenarios with 19.64% potential conflict rate, which is three times more likelihood than other cases. This shows that road crossing has an elevated risk when compared to other scenarios.

Table 4 shows the statistical results of the pedestrian appearance location. Nearly half (47.77%) of the pedestrians appears on the right side of the road in our pedestrian videos, which is reasonable considering that vehicles drive on right side in USA. Within all the pedestrian videos classified as potential conflicts videos, 34.93% are from pedestrians in road, 22.38% are from pedestrian on left side, 30.14% are from pedestrian on right side and 12.55% from other appearance locations. Pedestrian in road has the highest potential conflict rate (20.19%) and it is two times more likelihood than the average of other cases, which shows that there is an elevated risk for pedestrians to walk in road.

Table 5 shows the pedestrian statuses within all the pedestrian videos: walking (66.12%), standing (17.98%), jogging (2.48%), entering/exiting vehicle (2.26%), skating (0.09%) and other (11.06%). Most data collected are categorized into walking and standing. We observed that higher pedestrian speed may leads to higher rate of potential conflicts as can be seen from jogging (16.37%), and skating (12.50%). Note for skating case, we do not observe many cases to draw conclusion yet.

Table 6 shows the statistical results of potential conflicts with respect to different road types. Most of the collected data are from other category (67.74%) which consists of regular traffic way of non-traffic way. We focus more about the regions of interest such as cross walk (1.95%), intersection (28.71%) and junction (1.60%). We can see that potential conflicts rate is highest at cross walk (17.51%) and second highest is at the junction (15.75%), which are more than 100% likelihood than the other two cases. The potential conflict rate is much lower at intersection when compared to the above two cases. This could be because that intersection has clear traffic signals that pedestrians/drivers can easily follow.

Pedestrian Appearance Points and TTC for Potential Conflict Crossing Events

Figure 11 shows the pedestrian appearance points of all the potential conflict events. The pedestrian appearance point is defined as the first point that the full body of the pedestrian can be seen in the video. Different situations are included:

- “Pedestrian Crosses” situations refer to that the vehicle has given right-of-way to the pedestrians to allow them pass the potential conflict point first;
- “Vehicle Passes” situations refer that the pedestrian has given right-of-way to the vehicle to allow the vehicle pass the potential conflict point first;
- Potential conflict events happening in parking lots are separated from those happening in the traffic way.
- Vehicle movement is categorized into straight movement, left turn, and right turn when the events are happening in the traffic way.

The results show that the density of pedestrian appearance point is much higher in the range of 2 to 8 meters in lateral direction and 0 to 20 meters in longitudinal direction. Also the density of pedestrian appearance points gets lower when getting further away from the vehicle in both directions. For all the situations, the pedestrian appearance points are generally balanced without very obvious patterns in terms of both directions and sides towards the vehicle moving trajectory.

The distribution of time to collision (TTC) values is shown in Figure 12. Most potential conflict events have a TTC value ranging from 1 second to 6 seconds, with the range of 2 seconds to 4 seconds being associated with highest percentages of all the cases. The mean value of TTC is 3.84 seconds with standard deviation of 1.74. The maximum TTC value is 10.11 seconds, and the minimum is 0.7 seconds. Note that our observations are based on near-misses. Therefore the TTC for crash scenarios could be much shorter.

CONCLUSIONS

This collected data provides a promising approach to study pre-crash scenarios for vehicle-to-pedestrian collisions in United States. We observed: 1) children alone as pedestrians have an elevated risk; 2) three or more adults may be more likely to result in potential conflicts with vehicles than one or two adults; 3) parking lots, communities, school areas, shopping malls, etc. could have more potential conflicts than regular urban/rural driving environments; 4) when pedestrian crossing road, there is much higher potential conflicts than pedestrian walking along/against traffic; 5) there is an elevated risk for pedestrians walking in road (where vehicles can drive by); 6) when pedestrians are jogging, it is much more likely to have potential conflict than walking or standing; and 7) it is more likely to have

