

Pedestrian-cyclist Interactions at Bus Stops along Segregated Bike Paths: A Case Study of Montreal

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1 ABSTRACT

2 Safety is one of the major world health issues, and is even more acute for “vulnerable” road users,
3 pedestrians and cyclists. At the same time, public authorities are promoting the active modes of
4 transportation that involve these very users for their health benefits. It is therefore important to understand
5 the factors and designs that provide the best safety for vulnerable road users and encourage more people
6 to use these modes. Qualitative and quantitative shortcomings of collisions make it necessary to use
7 surrogate measures of safety in studying these modes. Some interactions without a collision such as
8 conflicts can be good surrogates of collisions as they are more frequent and less costly. To overcome
9 subjectivity and reliability challenges, automatic conflict analysis using video cameras and deriving users’
10 trajectories is a solution to overcome shortcomings of manual conflict analysis. The goal of this paper is
11 to identify and characterize various interactions between cyclists and pedestrians at bus stops along bike
12 paths using a fully automated process. Three conflict severity indicators are calculated and adapted to the
13 situation of interest to capture those interactions. A microscopic analysis of users’ behavior is proposed to
14 explain interactions more precisely. Eventually, the study aims to show the capability of automatically
15 collecting and analyzing data for pedestrian-cyclist interactions at bus stops along segregated bike paths
16 in order to better understand the actual and perceived risks of these facilities.

1 INTRODUCTION

2 Active modes of transportation including walking and cycling are becoming more popular among users
3 and planners. The growing interest in non-motorized transportation facilities is motivated by the healthy
4 and environmentally friendly nature of these modes. In Canada, one of the largest portions of Green
5 House Gas (GHG) emissions is caused by motorized transportation (1). Walking and cycling are strongly
6 associated with reduced risks of obesity and cardiovascular disease (2–4). In addition, there are benefits
7 from the perspective of the road agencies, e.g., reducing road congestion, traffic delay, and road
8 maintenance treatments.

9 A wider adoption of active modes of transportation requires attractive design of traffic facilities (5,6). The
10 design can be appealing based on increased mobility, easy accessibility, and improved safety. Road safety
11 is one of the major concerns for individuals, parents and governments. It is important for traffic facilities
12 which are aimed to encourage walking or cycling to improve both objective safety and users' perception
13 of safety. In particular, a major, yet poorly studied, conflict zone for active transportation facilities is at
14 bus stops along segregated bike paths. In these cases, pedestrians are forced to cross the bike path in order
15 to stand in line for the bus. Due to the fact that pedestrians usually move in groups especially in cases of
16 queuing for public transit, the limited space between the bus stop and the segregated bike paths generates
17 hazardous conditions. The problem is exacerbated in cases of dense areas with higher volumes of users, in
18 particular more vulnerable users such as students near schools or colleges. Those users typically
19 congregate into groups while waiting and may thus be more likely to collide with cyclists in the paths.

20 Interactions among road users can occur in various forms from severe fatal collisions to safe undisturbed
21 passages (7). Although safety has been traditionally measured using collision data, there are concerns in
22 the literature regarding the exclusive reliance on collisions. One of the strongest criticisms is that
23 collision-based models are reactive and require long observation periods. These shortcomings have led
24 researchers to develop pro-active approaches which can measure road safety in a timely manner and
25 ideally before accidents occur. Traffic Conflict Techniques (TCTs) are the most frequently applied among
26 the methods for surrogate safety analysis. Since their introduction in the late 1960's, several quantitative
27 indicators have been defined to capture users' proximities in time and space which can relate to a measure
28 of conflict "severity".

29 Conflict observation can be obtained manually, semi-automatically or fully automatically. Manual
30 observations raise questions about intra and inter-observer reliability in rating conflicts as observers may
31 make errors and have differing evaluations of the same interactions. The term interaction is used to refer
32 to more general situations than conflicts, in which two road users are close enough, *i.e.*, are present
33 simultaneously in the area of interest. Automated methods relying on video data offer a promising array
34 of tools for objective conflict assessment. Video cameras are inexpensive and widely deployed. Mobile
35 video units can be used for temporary data collection (8). Road user trajectories, *i.e.* their positions in
36 every image, can be extracted automatically from video data using computer vision techniques (9). These
37 methods can also be applied to pedestrians and cyclists, although the task is more complicated because of
38 their size (smaller than motorized road users), their varying appearance, and overall more complex
39 motions (fast changing speed and orientation). While surrogate safety analysis has been applied to
40 motorized safety in many studies, whether automated or not, few studies have been dedicated to
41 vulnerable users because of the aforementioned complexities.

1 The goal of this paper is to identify and characterize various interactions between cyclists and pedestrians
2 at bus stops along bike paths using a fully automated process. Three conflict severity indicators are
3 calculated and adapted to the situation of interest to capture those interactions. A microscopic analysis of
4 users' behavior is proposed to explain interactions more quantitatively. Eventually, the study aims to
5 show the capability of automatically collecting and analyzing data for pedestrian-cyclist interactions at
6 bus stops along segregated bike paths in order to better understand the actual and perceived risks of these
7 facilities.

8 **BACKGROUND**

9 According to a study in 2013, 27 % of fatal road collisions in Canada and 30 % of the ones in British
10 Columbia involved pedestrians and cyclists (10). These two modes are popular in the City of Montreal
11 (11). According to 2006 Canadian Census, 20 % of population use public transportation combined with
12 walking or cycling modes in Montreal (12). Due to the high portion of active mode users, many plans and
13 legislations are being applied to improve pedestrians' and cyclists' safety (13).

