Estimating the Risk of Collisions between Bicycles and Motor Vehicles at Signalized Intersections

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Abstract. Collisions between bicycles and motor vehicles have caused severe life and property losses in many countries. The majority of bicycle-motor vehicle (BMV) accidents occur at intersections. In order to reduce the number of BMV accidents at intersections, a substantial understanding of the causal factors for the collisions is required. In this study, intersection BMV accidents were classified into three types based on the movements of the involved motor vehicles and bicycles. The three BMV accident classifications were through-motor vehicle related collisions, left-turn motor vehicle related collisions, and right-turn motor vehicle related collisions. A methodology for estimating these BMV accident risks was developed based on probability theory. A significant difference between this proposed methodology and most current approaches is that the proposed approach explicitly relates the risk of each specific BMV accident type to its related flows. The methodology was demonstrated using a four-year (1992-1995) data set collected from 115 signalized intersections in the Tokyo Metropolitan area. This data set contains BMV accident data, bicycle flow data, motor vehicle flow data, traffic control data, and geometric data for each intersection approach. For each BMV risk model, an independent explanatory variable set was chosen according to the characteristics of the accident type. Three negative binomial regression models (one corresponding to each BMV accident type) were estimated using the maximum likelihood method. The coefficient value and its significance level were estimated for each selected variable. The negative binomial dispersion parameters for all the three models were significant at 0.01 levels. This supported the choice of the negative binomial regression over the Poisson regression for the quantitative analyses in this study.

Key words: bicycle accidents, traffic safety, signalized intersections, negative binomial regression

INTRODUCTION

Collisions between bicycles and motor vehicles have caused severe life and property losses in many countries. Fazio and Tiwari (1995) reported that bicycle-motor vehicle (BMV) accidents killed 116 people, or more than 10 percent of all traffic accident fatalities in Delhi in 1993. In Japan, more than 1,000 people have died each year in BMV accidents since 1988 (Institute for Traffic Accident Research and Data Analysis, 2000). This has accounted for about 10 percent of all traffic fatalities each year. The BMV-accident-resulted fatality rate is even higher in Tokyo. Of the 359 traffic accident fatalities, 53 (14.8 percent) died in BMV accidents in Tokyo in 2000 (Tokyo Metropolitan Police Department, 2001). More seriously, in Beijing, about 38.7 percent of traffic accident fatalities died from BMV collisions and nearly 7 percent of all traffic accidents were related to bicycles (Liu *et al*, 1995).

Intersections are definitely high-risk locations for BMV collisions because of the frequent conflicts between bicycle flows and motor vehicle flows. According to Traffic Safety Facts 2000 (US Department of Transportation, 2001), 32.6 percent of fatal accident and 56.6 percent of injury BMV collisions occurred at intersections in the US. Wachtel and Lewiston (1994) studied bicycle accidents in Palo Alto from 1981 to 1990, and found that 233 of the 314 reported BMV collisions (64 percent) took place at intersections. According to the Tokyo Metropolitan Police Department (2001), approximately 18 percent of all casualty accidents at intersections were BMV accidents. These figures indicate that special attention should be given to intersection BMV accidents.

Gårder (1994) analyzed the causal factors for bicycle accidents with data collected from 1986 to 1991 in Maine. He found that about 57 percent of intersection BMV collisions involved turning movements of motor vehicles. He also concluded that bicycle riders were at fault for most of the reviewed BMV collisions. Summala *et al* (1996) carefully studied the motor-vehicle driver's searching behaviors at non-signalized intersections and found that speed-reducing measurements, such as speed bumps, elevated bicycle crossings and stop signs, help drivers to begin searching earlier and detect bicycles properly. Wachtel and Lewiston (1994) specifically analyzed the effects of age, sex, direction of travel, and road position on intersection BMV collisions. Gårder *et al* (1994) reviewed previous studies on bicycle accident risks and applied the Bayesian method to estimate the change in accident risk for bicycle riders when a bicycle path is introduced in a signalized intersection. They stated that conclusions from previous studies were fairly confusing, and few reviewed studies from the Scandinavian countries were conducted with acceptable methodologies. They attributed these conflicts to the absence of several important factors associated with specific intersections and emphasized the importance of considering the detailed intersection design when studying bicycle accidents.

To quantitatively consider the factors associated with specific intersection designs in risk models, new modeling techniques and more detailed data are needed. Though the conventional black spot identification method, which marks the location of each accident with a pin on a map and labels locations with the most pins as "black spots", is an efficient way to identify high frequency accident sites, it does not provide any sufficient help in understanding accident causes. Without a proper understanding of accident causes, safety resources may be misused, and countermeasures may be ineffective. Hauer (1986) points out that a simple count of accidents is not a good estimate of safety and suggests estimating the expected value of accidents as a better alternative. Hauer *et al* (1988) demonstrated the effectiveness of this idea by classifying intersection vehicle-to-vehicle accidents into 15 patterns according to the movements of the involved vehicles before collision. They estimated the means for four major types of collision patterns using the flows involved in each collision type. Wang (1998) used a similar classification for accidents at signalized intersections and successfully estimated the risks of rear-end and angle accidents (corresponding to pattern 1 and 6, respectively, in the classification by Hauer *el al* (1988)) with a modified negative binomial regression. Summala *et al* (1996) classified bicycle accidents at non-signalized T intersections into 8 types and analyzed the visual search tasks involved in the major types of movements. Such detailed classifications clearly connect each type of accident to its related flows and environmental factors, and, therefore, make models and explanations more perceptive.

