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Assessing the impact of reduced visibility on traffic crash risk using microscopic data and surrogate safety measures

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ABSTRACT

Due to the difficulty of obtaining accurate real-time visibility and vehicle based traffic data at the same time, there are only few research studies that addressed the impact of reduced visibility on traffic crash risk. This research was conducted based on a new visibility detection system by mounting visibility sensor arrays combined with adaptive learning modules to provide more accurate visibility detections. The vehicle-based detector, Wavetronix SmartSensor HD, was installed at the same place to collect traffic data. Reduced visibility due to fog were selected and analyzed by comparing them with clear cases to identify the differences based on several surrogate measures of safety under different visibility classes. Moreover, vehicles were divided into different types and the vehicles in different lanes were compared in order to identify whether the impact of reduced visibility due to fog on traffic crash risk varies depending on vehicle types and lanes. Log-Inverse Gaussian regression modeling was then applied to explore the relationship between time to collision and visibility together with other traffic parameters. Based on the accurate visibility and traffic data collected by the new visibility and traffic detection system, it was concluded that reduced visibility would significantly increase the traffic crash risk especially rear-end crashes and the impact on crash risk was different for different vehicle types and for different lanes. The results would be helpful to understand the change in traffic crash risk and crash contributing factors under fog conditions. We suggest implementing the algorithms in real-time and augmenting it with ITS measures such as VSL and DMS to reduce crash risk.

1. Introduction

Adverse weather events related to fog has become a serious problem for the safety and operation of Florida highways. According to the data from the Fatality Analysis Reporting System between 2008 and 2012, there were a total of 4945 fog related crashes of which 132 were fatal. Over 30% of total fog related crashes are fatal-and-injury (KAB) crashes. Although the percentage of fog related crashes is small, these crashes tend to be more severe and involve multiple vehicles. An example for a fog related crash in Florida is the 70 vehicles pileup on I-4 in Polk County, Florida in January 2008 which caused 5 fatalities and many injuries (Hassan et al., 2011). Therefore, it is necessary to better understand the change of traffic flow

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characteristics during fog and then develop effective countermeasures to reduce fog related crashes. Till now, very few research studies have focused on investigating the effect of fog on traffic crash risk by using real-time microscopic vehicle based traffic data due to the difficulty of obtaining such data at the same time. This research is based on a new visibility and traffic detection system by mounting visibility sensor arrays at different levels above the ground. These sensor arrays are combined with adaptive learning modules to provide more accurate detections. The vehicle-based detector, Wavetronix SmartSensor HD, was installed at the same place to collect accurate traffic data, including vehicle speed, the length and category of vehicle and lane assignment. After collecting these accurate visibility and traffic data, this paper aims to investigate the impact of fog on traffic crashes by establishing the relationship between crash risk and microscopic traffic parameters during fog conditions.

There are not many research studies that discussed the effect of fog on traffic safety and operations. Most of the available studies focused on investigating the change of driver behavior during fog using data collected in driving simulator studies. Codling (1971) showed that fog crashes typically tend to involve multiple vehicles. Edwards (1998) pointed out that speed was a major contributing factor in fog-related crashes. Broughton et al. (2007) studied the car following behavior using driver simulator data and found that the average headway distance was reduced in reduced visibility conditions. The authors asserted that the headway distances decrease because drivers seek visible cues whereas foggy conditions obscure scenery and roadway visibility. Kang et al. (2008) studied the car following performance during fog and concluded that the headway distance increases under low visibility conditions. Wanvik (2009) discussed the effect of road lighting on fog related crashes and showed that the effect of lighting was significant and underestimated in safety studies. Caro et al. (2009) observed reduced headways in fog conditions and explained that the reduced headway could be a way for drivers to achieve faster discrimination of relative motion in foggy weather. Ni et al. (2010) examined age-related differences in car following behavior in foggy conditions. The authors used driving simulator data and found that the largest reduction in the car following performance occurs at moderate speeds under the highest fog density condition, with older drivers keeping a much closer headway distance (21% less) compared to young drivers. The result implies that older drivers are at higher risk especially under high fog density. Abdel-Aty et al. (2011) made a comprehensive effort to examine the effects of various factors on fog-related crash risk and found that head-on and rear-end crashes are the two most prevalent fog related crash types. Speed and lighting are two major contributing factors in fog-related crashes. Mueller and Trick (2012) investigated the influence of driving experience on driving speeds in simulated foggy conditions. This paper found that experienced drivers reduce their speed more than novice drivers in the same situation. Yan et al. (2014) examined the effect of fog conditions on the speed behavior using driving simulator data. It was shown that driving speeds were significantly reduced by the existence of fog on the straight segments. However, no significant difference was found between speeds in light and heavy fog conditions on straight segments. One of the important findings of this study is that the effect of fog is not consistent in different geometric alignments.

