MODELING THE SPEED, ACCELERATION AND DECELERATION OF BICYCLISTS FOR MICROSCOPIC TRAFFIC SIMULATION

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ABSTRACT

In this paper models are developed, calibrated and evaluated to describe the acceleration and deceleration processes of bicyclists in three states; while accelerating from a stop, decelerating to a stop and while fluctuating around the desired traveling speed. Such models are necessary to reliably simulate the speed profiles of bicyclists in microscopic traffic simulations. To accomplish this aim, a sample of 1030 processed trajectories from bicyclists at four intersections in Munich, Germany is used to analyze the dynamic characteristics of bicyclists. The average crossing speed, the fluctuation in crossing speed as well as the minimum and the maximum speeds of uninfluenced bicyclists who cross at a green light are analyzed and correlations between these variables are investigated. The acceleration and deceleration profiles of bicyclists who stop at a red light, but are uninfluenced by other bicyclists, are used to evaluate four acceleration/deceleration models; the constant model, linear decreasing model, two term sinusoidal model and polynomial model. Two adaptions of the models are developed and evaluated, one to derive acceleration and deceleration as a function of speed rather than time and the other to account for the observed fluctuation in bicyclist traveling speed. The polynomial model is found to be the most flexible and produces the overall best estimates of the acceleration profiles. The constant model was found to best estimate deceleration as well as acceleration and deceleration while fluctuation around the desired speed.

Keywords: Microscopic Traffic Simulation, Bicycle Modeling, Bicycle Dynamics

INTRODUCTION

Microscopic simulation of road traffic is frequently used to analyze the efficiency of road traffic and to forecast the effects of future transportation measures before implementation. More recently, traffic simulation tools have been used to analyze traffic safety. This is done by calculating surrogate traffic safety indicators such as Time to Collision (TTC), Post Encroachment Time (PET) and Deceleration Rate ensuing from interactions between simulated road users (*1*). In both types of assessment, the soundness of the analysis depends on the validity of the mathematical models used to recreate the movements of road users (*2*). However, the calculation of surrogate safety indicators is much more sensitive to the finite accuracy of the road user trajectories than are efficiency analyses. Even seemly small divergences between the trajectories followed by road users in reality and those of the simulated vehicles, pedestrians and bicyclists can cause significant errors in the resulting surrogate safety measures.

The desired speed of a motorized road user is typically modeled in a microscopic traffic simulation by taking the speed limit of the road segment. The desired speed of a bicyclist in contrast does not depend on the speed limit of the roadway, but rather on the personal preferences, physical capabilities and tactical maneuvers of the bicyclist, as well as the type and quality of the infrastructure, the traffic control and the given traffic situation (*3*). In the microscopic simulation, the speed of all road users is controlled in each time step by an acceleration input that is calculated from an acceleration model. The ability of acceleration models to deliver accurate speeds depending on the situation and the current state of the bicyclist are essential in creating realistic trajectories of bicyclists in microscopic traffic simulations, particularly for safety analyses.

A number of studies have been carried out to measure the speed of bicyclists as they cross signalized intersections, with mean speed estimates ranging between 3.2 m/s and 6.9 m/s (*4–10*). In most cases where acceleration is examined, constant acceleration is assumed and the mean acceleration is estimated from video data. Estimates of mean acceleration range between 0.23 m/s^2 and 1.07 m/s^2 (*6*, *9*, *11*, *12*).

Although a number of models have been proposed in the literature to describe the acceleration process of motorized vehicles, very few examinations of acceleration and deceleration profiles of bicyclists were found in the literature. The most common and simplistic approach for modeling acceleration is the constant acceleration model $a(t) = \bar{a}$, where the acceleration at any point during the acceleration process $a(t)$ is equal to the mean acceleration. In many applications, such as in the estimation of crossing times for calculating inter-green times at signalized intersections, the constant model provides sufficient level of detail. However, if the aim is to model dynamic behavior with enough accuracy to evaluate traffic safety, this approach lacks crucial details of the acceleration profile (*13*, *14*).

Another approach commonly used for modeling acceleration with more detail than the constant model is the linear decreasing acceleration model. In this model, the maximum acceleration is exerted when the acceleration maneuver is begun and decreases linearly until the desired speed is reached. Such an approach is used in the Necessary Deceleration Model for the modeling of bicyclist dynamics by (*14*), as described in equation 1.

$$a(s) = \frac{s_o - s}{t_a} \qquad (1)$$

where: $a(s)$ = acceleration at speed s
s_o = desired speed
t_a = total acceleration time

Haifeng et al. (*15*) proposed a non-linear decreasing model of acceleration as a function of time to model acceleration and deceleration of bicyclists. The maximum acceleration thus occurs at $t = 0$ and rapidly decreases during the acceleration process. Linear and non-linear decreasing acceleration models are expected to produce more realisitc results than constant acceleration approaches but do not reflect S-shaped acceleration curves that have been observed for motorized road users (*13*). Such curves are characterised by low acceleration at the beginning of the acceleration maneuver, maximum acceleration at some mid-point during the maneuver and decreasing acceleration until the desired speed is reached.

