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A Bayesian network based framework for real-time crash prediction on the basic freeway segments of urban expressways

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ABSTRACT

The concept of measuring the crash risk for a very short time window in near future is gaining more practicality due to the recent advancements in the fields of information systems and traffic sensor technology. Although some real-time crash prediction models have already been proposed, they are still primitive in nature and require substantial improvements to be implemented in real-life. This manuscript investigates the major shortcomings of the existing models and offers solutions to overcome them with an improved framework and modeling method. It employs random multinomial logit model to identify the most important predictors as well as the most suitable detector locations to acquire data to build such a model. Afterwards, it applies Bayesian belief net (BBN) to build the real-time crash prediction model. The model has been constructed using high resolution detector data collected from Shibuya 3 and Shinjuku 4 expressways under the jurisdiction of Tokyo Metropolitan Expressway Company Limited, Japan. It has been specifically built for the basic freeway segments and it predicts the chance of formation of a hazardous traffic condition within the next 4–9 min for a particular 250 meter long road section. The performance evaluation results reflect that at an average threshold value the model is able to successful classify 66% of the future crashes with a false alarm rate less than 20%.

1. Background

Road crash was conventionally believed to be a complex phenomenon involving the interaction of factors related to three major components: road geometry and environment, vehicle and human (Sabey and Staughton, 1975; Treat et al., 1977). Oh et al. (2001) introduced a fourth component, the traffic dynamics, suggesting that crashes involving safe vehicles regularly occur due to sudden formation of disrupted traffic condition even on geometrically correct roads under favorable driving condition. This contrived the opportunity to improve the shortcoming of the conventional crash prediction models that employ aggregated measures of traffic flow variables (e.g., speed limits for speed, AADT for flow, etc.) to identify hazardous locations. Since then, a small group of researchers, mainly from North America are promoting the idea of predicting crashes in real-time by using high-resolution detector data (Oh et al., 2001, 2005, 2006; Abdel-Aty et al., 2004, 2005, 2008; Abdel-Aty and Pande, 2005; Pande and Abdel-Aty, 2005, 2006a,b, 2007; Lee et al., 2003, 2006). They have advocated for developing a proactive system capable of timely spotting and evolving hazardous condition that can be countervailed with various traffic smoothing measures. Although this new concept of real-time crash prediction exhibits huge promise, being in its infancy, the available models are yet conceptual. As far as the authors of this paper are aware, none of these models have been implemented in practical scenario so far. Some of the major shortcomings of the existing models can largely be classified into three groups:

i) Location of detector: the performance of the proposed models vastly relies on the location of the detectors that are selected with respect to the crash location to fathom the risk of a future crash. Majority of the previous studies have been conducted in the USA, to be more precise, Interstate – 4 (Abdel-Aty et al., 2004, 2005; Abdel-Aty and Pande, 2005; Pande and Abdel-Aty, 2005, 2006a,b, 2007), 5 (Zheng et al., 2010), 405 (Oh et al., 2006), 880 (Oh et al., 2005). The rest took place in Gardiner Expressway of Toronto, Canada (Lee et al., 2003) and around the expressways near Utrecht region, Europe (Abdel-Aty et al., 2008). Most of these studies advocated for collecting data from both upstream and downstream of the crash location. However, the locations of the detectors varied due to high inter detector spacing. Where the study sections on I-4 have an inter detector spacing of around 0.8 kilometers, the inter detector spacing on I-5 vary between 0.6 and 3.9 kilometers. For the Utrecht region expressways (Dutch) the detector spacing is

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significantly different from that of the I-4 as it never exceeded 800 meters but has high standard deviation (Abdel-Aty et al., 2008). Hence, it is difficult for the expressway authorities interested in installing real-time hazard monitoring systems to decide how they will layout detector on future urban expressways. Likewise, if they are interested to monitor specific locations on an existing expressway with existing detectors then they may require further guidance on selecting the appropriate detector combinations to extract data for the system.

ii) Variable space: the potential variable space of the existing studies has been substantially large and diverse considering the crash sample size. Although the most common predictors have been within the average, standard deviation and coefficient of variation of speed, flow and occupancy aggregated at different upstream and downstream detector locations with respect to the crash location (Abdel-Aty et al., 2004, 2005; Abdel-Aty and Pande, 2005; Pande and Abdel-Aty, 2005, 2006b, 2007), some also involved density, queue length, exposure (Lee et al., 2003), longitudinal (Lee et al., 2003) and lateral (Lee et al., 2003, 2006; Pande and Abdel-Aty, 2006a) difference in traffic flow variables, safe stopping distance of individual vehicles (Oh et al., 2006), average flow ratio calculated from the peak flow (Lee et al., 2006), road geometry (directly or indirectly) (Pande and Abdel-Aty, 2006b; Lee et al., 2003), etc. This is because – (a) road crash is a highly complex phenomena and accounts a wider range of variables, and, (b) in many occasions the quality as well as availability of detector data need to be compensated with surrogate variables. This induces a classical situation involving large variable space and small sample size and it requires a suitable method to select the most important variables. Where some studies employed engineering judgment to choose the variables, others applied statistical methods (testing the significance by developing logistic regression models with one variable at a time) as a solution to the problem (Abdel-Aty et al., 2004, 2005; Abdel-Aty and Pande, 2005; Pande and Abdel-Aty, 2005, 2006b, 2007; Zheng et al., 2010). A more robust approach was adopted by Pande and Abdel-Aty (2006a), who applied classification trees and Abdel-Aty et al. (2008), who chose random forest to rank the variable importance. However, both random forest and classification trees can be susceptible to interval data as they can be biased towards variables with high number of categories (Strobl et al., 2007). Moreover, the studies either considered the traffic conditions in the upstream and the downstream or their longitudinal variation separately to model crash risk. They found positive correlation in both the situations indicating that considering both the variable types together might have improved the prediction performance of the models.

