Crash Risk Monitoring Method for Highways in Rain and Fog Conditions

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Abstract. As the volume of traffic on highways has increased, so too has the frequency of accidents. In particular, the risk of vehicular accidents is heightened in inclement weather conditions, such as precipitation and low visibility, due to the combined effect of reduced visibility and a slippery road surface. It is therefore of great significance to develop an effective method for monitoring the risk of collisions on highways in order to reduce the incidence of traffic accidents and ensure driving safety. This paper will examine the monitoring of highway collision risk in inclement weather conditions, namely rain and fog. The analysis will assess the collision risk in real time by evaluating the spacing and speed of vehicles. Furthermore, the utilisation of Python technology will facilitate the visualisation and characterisation of the risk situation.

Keywords: Collision risk, braking distance, python, HighD.

1. Introduction

In consequence of the accelerated growth of the economy and the concomitant increase in the volume of travel, highways have become an indispensable component of the transportation infrastructure of modern society. The efficient transportation capacity of highways has greatly promoted regional economic connectivity. However, this has also led to an increase in traffic safety problems. According to official statistics, highways account for a significant proportion of all kinds of traffic accidents, making it crucial to ensure highway traffic safety in order to protect people's lives and property and maintain social stability.

The risk of road traffic accidents escalates in adverse weather like rain, fog, and snow due to reduced visibility and slippery road surfaces. These conditions restrict the driver's line of sight, shorten reaction times, and extend braking distances, all of which heighten the likelihood of accidents. Weather can also affect drivers' emotions, potentially impairing judgment and increasing safety risks. While studies on highway safety and driving risks in inclement weather exist, they often focus on typical weather conditions and overlook the impact of atypical conditions like heavy precipitation and low visibility. There is also a gap in considering dynamic traffic patterns and real-time environmental changes in collision risk assessments. Moreover, there is a need for improved real-time monitoring and warning systems to address these shortcomings.

In order to address the shortcomings of existing research, this study proposes a rain and fog-oriented approach for monitoring highway collision risk posture. This study's contribution to the field is the development of a multi-dimensional collision risk assessment model that considers multiple influencing factors, including vehicle spacing, vehicle speed, and visibility. The model is constructed using Python technology, which provides an intuitive decision-support tool for traffic management departments. The effectiveness and practicality of the proposed method are demonstrated through the analysis of a large amount of actual data.

2. Methodology

2.1. Calculation of Braking Distance

Braking distance is the critical measure from the moment a driver decides to stop until the vehicle halts, significantly affected by weather conditions like rain and fog, which alter road friction and braking effectiveness. Moreno et al.'s study aimed to explore the link between highway gradients and traffic safety by examining braking characteristics under various conditions and weather's impact on braking distance. The fundamental formula for braking distance calculation involves the vehicle's stopping sight distance, defined as the minimum safe distance needed to stop upon detecting an obstacle under specific conditions. This calculation is essential for assessing and ensuring traffic safety, especially in adverse weather.

$$D_{brake} = v \cdot t + \frac{1}{2} a \cdot t^2 \tag{1}$$

Where, D_{brake} is the braking distance, a is the deceleration of the vehicle, t is the reaction time of the driver, v is the speed of the vehicle, μ is the coefficient of friction of the road surface, and g is the acceleration due to gravity.

Consider that road surface conditions have a significant effect on braking distance. Dry asphalt pavements usually have a high coefficient of friction, while wet or foggy pavements have a reduced coefficient of friction. The coefficient of friction μ can be expressed as:

$$\mu = \mu_0 \cdot (1 - k \cdot w) \tag{2}$$

Where μ_0 is the coefficient of friction for a dry road surface, k is the coefficient of the degree of wetness of the road surface, and w is the measure of the amount of rainfall or humidity.

