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Connecting Road Environment Features and Driver Glance Behavior in the Macro Level: Surrounding Vehicle Patterns, Traffic Density, and Driver Eye-Glance Behaviors

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Abstract—**Although integration of environment and driver information can be achieved at both micro- and macro- levels with different benefits towards driving safety, most studies focus only on the micro-level integration by coupling individual external environment events and driver responses. In the macro level, however, it is more important to understand overall effects of environment features on driver behavior, and their combined effects on driving safety. Based on some previous findings on the significant effects of driver glance behavior on crash risk and the prominent moderating effects of traffic density levels on this relationship, this paper tries to use surrounding vehicle patterns to classify traffic density levels and study the direct effects of traffic density levels on driver glance behavior. The datasets used for analysis are based on VTTI 100-car study. After proposing the measures of surrounding vehicle patterns, the classification of traffic density is completed using support vector machine (SVM). The results show that, although it is difficult to classify four traffic density levels based on the proposed surrounding vehicle patterns, the predication accuracy for two or three traffic density levels is good. Also, significant effects of traffic density on driver glance behaviors to the vehicle mirrors are identified.**

Index Terms—**Active safety, intelligent vehicles, driver behavior, road environment, surrounding vehicle patterns, support vector machine**

I. Introduction

With great progresses being made in developing advanced driver assistance systems, more and more sensors are equipped on modern vehicles. Relying on these sensor feedback, various types of vehicular safety systems have been developed, which include driver state monitoring and inattention detection [5] [6], vehicle crash avoidance systems [9], pedestrian detection and crash mitigation systems [7] [8], and others. Although these systems possess great capabilities to improve driving safety, they typically only focus on either inside or outside of the overall driving system. As a part of the efforts to further improve the active vehicular safety systems and support the development of autonomous driving vehicles, researchers have been trying to both look into and look out of vehicles simultaneously and connect the information together [10], [13]-[15]. According to [13], it is important to track three main components of the overall driving system, i.e., environment, vehicle, and driver, to fully understand the context. This is associated with two main benefits:

1. In the micro level, connecting individual prominent environment/road events with simultaneous driver behavior can help locate imminent road risk, detect abnormal driver state, and learn driver intention, which are achieved by comparing attention/responses needed from the environment and the attention devoted into the hot spots, as well as the actual responses taking place by drivers.
2. In the macro level, instead of focusing on individual environment events, it is more important to understand general environmental features, determine their effects on driver behaviors, and use the combined environment and driver behavior features/measures to estimate risks, analyze driving needs, and guide vehicle automation systems.

Although both micro- and macro- levels are important to support the parallel control of the vehicle and design of driver-in-the-loop vehicle automation systems [17], most related studies in literature have been focusing on the micro-level analysis. In [13], the researchers constructed one multimodal sensory platform based on computer vision and computer learning techniques, which can track environment, driver, and vehicle states simultaneously and provide complete support for driver-assistance system. Based on the concept of this platform, the group of researchers has proposed one driver distraction detection algorithm that integrates driver's viewing direction, driver's head pose, and surrounding traffic conditions based on an omni-camera [10]. They also investigated driver intentions by comparing driver's visual search and external stimulus [15]. In a similar study [14], the authors tried to examine the situational

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awareness of drivers based on the risks of surrounding vehicles and the actual gaze behavior of drivers. The results showed that based on this method, expert drivers are usually with better awareness of the risks compared to the non-expert drivers.

