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USING ACCIDENT OBSERVATIONS TO EVALUATE REAR END ACCIDENT RISK AT FOUR-LEGGED SIGNALIZED INTERSECTIONS

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Abstract

Based on the microscopic analysis of the vehicle movements before a rear end collision, the occurrence of rear end accidents is considered to have two indispensable premises in this study - one is the encountering of an obstacle vehicle, and the other is that the forthcoming vehicle driver failed to avoid the collision. Rear end accident risk is expressed as the product of the probability of the leading vehicle's deceleration and the probability of the following driver failed to response effectively. A negative binomial regression model for estimating rear end accident risk by using accident observations is developed, and several factors were found to affect rear end accident risk significantly.

INTRODUCTION

Traffic accidents are a heavy financial burden on the society. According to the estimation of Japan Association of Transportation Policy ("Social", 1994), total cost of traffic accidents in 1991 is as high as 5.03 trillion Japanese yen (about 40 billion US dollars). Although various countermeasures were adopted and a huge amount of money has been invested in order to achieve a safer road transportation all over the world, the traffic safety situation is still far from satisfactory.

In Japan, although many countermeasures against traffic accidents have been employed, traffic accidents are still increasing. While fatalities fluctuate around 10 thousands a year, traffic injuries keep on increasing since 1990. The record of casualty accident number, 720,880 in 1969, was reset by 761,789 in 1995, and was soon brushed up again by 771,084 in 1996 ("White", 1997). Moreover, the number of casualty accidents in 1996, the worst record so far, is about 70% more than that in 1977, with 460,649 casualty accidents occurred.

To stop the increasing trend of traffic accidents is an urgent task in Japan. The fact that about 58.7% of total accidents, or 44.7% of fatal accidents occurred in or near intersections in 1995, indicates that intersections are accident-prone areas. Effective countermeasures against intersection accidents are immediately needed. Our recongnition on the occurrence of intersection accidents, however, is still far from clear. As narrated by Japan Public Works Research Institute in its five year plan of traffic safety research, clearly identifiable black spots have been removed from Japanese highway system, the recent increase of accidents indicates that conventional countermeasures are not effective in reducing certain types of accidents and new comprehensive countermeasure against traffic accidents are urgently required ("Five-year", 1996).

Aimed at recognizing the relationship of accident risk and road environment related factors, more than 100 intersections were randomly selected and the disaggregated data were collected for this study. As rear end accident (in this paper, the term of "rear end accident" only indicates rear end accident of through traffic, those involved in turning are not included) is the most popular accident type accounting for about 28% of the total, this paper just focuses on evaluating REAR (rear end accident risk) based on the available data. Before developing the methodology for evaluating REAR from a microscopic perspective, previous works are briefly reviewed. As our modeling methodology requires quite disaggregated data, we will discuss the matter of data collection specifically. This is followed by a presentation of model estimation and findings. Whether data correlation problem has seriously affected our estimation results will be addressed as well. In the last section, this study is summarized and further works are recommended.

PREVIOUS WORKS

Most of the previous works have dealt with modeling relationships between accident number and geometric/road-environment elements. Methods often adopted are linear regression, Poisson regression and negative binomial regression. For example: Resende *et al* (1997) used traffic flow, median width and surface rating to predict accident number on rural interstate highways by linear equation. Hyodo *et al* (1993) studied the effects of landuse, and highway geometric factors on aggregated accident number of a region based on GIS oriented data by Poisson regression model. Shankar *et al* (1995) developed a negative binomial regression model for evaluating the impacts of road geometric and environment related factors on rural freeway accident frequencies. Concerning to the fitness of the models, several studies (e.g. Miaou *et al*, 1993; Wang *et al*, 1997) have addressed this matter. They concluded that despite of the lack of random features, linear models are very easy to be constructed and understood, it might be suitable for long interval and large sample data. Poisson model possesses most of the desirable features in describing vehicle accident events - discrete, nonnegative and random. The problem of Poisson models is that the requirement of the mean equaling to the variance is hardly met by most of the collected data. If data is overdispersed (i.e. the variance of accident frequency data is greater than its mean), Poisson model will result in biased coefficients and erroneous standard errors. A plausible way to deal with overdispersed data is to use negative binomial distribution model. Shankar *et al* (1995) and Poch *et al* (1996) have addressed the overdispersion issue by using negative binomial regression.