Akçelik & Biggs (1987) proposed and tested three models that all reflect the observed S-shaped speed curves measured by the researchers as well as the constraint of zero acceleration and jerk at the beginning and end of the acceleration process; the polynomial model, the two-term sinusoidal model and the three-term sinusoidal model. For motorized vehicles, the polynomial model of acceleration was found to outperform the other models. The equations proposed by Akçelik & Biggs (1987) are given in equations 2-4. Luo (2014) used GPS tracking data with a frequency of one observation per second from bicyclists to fit an adapted polynomial acceleration model. The model preformance was deemed satisfactory for acceleration but not deceleration.

$$a(t) = ra_m \theta^n (1-\theta^m)^2 \qquad \text{Polynomial Model} \qquad (2)$$

$$a(t) = Ca_m (\sin \pi\theta + B \sin 2\pi\theta) \qquad \text{Two-Term Sinusoidal Model} \qquad (3)$$

$$a(t) = Ra_m (0.5 - P\cos \pi\theta - 0.5\cos 2\pi\theta + P\cos 3\pi\theta) \qquad \text{Three-Term Sinusoidal Model} \qquad (4)$$

where: $a(t)$ = acceleration at time t

a_m = maximum acceleration

t_a = total acceleration time

r, n, m, C, B, R, P = model parameters

$\theta = \dfrac{t}{t_a}$ = time ratio

In this paper, trajectory data from a sample of 1030 bicyclists who are uninfluenced by other bicyclists are used to calibrate and evaluate four of the acceleration models found in the literature. A new method for modelling acceleration as a function of speed, which is understood in this paper as the momentary speed, or the speed of a given road user at a specific point in time, rather than time is defined based on the θ ratio proposed by Akçelik & Biggs (1987). This method has two advantages; first the trajectory data can be analysed without prior determination of the start time of a given acceleration maneuver and, second, the resulting acceleration profile can be used within a microscopic simulation to directly derive an acceleration value based on the given speed and maneuver of a bicyclist. In addition, an approach for including the fluctuation in the riding speed of bicyclists directly in the acceleration model is developed and evaluated. The research methodology is discussed in detail in the following section. The results of the model fitting are presented and discussed subsequently. Conclusions and outlooks for future work are included at the end of the paper.

METHODOLOGY

Data analysis

Video data analysis allows for the automated extraction of trajectories (position and velocity in each video frame) at a high temporal resolution for a large sample of road users. Dynamic situational variables, including the position and velocity of other road users and the phase of the traffic signal, can be easily extracted or appended.

Video data was collected at four intersections in Munich, Germany, for two to four days per intersection during the summer months. The study intersections were selected to ensure a wide variety in the type of bicycle infrastructure and traffic volume at the intersection. However, all intersections are located within the city center of Munich, less than 1.5 km from Marienplatz, the central square of

Munich, in mixed use areas. The layouts of the four intersections are shown in Figure 1 (frames extracted from the video data). Videos were recorded using a GoPro Hero3 Black Edition with a full HD resolution (frame size: 1920x1080 pixels) at 25 frames per second. A wide angle lens was used to collect trajectory and situation data from a larger area. This, however, introduced distortion issues in the automated video analysis that were later rectified. Two hours of video data from each intersection were selected from the total video footage for trajectory extraction. For all of the intersections, two hour continuous video segments were selected during the morning peak hour (from about 7:30 am to 9:30 am), with favorable lighting conditions (few shadows) and as little disturbance from wind as possible.

