Video-Based Automatic Counting For Short-Term Bicycle Data Collection in a Variety of Environments

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ABSTRACT
Short-term and long-term bicycle counts are important sources of information for researchers and practitioners in the transportation field. In comparison with other road users, automated data collection for cyclists is a challenging task. This paper presents and evaluates an automated video-based method for counting bicycles in different environments such as intersections and road segments. The method consists of three different elements: mobile video-camera-mast hardware, moving road user detection and tracking techniques, and classification-counting algorithms. The results indicate that the method is highly accurate at gathering short-term bicycle counts in locations where traditional technologies such as loop detectors and pneumatic tubes, do not work properly. One of the main advantages of the method is its ability to count cyclists flow for different movements with different origins and destinations, even in complex environments with mixed traffic such as intersections. In addition to counting cyclists, the trajectory data gathered through this method can also be used for a variety of purposes such as cyclist behaviour and road safety studies. For 5 minute interval counts, the accuracy of the proposed method ranged from 73 % for intersections without a cycle track to 90 % for road segments with a cycle track, while for 15 minute interval counts, the accuracy ranged from 81 % for intersections without a cycle track to 93 % for road segments with a cycle track.

Keywords: Bicycle Counting, Video Analysis, Traffic Data Collection, Bicycle Flow.

INTRODUCTION

Bicycle data, in particular cyclist counts at a set of locations (intersections, bicycle facilities, etc.), is an important piece of information for both practitioners and researchers in transportation. For instance, this type of information is typically required for road safety studies to generate exposure measures or safety performance functions *(1)*. In addition, during the planning and design stage, bicycle counts are necessary to estimate bicycle activity (ridership) and infrastructure needs. Counts are also required to quantify ridership growth over time after interventions *(2)*. In fact, in a recent research review published by the group Active Living Research on bicycle counting technologies and the state of cycling research, it was remarked that some governments are even beginning to consider bicycle count data when allocating funds for certain parks and evaluating potential projects *(3)*. This increased awareness has led to new research efforts to improve how counting data can be used such as; the development of extrapolation factors to estimate long-term trends based on short-term data. Data collection is not always an easy task because it can be time consuming and costly, particularly when counts have to be collected for a large sample of sites or when counts have to be taken over long periods of time. Several data collection methods have been used in an effort to increase spatial and temporal coverage. Short-term counting over a large set of locations in a timeframe of hours is a typical data collection strategy that is combined with long-term count data coming from permanent stations. That is, municipalities and cities are increasingly adopting strategies which involve obtaining short-term counts over large areas while at the same time having a large temporal coverage with permanent counting stations. From this, one can classify counting methods in long-term and short-term durations, where long-term counting efforts can vary from a few months to many years (long-temporal coverage) and short-term counting typically take place over a few hours during a single day (e.g., 2-8 hours of counting) and involve many sites (large-spatial coverage) *(4)*.

Count data collection methods can be automatic or manual. Automatic counts are often derived from technologies such as loop detectors, infrared sensors, pneumatic tubes, video recordings, etc. Manual counts can be obtained directly in the field or they can be obtained by manually processing video data. Although there are many technologies available for long-term automatic counting, little research has been conducted regarding automatic count data collection at intersections and wide roadway sections. Pneumatic tubes or loop detectors are not designed to count in open spaces or at intersections. These traditional technologies can also fail to accurately collect data in very wide roadway sections (with several road lanes) in which under-passing problems occur and vehicular traffic intensity is high. In addition, given the installation, maintenance and acquisition costs for the equipment involved, these techniques are not very practical for short-term data collection campaigns. Recently, video-based short-term data collection methods have emerged through research and private efforts; one can refer for instance to the technologies offered by a company named MioVision. However, their video-processing methods have not been well documented making it difficult to judge whether or not a fully automated method is used. While video counting does offer a number of important advantages such as low cost, multiple variable data collection, and non-intrusive installation, its use is generally limited to good lighting conditions and low intensity traffic. It performs well in counting objects, but work on determining how to categorize those objects is relatively new and untested. Most video counting methods also tend to require large amounts of calibration data.

This paper presents and evaluates an automated video-based method for counting bicycles in different environments such as intersections and wide road segments. This method consists of three different elements: mobile video-camera-mast hardware, moving road user detection and tracking techniques, and classification-counting algorithms. This method offers a large degree of flexibility because the camera-sensor can be installed on existing infrastructure which enables one to collect data in places where traditional technologies cannot be implemented or do not typically work well. In addition to all of the mentioned advantages, trajectory data gathered through this method can be used for other purposes, such as behaviour and road safety studies.

LITERATURE REVIEW

Cyclists may be counted in a variety of ways, depending on their movements and the temporal data requirements. The technologies and methods will depend on the type of counting specified by the researchers.

Technologies to Count Cyclists

There is an ever increasing need to develop and test pedestrian and cyclist counting techniques in order to better understand their importance in the urban transportation field *(3)*. Some of the most common techniques include on-site manual counting, manual video analysis, automated video analysis, active and passive infrared counting, inductive loops, and pneumatic tubes. In a research review on counting methods, Ryan and Lindsey *(3)* remarked that while manual counting methods have an accuracy rate ranging from 75 % to 99 %, it is an expensive technique that cannot practically serve as a solution for long-term counting. The authors found that results from infrared technology can provide anywhere from 5 % to 50 % error primarily due to object clustering. It was also noted that most studies tend to indicate that the accuracy of count data is higher at roadway and sidewalk segments compared to intersections primarily because of the high number of turning movements.

Nordback and Janson *(5)*tested the long-term accuracy of inductive loop detectors installed in 1998 on multi-use paths for cyclists by comparing automated results with manual counts. The 1.5 to 1.75 hour long manual counting sessions took place over 6 days in March of 2009 in the City of Boulder, Colorado and were conducted with two observers performing manual counts over 15 minute intervals in order to ensure the quality of the data. The results of the study indicated that the loop detectors typically under-detected cyclists by an average of 4 %. Of the 22 out of 24 detector channels or loops abled to be analyzed, 68 % of the channels were found to be accurate where an accurate channel was defined as a channel having an absolute percent difference of less than 15 %. The authors attributed a large majority of these errors to detector setting errors which could be caused by such things as improper installation and paving of the road. It is also interesting to note that the study found a 6 % average absolute difference with a 6 % standard deviation between the separate manual counts.