14 The current state of practice for assessing active transportation safety is based on collision records data
15 and collision prediction models (4,14). However, the use of collision records for safety diagnosis has
16 serious drawbacks. The most challenging issue with road collisions is their rare occurrence and costs (15).
17 Also, not all collisions are reported and levels to reporting vary for different road users, locations, and
18 severities. This is compounded due to the limited details and accuracy of collision records. Drawbacks of
19 collision-based approaches are even more acute for vulnerable road users (16). While pedestrian
20 collisions have more severe consequences, they are even less frequent than collisions involving motorized
21 road users. Therefore, it is a practical necessity to define other safety indicators that are based on frequent
22 events, observable in traffic, that have a logical and statistical relationship with collisions and cover more
23 levels of severity (15).

24 The concept of traffic conflicts was first proposed by Perkins and Harris in 1967 (17). A common
25 conceptual definition of a conflict is "a traffic conflict is "an observable situation in which two or more
26 road users approach each other in space and time to such an extent that a collision is imminent if their
27 movements remain unchanged" (18). To estimate what would happen if movements remain unchanged;
28 this definition requires specifying a motion prediction method at each instant to determine the existence
29 of a collision course. The often used and rarely justified method is motion prediction at constant velocity.
30 Other methods have been tried and are demonstrated to produce more robust identifications of the
31 collision course and indicator measurements (19). Several quantitative indicators for traffic conflicts were
32 developed over the years to capture the "severity" or proximity of the conflict to a potential collision or
33 probability of collision (20). Lareshyn (21) provides an exhaustive list of such indicators. Time To
34 Collision (TTC) and Post Encroachment Time (PET) are among the most used indicators, with different
35 capabilities of capturing the conflict severity.

36 There is a fundamental difference between PET and the other indicators: the latter depend on motion
37 prediction methods used at each instant while PET is observed and yields only one measure for a whole
38 conflict. TTC is the most used conflict indicator in the literature due to its ability to capture severity. It is
39 defined as "the time that remains until a collision between two vehicles would have occurred if the
40 collision course and speed difference are maintained" (22). PET, however, is defined only in cases where

1 the road users' observed trajectories cross as the time difference between the instants at which the two
2 road users pass the crossing zone (23,24). According to (25), none of the evaluated indicators, including
3 TTC based on constant velocity and PET, was solely capable of capturing a significant amount of
4 conflicts. A combination of these indicators, however, was well capable of identifying the majority of
5 conflicts (25). The issue of the lack of collision course is largely caused by the use of inadequate and
6 restrictive motion prediction methods and can be easily addressed with recent work (19). However,
7 determining which indicators are sufficient to describe conflict severity and can best measure safety is
8 still an open question.

9 To the authors' best knowledge, although there is some collision-based research on cyclist-pedestrian
10 interactions in the literature, there is no previous work on assessing conflicts and interaction behavior
11 between these two types of users.

12 **METHODOLOGY**

13 **General Framework**

14 Based on past research in Traffic Conflict Techniques (TCT) and other methods for surrogate safety
15 analysis, this paper describes a framework for the analysis of hazards for vulnerable road users including
16 cyclists and pedestrians at bus stops along segregated bike paths. Tracks of cyclists and pedestrians are
17 automatically extracted using computer vision techniques. Subsequently, the analysis evaluates cyclists
18 and pedestrians at high risk areas where pedestrians have to cross bike paths to get on the bus. Such
19 interactions involve the behavior of the passing user who first arrives at the conflicting area (offended)
20 and the approaching user who creates un-safe conditions to the offended user (conflicting). While PET is
21 used in this study as the primary conflict indicator to capture severity, the TTC and predicted PET
22 (pPET), as defined later, are also evaluated.

23 Recorded videos are analyzed and users' trajectories are extracted using computer vision techniques. The
24 conflict indicators are calculated using kinetic laws on the output trajectories by the video analysis
25 software. Interactions of different levels of severity are then identified and compared to a minimum
26 threshold to identify unsafe interactions. The final output of this framework is the visualization and
27 evaluation of cyclist-pedestrian behavior at bus-stops along segregated bike paths. Users' trajectories
28 along with a distribution of PETs, TTCs and other indicators describing the interaction such as speed are
29 used to evaluate the safety associated with the facilities.

30 **Video Analysis**

31 Videos are captured by cameras installed on mobile poles at desired locations at a height of about 12 m
32 (8). The first step of video analysis is camera calibration, correcting for perspective error. Perspective
33 makes objects further from the camera appear smaller and the camera optics may cause distortion. There
34 are two main types of methods to recover or estimate the object actual coordinates on the ground plane in
35 distance units, e.g. meters: the first is to obtain a complete camera calibration (28), the second is to
36 directly estimate a homography matrix that can transform image coordinates into world coordinates. The
37 second, simpler method is used in this study. The homography is estimated using at least four non-
38 collinear points with known real world coordinates.

1 The camera used in this study exhibited visible distortion, known as “fish eye effect”. Because the
2 distortion in the central area of the field of view where the analysis is performed was limited (Figure 1)
3 and because simple available methods to correct this distortion involve re-mapping the images with
4 various methods for interpolation and re-compressing the video and therefore degrade the video quality,
5 no correction was done for this study.



6
7 **Figure 1. Video frame image affected by perspective and fish eye effect**

8 Tracking is based on the Kanade – Lucas - Tomasi algorithm and the grouping of these features into a
9 coherent object described in (9). Speed and direction of movement are selected as the criteria for
10 automated user classification (to differentiate trajectories of pedestrians with cyclists). While the
11 velocities of cyclists have the same direction as the segregated bike path, pedestrians cross the bike path.
12 Hence, comparing angles of velocity vectors with a reference vector, users are differentiated by their
13 direction of movement. A set of straight-moving cyclists’ velocities along the bike path are selected and
14 the 85th percentile of the entire set of velocities is considered as the reference. All the tools used in this
15 section to extract road user trajectories are available in the open source Traffic Intelligence project
16 (8)(29).

