Accident Analysis and Prevention 117 (2018) 346–356

Contents lists available at ScienceDirect

Accident Analysis and Prevention

journal homepage: www.elsevier.com/locate/aap

Key risk indicators for accident assessment conditioned on pre-crash vehicle trajectory

X. Shi[a,*], Y.D. Wong[a], M.Z.F. Li[b], C. Chai[c]

[a] School of Civil & Environmental Engineering, Nanyang Technological University, 639798, Singapore
[b] Nanyang Business School, Nanyang Technological University, 639798, Singapore
[c] College of Transportation Engineering, Tongji University, 201804, China

ARTICLE INFO

Keywords:
Key risk indicator
Risk exposure
Pre-accident risk
Vehicle risk

ABSTRACT

Accident events are generally unexpected and occur rarely. Pre-accident risk assessment by surrogate indicators is an effective way to identify risk levels and thus boost accident prediction. Herein, the concept of Key Risk Indicator (KRI) is proposed, which assesses risk exposures using hybrid indicators. Seven metrics are shortlisted as the basic indicators in KRI, with evaluation in terms of risk behaviour, risk avoidance, and risk margin. A typical real-world chain-collision accident and its antecedent (pre-crash) road traffic movements are retrieved from surveillance video footage, and a grid remapping method is proposed for data extraction and coordinates transformation. To investigate the feasibility of each indicator in risk assessment, a temporal-spatial case-control is designed. By comparison, Time Integrated Time-to-collision (TIT) performs better in identifying pre-accident risk conditions; while Crash Potential Index (CPI) is helpful in further picking out the severest ones (the near-accident). Based on TIT and CPI, the expressions of KRIs are developed, which enable us to evaluate risk severity with three levels, as well as the likelihood. KRI-based risk assessment also reveals predictive insights about a potential accident, including at-risk vehicles, locations and time. Furthermore, straightforward thresholds are defined flexibly in KRIs, since the impact of different threshold values is found not to be very critical. For better validation, another independent real-world accident sample is examined, and the two results are in close agreement. Hierarchical indicators such as KRIs offer new insights about pre-accident risk exposures, which is helpful for accident assessment and prediction.

1. Introduction

Traffic accidents cause great loss of lives and property damage. Reliable accident prediction and proactive prevention are undoubtedly of great benefit and necessity.

Numerous studies have been conducted on traffic accident assessment and prevention. Accident occurrence is a complex mechanism, with many contributing factors (Mannering et al., 2016). Unsafe traffic conditions and risky driving behaviours have been explored to characterise accidents, including human errors, traffic speed and occupancy, weather and visibility (e.g. Saifuzzaman and Zheng, 2014; Young, 2017). Statistical models and machine learning approaches are being widely applied to analyse the relationship between accidents and influencing factors, such as random forests (Abdel-Aty and Haleem, 2011), support vector machine (Dong et al., 2015), among others. These studies are helpful to describe general linkages between accident numbers and coexisting factors or concurrent scenarios. Nevertheless, even under equivalent situations, actual accident occurrence remains unreliable to be assessed or predicted if merely relying on these trends and factors. Due to uncertainty and randomness, effective accident assessment and prediction has been found to be extremely difficult.

Risk assessment is essential when making any accident prediction. Pre-accident risk exposure is more meaningful for accident prediction and prevention. Although the occurrence of an accident is generally unexpected, for certain types of accidents, there is an accident-forming process, especially for accidents associated with traffic conflicts. Traffic conflict represents a transitional state between safety and a potential accident. A conflict is an observed situation in which two or more road users approach each other in space and time to such an extent that there is a risk of collision if their movements remain unchanged (Amundsen and Hydén, 1977). Conflicts can improve the understanding of the accident mechanism and chain of events which may lead to a collision (Mahmud et al., 2017). Compared with actual accidents, incidences of traffic conflicts, with attendant collision risks of various degrees, are more frequent (Chin and Quek, 1997). Moreover, a strong relationship has been found between traffic conflicts and actual crashes in many

* Corresponding author.
E-mail addresses: XSHI004@e.ntu.edu.sg (X. Shi), CYDWONG@ntu.edu.sg (Y.D. Wong), ZFLI@ntu.edu.sg (M.Z.F. Li), chaichen@tongji.edu.cn (C. Chai).

https://doi.org/10.1016/j.aap.2018.05.007
Received 27 December 2017; Received in revised form 4 May 2018; Accepted 7 May 2018
0001-4575/

studies (e.g. El-Basyouny and Sayed, 2013, Wu et al., 2014). Herein, the scope of risk assessment should therefore focus on pre-accident traffic conflicts, as an alternative to actual accident numbers.

Surrogate measures are widely utilised in traffic conflict techniques (TCT) for safety evaluation (e.g. Zheng et al., 2014). Mahmud et al. (2017) provides a comprehensive review on the developments and applications of 17 proximal surrogate indicators. The reliability and validity of surrogate indicators are well accepted for safety evaluation (Chai and Wong, 2015). In practice, FHWA developed a Surrogate Safety Assessment Model (SSAM) as a post processor to determine the number and severity of conflicts obtained from simulation packages (Sobhani et al., 2013). Many advanced driving assistance systems (ADAS) have used surrogate indicators as important warning criteria (Wang et al., 2013). Nevertheless, the effectiveness of surrogate indicators under real-world accidents has not been properly investigated. In particular, it remains unclear the extent to which the surrogate indicators are useful for pre-accident risk assessment. Besides, indicators are often designed under simplified assumptions, such as unchanged trajectory, constant speed and predefined deceleration rate. To represent complex accident mechanism, combined use of various indicators has been suggested (e.g. Laureshyn et al., 2010). However, no consensus has been reached yet on which indicators should be selected and how to combine them.