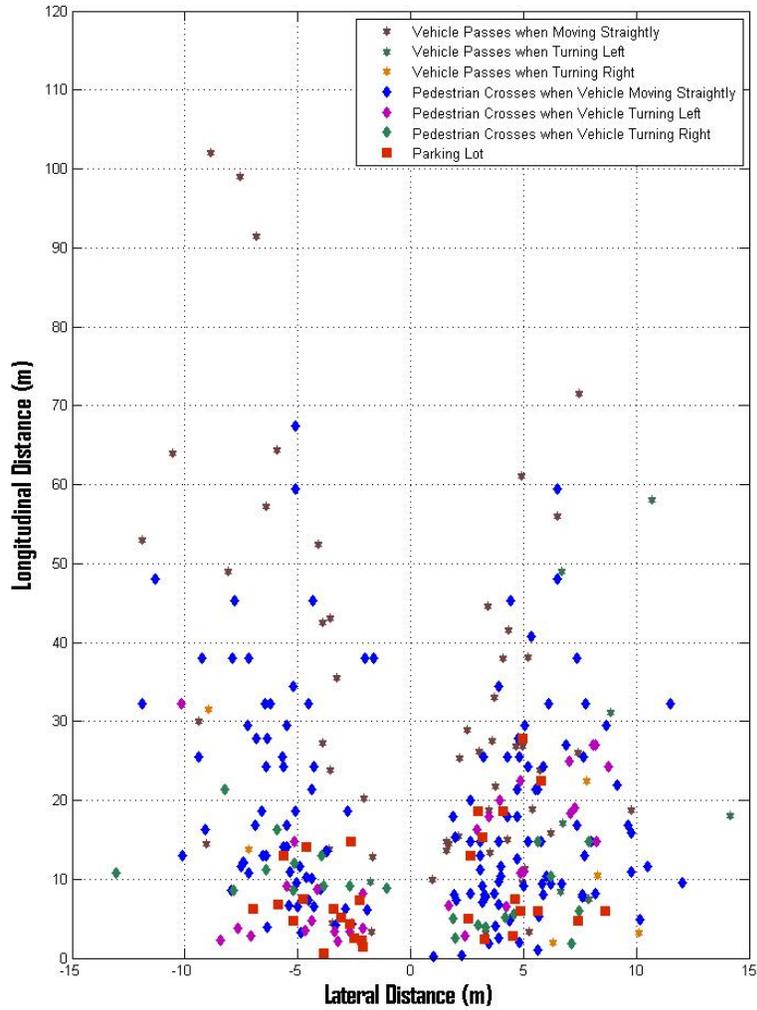


Figure 11 Map of Pedestrian Appearance Points of All the Potential Conflict Events

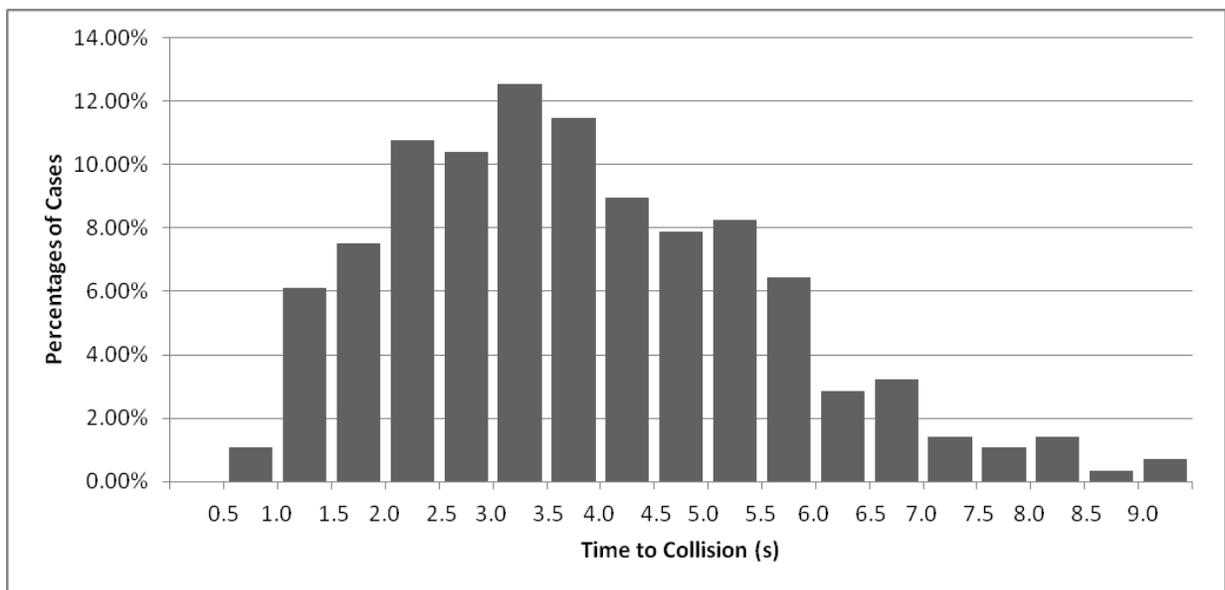


Figure 12 Distribution of Time to Collision Value

potential conflict at cross walk and junction than other road types.

Furthermore, we estimated the pedestrian appearance points of all potential conflict events and time to collision (TTC). Most potential conflict events have a TTC value ranging from 1 second to 6 seconds, with the range of 2 seconds to 4 seconds being associated with highest percentages of all the cases. The mean value of TTC is 3.84 seconds with standard deviation of 1.74. Note that our observations are based on near-misses. Therefore the TTC for crash scenarios could be much shorter.

A limitation of our research is that the collected data does not provide information about drivers' and occupants' behaviors during the conflicts. Therefore, this project is not designed to provide driver's behavior information.

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REFERENCE

- [1] R. J. Hanowski, R. L. Olson, J. S. Hickman, and T. A. Dingus, "The 100-Car Naturalistic Driving Study: A Descriptive Analysis of Light Vehicle-Heavy Vehicle Interactions from the Light Vehicle Driver's Perspective," *US Department of Transportation Federal Motor Carrier Safety Administration Technical Report* vol. FMCSA-RRR-06-004, 2006.
- [2] J. ANTIN, S. LEE, J. Hankey, and T. Dingus, "Design of the In-Vehicle Driving Behavior and Crash Risk Study: In Support of the SHRP 2 Naturalistic Driving Study," *Transportation Research Board Report S2-S05-RR-1*, 2011.
- [3] K. Yang, E. Y. Du, P. Jiang, Y. Chen, R. Sherony, and H. Takahashi, "Automatic categorization-based multi-stage pedestrian detection," *Intelligent Transportation Systems (ITSC), 2012 15th International IEEE Conference on*, pp. 451-456, 16-19 Sept. 2012 2012.
- [4] G.-B. Huang, L. Chen, and C.-K. Siew, "Universal approximation using incremental constructive feedforward networks with random hidden nodes," *Neural Networks, IEEE Transactions on*, vol. 17, pp. 879-892, 2006.
- [5] G.-B. Huang, X. Ding, and H. Zhou, "Optimization method based extreme learning machine for classification," *Neurocomputing*, vol. 74, pp. 155-163, 2010.
- [6] G.-B. Huang, H. Zhou, X. Ding, and R. Zhang, "Extreme learning machine for regression and multiclass classification," *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on*, vol. 42, pp. 513-529, 2012.