Accident Analysis and Prevention 43 (2011) 1364–1370

Contents lists available at ScienceDirect

Accident Analysis and Prevention

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

Indexing crash worthiness and crash aggressivity by vehicle type

Helai Huang[a,*], Chowdhury Siddiqui[b], Mohamed Abdel-Aty[c]

[a] Urban Transport Research Center, School of Traffic & Transportation Engineering, Central South University, Changsha 410075, China
[b] Department of Civil, Environmental and Construction Engineering, University of Central Florida, Orlando, FL 32816, United States
[c] Department of Civil, Environmental and Construction Engineering, University of Central Florida, Engineering II – 211L, Orlando, FL 32816, United States

ARTICLE INFO

Article history:
Received 21 November 2010
Received in revised form 14 January 2011
Accepted 8 February 2011

Keywords:
Crash compatibility
Crash worthiness
Crash aggressivity
Bayesian hierarchical model
Ordered logistic model

ABSTRACT

Crash aggressivity (CA), along with conventional crash worthiness (CW), has been recently studied to deal with the crash incompatibility between vehicles on roads. Clearly, injury severity depends on the attacking ability of striking vehicle as well as the protective ability of struck vehicle. This study proposes a systematic crash-based approach to index CA and CW of various vehicles. The approach deviates from existing methods in three aspects: (a) an explicit definition and specification in the model for CW and CA; (b) Bayesian hierarchical analysis to account for the crash-vehicle two-level data structure; (c) a five-level ordinal model to explicitly consider all levels of crash severity. The case study on major vehicle types illustrated the method and confirmed the consistency of results with previous studies. Both crash worthiness and crash aggressivity significantly vary by vehicle types, in which we identified the dominating effect of vehicle mass, and also highlighted the extraordinary aggressivity of Light Trucks and Vans (LTVs). While it was not surprising to identify least CA and CW of motorcycles, buses were unconventionally found to be less aggressive than other motor vehicles. The method proposed in this research is applicable to detailed crash-based vehicle inspection and evaluation.

1. Introduction

This study proposes an empirical model to systemically index crash worthiness (CW), i.e. self-protective capacity of a vehicle, and crash aggressivity (CA), i.e. hazardousness that the subject vehicle imposes on counterpart vehicle(s) involved in the same crash.

Safety characteristics of various vehicles have long been a prominent focus of both safety researchers and vehicle designers (Evans, 2004). Given that a crash occurs, of particular concern is the crash severity. The most important components affecting crash severity include CW of the struck vehicle and CA of the striking vehicle (for multi-vehicle crashes), and other external factors regarding road infrastructure, collision circumstances, driver behavior and casualty characteristics, etc.

Crash data have been extensively used to empirically investigate vehicle safety around the world (e.g. Cameron et al., 1996, 1999 in Australia; Broughton, 1994, 1996 in U.K.; Gustafsson et al., 1989; Vadeby, 2000 in Sweden; Tapio, 1995; Tapio et al., 1995; Huttula et al., 1997 in Finland; and Subramanian, 2006; Wenzel and Ross, 2005 in U.S.). One of the major criteria in large-scale evaluation is fatality rate associated with different vehicle types controlled by the number of registered vehicles (e.g. Subramanian, 2006; Wenzel and Ross, 2005), or by distance traveled (e.g. Kahane, 2003). As it controls exposure, the per-mile approach is comparatively better in reflecting fatality risk than the per-vehicle approach. But doubtless, without controlling for crash propensity (how the vehicle is driven), the per-mile approach is not able to evaluate the components affecting crash severity, i.e. CW and CA (Kahane, 2003).

Clearly, in order to examine safety performance associated with various vehicles, a crash-specific approach has to be adopted. With crash-specific approach, safety protection effect of vehicles, reflected by crash severity, could be separated from effects of crash exposure and crash propensity. Numerous crash-specific research efforts have been conducted to relate vehicle damage or occupant injury to various vehicle properties (type, make, model, etc.) by controlling for other external or instant factors (Evans and Frick, 1992, 1993; Farmer et al., 1997; Broyles et al., 2001, 2003; Ulfarsson and Mannering, 2004; Acierno et al., 2004; Huang et al., 2008; Fredette et al., 2008). Those models have usually been used to evaluate CW of different vehicle properties.