Considering the speed condition, the higher the speed, the longer the braking distance. The deceleration of a vehicle a can be calculated by the following formula:

$$a = \frac{\mu \cdot g}{1 + (c \cdot v)^2} \tag{3}$$

Where g is the gravitational acceleration and c is a nonlinear coefficient of the vehicle braking system.

In rainy conditions, the braking distance increases due to the reduced friction coefficient caused by water on the road surface. The effect of rain can be quantified by adjusting this coefficient. Similarly, high atmospheric moisture levels in foggy conditions reduce visibility, lengthening the driver's reaction time and thus the stopping distance. Fog can also make the road surface wet, further decreasing the friction between the tires and the road, adding to the braking distance.

2.2. Crash Risk Assessment Indicators

In crash risk assessment, the selection of key indicators is critical to the accurate prediction and prevention of traffic accidents. Based on the above summary of braking distance calculation methods, the key collision risk assessment indicators are derived and standardized to describe the degree of impact on collision risk. The key indicators for collision risk assessment include Headway, Speed, and Visibility.

Vehicle spacing is pivotal for preventing rear-end collisions and is measured through traffic monitoring. Speed and visibility are critical metrics in collision risk, with MCDM used to assign weights to these and other factors like road conditions, ensuring a total weight of 1. Risk weights adjust with weather: rainy conditions assign 30% to speed due to skidding and 40% to visibility for reaction time; sunny days reduce speed weight to 20% and visibility to 30%, emphasizing caution; foggy days prioritize visibility at 60% and speed at 20% due to low visibility. Braking distance weights are 30% in rain, 50% in sun for road defects, and 20% in fog for wet conditions.

Table 1. Indicator weights for different weather conditions

weights	speed	visibility	braking distance
sunny	0.2	0.3	0.5
rainy	0.3	0.4	0.3
foggy	0.6	0.2	0.2

Standardized indicators: Each indicator is converted into a standardized score to eliminate the effects of different indicator scales.

Risk score calculation: Use the following formula to calculate the risk score for each indicator:

$$Risk\ Score = Normalized\ Value \times Weight \tag{4}$$

Overall risk calculation: add up the risk scores of all indicators to get the overall risk value:

$$Total\ Risk = \sum (Risk\ Score) \tag{5}$$

The following equation is employed for the purpose of normalisation:

$$Normalized\ Value = \frac{Value - Min\ Value}{Max\ Value - Min\ Value} \tag{6}$$

2.3. Risk Situation Representation

In order to illustrate the potential for collisions on the highway, this paper employs the use of Python technology to generate a heat map, which represents the level of collision risk through the use of colour shades.

A heat map is an effective method of data visualisation, whereby the size or density of the data is indicated by colour shades. In this study, heat maps were selected as a means of displaying the crash risk levels of different areas on the highway. The variation of colour shades allows for the visualisation of the level of risk, thus providing an immediate understanding of the risk situation.

The Python programming language is widely used and offers a comprehensive range of libraries for data processing and visualisation, including Matplotlib, Seaborn, and Plotly. These libraries provide powerful features for the generation of high-quality charts and visualisations.

The utilisation of the aforementioned visualization libraries in Python facilitates the mapping of the processed risk data to the geographic coordinates of the highway. The generation of heat maps is achieved through the setting of varying colour thresholds and the conversion of the risk level to colour shades. For illustrative purposes, the colour red can be employed to indicate high-risk areas, yellow to indicate medium-risk areas, and green to indicate low-risk areas.

3. Literature References

3.1. Data Collection and Preprocessing

In this study, HighD data were collected under a variety of meteorological conditions, including precipitation and low visibility, which encompass a range of parameters essential for traffic collision risk analysis, such as vehicle speed, position, and time. The HD data were collected from a specific "03_highway" roadway to examine the traffic collision dynamics under adverse weather conditions, and two segments were selected for analysis (Figure 1).