Although most of the previous studies did not directly focus on the analysis of REAR at intersections, they have provided methodological insights on evaluating intersection accident risk. Hauer *et al* (1988) clearly classified intersection vehicle-to-vehicle accidents into 15 types according to the vehicle movements before collisions. Also, the frequency of each accident type is attributed to the relevant traffic flows. This classification provided a microscopic perspective in analyzing intersection vehicle-to-vehicle accidents. Besides the impacts of the related traffic flow on accident frequency, Poch *et al* (1996) further studied the effects of intersection approach conditions on accident frequency as well. Negative binomial regression models were developed for calculating various types of accidents. Their work advanced a reasonable method for modeling intersection rear end accident risk.

METHODOLOGY OF THIS STUDY

The necessity of evaluating vehicle-to-vehicle accident risk

When evaluating the effects of a countermeasure, we need to know how will accident risk change due to the countermeasures. Accident risk here, measured by accident number per vehicle-year, indicates the possibility for a driver to be involved in an accident when passing an intersection. As we have known, road traffic constitutes an organic system, in which human beings, roads, and vehicles are always in interaction with one another. The occurrence of traffic accidents are known to be related with three categories of factors as shown in Figure 1, in which, (1), (2) and (3) indicate vehicle, human and road environment factors respectively while (4), (5), (6) and (7) shows the overlapped parts of the categories. Since the occurrence of accidents is normally an integrated effect of all the three, a study of accident risk must consider the three groups simultaneously.

For a certain intersection, the observed accident number is normally correlated strongly to its traffic volume as the case of Denenchofu area (R^2=0.81) shown in Figure 2. This sometimes gives us the illusion that accident number can be explained by using only traffic flow. Models describing the relationship between accident number and traffic volume may fit well for the specific situations under which they are developed, but once they are transferred to a different situation, the result is normally poor since accident risk is not only decided by traffic flow. If, however, we know the relationship between accident risk and various kinds of accident causal factors, we can easily predict accident number according to traffic volume and accident risk. To simplify the situation, here we assume REARs are equal for all drivers. Then observing the rear end accidents is just like making Bernoulli trials – if we do more, we can observe more. Therefore to evaluate accident risk properly is quite significant for improving traffic safety.

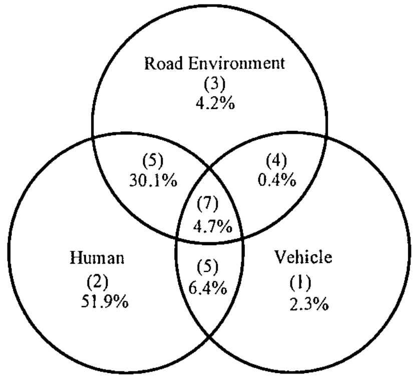

Figure 1 - Accident causal factors and their accounts
Data source: Kontaratos (1974)

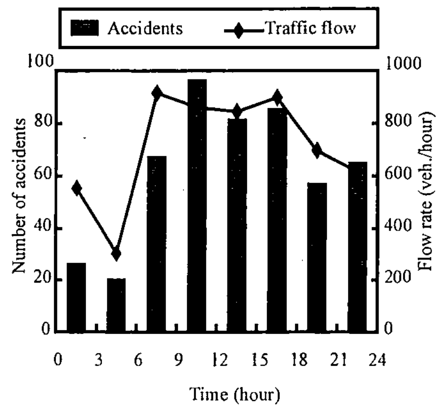

Figure 2 - The relationship of accident number and hourly traffic volume in Denenchofu area

The mechanism of accident occurrence

To evaluate accident risks properly, we need to further analyze how do accidents occur. Fridstrom *et al* (1996) pointed that random causal factors ("noise", "disturbance") had a decisive effect on accident occurrence at a microscopic level. Despite the specifics of different accident types, the occurrence of accidents is considered to be based on two premises in this study, one is the encountering of an obstacle vehicle, and the other is that the forthcoming vehicle driver failed to avoid the collision. Obstacle vehicles are usually due to the emerging of "disturbances". A disturbance here can be anything that can interrupt the smooth moving of traffic flow. In the case of rear end accidents, disturbances can be signal-disregarding pedestrians, right-turn vehicles (please note that vehicles go along the left side in Japan), red signal and so on. If the emergence of a disturbance has caused the deceleration/stop of the leading vehicle, then the leading vehicle became an obstacle vehicle for the following vehicle. The following vehicle, also called as the forthcoming vehicle, has to adopt some measure to avoid the collision. If the following vehicle driver fails to avoid the collision, a rear end accident will occur. To illustrate the concept, a flow chart of rear end accident type is given in Figure 3.