To the best of our knowledge, there is very few research addressing the concept from macro- level. In our research efforts, we are trying to connect the general road environment features with driver behavior and study the combined effects on driving safety. Among different measures of driver behavior, driver eye-glance behavior has been widely used to detect driver distraction and inattention [18] [19]; and one of the driver eye-glance behavior measures, off-road eye glance duration, has been proved to be strongly associated with crash risks [2] - [4]. As a part of our efforts to connect road environment and driver behavior together and learn their effects on driving safety, one of our earlier paper successfully modeled the relationship between driver off-road glance duration and the relative risk of crashes, and proved that traffic density measured by the level of service is one significant moderating factor of this relationship [1]. However, there are still two questions need to be answered in order to improve the results:

1. Although it has been proved that traffic density has significant moderating effects on the relationship between off-road eye glance duration and crash risk, the direct effects of traffic density on the driver eye-glance behavior were not studied;
2. Since traffic density is not one variable that can be measured directly by vehicle sensors, it is important to be able to estimate the traffic density of the road by some other measurable variables.

In this paper, we firstly focus on investigating the possibility of estimating traffic density based on the patterns of surrounding vehicles; then we study the direct effects of traffic density on driver eye-glance behaviors. As a part of the overall efforts to connect road environment and drivers together to study the combined effects on driving safety, the main contributions of this paper include: (1) innovatively proposing a list of variables to model the surrounding vehicle patterns; (2) using Support Vector Machine (SVM) methods to classify traffic density levels based on the surrounding vehicle patterns at a reasonable accuracy; (3) practically enabling the use of on-vehicle sensors to estimate traffic density on road since the proposed surrounding vehicle patterns are directly measurable using radar sensors; and (4) together with previous efforts [1], proposing one application of connecting road environment features and driver behavior in macro- level with their combined effects on crash risk proved.

II. Surrounding Vehicle Patterns, Traffic Density, and Driver Eye-Glance Behavior

Fig. 1 illustrates the overall picture of connecting road environment features and driver behavior to study their combined effects on crash risk. The dotted lines indicate the proved relationships in [1] that the driver eye-glance behavior significantly affects crash risk, and this effect is moderated by traffic density on road.

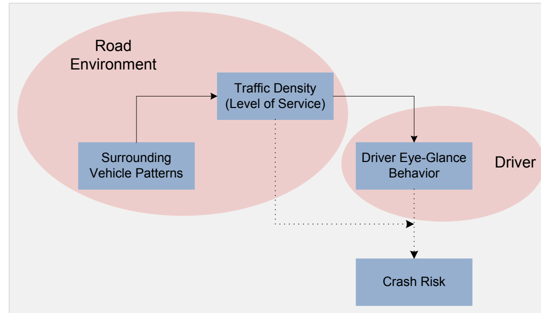

Fig. 1 Hypothesized Model for the Effects among Surrounding Vehicle Patterns, Traffic Density, and Driver Eye-Glance Behavior.

Two hypotheses of this study are illustrated as solid lines in Fig. 1, which includes:

Hypothesis I: traffic density measured by the level of service can be classified using surrounding vehicle patterns.

The common measures of surrounding vehicle patterns used in literature are relatively simple. Some examples of these measures include: reaction time of the driver in the following vehicle [11], vehicle paths in the road [16], distance, velocity, and orientation of other vehicles [12], and time-to-collision to vehicles in the eight surrounding zones [14]. Clearly, these measures will not be able to serve as classifiers towards traffic density levels due to shortage of important information. Thus, one complicated temporal measurements of the surrounding vehicle patterns are needed in this paper to carry enough information and serve as the traffic density classifier. In literature, the related studies either define a new level of service measures based on the surrounding vehicles [21], or use self-vehicle and surrounding vehicle information to detect traffic congestions [20]; and to the best of our knowledge, there is no published study focusing on classifying traffic density levels using surrounding vehicle patterns.

Hypothesis II: traffic density levels have significant effects on driver eye-glance behavior.

Although there are plenty of studies talking about the effects of external visual stimulus or driver workload on driver gaze patterns and glance behaviors [22] [23], the effects of traffic density on driver eye-glance behavior, especially driver off-road eye-glance behaviors, have not been sufficiently discussed in literature. According to [23], even the relationship between driver looking behavior and the workload is still under debate, and there are no solid conclusions being made due to the lack of data. Thus, it is meaningful to check the effects of traffic density levels on the driver eye-glance behaviors, or more specifically, off-road glance or mirror glance behaviors, in this paper.