Hyde-Wright et al. *(6)* compared the accuracy of pneumatic tubes designed specifically for cyclists and pneumatic tubes designed to count cyclists and motor vehicles. The study used three general purpose counters (GPC) from MetroCount and one bicycle-specific counter (BSC) from Eco-Counter. The readings from the tubes were compared to over 2,000 manual counts collected over 17.25 hours. The study found that the one BSC was between 94 % to 95 % accurate up to a distance of 27 feet (8.23 meters) away from the counter, but only around 57 % accurate for a distance between 27 feet and 33 feet (10.06 meters). The best GPC had a high accuracy around 95 % for only up to a distance of 4 feet (1.22 meters). The accuracy from 4 feet to 27 feet and 27 feet to 33 feet were roughly 55 % and 60 %, respectively.

Brewer et al. *(7)* tested the counting accuracy along with other characteristics such as ease of installation of three pedestrian and cyclist counters. The study was conducted at three sites over 4 hour long study periods. Ground truth data was established through manual video-based analysis. The overall error rate of the best tested sensor in this study for counting cyclists, reported to be 26 %.

Methods for Video-based Counting

According to a report by Ryan and Lindsey *(3)*, one can see that although many of the traditional methods perform reasonably well in terms of accuracy and cost, it is clear that automated video analysis offers the most in regards to the data types it can generate such as speed, volume, and trajectory. Two other important advantages are that they do not require any physical alteration to the road surface as other sensors do, in particular inductive loops, and they are more discreet.

The three fundamental tasks of all video tracking systems are to detect, track and classify the type of objects *(8)*. However, when these systems were first introduced, similar to a loop detector, it just collected basic vehicle data such as speed and volumes, at specific points on the road without tracking them *(9)*. These systems known as 'tripwire systems' essentially look at specific points along a road segment and count whenever the image intensity changed. Newer systems also track vehicles and provide engineers with microscopic data for individual vehicles such as acceleration and deceleration patterns *(10)*. The primary issues of detecting and tracking vehicles or any other road user are related to visibility, or lack thereof due to poor weather and lighting conditions, congested traffic, occlusion of complete or partial vehicle segments, and vehicle shadows *(9)*. In particular, for congested conditions and instances where the sun creates vehicle shadows, most systems have issues with identifying individual vehicles and often group several vehicles with their shadows into large masses. These issues are even more prevalent for pedestrian and cyclist tracking systems because of user variability in both appearance and movement *(11)*.

Other imaging technologies have also been developed and tested. One promising solution in the cases of poor lighting and shadows is the use of infrared thermal imaging, particularly for monitoring traffic nighttime conditions *(12, 13)*. The contrast between the typically low thermal background signature of the road and high thermal foreground signature of the vehicle makes it easier to identify moving vehicles especially in bad weather conditions. However, this contrast is heavily dependent on weather and temperature conditions, with worse performance in warm weather. Although infrared technology has already been extensively used for military purposes such as weapon guidance systems, it is yet to gain prominence in the field of traffic monitoring.

The four main tracking techniques are model-based, region-based, active contour-based, and feature-based tracking *(9)*. Model-based tracking functions by matching an approximate model, typically a wire-frame model, to the detected road user shapes through proper scaling and orientation *(14)*. The second tracking technique, region-based tracking, works by identifying road users pixel groups often called blobs typically using background subtraction. This technique works well when few road users are present on the road. However, in situations of congestion, road users too close to each other may be accidentally grouped together and tracked as a single large object. Similarly to the previous method, active contour-based tracking identifies road users by their borders or contours. Although it is computationally less intensive than region-based tracking, it suffers from the same issue of occlusion. In these first three techniques, the road user detection (characterized by 3D model, shape or contour) is then updated using a specified filtering technique to estimate its new position based on its velocity and angle. The fourth is feature-based tracking which essentially works by identifying distinct points or features such as corners to track *(9, 15)*. The most important advantage of this technique is that vehicles may be tracked even in cases of partial occlusion *(9)*. It is also advantageous to use in varying lighting conditions because it focuses on identifying the most obvious features that can be used to identify a vehicle.

Classification can then be performed on the output to distinguish between vehicles, pedestrians and cyclists such as in the case of intersections with mixed traffic *(11)*.

Among the few more recent studies evaluating the counting performance of video analysis, Zaki et al. *(16)* focused on collecting cyclist count and speed data from a single roundabout located at one of the entrances to the University of British Columbia campus using an automated computer vision technique. The study consisted of two twelve hour recordings taking place over two consecutive days in March 2011. In regards to counting, the results of the study were found to be over 84 % accurate when compared to a manual video analysis. It was noted that the accuracy of counts depended on the camera position relative to the four screen line positions evaluated. Similarly, Somasundaram et al. *(17)* presented a number of computer vision methods or classifiers to deal with the issue of classifying objects as pedestrians or cyclists. Some of the methods included were individual in nature such as, bag-of-visual-words (BoVW), bag of salient words, and classification with discriminative dictionaries while others were simply a combination of individual approaches such as a combined naïve Bayes method and a combined histogram method. The study tested the different techniques along with other techniques described in the literature on two video sets which featured a cycling path with a high percentage of cyclists and a university walkway with a high percentage of pedestrians in Minneapolis. The results found that the combined approach described in the paper produced the most accurate results in regards to frame-by-frame classification (92 %) and counting (95 %). A study by Belbachir et al. *(18)* focused on testing an event-based 3D vision system to classify 128 test trips along a path designated for pedestrians and cyclists only. The system functioned by first clustering similar objects and then classifying them based on length, width, and time. The results of the study indicate that the system was more than 92 % accurate in classifying an object as a riding cyclist, walking cyclist or pedestrian. The most important shortcoming of the most previous works was reporting the accuracy of the counting for the entire period. Accuracy reported for long periods of time can be subject to uncertainty and randomness as over-counting and under-counting errors in shorter time periods do not always compensate the effect of each other.

METHODOLOGY

This section describes the proposed methodology for the automated bicycle counting technique that consists of three steps:

1. Site selection and video collection
2. Data processing
3. Assessing counting accuracy

Site Selection and Video Collection

For investigating the bicycle counting accuracy of the proposed method, a set of sites with different environment types and volume intensities were selected in Montreal. The sites consisted of intersections and road segments with or without cycle tracks. In each site, several hours of video were recorded:

- Two road segments with separated cycle tracks (7 hours)
- Five intersections with separated cycle tracks (14 hours)
- Three road segments without a cycle track (6.5 hours)
- Three intersections without a cycle track (8.5 hours)

All the videos were recorded during the weekday and afternoon peak hours in the summer in order to ensure significant count variability. In addition, videos were collected in good weather conditions, since issues related to bad weather were not the focus of this paper. Figure 1 shows the locations of the selected sites.