The initial segment, designated as Segment 1, encompasses a distance of 18 to 100 meters along the x-axis and 8 to 9 meters along the y-axis. This zone is situated in close proximity to the emergency lane on the right-hand side of the roadway, offering a distinctive vantage point for the observation of traffic behaviour in conditions of precipitation and low visibility.

The second zone, designated as Zone 2, extends from 0 to 100 metres along the x-axis and from 22 to 25.5 metres along the y-axis. This zone was selected due to its particular attributes, which have the potential to impact traffic flow and the risk of collisions during inclement weather.

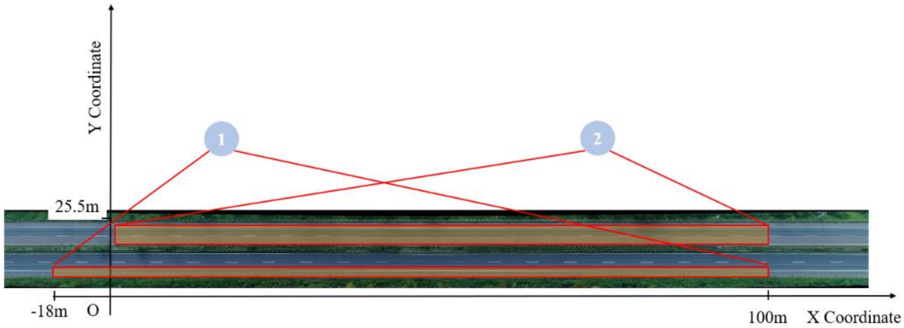

Figure 1. The source segment of the trajectory data

The preprocessing of data entails the elimination of undesirable elements, such as noise, outliers, and inconsistencies. These are identified through statistical techniques, including the utilisation of standard deviation and interquartile range (IQR) methods, and subsequently excluded to prevent their detrimental impact on the analytical outcomes. The data sources encompass historical highway data and real-time monitoring data, as illustrated in Table 2.

Table 2. The Schematic representation of HighD data

Track point number	x	y	x Velocity	y Velocity	frontSight	backSight
1	-18 35	9.00	22.98	0.04	9.85	421.22
2	-17.43	9.00	22.98	0.04	9.85	421.22
3	-16.96	9.58	23.58	0.26	9.02	420.51
4	-16.72	9.01	20.67	0.09	9.01	420.46
...	...	...	...	...	...	...

In accordance with the data presented in Table 2, a two-dimensional trajectory map can be constructed, as illustrated in the figure below (Figure 2). This map corresponds to the two selected road segments, with the blue points representing the trajectory data points and the green folded line representing the trajectory schematic.

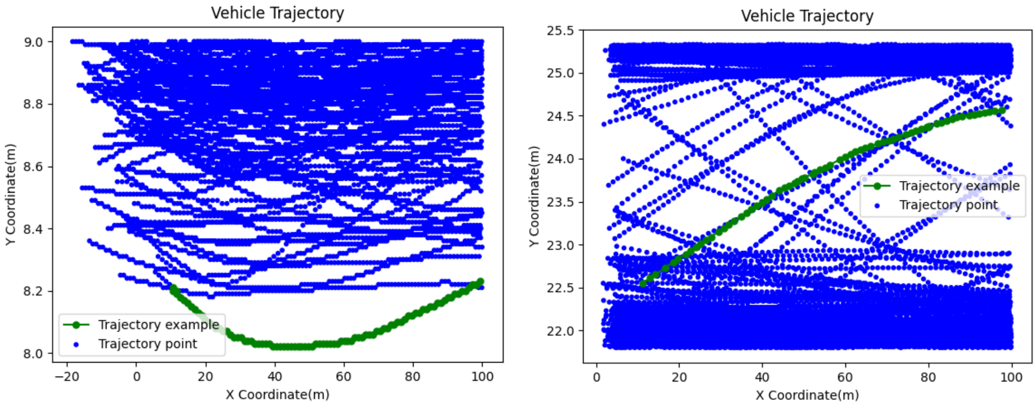

Figure 2. Two-dimensional trajectory diagram

3.2. Collision Risk Evaluation

The preprocessed data was subjected to the braking distance calculation method delineated in Section 2.1 and the assessment indexes outlined in Section 2.2, thereby enabling an evaluation of the collision risk associated with each vehicle.