III. Data Preparation and Analysis

A. Data Sources and Data Processing Procedures

The data used in this paper is from the VTTI (Virginia Tech Transportation Institute) 100-car naturalistic driving data collection [27]. For more detailed descriptions of the dataset, please refer to [3] [4] [27]. In one of our previous paper [1], the publicly accessible databases and the secondary analysis of the collected data have been elaborately discussed.

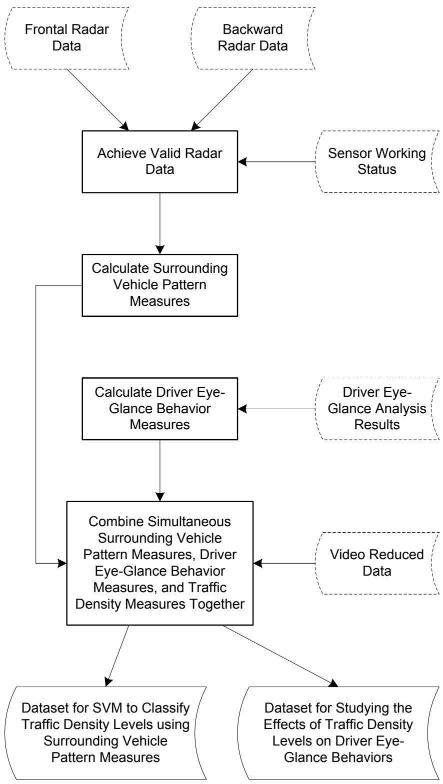

Fig. 2 Data Processing Procedure.

The data processing procedures are shown in Fig. 2 above. In Fig. 2, the datasets in dashed lines are from VTTI 100-car study and the datasets in solid lines are generated for the data analysis in this paper. Starting from the frontal radar data and the backward radar data, valid radar data were firstly obtained by checking the recorded sensor working status logs. These radar data include information on the number of surrounding vehicles, the distance of these vehicles from the subject car, the azimuth angles between the lines connecting the subject car and the surrounding vehicles and the center line of the subject car, and the relative speeds of surrounding vehicles. Upon obtaining these data from radar, surrounding vehicle pattern measures can be calculated. Then relying on the driver eye-glance analysis results, the driver eye-glance behavior measures can be obtained. After synchronization, these two measures can be combined with the actual traffic density levels assigned by data reductionists who watched the videos to generate the datasets used for testing the hypotheses in this paper.

B. Surrounding Vehicle Patterns Measurement

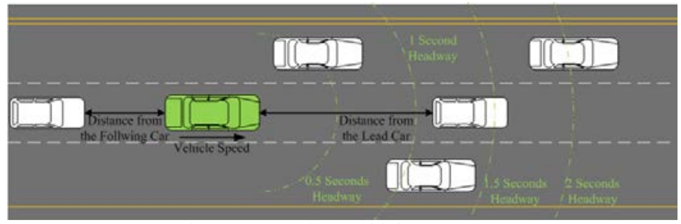

Fig. 3 Surrounding Vehicle Patterns.

The surrounding vehicle pattern measurement developed in this paper focuses on carrying as much useful information as possible to support the classification of traffic density. As illustrated in Fig. 3, the interested information includes distance from the lead car, distance from the following car, number of vehicles in front of the car, lane numbers, vehicle speed, and number of vehicles at different headways. The design of these headways are based on several references [24] - [26] including 0.5 seconds, 1 second, 1.5 seconds, and 2 seconds. Temporal variables are also included in the measurement. These measurements mainly include:

- Number of seconds with different numbers of vehicles in front of the car;
- Maximum number of vehicles driving in front of the car at different distances and the corresponding durations;
- Total number of times of vehicle increasing/decreasing in front of the car;
- The shortest time gap between the car and the lead and the following vehicles.