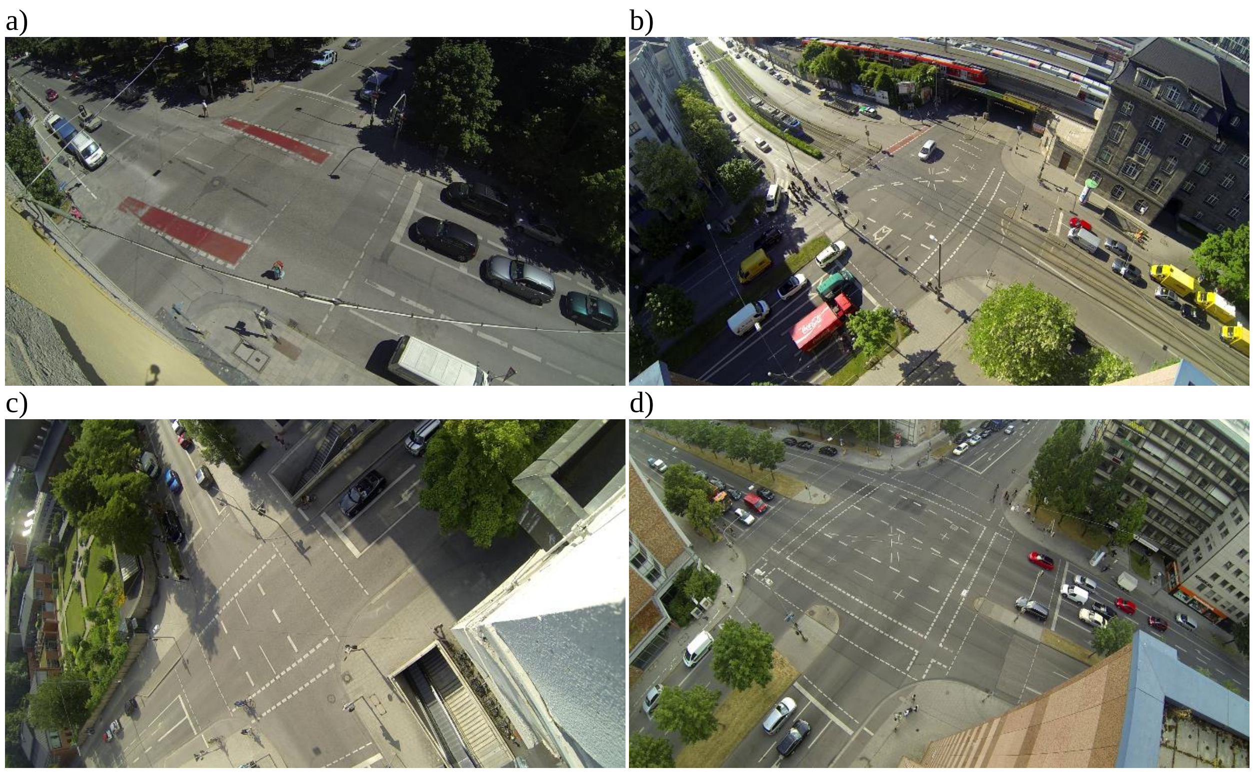

FIGURE 1 Camera view of the intersections a) Arcisstrasse-Theresienstrasse b) Arnulfstrasse-Seidlstrasse c) Karlstrasse-Luisenstrasse d) Marsstrasse-Seidlstrasse.

The open source software *Traffic Intelligence* (*17*) was used to extract trajectory data from the selected video segments. The software is based on a two-step process in which all moving features in the video are tracked in the first step and grouped into road user hypotheses based on proximity and similarity in the second step. Both steps are regulated by a number of parameters that are calibrated depending on the image quality and the size and speed of the road users. A dual calibration method was developed and implemented that categorizes the features based on their location in the video frame as probable cars or pedestrians/bicyclists in the first step (*18*). The grouping parameters were independently adjusted to the respective speed and size of the specific road users for the second step. Thus the road users were classified as cars, bicyclists or pedestrians based on their speed and location.

The calibration parameters were intentionally set to be over sensitive and to over-segment rather than over-group road users. This ensured that trajectory data was extracted for a maximized portion of bicyclists. However, this made it necessary to invest a considerable amount of work in manually post-processing the trajectory databases. Erroneous or superfluous trajectories were removed, disjointed trajectories belonging to the same road user were combined and falsly classified objects were corrected. The distortion that was introduced through the wide angle lens was corrected by post-processing the SQLite trajectory databases produced by *Traffic Intelligence* (the current version of *Traffic Intelligence* includes a method for rectifying video data before processing). OpenCV (opencv.org) was used to determine the intrinsic camera parameters and the distortion coefficients of the GoPro Hero3 camera with the waterproof housing. The position points of the trajectories were remapped based on the resulting matrices and the velocites were recalculated in each frame.

The high resolution of the video images as well as the height and angle of the camera during recording allowed for the extraction of high quality trajectory data. The relative accuracy of the positions recorded in each time step is estimated to be between 5-10 cm. However, position values are calculated by *Traffic Intelligence* for a single road user by finding the mean of the positions of all features that are grouped into that road user in each frame. As a result, the position data can jump slightly from frame to frame as new features are detected and others are lost. The resulting noise in the data becomes more pronounced as the position values are differentiated once to get velocities and twice to obtain accelerations. In order to reduce this effect, the data was aggregated from a frequency of 25 observations per second to 5 observations per second for the velocity values and 2.5 observation per second for the acceleration values. At both differentiation steps, the data was filtered using the Savitzky-Golay method (*19*) with the window size of 15 and an order of two. This aggregation and filtering method proved to produce valid distance-time, speed-distance and acceleration-distance plots of the road user trajectories when compared to manually calculated values.

The City of Munich provided data from the traffic signals at three of the four research intersections for the data collection period. Each of these signals is traffic actuated and information regarding the time of each phase change is automatically catalouged (1 second precision). Intersection 4 is controlled by a fixed-time signal control and therefore the phase change time data is not recorded. This information was extracted manually from the video data with slightly less precision.

The resulting trajectory data was filtered to include only uninfluenced bicyclists. The behavior of a bicyclist can be hindered at urban intersection by two main factors; the presence and actions of other road users and the traffic signal control. In order to isolate the uninfluenced (or desired) behavior of the bicyclist as well as the non-confounded response to both the signal control and the actions of other road users, the bicyclists were divided into four groups, as shown in Table 1. Bicyclists in Group A arrive at the stop line of the intersection while the traffic signal is green and have more than a two second time gap to any leading bicyclists (uninfluenced). Group B bicyclists arrive while the traffic signal is red and there are no other bicyclists stopped at the intersection (traffic signal influence).

TABLE 1 Classification of Bicyclist Groups

		Interference from other bicyclists (following $t_{gap} < 2\ s$)	
		No	Yes
Interference from signal control (red signal upon approach)	No	Group A (N=704)	Not analyzed
	Yes	Group B (N=326)	Not analyzed

The qualitatively verified trajectory data from the 1030 bicyclists in Group A and Group B are used to investigate the crossing speed, acceleration and deceleration of bicyclists at signalized intersections. The average crossing speed, the variation in crossing speed as well as the minimum and the maximum speeds of bicyclists in Group A are analyzed and correlations between the analysis variables are investigated. The acceleration, deceleration and speed observations from the trajectories of bicyclists in Group B are used to examine the acceleration models presented in the introduction.

Modeling acceleration and deceleration

Acceleration is typically modeled as a function of time. However, in reality, a bicyclist does not accelerate depending upon time, but rather depending upon his or her given speed, desired speed and the situational restraints. While processing the data, the acceleration and speed can be directly extracted from the trajectory. The identification of a starting time for the maneuver, on the other hand, is more challenging and in some situations not possible. Similarly, for the purpose of traffic simulation, modeling acceleration as a function of speed is more practical because time, as measured from the start of an acceleration process, is not readily available from the traffic simulation. Speed, however, is available in each simulation time step. Indeed, simulation software such as VISSIM allow users to set acceleration-speed curves, which are used to define the acceleration based on speed (*20*). To account for this aspect of traffic simulation, a new θ_s ratio is proposed in equation 5 based on the θ concept introduced by (*13*).

$$\theta_s = \frac{s - s_i}{s_f - s_i} \qquad (5)$$

where: θ_s = speed ratio
s = speed
s_i = initial speed
s_f = final speed

A similar parameter ρ is used by Akçelik & Biggs (1987) to evaluate the acceleration models developed in that paper. This parameter is adapted and used here to develop the acceleration curves. However, given the proposed definition of θ_s in equation 5, an acceleration of zero at $\theta_s = 0$ would lead to a situation in which a bicyclist would never accelerate from the initial speed of $s_i = 0$. To resolve this issue, equations with an θ_s-intercept at $\theta_s = 0$ must be altered to ensure an $a(\theta_s)$-intercept that is greater than zero. This is done by adding a shifted $\frac{1}{\theta_s^2}$ function with an θ_s-intercept at $\theta_s = 1$ and an adjustable $a(\theta_s)$-intercept that can be calibrated to fit the observed data.

The four acceleration models shown in equations 6-9 were assessed using the observed trajectory data. Initial testing of the three term sinusoidal model proved it to be similar to, but less accurate and more complex, than the two term sinusoidal. For this reason it was excluded from further examination. Similarly, initial testing of a new model, the square root model, indicated that this approach was not suitable for modeling acceleration or deceleration and was excluded from further analysis.

$$a(\theta_s) = \bar{a} \qquad \text{Constant Model} \qquad (6)$$

$$a(\theta_s) = a_m - a_m\theta_s \qquad \text{Linear Decreasing Model} \qquad (7)$$

$$a(\theta_s) = r a_m \theta_s^n (1-\theta_s^m)^2 + (a + \frac{1}{\theta_s^2 + c}) \qquad \text{Polynomial Model} \qquad (8)$$

$$a(\theta_s) = C a_m (\sin \pi\theta_s + B \sin 2\pi\theta_s) + (a + \frac{1}{\theta_s^2 + c}) \qquad \text{Two Term Sinusoidal Model} \qquad (9)$$

where: $a(\theta_s)$ = acceleration at speed ratio θ_v
$\bar{a}$ = mean acceleration
a_m = maximum acceleration
θ_s = speed ratio (equation 5)
r, n, m, a, c, C, B = model parameters ($a = \frac{-1}{1+c}$)

State definition

Two approaches are developed and evaluated using the observed trajectory data; a simplified approach that does not include fluctuation around the desired traveling speed and an oscillating approach that includes this fluctuation. While both approaches use the ratio θ_s introduced in equation 5, the definition of s_i and s_f differ in the two approaches.

Simplified approach

In the simplified approach, bicyclists accelerate with a given acceleration profile until they reach their desired crossing speed s_d. They continue at this speed without fluctuation until it becomes necessary to stop or slow down. In this approach, bicyclists are in one of three states:

State 1: Acceleration:	$s_i < s_d$ and $s_f = s_d$
State 2: Deceleration:	$s_i > 0$ and $s_f = 0$
State 3: Traveling steadily at desired speed:	$s_i = s_f = s_d$

Oscillating approach

In reality, bicyclists are unable to maintain a constant speed while riding (*11*). An approach for incorporating this fluctuation into the acceleration model and hence into traffic simulations, is given using the following four states. The parameters $\min s_d$ and $\max s_d$ represent the lower and upper speed threshold observed in the trajectories of a bicyclist riding normally. These values are subsequently used to calculate θ_s:

State 1: Acceleration from a stop (or a low speed):	$s_i < \min s_d$ and $s_f = \max s_d$
State 2: Deceleration to a stop (or a low speed):	$s_i > s_f$ and $s_f < \min s_d$
State 3: Acceleration as part of normal speed fluctuation:	$s_i \geq \min s_d$ and $s_f = \max s_d$
State 4: Deceleration as part of normal speed fluctuation:	$s_i \leq \max s_d$ and $s_f = \min s_d$

Model calibration and evaluation

The acceleration data derived from the trajectories was plotted using the newly defined θ_s, both using the simplified and oscillating approach. To produce the observation points, the acceleration data from all bicyclists with equal crossing speeds s_d when rounded to the nearest 1 m/s were aggregated. The θ_s values were rounded to the nearest 0.05 and aggregated to build large groups of observations. The plotted points in Figure 2 indicate the median of the observed accelerations for each aggregated θ_s group. The parameters were calibrated to an accuracy of 0.1 using the average root mean square error (RMSE) as a measure of good fit.

RESULTS

Speed analysis

The trajectories of bicyclists riding straight across the intersection on a bicycle lane in the intended direction of travel were taken as the reference group for the crossing speed analysis (Group A). The dynamic characteristics of this group are summarized in Table 2. The speed of the observed cyclists is found to vary as the cyclist crosses the intersection, which supports the hypothesis that bicyclists do not normally maintain a constant speed as they ride (*11*).