iii) Modeling method: the typical modeling methods employed for real-time crash prediction models so far can be broadly classified into: statistical methods and artificial intelligence or data mining based methods. The former includes matched case–control logistic regression (Abdel-Aty et al., 2004, 2005; Abdel-Aty and Pande, 2005; Pande and Abdel-Aty, 2007; Lee et al., 2006; Zheng et al., 2010), aggregate log linear model (Lee et al., 2003), Bayesian statistics (Oh et al., 2001), etc. The latter encompasses different kinds of neural networks (Abdel-Aty et al., 2008; Abdel-Aty and Pande, 2005; Pande and Abdel-Aty, 2006b; Oh et al., 2005), fuzzy logic (Oh et al., 2006) and classification trees (Pande and Abdel-Aty, 2006a). Traffic flow variables, e.g., speed, flow, occupancy are highly correlated in nature (Gazis, 2002). Thus, when modeled using statistical approaches, most of them get dropped as part of modeling process. Hence, it is important to employ methods that can accommodate correlated variables and make best use of every available piece of information to improve the prediction success. Neural network based modeling methods (e.g., probabilistic neural network) can accommodate correlated dependent variables. However, they expect sufficient prior knowledge regarding the problem domain exhibited through the interrelationship among the predictors. Furthermore, studies of this nature are highly resource demanding and many times data on all the variables are not available during the time of modeling. Therefore, a modeling method that can accommodate future new variables as well as knowledge from new data in course of time without requiring rebuilding or recalibrating the whole model is highly desirable.

This study addresses the aforementioned shortcomings by proposing a Bayesian belief net (BBN – also known as Bayesian network) based framework to develop real-time crash prediction models. The research selects an urban expressway harboring uniformly yet densely packed detectors. It applies variable importance measure of random multinomial logit (RMNL), a recently introduced hybrid of conventional multinomial logit and random forest methods that can handle interval data, to identify and rank the most important variables. Later, it applies BBN as the modeling method.

The manuscript is organized into five sections. The introductory section has laid out the background and stated the purpose and objective of the study. Section 2 describes the activities involving experimental design, data extraction and processing. Section 3 presents a brief but self containing introduction to RMNL and BBN. Section 4 discusses the model building and evaluation process. The concluding section summarizes the salient contributions and findings of the study along with identifying the limitations and subsequent future scopes.

2. Study area and data preparation

2.1. Study area

The study area has been chosen based on: (i) quality of detector data, (ii) accuracy in reported crash time and (iii) sample size. Considering these, based on the recommendation by the Tokyo Metropolitan Expressway Company Limited, Shibuya 3 and Shinjuku 4 routes under their jurisdiction are chosen as the study area. Both the expressways harbor mostly two lanes in each direction. They are two of the busiest expressways in Japan and are situated in the heart of Tokyo metropolitan area. Another salient feature of these expressways are their level of sophistication as they harbor 210 detectors within just 25.4 kilometers (Shibuya 3 = 11.9 kilometers; Shinjuku 4 = 13.5 kilometers – in each direction) with an inter detector spacing roughly around 250 meters. This provides an excellent opportunity to experiment with different detector combinations and identify the most suitable detector layout plan for monitoring hazardous traffic condition formation in real-time. The detectors in the study area store data of speed, vehicle count, occupancy and number of heavy vehicles per lane for each 8 milliseconds round the clock (24 h a day, 365 days a year). Later the data of all the lanes are aggregated for every 5 min by the authority. The crash data contain date, time in minutes, location (in nearest 10 meters), vehicles involved, type of crash, etc. related information. The data have been supplied by Tokyo Metropolitan Expressway in two stages. The first dataset contains detector data and corresponding crash data from December, 2007 to March, 2008 for Shibuya 3 expressway and December, 2007 to November, 2008 for Shinjuku 4 expressway. The second dataset covers data for the time period between April, 2008 and October, 2009 for Shibuya 3 expressway and December, 2008 and October, 2009 for Shinjuku 4 expressway.