In this study, BMV collisions at four-legged signalized intersections are classified into three types: through motor vehicle related collisions, left-turning motor vehicle related collisions, and right-turning motor vehicle related collisions. Data used for this study were collected from 115 randomly selected intersections in the Tokyo Metropolitan area. For each of the three BMV accident types, the expected accident risk is estimated by the maximum likelihood method using the negative binomial probability formulation. Since traffic travels along the <u>left side</u> of the roadway in Japan, special attention is needed when interpreting the descriptions for countries where traffic travels along the right side.

BICYCLE-MOTOR VEHICLE ACCIDENT CLASSIFICATION

Typically, a BMV collision involves one motor vehicle and one bicycle. In Japan, bicycles share roads with pedestrians rather than motor vehicles. Thus, a BMV accident is most commonly happened when a bicycle is crossing an intersection approach via the bicycle channel, while a motor vehicle is making any of the three possible movements: through, right turn, or left turn. Intersection BMV accidents are, therefore, classified into three types based on the movements of the involved motor vehicles:

(1) BMV-1: BMV accident type 1. Collisions between bicycles and through motor vehicles;

(2) BMV-2: BMV accident type 2. Collisions between bicycles and left-turning motor vehicles; and

(3) BMV-3: BMV accident type 3. Collisions between bicycles and right-turning motor vehicles.

Fig. 1 illustrates these three accident types.

Any BMV accident can be easily classified according to the movement of the involved motor vehicle. For BMV-1 accidents, collisions can occur before motor vehicles enter an intersection or before they exit the intersection. Since the collision styles are very similar, we consider these two collision situations together in BMV-1. We believe that the causal factor set for each BMV accident type is different, and an obvious advantage of using such a classification is the capability of independently identifying the causal factors to each specific BMV accident type.

DATA

About 150 four-legged signalized intersections were randomly selected in the Tokyo Metropolitan area at the beginning of this study. The selection was based on intersection size, surrounding land use pattern, and intersection shape (crossing angles, vertical or skewed, of the approaches). Intersection accident histories were not considered. The purpose of the random selection was to obtain samples representing normal situations of intersection traffic safety in Tokyo.

The BMV accident classification described in the previous section requires observation aggregation at intersection approach level rather than at intersection level (i.e. we need to know the accident number of each BMV type for each approach of an intersection rather than just the total number for the entire intersection). However, BMV accident data in the existing accident databases were, without exception, aggregated at the intersection level and without further classification into the three BMV types. Obviously, such databases are not directly useful for our study. Consequently, we had to design a new accident database and conduct data collection work to satisfy our specific study requirements. The new database recorded approach-level observations, including numbers of BMV-1, BMV-2, and BMV-3 accidents, traffic volumes of through, left-turn, and right-turn flows, geometric data, etc, for each approach.

Our accident data collection team followed a rigorous approach to guarantee the quality of data. They first obtained the index numbers of accidents occurred during the years 1992 through 1995 from the databases of the Tokyo Metropolitan Police Department. Then, they used these index numbers to find the original accident records for details of the accidents. The original record of an accident included a collision site figure and a brief description of the accident. With the collision site figure, a BMV accident can be easily located and assigned to one of the three accident types. Since some of the original records were missing, the locations and types for some BMV accidents could not all be identified. Intersections with unknown BMV accidents were dropped from the study and the number of sample intersections was reduced to 115. The total number of accidents of each intersection was then compared with the summary statistics of Ministry of Construction for verification. There were a total of 2,928 accidents recorded for the 115 intersections during the four-year study period. 585 of them, or about 20%, were BMV accidents.

Motor vehicle flow data and bicycle volume data were obtained from reports of annual site surveys (Tokyo Metropolitan Police Department, 1992-1995), conducted by the Tokyo Metropolitan Police Department and from highway sensor data (Tokyo Road Construction Bureau, 1997). Traffic control information and safety improvement histories were extracted from the corresponding databases and documents of government agencies. Geometric data for the intersection approaches were collected from published maps and site surveys. To reflect the effect of the information quantity to be processed by drivers and bicyclists while passing an intersection, an index of visual noise level (from low to high, values ranging from 0 to 4) was adopted for this study. For details on how the visual noise level for each intersection approach was estimated, please refer to Wang (1998).

Our methodology requires the classification of intersection approaches based on the orientation of accident-involved motor vehicle flows. For each approach, there may be observations of BMV accidents directly caused by motor vehicles that enter the intersection from the approach. The approach where the involved motor vehicle enters the intersection is designated as the "entering approach". A number of BMV accidents of each type may be observed during the study period for each entering approach. The other three approaches are, clockwise, named the "left approach", "opposing approach", and "right approach". Each intersection BMV accident associates with an entering approach. When the entering approach changes, the designations for the other three approaches change correspondingly. The illustration of approach naming is shown in Fig. 2.

To help understand the data for this study, Table 1 provides summary statistics for selected continuous variables and Table 2 provides frequency results for selected dummy variables in the database. In Table 1, we see that the minimum values for motor vehicle flows are all zero. The major reason for these zero values is the traffic regulatory bans for certain movements. Obviously, such samples with specific regulatory bans lacked generality and needed to be excluded from this study. Consequently, the actual sample numbers applied to the model estimations were smaller than 460 (=115×4), and varied from type to type.