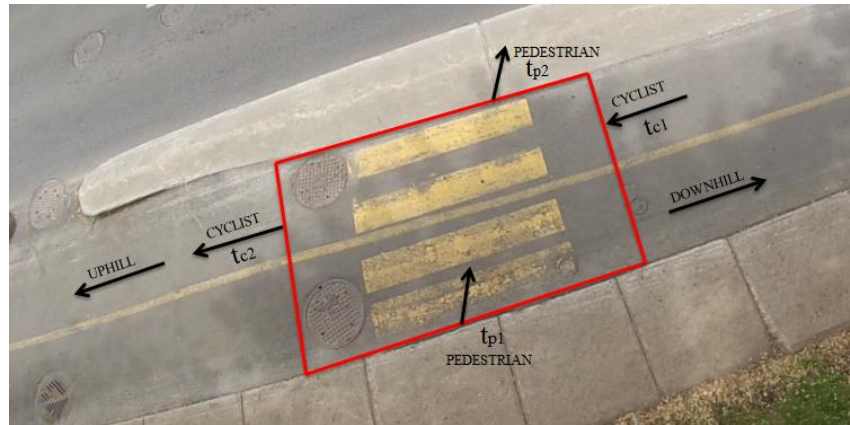
17 **Conflicting Zones and Safety Analysis**

18 In order to evaluate the interactions between cyclists and pedestrians who intend to get on a bus, specific
19 zones with the potential for collisions between the two categories of road users are identified. In order to
20 cover a wider zone and accordingly more interactions, the whole area used by embarking passengers,
21 which encompasses a larger zone than the crosswalk, is selected as the conflicting zone. This zone is
22 fixed during the whole analysis.

23 Three conflict indicators are used in the safety analysis to characterize the interactions: PET, TTC and
24 pPET. Important events are defined as situations when cyclists and pedestrians temporally co-exist inside
25 the conflicting zone, in which case a PET can be computed. When interacting in the area under study, the
26 users may be before, inside or after the zone. This study considers all situations in which a cyclist is
27 moving toward a pedestrian that is in or about to enter the bike paths to get on a bus, as well as cyclist
28 already past such a pedestrian. These situations are called interactions and are the basic precursor
29 considered for more severe interactions (conflicts with urgent evasive actions) and collisions. In fact,
30 important events are a subset of interactions, since a PET may not be computed for all interactions.

31 PET is calculated as the *observed time difference* that it takes for the second user to enter the crossing
32 zone after the first one leaves. To calculate PET for pairs of users, offended user’ trajectories are analyzed

1 to derive the moment it leaves the region of interest (t_{p2} or t_{c2}). The whole bike path area in the video
 2 image is then analyzed to identify all other conflicting users existing at that time (valid conflicting users).
 3 Subsequently, all valid conflicting users are being tracked until the moment that they enter the region (t_{c1}
 4 or t_{p1}). PET will be the difference between these observed instants ($t_{c1} - t_{p2}$ or $t_{p1} - t_{c2}$) (Figure 2).



5

6 **Figure 2. Region of interest for PET Analysis; Time instants of users' entrance and departure**

7 The other indicator used to capture conflicts severities is TTC. To simplify the TTC calculations, motion
 8 prediction at constant velocity is used, which is reasonable at least for the cyclist in the bike path. The
 9 intersection of the road users' trajectories, or potential collision point, is identified, and whether the road
 10 users are getting further (diverging interaction) or closer (crossing interaction). For crossing interactions,
 11 the road users' predicted arrival times at constant speed can be computed. A collision threshold $D_{collision}$ is
 12 used to represent the road user's volume, the noise in the data and the uncertainty of the prediction. The
 13 times t_{up} and t_{down} at which each road user reaches the points at $D_{collision}/2$ upstream and downstream of the
 14 collision point are computed and compared. If the intervals $[t_{up}, t_{down}]$ for the two road users overlap, the
 15 road users are on a collision course and TTC is computed as the center of the intersection of the two
 16 intervals. Otherwise, pPET is computed as the smallest time difference between the two intervals. The
 17 implementation is available in the Traffic Intelligence project (29). Other prediction methods taking into
 18 account the road users' normal adaptation are being explored for future improvements.

19 RESULTS AND DISCUSSION

20 Data

21 The case study presented in this paper is a bus stop along a segregated bike path in the city of Montreal,
 22 Canada, on Chemin de la Côte-Sainte-Catherine. At the bus stop, close to Avenue Claude-Champagne,
 23 pedestrians must cross the bike path in order to reach the bus. There is also a music college near the bus
 24 stop which creates dense pedestrian traffic. Moreover, the vertical alignment is not completely straight
 25 and it contains a steep slope going downhill. Data is collected using recorded videos by a camera installed
 26 at the site for more than two hours (158 minutes). Starting at 2:00 pm, the entire video covers peak hours
 27 of pedestrians traffic (in this case the end of class at the college). The video image frame is 1280×960
 28 pixels and the frame rate of the camera is approximately 30 frames per second.

1 Relative coordinates of eight points were measured in the location to directly compute the homography
2 matrix. Four main edges of the crosswalk in addition to four edges of pedestrian markings were selected
3 based on their visibility on the video image frame such that the entire area of interest can be covered for
4 coordinate transformation. Cyclists going up and down the hill were separated due to their different
5 behavior. The conflict zones were considered one meter wider than crosswalks on each side.