Compared to the limited research on the impact of low visibility due to fog on traffic, there are some researches on investigating the impact of other weather phenomena including rain and snow. In an earlier study conducted by Jones and Goolsby (1970), it was shown that rain results in a 12–19% reduction of capacity of the freeway. Hassan and Barker (1999) studied the impact of snow on urban traffic and pointed out that up to 10–15% traffic reduction is caused by snow lying on the ground. Smith et al. (2004) examined the impact of rain at various levels of intensity on the capacity and operating speeds to identify the impact of weather conditions on traffic parameters. The authors used a maximum observed throughput approach to estimate the freeway link capacity; the mean of the highest 5% flow rates was used to determine the percentage changes in capacity due to rain. It was found that the capacity was reduced as the rainfall intensity becomes greater. Light rain reduces the freeway link capacity by 4–10%, whereas heavy rain lowers it by 25–30%. Maze and Burchett (2006) showed that reduced visibility decreased traffic speed by 12% on freeways in the metropolitan area. Hou et al. (2013) calibrated the effects of rain on traffic parameters. They found that visibility and precipitation intensity significantly impact both free flow speed and maximum flow rate.

Crash frequency is usually considered as a direct measure of crash risk. In this research, since fog related crashes are less frequent compared to crashes occurring in clear visibility conditions and the real-time vehicle based traffic data are difficult to obtain, there are not enough fog crashes that have occurred at the study location. Therefore, this research uses surrogate measures of safety to overcome the lack of sufficient crash data. Multiple previous researchers have discussed the application of surrogate measures of safety. One of the major surrogate measures of safety that has been proposed in the literature is the time to collision (TTC). TTC was first introduced in 1971 and has been applied as a safety indicator in many safety analyses since then. It was well recognized that the higher a TTC value, the safer a situation is (Hydén, 1987, 1996; Minderhoud and Bovy, 2001; Svensson and Hydén, 2006). Garber and Gadiraju (1988) concluded that crash rates will increase as the speed variance increases on all types of roadways. Harkey et al. (1990) and Fildes et al. (1991) also found a trend of increasing crash involvement for speeds above the mean speed in both rural and urban conditions. Stuster et al. (1998) investigated a relationship between vehicle speed and crash incidence on rural highways and concluded that crash rates were lowest for travel speeds near the mean speed of traffic and increased with greater deviations above and below the mean speed.

It can be seen from the previous traditional statistical crash modeling (Miaou and Lum, 1993) that they may not be able to fully reflect the fundamental cause and effect relationship without using the detailed traffic data. Lord and Mannering (2010) also pointed out that one promising new direction of research should potentially open up if the detailed vehicle based traffic data are available. Therefore, this research aims to investigate the change of traffic crash risk in foggy conditions using real vehicle based traffic and weather data. At first, fog cases were selected and analyzed by comparing them with clear cases to identify the difference of TTC under different situations. Moreover, vehicles were divided into different types and the vehicles in different lanes were compared in order to identify whether the impact of reduced visibility due to fog on traffic crash risk varies depending on vehicle types and lanes. Inverse-Gaussian regression modeling was then applied to explore the relationship between time to collision and visibility together with other traffic parameters.

2. Evaluation of existing visibility and traffic detection systems

Visibility and traffic detection systems have been installed across the US. Several systems were installed more than a decade ago, such as the systems used for I-75 in southeastern Tennessee, state route 99 near the San Joaquin Valley in California, and I-10 in Alabama. With the introduction of new technologies, some existing systems have been upgraded and several new types of systems have been proposed.

As for the fog detection system, Fog Pilot is one of the pilot programs of the ROADIDEA project organized under 7th Framework Program of the European Union (Lindqvist et al., 2009). This system includes information obtained from a variety of data sources such as satellite direct visibility measurements, standard meteorological measurements, web cams, and visibility meters. Fog Pilot aims to test the usefulness of such a product by involving end user testing. The plan is to evaluate the best threshold of visibility for a "Dense Fog Presence" alert; possible choices to be evaluated could include 100, 150 and 200 m. In this pilot system, 10 visibility meters were built. However the visibility is calculated by a statistical analysis of original data archives and should not be as accurate as directly measured data.

An advanced fog and traffic detection system has been proposed by the Virginia Department of Transportation for use on a 14-mile corridor of I-77 that runs between the North Carolina state line and US 58/221(Murphy et al., 2012). New forward-scatter visibility sensors are currently being used to improve the accuracy of fog detection systems. Along with these sensors, upgraded millimeter wave traffic detectors are equipped to monitor traffic speed, volume, and occupancy data. Traffic detectors are placed upstream and downstream from the visibility sensors. Traffic sensors detect unusual changes in travel speeds or occupancy rates to alert upstream drivers that the speed of traffic ahead is slower due to fog or incident. However, the length and the category of the vehicle are not detected by the traffic sensor.

Tennessee DOT and the Tennessee Department of Safety implemented a low visibility and traffic detection system on I-75 in Tennessee. The system covers 19 miles and includes two Environmental Sensor Stations (ESS), eight forward-scatter visibility sensors and 44 vehicle detectors (Murphy et al., 2012). Traffic and environmental data are transmitted from the sensors to an on-site computer for processing through underground fiber optic cables. Then the data are submitted to the central computer in the Highway Patrol office in Tiftonia via a microwave communication system. However, the length and the category of the vehicle can not be detected by the traffic sensor as well.