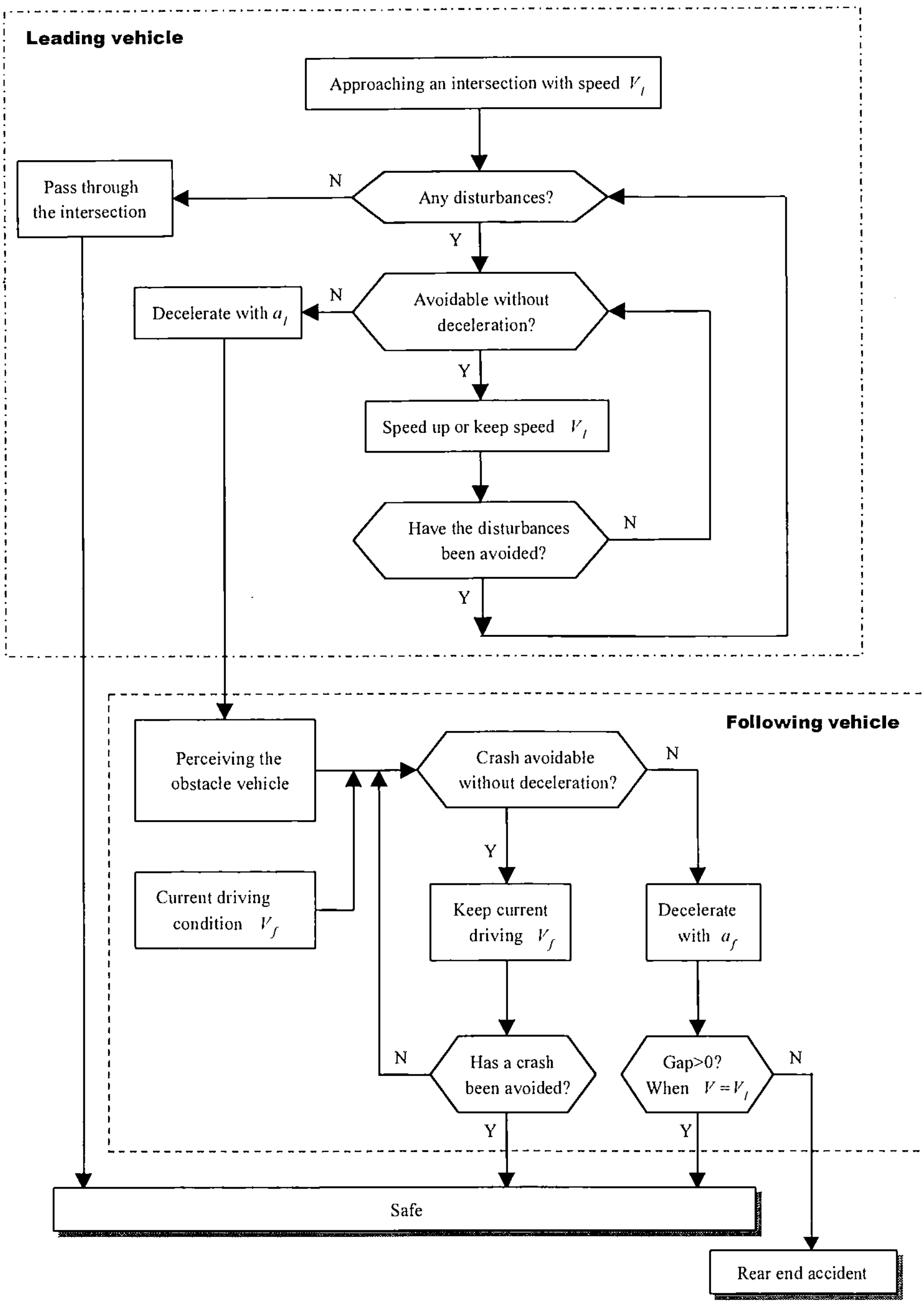

Figure 3 – Flow chart of intersection rear accident occurrence

We can see that drivers' performance, when passing through an intersection, consists of three successive procedures: the first is to perceive the change of traffic environment; the second is to make a decision for dealing with the change; and the third is to carry out the maneuver. Factors affecting drivers' abilities of perceiving, thinking and acting will definitely affect accident risk. Another important side affecting intersection safety is how often will a driver encounter an obstacle vehicle. This is closely related to the frequency of disturbance emergence. Maybe you have the experience to see that, in a "prosperous" commercial area, there are some signal-disregarding pedestrians, or in the evening, when traffic density is low, some drivers are found to run a red signal. All those examples are implying some relationship between disturbances and their influencing factors. Reducing the frequency of disturbances is also a very important measure for improving intersection safety.