The crash risk for each vehicle is evaluated using preprocessed data, applying the braking distance method and assessment indexes from previous sections. The risk quantification process involves assigning weights to metrics like speed, following distance, traffic density, and weather conditions, which collectively influence the likelihood of a collision. Each metric's impact determines its weight, and a risk score is calculated by multiplying each metric's value by its weight and summing these products. This composite score, normalized to a 0 to 1 range, represents the collision likelihood, with 0 being no risk and 1 the highest.

The risk scores are categorized into risk classes based on the criteria in Table 3:

A score of 0 or below 0.33 indicates low risk, requiring no special intervention.

A score between 0.33 and 0.66 is medium risk, warranting attention and preventive measures.

A score between 0.66 and 1 signifies high risk, necessitating immediate preventive actions.

Table 3. The Risk level classification

risk level	low risk	medium risk	high risk
risk score	0-0.33	0.33-0.66	0.66-1

3.3. Visualization of Results

The visualisation of results constitutes a pivotal aspect of our research methodology, as it offers a transparent and intuitive representation of the assessment of crash risk. To this end, we employed the Python programming language, which offers a high degree of flexibility and power, in conjunction with data visualisation libraries such as Matplotlib, Seaborn, or Plotly, with the objective of creating informative and visually appealing graphics.

By employing the Python programming language in conjunction with data visualisation techniques, a colour gradient was utilised to indicate the speed of vehicles on the highway. This was done with the intention of highlighting areas where vehicle speeds are lower, which may suggest the presence of higher traffic densities or potential congestion points (Figure 3). In the Vehicle Crash Risk Indication study, the thickness of the trajectory lines was proportional to the crash risk of each vehicle, with thicker lines indicating a higher crash risk. This allows for the identification of areas where precautions may be required (Figure 4). Heat maps were employed to illustrate the density and distribution of crash risk on highways, with dark red indicating high-risk areas and light red representing low-risk areas, with darker colours indicating higher crash risk in that area (Figure 5).