6 **Indicators Capability of Capturing Events**

7 PETs were calculated for all interactions of interest for which classified road users entered and left the
8 conflicting zone. The PET for users that both spatially and temporally co-exist in the area was set to be
9 zero by definition (most severe interaction). Predicted PETs and TTCs were also computed for the same
10 users that were evaluated for PETs. In order to identify “unsafe” events, a minimum threshold of 1.5
11 seconds was selected for minimum TTC (TTC_{min}) based on the literature. Also, while minimum
12 thresholds of PET in the literature vary between 1.5 to 3 seconds, an arbitrary threshold of 3 seconds was
13 set for PET and minimum pPET ($pPET_{min}$). Accordingly, all events with indicators less than the minimum
14 thresholds were defined as unsafe and the ones above the minimum threshold as safe events. In total, 225
15 interactions were observed and investigated using the three selected indicators. Among important events,
16 i.e. for which a PET can be computed, it was observed there were only a few cases that were covered by
17 TTC and pPET. The results are presented in Table 1. Based on manual observations of the videos, it was
18 observed that unsafe interactions identified by PET and pPET do not have a collision course. It was also
19 observed that cyclists tend to maintain their speed in various situations and pedestrians adapt their speed,
20 angle of movement and acceleration in cases where they are the offended users.

21

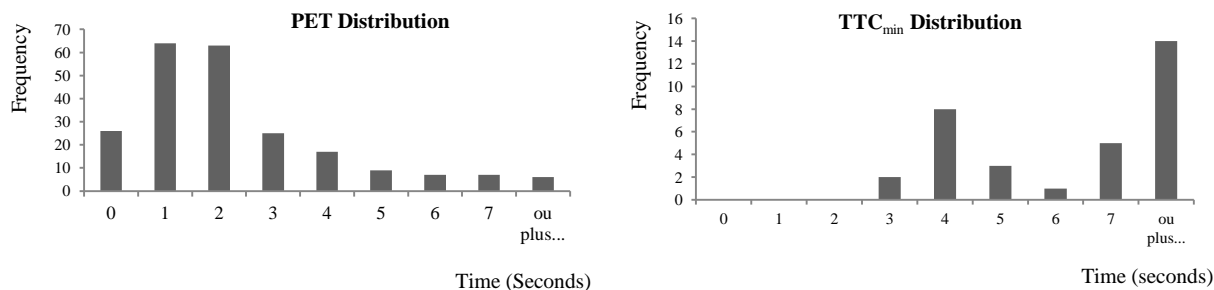
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Table 1. Conflict indicators for users' interactions

Indicator	All Important Events	Common Important Events with PET	Common Important Events with TTC	Common Important Events with pPET	Safe Events	Common Safe Events with PET	Common Safe Events with TTC	Common Safe Events with pPET	Unsafe Events	Common Unsafe Events with PET	Common Unsafe Events with TTC	Common Unsafe Events with pPET
PET	225	-	33	133	50	-	33	49	175	-	0	2
TTC	33	33	-	17	33	33	-	17	0	0	-	0
pPET	133	133	17	-	131	49	17	-	2	2	0	-

2

3 The number of events with computable TTC reported in the table shows that the TTC did not capture
 4 many events, i.e. there were few collision courses at constant velocity between cyclists and pedestrians,
 5 and all events were safe (TTC_{min} superior to 1.5 s). pPET, however, can be computed for more
 6 interactions as it only requires the two predicted trajectories to cross. Although PET and pPET could both
 7 be compute for 133 important events, only 49 safe and 2 unsafe events were commonly reported by these
 8 two indicators. That means that safe and unsafe events reported by PET and pPET do not necessarily
 9 match. Figure 3 illustrates the distribution of all important events reported by PET and TTC_{min} .



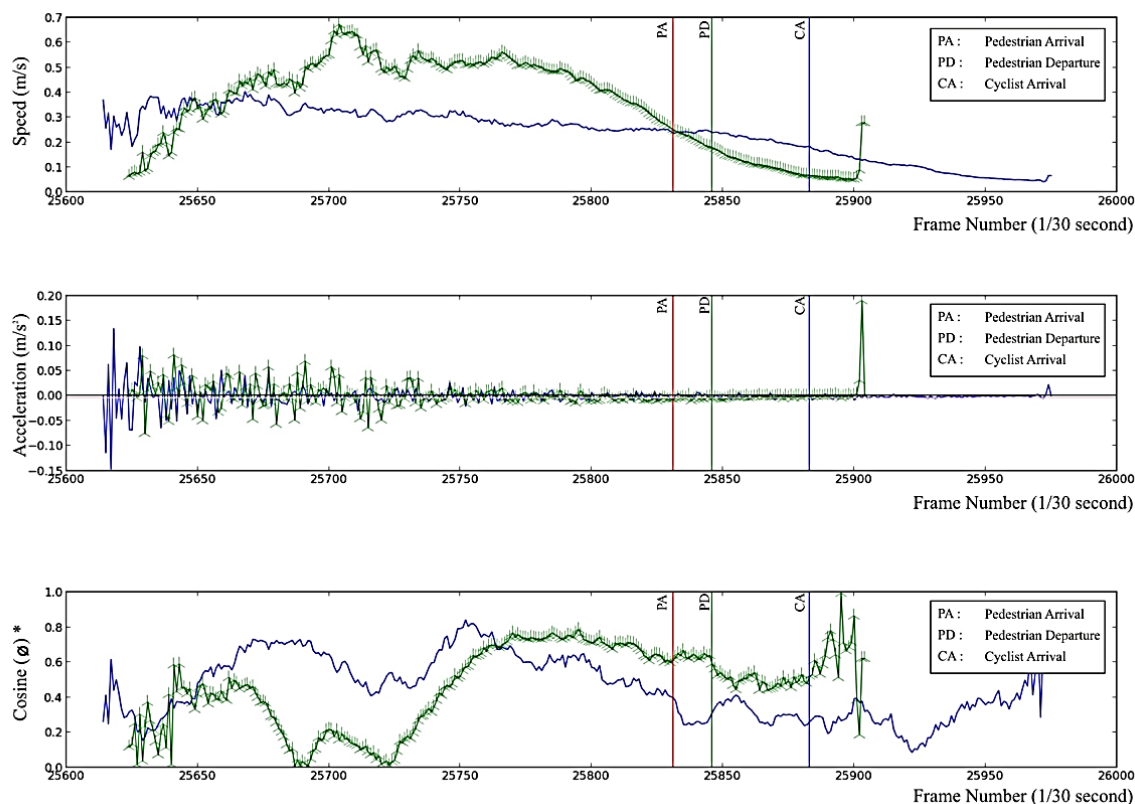
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11 **Figure 3. Distribution of important events captured by PET and TTC_{min} ; Thresholds for safe interactions are**
 12 **defined as $PET \leq 3$ s and $TTC_{min} \leq 1.5$ s**