Modeling approach

Following the logic presented, a rear end accident is caused by both the braking of the leading vehicle and the "ineffective" response of the following driver. Considering a vehicle negotiating an intersection, the probability of having a rear end accident is decided by both the probability of encountering an obstacle vehicle, denoted by P_o, and the probability of the forthcoming vehicle driver failed to avoid the collision, denoted by P_f. As P_o and P_f are normally independent, rear end accident risk of the vehicle (P_{RE}) can be expressed as their product. That is:

$$P_{RE} = P_o \cdot P_f \tag{1}$$

As we do not know the exact forms of P_o and P_f, empirical log link functions are adopted as the following:

$$\ln(P_d) = \beta_d \mathbf{X}_d \quad \text{and} \quad \ln(P_f) = \beta_h \mathbf{X}_h \tag{2}$$

where X_d and X_h are vectors of explanatory variables for P_o and P_f respectively, and β_d and β_h are the vectors of the corresponding unknown parameters to be estimated. Then REAR can be expressed as

$$\ln(P_{RE}) = \beta_d \mathbf{X}_d + \beta_h \mathbf{X}_h = \beta \mathbf{X} \tag{3}$$

where β=(β_d, β_h) and X=(X_d, X_h)'.

To simplify the problem, we assume all the vehicle pairs within a traffic flow have the same accident risk. Then, number of accidents that occurred within this flow follows binomial distribution:

$$P(n) = \binom{f}{n} P_{RE}^{n} (1 - P_{RE})^{f-n} \tag{4}$$

where f: through traffic volume of the entering approach
n : number of rear end accidents occurred.

The expectation and variance of binomial distribution are given in formulae (5) and (6) respectively:

$$E(n) = f \cdot P_{RE} \tag{5}$$

$$V(n) = f \cdot P_{RE} \cdot (1 - P_{RE}) \tag{6}$$

Since we know that an accident is very rare case, P_{RE} is normally very small and traffic volume f is very large, Poisson distribution is a good approximation to binomial distribution (Pitman, 1993):

$$P(n) = \frac{m^n \cdot \exp(-m)}{n!} \tag{7}$$

with Poisson distribution parameter

$$m = f \cdot P_{RE} = f \cdot \exp(\beta \mathbf{X}) \tag{8}$$

Poisson distribution has been commonly used in predicting accident number. Due to the features of nonnegative, discrete and random, Poisson model is usually the first choice when modeling traffic accidents. Poisson model, however, has only one parameter, and this requires the expectation and variance to be equal. As most accident data are likely to be overdispersed, the applicability of a Poisson model is therefore limited. An easy way to overcome this difficulty (i.e. the mean must be equal to the variance), is by adding an error term, ε, to the link function as shown by Formula (9). That is:

$$\ln m = \ln(fP_{RE}) + \varepsilon \tag{9}$$

Assume $\exp(\varepsilon)$ is a Gamma distributed variable with mean 1 and variance α. Substitute m in Formula (7) by Formula (9), we have

$$P(n \mid \varepsilon) = \frac{\exp(-fP_{RE}\exp(\varepsilon)) \cdot (fP_{RE}\exp(\varepsilon))^n}{n!} \tag{10}$$

Integrating ε out of Formula (10), we can directly derive negative binomial distribution as the following:

$$P(n) = \frac{\Gamma(n+\theta)}{\Gamma(n+1)\Gamma(\theta)}\left(\frac{\theta}{f \cdot P_{RE} + \theta}\right)^{\theta}\left(\frac{fP_{RE}}{f \cdot P_{RE} + \theta}\right)^{n} \tag{11a}$$

where $\theta = 1/\alpha$. To write Formula (11a) in a more general way, we use subscript i to denote time category (year in this study), j to denote intersection code and k to denote leg number, then the probability of having certain number of accidents at the k^{th} leg of the j^{th} intersection in year i, n_{ijk}, can be expressed as:

$$P(n_{ijk}) = \frac{\Gamma(n_{ijk}+\theta)}{\Gamma(n_{ijk}+1)\Gamma(\theta)}\left(\frac{\theta}{f_{ijk} \cdot P_{REijk} + \theta}\right)^{\theta}\left(\frac{f_{ijk}P_{REijk}}{f_{ijk} \cdot P_{REijk} + \theta}\right)^{n_{ijk}} \tag{11b}$$