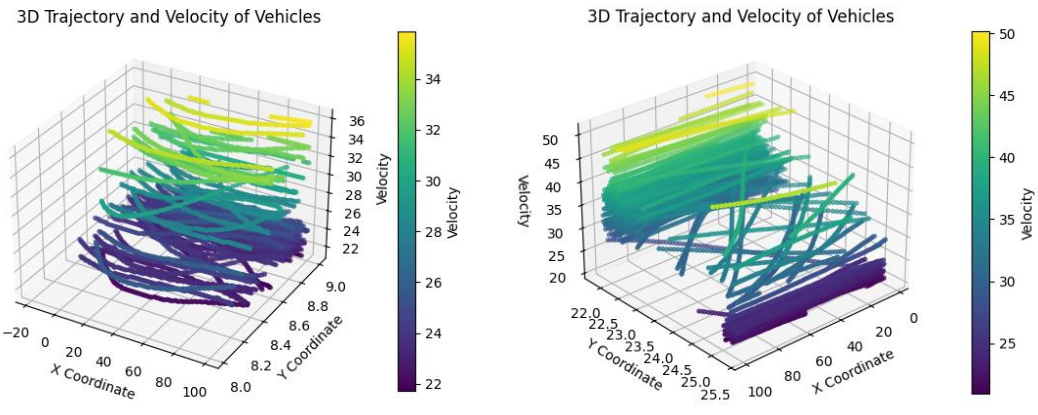

Figure 3. Consider the 3D trajectory plot of the velocity

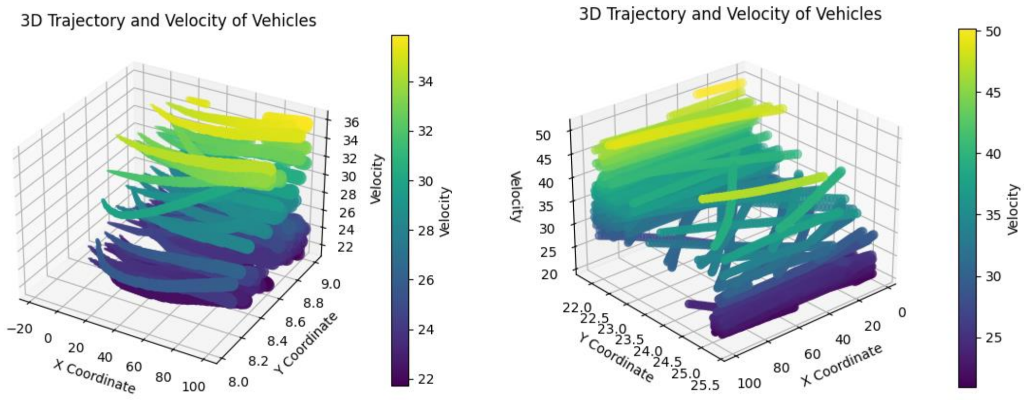

Figure 4. Consider the trajectory plot of the velocity and risk situation

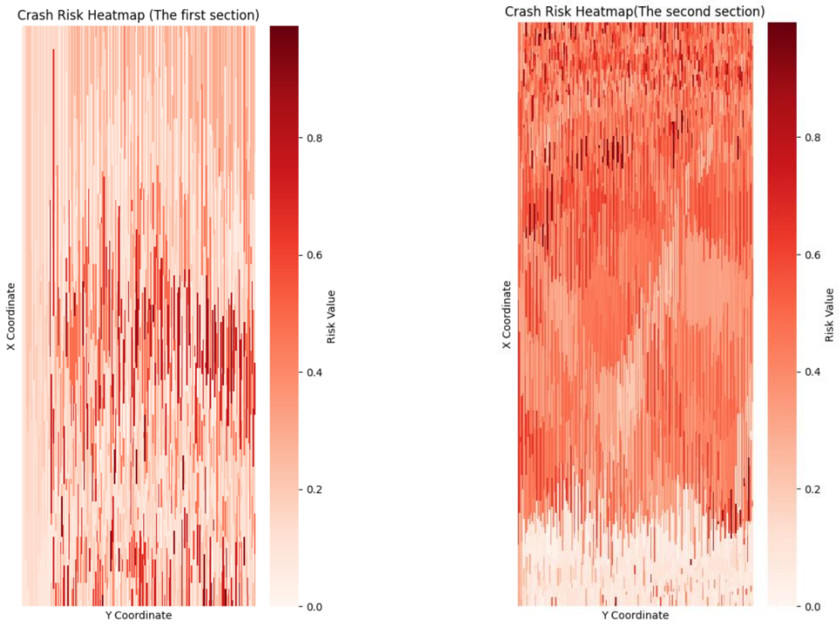

Figure 5. Thermodynamic diagram of collision risk

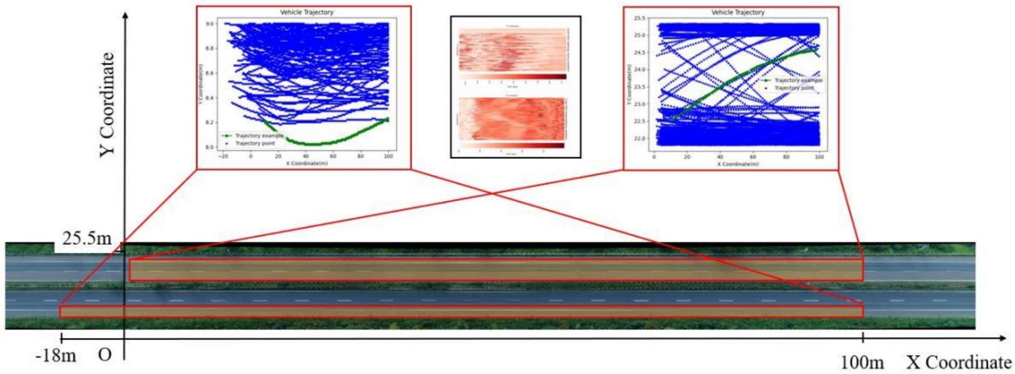

Figure 6. Collision risk posture diagram

4. Conclusion

The collision risk monitoring method for highways under rainy and foggy conditions proposed in this paper can effectively assess and visualise driving risks, thereby providing a new tool for traffic management authorities and assisting in the prevention and reduction of traffic accidents.

In conditions of precipitation, the assessment results indicate an elevated risk of collision. This is attributable to a number of factors, including longer braking distances due to slippery road surfaces, reduced vehicle spacing, and reduced visibility, which collectively elevate the probability of collisions. The risk of collision is also heightened in conditions of low visibility, such as fog, due to the difficulty drivers face in detecting obstacles or abnormalities ahead in a timely manner, which in turn results in shorter reaction times.

References

[1] Tian Xuejian, Hu Jiangbi. Analysis of factors affecting vehicle braking distance[C]// China Intelligent Transportation Association. Proceedings of the Seventh Annual Conference on Intelligent Transportation in China - Intelligent Transportation Technology. Beijing Key Laboratory of Traffic Engineering, Beijing Institute of Technology; 2012: 7.

[2] Xiao Na, Zhang Luoming. Mechanical Analysis of Vehicle Braking Distance and Exploration of Influencing Factors [J]. Journal of Yellow River Institute of Science and Technology, 2019, 21 (05): 23-25+64. DOI: 10.19576/j.issn.1008-5424.2019.05.006.