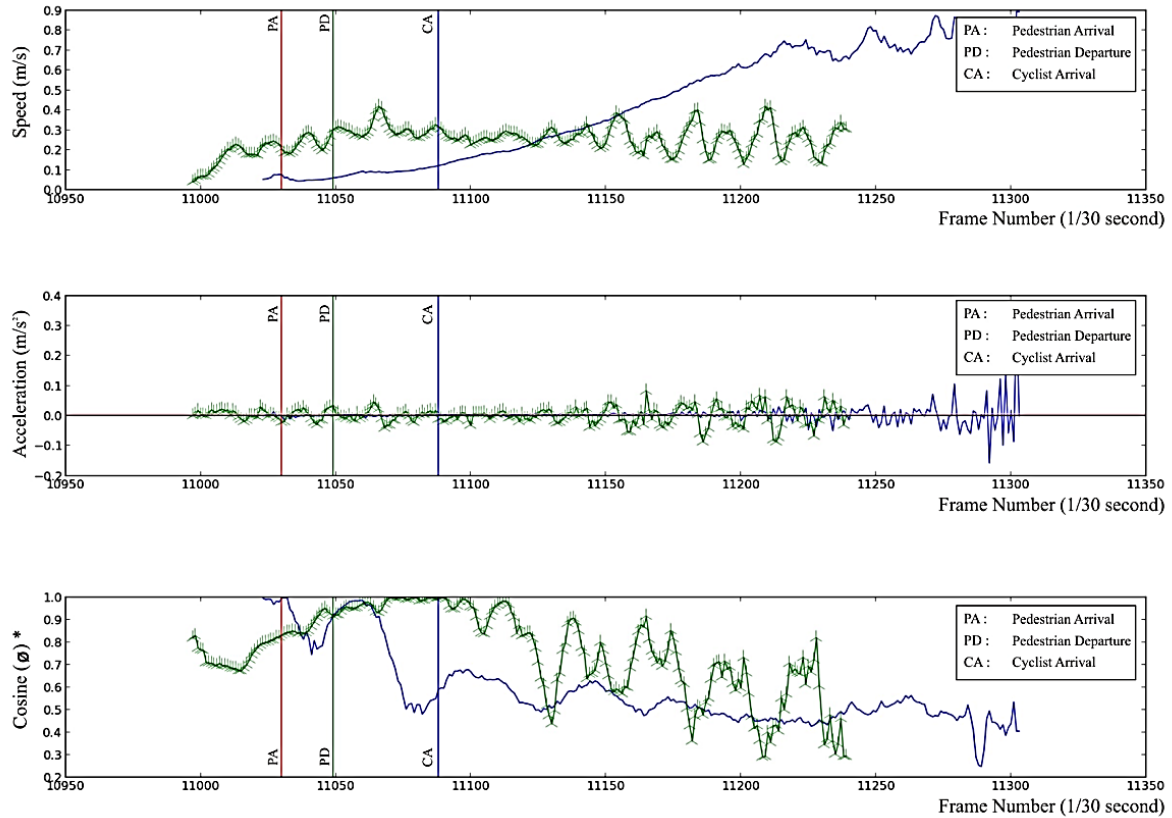
13 The PET distribution also shows the strength of the indicator to capture safe and unsafe events. While the
 14 TTC_{min} distribution does not show any unsafe events, it reports a high proportion of safe events.
 15 Considering the manual observations of interactions in videos, it seems that the opposite frequencies of
 16 the two distributions show that PET may be more suitable for interactions between cyclists and
 17 pedestrians. However, testing different motion prediction methods is necessary before drawing final
 18 conclusions.