METHODOLOGY

Modeling the BMV-1 Accident Risk

For a given intersection i and its approach k, if the risk that a through motor vehicle will be involved in a BMV-1 accident is p_{1ik} (the subscript "1" corresponds to the type code for BMV accidents), then the number of BMV-1 accidents that may occur follows a binomial distribution. The probability of having n_{1ik} accidents is

$$P(n_{1ik}) = \binom{f_{1ik}}{n_{1ik}} p_{1ik}^{n_{1ik}} (1 - p_{1ik})^{f_{1ik} - n_{1ik}} \tag{1}$$

where i = intersection index;

k = approach index;

f_{1ik} = through motor vehicle volume of intersection i, approach k;

n_{1ik} = number of BMV-1 accidents involving vehicles in f_{1ik};

$P(n_{1ik})$ = probability of having n_{1ik} accidents.

p_{1ik} = BMV-1 accident risk for a motor vehicle in f_{1ik}.

Since it is quite rare to have a BMV-1 accident over the course of normal traffic flow, p_{1ik} is very small compared to traffic volume f_{1ik}. Thus, the Poisson distribution is a good approximation to the binomial distribution (Pitman, 1993) for BMV accident analyses, and Equation (1) can be approximated by:

$$P(n_{1ik}) = \frac{m_{1ik}{}^{n_{1ik}} \cdot \exp(-m_{1ik})}{n_{1ik}!} \tag{2}$$

Where the Poisson distribution parameter

$$m_{1ik} = E(n_{1ik}) = f_{1ik} \cdot p_{1ik} \tag{3}$$

and E(n_{1ik}) denotes the expected value of n_{1ik}.

Poisson distribution models are commonly used for accident prediction. They are usually the first choice when modeling traffic accidents because of the nonnegative, discrete and random features of accidents. A Poisson model, however, has only one distribution parameter, and requires that the distribution's expected value and variance be equal. In many cases, however, accident data are over-dispersed, and the applicability of Poisson models is seriously limited. An easy way to overcome this constraint (i.e. the mean must be equal to the variance) is to add an independently distributed error term, ε_{1ik}, to the log transformation of Equation (3) (Poch and Mannering, 1996). That is:

$$\ln m_{1ik} = \ln(f_{1ik} p_{1ik}) + \varepsilon_{1ik} \tag{4}$$

Assume exp(ε_{1ik}) is a Gamma distributed variable with mean 1 and variance δ_1. Substituting Equation (4) into Equation (2) yields

$$P(n_{1ik} \mid \varepsilon_{1ik}) = \frac{(f_{1ik} p_{1ik} \exp(\varepsilon_{1ik}))^{n_{1ik}} \cdot \exp(-f_{1ik} p_{1ik} \exp(\varepsilon_{1ik}))}{n_{1ik}!} \tag{5}$$

Integrating ε_{1ik} out of Equation (5), a negative binomial distribution model can be derived as follows:

$$P(n_{1ik}) = \frac{\Gamma(n_{1ik} + \theta_1)}{\Gamma(n_{1ik} + 1)\Gamma(\theta_1)} \left(\frac{\theta_1}{f_{1ik} \cdot p_{1ik} + \theta_1}\right)^{\theta_1} \left(\frac{f_{1ik} p_{1ik}}{f_{1ik} \cdot p_{1ik} + \theta_1}\right)^{n_{1ik}} \tag{6}$$

where $\theta_1 = 1/\delta_1$. δ_1 is often referred to as the negative binomial dispersion parameter. The expected value of this negative binomial distribution is equal to the expected value of the Poisson distribution shown in Equation (3). Its variance is

$$V(n_{1ik}) = E(n_{1ik})[1 + \delta_1 E(n_{1ik})] \tag{7}$$

Since δ_1 can be larger than 0, the constraint of the mean equaling the variance in the Poisson models is removed. If θ_1 is significant in our estimation, the negative binomial regression is appropriate. Otherwise, the Poisson regression should be the correct choice.

The BMV-1 collision risk, p_{1ik}, is explained by bicycle volume and a set of explanatory factors. It is non-negative and ranges from 0 to 1. Several functions that satisfy the above conditions were tested, and the researchers eventually selected Equation (8) as the BMV-1 accident risk model.

$$p_{1ik} = \frac{b_{1ik}}{b_{1ik} + \exp(-\boldsymbol{\beta}_1 \mathbf{X}_{1ik})} \tag{8}$$

Where b_{1ik} = volume of the bicycle flow directly involved in the BMV-1 accident at intersection i, approach k (this should be the sum of bicycle volumes crossing the entering approach and the opposing approach).

$\boldsymbol{\beta_1}$ = vector of unknown coefficients;

$\boldsymbol{X_{1ik}}$ = vector of explanatory variables at intersection i, approach k.

One important advantage of using Equation (8) is that it gives zero BMV-1 accident risk when there is no bicycle crossing the entering approach or the opposing approach, i.e. $p_{1ik} = 0$ when $b_{1ik} = 0$. Additionally, the sign of each estimated coefficient in vector $\boldsymbol{\beta_1}$ is consistent with the corresponding explanatory variable's effect on p_{1ik} – "+" indicates increasing effect and "-" indicates decreasing effect. This feature makes our estimation results intuitively appealing.