Shahabi et al. (2012) introduced various fog detection tools which are currently being utilized by different agencies' fog forecasting processes. Sounding profiles can be a valuable method of diagnosing and forecasting fog. However, this tool has three limitations. First, it is unreliable for predicting local events because the observations are sparse. Second, the intervals between sounding observations can be quite large, which makes it difficult to identify timely any changes in conditions. Third, the resolution of the sounding instrument affects the accuracy of the detection of fog formation and dissipation.

Using existing highway cameras to detect fog is of great interest to researchers. There are two general approaches to measuring meteorological visibility with a camera. The first is to detect the contrast between the most distant targets. The second general approach is based on machine learning and requires a calibration phase, with meteorological data collected with a visibility meter. Babari et al. (2012) used existing highway cameras and a technique based on the gradient magnitude to estimate visibility. The module of the Sobel gradient indicates the value of the largest change from bright to dark at each pixel. Researchers established a link between visibility and the gradient in the image. The visibility estimates were obtained with an average error of 30%.

Another real-time fog and traffic detection system was proposed in Abu Dhabi (Ali et al., 2013). It has three main components: a fog sensing component, a fog density data collection and analysis component, and a traffic sensing component. Fog sensors were installed on light poles, radar stations, and cell phone towers along the highway. In addition, the detection of slow traffic movement due to poor visibility by the wireless device inside vehicles will also pass to the fog analysis component. Data collected from the fog sensors and traffic movement will be used to conduct the appropriate analyses necessary to determine the geographical boundaries of the poor visibility sectors of the highway. The fog density data collection and analysis component conducts the analysis to decide the boundaries of poor visibility zones, and it can also identify which area is affected frequently by fog. However, the detail traffic information of each vehicle can not be detected by this system.

With the advancements that have been made in data collection technology, it is plausible to detect accurate low visibility due to fog and traffic data in real time. The credibility of visibility and traffic detection systems is essential to analyze the relationship between low visibility and traffic crash risk. This research was conducted based on a new visibility and traffic detection system which provides more accurate visibility and traffic information.

3. Data collection and methodology

The site selected for data collection is based on an earlier report by Abdel-Aty et al. (2012) on I-4 in Polk County, mile posts 22.528–22.628 and 21.426–21.928, where higher fog-related crashes have occurred. The aerial view of the selected

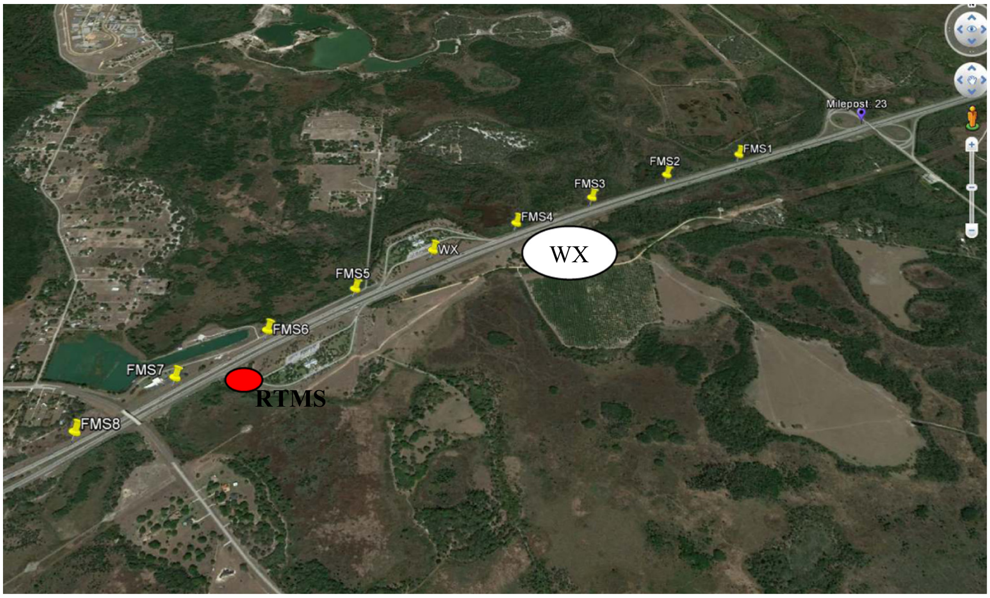

Fig. 1. Aerial view of the study area showing the locations of weather stations and remote traffic microwave sensor.

study area is shown in Fig. 1. The study area is roughly situated between State Roads 559 and 557. Each pinpoint marker represents the location of a fog monitoring system (FMS) installed as part of this study, and the distance between two consecutive yellow[1] pinpoints is 0.25 miles. The remote traffic microwave sensor (RTMS) was installed close to it. There are three lanes in each direction at the location of data collection.