High-quality data is necessary for risk measurement. Existing studies widely use accident data from police recording and self-reports, controlled experiments and simulation, loop detectors, etc. From such sources, it is extremely difficult to obtain pre-accident data of high-quality (e.g. accurate, 1-s resolution or less, vehicle level) (Imprialou and Quddus, 2017). Besides, real-world accidents are generally unexpected and occur rarely, and purposive tracking is very costly (Hakkert and Gitelman, 2014). Note that it is near impossible to pinpoint the precise time and location of an accident before-hand. Herein, a practical way to obtain pre-accident information is by retrieving the video footage that contains an accident event. Such video footage can be gathered by a surveillance camera system that continuously records traffic movements for the entire road network.

However, data extraction from video recording is also challenging. Existing methods in computer vision are useful for vehicle detection and tracking (e.g. vehicle/non-vehicle classification, vehicle counting) (e.g. Sivaraman and Trivedi, 2013), but they are problematic for accurate data extraction and measurement (e.g. vehicle trajectory, gap, speed). Additionally, there are many constraints in camera-based data acquisition, such as lens distortion from camera angles, object overlapping in dense conditions. The solution for exact measurement is lacking. Chai and Wong (2013) developed and applied a technique of measuring a vehicle trajectory by a projective transformation of video frames at first, and then indicating vehicle positions by means of computer-aided annotation; this hybrid approach is flexible and easy to use, albeit involving certain tedium.

Being different from previous studies in the literature, this paper focuses on developing hybrid indicators, namely the key risk indicators (KRIs), to hierarchically assess pre-accident risk exposures. Section 2 develops the concept of KRI, and elaborates the selection of basic indicators. Section 3 describes the data extraction of pre-accident vehicle trajectory, and proposes a grid remapping method for coordinates transformation. Section 4 constructs the KRIs based on the findings from a spatial-temporal case-control and conducts the validation by another accident event. The final two sections cover the discussion and conclusion.

2. Concept of key risk indicator

2.1. Introduction of KRI

The concept of KRI has important applications in several areas, such as operational risk management (Scandizzo, 2005) and enterprise risk management (ERM) (Hwang et al., 2010) and financing, among others.

As applied to road safety, KRIs are metrics capable of revealing risk exposures in traffic flow, and providing predictive signals of a potential accident. KRIs enable us to identify risks that may lead to an accident, and grasp insights of an impending accident (such as at-risk vehicles, potential locations and time), thus the prevention strategy can be applied in a targeted and pre-emptive way. Hence, for accident assessment and prediction purposes, it is crucial that KRIs are designed effectively and reliably.

KRIs are developed based on a set of basic indicators that are effective and reliable in measuring risks. The design of KRIs starts with first shortlisting a set of existing metrics and then identifying the most critical ones that can serve as the basic indicators. The guiding principles for selecting metrics are outlined, such as meaningfulness, measurability, predictability (e.g. leading indicators), etc. Shortlisted metrics should offer useful insights about accident risks and be easy and clear to interpret. Complex metrics would make it difficult to track and manage. In addition, leading indicators should be included to offer predictive signals of a potential accident.

2.2. Risk behaviour indicators

Driving behaviour plays a major role in accident risk. High-risk driving behaviours may result in high likelihood of an accident, such as excessive speeding, driving too close to the preceding vehicle, etc. As a result, temporal and spatial proximity can be used to evaluate such risk behaviours. In addition, indicators based on temporal proximity are relatively popular and objective, because they integrate both the spatial proximity and speed difference (Zheng et al., 2014). Among time-based indicators, Time to Collision (TTC) is well-recognised and widely-used in practice, for theoretical and reliability reasons (Mahmud et al., 2017). Based on TTC, Time Exposed TTC (TET) and Time Integrated TTC (TIT) were further proposed (Minderhoud and Bovy, 2001), to measure risk duration and risk integration, respectively. The three time-based indicators are shortlisted.

(1) The basic TTC is defined by the time to a potential collision between two vehicles (van der Horst, 1990), as follows:

$$TTC_i(t) = \begin{cases} \frac{X_{i-1}(t) - X_i(t) - L_{i-1}}{V_i(t) - V_{i-1}(t)} & V_i(t) > V_{i-1}(t) \\ \infty & V_i(t) \le V_{i-1}(t) \end{cases}$$

where $x_i(t)$ and $v_i(t)$ are the position and velocity of targeted (following) vehicle (i) at timestamp t, and L_{i-1} is the length of preceding (leading) vehicle (i−1).

Generally, risk behaviours are flagged for any vehicle pair with a TTC value less than a given threshold. However, risk severity associated with TTC is not obvious. TTC notion is illustrated with vehicle trajectories in Fig. 1(a).

(2) TET expresses the total time of a vehicle exposed in risk situations, as follows:

$$TET_i = \sum_{t=0}^{N} \delta_i(t) \cdot \tau_{sc}$$

$$\delta_i(t) = \begin{cases} 1 & \forall \ 0 \le TTC_i(t) \le TTC^* \\ 0 & otherwise \end{cases}$$

where, for a period $T = N \cdot \tau_{sc}$, there are N small time intervals, each interval is τ_{sc} (e.g. 0.1 s). $\delta_i(t)$ is a switching variable between 1 and 0, and value 1 indicates a signal of risk condition, when the TTC value is below threshold TTC*.

(3) TIT takes into account the accumulated impact of risk behaviour, using integration of TTC profile below specified threshold, as follows: