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A real-time crash prediction model for the ramp vicinities of urban expressways☆

Moinul Hossain *, Yasunori Muromachi [1]

Department of Built Environment, Tokyo Institute of Technology, Nagatsuta-machi, Midori-ku, Yokohama, Kanagawa 226-8502, Japan

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ABSTRACT

Ramp vicinities are arguably the known black-spots on urban expressways. There, while maintaining high speed, drivers need to respond to several complex events such as maneuvering, reading road signs, route planning and maintaining safe distance from other maneuvering vehicles simultaneously which demand higher level of cognitive response to ensure safety. Therefore, any additional discomfort caused by traffic dynamics may induce driving error resulting in a crash. This manuscript presents a methodology for identifying these dynamically forming hazardous traffic conditions near the ramp vicinities with high resolution real-time traffic flow data. It separates the ramp vicinities into four zones – upstream and downstream of entrance and exit ramps, and builds four separate real-time crash prediction models. Around two year (December 2007 to October 2009) crash data as well as their matching traffic sensor data from Shibuya 3 and Shinjuku 4 expressways under the jurisdiction of Tokyo Metropolitan Expressway Company Limited have been utilized for this research. Random multinomial logit, a forest of multinomial logit models, has been used to identify the most important variables. Finally, a real-time modeling method, Bayesian belief net (BBN), has been employed to build the four models using ramp flow, flow and congestion index in the upstream and flow and speed in the downstream of the ramp location as variables. The newly proposed models could predict 50%, 42%, 43% and 55% of the future crashes with around 10% false alarm for the downstream of entrance, downstream of exit, upstream of entrance and upstream of exit ramps respectively. The models can be utilized in combination with various traffic smoothing measures such as ramp metering, variable speed limit, warning messages through variable message signs, etc. to enhance safety near the ramp vicinities.

1. Introduction

Ramp vicinities are arguably the most crash prone locations on urban expressways. There, the drivers need to maintain high speed and yet respond to several complex events, such as, maneuvering, taking decisions regarding routes, reading road signs and not to mention, maintaining safe distance from other maneuvering vehicles simultaneously. Hence, any additional disruption in the traffic condition may force driving error which can eventually lead to a crash. If the formation of a disrupted traffic condition can be spotted early, road authorities can take proactive measures by warning the drivers as well as applying various traffic smoothing methods such as variable speed limits, ramp metering, main line metering, etc. to bring the traffic condition back to normal. Recently, a small group of researchers, mainly from North America, are actively pursuing studies with loop detector data to reveal the interrelationship between crash and traffic flow variables [1,19,20,23–25,27]. They have emphasized that certain traffic conditions can be associated with high crash likelihood. Oh et al. [25] implied causal relationship between crash likelihood and 5 minute standard deviation of speed and average occupancy. Abdel-Aty et al. [3] ascertained that traffic leading to crash differs between high speed and low speed scenarios. At high speed, quick formation and subsequent dissipation of queues cause a backward shock wave and in case of low speed scenario, the impact between a congested downstream and a fast paced upstream impends driving errors. Dias et al. [11] discovered positive correlation between level of congestion and crash occurrence. Zheng et al. [32] underscored that recurring patterns of decelerations followed by acceleration increases crash risk. The findings have also stimulated idea of building models that can eventually forecast the crash potential for a short time window in near future taking the real-time loop detector data as input [4,5,12,13,15,16,24,25]. As

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* Corresponding author. Tel.: +81 80 3509 7060; fax: +81 45 924 5524.
E-mail addresses: moinul048i@yahoo.com (M. Hossain), ymuro@enveng.titech.ac.jp (Y. Muromachi).
[1] Tel./fax: +81 45 924 5524.

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the research field is in its infancy, the existing models are yet theoretical and have several major drawbacks. Considering crash phenomena as generic throughout the road section is one of the major drawbacks of the previous studies. Pande and Abdel-Aty [28] affirmed that presence of ramp in the downstream has impact on crash but did not shed light on the types of ramps and their relative vicinity. Jovanis and Chang [18] implied that traffic conditions vary substantially between the basic freeway segments and the ramp areas. General observation may verify that traffic conditions even vary among different types of ramps and their locations. For example, a high proportion of merging traffic can be observed at the downstream of an entrance ramp whereas diverging traffic is quite predominant near the upstream of an exit ramp. On the contrary, maneuvering frequency is comparatively lower in the basic freeway segments than the ramp vicinities. Therefore, it may not be suitable to use a universal model for both the basic freeway segments and the ramp areas. This may be one major reason behind the low detection and high false alarm rate of the existing models. Hossain and Muromachi [13] have dealt with this issue and developed real-time crash prediction models solely for the basic freeway segments and obtained a high detection rates for future crashes with low false alarm. Also, in a later study, Hossain and Muromachi have demonstrated that underlying phenomena behind crash is substantially different among basic freeway segments as well as different ramp vicinities. Likewise, building separate real-time crash prediction models for the ramp vicinities have another advantage. The existing models were developed assuming that they will be implemented throughout the length of the expressway rather than on specific areas of interest. Nevertheless, this may often deter the expressway authorities as it involves huge initial investments as well as regular maintenance cost. On the contrary, ramp vicinities, which are widely regarded as black-spots, cover only a fraction of the total length of the expressway and it is cost effective for authorities interested in real-time monitoring of hazardous location to implement the models first in these locations.

This study separates the ramp vicinities into four zones — upstream and downstream of the entrance and exit ramps; and develops four different real-time crash prediction models. As per the knowledge of the authors, this may be the first attempt to build real-time crash prediction models specifically for the ramp vicinities. The manuscript is organized into five major sections. The introductory section has stated the motivation of the study, its theoretical background and its objectives. Section 2 describes the activities involving experimental design, data extraction and processing. The third section provides a concise yet adequate introduction to Bayesian belief net (BBN), the real-time modeling method employed in the study. It also briefly explains random multinomial logit (RMNL) model which has been applied for variable selection. The subsequent section discusses the model building process as well as their performance evaluation. The concluding section summarizes the noble findings, mentions the limitations and lays out the future directions.

2. Study area and the data

2.1. Study area

A research of this nature demands large sample size as well as a detector layout that is to some extent uniform. The Shibuya 3 and Shinjuku 4 are arguably the two busiest urban expressways in Japan and every year they sustain a substantial number of crashes. Moreover, they have a relatively uniform (approximately 250 m center to center) detector spacing which makes them highly suitable for this research. The Shibuya 3 and Shinjuku 4 routes have two lanes in each direction and are respectively 11.9 and 13.5 km long. The expressways all together harbor 14 entrance and 15 exit ramps and 210 detectors. A detailed map has also been provided by the Tokyo Metropolitan Expressway Company Limited to identify the location of ramps (see Fig. 1). They have also provided access to a separate dataset containing the location of detectors in nearest 10 m to facilitate the research. The detectors installed in the expressways yield data of speed, vehicle count, occupancy and number of heavy vehicles for each 8 ms round the clock (24 h a day, 365 days a year) for each lane. However, the Tokyo Metropolitan Expressway Company Limited later archives the data by aggregating for all lanes for every 5 min. Hence, the supplied dataset contains 5 minute vehicle count, 5 minute vehicle count for heavy vehicles only, 5 minute average speed as well as occupancy for each detector location. The crash data contain information on date, time, location (in nearest 10 m), route number, direction (in-bound or out-bound), lane, and number of vehicles involved along with their types and type of crash. The data have been collected in two phases spanning over two different time frames. The first dataset contains both crash and detector data from December 2007 to March 2008 for Shibuya 3 route and from December 2007 to October 2008 for Shinjuku 4 route (Phase I). The second phase data collection encompassed data from May 2008 to October 2009 for Shibuya 3 route and November 2008 to October 2009 for Shinjuku 4 route. Thus, the final dataset contains 22 and 23 month detectors as well as crash data for these routes respectively. Another crucial point in the study is the accuracy of the reported time of crash as real-time crash prediction models are supposed to identify hazard risk for a very short time window and error in reported crash time in data will make the newly built models highly erroneous. In an interview the authority responsible for identifying the time of crash has confirmed that the reported crash time can be considered to be within a minute of its occurrence for various reasons. These two expressways are located in the heart of Tokyo, one of the busiest mega cities in the world and serve substantial number of traffic even during night time on the weekends. A portion of the routes are under constant camera surveillance. Safety cars are in operation round the clock on these routes. Moreover, as they have only two lanes in each direction, any incident on road creates high impact and gets detected very quickly. Interestingly, the crash type recorded in the crash database included — rear end, side swipe, hitting road furniture, tipping over along with some other types which may not be directly related to crash. They include vehicles catching fire, hitting objects accidentally fallen from other vehicles or objects falling from vehicles but not hitting any other vehicle, etc. As these incidents are not directly related to crash which might have taken place due to hazardous traffic conditions, they were excluded from the crash samples under consideration. The final crash dataset contains 3018 crash cases (1141 for Phase I and 1877 for Phase II).

2.2. Experimental design

Preliminary analysis on the crash dataset suggests that approximately 55% of the crashes took place within 375 m from the ramp vicinities and crash concentration reduces beyond 375 m from the ramp locations. As mentioned earlier, this manuscript develops crash prediction models for the upstream and downstream of entrance and exit ramps separately. Therefore, these four models are built with crashes that had occurred within 375 m upstream and downstream of entrance and exit ramps. The underlying concept of the model is to treat the possibility of a crash occurrence as a classification problem, associate a dataset with hazardous traffic condition and identify its corresponding normal traffic condition data, build a classification based model with them and calculate the probability of a future traffic condition data belonging to any of these two traffic conditions. Hence, it is important to define hazardous and normal traffic conditions. Oh et al. [23] selected a 5 minute time period ending at the time of crash as hazardous traffic condition. They retrieved the corresponding normal traffic condition by taking another 5 minute time period ending 30 min before the reported crash time. Zheng et al. [32] seconded the approach but considered a larger interval (10 min). Abdel-Aty et al. [6] argued that the objective of a real-time crash prediction model is to identify the evolving risk of a crash so that countermeasures can be taken to pacify the traffic. They emphasized that the model must allow adequate