[3] MORENO A T, LIORCA C, GARCIA A. Operational impact of horizontal and vertical alignment of two-lane highways [J]. Transportation Research Procedia, 2016(15): 319-330.

[4] R. Krajewski, J. Bock, L. Kloeker and L. Eckstein, "The highD Dataset: A Drone Dataset of Naturalistic Vehicle Trajectories on German Highways for Validation of Highly Automated Driving Systems," 2018 21st International Conference on Intelligent Transportation Systems (ITSC), Maui, HI, USA, 2018, pp. 2118-2125, doi: 10.1109/ITSC.2018.8569552. keywords: {Roads; Sensors; Drones; Trajectory; Safety}.

[5] Zhao, P., Lee, C., 2018. Assessing rear-end collision risk of cars and heavy vehicles on freeways using a surrogate safety measure. Accid. Anal. Prev. 113, 149–158.

[6] Wu Y, Abdel-Aty M, Lee J. Crash risk analysis during fog conditions using real-time traffic data [J]. Accident Analysis and Prevention, 2018, 114 4-11.

[7] Tan J, Gong L, Qin X, et al. Multiple-vehicle collision influenced by misjudgment of space headway in traffic flow under fog weather condition [J]. IOP Conference Series: Earth and Environmental Science, 2019, 304 (3): 032077-032077.

[8] Zhang Y, Liang Y. Collusion or monitoring? Connected institutional investors and stock price crash risk in China [J]. Systems Research and Behavioral Science, 2022, 40 (6): 901-923.

[9] Young J, Jiyong J, Subin P, et al. Connected vehicle-based road safety information system (CROSS): Framework and evaluation [J]. Accident Analysis and Prevention, 2021, 151 105972-105972.

[10] Jie L, Lidan W, Zhong-Qiang Z, et al. Monitoring or tunneling? Information interaction among large shareholders and the crash risk of the stock price [J]. Pacific-Basin Finance Journal, 2021, 65 101469-.