Substituting Equation (8) into Equation (6) and rearranging terms yields the final formulation for the probability of having n_{1ik} BMV-1 accidents as shown in Equation (9)

$$P(n_{1ik}) = \frac{\Gamma(n_{1ik} + \theta_1)}{\Gamma(n_{1ik} + 1)\Gamma(\theta_1)} \cdot \left(\frac{\theta_1(b_{1ik} + \exp(-\boldsymbol{\beta}_1 \mathbf{X}_{1ik}))}{f_{1ik} b_{1ik} + \theta_1(b_{1ik} + \exp(-\boldsymbol{\beta}_1 \mathbf{X}_{1ik}))}\right)^{\theta_1} \cdot \left(\frac{f_{1ik} b_{1ik}}{f_{1ik} b_{1ik} + \theta_1(b_{1ik} + \exp(-\boldsymbol{\beta}_1 \mathbf{X}_{1ik}))}\right)^{n_{1ik}} \tag{9}$$

Modeling the BMV-2 and BMV-3 Accident Risks

Following a similar procedure to that described for the BMV-1 accident risk model, we obtain the final formulation for the probability of having n_{2ik} BMV-2 accidents as

$$P(n_{2ik}) = \frac{\Gamma(n_{2ik} + \theta_2)}{\Gamma(n_{2ik} + 1)\Gamma(\theta_2)} \cdot \left(\frac{\theta_2 (b_{2ik} + \exp(-\boldsymbol{\beta}_2 \mathbf{X_{2ik}}))}{f_{2ik} b_{2ik} + \theta_2 (b_{2ik} + \exp(-\boldsymbol{\beta}_2 \mathbf{X_{2ik}}))}\right)^{\theta_2} \cdot \left(\frac{f_{2ik} b_{2ik}}{f_{2ik} b_{2ik} + \theta_2 (b_{2ik} + \exp(-\boldsymbol{\beta}_2 \mathbf{X_{2ik}}))}\right)^{n_{2ik}} \quad (10)$$

where

f_{2ik} = left-turn motor vehcle volume of intersection i, approach k;

n_{2ik} = number of BMV-2 accidents involving vehicles in f_{2ik};

$P(n_{2ik})$ = probability of having n_{2ik} accidents.

p_{2ik} = BMV-2 accident risk for a motor vehicle in f_{2ik}.

b_{2ik} = volume of bicycle flow directly involved in BMV-2 accidents at intersection i, approach k (this should be the bicycle volume crossing the left approach as shown in Fig. 1);

$\boldsymbol{\beta_2}$ = vector of unknown coefficients;

$\boldsymbol{X_{2ik}}$ = vector of explanatory variables at intersection i, approach k.

θ_2 = reciprocal of the negative binomial dispersion parameter for BMV-2 accidents.

Similarly, the formulation for BMV-3 accidents is presented in Equation (11).

$$P(n_{3ik}) = \frac{\Gamma(n_{3ik} + \theta_3)}{\Gamma(n_{3ik} + 1)\Gamma(\theta_3)} \cdot \left(\frac{\theta_3 (b_{3ik} + \exp(-\boldsymbol{\beta}_3 \mathbf{X_{3ik}}))}{f_{3ik} b_{3ik} + \theta_3 (b_{3ik} + \exp(-\boldsymbol{\beta}_3 \mathbf{X_{3ik}}))}\right)^{\theta_3} \cdot \left(\frac{f_{3ik} b_{3ik}}{f_{3ik} b_{3ik} + \theta_3 (b_{3ik} + \exp(-\boldsymbol{\beta}_3 \mathbf{X_{3ik}}))}\right)^{n_{3ik}} \quad (11)$$

where

f_{3ik} = right-turn motor vehicle volume of intersection i, approach k;

n_{3ik} = number of BMV-3 accidents involving vehicles in f_{3ik};

$P(n_{3ik})$ = probability of having n_{3ik} accidents.

p_{3ik} = BMV-3 accident risk for a motor vehicle in f_{3ik}.

b_{3ik} = volume of bicycle flow directly involved in BMV-3 accidents at intersection i, approach k (this should be the bicycle volume crossing the right approach as shown in Fig. 1);

$\boldsymbol{\beta_3}$ = vector of unknown coefficients;

$\boldsymbol{X_{3ik}}$ = vector of explanatory variables at intersection i, approach k.

θ_3 = reciprocal of the negative binomial dispersion parameter for BMV-3 accidents.

ESTIMATION RESULTS AND DISCUSSION

The unknown coefficients, β_j and θ_j (j=1, 2, 3), can be estimated using the maximum likelihood estimation (MLE) method. The log-likelihood functions used for model estimations have the general form shown in Equation (12).

$$l(\boldsymbol{\beta}_j,\theta_j)=\sum_{i=1}^{115}\sum_{k=1}^{4}\frac{\Gamma(n_{jik}+\theta_j)}{\Gamma(n_{jik}+1)\Gamma(\theta_j)}\cdot\left(\frac{\theta_j(b_{jik}+\exp(-\boldsymbol{\beta}_j\mathbf{X}_{j\mathbf{ik}}))}{f_{jik}b_{jik}+\theta_j(b_{jik}+\exp(-\boldsymbol{\beta}_j\mathbf{X}_{j\mathbf{ik}}))}\right)^{\theta_j}\cdot\left(\frac{f_{jik}b_{jik}}{f_{jik}b_{jik}+\theta_j(b_{jik}+\exp(-\boldsymbol{\beta}_j\mathbf{X}_{j\mathbf{ik}}))}\right)^{n_{jik}}$$

for j=1, 2, 3 (12)

By choosing j=1, 2 and 3, BMV-1, BMV-2 and BMV-3 models can be estimated respectively. For each BMV model, initial variables in $\boldsymbol{X_{jik}}$ are selected, based on accident type and its occurrence mechanism, from more than 70 variables in our database. For example, for BMV-2 accidents, all variables that affect the frequency and quality of conflicts between left-turn motor vehicles and bicycles crossing the left approach are included in the model. Insignificant variables are gradually removed during the estimation process, and only those variables significant at 0.05 levels are remained in the final form of each model.

