MODELING PEDESTRIAN CROSSING SPEED PROFILES CONSIDERING SPEED CHANGE BEHAVIOR FOR THE SAFETY ASSESSMENT OF SIGNALIZED INTERSECTIONS

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ABSTRACT

Pedestrian safety is one of the most challenging issues in the road network. Understanding how pedestrians maneuver across an intersection is the key to applying countermeasures against traffic crashes. It is known that behaviors of pedestrians at signalized crosswalks are significantly different from ordinary walking spaces and they are highly influenced by signal indication, potential conflicts with vehicles and intersection geometries. One of the most important characteristics of pedestrian behavior at crosswalks is the possible sudden speed change while crossing. Such sudden behavioral change may not be expected by conflicting vehicles, which may lead to hazardous situations. This study aims to quantitatively model the pedestrians' sudden speed changes as they cross signalized crosswalks under uncongested conditions. Pedestrian speed profiles are collected from empirical data and speed change events are extracted assuming that the speed profiles are stepwise functions. The occurrence of the speed change events is described by a discrete choice model as a function of the necessary walking speed to complete crossing before red interval, current speed, and the presence of turning vehicles in the conflict area. The amount of speed change before and after the event is modeled using regression analysis. A Monte-Carlo simulation is applied for the entire speed profile of the pedestrians. The results showed that the model was able to represent the pedestrian travel time distribution more accurately than the constant speed model.

Keywords: Pedestrian crossing behavior; speed change; crossing time; pedestrian-vehicle conflicts; signalized crosswalks

1. INTRODUCTION

Pedestrian safety is one of the main challenges that city planners and policy makers face. Pedestrian–vehicle crashes have become a major safety problem that has resulted in a high rate of fatalities (National Police Agency in Japan, 2015). Worldwide, 22% of total road crash fatalities are pedestrians (World Health Organization, 2015). In Japan, 37% of total road fatalities nationwide in 2015 were pedestrians (National Police Agency in Japan, 2015). In Tokyo alone, the traffic police department reported that 48% of total road crash fatalities were pedestrians (Metropolitan Police Department in Japan, 2016). These percentages are increasing with time due to the growth of pedestrian activities and the expansion of urban areas. Therefore, pedestrian safety is a critical issue and concrete measures should be taken to improve the current situation. Various speed calming measures, control policies, and geometric improvements have been implemented, combined with different technologies from various countries worldwide in order to provide pedestrians with a safer crossing experience. In spite of all these extensive efforts, pedestrian safety remains one of the main problems that transportation engineers face especially in urban areas.

Although pedestrians have the right-of-way over vehicles both at unsignalized and signalized crosswalks where the priority is given by signal indication, drivers still compete with pedestrians over the right-of-way and put pedestrian safety at risk. Understanding pedestrian and vehicle behaviors is crucial to provide rational and reliable safety assessment. In reality, road users anticipate other users' behavior in order to avoid collisions. Thus, widely varying pedestrian and/or vehicle maneuvers may result in misunderstanding of each other's decisions, which can lead to safety problems. Pedestrians are subject to behavioral changes while crossing as reported by Iryo-Asano et al. (2014a). Crosswalk geometry and signal time settings, among other contributing factors, may cause pedestrians to suddenly change their velocity without paying attention to the surrounding conditions (Iryo-Asano et al., 2014a; Alhajyaseen and Iryo-Asano, 2017). Such behavioral changes cannot be predicted by drivers and may lead to severe conflicts.

This study aims to develop a method for the estimation of pedestrian speed profiles at signalized crosswalks considering possible behavioral changes such as abrupt acceleration and/or deceleration. The developed model takes into account the impact of crosswalk geometry, signal settings, and the interaction with turning vehicular traffic. The availability of a reliable model that can reproduce realistic pedestrian maneuvers at crosswalks is crucial to provide a reliable assessment of pedestrian–vehicle conflicts and their severity.

2. LITERATURE REVIEW

A majority of existing studies related to pedestrian–vehicle conflicts concentrate on the microscopic parameters of vehicle behavior, such as speed profiles including acceleration and deceleration events, assuming that vehicles are the main contributing element in pedestrian–vehicle crashes. In this regard, Alhajyaseen et al. (2013a, 2013b, 2012a, 2012b) intensively analyzed turning vehicle maneuvers at intersections including paths, speed profiles, and gap acceptance for better assessment of pedestrian–vehicle conflicts. They identified significant variations in vehicle paths and speeds at conflict points with pedestrians. The presence of significant variations in the turning maneuvers of vehicles considerably affects the probabilities and severities of conflicts with pedestrians.

On the other hand, pedestrian behavior plays an important role in conflicts with vehicular traffic. Many studies analyzed pedestrian crossing behavior at intersections including stop-go decisions, compliance with signal indications, and average crossing speed. However, the analysis of instantaneous behavior of pedestrians while crossing, particularly the velocity profile to identify possible behavioral changes, is missing. Such analysis is important since sudden behavioral changes cannot be predicted by other road users who probably will fail to make the appropriate reactions to avoid conflicts with pedestrians.

In a previous study in Japan, Iryo-Asano et al. (2015) and Alhajyaseen and Iryo-Asano (2017) videotaped several signalized crosswalks to collect microscopic characteristic of pedestrian maneuvers. They have used image processing software to collect pedestrian position and timing information every 0.5 sec time interval. They identified empirical evidence that some pedestrians exhibit sudden speed changes while crossing which could be a reaction to pedestrian signal indications, the crosswalk layout, or a combination of different factors. Many of the identified acceleration and deceleration events occur near conflict areas, which may cause pedestrians to arrive more quickly to conflict areas or stay longer in them. Either way, drivers cannot anticipate such abrupt behavioral changes, which may lead to severe conflicts with pedestrians. Such differing behaviors make it difficult for drivers to correctly predict pedestrian reactions. This increases the probability of improper maneuvers that put pedestrian safety at risk. However, a method to predict the location and timing of such speed changes and to integrate them with vehicle maneuvers for the safety assessment of intersections is not developed in their study.

In another study, Alhajyaseen (2014) studied pedestrian average crossing speeds at signalized crosswalks in Japan considering the impact of signal timing and crosswalk geometry. He found that pedestrian crossing speed increases as pedestrian green (PG) phase proceeds especially at the end of PG and the onset of pedestrian flashing green (PFG) phase. Furthermore, he demonstrated empirically that pedestrians hurry when entering crosswalks as the green light flashes and then tend to significantly decrease their speed while crossing, which is in accordance with other recent studies (Iryo-Asano et al., 2014a; Iryo-Asano and Alhajyaseen, 2014). Iryo-Asano et al. (2014a) proposed method to estimate pedestrian travel speeds in the first and second halves of the crosswalk considering crosswalk geometry and signal settings. However, these travel speeds are useful in the estimation of crossing time but not on the analysis of pedestrian–vehicle conflicts. Pedestrian instantaneous speeds are crucial for the estimation of pedestrian arrival to the conflict area and the safety assessment of their conflicts with vehicles.

Koh et al. (2014) analyzed pedestrian crossing speed in Singapore and yielded to similar results where they found that crossing speeds significantly differ during the PG phase compared to the pedestrian flashing green (PFG) phase. Schmitz (2011) also confirmed the significant impact of pedestrian signal settings on pedestrian behavior from empirical data in the US; for instance, he concluded that pedestrian countdown timers significantly increase the pedestrian crossing speed.

Other studies in different countries in the world confirmed the significant impact of crosswalk layout including width, length, position, and the usage of channelization on pedestrian compliance to signals (Supernak et al., 2013; Yang and Sun, 2013; Xu et al., 2013), which is in accordance with authors' previous studies (Iryo-Asano et al., 2014a and 2014b; Iryo-Asano and Alhajyaseen, 2014). Pedestrian compliance to signals was also analyzed by Wang et al. (2011) who identified several contributing factors to pedestrian violation to traffic signals such as the waiting time or delay, personal characteristics (e.g., age and gender), trip purpose, and traffic conditions (e.g., pedestrian flow rate and vehicular traffic volume).