C. Traffic Density and Driver Eye-Glance Behavior Measures

The measures of traffic density in this paper are the same as in [1], which is based on the level of service definitions used by the VTTI 110-car data collection [27]. Please refer to [27] for the detailed definitions for the four levels of free flow, flow with restrictions, stable flow with more restrictions, and unstable flow with reduced driving speed.

The driver eye-glance behavior measures used in this paper include: (1) off-road eye-glance frequency, (2) off-road eye-glance duration, (3) mirror eye-glance frequency, and (4) mirror eye-glance duration.

IV. Results

Recall that in Fig. 2, the process of preparing the two datasets for testing our two hypotheses is described. The first dataset is analyzed using SVM to test the classification accuracy of traffic density based on surrounding vehicle patterns, and the second dataset is used to study the effects of traffic density on driver eye-glance behaviors.

A. Classification of Traffic Density

The dataset used for classifying traffic density (based on surrounding vehicle patterns) contains 393 25-second cases. For each case, the variables describing surrounding vehicle patterns and the assigned traffic density level to the case based on the video are recorded. The SVM code and data analysis procedures are mainly based on [28], and the kernel of the SVM used is radial basis function (RBF). One cross-validation process was added for the SVM analysis, which was repeated five times. The results of the continuous five runs are recorded. Table 1 shows the classification accuracies of the four traffic densities using the variables describing surrounding vehicle patterns, corresponding to five continuous runs and the average value. The results show that the accuracy is about 43% to 44%; this means that after training, 43% to 44% of the prediction outputs of the SVM about the traffic density levels are correct. The prediction accuracies for the five continuous runs are reasonably consistent.

TABLE 1
PREDICATION ACCURACIES OF FIVE TESTS AND THE AVERAGE VALUE FOR THE SVM CLASSIFICATION OF FOUR TRAFFIC DENSITY LEVELS

	Test Trial 1	**Test Trial 2**	**Test Trial 3**	**Test Trial 4**	**Test Trial 5**	**Average**
Accuracy	43.08 %	41.03 %	42.05 %	44.10 %	47.18 %	43.49%

In order to better understand the prediction accuracy of the trained SVM, the prediction accuracy (A) for each predicted traffic density level (PD) is defined as $\mathrm{A(PD = \alpha)}$, and the prediction error for each predicted traffic density level (PD) with the true traffic density level (TD) is defined as $\mathrm{E(PD = \alpha, TD = \beta)}$. So we have

$$A(PD = \alpha) = \frac{\#\ of\ cases\ when\ PD = TD = \alpha}{\#\ of\ cases\ when\ PD = \alpha} \quad (1)$$

$$E(PD = \alpha, TD = \beta) = \frac{\#\ of\ cases\ when\ PD = \alpha\ and\ TD = \beta}{\#\ of\ cases\ when\ PD = \alpha} \quad (2)$$

Using equations (1) and (2), the prediction accuracy and prediction error for each predicted level towards each true density level are calculated for all five runs of SVM classification. The results can be summarized that: (1) the accuracy for traffic density level 1 predictions are about 60%, and for both the traffic density level 2 and level 3, the accuracies of predications are about 40%, and there is no case being predicted to be traffic density level 4.

The results of classifying four different traffic density levels have shown that the trained SVM has good power to predict traffic density level 1, and reasonable power to predict traffic density level 2 and level 3. When there are errors in the prediction, the adjacent traffic levels are highly possible to be the true value. Considering that the trained SVM can: (1) separate level 1 from the other three levels pretty well, and (2) cannot separate traffic density level 2 and level 3 very well, the following two other classification modes are applied. The first one is to separate traffic density level 1 from the other three density levels, which is called two traffic density levels classification. The other one is to separate density level 1, combined density level 2 and level 3, and density level 4, which is called three traffic density levels classification. Each classification was repeated five times using the cross validation process, and all accuracies are shown in Table 2 below. The predication accuracies and predication errors for every predicted level, as defined in equations (1) and (2), are also calculated. The results show that the trained SVM has good predication powers for these two types of traffic density level classifications. The overall accuracies are about 70% or better. For prediction accuracy of each predicted traffic level as defined in equation (1), the accuracies are all in the 70% to 90% ranges except for traffic density level 4 in the three-density-level classification. The predication errors for each predicted traffic level calculated using equation (2) are less than 30% for the two density level classification and less than 15% for the three density level classification.