3.1. Weather data collection

The weather data were then collected from those FMS on I-4. The dataset consists of twenty-one variables including air temperature, dewpoint, surface moisture, humidity, wind speed and other important weather parameters such as barometric pressure and rainfall. The weather station marked as WX includes also a Vaisala visibility forward scatter visibility sensor. It is a kind of sensor calibrated through a scientifically valid chain of reference. The FMS consists of three sensors at increasing elevations beginning at one foot one inch. A soil probe is inserted under the immediate ground surface. An anemometer is placed at every other FMS at a height of eight feet above the ground. The anemometer used was specifically chosen for its low-speed detection capabilities. A 5-watt solar panel and 12AH battery keep the FMS powered at all times so data is reported at 5-min intervals 24/7. There are a total of eight FMS's spaced 0.25 miles apart. All sensors are secured to a 2-in. aluminum pole and a NEMA enclosure houses the battery, wiring, 802.15.4 radio, and Wireless Sensor Node Microprocessor circuit board to handle the multiple sensor inputs while providing extremely low power consumption. This enables a high rate of data transmissions because of the very low power budget of the system.

3.2. Traffic data collection

The traffic data including vehicle speed, vehicle length and lane assignment was collected by RTMS (Fig. 1) installed in the abovementioned area. Device Click 514 which monitors individual vehicle data pushed from the traffic sensor and forwards it as tabular data to serial data logger devices was added to the radar sensor to collect data by vehicle instead of aggregated by every 0.5 or 1 min. This enabled us to measure the headways for each vehicle. The dataset includes eight important variables related to traffic parameters including speed and length of each vehicle, duration of detection and lane assignment. The headway of each vehicle can also be calculated from the original dataset. Table 1 shows a sample of the dataset collected during two time periods: January 31st 2014 to March 12th 2014 and March 2nd 2015 to May 20th 2015.

Since there are two common variables in the weather and the traffic datasets: date and time. These two original datasets were merged into one combined dataset. The combined dataset was then used to analyze the relationship between visibility and traffic parameters. The following Table 2 included the definition and measurement units of each variable in the combined dataset.

[1] For interpretation of color in 'Fig. 1', the reader is referred to the web version of this article.

Table 1
Sample of traffic parameter dataset.

Date	Time	Lane	Speed (mph)	Length (ft)	Range (ft)	Class	Duration (0.001 s)
1/31/2014	12:54.2	2	71	23.8	84	1	286
1/31/2014	12:54.7	3	70.9	21.1	160.1	1	260
1/31/2014	12:55.4	2	66.4	23.5	84	1	302
1/31/2014	12:55.6	4	69.1	24.7	174.1	1	302
1/31/2014	12:55.8	3	76.3	24.9	160.1	1	275
1/31/2014	12:55.9	1	65.2	19.1	72	1	261
1/31/2014	12:56.5	4	66.5	18	173.1	1	245
1/31/2014	12:56.7	3	72.4	20.8	158.1	1	252
1/31/2014	12:58.1	3	72.4	25.2	159.1	2	293
1/31/2014	12:58.8	2	72.4	24.9	84	1	291

Table 2
Description of variables in the combined dataset.

Variable	Definition of the variable	Measurement units
Visibility	Visibility distance detected by the weather sensor	m
Speed	Speed of each vehicle	mph
Length	Length of each vehicle	ft
Range	The distance between the traffic sensor and each vehicle	ft
Duration	The duration of detecting each vehicle	0.001 s
Class	Classification of different types of vehicles	
Date	Date of data collection	
Time	Time of data collection	
Lane	Lane number of each vehicle	

3.3. Methodology

In addition to time to collision (TTC), speed variance and headway variance were considered as surrogate measures of safety in this paper. It was well recognized that the higher a TTC value and the lower a speed and headway variance is, the safer a situation (Minderhoud and Bovy, 2001; Svensson and Hydén, 2006; Garber and Gadiraju, 1988). There are two definitions of TTC and both were utilized in this study. The following Eq. (1) was used to calculate both kinds of TTC:

$$TTC = L/(V_1 - V_2) \tag{1}$$

L is the clearance which is the distance between the rear bumper of the leading vehicle and the front bumper of the following vehicle. V_1 is the speed of leading vehicle and V_2 is the speed of the following vehicle. TTC1 was calculated when V_1 maintained its own speed and TTC2 which was also called TTC at braking was calculated when the leading vehicle suddenly stopped. It is noted that the visibility distance was used to replace the actual clearance when the visibility distance is less than clearance because the following car will not make any changes until the driver will be able to see the leading vehicle (see Fig. 2).

Analysis of variance (ANOVA) was applied in this study to compare the differences between several group means and their associated variations, which provides a statistical test of comparing means of more than two groups. Since conducting multiple two-sample *t*-tests is not convenient and would result in an increased chance of errors, ANOVA is applied to analyze the three surrogate measures of safety under different visibility classes and the effects of reduced visibility on different vehicle types and lanes.