All previous studies analyze pedestrian behavior in terms of decision-making and average crossing speeds without developing methodologies to produce their maneuvers for realistic representation of pedestrian-vehicles conflict. In this study, a method to predict the location and timing of possible acceleration and deceleration events is developed considering the impact of crosswalk layout, signal indication, pedestrian arrival time to the crosswalk, pedestrian approaching speed and others. The availability of a reliable model that can produce realistic maneuvers of pedestrians can facilitate the development of proper safety countermeasures, such as improving intersection layouts and signal control or developing safety information provision systems. Moreover, it can be utilized in autonomous vehicles for the detection of pedestrians and prediction of any possible behavioral changes, so that vehicles can take proper maneuvers to avoid severe conflicts with crossing pedestrians.

3. MODELING PEDESTRIAN SPEED PROFILE CONSIDERING SUDDEN SPEED CHANGE EVENTS

3.1 Speed profile using stepwise functions

According to Iryo-Asano et al. (2015), the profiles of pedestrian longitudinal speed on the crosswalks under low demand conditions can be expressed by the stepwise functions $v_s(t)$ as Equation (1).

$$v_s(t) = \begin{cases} v_1 & where\, t < t_1 \\ v_2 & where\, t_1 \le t < t_2 \\ & \cdots \\ v_{m+1} & where\, t_m \le t \end{cases} \tag{1}$$

where m is the number of speed changing events, t_i is the timing of the speed change event i, and v_i is the constant speed during the time period between t_i and t_{i+1}. The value of m differs for each individual speed profile and should be 0 if there are no speed changes. The speed profiles of each pedestrian can be fit to this stepwise function by determining t_i, v_i, and m.

This implies that the pedestrian speed change events are approximated by the set of discrete events. Thus, in this study, it is assumed that pedestrians have a discrete choice to determine whether they will accelerate/decelerate or not at each time and location. Therefore, the proposed pedestrian speed profile model in this study consists of two sub models. The first one is to represent the pedestrians' reaction—when and where they accelerate or decelerate. The other sub model is to calculate the actual amount of speed change at the event.

3.2 Sudden speed change sub model

At each time interval Δt, it is assumed that pedestrians choose their maneuver from three alternatives: keeping the current speed, acceleration, or deceleration. This decision process is represented by the sudden speed change sub model, which determines the probability of choosing an alternative considering the influencing factors. Let us denote the probability for pedestrian i to choose to maintain constant speed, accelerate, or decelerate at condition $\boldsymbol{\theta}$ as $P_{cur,i}(t|\boldsymbol{\theta})$, $P_{acc,i}(t|\boldsymbol{\theta})$ and $P_{dec,i}(t|\boldsymbol{\theta})$ respectively. $\boldsymbol{\theta}$ includes the information of the pedestrian's state and surrounding conditions. Then, the likelihood function can be presented as follows.

$$L = \prod_{i=1}^{N}\prod_{t=1}^{T_i} P_{acc,i}(t|\boldsymbol{\theta})^{\delta acc} \cdot P_{dec,i}(t|\boldsymbol{\theta})^{\delta dec} \cdot P_{cur,i}(t|\boldsymbol{\theta})^{1-\delta acc-\delta dec} \tag{2}$$

where $\delta_{acc}=1$ if pedestrian i chooses acceleration at time t ; otherwise $\delta_{acc}=0$. $\delta_{dec}=1$ if pedestrian i chooses deceleration at time t ; otherwise $\delta_{dec}=0$. The probability to take each choice is based on the utility functions. If all decisions are assumed to be independent and the Gumbel distribution is assumed for the error terms of the utilities of each alternative, the probabilities can be presented as shown below.

$$P_{acc,i}(t|\boldsymbol{\theta}) = \frac{\exp(U_{acc,i}(t|\boldsymbol{\theta}))}{\exp(U_{acc,i}(t|\boldsymbol{\theta})) + \exp(U_{dec,i}(t|\boldsymbol{\theta})) + \exp(U_{cur,i}(t|\boldsymbol{\theta}))} \tag{3}$$

$$P_{dec,i}(t|\boldsymbol{\theta}) = \frac{\exp(U_{dec,i}(t|\boldsymbol{\theta}))}{\exp(U_{acc,i}(t|\boldsymbol{\theta})) + \exp(U_{dec,i}(t|\boldsymbol{\theta})) + \exp(U_{cur,i}(t|\boldsymbol{\theta}))} \tag{4}$$

$$P_{cur,i}(t|\boldsymbol{\theta}) = \frac{\exp(U_{cur,i}(t|\boldsymbol{\theta}))}{\exp(U_{acc,i}(t|\boldsymbol{\theta})) + \exp(U_{dec,i}(t|\boldsymbol{\theta})) + \exp(U_{cur,i}(t|\boldsymbol{\theta}))} \tag{5}$$

$$U_{acc,i}(t|\boldsymbol{\theta}) = \boldsymbol{\alpha}\mathbf{X}_i(t|\boldsymbol{\theta}) \tag{6}$$

$$U_{dec,i}(t|\boldsymbol{\theta}) = \boldsymbol{\beta}\mathbf{Y}_i(t|\boldsymbol{\theta}) \tag{7}$$

$$U_{cur,i}(t|\boldsymbol{\theta}) = 0 \tag{8}$$

where, $\mathbf{X}_i, \mathbf{Y}_i$ are vectors of explanatory variables of the utility functions for acceleration and deceleration choices, respectively. $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are vectors of coefficients.

3.3 Acceleration/deceleration sub models

Once pedestrians react by acceleration/deceleration, they need to also determine the amount of acceleration/deceleration. It should be noted that occurrence of acceleration and deceleration events in terms of location and timing is not similar. Acceleration events often occur at crosswalks when pedestrians try to exceed their desired speed so that they can safely complete crossing. Therefore, as a hypothesis, it can be assumed that the amount of acceleration is correlated to the motivation of pedestrians to speed up. On the other hand, deceleration events in uncongested crosswalks often happen when pedestrians rush to start crossing at the end of the green interval; after stepping in the crosswalk, they may feel secured and safe and as a result, they decelerate. Thus, the walking speed after deceleration may depend on the original desired speed of each pedestrian, which cannot be measured before they decelerate.

Taking into account the above characteristics of acceleration and deceleration events, different sub models are applied to predict the acceleration and deceleration events in this study. For acceleration events, it is expected that pedestrians try to adjust their behavior to

Table 1. Surveyed sites for pedestrian analysis

Intersection name	Subject crosswalk	Survey date	Radius of corner R_C (m)	Intersection angle θ_I (°)	Number of exit lanes N_O	Crosswalk setback distance D_S (m)	Crosswalk length L (m)	Crosswalk width (m)
Kanayama	East	9:00–13:00 10/19/2012	13.4	93	1	5.0	16.2	5.8
	North	9:30–13:00 10/19/2012	8.0	86	3	12.0	36.2	6.0
Ueda	East	7:00–10:00 and 14:00–16:30 11/29–30/2012	11.5	65	2	7.5	28.7	6.3
	South	14:00–16:30 11/29/2012	14.5	119	2	18.9	20.8	5.8
		7:00–10:00 and 14:00–16:30, 11/30/2012						
Fushimi	South	10:00–11:00 and 14:00–15:00, 11/5/2012	12.2	90	3	13.3	30.4	6.9

surrounding circumstances, and so linear regression models are applied in which the explanatory variables come from observed variables. Furthermore, the linear regression approach produced the best fitting results among other models, which were tested. Meanwhile, for the deceleration events, it is expected that unobservable variables (such as desired speed of individual pedestrians) can be one of the dominant factors. Considering that, the main objective of the model is to have realistic representation of pedestrian-vehicle conflicts for safety assessment, the variation of the deceleration due to such explicit variables is important and needs to be reflected. Hence, normal distribution models are applied in which the mean and standard deviation are assumed to be linear function of variables, such as current speeds or locations. In the normal distribution model, constant value of standard deviation is expected to imply the impact of the unobservable variables. The maximum likelihood function is used to estimate the model parameters.

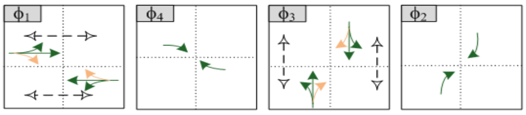
4. DATA COLLECTION AND PROCESSING

4.1 Study sites

Empirical data collected by Iryo-Asano et al. (2015) are used for the parameter estimation. Table 1 shows the information of the surveyed sites. Five crosswalks at three intersections in Nagoya City, Japan, are selected for the video survey. They are operated with a four-phase traffic signal plan as presented in Table 2. The observation sites are characterized with low-to-medium pedestrian demand as shown in Table 3. Such sites were selected to minimize the impact of interactions between pedestrians. With high pedestrian demand, the interaction between pedestrians significantly affects their maneuvers, which makes identifying the impact of the crosswalk geometry and signal timing very difficult and even impossible. The turn on red is prohibited at all sites. Furthermore, all observation sites have ordinary pedestrian signal indicators without countdown signals.

Pedestrian demand is divided into near side and far side. Near side pedestrians are those who start crossing from the side of the vehicular traffic that is exiting the intersection while far-

Table 2. Signal timing plans at observed intersections

	Signal phasing length (sec)														Cycle length (sec)
	f 1				f 2			f 3				f 4			
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	
/ehicle															
location S and N)															
urning vehicle		Shared													
/ehicle															
location E and W)															
urning vehicle									Shared						
anayama	39	9	3	3	7	2	5	54	6	5	3	17	2	5	160
Ueda	54	8	2	3	9	2	5	45	10	4	4	7	2	5	160
'ushimi	40	10	2	4	7	2	5	62	7	3	4	8	1	5	160
plan															

------ Right-turning arrow | | | | | Pedestrian flashing green /\/\/ Amber ═══ Red

ignal phasing length (sec)				
f 2		f 3		
6	7	8	9	10
			Shared	
2	5	54	6	5
2	5	45	10	4
2	5	62	7	3

ı flashing green Aı

Table 3. Turning traffic and pedestrian demands at study sites

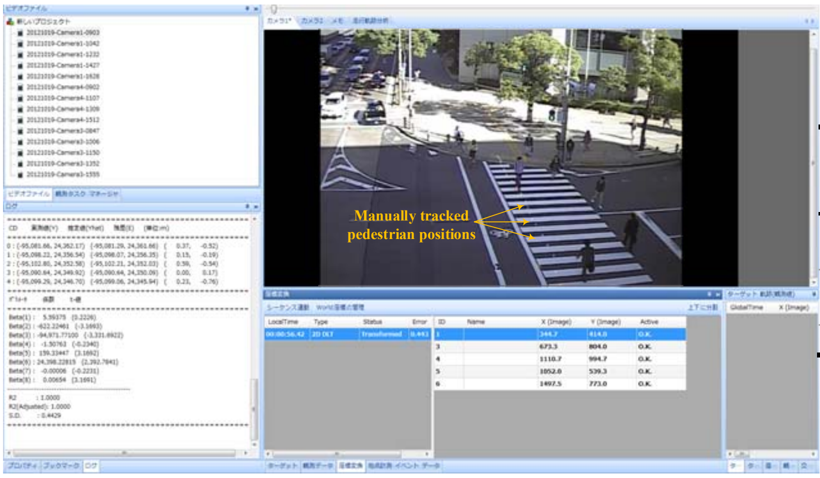
Intersection name	Subject crosswalk	Turning vehicle demand (veh/h)		Pedestrian demand (ped/h)		Number of observed pedestrians (ped)	
		Left turning	Right turning	Near side	Far side	Near side	Far side
Kanayama	East	148	56	103	76	189	74
	North	124	36	185	153	106	267
Ueda	East	46	264	49	41	39	32
	South	176	52	58	56	64	71
Fushimi	South	122	112	155	167	56	72

side pedestrians are those who start crossing from the side of the incoming vehicular traffic. It is important to mention that pedestrian signal indications were visible in the video data, which allow authors to collect all need signal information.

4.2 Data processing and speed change event extraction

The positions of pedestrians at each time are extracted by manual tracking using the video image processing system TrafficAnalyzer (Suzuki and Nakamura, 2006). The positions are recorded every 0.5 s, and the video coordinates are transferred to global coordinates by projective transformation (Figure 1). The absolute coordinate transformation error when using the image processing system TrafficAnalyzer is shown in Figure 1. The expected errors of measurement depend on the camera angles, pedestrian positions in the camera, manual tracking error, and others. The means of possible measurement error at each site are between 0.14 *m* and 0.38 *m*.

For the extraction of speed change events, the method of Iryo-Asano et al. (2015) is applied under the assumption of stepwise speed function as shown in Equation (1). The sudden speed change events are determined so that the difference of mean speeds before and after the speed change event is statistically significant, and the absolute difference is larger than a threshold of 0.5 m/s. According to the data obtained by Alhajyaseen et al. (2011), the difference



Site		Absolute coordinate transformation error (*m*) Min.	Max.	Ave.
Kanayama	East	0.00	0.76	0.35
	North	0.02	0.62	0.18
Ueda	East	0.01	0.48	0.12
	South	0.01	0.57	0.26
Fushimi	South	0.03	0.61	0.27

Figure 1: Image processing system TrafficAnalyzer used to track pedestrians and associated coordinate transformation error

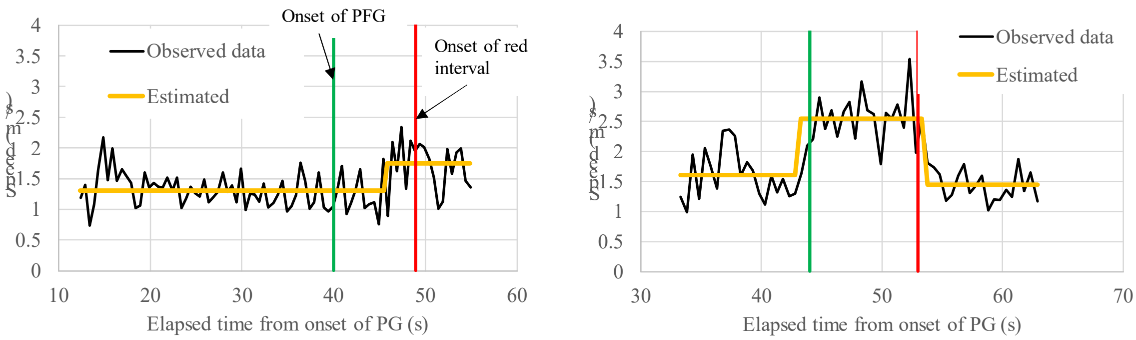


Figure 2. Examples of speed change event extraction

between the 90th and 10th percentiles in the speed distribution of pedestrians under the free flow condition is approximately 0.5 m/s. This implies that a speed change of > 0.5 m/s can be considered significant. Therefore, the threshold is set to 0.5. Figure 2 shows the examples of estimated speed change events by this method for individual pedestrians. As in these figures, the method can successfully distinguish between random speed fluctuations and the significant speed changes.

4.3 Data Analysis

The collected data is analyzed to understand the impact of signal timing, crosswalk geometry, and interaction with vehicular traffic on speed change events. Detailed analysis can be found in Iryo-Asano et al. (2015). Mainly, the study concluded that crosswalk length, pedestrian signal indication, and the presence in the conflict area with turning traffic significantly affect the probability of speed change events and their occurrence in terms of timing and location. Figure 3 shows the number of observed pedestrian speed profile that have no speed change, one speed change, two speed changes and three or more speed changes. Longer crosswalks (Kanayama North and Fushimi South) have significantly larger number of speed changes compared to other sites. In Figure 4, the distribution of the timing of speed change events is presented. It is clear the onset of PFG is point of change. Significantly, larger number of speed change events (especially acceleration events) occurred after the onset of PFG. For this reason, this study develops different models for the periods before and after the onset of PFG.