TABLE 2
PREDICATION ACCURACIES OF FIVE TESTS AND THE AVERAGE VALUE FOR THE SVM CLASSIFICATION OF TWO AND THREE TRAFFIC DENSITY LEVELS

	Test 1	**Test 2**	**Test 3**	**Test 4**	**Test 5**	**Average**
Two Traffic Density Levels	77.04%	78.06%	75.51%	77.55%	76.53%	76.94%
Three Traffic Density Levels	70.41%	69.39%	67.86%	68.37%	70.41%	69.29%

B. *Effects of Traffic Density on Eye-Glance Behaviors*

Generated through the process shown in Fig. 2, the second dataset is used to study the effects of traffic density levels on eye-glance behaviors. This dataset contains 817 6-second cases, whose traffic density level and eye-glance behavior measures are recorded. Since the interested eye-glance behaviors in this paper mainly include off-road glance and mirror glance (including rearview mirror and two side mirrors), 330 cases with off-road glances and 210 cases with mirror glances are selected out of the 817 cases. Within the period of six seconds, the total accumulative length of eye glance durations to the mirrors and off-road locations, the total number of glances to the mirrors and off-road locations, and the average length of the glances are analyzed.

Fig. 4 below shows the analysis results for the glance behaviors to the mirrors, and Fig. 5 shows the analysis results for the off-road eye-glance behaviors. From the plots, it is not difficult to see that, for the glances to the mirrors, with increased traffic density levels, the total accumulative eye-glance duration and the total numbers of glances are both increasing, while the average duration for each glance is almost the same. The one-way ANOVA test confirms this finding to show that, traffic density level is one significant factor in affecting total accumulative glance duration to the mirrors ($p<0.001$) and number of mirror glances ($p<0.0001$), but is not one significant factor in affecting averaged mirror glance duration ($p=0.73$).

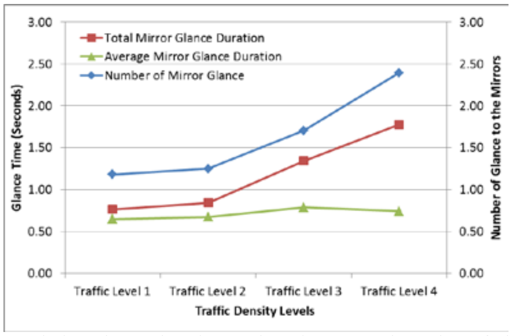

Fig. 4 Cumulative glance duration to the mirrors, total number of glances to the mirrors, and average glance duration to the mirrors during the sampled 6-second periods.

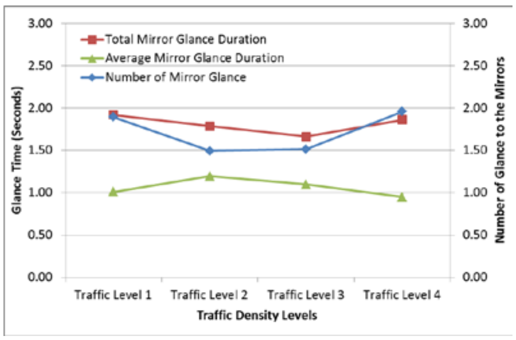

Fig. 5 Cumulative off-road glance durations, total number of off-road glances, and average off-road glance durations during the sampled 6-second periods.