The expectation of this negative binomial distribution equals to the expectation of Poisson distribution as shown in Formula (8). Its variance is changed to be

$$V(n_{ijk}) = E(n_{ijk})[1 + \alpha E(n_{ijk})] \tag{12}$$

Since α can be larger than 0, the restraint of the mean equal to the variance in Poisson model is released. Therefore, negative binomial distribution can deal with the overdispersed data.

REAR, P_{REijk}, can be estimated by using MLE method. In this study, annual rear end accident data were used for the estimation of REAR model. Combining Formulae (3) and (11b), we can get

$$P(n_{ijk}) = \frac{\Gamma(n_{ijk}+\theta)}{\Gamma(n_{ijk}+1)\Gamma(\theta)}\left(\frac{\theta}{f_{ijk} \cdot \exp(\beta \mathbf{X}_{ijk}) + \theta}\right)^{\theta}\left(\frac{f_{ijk} \cdot \exp(\beta \mathbf{X}_{ijk})}{f_{ijk} \cdot \exp(\beta \mathbf{X}_{ijk}) + \theta}\right)^{n_{ijk}} \tag{13}$$

Log-likelihood function can be derived straight forward as

$$\varphi(\beta) = \sum_i \sum_j \sum_k \ln\left[\frac{\Gamma(n_{ijk}+\theta)}{\Gamma(n_{ijk}+1)\Gamma(\theta)}\left(\frac{\theta}{f_{ijk} \cdot \exp(\beta \mathbf{X}_{ijk}) + \theta}\right)^{\theta}\left(\frac{f_{ijk} \cdot \exp(\beta \mathbf{X}_{ijk})}{f_{ijk} \cdot \exp(\beta \mathbf{X}_{ijk}) + \theta}\right)^{n_{ijk}}\right] \tag{14}$$

Formula (14) is used to estimate β - the unknown parameter vector of the REAR model. If our estimation gives α significantly different from 0, Poisson model is inappropriate in this specific problem and negative binomial is the correct choice.

DATA COLLECTED

To estimate REAR model, we need quite disaggregated data of each of the four approaches (i.e. eastbound, southbound, westbound and northbound) of an intersection, such as average daily through, left turn, and right turn traffic volumes, rear end accident number, traffic regulation, geometric and environment related factors and etc.

About 150 four-legged signalized intersections were randomly selected within Metropolitan Tokyo at the beginning of this study. This selection was based only on the consideration of intersection size, surrounding landuse pattern, and the crossing angle (be it vertical or skewed) of the approaches. Intersection accident history was not considered. The purpose of this selection was to choose the samples representing the normal situation of intersection traffic safety. Since the existing accident database could not meet our needs, accident data had to be rearranged by checking the original accident records according to the registered code. Four years' data, from 1992 to 1995, were collected for this study. Unfortunately, many original records could not be found and the number of sample intersections was reduced to 116. The unit of observation is defined as an intersection approach in this study. In total we have 1856 observations, within which 1,105 were qualified for REAR model estimation (those with through traffic ban or incomplete data were excluded). In our discussion, we often use terms like entering approach, opposite approach and so on. The illustration of these terms can be found in Figure 4.

