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Modeling secondary accidents identified by traffic shock waves

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ABSTRACT

The high potential for occurrence and the negative consequences of secondary accidents make them an issue of great concern affecting freeway safety. Using accident records from a three-year period together with California interstate freeway loop data, a dynamic method for more accurate classification based on the traffic shock wave detecting method was used to identify secondary accidents. Spatio-temporal gaps between the primary and secondary accident were proven be fit via a mixture of Weibull and normal distribution. A logistic regression model was developed to investigate major factors contributing to secondary accident occurrence. Traffic shock wave speed and volume at the occurrence of a primary accident were explicitly considered in the model, as a secondary accident is defined as an accident that occurs within the spatio-temporal impact scope of the primary accident. Results show that the shock waves originating in the wake of a primary accident have a more significant impact on the likelihood of a secondary accident occurrence than the effects of traffic volume. Primary accidents with long durations can significantly increase the possibility of secondary accidents. Unsafe speed and weather are other factors contributing to secondary crash occurrence. It is strongly suggested that when police or rescue personnel arrive at the scene of an accident, they should not suddenly block, decrease, or unblock the traffic flow, but instead endeavor to control traffic in a smooth and controlled manner. Also it is important to reduce accident processing time to reduce the risk of secondary accident.

1. Introduction

Freeway accidents not only cause severe travel delays, but can also result in secondary accidents, the risk of which is estimated to be six times greater than that for a primary accident (Tedesco et al., 1994). The high potential for occurrence and the negative consequences of secondary accidents make them an issue of great concern affecting freeway safety. However, secondary accidents and their relationships to primary accidents are usually not specifically mentioned in the accident database. Therefore, in much of the previous research, great effort has been made to identify the secondary accidents as shown in Table 1. Most of the existing research classified secondary accidents by predefining fixed spatio-temporal boundaries—a method that can be very subjective (Raub, 1997; Karlaftis et al., 1999; Moore et al., 2004; Hirunyanitiwattana and Mattingly, 2006). By studying operating traffic data, some study approaches compensated for the static method by proposing a range of dynamic definition methods based on concepts such as queuing theory, speed contour plot of the primary incident, and simulation (Zhan et al., 2009; Sun and Chilukuri, 2010; Green et al., 2012; Chung, 2013; Yang et al., 2013a, 2014b).

Shock wave theory can be used to illustrate how the conversion between two different conditions travels along traffic flow. Moore et al. (2004) applied shock wave filtering using fixed boundaries to identify secondary accidents, which required close manual attention to distinguish shock waves in loop data. However, limited installation of detectors, lack of data, and corrupted records of output data reduced data availability, which resulted in data for only sixteen accidents sufficient to execute this filtering method. Zheng et al. (2014) proved that the shock wave could be a fair tool to identify the secondary accident. He firstly extracted spatially and temporally nearby crash pairs (up to custom static thresholds) from a large network on the basis of a crash-pairing algorithm. In the second phase, two filters are used to select crash pairs that are more likely to be primary–secondary crash pairs. One of the filters uses shockwave theory to evaluate the dynamic traffic impact of the primary incidents. Then the manual review of identified police reports was carried out to confirm actual secondary crashes. Zheng also extended the shockwave filter to a freeway network scale. However Zheng just considered the release shockwave and queuing shockwave. In an incident when the rescue party or the policeman comes

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Table 1
Identification of secondary accident results in previous research.