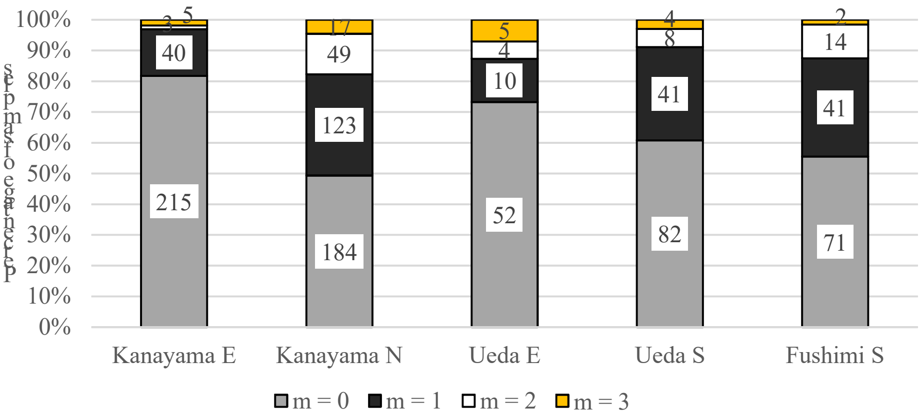


Figure 3. Number of observed speed profiles classified by number of identified speed change events (Iryo-Asano et al. 2015)

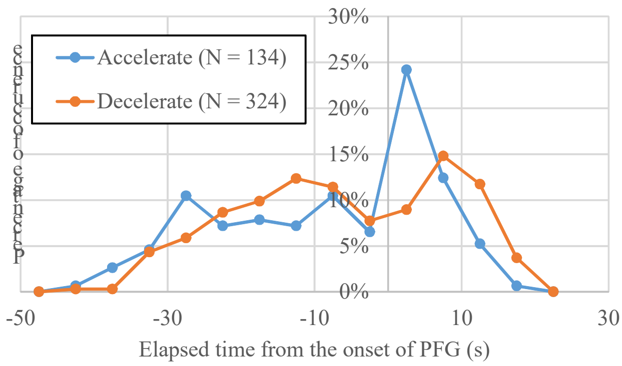


Figure 4. Distribution of timing of speed change events (Iryo-Asano et al. 2015)

5. MODEL PARAMETER ESTIMATION

5.1 Speed change event sub models

The parameters of the models were estimated using R Programming Language and its libraries. Up to the previous section, the location and the speed of the pedestrians are analyzed for the interval of 0.5s. Even though 20-50% of pedestrians change their speed at least once as shown in Figure 3, the occurrence of the speed change events is still limited. The utility functions of Equations (6) and (7) are not estimated well for such rare events. Therefore, the trajectory data are aggregated for each five seconds instead of 0.5 second. The acceleration and deceleration events are defined when there is a speed change event within the five seconds. The condition at the beginning of the five second period is used as the input of the model. Following this procedure, 4009 data samples were obtained.

The estimation results of the speed change events are shown in Table 4. As one of the explanatory variables, a concept of necessary speed to complete crossing is applied (Iryo-Asano et al., 2015). The necessary speed to complete crossing V_{nec} is defined as the remaining distance to complete crossing divided by the remaining time until the end of PFG. As the absolute difference between V_{nec} and current time V_{cur} increases, pedestrians are expected to have higher motivation to adjust their speed. In Table 4, the previous acceleration event

Table 4. Estimation results of speed change event choice

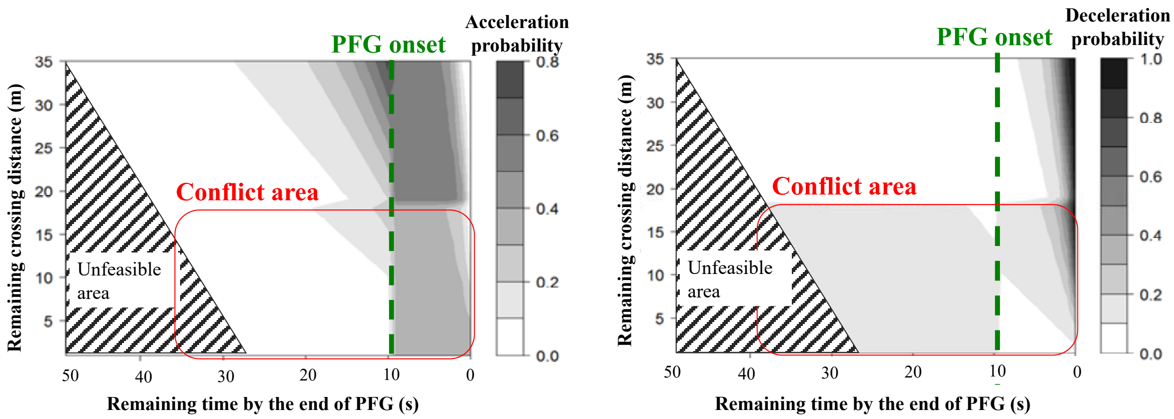
		Variables	Coefficients	t-values
Before PFG onset	Acceleration events	Constant	-0.969	-4.17
		$V_{nec} - V_{cur}$ (m/s)	1.65	6.18
		Conflict area dummy	-0.597	-2.94
	Deceleration events	Constant	-2.05	-11.7
		$V_{nec} - V_{cur}$ (m/s)	-0.190	-1.37
		Previous acceleration event dummy	1.45	6.82
		Conflict area dummy	-1.12	-3.89
After PFG onset	Acceleration events	Constant	-0.529	-4.91
		$V_{nec} - V_{cur}$ (m/s)	0.0571	2.39
		Conflict area dummy	0.911	3.05
	Deceleration events	Constant	-1.53	-5.00
		V_{cur} (m/s)	0.371	2.69
		Previous acceleration event dummy	3.12	15.0
		Conflict area dummy	-0.67	-4.92
Sample size		4009		
Initial log likelihood		-2442.2		
Log likelihood		-1378.8		
Modified ρ^2		0.431		

dummy variable is equal to one if the pedestrian has experienced an acceleration event at the previous time intervals. Furthermore, the conflict area dummy variable is equal to one when the pedestrian is located within the area of conflict with the exiting turning vehicles.

Different models are developed for the periods before and after the onset of PFG. Before the onset of PFG, the difference between V_{nec} and the current speed has a significant impact upon the choice. The smaller the current speed is, the higher the utility to choose acceleration becomes. However, for the deceleration choice, the opposite tendency is observed. This implies that pedestrians try to adjust their speed to V_{nec} during crossing. When the pedestrians are in the conflict area with the vehicles, the probability to choose acceleration or deceleration becomes lower in the before PFG onset models. This can be explained by the limited motivation of pedestrians to accelerate/decelerate since they expect that sufficient time to complete crossing is still available. Furthermore, they may behave based on the understanding that during PG they have priority over turning vehicles thus they do not need to change their speed. However, pedestrians may still react to turning vehicles and change their maneuver if they are subjected to direct threat. This is not captured by our model since it does not consider the real interaction between pedestrians and turning vehicles.

After the onset of PFG, the initial utilities of acceleration and deceleration choices become higher as the constant value of both events are higher than the case before PFG onset. Therefore, a higher probability to choose acceleration or deceleration is expected. The conflict area dummy has a positive impact on acceleration choice. When pedestrians are in the conflict area during PFG, they feel unsecure considering the available time to the end of PFG and the possible conflicts with vehicles; thus, they tend to accelerate to clear the hazardous area. This is rational considering human decision making process to avert risks. Meanwhile, such behavior may surprise drivers and lead to severe conflicts.