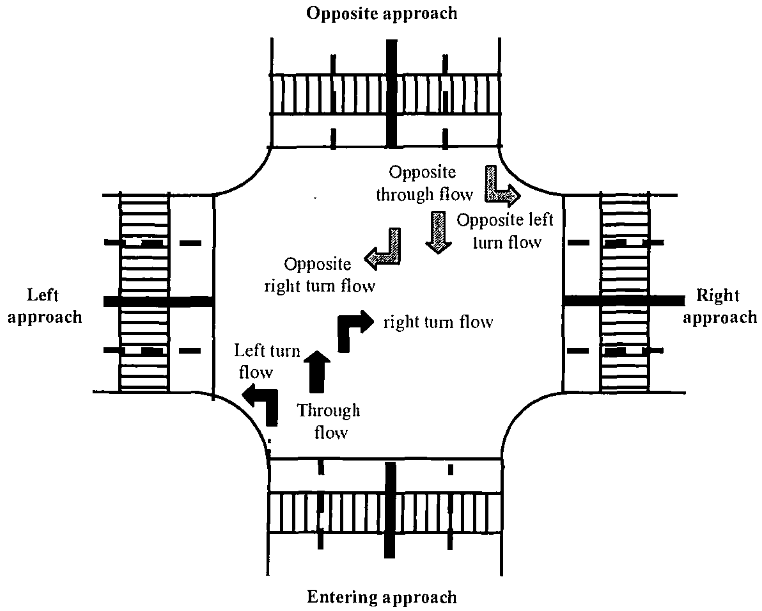

Figure 4 - Terms of Intersection legs and flows

Only police recorded traffic accident data were collected in this study. Accidents caused by pure human error, such as drunkenness or dozing while driving, are beyond our consideration. All the applicable rear end accidents were cataloged according to their movements before the collisions, and assigned to the corresponding approach, to which the involved vehicles belong.

Traffic flow data came from the annual site survey reports ("Traffic", 1992-1995) conducted by Tokyo Metropolitan Police Department and highway sensors' data ("Report", 1997). Traffic control information and safety improvement history data are collected from corresponding documents. Road and environment related factors are selected according to the findings of the previous studies and our logical inference. For example, Miura (1992) studied the effect of driving environment on drivers' behavior and found that with the increasing complexity of driving environment, response eccentricity (size of functional field of view) decreases and reaction time increases. This means that the increased amount of information for processing significantly lengthens drivers' perception reaction time. To reflect the effect of information quantity to be processed while passing an intersection, an index of visual noise level (values ranging from 0 to 4) is adopted in this study. To evaluate the level, a site survey for 30 intersections (120 approaches) was conducted. Surveyors were required to judge the visual noise level of the surveying approaches according to the description in Table 1. The investigated data were regressed with respect to the officially published map data - land use type (values ranging from 0 to 5) and building density (values ranging from 0 to 10) along the street, and multiple correlation index R^2 was found as high as 0.92. Therefore, visual noise level for the remaining intersection approaches were estimated by the regressed function.

Table 1 - Description of visual noise level classification

Level 0	areas of isolated residential houses and factories;
Level 1	residential areas of concentrated multistory residential houses;
Level 2	public residential areas and general office districts;
Level 3	concentrated office areas or near a railway station;
Level 4	the most prosperous commercial areas or the area with two or more railway stations concentrated.

For each observation, a total of 72 possible explanatory variables, affecting either the probability of leading vehicle's deceleration, P_o, or the probability of the following driver failed to avoid a collision, P_f, were collected or converted from other variables.

MODEL ESTIMATION AND FINDINGS

Unknown parameters were estimated by maximum likelihood estimation method using the log-likelihood function shown by Formula (14). Of the 72 explanatory factors, 16 were found significantly affect REAR at a level of p=0.15. Summary of the estimation is presented in Table 2. Likelihood ratio index, ρ^2, showing the fitness of negative binomial regression model in this study is 0.23. This is a fairly good result as ρ^2 is generally lower than typical R^2 values in multiple linear regression. The estimated coefficient values and their corresponding t-ratios are given in Table 3.

Table 2 - Summary of REAR model estimation

Number of observations	1105
Log-likelihood with constant only (coefficients of explanatory variables are set to zero): $\psi(C,\theta)$	-1189.50
Log-likelihood at convergence: $\psi(\beta,\theta)$	-910.60
Likelihood ratio index * ρ^2	0.23

* note: likelihood ratio index is calculated as $1-\psi(\beta,\theta)/\psi(C,\theta)$.

Turning vehicles, including both right-turn and left-turn, were found to increase accident risk. This is possibly because (1) turning vehicle number is proportional to the lane change frequency which will increase the probability of leading vehicle deceleration; (2) their waiting for turning restricts other drivers' sight distance and hence increase the possibility of response failure; (3) for approaches without specific turning lane, turning vehicle number will increase the stop frequency of through traffic. Right-turn volume of opposite approach also increases REAR as the estimated coefficient is 0.024. This can be explained by the conflicts between through traffic and opposite right-turn traffic. More conflicts will definitely increase the probability of leading vehicle's deceleration, and therefore increase REAR. If signal control is changed from 2-phase to 4-phase control, potential conflict points in the intersection will be reduced and therefore REAR will go down. Approaches with a higher speed limitation (more than 50 km/h) are more dangerous as rear end accident severity is directly related to vehicle's speed. Our estimation results of signal control and speed limitation also support our judgements.