The software package used for model estimations was SYSTAT 7.0.

Results for the BMV-1 Accident Risk Model Estimation

Six variables are included in the BMV-1 risk model. The estimated coefficients and their significance levels shown by t-ratios and corresponding p's are presented in Table 3. As shown in Equation (8), p_{1ik} has monotonic relationships with the variables in vector $\boldsymbol{X_{1ik}}$. For any variable in $\boldsymbol{X_{1ik}}$, if the corresponding coefficient in $\boldsymbol{\beta_1}$ is positive, its positive increment increases the value of p_{1ik} (increasing effect). Otherwise, its positive increment decreases the value of p_{1ik} (decreasing effect). The signs of the estimated coefficients in Table 3 are consistent with their effect directions on p_{1ik}. Thus, we can tell whether the effect of a variable on p_{1ik} is increasing or decreasing by looking at the sign of the estimated coefficient. This is also true for Tables 4 and 5.

Three of the six variables are discerned to have decreasing effects on p_{1ik}. Since there are no legal conflicts between through vehicular flow and bicycle flows (crossing the entering approach or the opposing approach) at signalized intersections, the occurrence of BMV-1 accidents is attributed to disregarding red signals, either by bicyclists or by through motor vehicle drivers. Factors that reduce the probability of running red signals should have decreasing effects on the BMV-1 risk. Heavier traffic flows from both the entering and opposing approaches make the time headway for each direction shorter and curtail the chances for illegally crossing the approaches. Thus, an increment in the total through motor vehicle volume (both directions) decreases p_{1ik}. When there are more right-turning vehicles at the opposing approach, conflicts between the through flow and the opposing right-turn flow disturb the smooth movements of through vehicles and result in slower speeds. Slower speeds can give drivers more time to detect signal changes and conduct stop actions when necessary. Therefore, an increase in the average daily right-turning motor vehicle volume of the opposing approach lowers the BMV-1 accident risk. Finally, intersections located in the central business district (CBD) have lower p_{1ik} values. This is probably due to the fact that continuous efforts toward improving traffic safety, such as the strict enforcement of traffic regulations and vehicle monitoring in the CBD area, may have resulted in behavior improvements for both motor vehicle drivers and bicyclists.

The existence of a pedestrian overbridge is generally thought to decrease bicycle and pedestrian accidents because the conflicts between bicycle/pedestrian flow and motor vehicle flow can be significantly reduced by the overbridge. However, our estimation result shows that the existence of a pedestrian overbridge has an increasing effect on p_{1ik}. A possible explanation is that, although overbridges reduce legal conflicts, they may increase the frequency of bicyclists running red-signals at street-level. Typically, approaches with overbridges do not have protective signals for crossing pedestrians and bicyclists. This indicates that if pedestrians/bicyclists do not cross the approaches via the overbridges, they will have to run red signals to cross at street-level. Because an overbridge normally requires bicyclists to walk up and down the bridge with their bicycles in order to cross the approach, some bicyclists may think it too troublesome to cross via the overbridge and decide to cross directly at street-level (running a red signal). If this assumption is true, the estimation result is reasonable, since every BMV-1 accident involves red signal running behavior, and it is the bicycle rider who is most likely at fault (Gårder, 1994).

Miura (1992) studied the effect of driving environment on drivers' behavior and found that with the increasing complexity of driving environment, response eccentricity (the size of the 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. The visual noise dummy variable is employed in this study to reflect the effect of information quantity to be processed while passing an intersection. Our estimation results in Table 3 show that the increase of the visual noise level enlarges p_{1ik}. Since the background visual noise distracts a driver's attention and makes it difficult for drivers to detect traffic lights, the increasing effect of the visual noise level is easy to understand. The fact that the ratio of motorcycle volume to motor-vehicle volume in through traffic flow heightens p_{1ik} is probably because of the higher motorcycle speeds and obstructed visions, for both motorcyclists and bicyclists, caused by other motor vehicles. Since most motorcyclists tend to travel at the outer lanes, vision is very likely to be blocked by motor vehicles traveling in the insider lanes. This makes it hard for bicyclists and motorcyclists to find each other early. Additionally, higher motorcycle speeds give motorcyclists less time to react when bicyclists show up.

Results for the BMV-2 Accident Risk Model Estimation

Estimation results for the BMV-2 accident risk model are shown in Table 4. Eight variables are included in the p_{2ik} model, and five of them have decreasing effects. It is not surprising that the signal control pattern does not significantly affect BMV-2 accident risk since conflicts between bicycle flow and left-turn flow (in Japan, vehicles travel along the left side of the road) are legal under certain control periods for both two-phase and four-phase controls. The bicycle volume and the ratio of left-turning motor vehicle volume to total motor-vehicle volume are found to decrease p_{2ik} as shown in Table 4. These two findings, however, may not reflect the entire spectrum of the relationship between the volumes and p_{2ik}, since we believe that p_{2ik} should initially increase with motor vehicle and bicycle volumes until certain levels are reached and decrease thereafter. Due to the model structure in this study and the sampling bias in our data, the increasing phase appears absent.