The mean, standard deviation, standard error, and post hoc analysis results of the variables associated to the glance behaviors to the mirrors are shown in Table 3. The post hoc analysis results show that, for total glance durations to the mirrors and total number of glances to the mirrors, there are more glances and longer accumulative glance durations for traffic levels 3 and 4 compared to the traffic levels 1 and 2; however, the average duration for each glance is kept unchanged. This means that, although each time the driver spends similar amount of time to complete one glance to the mirrors, they watch more frequently when the driving density increases. For the off-road eye-glance behaviors, however, it looks like the cumulative eye-glance durations, average off-road glance duration, and the total numbers of glances are not affected by the traffic density levels significantly. This conclusion is also confirmed by the one-way ANOVA analysis with insignificant differences among the mean values for different traffic levels.

V. Conclusions and Discussions

As one extension of our previous work [1], this paper talks about connecting the surrounding vehicle patterns with traffic density and driver eye-glance behaviors in the macro-level. The previous study in [1] has shown that the traffic density level is one important moderator to the significant effects of driver eye-glance behavior on driving safety. In this paper, classification of the traffic density levels based on the proposed surrounding vehicle pattern measures is firstly tested using SVM. The results show that although the trained SVM could not classify the four traffic density levels very accurately, it has good capability to classify traffic density level 1 (free flow) and combined traffic density level 2 and 3 (stable flow with slight and increased restrictions).

TABLE 3
VARIABLE STATISTICS AND POST HOC (LSD) ANALYSIS RESULTS FOR CUMULATIVE GLANCE DURATION, NUMBER OF GLANCES, AND AVERAGE GLANCE DURATION OF GLANCES TO THE MIRRORS

	Density Level	Mean Value	Standard Deviation	Standard Error	Post Hoc Results*
Cumulative Glance Duration	1	7.66	5.61	0.85	a
	2	8.42	8.63	1.02	a
	3	13.43	11.77	1.51	b
	4	14.57	12.45	2.35	b
Number of Glances	1	1.18	0.39	0.06	a
	2	1.25	0.62	0.07	a
	3	1.70	1.10	0.14	b
	4	1.96	1.23	0.23	b
Average Glance Duration	1	6.47	4.19	0.63	a
	2	6.92	7.55	0.89	a
	3	7.73	5.27	0.67	a
	4	6.87	4.37	0.83	a

*The same group is using the same letter, which means that there are no significant differences between the means in the same group; but the means are significantly different between the groups.

Another finding in this paper is about the direct effects of traffic density levels on driver eye-glance behaviors. The analysis is not able to show any significant connection between the traffic density levels and driver off-road glance behavior, although the later one is the prominent factor to detect driver distraction and thus affecting driving safety. However, one interesting finding is that traffic density levels show significant effects on driver eye-glance behaviors to the rearview and side mirrors. With increased traffic, the driver tends to check the mirrors more frequently, but still keep relatively consistent duration for each glance.

This study has two limitations mainly related to the datasets being used for the analysis. The data used are based on the released event datasets from VTTI 100-car study, which means that the sampled cases are all associated with crash or near-crash events. This bias should not have effects on classification of traffic density levels using surrounding vehicle patterns, but may affect the generalization of the driver behavior analysis results. More baseline data should be used for future analysis to evaluate the findings in this paper. Also, the dataset is moderately imbalanced in regarding to the traffic density levels. For the four traffic density levels we are interested, the ratios of the total numbers of available cases are 1:1.26:0.86:0.30 for traffic density levels 1 to 4. According to [29] and [30], although imbalanced datasets usually affect the predication accuracy of machine learning algorithms, SVM performs relatively well to deal with moderately imbalanced datasets. Thus, in this paper, the datasets are not sampled again to balance the number of cases in different conditions. In the future analysis, different weightings may also be assigned to different conditions during the training process of the SVM to solve the problem.

REFERENCES

[1] R. Tian, L. Li, M. Chen, Y. Chen, and G. J. Witt, "Studying the effects of driver distraction and traffic density on the probability of crash and near-crash events in naturalistic driving environment," *IEEE Trans. Intelligent Transportation Systems*, vol. 14, no. 3, pp. 1547 – 1555, September 2013.