In order to incorporate the speed fluctuation into the acceleration model, it is necessary to investigate the range of traveling speeds observed for bicyclists riding unhindered though the intersection.

As shown in Table 2, an average fluctuation of 1.82 m/s was observed. However, when taking the average maximum and minimum speeds of the bicyclists in Group A into account, 4.20 m/s and 6.02 m/s respectively, the range of normal riding velocities can be approximated as $0.8s_d < v < 1.15s_d$. It is assumed that all bicyclists in Group A and Group B are part of the same population of bicyclists because arrival at a red light is distributed randomly amongst bicyclists. The results in Table 2 are therefore used as a reference for the desired riding speed of all bicyclists in the following analyses.

TABLE 2 Dynamic Characteristics of Bicyclists in Group A

Group A ($t_{gap} > 2s$ and Signal Phase: Green, N=466)	**Mean**	**Std.**	**Correlation Coefficient R^2 (p value)**		
			Speed range (m/s)	Min. speed (m/s)	Max. speed (m/s)
Crossing speed (m/s)	5.23	1.25	**-0.128 (p=0.006)**	Direct correlation	Direct correlation
Crossing speed range (m/s)	1.82	1.11		**-0.535 (p=0.000)**	**0.250 (p=0.000)**
Minimum speed (m/s)	4.20	1.48			**0.684 (p=0.000)**
Maximum speed (m/s)	6.02	1.29			

Acceleration

The trajectory data from Group B was used to test and calibrate the acceleration and deceleration models for State 1 and State 2, for both the simplified and the oscillating method. Data from the bicycles at all four research intersections was aggregated to attain a suitably large dataset. In order to estimate the desired crossing speed s_d of each bicyclist, an exit line was drawn between the two edges of the sidewalk pavement on the opposite side of the intersecting road. The distance between the stop line and the exit line ranged from 13m to 40m, depending on the intersection and approach. According to (*11*), the majority of bicyclists complete an acceleration process in less than 11m. It was therefore assumed that the observed bicyclists reached their desired crossing speed before crossing the exit line and s_d was defined as the mean speed of the bicyclist after crossing this line. It should be noted that the desired crossing speed is the desired speed while crossing an intersection and the desired speed on segments between intersections maybe greater or less.

The calculated θ_s and corresponding acceleration values of bicyclists accelerating from a stop are shown in Figure 2. As the oscillating approach was found to produce better estimations of the observed acceleration data, only results from this approach are shown below. The resulting RMSE values for all the tested models are included in Table 3.

As seen in Figure 2, the maximum acceleration of the observed trajectories increases with the desired speed s_d. The calibrated parameters for the models for each desired speed group are included in the top left corner of the chart. The small range of the parameters r and C, which control the amplitude of the polynomial and two term sinusoidal models, indicates that the differences between the curves of the different desired speed groups is largely accounted for by the different a_m values associated with the desired speed group.

The maximum acceleration is reached in all cases at $\theta_s \cong 0.4$. In theory, $a(\theta_s)$ should equal 0 at $\theta_s = 1$. However, the observed data tends towards zero but does not reach zero for any of the desired speed groups. This is because s_d is defined as the average observed speed of a specific bicyclist. The speed range on the other hand is defined for all bicyclist as $0.8s_d < v < 1.15s_d$, which reflects the average values. Per definition, many observed trajectories include maximum speeds larger than this value. The acceleration values measured at these high speeds, however ranged between zero and 0.2 m/s, which is consistent with the acceleration values observed for bicyclists fluctuating during normal riding (Figure 4).