For the purpose of exploring the relationship between TTC and visibility together with other traffic parameters, four different types of regression modeling (Normal, Log-Normal, Log-Gamma and Log-Inverse Gaussian) were applied and the goodness of fit were compared. The Log-Inverse Gaussian regression model shows the best fit and was applied in this paper. The density function of Inverse Gaussian distribution is defined by

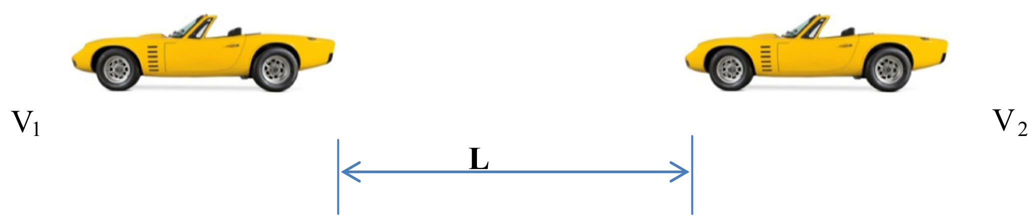

Fig. 2. TTC calculation.

$$f(x,\theta) = \left(\frac{\lambda}{2\pi x^3}\right)^{\frac{1}{2}}\left\{-\frac{\lambda(x-\mu)^2}{2\mu^2 x}\right\}, \quad x \geqslant 0, \quad \theta = (\mu,\lambda)^T \subset R^2 \tag{2}$$

μ is the mean and λ is the shape parameter for the above equation.

Several previous researchers have investigated the application of Inverse Gaussian distribution on traffic crash analysis. Meng and Qu (2012) investigated rear-end vehicle crash frequencies in urban road tunnels. They analyzed the time to collision collected from two road tunnels of Singapore and pointed out that Inverse Gaussian distribution is the best-fitted distribution. Zha et al. (2014) examined the application of the Poisson inverse Gaussian (PIG) regression model for modeling motor vehicle crash data and pointed out that this type of model has the potential for modeling highly dispersed count data due to the flexibility of inverse Gaussian distribution.

4. Comparison results of surrogate measures of safety

4.1. Comparison results of all the vehicles

Table 3a shows the comparison of three surrogate measures of safety by dividing the whole period into different cases based on the value of visibility. According to the characteristics of the weather dataset and previous literature (Hassan and Abdel-Aty, 2013), the visibility was divided into three classes. The visibility is considered as good visibility and classified as 1 when the visibility is greater than or equal to 2000 m. The visibility is considered as moderate visibility and classified as 2 if the visibility is less than 2000 m but greater than 100 m. The visibility is considered as low visibility and classified as 3 if the visibility is less than or equal to 100 m. There are mainly two reasons for the classification: at first the maximum distance recorded by the weather sensor is 2000 m and it will significantly affect driving when the visibility is very low (Hassan and Abdel-Aty, 2013). In addition, the sample size of the dataset in the range of very low visibility will be too small to conduct a statistically significant analysis if we selected another lower distance. It is noted that this research also tried the other classification ($\geqslant$2000, between 200 and 2000, $\leqslant$200). The modeling result about contrasts of means is consistent. The duration of one minute was considered as a sample of good visibility, moderate visibility or low visibility. The sample size of good visibility, moderate visibility and low visibility is 13,701, 1662, and 211, respectively. It can be seen from Table 3a that both TTC1 and TTC2 would decrease significantly as the visibility is reduced and the standard deviation of headway increases significantly as the visibility is reduced from good to low visibility, which means that the crash risk would be higher during the reduced visibility and the crash risk keeps increasing when visibility drops. The standard deviation of speed is higher in reduced visibility but the result is not significant.

It can be seen from Table 3b that the TTC1 drops from 75 s to 50 s and TTC2 decreases from 3.89 s to 1.73 s when visibility drops from 2000 m to below 100 m. The average human perception-reaction time t_p is 2.5 s according to AASHTO's Green Book and the required stopping sight distance for the vehicles based on different design speed is shown in Table 3c (AASHTO, 2004). The proportion of speeding was calculated by comparing the actual stopping distance for each vehicle with the required stopping sight distance. It is noted that the reduced visibility was used to replace the required stopping sight distance when the visibility drops below the required sight distance. It can be seen from Table 3d that the proportion of speeding under low visibility condition is 95.4%, which means the crash risk would increase significantly during low visibility conditions because most of the vehicles will not be able to stop in time to avoid a rear-end crash if the leading vehicle stops suddenly. Although the average speed is slightly reduced when visibility drops, most of the vehicles were still speeding especially under low visibility condition.

4.2. Comparison results of different types of vehicles

The vehicles were then divided into two types: passenger cars and trucks in this section in order to figure out whether the impact of visibility on Surrogate Measures of Safety is different by different vehicle types. Vehicles were classified based on the length of vehicles. The vehicle is considered as a truck when the length of vehicle is more than 30 ft and it is considered as a passenger car when the length of vehicle is equal to or less than 30 ft. Table 4 shows the summary for the results of comparison. The datasets used in this section were the same as the above Section 4.1 and the sample size of good visibility, moderate visibility and low visibility is 13,701, 1662, and 211, respectively. It can be seen from Table 4 that both TTC1 and TTC2 would decrease significantly as the visibility is reduced and the standard deviation of headway would increase significantly as the visibility is reduced from good to low visibility. It means that the crash risk would be higher during the reduced visibility and the crash risk keeps increasing when visibility drops for both types of vehicles. The standard deviation of speed significantly increases when the visibility drops for the passenger cars while the change is not significant for trucks. Compared to passenger cars, the effect of reduced visibility on standard deviation of headway and speed are smaller while the effect on TTC is larger for trucks. Specifically, the value of TTC1 and TTC2 decrease to 25.82 s and 2.09 s respectively for passenger cars while it decreases to 26.58 s and 2.89 s respectively for trucks when the visibility drops from class 1 to class 3. The standard deviation of headway and speed increase by 1.44 s and 0.24 mph, respectively, for passenger cars while the standard deviation of headway and speed increase only by 0.98 s and 0.01 mph, respectively, for trucks. Therefore, con-

Table 3a
Comparison of surrogate measures of safety under different visibility classes.