[2] Y. Liang, J. D. Lee, and L. Yekhshatyan, "How dangerous is looking away from the road? Algorithms predict crash risk from glance patterns in naturalistic driving," *Human Factors*, vol. 54, no. 6, pp. 1104 – 1116, December 2012.

[3] S. G. Klauer, F. Guo, J. D. Sudweeks, and T. A. Dingus, "An analysis of driver inattention using a case-crossover approach on 100-car data: final report." *NHTSA report DOT HS 811 334*, May 2010.

[4] S. G. Klauer, T. A. Dingus, V. L. Neale, J. D. Sudweeks, and D. J. Ramsey, "The impact of driver inattention on near-crash/crash risk: an analysis using the 100-car naturalistic driving study data," *NHTSA report DOT HS 810 594*, April 2006.

[5] Y. Dong, Z. Hu, K. Uchimura, and N. Murayama, "Driver inattention monitoring system for intelligent vehicles: A review." *IEEE Transactions on Intelligent Transportation Systems*, vol. 12, no. 2, pp. 596-614, June 2011.

[6] Y. Liang, M. L. Reyes, and J. D. Lee, "Real-time detection of driver cognitive distraction using support vector machines." *IEEE Transactions on Intelligent Transportation Systems*, vol. 8, no. 2, pp. 340-350, June 2007.

[7] C. G. Keller, T. Dang, H. Fritz, A. Joos, C. Rabe, and D. M. Gavrila, "Active pedestrian safety by automatic braking and evasive steering," *IEEE Trans. Intelligent Transportation Systems*, vol. 12, no. 4, pp. 1292 – 1304, December 2011.

[8] T. Gandhi, and M. M. Trivedi, "Pedestrian protection systems: issues, survey, and challenges," *IEEE Trans. Intelligent Transportation Systems*, vol. 8, no. 3, pp. 413–430, September 2007.

[9] T. Kim and H. Jeong, "A novel algorithm for crash detection under general road scenes using crash probabilities and an interactive multiple model particle filter," *IEEE Trans. Intelligent Transportation Systems*, DOI: 10.1109/TITS.2014.2320447, 2014.

[10] K. S. Huang, M. M. Trivedi, and T. Gandhi, "Driver's view and vehicle surround estimation using omnidirectional video stream," in *Proc. IEEE Intelligent Vehicles Symposium*, Columbus, OH, USA, pp. 444 – 449, June 2003.

[11] H. Fukuoka, Y. Shirai, K. Yamada, "Driving support system adaptive to the state of surrounding vehicle drivers," in *Proc. IEEE Intelligent Vehicles Symposium*, Xi'an, China, pp. 1215 – 1220, June 2009.

[12] J. Nuevo, I. Parra, J. Sjoberg, and L. M. Bergasa, "Estimating surrounding vehicles' pose using computer vision," in *13th International IEEE Annual Conference on Intelligent Transportation Systems*, Madeira Island, Portugal, pp. 1863 – 1868, September 2010.

[13] M. M. Trivedi, T. Gandhi, and J. McCall, "Looking-in and looking-out of a vehicle: Computer-vision-based enhanced vehicle safety," *IEEE Trans. Intelligent Transportation Systems*, vol. 8, no. 1, pp. 108 – 120, March 2007.

[14] M. Mori, C. Miyajima, P. Angkititrakul, T. Hirayama, Y. Li, N. Kitaoka, and K. Takeda, "Measuring driver awareness based on correlation between gaze behavior and risks or surrounding vehicles,", in *15th International IEEE Conference on Intelligent Transportation Systems*, Anchorage, Alaska, USA, pp. 644 – 647, September 2012.