Recently, crash compatibility has been more of a concern. In the context of crash compatibility, CA of the counterpart vehicles is known as an important component affecting the severity of subject vehicle with certain level of CW. A majority of research have been focused on car-LTV compatibility due to the substantial increase of light trucks including sport utility vehicles and vans (LTV) especially in North America (Wenzel and Ross, 2005; Kahane, 2003; Acierno et al., 2004; Fredette et al., 2008; Toy and Hammitt, 2003). Various vehicle–vehicle interactions have been investigated,

* Corresponding author. Tel.: +86 731 82655326.
E-mail addresses: huanghelai@alumni.nus.edu.sg (H. Huang), kawsar_arefin@knights.ucf.edu (C. Siddiqui), mabdel@mail.ucf.edu (M. Abdel-Aty).

0001-4575/$ – see front matter © 2011 Elsevier Ltd. All rights reserved.
doi:10.1016/j.aap.2011.02.010

including distinct physical performances such as mass and size (Evans and Frick, 1992, 1993), structural and geometric incompatibility etc. (Wenzel and Ross, 2005; Acierno et al., 2004), and crash configuration and trends impacted by LTVs (Abdel-Aty and Abdelwahab, 2003, 2004a,b; Abdelwahab and Abdel-Aty, 2004).

Approaches have been proposed to simultaneously model CW and CA. Wenzel and Ross (2005) studied a 'combined risk' associated with each vehicle model by summing up the risk-to-drivers in all kinds of crashes and the risk-to-drivers-of-other-vehicles in two-vehicle crashes. Toy and Hammitt (2003) and Fredette et al. (2008) proposed binary logistic regression to estimate the effects of vehicle incompatibility on the risk of death and/or severe injuries in two-vehicle crashes. While most of the existing studies focused on specific vehicle types or makes, there is a need to establish a systematic approach for general vehicle safety inspection with state-of-the-art modeling techniques.

Developing from previous studies, this paper presents a systematic crash-based approach to examine CW and CA of various types of vehicles. This approach deviates from existing methods in three aspects: (a) an explicit definition and specification in the model for CW and CA; (b) Bayesian hierarchical analysis to account for the two-level data structure, or simply speaking, severity correlation of vehicles in a same crash is accommodated; (c) a five-level ordinal model to explicitly consider all levels of crash severity. Although the model is applicable to safety evaluation for any vehicle type, make, model or other properties, in this paper we only illustrate the method by an example evaluating general vehicle types.

2. Developing Crash Worthiness Index and Crash Aggressivity Index

A crash with major harmful event as "collision between two moving vehicles" is supposed to be the most similar case to laboratory vehicle-to-vehicle collision experiments. Let $i[m]$ (m = 1, 2) denote two vehicles involved in the crash i (i = 1, ... I), with injury severity levels $IS_{i[m]}$. The injury severity levels are commonly defined as five ordered categories:

- Category 1 (C1): no injury/property damage only (PDO),
- Category 2 (C2): possible injury,
- Category 3 (C3): non-incapacitating injury,
- Category 4 (C4): incapacitating injury, and
- Category 5 (C5): fatality.

For this ordered outcome of severity, an ordinal model could be specified to examine the effects of various risk factors. Moreover, Huang et al. (2008) found significant severity correlations between vehicles involved in the same crashes and thus recommended a hierarchical approach to account for the crash-specific effects given the multilevel data (Huang and Abdel-Aty, 2010). Hence, a two-level specification, i.e. crash level and vehicle level, is developed for ordered logistic model (OL), called hierarchical ordered logistic model (HOL) in this study.