Visibility classes	TTC1			TTC2		
	Mean difference	95% Confidence interval		Mean difference	95% Confidence interval	
1–2	7.36*	5.54	9.18	0.95*	0.83	1.07
2–3	18.24*	14.06	22.41	1.20*	0.93	1.47
1–3	25.60*	21.66	29.54	2.15*	1.90	2.41
Visibility classes	Standard deviation of speed			Standard deviation of headway		
	Mean difference	95% Confidence interval		Mean difference	95% Confidence interval	
1–2	−0.07	−0.26	0.11	−0.78*	−1.18	−0.36
2–3	−0.13	−0.54	0.27	−0.61*	−1.12	−0.11
1–3	−0.21	−0.58	0.16	−1.39*	−1.70	−1.08

* Means the difference is significant on 5% level.

Table 3b
Mean and standard deviation of TTC under different visibility classes.

Visibility classes	TTC1		TTC2	
	Mean (s)	Standard deviation (s)	Mean (s)	Standard deviation (s)
1	75.65	68.00	3.89	4.68
2	68.29	62.41	2.93	2.97
3	50.05	50.75	1.73	0.77

Table 3c
AASHTO required stopping sight distance. *Source*: AASHTO, 2004.

Design or operating speed (mph)	$t_p = 2.5$ s	50	60	70	80	90	100	110
Stopping distance (m)		63	85	111	139	169	205	246

Table 3d
Proportion of speeding under different visibility classes.

Visibility classes	Mean speed (mph)	Proportion of speeding (%)
1	71.61	62.65
2	70.71	68.31
3	70.24	95.4

sidering the larger decrease of TTC and relatively larger response and perception time, truck drivers should be more careful about speeding during the reduced visibility conditions.

4.3. Comparison results of vehicles on different lanes

The vehicles in three different lanes including outer lane that is close to the roadside, middle lane and inner lane in this section were analyzed in order to understand whether the impact of visibility on surrogate measures of safety is different for different lanes. The datasets used in this section were the same as the above Sections 4.1 and 4.2.

It can be seen from Table 5 that both TTC1 and TTC2 decrease significantly as the visibility is reduced from good to low visibility, which means that the crash risk would be higher during the reduced visibility. The crash risk keeps increasing when visibility drops for all the lanes. The standard deviation of speed significantly increases when the visibility drops from good to low visibility for the middle and inner lanes while the change is not significant for the outer lane. Compared to the outer lane, the effect of reduced visibility on the standard deviation of headway and speed are larger while the effect on TTC is smaller for the vehicles in middle and inner lanes. Specifically, the value of TTC1 and TTC2 decrease to 32.96 s and 4.24 s for vehicles in outer lane while it decreases only to 25.44 s and 1.73 s for vehicles in middle lane, respectively. The TTC1 and TTC2 decrease only to 22.71 s and 1.53 s for vehicles in the inner lane when the visibility drops from class 1 to class 3. The change of standard deviation of speed is not significant in the outer lane while it increases significantly in the middle and inner lanes when the visibility drops from class 1 to class 3. For the headway variance, the effect of reduced visibility on the inner and outer lanes is higher than the effect on the middle lane. It is noted that although the decrease of TTC value is largest in the outer lane, the mean value of both TTC1 and TTC2 under low visibility condition are still smallest in the inner lane. Overall, the drivers in the inner lane should be more careful about speeding during the reduced visibility conditions.

Table 4
Comparison of surrogate measures of safety for different vehicle types.

a. Passenger car						
Visibility classes	TTC1			TTC2		
	Mean difference	95% Confidence interval		Mean difference	95% Confidence interval	
1–2	6.42*	4.54	8.30	0.89*	0.77	1.01
2–3	19.40*	15.02	23.79	1.19*	0.91	1.48
1–3	25.82*	21.68	29.97	2.09*	1.82	2.35
Visibility classes	Standard deviation of speed			Standard deviation of headway		
	Mean difference	95% Confidence interval		Mean difference	95% Confidence interval	
1–2	−0.16*	−0.30	−0.02	−0.83*	−1.33	−0.33
2–3	−0.08	−0.54	0.38	−0.63*	−1.11	−0.15
1–3	−0.24	−0.76	0.28	−1.44*	−1.86	−1.02
b. Truck						
Visibility classes	TTC1			TTC2		
	Mean difference	95% Confidence interval		Mean difference	95% Confidence interval	
1–2	14.09*	7.06	21.12	1.31*	0.81	1.81
2–3	12.49*	0.687	24.311	1.58*	0.61	2.55
1–3	26.58*	14.665	39.507	2.89*	2.01	3.78
Visibility classes	Standard deviation of speed			Standard deviation of headway		
	Mean difference	95% Confidence interval		Mean difference	95% Confidence interval	
1–2	0.02	−0.04	0.08	−0.36*	−0.66	−0.06
2–3	−0.03	−0.07	0.01	−0.52*	−0.83	−0.21
1–3	−0.01	−0.05	0.03	−0.98*	−0.62	−1.35

* Means the difference is significant on 5% level.