Author	Spatial Boundaries	Temporal Boundaries	Results	Data
Raub (1997)	1 mile	15 min	More than 15% of the crashes may be secondary	Northern Chicago, metropolitan region (sample size 1796 crashes)
Karlaftis et al. (1999)	1 mile	15 min	34.7% of the crashes may be secondary	Borman Expressway (741 crashes)
Hirunyanitiwattana and Mattingly (2006)	2 miles	60 min	4.35%, more secondary accidents in rural districts	California highway system (sample size: more than 350,000 incidents)
Moore et al. (2004)	2 miles	2 h	1.5% to 3%, lower frequency of secondary accidents	Los Angeles Freeway (sample size 84,684 crashes)
Zhan et al. (2009)	Max queue length 1.09–1.49 miles	Incident recovery time: 33.34–52.6 min. Incident dissipation time: 0–21.76 min	3.23%	Florida District 4 I-595 and I-75. (sample size 7895 crashes)
Sun and Chilukuri (2010)	Incident Progression Curve based		7.14%	I-70 and I-270 in Missouri (sample size 5514 crashes)
Green et al. (2012)	Determine the time and distance relationships between the primary and subsequent-related crashes		3.88% are secondary and able to identify 87% of the secondary crashes that were manual searched	Roadways in Kentucky (sample size 9330 crashes)
Chung (2013)	Speed matrix based		7.5% and 3.8% in 2 directions respectively	California interstate freeways (sample size 6200 crashes)
Yang et al. (2013a)	Binary speed contour plot based		8.4% are secondary (user's defined speed reduction factor 0.7)	A 27-mile segment of a major highway in New Jersey (case study sample size 1188 crashes)
Yang et al. (2014b)	An on-line scalable approach		An automatic detection procedure.	Acquire traffic data from various third-party traffic map services.
Wang et al. (2015)	Shock wave based		1.08% of California interstate freeway accidents were secondary	2012 California interstate freeway accident (10,762 crashes)

to the crash site to manage the traffic, one more shock wave can be created. Moreover, the shock waves can trace each other, and this situation will be more complicated than Zheng's model. These problems could also happen in Chung (2013) and Yang's (2013, 2014) method.

A shock wave boundary filtering (SWBF) method was applied to identify 2012 California interstate freeway secondary accidents, and a lower frequency of 114 (1.08%) was found compared with findings from previous research (Wang et al., 2015). In this paper, SWBF is sequentially used to amplify the secondary accident sample in order to develop a more accurate secondary accident causation model. A total of 49,753 accidents that occurred from 2010 to 2012 on California interstate freeways, along with their corresponding upstream loop data were analyzed by the proposed method to demonstrate its reliability and efficiency. In addition, spatio-temporal gaps between the primary and secondary accident were subsequently studied.

Previous studies have investigated major factors contributing to secondary incident occurrence as shown in Table 2. Most of these studies used logistic regression models to explore the characteristics of secondary crashes (Karlaftis et al., 1999; Latoski et al., 1999; Zhan et al., 2008, 2009; Yang et al., 2013a). Some of the studies used probit models to assess the presence of significant differences between secondary crashes and primary crashes (Hirunyanitiwattana and Mattingly, 2006; Vlahogianni et al., 2012; Yang et al., 2013b, 2014a,c). In addition, other models were applied, including ordinal regression, binary probit regression, and Bayesian network (Khattak et al., 2009; Vlahogianni et al., 2010; Zhang and Khattak, 2010, 2011).

According to the literature, factors such as accident type, weather, duration, AADT, and vehicle involved have significant effects on the likelihood of incident occurrence. However, traffic situations resulting in secondary accidents were not further studied, as the AADT and time period of the incidents could not reflect the real traffic state at the time when the secondary accident occurred. Demonstrating the shock waves of each accident, a logistic regression model was built to compare primary accidents that led to secondary accidents with independent accidents.

2. Method

2.1. Shock wave boundary filtering (SWBF) method

In this study, a shock wave boundary filtering method (SWBF) (Wang et al., 2015) was used for secondary accident classification. Unlike most of the static filtering methods and dynamic methods based on queuing theory, SWBF provides real-time accident impact scope and is equipped with an automatic algorithm to conduct the filtering work circularly.

The SWBF method includes three main steps: (1) calculate traveling speed of primary accident impact through flow and density information; (2) determine a feasible spatio-temporal district for secondary accidents by estimating the real time space-time scope of shock waves generated by every potential primary accident; and