1 **Microscopic Behavior Analysis of Cyclists and Pedestrians**

2 To evaluate the behavior of interacting users, microscopic behavior analysis was done based on speed and
 3 acceleration profiles for both offended and conflicting users. In order to identify yielding behavior or
 4 movement adaptation as well as evasive actions, speed magnitude and angle were plotted for both users
 5 during the whole passage of pedestrians in the conflicting zone. Acceleration magnitude was also selected
 6 to identify users' reaction to the conflict situation. Several situations could not be taken into account
 7 because the speed data was not available for a sufficient amount of time, e.g. when the cyclist was
 8 detected and tracked only in the conflicting zone or because of noisy trajectories and grouping errors. In
 9 total, 17 cases of interaction situations in which cyclists were approaching pedestrians were analyzed in
 10 two hours of video; 13 cases out of 17 showed very similar patterns that can be seen in Figures 4 and 5.
 11



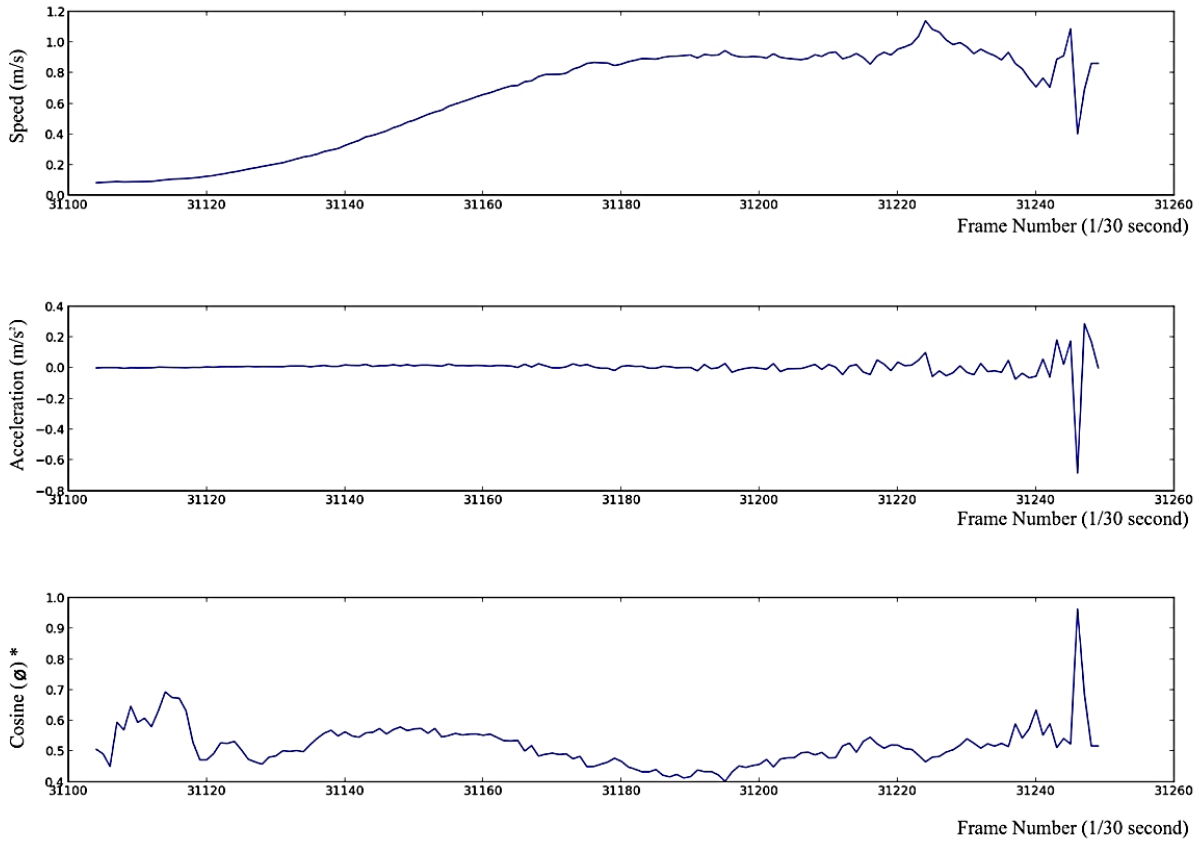
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 13 **Figure 4. Speed and acceleration profiles of pedestrians and cyclists going downhill in important events;**
 14 **cyclists are shown in continuous and pedestrians in crossed lines; * ϕ is the angle of the velocity vector with**
 15 **the reference orientation along the cycle path**



1

2 **Figure 5. Speed and acceleration profiles of pedestrians and cyclists going uphill in important events; cyclists**
 3 **are shown in continuous and pedestrians in crossed lines; * θ is the angle of the velocity vector with the**
 4 **reference orientation along the cycle path**