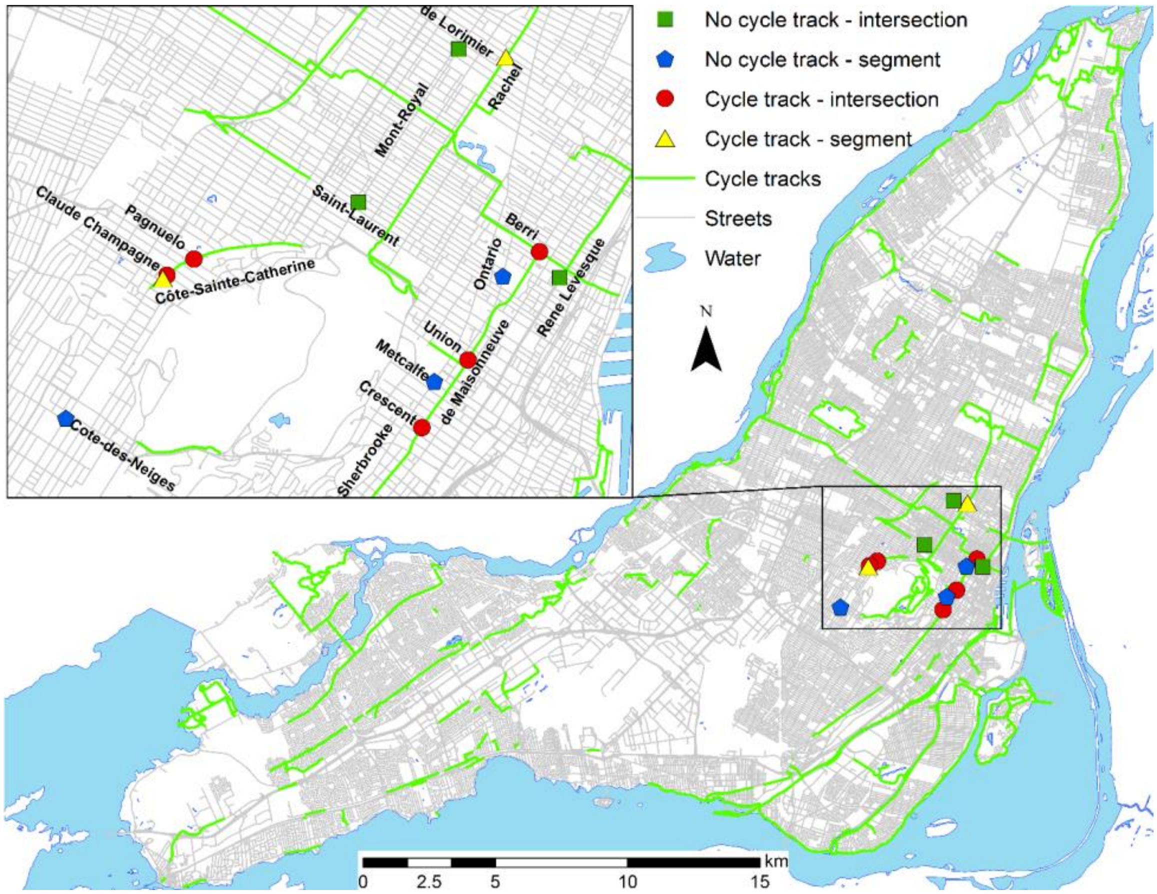


Figure 1. Location of sites selected for recording video in Montreal.

For the video data collection, GoPro's Hero 3+ Black Edition cameras were used to record video in high definition (HD) at 15 frames per second. With each single charge of the camera, around 3.5 hours of video could be recorded. These cameras were mounted on tall adjustable poles which were then installed next to an existing pole at an intersection to support and provide stability for the pole in order to prevent the camera view from changing throughout the video. The camera angle was adjusted for each site in order to optimize the viewing of the site. Depending on the width of the road, the location of an appropriate pole as well as other obstacles, the camera setup differed for each site.

Data Processing

Data processing involves three steps: detecting and tracking moving objects in the video, classifying the tracked objects into road users of different types (pedestrian, cyclist or vehicle), and selecting the trajectories associated with the road users subject to count (cyclists in each direction).

Tracking Objects in Video

An existing feature-based tracking tool from an open-source project called *Traffic Intelligence (19)* was used for detecting and tracking the objects in a video. The proposed approach uses the output of the moving object tracker *(20)*. This algorithm can be summarized in two steps:

1. Individual pixels are detected and tracked from frame to frame and recorded as feature trajectories using the Kanade Lucas Tomasi feature tracking algorithm *(21)*.
2. A moving object is composed of many features which must be grouped. Feature trajectories are grouped based on consistent common motion. In other words, features that have relatively the same movements will be grouped together to form an object.

The tracker output is a set of trajectories (sequences of object positions at each frame) of each moving object in a video. The parameters of this algorithm are calibrated through trial and error, leading to a trade-off between over-segmentation (one object being tracked as many) and over-grouping (many objects tracked as one). Readers are referred to *(20)* for more details.

Object Classification

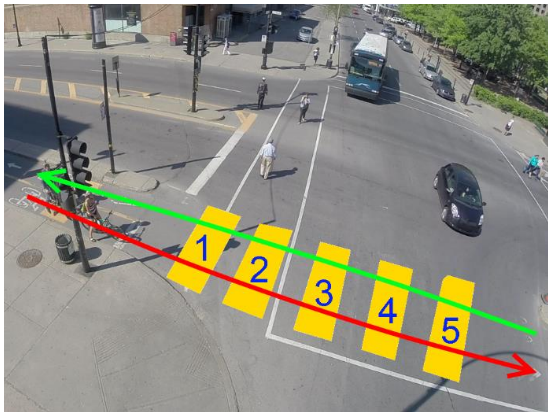
At intersections with several different road user types, object classification is needed, especially when the subject of study is the interaction between two different road user types. In this paper, a modification of previously developed method for object classification in video *(11)* was used. Classification is done based on the object appearance in each frame combined with its aggregated speed and speed frequency (or gait parameters). The overall accuracy of this classification method at intersections with high volumes and mixed road user traffic is more than 90 %. The classifier is capable of classifying objects into three main road user types: pedestrian, cyclist, and motor vehicle. For more details regarding the original classification method, readers are referred to *(11)*.

Selecting What is Counted

The next required step was to define what is counted, i.e. for which pairs of origin and destination zones the cyclists were counted. This step was done by defining seperate origin and destination areas for cyclists, for each movement, in a video. Since it is possible that an object trajectory appears or disappears somewhere in the middle of the camera view (if it stops and then starts moving, or as a result of problems with the quality of the video), five areas for origins and destinations were defined (instead of just one origin and one destination). This increased the chance of a cyclist being detected and counted. Origins and destinations were defined in a way to count specific movements of cyclists. By changing the position, shape or size of these areas, one can count the cyclists of another movement. A trajectory was counted as a cyclist if:

1- the moving object was classified as a cyclist
2- it passed through one of the origin areas defined for each movement
3- after it passed through one of the origin areas, it passed through one of the destination areas defined for that movement.

For example in Figure 2, to be counted as a cyclist in the movements indicated by the red arrows, a cyclist had to first appear in one of the yellow areas (origin) and then appear in another yellow area with a higher number (destination). Even if a cyclists passed through multiple origins and destinations it was counted as one cyclist. Figure 2a shows an intersection with two directions subject to counting (counting in the direction of movement represented by the green arrow is different from the opposite direction only for considering destination areas with lower numbers than origin areas), while Figure 2b shows another intersection with only one direction subject to counting, since the origin of the other movement is not visible in the camera's field of view.



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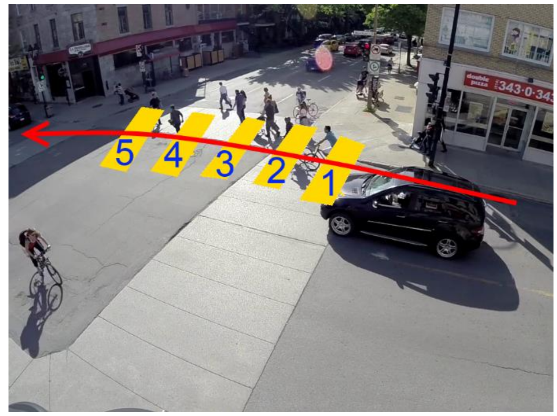
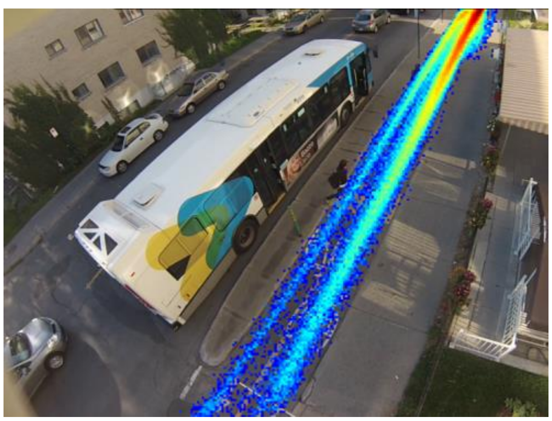


(b)

Figure 2. Examples of origins and destinations for (a) an intersection with two directions for counting, and (b) an intersection with only one direction for counting.

Samples of the density maps derived from the trajectories extracted and filtered by this algorithm are shown in Figure 3. These heat-maps are useful to see the most used locations of the map by the counted cyclists.



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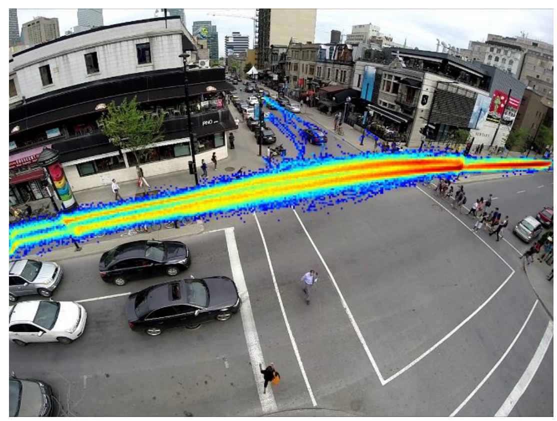

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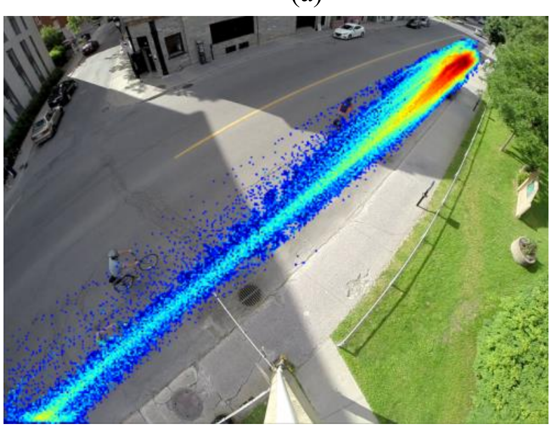

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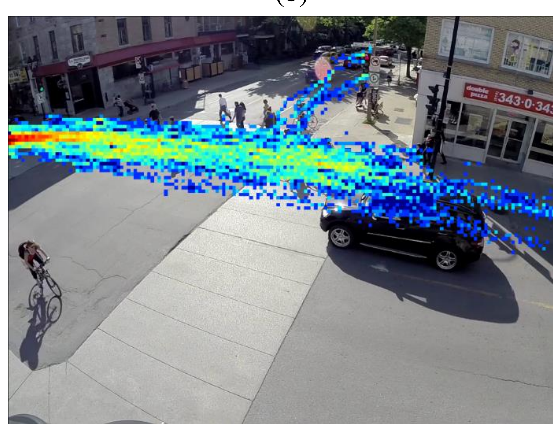


(d)

Figure 3. Densities of the positions of the counted cyclists for different environments (the most and least used map locations are respectively red and blue; heat-map colours range from blue to red, passing through cyan, yellow, and orange): (a) road segment with a cycle track, (b) intersection with a cycle track, (c) road segment without a cycle track, and (d) intersection without a cycle.

Measuring Counting Accuracy

Sources of error in the proposed automated counting method can be grouped into four main categories:

- Not being tracked: this error mostly happens when the quality of the recorded videos is not high enough and the tracker cannot track the moving features in the video. The other cause of this error is cyclists being occluded in the video by a larger vehicle.
- One object being grouped to two or more objects by the tracker: this type of error happens when the features of one object are far from each other and move relative to each other.
- Two or more objects group into one object by the tracker: this type of error is more common in situations where a lot of cyclists arrive in the video and move together.
- Misclassification: this type of error is more common in environments with mixed traffic, like intersections which have mixed high volume traffic.

To test both the accuracy and precision of the proposed automatic bicycle counting method, four measures are computed: the R squared of the best linear fit, the Root Mean Square Deviation (RMSD), the Mean Absolute Percentage Deviation (MAPD), and the Standard Deviation of Percentage Deviations (SDPD).

RMSD, a frequently used measure of accuracy, is the difference between predicted values and the actual observed values. RMSD can be computed as:

$$RMSD = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(AC_t - MC_t)^2}$$

Where, AC_t stands for the automatic counts for each time interval, t. MC_t stands for the manual counts during the same time interval, n stands for the number of time intervals.

MAPD is a relative measure of accuracy and is defined by this formula:

$$MAPD = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{AC_t - MC_t}{MC_t}\right|$$

SDPD is the standard deviation of MAPD and can be calculated as:

$$SDPD = \sqrt{\frac{1}{n-1}\sum_{t=1}^{n}\left[\left(\frac{AC_t - MC_t}{MC_t}\right) - MAPD\right]^2}$$

RESULTS

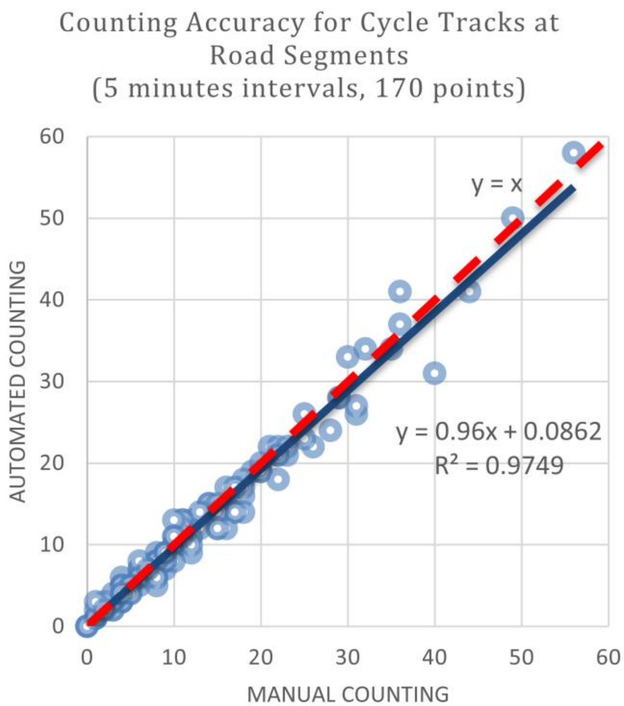
The proposed automated counting method was applied to the selected sites and compared to the manual counts from the videos. From the selected sites, the views at five sites were not adequate enough to count bicycle flows traveling in both directions (either because of the high fish eye effect of the camera at the edges of the field of view or because the counting area was not fully in view, e.g. the origin or destination area was not visible). In such cases, the automated counts were obtained only for one direction (Figure 2).

On average, the number of cyclists was higher on road segments and intersections with cycle tracks. Cyclist flow per direction range from as low as 8 cyclists on average per hour where there was no cycle track to as high as 464 cyclists on average per hour where there was a cycle track (see Table 1). A simple, but naïve way to show the overall accuracy of the automated counting method is to find the ratio of the overall counts done by automated method to the overall manual counts. Based on this measure, automated counts to manual counts ratios ranged from 0.73 to 1.04 for different environment types. A summary of the analyzed videos, flows, and aggregated automated to manual count ratio results are shown in Table 1.

Table 1. Summary of the analyzed videos for bicycle counts and aggregated performance

Environment type	Site	Hour	Travel Direction	Manual bicycle count	Automated bicycle count	Manual bicycle count per hour	Automated bicycle count per hour	Automated to Manual Ratio
Road segment with cycle track	Cote Sainte Catherine/ Claude Champagne (at Bus Stop)	5.28	East	599	587	113	111	0.98
			West	612	563	116	107	0.92
	Rachel / Messier (at Bus Stop)	1.75	West	533	530	305	303	0.99
			East	145	148	83	85	1.02
Intersection with cycle track	Berri / Maisonneuve	1.21	South	170	130	140	107	0.76
			North	561	487	464	402	0.87
	Cote Sainte Catherine / Claude Champagne	3.5	East	182	164	52	47	0.90
			West	489	433	140	124	0.89
	Cote Sainte Catherine / Pagnuelo	3.95	East	235	204	59	52	0.87
			West	287	266	73	67	0.93
	Maisonneuve / Crescent	3.5	West	1083	901	309	257	0.83
			East	772	674	221	193	0.87
	Maisonneuve / Union	1.8	West	393	404	218	224	1.03
			East	521	468	289	260	0.90
Road segment without cycle track	Ontario / Bullion	3.44	East	714	703	208	204	0.98
	Sherbrooke / Metcalfe	1.05	East	129	134	123	128	1.04
	Cote Sainte Catherine / Cote Des Neiges	2.06	East	16	14	8	7	0.88
Intersection without cycle track	Mont Royal / Lorimier	2.88	West	116	109	40	38	0.94
	Mont Royal / Saint Laurent	2.71	East	115	119	42	44	1.03
			West	73	53	27	20	0.73
	Saint Denis / Rene Levesque	3	West	81	69	27	23	0.85
Road segments with cycle track		7.03		1889	1828	269	260	0.97
Intersections with cycle track		13.96		4693	4131	336	296	0.88
Road segments without cycle track		6.55		859	837	131	128	0.97
Intersections without cycle track		8.59		385	364	45	42	0.95

To visually evaluate the quality of the proposed automatic counting method and explore the effect of the temporal aggregation, x-y plots between automatic and manual counts were generated at 5 and 15 minutes intervals. In the following Figures 4-7 points corresponding to counting accuracy for 5 and 15 minutes intervals pooled for different environments are shown. Each figure shows the automated counts versus manual counts for all the sites and directions in that category. In these figures, the dashed red line shows the ideal counts: “y=x” or “manual counting = automated counting” and the blue line represents the best linear fit. R^2 which is a measure for precision is also shown for each figure.



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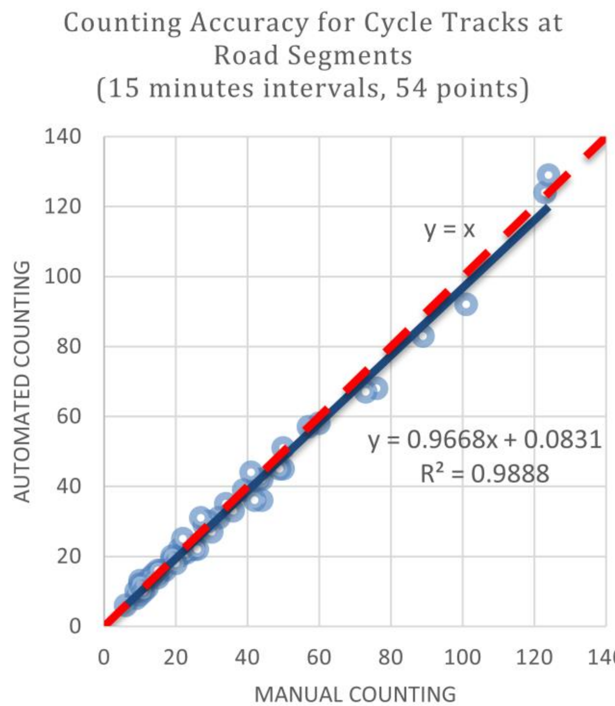
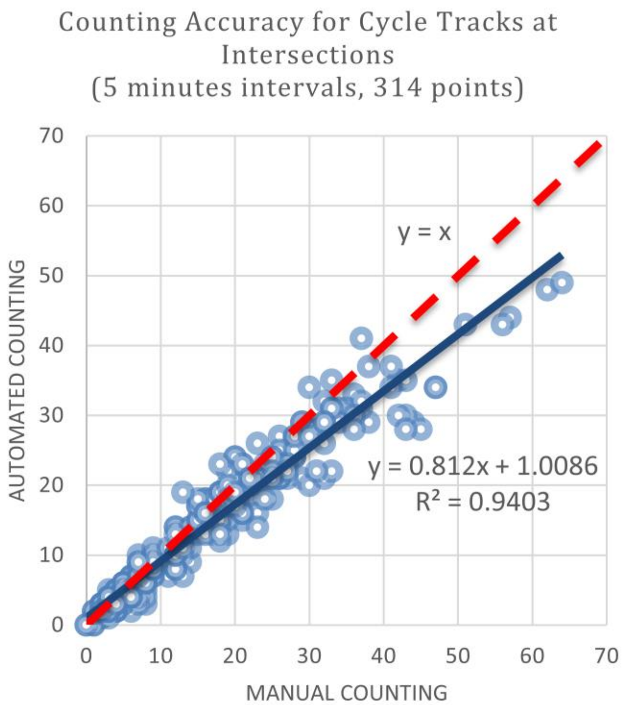


(b)

(c)

(d)

Figure 4. Bicycle counting accuracy for road segments with a cycle track. (a) for 5 minutes intervals, and (b) for 15 minutes intervals. (c, d) show the field of views of the corresponding sites.



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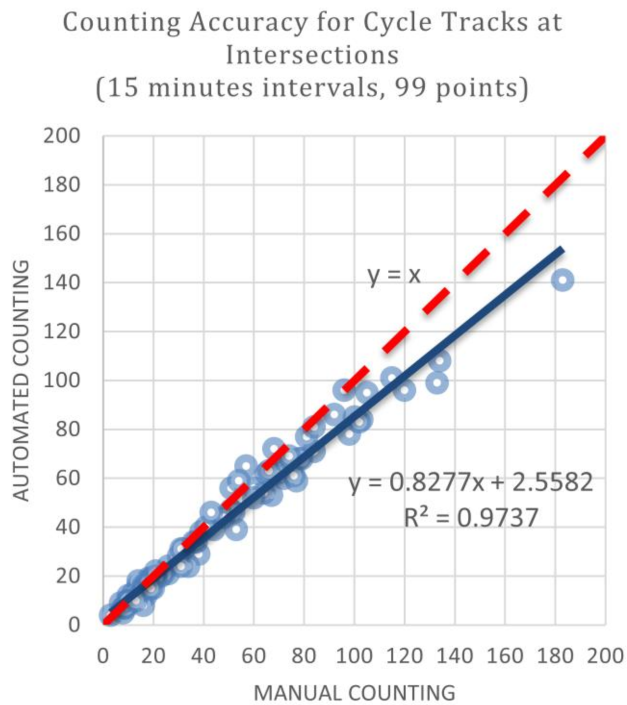

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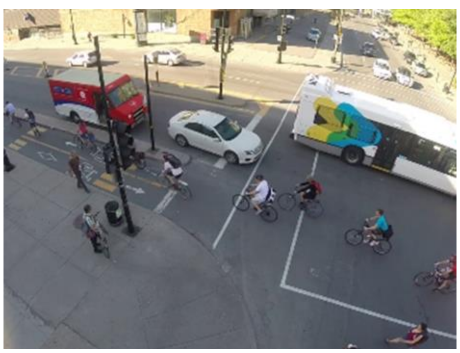

(c)

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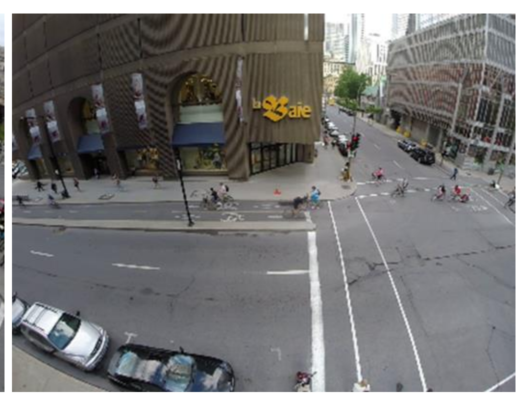
(e)

(f)



(g)

Figure 5. Bicycle counting accuracy for intersections with a cycle track. (a) for 5 minutes intervals, and (b) for 15 minutes intervals. (c, d, e, f, g) show the field of views of the corresponding sites.

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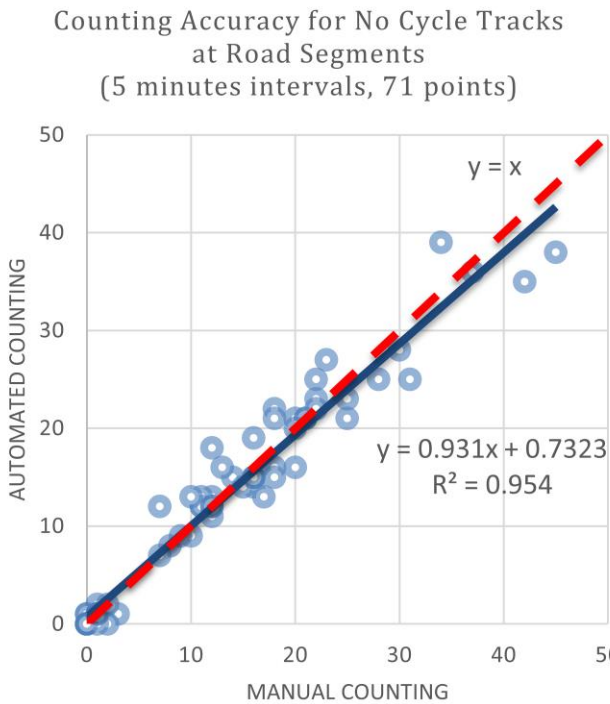
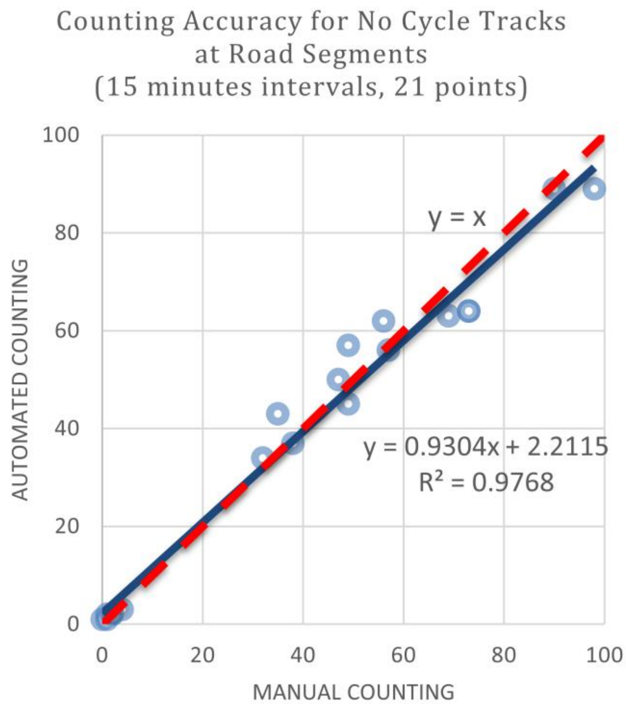
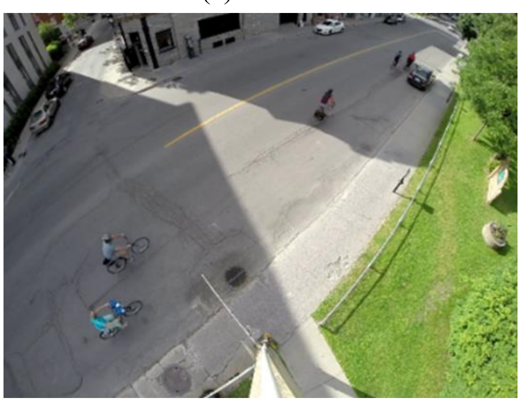


(a)

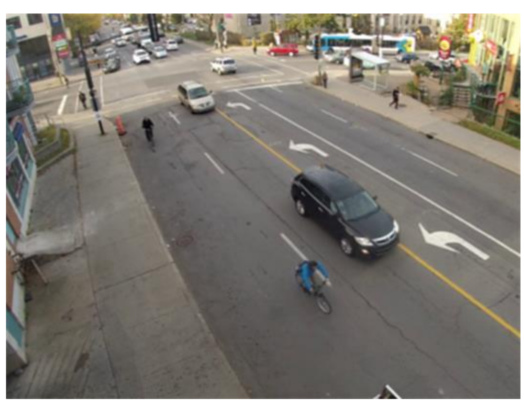


(b)



(c)

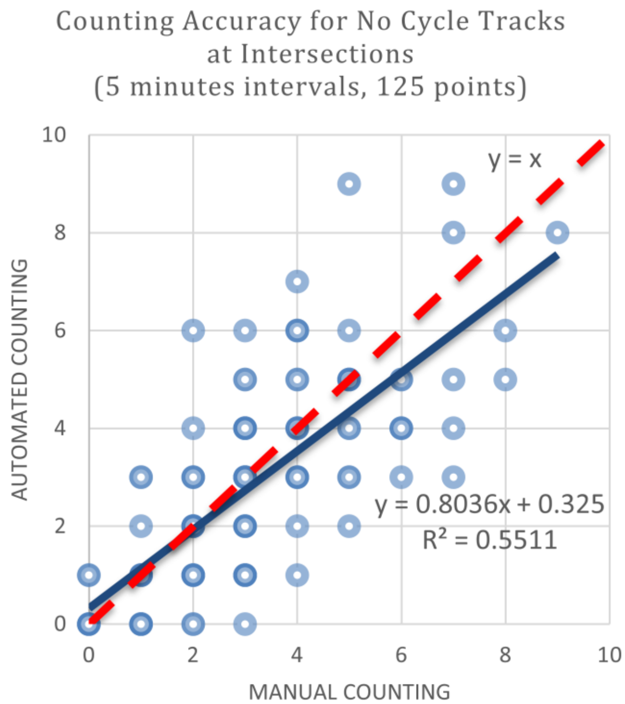
(d)



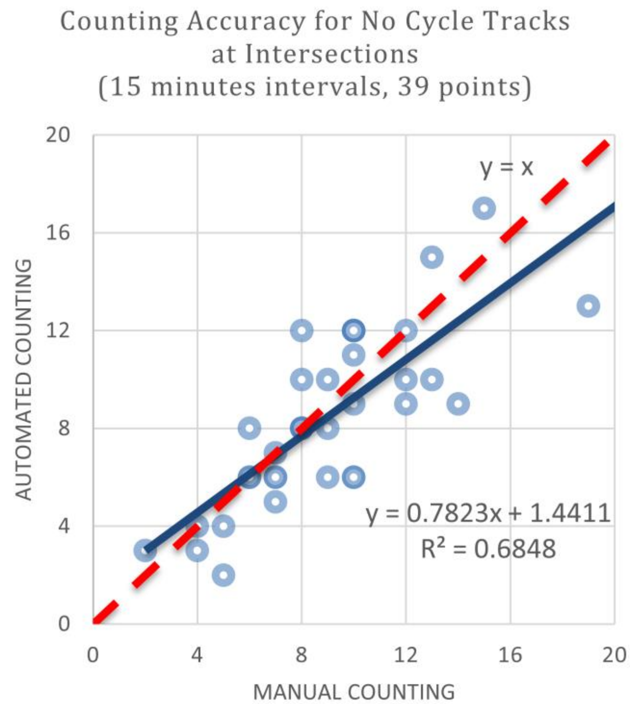
(e)

Figure 6. Bicycle counting accuracy for road segments with no cycle track. (a) for 5 minutes intervals, and (b) for 15 minutes intervals. (c, d, e) show the field of views of the corresponding sites.