Pedestrian direction of movement (far side and near side) has been used as a dummy variable since the location of conflict area is different for pedestrians crossing from both sides of the



(a) Acceleration (b) Deceleration

Figure 5. Example of acceleration / deceleration probability contours

crosswalk, however the estimation results showed that this parameter is insignificant. Meanwhile, the conflict area dummy and $V_{nec}–V_{cur}$ are found to be significant parameters (Table 4). $V_{nec}–V_{cur}$ considers the remaining distance and time to complete crossing; and whether current speed will allow the pedestrian to cross safely. Thus, the impact of direction of movement is indirectly considered in the developed models.

Other factors such as PFG/PG length, crosswalk length, elapsed time from onset of PFG and location of pedestrians are tested as explanatory variables of each model. However, none of them were found to be significant. Although the impact of some of these variables are expected to be significant, however the models could not capture their impact due to the limited sample size collected from 5 sites only.

For a better understanding, Figure 5 provides an example of the probability distributions of acceleration and deceleration at each time and location in a form of contour map as a demonstration. A far side pedestrian with no speed change before crossing is assumed. The current pedestrian speed is assumed to be 1.5 m/s, which is the average speed of pedestrians when they entered the crosswalks at the observed sites. The crosswalk length is set as 35m, which is within the range of crosswalk lengths at observed sites, and latter half of the crosswalk is considered as the conflict area with vehicles. PFG length is set as 10 seconds. Figure 5(a) and 5(b) graphically explain the characteristics of the developed models. According to the model, if pedestrians are at the first half of the crosswalk, they are likely to accelerate in the beginning of PFG (with probability of more than 0.6) and decelerate at the last moment of PFG. Figure 5(a) shows that there is a high probability (>0.5) that pedestrians will accelerate before entering the conflict area during PFG which leads to earlier arrival.

The high probability of acceleration during PFG is rational and reasonable but why would some pedestrians choose to decelerate at the end of PFG. This can be attributed to several reasons. Japanese pedestrian signal setting is characterized with short pedestrian flashing green intervals (L/2V) followed by long red buffer times until the start of the following conflicting vehicle phase as shown in the Figure 6 (Iryo-Asano and Alhajyaseen 2014b). Some pedestrians who are familiar with the site, they may know that there is sufficient time after the end of PFG until releasing the conflicting traffic. Thus they might not accelerate to

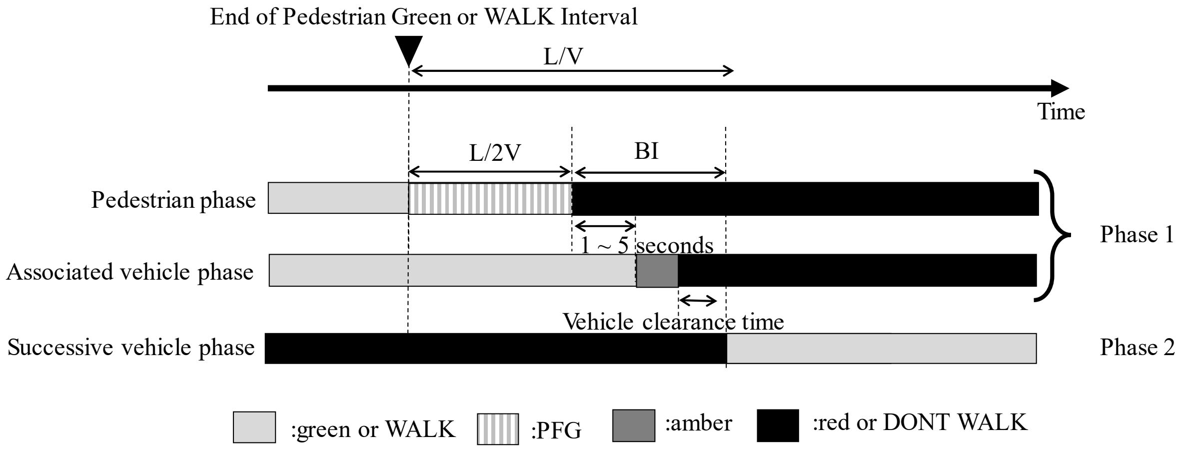


Figure 6. Illustration of signal indications and their intervals in Japan

Table 5. Estimation results of acceleration sub model

Variables	**Coefficients**	**t-values**
Constant	0.689	7.17
Current speed (m/s)	1.08	22.1
Remaining crosswalk distance (m)	0.00544	2.10
Sample size	153	
Modified R^2	0.765	

finish crossing before the end of PFG. Moreover, some pedestrians might enter the crosswalk with higher speeds than their desired speed to start the crossing or to avoid a conflict with turning traffic but later they slow down.

In general, Figure 5 shows that PFG interval is critical for the safety assessment since it contains high probability of pedestrian behavioral changes. By changing the input parameters, the model enables to show the impact of parameters upon speed change probability distributions. This information is of prime importance when considering autonomous vehicles and their interaction with pedestrians since they need to predict the behavior of pedestrians while crossing to avoid conflicts.

5.2 Acceleration/deceleration sub models

Table 5 shows the results of the acceleration sub model, which determines the pedestrian speed after the acceleration events. The speed is simply described by the current speed and the remaining crosswalk distance. Other parameters such as V_{nec}, time before or after the PFG onset, conflict area dummy, and others are tested as explanatory variables, but they are not significant. Table 6 shows the results of deceleration sub model based on the normal distribution. The analysis showed that the current speed is the only significant variable in this model. It is expected that the impact of $V_{nec} - V_{cur}$ is significant in the deceleration behavior however collected data could not capture this impact, probably due to the limited sample size.

Table 6. Estimation results of deceleration sub model

Variables	Coefficients	t-values
Mean		
Constant	0.155	2.33
Current speed (m/s)	0.553	22.5
Standard deviation	0.290	2.10
Sample size	300	
Initial log likelihood	203.2	
Log likelihood	132.9	
Modified R^2	0.725	

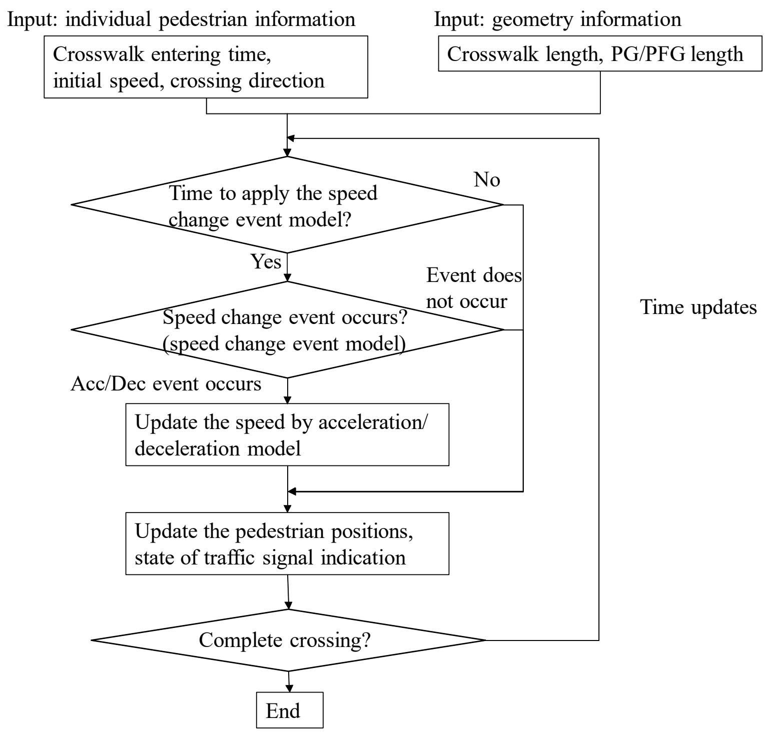


Figure 7. Model flowchart

6. MODEL VERIFICATION

6.1 Comparison of speed change maneuvers between observed and simulated data

The speed change event sub model as well as the acceleration/deceleration choice sub models are combined to estimate the whole speed profile of the pedestrians using C++ program. Figure 7 shows the framework of the simulation. The input variables of the models are the initial speed and time when pedestrians start to cross, crosswalk length and PG/PFG lengths. Observed parameters for individual pedestrians from empirical data are used in the model to generate pedestrian speed profiles including initial speeds, arrival time to the crosswalk and walking direction. The model updates the location and speed of each pedestrian at each time interval Δt (= 0.5s), and the probability of speed change event is estimated in every 5 seconds using the current location and speed information. The pedestrian selects whether he accelerate/decelerate by the estimated probability. Once the pedestrian selects to change his speed, acceleration/deceleration sub models are applied to determine his speed for the next time interval. Then the location and the speed of the pedestrian is updated proceeding the time