[15] A. Doshi, and M. Trivedi, "Investigating the relationships between gaze patterns, dynamic vehicle surround analysis, and driver intentions," in *Proc. IEEE Intelligent Vehicles Symposium*, Xi'an, China, pp. 887 – 892, June 2009.

[16] B. Morris, and M. Trivedi, "Unsupervised learning of motion patterns of rear surrounding vehicles," in *Proc. IEEE International Conference on Vehicular Electronics and Safety*, Pune, India, pp. 80 – 85, November 2009.

[17] N. Merat, J. D. Lee, "Preface to the special section on human factors and automation in vehicles: designing highly automated vehicles with the driver in mind," *Human Factors*, vol. 54, no. 5, pp. 681 – 686, October 2012.

[18] M. Sodhi and B. Reimer, "Glance analysis of driver eye movements to evaluate distraction," *Behavior Research Methods, Instruments, and Computers*, vol. 34, no. 4, pp. 529-538, 2002.

[19] A. Azman, Q. Meng, and E. Edirisinghe, "Non-intrusive physiological measurement for driver cognitive distraction detection: eye and mouth movements," in *Proc. 3rd International Conference on Advanced Computer Theory and Engineering*, 2010.

[20] G. Marfia, and M. Roccetti, "Vehicular congestion detection and short-term forecasting: a new model with results," *IEEE Trans. Vehicular Technology*, vol. 60, no. 7, pp. 2936 – 2948, September 2011.

[21] H. Kita, "Level-of-service measure of road traffic based on the driver's perception," in *4th International Symposium on Highway Capacity*, Maui, Hawaii, USA, pp. 53 – 62, June 2000.

[22] M. A. Recarte and L. M. Nunes, "Effects of verbal and spatial-imagery tasks on eye fixations while driving," *Journal of Experimental Psychology: Applied*, vol. 6, no. 1, pp. 31 – 43, March 2000.

[23] P. Green, "Where do drivers look while driving (and for how long)?", in *Human Factors in Traffic Safety*, 2nd ed., R. E. Dewar, and R. Olsen, (Eds.), Lawyers & Judges Publishing, Tucson, AZ, pp. 57–82.

[24] C. J. Colbourn, I. D. Brown, and A. K. Copeman, "Drivers' judgments of safe distances in vehicle following," *Human Factors*, vol. 20, no. 1, pp. 1 – 11, February 1978.

[25] B. Lewis-Evans, D. D. Waard, and K. A. Brookhuis, "That's close enough—A threshold effect of time headway on the experience of risk, task difficulty, effort, and comfort," *Accident Analysis & Prevention*, vol. 42, no. 6, pp. 1926 – 1933, November 2010.

[26] M. Taieb-Maimon, and D. Shinar, "Minimum and comfortable driving headways: reality versus perception," *Human Factors*, vol. 43, no. 1, pp. 159 – 172, February 2001.

[27] T. A. Dingus, S. G. Klauer, V. L. Neale, A. Petersen, S. E. Lee, J. Sudweeks, M. A. Perez, J. Hankey, D. Ramsey, S. Gupta, C. Bucher, Z. R. Doerzaph, J. Jermeland, and R. R. Knipling, "The 100-car naturalistic driving study, phase II- Results of the 100-car field experiment," *NHTSA report DOT HS 810 593*, April 2006.

[28] C. -C. Chang and C. -J. Lin, "LIBSVM: A library for support vector machines," *ACM Transactions on Intelligent Systems and Technology*, vol. 2, no. 3, pp. 27:1 – 27:27, April 2011. Software available at http://www.csie.ntu.edu.tw/~cjlin/libsvm

[29] G. Menardi, and N. Torelli, "Training and assessing classification rules with unbalanced data," *Data Mining and Knowledge Discovery*, vol. 28, no. 1, pp. 92 – 122, January 2014.

[30] R. Akbani, S. Kwek, and N. Japkowicz, "Applying support vector machines to imbalanced datasets," *Lecture Notes in Computer Science*, vol. 3201, pp. 39-50, 2004.