In an ordinal response model, a series of latent thresholds are generally formulated. Specifically, the real line is divided into five intervals by four thresholds (γ_{ik}, k = 1, 2, 3, 4), corresponding to the five ordered categories (C_{1-5}). It is noted that differing from OL model, the HOL model accounts for the cross-crash heterogeneities by specifying a set of variable thresholds for individual crashes. The thresholds define the boundaries between the intervals corresponding to observed severity outcomes. The latent response variable is denoted by $IS^*_{i[m]}$ and the observed categorical variable $IS_{i[m]}$ is related to $IS^*_{i[m]}$ by the "threshold" model defined as,

$$IS_{i[m]} = \begin{cases} 1 & if \quad -\infty < IS^*_{i[m]} \le \gamma_{i1} \\ k & if \quad \gamma_{i(k-1)} < IS^*_{i[m]} \le \gamma_{ik}, \quad k = 2, 3, 4 \\ 5 & if \quad \gamma_{i4} < IS^*_{i[m]} < +\infty \end{cases}$$

The ordinal models can be written as

$$IS^*_{i[m]} = \theta_{i[m]} + \varepsilon_{i[m]}$$

in which $\theta_{i[m]}$ is the linear predictor for covariates and $\varepsilon_{i[m]}$ is the disturbance term, which is assumed a logistic distribution with F as the cumulative density function. Thus, the cumulative response probabilities for the five categories of the ordinal outcome could be denoted as,

$$P_{i[m],k} = Pr(IS_{i[m]} \le k) = F(\gamma_{ik} - \theta_{i[m]}) = \frac{\exp(\gamma_{ik} - \theta_{i[m]})}{1 + \exp(\gamma_{ik} - \theta_{i[m]})}, \quad k = 1, 2, 3, 4$$

The idea of cumulative probabilities leads naturally to the cumulative logistic model

$$\mathrm{logit}(P_{i[m],k}) = \log\left[\frac{P_{i[m],k}}{1 - P_{i[m],k}}\right] = \log\left[\frac{Pr(IS_{i[m]} \le k)}{Pr(IS_{i[m]} > k)}\right] = \gamma_{ik} - \theta_{i[m]}, \quad k = 1, 2, 3, 4.$$

At the crash level, γ_{ik} could be specified as random effects,

$$\gamma_{ik} = \gamma_k + b_i, \quad k = 1, 2, 3, 4.$$

where the intercept γ_k represents a constant component for thresholds for all crashes. b_i is the random effect to accommodate for the cross-crash heterogeneities, which is normally distributed with mean of zero and variance σ^2.

In the model specification, of most interest is to define $\theta_{i[m]}$, the predictor for injury severity of the individual vehicle involved in a two-vehicle crash. Ideally, given all other factors equal, the injury severity is dependent on the difference between defensive ability of struck vehicle and attacking impact of striking vehicle. This defines the two key vehicle-safety-performance indices: Crash Worthiness Index (CWI) and Crash Aggressivity Index (CAI). Most of the previous concerns for vehicle safety in practice are only focused on CW, i.e. how a vehicle can protect its own occupants. However, very little attention has been paid to CA, i.e. how hazardous the vehicle could injure the occupants in the counterpart vehicle in the same crash. Accordingly, we define the $\theta_{i[m]}$ as,

$$\theta_{i[1]} \sim \mathrm{CAI}_{i[2]} - \mathrm{CWI}_{i[1]} + \mathrm{control} \quad \mathrm{variable}$$

$$\theta_{i[2]} \sim \mathrm{CAI}_{i[1]} - \mathrm{CWI}_{i[2]} + \mathrm{control} \quad \mathrm{variables}$$

Using this model, we will be able to establish both CWI and CAI for any vehicle with its historic crash data. This could, of course, be used to analyze results from collision experiments to test the safety performance of different vehicle designs.

The selection for control variables is very important as they are presumably able to filter external effects apart from vehicle configurations on injury severity. For example, since elderly may be more vulnerable than the youth to sustain an injury from collision of the same level, driver age should be controlled. Collision type and collision relative speed may also be controlled as different type and speed of collision may lead to different injury levels for occupants in even the same vehicle type. It should be noted that the selection of control variables could be case-specific and also depends on data availability. Following sections of this paper illustrate the method