Table 7. Number of successful acceleration event generations

		Model		Total
		Acceleration	**No acceleration**	
Observation	**Acceleration**	**86 (56.2%)**	67 (43.8%)	153
	No acceleration	214 (23.6%)	**692 (76.4%)**	906
	Total	300	749	1059

Table 8. Number of successful deceleration event generations

		Model		Total
		Deceleration	**No deceleration**	
Observation	**Deceleration**	**208 (69.3%)**	92 (30.7%)	300
	No deceleration	275 (36.2%)	**484 (63.8%)**	759
	Total	483	576	1059

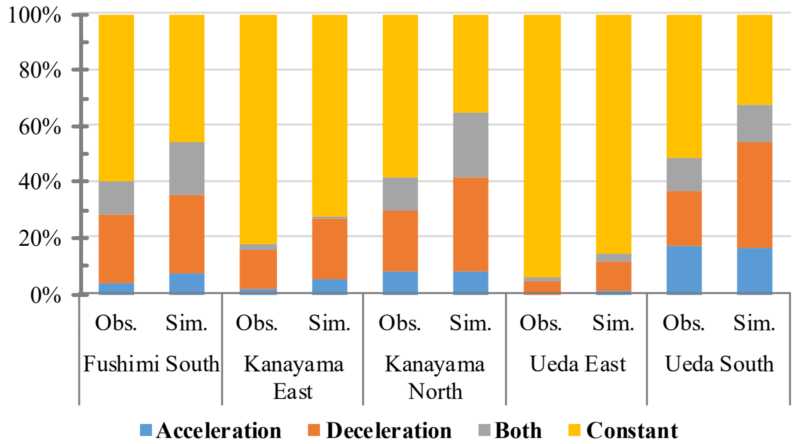
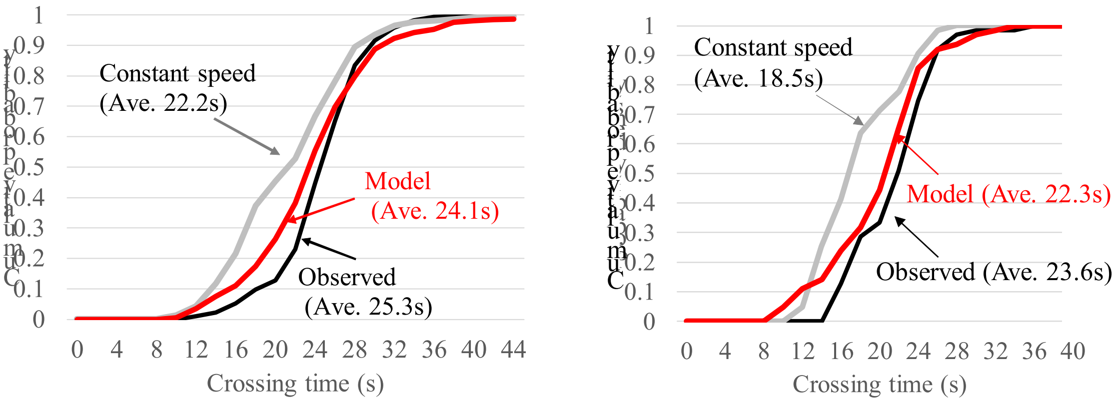


Figure 8. Comparison between observed and simulated percentages of pedestrians who had acceleration/deceleration events at each crosswalk

by Δt. This process is iteratively continued until the pedestrian complete crossing. The simulation was run 10 times for each pedestrian data set with different random seeds. The average of the results is presented in the following analysis.

The number of acceleration events generated by the simulation is compared with the empirical data as presented in Table 7. There are two types of failures in detecting the events. There is a 23.6% error in detecting the non-acceleration events, while there is a 43.8% estimated error in predicting the actual acceleration events. Therefore, the model tends to underestimate the probability of acceleration events. Similarly, Table 8 shows the number of deceleration events that are successfully estimated. For a better assessment of the model performance, Figure 8 is presented. It shows the percentage of pedestrians who had acceleration and deceleration events at each crosswalk in the observed and simulated data. The figure indicates that the overall tendency of the estimation results is similar to the observed ones.

Figure 9 compares the observed and simulated crossing time distributions. Since the observation sites had similar tendencies in the comparison, this study only presents the case at



(a) All pedestrians (N=396)

(b) Pedestrians started to cross during PG and faced the onset of PFG at the first half of crossing (N=63)

Figure 9. Total crossing time distribution at the North crosswalk of Kanayama intersection.

the North crosswalks of Kanayama Intersection. For reference, the crossing time distribution assuming a constant walking speed for whole crossing maneuver, is also calculated. To generate crossing times in the constant speed model, we assumed that observed initial speed at the entrance of the crosswalk is the speed that the pedestrian will keep throughout the crossing. This is logical since assuming any other speed like average speed means that the pedestrian is actually changing his speed while crossing.

For all pedestrians in Figure 9(a), the observed crossing time distribution is significantly higher than that of the constant speed. This means that some pedestrians decelerate during crossing. The proposed model provides more accurate crossing time distribution compared to those estimated using constant speed.

Figure 9(b) shows apparent improvement of the proposed model over the estimation based on the constant speed. It presents the cumulative crossing time distribution of pedestrians who started crossing during PG and then observed the signal change into PFG while crossing the first half of the crosswalk. The reason that the model fits well for these pedestrians is that they have higher probability to react to traffic signals. The proposed model can explain the speed change events while the constant speed assumption does not reflect these events and thus fails to generate realistic maneuvers.

To investigate the reliability of the developed model considering the location and timing of acceleration/deceleration events, Figure 10 is presented. It compares between observed and simulated probabilities of acceleration and deceleration events at Kanayama North Crosswalk for pedestrians crossing from the far-side of the crosswalk. The acceleration and deceleration probabilities are estimated separately for the first half and the second half of the crosswalk during three time intervals; first half of the pedestrian green interval (PG), second half of PG, and pedestrian flash green interval (PFG). Figure 10 indicates that the simulated acceleration/deceleration probabilities during different signal indication intervals and in both halves of the crosswalk are close to the observed ones. Although few significant differences are found, as shown in the comparison between the data of second half of PG at the second half of the crosswalk. This can be attributed to the probabilistic nature of the model and to the