5. Modeling the relationship between TTC, reduced visibility and traffic parameters

The above analysis was based on traffic data for each vehicle. However, since most of the archived traffic data available are aggregated, it is meaningful to further explore the relationship between average TTC and these aggregated traffic parameters. Transportation authorities would then be able to identify the effect of reduced visibility as well as traffic conditions with high risk based on the results. Four different approaches of regression modeling including Normal, Log-normal, Log-Gamma and Log-Inverse Gaussian were applied and compared for the best fit. It is noted that visibility was converted to categorical variable similar to Section 4 (class 3 is low visibility class when average visibility is less than 100 m, class 2 is moderate visibility class when average visibility is less than 2000 m but greater than or equal to 100 m and class 1 is good visibility class when average visibility is 2000 m). The dependent variable is the mean of TTC of all the vehicles within a five minutes interval. The independent variables are mean headway, mean speed, volume per lane in five minutes and visibility class. The basic statistics of the five parameters used in the model are summarized in Table 6a and the result of checking correlation of all the independent variables was shown in Table 6b. It was shown in Table 6b that all the independent variables were not correlated. The comparison results of the four different regression analyses are shown in Table 6c. It can be shown from Table 6c that the performance of the Inverse-Gaussian regression model achieved the best fit. Therefore, the Log-Inverse Gaussian regression model was used to explore the relationship between time to collision and visibility together with the other traffic parameters.

The results in Table 6d indicate that the TTC will decrease significantly as the visibility and mean of headway are reduced while it will decrease significantly as mean speed and volume increase. Moreover, it can be seen from the Table 6d that coefficients of visibility are 1.1361 and 0.8790. They are much higher than the absolute value of coefficients of other traffic parameters including mean headway, mean speed and volume, which means the effect of visibility on TTC is more significant compared to these traffic parameters. There are few research efforts exploring the relationship between crash risk and headway. The result of the Table 6d concludes that the decrease of mean headway would increase the crash risk because the TTC will decrease significantly. The effect of mean headway on TTC is more significant compared to mean speed as the absolute value of the coefficient of mean headway is 0.0702, which is much higher than the absolute value of the coefficient of mean speed 0.0088 and the coefficient of volume 0.0067. Therefore, it can be concluded from the result that the marginal effect of visibility class is the most significant one. Compared to the change of mean speed and volume, the marginal effect of mean headway is much higher.

Table 5
Comparison of surrogate measures of safety for vehicles in different lanes.

a. Outer lane

Visibility classes	TTC1			TTC2		
	Mean difference	95% Confidence interval		Mean difference	95% Confidence interval	
1–2	7.36*	5.54	9.18	1.89*	1.53	2.24
2–3	25.60*	21.66	29.54	2.35*	1.58	3.13
1–3	32.96*	26.06	39.86	4.24*	3.51	4.97
Visibility classes	Speed variance			Headway variance		
	Mean difference	95% Confidence interval		Mean difference	95% Confidence interval	
1–2	−0.05	−0.37	0.27	−1.16*	−1.78	−0.54
2–3	−0.12	−0.56	0.32	−0.64	−1.42	0.12
1–3	−0.18	−0.74	0.38	−1.81*	−2.28	−1.33

b. Middle lane

Visibility classes	TTC1			TTC2		
	Mean difference	95% Confidence interval		Mean difference	95% Confidence interval	
1–2	7.91*	5.16	10.67	0.74*	0.59	0.89
2–3	17.52*	11.16	23.89	0.98*	0.64	1.34
1–3	25.44*	19.45	31.43	1.73*	1.40	2.06
Visibility classes	Speed variance			Headway variance		
	Mean difference	95% Confidence interval		Mean difference	95% Confidence interval	
1–2	−0.19	−0.41	0.02	−0.64	−1.37	0.09
2–3	0.005	−0.25	0.26	−0.26*	−1.15	−0.62
1–3	−0.18*	−0.33	−0.03	−0.90*	−1.43	−0.38

c. Inner lane

Visibility classes	TTC1			TTC2		
	Mean difference	95% Confidence interval		Mean difference	95% Confidence interval	
1–2	4.71*	1.77	7.66	0.63*	0.47	0.78
2–3	17.98*	11.06	24.91	0.89*	0.52	1.28
1–3	22.71*	16.13	29.27	1.53*	1.17	1.88
Visibility classes	Speed variance			Headway variance		
	Mean difference	95% Confidence interval		Mean difference	95% Confidence interval	
1–2	−0.21*	−0.29	−0.13	−0.17	−0.98	0.64
2–3	−0.05	−0.25	0.15	−1.09*	−2.10	−0.08
1–3	−0.26*	−0.47	−0.05	−1.26*	−1.88	−0.64

* Means the difference is significant on 5% level.

Table 6a
Summary of statistics of parameters.