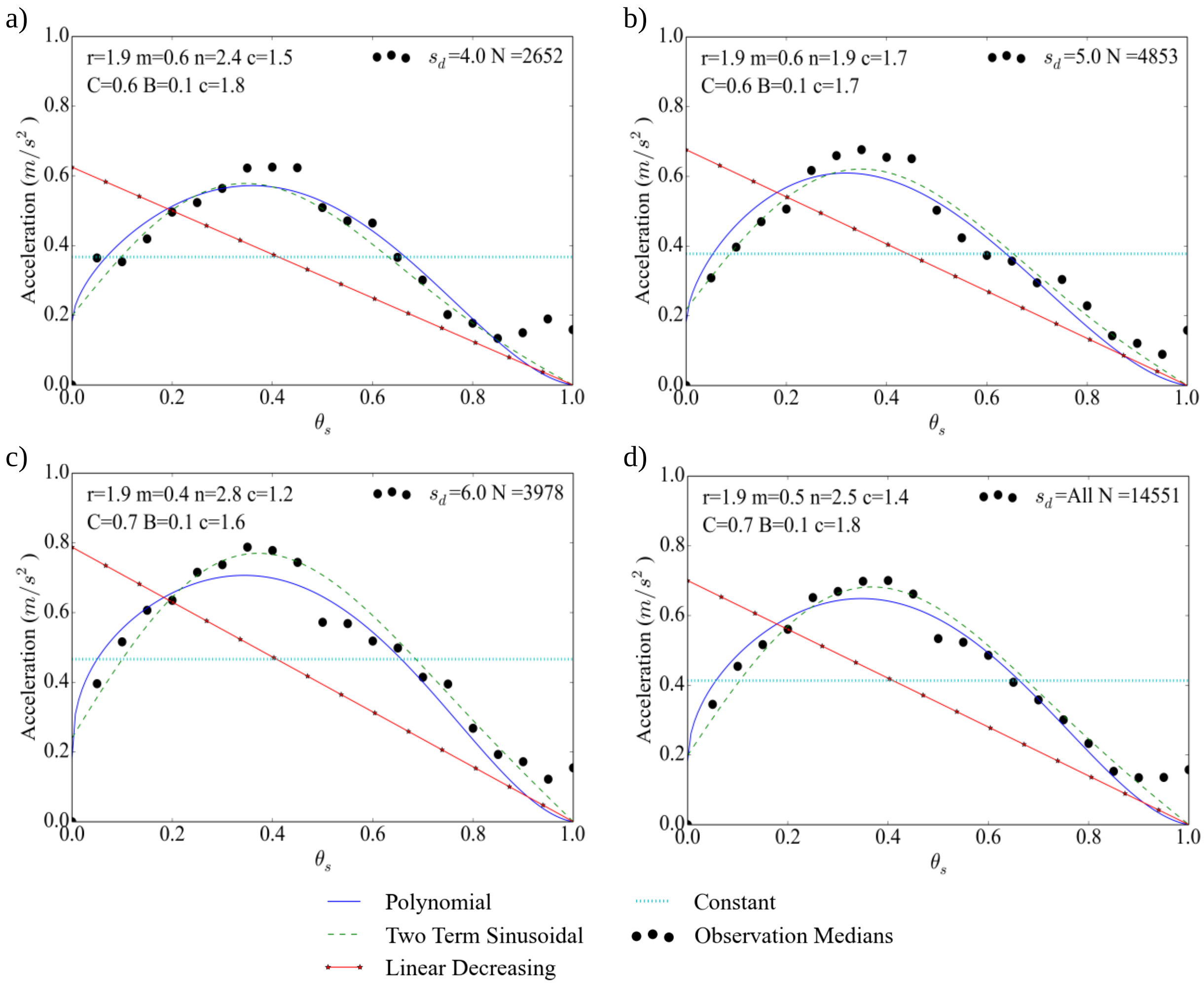

FIGURE 2 Acceleration profiles of bicycles in State 1: acceleration from a stop using the oscillating approach a,b,c) clustered according to the desired speed s_d and d) aggregated.

Deceleration

The simplified and the oscillating approach are identical when considering the deceleration of bicyclists in Group B because all of the bicyclists have a s_d value of 0, or in other words decelerate to a complete stop. The θ_s and deceleration values of bicyclists in State 2 for three desired speed groups (a-c) and aggregated (d) are shown in Figure 3.

The portion of trajectories from bicyclists in Group B that included the deceleration phase was relatively small compared to the acceleration phase. This is because a number of the approaches were not clearly visible over a sufficiently long segment in the video data. As a result, the deceleration profiles are noisier than the acceleration profiles. The evaluation of the different models suggests that the best fit to the observed data is achieved by the constant model. Although a slight curve with a maximum deceleration occurring at about $\theta_s = 0.3$ can be observed in three of the plotted profiles, the noise in the data could have prevented an accurate fitting of the other tested models. The best approximation of the maximum deceleration was attained by the two term sinusoidal modal, but these results were inconsistent between the s_d groups.