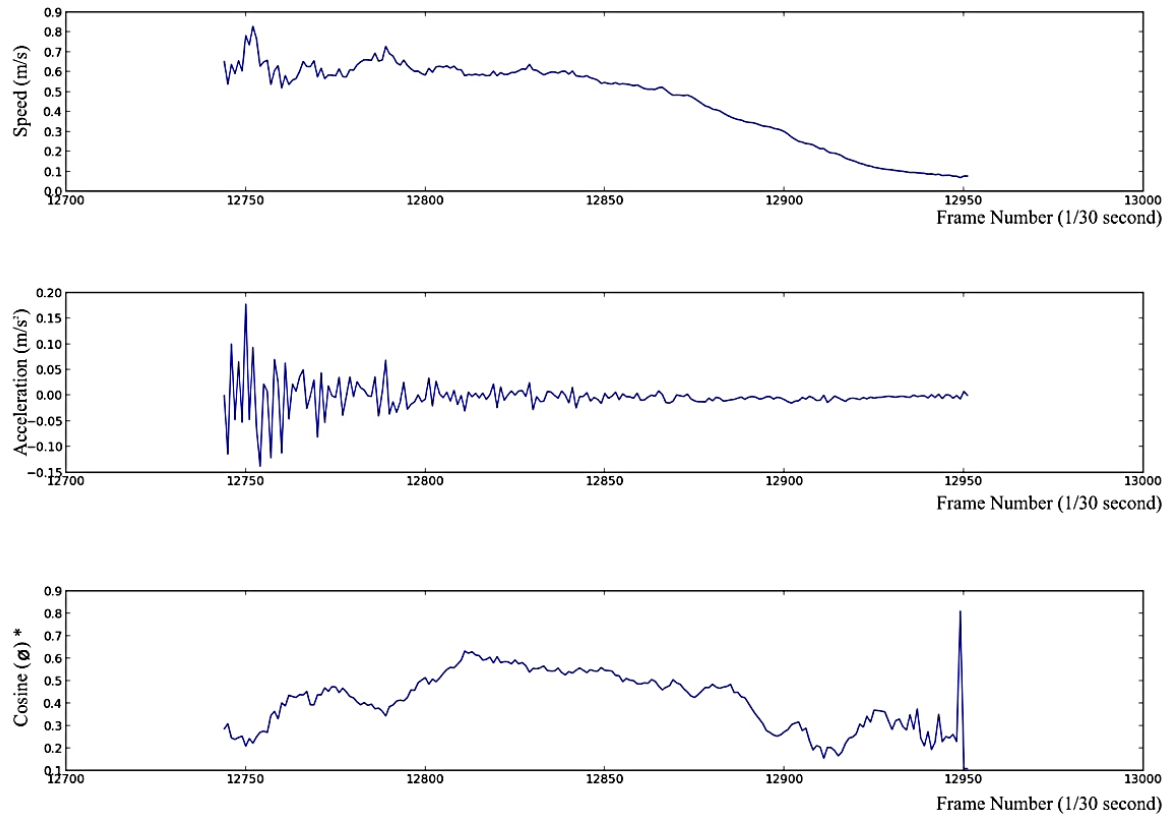
5 Pedestrians usually move more randomly than cyclists, which tend to keep their speed and orientation in
 6 the almost straight cycle path. Common interaction plots showed a significant fluctuation in acceleration
 7 of pedestrians which indicates large speed differences during short periods of time. Cyclists on the other
 8 hand, seemed to have less deviation in their speed and acceleration. Pedestrians, however, were observed
 9 to either reduce their speed (slow down) or to suddenly increase (run) to avoid collision with cyclists.



1

2 **Figure 6. Speed and acceleration profiles of cyclists going downhill in the absence of pedestrians; *∅: the**
 3 **angle of the velocity vector with the reference orientation along the cycle path**

4 Evaluating changes in speed and acceleration along the conflicting zone would require pattern recognition
 5 techniques. However, there are various factors influencing cyclists' behavior such as the presence of
 6 obstacles on the pavement surface (e.g. manholes) which are hard to track. Furthermore, there is an
 7 intersection downstream of the route which affects cyclists speed and acceleration. To compensate for the
 8 effects of these underlying factors, cyclists' speeds and acceleration profiles in the absence of pedestrians
 9 were also plotted in Figures 6 and 7 to compare with the ones in interaction situations.



1
2 **Figure 7. Speed and acceleration profiles of pedestrians and cyclists going uphill; $\ast\theta$ is the angle of the**
3 **velocity vector with the reference orientation along the cycle path**

4 Figure 6 shows that in the absence of pedestrians, cyclists going downhill initially increase their speed
5 until they reach the intersection with the local avenue. Their acceleration is almost zero before the
6 intersection which indicates a constant speed. At the intersection however, they suddenly brake and
7 reduce their speed with a significant change in acceleration. Although the cyclists' maximum speeds are
8 smaller in the presence of pedestrians, which may be expected, they tend to maintain their speed with
9 almost no acceleration. Although the sample size is too small, it seemed that in most cases pedestrians
10 were the first users that adapt themselves to cyclists. Due to the fact that almost all conflicts occurred for
11 cyclists going downhill, their resistance to yield against pedestrians seems logical. However, the rare
12 cases of uphill conflicts also illustrated the same observations.

13 To verify these observations, speed and acceleration changes were investigated quantitatively for
14 pedestrians and cyclists going uphill or downhill. Users' reactions (response) in interactions were
15 explained by six different measures of speed and acceleration: the values at the pedestrian's instant of
16 entry in the conflicting zone and of departure from it, the 85th and 15th percentile of speed and
17 acceleration over this interval (during the passage of the pedestrian into the conflicting zone), the
18 difference between the maximum and minimum values and the mean of the measures. Results are
19 presented in tables 2 and 3. Reported numbers support manual observations from videos and plotted
20 figures of speeds and acceleration. Cyclists have high speeds whether pedestrians are present or not. In
21 both situations, speed difference of cyclists and accordingly their acceleration is relatively small during
22 the associated time interval of pedestrians' passage. Pedestrians on the other hand, have large numbers of

1 speed difference (relative to their initial speed) and acceleration during their passage which indicates their
 2 adaptation to cyclists' high speed.

3

4 **Table 2. Speed and acceleration measurements for cyclists in the presence and absence of a pedestrian**

Measurement	Number of Observations	Pedestrian* Arrival Instant	Pedestrian** Departure Instant	85 th Percentile (Maximum)	15 th Percentile (Minimum)	Difference***	Mean
Cyclists Heading Downhill Without Pedestrians							
Speed (m/s)	402	8.5	11.8	10.9	8.4	2.5	10.5
Acceleration (m/s ²)	402	1.0	1.2	1.0	0.9	0.1	1.1
Interacting Cyclists with Pedestrians Heading Downhill							
Speed (m/s)	120	6.7	8.2	8.2	6.7	1.5	7.2
Acceleration (m/s ²)	120	0.6	0.8	0.8	0.6	0.2	0.7
Cyclists Heading Uphill Without Pedestrians							
Speed (m/s)	122	4.3	3.6	4.4	3.5	0.9	4.0
Acceleration (m/s ²)	122	0.6	0.5	0.4	0.4	0.1	0.4
Interacting Cyclists with Pedestrians Heading Uphill							
Speed (m/s)	51	2.1	2.4	2.4	1.5	0.9	2.0
Acceleration (m/s ²)	51	0.2	0.2	0.4	0.1	0.3	0.2

5 * and ** For cyclists in the absence of pedestrians, these instants are associated to the average positions of pedestrians arrival and
 6 departure in cases of their presence.