The decreasing effect of the pedestrian overbridge at the left approach may be due to the lowered conflict level. The width of the entering approach is also found to decrease BMV-2 accident risk. A possible explanation for this variable may be the better vision afforded by the wider road, or the longer green time for pedestrians/bicyclists (pedestrian green time for crossing the left approach is very likely to be proportional to the green time for through traffic of the entering approach). The decreasing effect of intersection location (in CBD or not) is probably due to the same factors explained in the BMV-1 risk model discussion, i.e., stricter enforcement and monitoring in CBD areas.

When there are more right-turn lanes at the opposing approach, conflicts between left-turning vehicles and opposing right-turning vehicles will increase at the merging section in the left approach, and such conflicts will consequently affect the left-turning drivers' ability to detect crossing bicyclists. Therefore, the number of right-turn lanes in the opposing approach increases p_{2ik}. Similarly, the number of outgoing lanes at the left approach heightens the BMV-2 accident risk, since it is proportional to potential conflict points a bicyclist may face when crossing the left approach. The average time headway of left-turn flow also increases the value of p_{2ik}. This is likely due to the higher left-turning motor vehicle speed and the slacken bicyclist caution when the left-turning volume is low.

Results for the BMV-3 Accident Risk Model Estimation

Seven variables are included in the p_{3ik} model, and the estimation results are listed in Table 5. Of the seven variables, four increase the p_{3ik} and the three decrease it. Changing the signal control pattern from two phases to four phases reduces conflicts between bicycle flow and right-turn vehicular flow, and therefore, lowers p_{3ik}. The decreasing effect of speed limit at the opposing approach must be interpreted with caution. It could be related to the turning maneuvers of right-turning vehicle drivers. When speeds of opposing through vehicles are high, right-turning drivers may tend to drive conservatively. They are very likely to stop first to wait for right-turn chances under two-phase signal control. This may reduce the average right-turn vehicle speed and, hence, lower the p_{3ik}. As for the estimated decreasing effect of the bicycle volume at the right approach, the same explanation for the bicycle volume at the left approach in the BMV-2 accident risk model may apply.

Approaches with a wider road median are concluded to have higher BMV-3 accident risk. This may be largely due to the fact that a poor vision angle makes it harder to effectively detect opposing through vehicles and bicycles at the right approach. Using the same data set, Wang and Nihan (2001) also found that this variable significantly increases the angle collision risk between right-turning vehicles and opposing through vehicles. The number of right-turn lanes at the entering approach has an increasing effect on p_{3ik}. This is possibly because, when there are two or more right-turn lanes, right-turning vehicles in different lanes obstruct the vision of each other during the turning movement. The increasing effect of the number of approaches sheltered by elevated roads may be also due to vision problem. When elevated roads in one or more directions shelter an intersection, luminance of the intersection is normally much lower than that for the rest of the roadway leading to or from the intersection. This makes it more difficult for bicyclists and right-turning motor vehicle drivers to detect each other, as their eyes need time to adapt to the lower luminance level. Lengthened perception time will absolutely increase accident risk. The reason that average time headway of right-turning vehicles increases p_{3ik} is analogous to the left-turning vehicle headway variable in the BMV-2 model. Duplicate explanation is omitted here.

SUMMARY AND CONCLUSIONS

Intersections are BMV accident-prone locations. Determining the quantitative impacts of causal factors on BMV accidents is an important step in reducing such accidents at intersections. In this study, intersection BMV accidents were classified into three categories based on the movements of the involved motor vehicles. A methodology for BMV accident risk estimation was developed based on probability theory. The methodology was demonstrated with a four-year (1992-1995) data set collected from 115 signalized intersections in the Tokyo Metropolitan area. The negative binomial dispersion parameters for all three models were significant at 0.01 levels. This supports the appropriateness of the negative binomial regression for BMV accident analyses in this study.

An important advantage of the proposed methodology is that the risk of each BMV accident type is explicitly attributed to its related flows. Therefore, each model corresponds to only one collision pattern. This makes it possible to select explanatory variables in accordance with the specific characteristics of each BMV accident type and to interpret the estimation results more intuitively. In this study, different sets of explanatory variables were identified for each BMV accident type, and the corresponding coefficient values together with their significance levels were estimated. Some variables, such as the existence of pedestrian overbridges, may have different conflict effects for different accident types. The net effect of such variables needs to be calculated for comprehensive safety improvement plans.

Our interpretation of the estimation results for each model was based on a single data set. Further studies using data from other locations are necessary for model verification. Also, a more flexible model structure that can reflect the non-linear relationships between the BMV accident risks and the involved motor vehicle and bicycle volumes can help us gain an understanding of the entire spectrum of relationships. The accident classification and model estimation methodology presented in this paper may be applicable to pedestrian-motor vehicle accidents as well.

REFERENCES

Fazio, J., Tiwari, G., 1995. Nonmotorized-motorized traffic accidents and conflicts on Delhi streets. Transportation Research Record 1487, 68-74.

Gårder, P., 1994. Bicycle accidents in Maine: an analysis. Transportation Research Record 1438, 34-41.

Gårder, P., Leden, L., Thedeen, T., 1994. Safety implications of bicycle paths at signalized intersections, Accident Analysis and Prevention, Vol. 26, No. 4, 429-439.

Hauer, E., 1986. On the estimation of the expected number of accidents, Accident Analysis and Prevention, Vol. 18, No. 1, 1-12.

Hauer, E., Ng, C.N.J., Lovell, J., 1988. Estimation of safety at signalized intersections, Transportation Research Record 1185, 48-60.

Institute for Traffic Accident Research and Data Analysis, 2000. Traffic Statistics, Tokyo (in Japanese).