Table 3 - Negative binomial estimation result of REAR model

Parameter	Estimated coefficients	*t*-ratio	Elasticity
Constant	-4.237	-6.12	----
Angle of entering approach and left-turn approach (0 if within 75 to 105 degree, 1 otherwise)	0.294	2.40	----
Pedestrian overpass at left approach (1 if there is, 0 otherwise)	-0.481	-1.65	----
Right-turn volume in thousands of the opposite approach	0.024	1.07	0.006
Signal control pattern (1 for 4 phase control, 0 for 2 phase control)	-0.253	-1.43	----
Average time headway in seconds of entering approach's through traffic flow	-0.036	-2.07	-0.375
Angle of entering approach and opposite approach (0 if within –15 to 15 degree, 1 otherwise)	0.211	1.19	----
Average daily left-turn volume in thousands	0.064	2.58	0.043
Pedestrian overpass of the entering approach (1 if there is, 0 otherwise)	-0.793	-2.59	----
Speed limit (1 if larger than 50, 0 otherwise)	0.385	1.41	----
Average daily right-turn volume in thousands	0.095	3.58	0.222
Average time headway in seconds of the opposite through traffic flow	0.474	4.09	1.500
Level of visual noise (five levels from 0 to 4)	0.145	1.62	---
Lane number of entering approach	-0.037	-1.89	---
Intersection location (1 if in central business district (CBD), 0 otherwise)	-0.359	-2.21	----
The existence of fence median (1 if there is, 0 otherwise)	-0.218	-1.71	----
Percentage of large vehicles	0.018	1.58	0.217
α (Negative binomial dispersion parameter)	0.610	4.42	----

The existence of pedestrian overpass or fence median at the entering approach reduces REAR according to our estimated results in Table 3. This can be attributed to the reduced frequency of deceleration caused by illegal crossing pedestrians. What might be difficult to understand are that lane number of entering approach decreases REAR and average time headway of the opposite through traffic increases REAR in our estimation. Again this can be explained by their effects on pedestrian behaviors. The probability of a pedestrian disregarding a red signal is related to the available crossing interval as well as the time needed for crossing (Imada 1990). Crossing time is proportional to road width (measured by lane number here), and available crossing time is inverse proportional to the time headway of opposite through traffic when headway of entering approach is fixed.

Time headway, visual noise level and large vehicle percentage are related to the probability of response failure. If the time headway is longer, the following driver has sufficient time to response when the leading vehicle decelerates. Thus his/her failure chance will become lower. Visual noise level was found increase REAR as visual noise detracts drivers from paying enough attention to driving. Large vehicles, including bus and various trucks, can seriously restrict the following drivers' sight distance. This makes the following drivers perceive the forthcoming danger late and therefore increase their failure probability. Our estimated results of these three factors also consist with our analysis.

Many previous works (Wang *et al* 1997, Amano 1982) have shown that intersections with irregular forms have higher accident rate per million entering vehicles. In our REAR model, the angles, either between left turn approach and entering approach or between opposite approach and entering approach, increase REAR because drivers' action accuracy decreased due to their unfamiliarity to drive under the specific intersection. The existence of overpass at left turn approach affects REAR, but indirectly. If opposite right turning vehicles are often stopped due to the crossing pedestrians, the smooth moving of through traffic will also be interrupted. Therefore, the existence of pedestrian overpass at left turn approach can reduce REAR as shown in Table 3.

Our finding that intersections located in central business district (CBD) have lower REAR is a little different from our imagination. Poch *et al* (1996) got the same result when analyzing intersection rear end accident frequency using negative binomial regression. They attributed this result due to the progressive signal control in CBD. This is, of course, also a reasonable explanation for the result in this study. Besides, the persistent efforts in improving traffic safety situation and strict superintendence in CBD might have resulted in some behavior change unable to be reflected in this model.

Together with the coefficients, elasticity of variables with continuous values was also estimated as shown in Table 3. The elasticity of variable X_l, e_l, is defined as:

$$\frac{dP_{RE}}{P_{RE}} = e_l \cdot \frac{dX_l}{X_l} \tag{15}$$

Using Formula (3) and (15) gives

$$e_l = \beta_l X_l \tag{16}$$

The elasticity of a variable is a direct measure of the effect of the variable. For example, the elasticity of average time headway, -0.375, indicates that if average time headway increase 1%, REAR will reduce 0.375%. Elasticity of dummy variables was not calculated, as they do not have any meaning.