7 *** Difference between 85th and 15th percentile values (maximum and minimum)

8

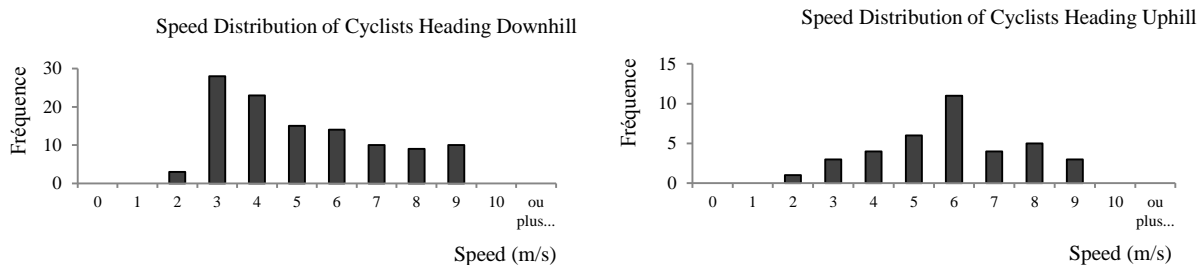
9 **Table 3. Speed and acceleration measurements for pedestrians interacting with cyclists**

Measurement	Number of Observations	Pedestrian* Arrival Instant	Pedestrian** Departure Instant	85 th Percentile (Maximum)	15 th Percentile (Minimum)	Difference***	Mean
Interacting Pedestrians with Cyclists Heading Downhill							
Speed (m/s)	21	2.5	2.3	4.1	1.7	2.4	2.3
Acceleration (m/s ²)	21	2.1	2.2	3.9	1.4	2.4	2.0
Interacting Pedestrians with Cyclists Heading Uphill							
Speed (m/s)	21	2.5	2.3	4.1	1.7	2.4	2.3
Acceleration (m/s ²)	21	2.1	2.2	3.9	1.4	2.4	2.0

10 * and ** For cyclists in the absence of pedestrians, these instants are associated to the average positions of pedestrians arrival and
 11 departure in cases of their presence.

12 *** Difference between 85th and 15th percentile values (maximum and minimum)

13



1

Interacting Cyclists Heading Downhill				
Measurement	Number of Observations	Mean	Standard Deviation	85 th Percentile
Speed (m/s)	112	4.6	2.0	7.5
Interacting Cyclists Heading Uphill				
Speed (m/s)	34	5.3	1.8	7.5

2

3 **Figure 8. Speed distribution of cyclists at the instant of the pedestrians’ entry into the conflicting zone**

4 Yielding of pedestrians against cyclists was further investigated by studying the speed distributions of
 5 conflicting cyclists at instants when pedestrians started to step in the crosswalk (Figure 8). Considering
 6 that speed is an important contributor to the severity of collisions, it is highly related to the pedestrians’
 7 perception of safety and can thus affect the yielding-adaptation behavior. The statistics reported in figure
 8 8 show high speeds for downhill and uphill cyclists at the moment of pedestrian crossing which may
 9 explain why the cyclists are reluctant to yield to crossing pedestrians.

10 **CONCLUSIONS**

11 This study aimed to automatically evaluate the microscopic interactions of cyclists and pedestrians at bus
 12 stops along segregated bike paths. Despite the movement complexities of cyclists and pedestrians, the
 13 video analysis could appropriately detect and track most of them. The user classification criteria were
 14 capable of classifying users with acceptable errors. However, due to random behavior of road users,
 15 specifically pedestrians, future work can be dedicated to investigate more techniques for user
 16 classification.

17 A wide polygon of one meter margins around the crosswalk was selected as the conflicting zone in which
 18 situations of proximity between users may be severe interactions. Three conflict indicators were
 19 investigated to capture important events: PET, TTC and pPET. Although some bias was observed due to
 20 over-segmentation or multiple tracking for an object which created erroneous indicator measurements, it
 21 was concluded that a combination of PET, predicted PET and TTC can almost cover all the interactions,
 22 i.e. at least one of these indicators could be computed for all interactions of interest. Using arbitrary
 23 thresholds based on the literature, interactions captured by TTC are all identified as safe events, while the
 24 PET and pPET indicators allowed observing unsafe events.

25 A microscopic evaluation of speed and acceleration were applied to further investigate yielding-
 26 adaptation behavior of vulnerable users. The speeds of cyclists were compared whether they were in the
 27 presence or absence of pedestrians. Speed and acceleration profiles, as well as specific measurements and

1 statistics showed that almost all cyclists maintain their speed and acceleration. Pedestrians, however, take
2 evasive actions (reducing speed and acceleration) and adapt their movement to the approaching cyclists.
3 Future work is needed to validate these observations on longer observations periods as well as on other
4 sites. The computation of other indicators and the use of more suitable motion prediction methods may
5 yield more measurements. Another angle will be to investigate the compliance of pedestrians with the
6 crosswalk and whether it is related to more or less dangerous situations.

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