Liu, X., Shen, L.D., Huang, J., 1995. Analysis of bicycle accidents and recommended countermeasures in Beijing, China. Transportation Research Record 1487, 75-83.

Miura, T., 1992. Visual search in intersections, IATSS Research, Vol. 16, No. 1, 42-49.

National Highway Safety Administration, 2001. Traffic Safety Facts 2000: A Compilation of Motor Vehicle Crash Data from the Fatalities Analysis Reporting System and the General Estimates System. US Department of Transportation, Washington, D.C.

Pitman, J., 1993. Probability. Springer-Verlag New York, Inc, New York.

Poch, M., and Mannering, F., 1996. Negative binomial analysis of intersection-accident frequencies. Journal of Transportation Engineering, Vol. 122, No. 2, 105-113.

Summala, H., Pasanen, E., Räsänen, M., Sievänen, J, 1996. Bicycle accidents and drivers' visual search at left and right turns, Accident Analysis and Prevention, Vol. 28, No. 2, 147-153.

Tokyo Metropolitan Police Department, 1992. Traffic Volume Statistics. Tokyo (in Japanese).

Tokyo Metropolitan Police Department, 1993. Traffic Volume Statistics. Tokyo (in Japanese).

Tokyo Metropolitan Police Department, 1994. Traffic Volume Statistics. Tokyo (in Japanese).

Tokyo Metropolitan Police Department, 1995. Traffic Volume Statistics. Tokyo (in Japanese).

Tokyo Metropolitan Police Department, 2000. Traffic Year Book. Tokyo (in Japanese).

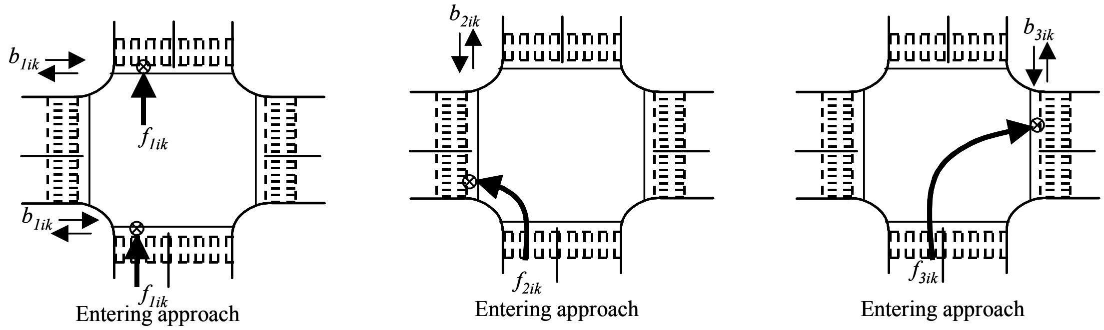
Tokyo Road Construction Bureau, 1997. Report of Traffic Volume Survey. Tokyo (in Japanese).

Wachtel, A., Lewiston, D., 1994. Risk factors for bicycle-motor vehicle collisions at intersections, ITE Journal, Vol. 64, No. 9, 30-35.

Wang, Y., 1998. Modeling Vehicle-to-Vehicle Accident Risks Considering the Occurrence Mechanism at Four-Legged Signalized Intersections, Ph.D. Dissertation, the University of Tokyo.

Wang, Y., and Nihan, N. L., 2001. "Quantitative analysis on angle-accident risk at signalized intersections." World Transport Research, Selected Proceedings of the 9th World Conference on Transport Research (in print).

List of Figures and Tables:



(a) BMV Accident Type 1 (BMV-1) (b) BMV Accident Type 2 (BMV-2) (c) BMV Accident Type 3 (BMV-3)

Fig. 1. Classification of bicycle-motor vehicle (BMV) accidents at intersections. BMV-1 represents bicycle and through motor vehicle collisions; BMV-2 denotes bicycle and left-turning motor-vehicle crashes; and BMV-3 corresponds to bicycle and right-turning motor vehicle accidents.

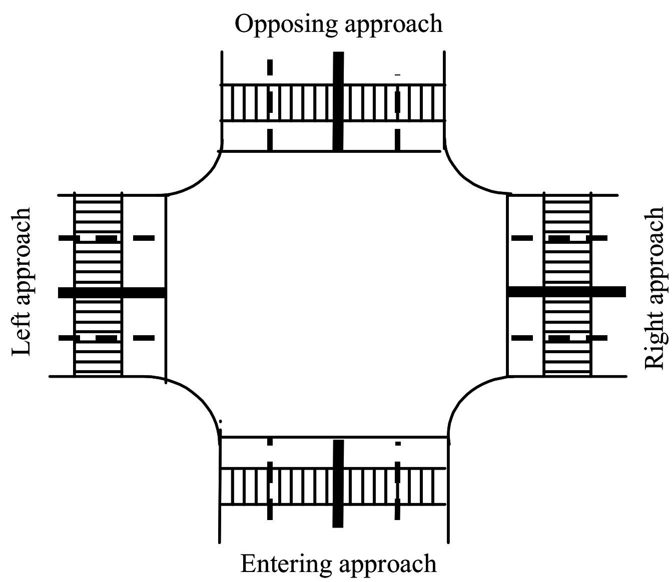


Fig. 2. Names of intersection approaches. Once an approach is determined to be an entering approach, all three other approaches are named clockwise as left approach, opposing approach, and right approach, relative to the entering approach.