Negative binomial dispersion parameter was found to be 0.610 with t-ratio as high as 4.42. This indicates that Poisson regression is not suitable in this study.

A DISCUSSION ON THE DATA CORRELATION PROBLEM

Although the applied observations for model estimation are not exactly the same set from year to year due to the missing of accident data, the correlation problem caused by the repeat use of same road environment data is still of our concern, since only few of the road environment related factors have been changed within these four years. Thus the gamma error term in the negative binomial model could be correlated from one observation to the next, which is a violation of the error-term independence assumption made to derive the model. As pointed by Poch *et al* (1996), the consequence of non-independence of error terms is a loss in estimation efficiency (i.e. standard errors of estimated coefficients will become larger), and this could lead one to draw erroneous conclusions regarding coefficient estimates. Similar to the test conducted by Poch *et al* (1996), a series of likelihood ratio tests are also employed in this study. The basic idea of the tests is to segment the sample into subsets of data that are less likely to be afflicted correlation problems. If these smaller data subsets produce model estimation results that are not significantly different from those produced by the overall data sample, it can be concluded that any independence violations are not significantly affecting model results. The procedure of making this test is as follows.

Data are segmented into four subsets according to the observed year. Total sample N should be equal to the sum of subset sample N_g, g=1,2,3,4. For testing purpose the likelihood ratio statistic is

$$-2[\varphi_N(\beta)-\sum_{g=1}^{4}\varphi_{N_g}(\beta_g)] \tag{17}$$

where $\varphi_N(\beta)$ is the log-likelihood at convergence of the model estimated on all data N with a single coefficient vector β; and $\varphi_{N_g}(\beta_g)$ is the log-likelihood at convergence of the model estimated on the gth subset of the data. This test statistic is χ^2 distributed with the degrees of freedom equal to

$$\sum_{g=1}^{4} K_g - K \tag{18}$$

where K_g equal to the number of coefficients in the gth data subset model; and K is the number of coefficients in the full sample model. Since we have 18 parameters in REAR model, the degree of freedom is 54 according to Formula (18). The tested results are shown in Table 4.

Table 4 - Test for the effects of correlated road environment related factors

Group (Year)	$\varphi_N(\beta)$ 4 years	$\varphi_{N_1}(\beta_1)$ 1992	$\varphi_{N_2}(\beta_2)$ 1993	$\varphi_{N_3}(\beta_3)$ 1994	$\varphi_{N_4}(\beta_4)$ 1995	χ^2	Degree of freedom	p-value
Log-likelihood	-910	-183	-220	-236	-249	44	54	0.83

The test result in Table 4 shows that we have only 17% confidence to say the correlation among observed years is significantly affecting our estimation results.

In our modeling, we assumed that the error term, exp(ε), is Gamma distributed. Whether or not it is Gamma distributed may also affect our estimation results. Lawless (1987) compared the effects of error terms with various distribution and concluded that the assumption of exp(ε) being Gamma distributed does not lead biased estimation.

SUMMARY

When evaluating the effects of a countermeasure, we need to know how will accident risk change due to the countermeasure. Different from most of the previous studies, this study focus on the evaluation of accident risk rather than accident number. If the effects of explanatory factors on intersection accident risk is obtained, we might be able to find some efficient measures to improve intersection traffic safety. Based on the microscopic analysis of the vehicle movements before a rear end collision, the occurrence of rear end accidents is considered to have two indispensable premises in this study - one is the encountering of obstacle vehicle, another is the response failure of the forthcoming vehicle driver. Accident risk is expressed as the product of the probability of encountering an obstacle vehicle (P_o) and the probability of the forthcoming vehicle driver failed to response effectively (P_f). Empirical link functions were adopted to relate factors affecting leading vehicle's deceleration and following drivers' response to P_o and P_f respectively. A negative binomial regression model for assessing REAR was developed and successfully estimated by using MLE. Several factors were found to affect REAR significantly.

Although only REAR model is estimated in this study, the same method can be applied to other types of accidents as well. Besides, further works for exploring the actual forms of P_o and P_f should also be put into action as to understand properly the effects of various controllable factors on P_o and P_f is very important for the practice of safety improvement at intersections.

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