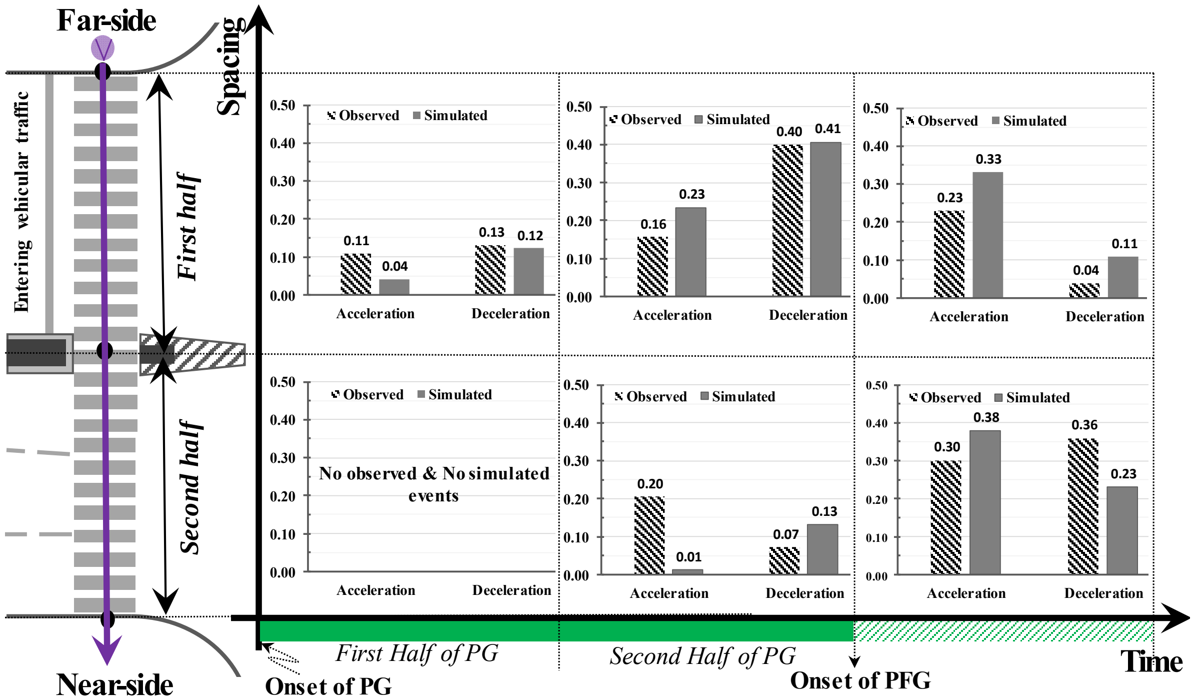


Figure 10. Comparison between observed and simulated probabilities of speed change events considering timing and location at the North crosswalk of Kanayama intersection

unconsidered influencing factors including pedestrian age, gender and the potential interaction with turning traffic.

6.2 Sensitivity analysis of pedestrian speed change model for vehicle-pedestrian safety assessment

The proposed pedestrian speed change model is integrated with the vehicle maneuver model by Alhajyaseen et al. (2012a and 2013a), and Wolfermann et al. (2011) in order to estimate the impact of the pedestrian speed change model on safety indicator. The vehicle maneuver model is a comprehensive model, which can represent the paths and speed profiles of left turning vehicles reacting to intersection layout (e.g. corner radii and intersection angles) and existence of pedestrians, while assuming constant pedestrian speed (Tan et al., 2013). The purpose of integrating the pedestrian speed change model is to understand the sensitivity of the surrogate safety measures obtained by the vehicle maneuver model to pedestrian speed change behavior. Figure 11 demonstrates the integration process of vehicle maneuvers model and the proposed pedestrian speed change model for the simulation of vehicle-pedestrian conflicts.

The vehicle maneuver model contains three sub models: turning path model (Alhajyaseen et al., 2013a), free-flow speed profile model (Wolfermann et al., 2011) and gap acceptance model (Alhajyaseen et al., 2013b). The first two models determine the probability distributions of vehicular paths and speed profiles as functions of intersection layouts and vehicle entering speed to intersection. Vehicles follow the generated paths and speed profiles from these models when they do not face pedestrians.

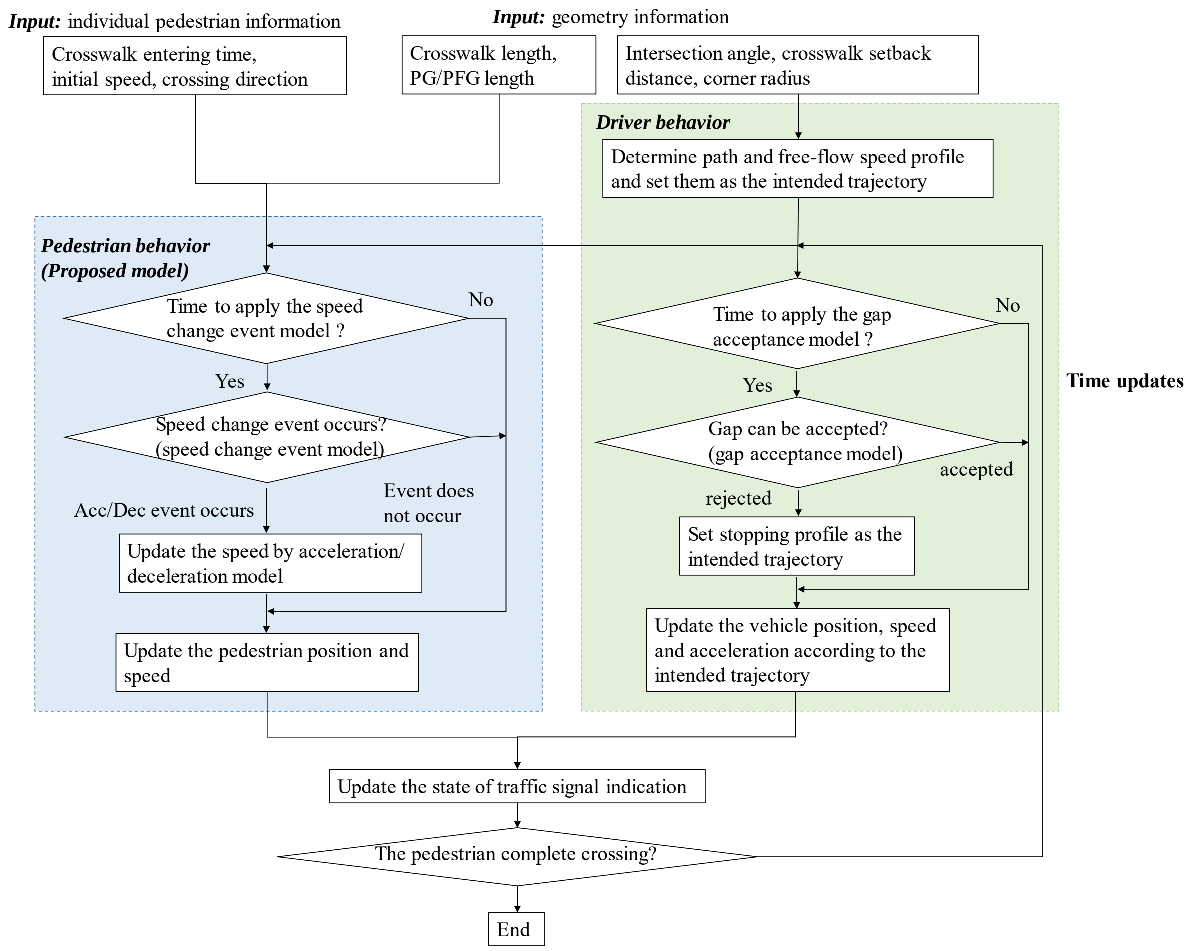


Figure 11. Flow chart of the vehicle-pedestrian conflict simulation

In case pedestrians exist around the crosswalks, vehicles calculate expected gaps (difference between expected arrival times of pedestrians at conflict point) and lags (difference between expected vehicle and earliest pedestrian arrival time at conflict point) and decide whether they continue to proceed or stop in front of the crosswalk (gap acceptance model). If they decide to proceed, they keep following the free-flow speed profiles. The gap acceptance model (Alhajyaseen et al., 2013b) assumes constant pedestrian speed for the expected arrival time calculation. However, the pedestrian speed may change on crosswalks as already been empirical observed by Iryo-Asano et al. (2015). The proposed speed change model is combined for the representation of pedestrian maneuver and for testing the impacts on the safety measure, which is PET (Post Encroachment Time). The gap acceptance model is applied every second.