Parameter	Min	Mean	Max	Std
Averaged TTC at break (s)	1.16	8.46	69.23	8.45
Visibility class	1	1.22	3	0.46
Average headway (s)	1.28	10.15	96.52	10.37
Average speed (mph)	40.82	71.98	87.70	4.42
Volume per lane per five minutes	1	43	152	27

6. Summary and conclusions

In summary, real-time vehicle based traffic and weather data were collected at the same time in this research by using this new visibility and detection system. Accurate visibility data and more detail traffic information about each vehicle including vehicle speed, the length and category of vehicle and lane assignment were provided by these sensors. Fog cases were then selected and analyzed by comparing them with clear cases to identify the differences in several surrogate measures of safety under different visibility conditions according to the data detected by these sensors. Moreover, since the traffic sensor can provide detail information about the length, category and lane assignment of each vehicle, the vehicles were divided into different types and lanes in order to identify whether the impact of reduced visibility due to fog on traffic crash risk varies for vehicle types and lanes. Inverse-Gaussian regression modeling was applied to explore the relationship

Table 6b
Correlation matrix of independent variables.

	Visibility class	Average headway (s)	Average speed (mph)	Volume per lane per five minutes
Pearson correlation coefficient, Prob >|r| under H0:Rho = 0				
Visibility class	1.0000	−0.2832	−0.1735	0.1018
		<0.0001	<0.0001	<0.0001
Average headway (s)	−0.2832	1.0000	0.5092	−0.1748
	<0.0001	<0.0001	<0.0001	<0.0001
Average speed (mph)	−0.1735	0.5092	1.0000	0.1124
	<0.0001	<0.0001	<0.0001	<0.0001
Volume per lane per five minutes	0.1018	−0.1748	0.1124	1.0000
	<0.0001	<0.0001	<0.0001	<0.0001

Table 6c
Comparison of performance of different kinds of modeling.

Model comparison	AIC	BIC
Normal	15,550	15,592
Log-Normal	15,395	15,437
Log-Gamma	11,585	11,627
Log-Inverse Gaussian	11,475	11,517

Table 6d
Modeling results of Log-Inverse Gaussian model.

Parameter	DF	Estimate	Standard error	Wald 95% confidence limits		Wald chi-square	Pr > ChiSq
Analysis of maximum likelihood parameter estimates							
Intercept	1	1.0525	0.0913	0.8736	1.2314	132.96	<0.0001
Visibility class 1	1	1.1361	0.0206	1.0958	1.1765	3045.19	<0.0001
Visibility class 2	1	0.8790	0.0222	0.8356	0.9224	1573.46	<0.0001
Average headway	1	0.0702	0.0021	0.0661	0.0743	1126.09	<0.0001
Average speed	1	−0.0088	0.0011	−0.0110	−0.0066	59.12	<0.0001
Volume per lane per five minutes	1	−0.0067	0.0003	−0.0072	−0.0062	677.61	<0.0001
Scale	1	0.1037	0.0013	0.1012	0.1064	–	–

between time to collision and visibility together with other traffic parameters. There are several major conclusions based on the analyses.

Both TTC1 and TTC2 for all the vehicles decrease significantly as the visibility is reduced and the standard deviation of headway increases significantly as the visibility is reduced from good to low visibility. This means that the crash risk would be higher during reduced visibility and the crash risk keeps increasing when visibility drops. The proportion of speeding under low visibility condition for all the vehicles is 95.4%, which means the crash risk will increase very significantly during low visibility conditions because most of the vehicles will not be able to stop in time to avoid a rear-end crash once the leading vehicle slow down or stop. Compared to passenger cars, the effects of reduced visibility on standard deviation of headway and speed are smaller while the effect on TTC is larger for trucks. Considering the larger decrease of TTC and relatively larger response and perception time, the truck drivers should be more careful about speeding during the reduced visibility conditions. Compared to the outer lane, the effects of reduced visibility on standard deviation of headway and speed are larger while the effect on TTC is smaller for the vehicles in middle and inner lanes. For the headway variance, the effect of reduced visibility on inner and outer lanes is higher than the effect on middle lane. Overall, the drivers on inner lanes should be more careful about speeding during the reduced visibility conditions.

The Inverse Gaussian modeling results indicate that the TTC would decrease significantly as the visibility and mean of headway decrease while it would decrease significantly as the mean speed and volume increase. The result also concludes that the decrease of mean headway would increase the crash risk because the TTC will decrease significantly. The effect of mean headway on TTC is more significant compared to mean speed.

Due to the difficulty of obtaining accurate real-time visibility and vehicle based traffic data at the same time, there are only few research studies that addressed the impact of reduced visibility on traffic crash risk. This study investigated for the first time the relationship between crash risk and fog related reduced visibility based on the real-time visibility and traffic data collected by a new visibility and traffic detection system which provides more accurate and detail information about weather and traffic. The results would be helpful to understand the change of traffic crash risk and identify the fundamental reasons for higher crash frequency under fog conditions. The results could also be helpful to identify high crash risk conditions. Implementing the algorithms in real-time and augmenting it with ITS measures such as VSL and DMS can be implemented to reduce crash risk.

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