Table 1 Summary statistics for selected continuous variables for each approach

Variable	Mean	Standard Deviation	Minimum	Maximum
BMV-1 accidents per approach	0.265	0.924	0	16
BMV-2 accidents per approach	0.443	0.878	0	7
BMV-3 accidents per approach	0.563	1.433	0	15
Daily through motor vehicle volume (in thousands)	12.566	9.466	0	52.962
Daily left-turn motor vehicle volume (in thousands)	3.243	3.712	0	47.373
Daily right-turn motor vehicle volume (in thousands)	3.335	3.125	0	39.140
Daily bicycle volume (in thousands)	0.793	0.889	0	10.891
Ratio of motorcycle volume to motor vehicle volume in through traffic flow	0.090	0.105	0	0.398
Ratio of left-turn motor vehicle volume to total volume	0.186	0.156	0	1.000
Ratio of right-turn motor vehicle volume to total volume	0.204	0.170	0	0.995
Speed limit (km/h)	49.348	9.265	30	60
Total number of lanes	4.965	1.919	1	12
Number of left-turn lanes	0.178	0.426	0	3
Number of right-turn lanes	0.846	0.583	0	3

Table 2 Frequency results for selected dummy variables

Variable	Number and frequency (in the parentheses) of observations for each value				
	0	1	2	3	4
Intersection location (1 if in central business district (CBD), 0 otherwise)	218 (47.4%)	242 (52.6%)	–	–	–
The existence of pedestrian overbridge	429 (93.3%)	31 (6.7%)			
Road median width (0 if none, 1 if less than 2 meters wide, and 2 if wider than 2 meters)	274 (59.6%)	111 (24.1%)	75 (16.3%)	–	–
Signal control pattern (0 for two phase control, 1 otherwise)	127 (27.6%)	333 (72.4%)	–	–	–
Visual noise (ranging from 0 to 4)	66 (14.3%)	108 (23.5%)	151 (32.8%)	98 (21.3%)	37 (8.1%)
Number of intersection approaches sheltered by elevated roadways	336 (73.0%)	116 (25.2%)	8 (1.8%)	–	–

Table 3 Estimation results for the BMV-1 accident risk model

Variable	Estimated Coefficient	t-ratio	p
Constant	-18.793	-30.31	0.00
Intersection location (1 if in central business district (CBD), 0 otherwise)	-0.868	-2.37	0.02
Sum of the average daily through motor-vehicle volumes (in thousands) for the entering approach and the opposing approach	-0.037	-3.85	0.00
Average daily right-turn motor-vehicle volume (in thousands) for the opposing approach	-0.128	-1.96	0.05
Ratio of motorcycle volume to motor vehicle volume in through traffic flow	7.881	2.86	0.00
The existence of pedestrian overbridges (2 if both the entering and opposing approaches have overbridges, 1 if only one of them has, and 0 if none of them has)	0.508	2.34	0.02
Visual noise level (ranging from 0 (low) to 4 (high)) for the entering approach	0.515	2.16	0.03
Reciprocal of negative binomial dispersion parameter ($\theta_1 = 1/\delta_1$)	0.425	3.68	0.00
Number of observations	327		
Restricted Log likelihood (constant only)	-258.06		
Log likelihood at convergence	-217.25		
Likelihood ratio index, ρ^2	0.16		

Table 4 Estimation results for the BMV-2 accident risk model

Variable	Estimated Coefficient	t-ratio	p
Constant	-17.073	-32.49	0.00
Width of the entering approach (in meters)	-0.100	-2.40	0.02
Average daily bicycle volume (in thousands) of the left approach	-0.250	-3.28	0.00
Number of right-turn lanes at the opposing approach	0.581	2.23	0.03
Ratio of left-turn motor vehicle volume to total volume for the entering approach	-1.630	-2.68	0.01
Number of outgoing lanes at the left approach	0.424	4.74	0.00
Intersection location (1 if in central business district (CBD), 0 otherwise)	-0.574	-2.96	0.00
The existence of pedestrian overbridges at the left approach (1 if there is an overbridge, 0 otherwise)	-0.866	-2.63	0.01
Average time headway in seconds for left-turn motor vehicle flow from the entering approach	0.003	2.66	0.01
Reciprocal of negative binomial dispersion parameter ($\theta_2 = 1/\delta_2$)	3.939	2.58	0.01
Number of observations	330		
Restricted Log likelihood (constant only)	-388.69		
Log likelihood at convergence	-279.14		
Likelihood ratio index, ρ^2	0.28		

Table 5 Estimation results for the BMV-3 accident risk model

Variable	Estimated Coefficient	t-ratio	p
Constant	-13.199	-17.34	0.00
Road median width at the entering approach (0 if none, 1 if less than 2 meters wide, and 2 if wider than 2 meters)	0.591	4.11	0.00
Number of intersection approaches sheltered by elevated roadways	0.462	2.05	0.04
Average daily bicycle volume (in thousands) for the right approach	-0.569	-3.93	0.00
Number of right-turn lanes at the entering approach	0.545	2.41	0.02
Speed limit (km/h) for the opposing approach	-0.058	-3.28	0.00
Signal control pattern (0 for two-phase control, 1 for four-phase control)	-0.501	-2.31	0.02
Average time headway in seconds for the right-turn motor vehicle flow from the entering approach	0.330	3.38	0.00
Reciprocal of negative binomial dispersion parameter ($\theta_3 = 1/\delta_3$)	0.736	4.40	0.00
Number of observations	302		
Restricted Log likelihood (constant only)	-515.16		
Log likelihood at convergence	-317.25		
Likelihood ratio index, ρ^2	0.38		