1



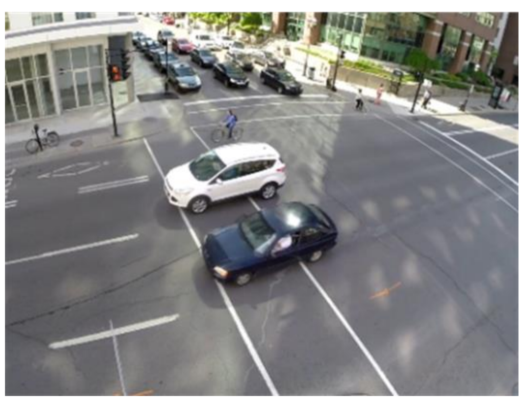
(a)



(b)

(c)

(d)



(e)

Figure 7. Bicycle counting accuracy for intersections with no cycle track. (a) for 5 minutes intervals, and (b) for 15 minutes intervals. (c, d, e) show the field of views of the corresponding sites.

1

Table 2. Statistical tests on automated counting accuracy

Environment Type	Counting Interval (minutes)	Average Flow	Linear Coefficient, a*	Linear Constant, b*	Linear R^2	RMSD	MAPD	SDPD
Road segments with cycle track	5	11.3	0.96	0.09	0.97	1.59	10 %	4 %
	15	33.8	0.97	0.08	0.99	3.10	7 %	0.3 %
Intersections with cycle track	5	15.0	0.81	1.01	0.94	3.92	17 %	3 %
	15	44.3	0.83	2.56	0.97	9.33	12 %	1 %
Road segments without cycle track	5	12.3	0.93	0.73	0.95	2.40	13 %	5 %
	15	40.8	0.93	2.21	0.98	4.77	11 %	4 %
Intersections without cycle track	5	3.1	0.80	0.33	0.55	1.47	37 %	18 %
	15	9.4	0.78	1.44	0.68	2.32	19 %	2 %

* in "Manual Count = a * Automated Count + b"

Table 2 shows the acceptable performance of the proposed methodology for counting bicycle flows in different environments. Based on the MAPD, for 5 minutes interval counts, the accuracy ranged from 73 % for intersections without a cycle track to 90 % for road segments with a cycle track. With the same measure, for 15 minutes interval counts, the accuracy ranged from 81 % for intersections without a cycle track to 93 % for road segments with a cycle track. RMSD describes the absolute error value for each type of environment, meaning that the value given by the automated method has the absolute average error of RMSD. Since this is not a normalized value, RMSD tended to be higher for situations with a higher number of cyclists, like intersections with a cycle track. Regarding the time interval of the counts, due to the possibility of under-counting in one time interval being compensated by over-counting in another, the accuracy of the counts was higher for the longer time intervals (15-min vs 5-min).

Due to the usage of the modified classifier from the movements and positions of each object in the video (by defining the areas that each road user can be present in), the counting accuracy was higher for roads and intersections with separated bicycle flow (with cycle track) compared to those with mixed traffic (without cycle track). Similarly, due to less mixed movements at road segments (and fewer pedestrians) the counting accuracy was higher than for intersections. The only source of error for road segments with a cycle track was misclassification of the pedestrians who had to cross the cycle track to get on a bus (or get off) at bus stop. Due to the strong capability of the modified classifier to distinguish pedestrians from cyclists, the counting accuracy for road segments with separated cycle tracks was very high (Figure 4). The main source of error in the videos of intersections with a cycle track was the camera angle which could have caused cyclists to be occluded by larger vehicles and partially or completely hidden in the video. Another source of error was the high amount of road user interactions at intersections and cyclists stopping at intersections which can cause disruptions in the tracking (Figure 5). In road segments and intersections without a cycle track, the classifier might have misclassified road user types (Figure 6 and Figure 7). Examples of this misclassification include a vehicle or a pedestrian classified as a cyclist (over-counting) or a cyclist classified as a vehicle or a pedestrian (under-counting).

CONCLUSION

In this paper, an automatic method for counting cyclists at road segments and intersections was proposed. The results indicate that this method can be a feasible and highly accurate technique for gathering short-term bicycle counts in locations where traditional technologies such as loop detectors and pneumatic tubes, do not work well. The proposed method consists of several steps: recording video, tracking and classifying objects in the video, and defining origins and destinations for movements subject to counting.

One of the main advantages of this method is its ability to count cyclist flow for different movements with different origins and destinations, even in complex environments with mixed traffic such as intersections. In addition, the cyclists trajectories derived from this method for different movements can be used for other purposes such as road safety studies *(22)*.

One of the shortcomings of most previous works was reporting the accuracy of counting cyclists for the entire period of the data collection. Because over-counting and under-counting errors in shorter time periods cannot always compensate the effect of each other, accuracy reported for longer periods of time can be subject to uncertainty and randomness. Due to this reason, the accuracy of the proposed method was reported for two short time intervals of 5 and 15 minutes. Using MAPD as an accuracy measure, road segments with cycle tracks had the least error (10 % for 5 minutes intervals and 7 % for 15 minutes interval). Road segments without a cycle track had the second best accuracy, 13 % and 11 % error for 5 and 15 minutes intervals respectively. Due to the complex movements at intersections, the accuracy for bicycle counts at intersections was relatively lower compared to road segments. 17 % and 12 % were the errors associated for intersections with a cycle track respectively for 5 and 15 minutes intervals, while 37 % and 19 % were the errors associated for intersections without cycle track respectively for 5 and 15 minutes intervals.

Several factors can cause the proposed method to be inaccurate such as a bad camera angle in a way that cyclists being occluded by larger vehicles, high distance between camera and cyclists subject to count, bad weather conditions, presence of shadow, and movements of two or more cyclists next to each other. These factors can affect the accuracy of counting cyclists in different environments, making counting in road segments with a cycle track and at intersections without a cycle track the best and worst environments for which to accurately count cyclists.

In regards to future developments, one can improve the accuracy of the used tracker and classifier to reduce the error in tracking, grouping, and classifying moving objects in a video. Alternative video sensors can also be used such as thermal cameras, to deal with some of the limitations of the regular cameras in low light, shade, and adverse weather conditions. Changing the camera angle by using a taller pole or mounting the camera to a drone can mitigate the problem with occlusion in high density conditions. In addition, installing multiple cameras at intersections to capture all the possible movements, origins and destinations, can be a useful addition to the current method.

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