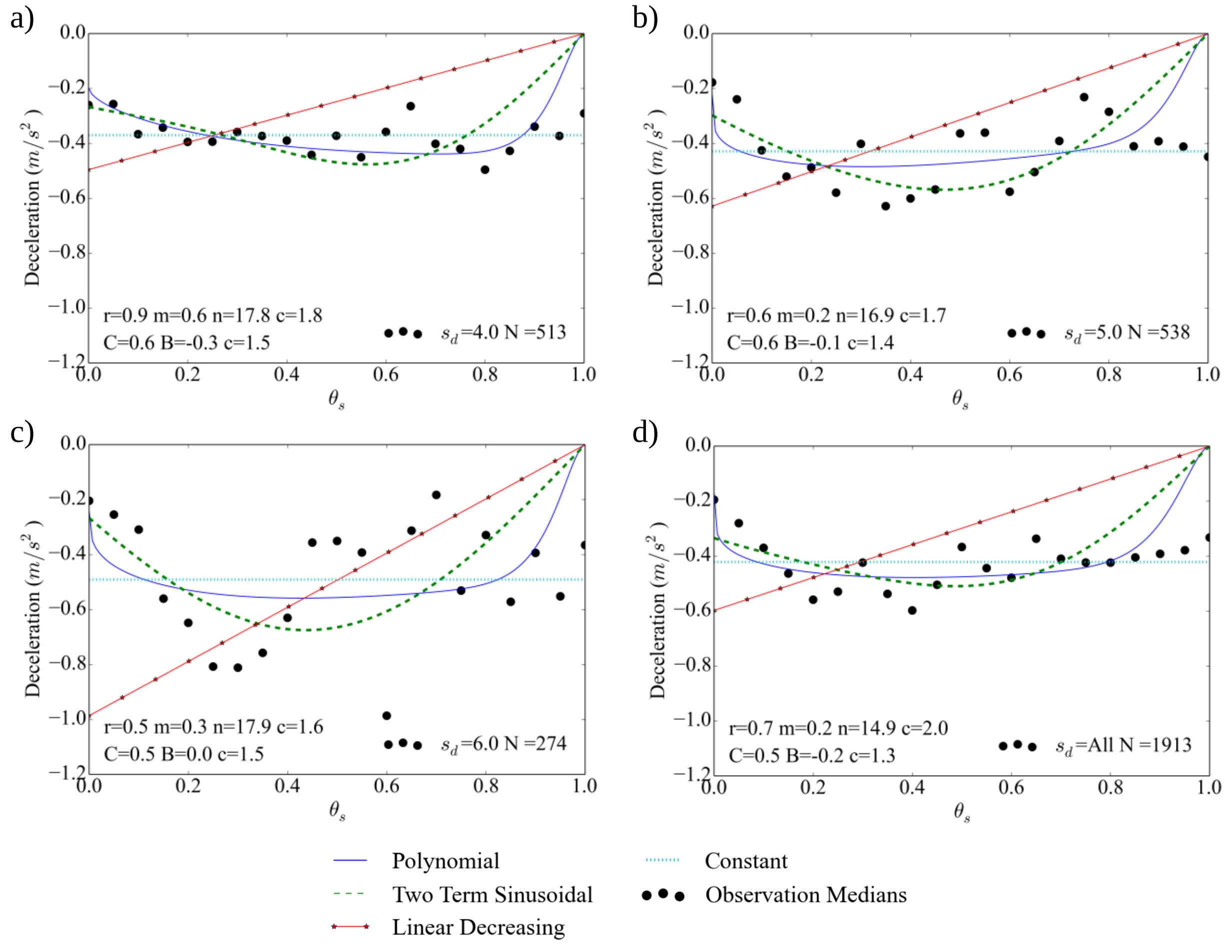

FIGURE 3 Deceleration profiles of bicycles in State 2: deceleration to a stop a,b,c) clustered according to the desired speed s_d and d) aggregated.

Speed fluctuation

Data from bicyclists who passed unhindered through a green light (Group A) were used to investigate States 3 and State 4, accelerating and decelerating respectively during normal riding as a result of fluctuating traveling speed. The plotted acceleration and deceleration data from the observed trajectories and the tested mathematical models are shown in Figure 4. Only the aggregated curves of all bicyclists in Group A are shown because no discernable difference based on the desired speed s_d was observed. The resulting curves suggest that acceleration and deceleration values that lead to the fluctuation in riding speed are uniform across θ_s values and tend to be around ±0.2 m/s^2.

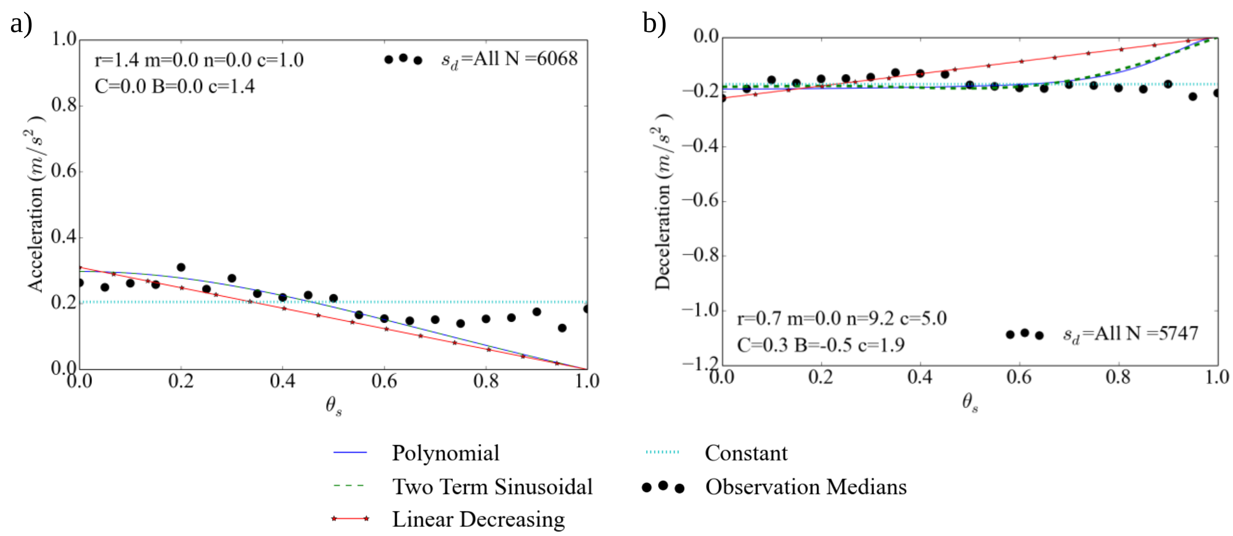

FIGURE 4 Acceleration and deceleration profiles of bicycles in a) State 3 and b) State 4: accelerating and decelerating as part of normal speed fluctuation, respectively.