The selected intersection layout for the simulation is that of the North crosswalk of Kanayama intersection (Table 1) which is the longest among study sites. Vehicle entry speed to the intersection is set as 40 km/h. To simplify the calculation process, only one pedestrian and one vehicle are generated at once. All pedestrians are assumed to approach the crosswalk from near side. Although the original model by Alhajyaseen et al. (2012a) generates free-flow vehicle speed profiles probabilistically, only the average profile was used for the simulation in order to concentrate on the impact of pedestrian speed change behavior. The elapsed time from PFG onset to the pedestrian entry time to the crosswalk T_p and that from PFG onset to the vehicle entry time to the intersection (stop line passing time) T_v were given

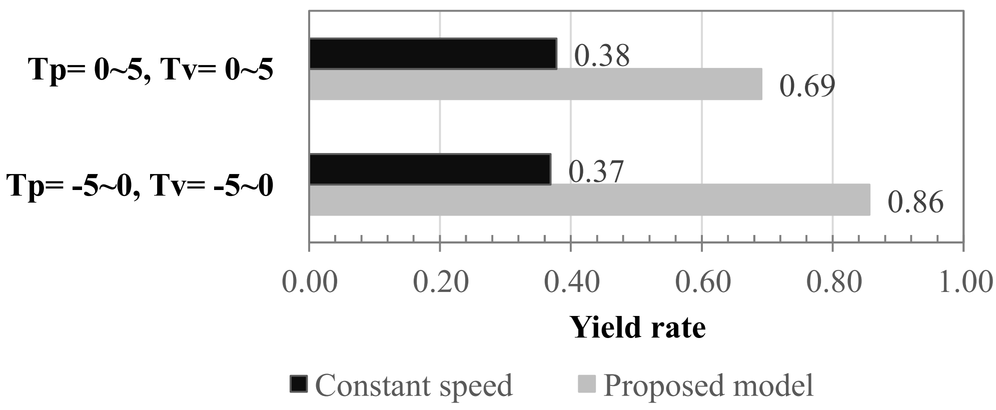


Figure 12. Vehicle yield rate calculated by the vehicle-pedestrian conflict simulation

randomly within the assumed intervals. Two scenarios were tested for the values of T_p and T_v. In scenario 1, both are generated in the interval from -5 to 0 second while in scenario 2 both are generated in the interval from 0 to 5 second. For each scenario, the simulation was run 1000 times with the proposed pedestrian speed change model and also with the constant pedestrian speed setting.

Figure 12 shows the vehicle yield rate in the simulations using the constant speed model as well as the proposed speed change model. It is clear that the proposed model provides significantly higher yield rate than the constant speed case. This is rational since vehicles need to react more frequently to pedestrians due to their sudden speed change events. Furthermore, it should be noted that the yield rates of the proposed model with different T_p and T_v ranges are significantly different (with 1% significance level), while those of the constant speed case are not. This is because the proposed model can reflect the impact signal timing and V_{nec} which varies by the entry timing of the pedestrians.

Figure 13 shows probability density distributions of PET calculated by the simulation. Here again, the PET distributions of the constant speed cases are not influenced by T_p and T_v but those of the proposed model are significantly different. Scenario 1, in which T_p and T_v are between -5 and 0, resulted in significantly smaller PETs. This simulation example clearly demonstrates the significant impact of speed change behavior on the safety assessment of pedestrian-vehicle conflicts.

7. CONCLUSION

This study proposed a method to generate pedestrian crossing speed profiles considering sudden speed change events. A probabilistic discrete choice model is developed to determine acceleration/deceleration timing. The analysis revealed that the difference between the necessary speed to complete crossing and the current speed, conflict area dummy, and flashing green indication have significant impacts upon acceleration and deceleration choices. The comparison with the empirical data showed that the model was successful in representing the observed crossing time distributions with better accuracy compared to the crossing time distributions that are estimated based on constant crossing speed, though the accuracy of the individual speed change event detection still needs improvement. Although the variable of the conflict area did not significantly work in the model estimation, more precise representation

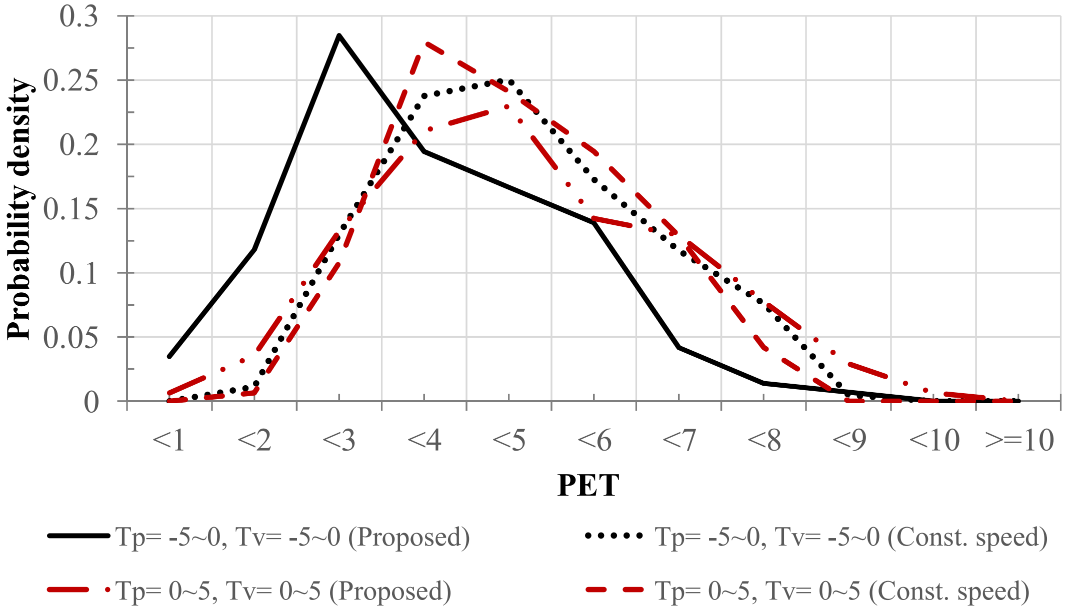


Figure 13. Distribution of PET calculated by the vehicle-pedestrian conflict simulation

of approaching vehicle information may help improving the accuracy of the model. Furthermore, in this study, pedestrian-pedestrian interaction is not considered since the pedestrian traffic volumes at the study sites were relatively low and thus there was less probability to interact with each other. Pedestrian characteristics such as age and gender are important factors to be investigated, especially in aging communities where elderly are in high risk of conflicts with vehicles because of their limited communication with the surroundings. Moreover, pedestrian distraction because of using entertainment and telecommunication devices (such as smartphones and gadgets) is becoming an important issue recently. Such distraction may limit pedestrian interaction with the surrounding environment including the avoidance behavior to conflicts with vehicular traffic. Investigating the impacts of pedestrian distraction on their maneuvers is a contemporary issue that needs to be considered.

Sudden pedestrian speed changes are important events that may significantly contribute to the severity of pedestrian–vehicle conflicts since drivers cannot easily expect them. The developed pedestrian speed profile model can contribute to realistic representation of conflicts with vehicles. This can be utilized to estimate the pedestrian-vehicle conflict risk as a part of traffic simulation for safety assessment, by integrating with other maneuver models of vehicles and pedestrians. Another application can be a real-time information provision to vehicles to alert the risk of hazardous conflicts. Such system is expected to be useful not only for drivers but also for the development of avoidance maneuver modeling of autonomous vehicles.

Moreover, this study used manual tracking of pedestrians using image-processing software (TrafficAnalyzer) which may lead to tracking errors that can be minimized using advanced techniques such as laser scanning techniques (Caputcu et al., 2016). Such techniques may lead to higher precision and more accurate measurements that can be used for future data collection.

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