Evaluation

The average root mean square error (RMSE) and the percentage error in the predicted maximum acceleration attained using the simplified and the oscillating approaches are given in Table 3. The RSME values given in the table are the average RMSE value for all the clustered desired speed groups (4.0-6.0 m/s) for State 1: acceleration from stop and State 2: decelerating to a stop. For State 3 and 4: accelerating and decelerating while fluctuating around the desired speed, respectively, only the RMSE value for the aggregated case is given as no difference in profiles of the clustered desired speed groups could be discerned. In each of the states examined, the lowest RMSE value, or the best model fit, as well as the lowest percentage error in the maximum speed estimation are bolded. The following conclusions were reached for each of the investigated models:

- The constant acceleration model does not produce good approximations of the acceleration profiles of bicyclists accelerating from a stop or a very low speed (State 1). This model, however, proved to best match the deceleration profiles of bicyclists decelerating to a stop or very low speed (State 2). This was also the case for bicyclists fluctuating around the desired traveling speed (State 3 and State 4). While this model by definition meets the requirement that $a(\theta_s) \neq 0$ when $\theta_s = 0$, it does not meet the requirement that $a(\theta_s) = 0$ when $\theta_s = 1$. This will lead to discontinuous jumps between acceleration and deceleration, which does not reflect the smooth transitions observed in reality. Another disadvantage of this model is the inherent poor estimation of maximum acceleration or deceleration, which can be vital in some cases, such as the investigation of surrogate safety indicators.
- The linear decreasing model was found to produce very poor approximations of the acceleration and deceleration profiles of bicyclists in State 1 and State 2. The approximation of the profiles of bicyclists in State 3 and State 4 were better, but were still outperformed by the constant model.
- The polynomial model is found to be the most adaptable of the models tested and was found to deliver the best approximation of the observed trajectory data in State 1 and State 3. The RMSE values for the other cases were very near to the constant model. This model, however, was found to consistently underestimate the maximum acceleration and deceleration values. Another disadvantage of this model is the comparatively large number of parameters that must be calibrated to produce precise results.
- The two term sinusoidal model produces good estimations of the acceleration profiles in all the examined states. The attained maximum acceleration and deceleration were also very consistent

when compared to the other models. Because this model has one less parameter than the polynomial model, it is slightly easier to calibrate.

TABLE 3 Root Square Mean Error (RMSE) and the Percent Error in the Maximum Acceleration/Deceleration of the Tested Models

State		Constant		Linear Decreasing	Polynomial		Two Term Sinusoidal	
		RMSE	$\%_e a_m$	RMSE	RMSE	$\%_e a_m$	RMSE	$\%_e a_m$
Simplified approach	1	0.039	-33%	0.092	0.010	-9%	**0.009**	**4%**
	2	**0.022**	-36%	0.079	0.026	-26%	0.032	**-15%**
Oscillating approach	1	0.043	-42%	0.053	**0.005**	**-6%**	0.006	-8%
	2	**0.022**	-36%	0.079	0.026	-26%	0.032	**-15%**
	3	**0.003**	-34%	0.006	0.004	**-4%**	**0.003**	**-4%**
	4	**0.001**	-22%	0.010	0.005	-15%	0.005	**-16%**

The slightly lower RMSE values derived using the oscillating approach suggest that the observed acceleration data can be better fit if the speed fluctuation around the average riding speed are taken into account. The method introduced in this paper provides a valid possibility for including this fluctuation in the acceleration and deceleration model. There are however other methods that could be used to define θ_s, such as the usage of the maximum observed speed for s_d instead of the average speed.

CONCLUSIONS AND OUTLOOK

In this paper the acceleration-speed profiles from a sample of 1030 bicyclists who were uninfluenced by other bicyclists are used to evaluate four acceleration and deceleration models; constant, linear decreasing, two term sinusoidal and polynomial. The bicyclists are separated into two groups, one group that rode unhindered through an intersection at a green light, and another that stopped at a red light, A new ratio θ_s is defined and implemented based on the θ as a time ratio concept introduced by Akçelik & Biggs (1987). The new concept uses the acceleration state as well as the speed rather than the start time and duration of a process as a basis for deriving acceleration. This allows for the direct analysis of the trajectory data without first needing to extract the start and end time of an acceleration or deceleration process. A further benefit of this definition is that the speed is readily available in microscopic simulations, making direct implementation of the the adapted models possible.

The evaluation of the four models indicates that the polynomial model provides the most flexibility and obtains the most consistently low RMSE values for all the acceleration states. The maximum acceleration and deceleration values were, however, underestimated by this model. The constant model slightly outperforms the polynomial model in State 2: deceleration to a stop and in States 3 and 4, accelerating and decelerating as part of normal speed fluctuation, respectively. The two term sinusoidal model produces good estimations of the acceleration and deceleration profiles while also providing accurate estimates of the maximum acceleration and deceleration. The selection between these three acceleration models therefore depends on the application and whether an overall good fit, the maximum acceleration or deceleration or the ease of implementation are priority. The linear decreasing model was found to produce the poorest estimations of the acceleration profiles.

Finally, a method for including the fluctuation in riding speed directly in the acceleration model is developed. A comparison between the RMSE values derived using the simplified approach, which does not include speed fluctuation, and the oscillating approach, which does include speed fluctuations indicates that oscillating approach better fits the observed acceleration data. The simplified approach, however, is less complicated to implement in microscopic simulations and still adequately matches the observed acceleration and deceleration profiles.

The results of this paper can be used by traffic engineers and researchers to more accuratly model the acceleration and deceleration profiles of bicyclists as they cross signalized intersections. This will enable a more realistic simulation of bicycle traffic, which will in turn increase the accuracy and reliability of efficiency and safety analyses carried out using simulated or modelled traffic scenarios.

In future work, the developed acceleration and deceleration curves in combination with the regression model for estimating the desired speed based on the driving maneuver, direction of travel and type of infrastructure can be implemented in microscopic traffic simulation software to model the dynamic characteristics of bicyclists with increased detail. Subsequent analyses of traffic efficiency and safety in urban areas that include significant levels of bicycle traffic will produce more reliable results.

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