Automated Collection of Cyclist Data Using Computer Vision Techniques

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Abstract

One of the main challenges in conducting detailed analysis of cyclist behavior is the lack of reliable data. Collecting data through manual methods is a labour-intensive and time consuming process. Two of the important areas of cyclist data collection are volume counts and average speed measurement. A volume count is important as it provides the basis for necessary exposure measures and conveys essential information of traffic patterns. It can also serve as a performance measure of the facility. Cyclist speed data is used for traffic control and safety studies. Video sensors, when complemented with computer vision can offer a promising approach for the automated collection of traffic data. The approach is characterized by the wealth of data they can capture, store and analyze.

Through the application of computer vision techniques, it is possible to obtain precise spatial and temporal measurements of the road-users in a resource-efficient way. This paper demonstrates the use of a set of computer vision techniques for the automated collection of cyclist data. The cyclist tracks obtained from video analysis are used to perform screen line counting as well as cyclist speed measurements. The applications are demonstrated using a real-world data set from a roundabout in Vancouver, British Columbia. Further analysis was conducted on the mean speed of cyclists with regards to several factors such as the travel path, helmet usage, and group size. The motivation of this research is to improve the understanding of cyclists' behavior and how it varies under different conditions. Several conclusions can be drawn from the analysis of cyclist speed behaviour. Group size, travel path, lane position and helmet usage were found affect the cyclist mean speed. Single cyclists had a slightly, but significantly higher mean cycling speed compared to group cyclists. The mean cycling speed was highest for the cyclists using the road rather than the sidewalk. The mean cycling speed decreases for non-helmet users.
Motivation

As modern cities are changing to become greener and to provide a more liveable environment, there is a pressing demand to shift towards active modes of transportation such as cycling. These active modes of transportation can play a very important role in achieving efficient transportation systems as they offer many benefits. Cycling is considered as one of the most environmentally sustainable forms of transportation [1]. Its benefits include improving public health by increasing the amount of physical activity [2], reduced congestion, energy conservation, and pollution reduction. However, several challenges can inhibit a wider endorsement of cycling as a mainstay commuting mode. These challenges relate to the mobility, accepted levels of safety and efficient resources [3]. The fear of injury on the road, the weather affecting the road conditions and congestion of road traffic are some of the common concerns for daily commuting cyclists. For instance, Winters et al. [4] conducted a comprehensive study in Vancouver that investigated a total of 73 potential motivators and deterrents which influence cyclists’ decisions. Overall, cycling was shown to provide more benefits in the long term that outweigh its negative perceptions. Therefore, it is of great interest to understand and study in greater details the elements that constitutes cyclist trip behavior in order to develop effective policies and infrastructure.

One of the main challenges in conducting detailed analysis on cyclists’ behavior is the lack of reliable data. Collecting reliable data is often labour-intensive and time consuming as it is usually collected by manual counts or measurements [5] [6]. This lack of reliable data can have a significant impact on several transportation engineering and planning aspects. Two of the important areas of cyclist data collection are volume count and average speed measurement. Volume count is important as it provides a basis for the necessary exposure measures [7] and conveys essential information of the traffic patterns along the road segments of interest. It can also serve as a performance measure of the facility [8] [9]. Cyclist speed data is used for traffic control and safety studies. In recent years, some degree of automation has been implemented for cyclist data collection [10] [5] [11]. However, these approaches have geometric restrictions such as the need for physical choke points or the feasibility of implementing overhead structures at cyclist walkways [6]. As a result, most cyclist counts in open space such as unconstrained street networks are still performed manually. Inconsistent and scarce cyclist counts make it difficult to justify capital for implementing cyclist facilities. Given the aforementioned issues, there is a significant need to explore methods of increasing the availability of cyclist data. One of these methods is to develop reliable automated techniques for data collection such as the use of computer vision (CV) techniques. Computer vision techniques are not new to the transportation field. For example, in recent years, computer vision has been used to track vehicle and cyclist trajectories to study traffic conflicts and their implications on traffic safety [12] [13].

The paper will demonstrate the use of a set of computer vision techniques for the automated collection of cyclist data. The cyclist tracks obtained are used to perform screen line based cyclist counting as well as cyclist speed measurements. The applications are demonstrated using a real-world data set from a roundabout in Vancouver, British Columbia. Further analysis was conducted on the mean cycling speed of cyclists with regards to several factors such as the travel path, helmet usage, and group size. The goal of this research is to improve the understanding of cyclists’ behavior in order to improve the riding condition and provide an efficient and safe commuting environment. Examining the different attributes affecting the cycling performance provides valuable information that aid in accommodating a wide range of potential users. Several benefits can be withdrawn for transportation applications. Those include applications in cyclists’ simulation models, planning and management of cyclists’ trips, evaluating facility level-of-service and cyclists signals design [14] [9].
Previous Studies

Cyclists Data Collection

Cyclists’ data collection and behavior analysis have been an active research topic in the last decade. The focus has been on studying cyclists speed in different route configurations from signalized intersection in mixed and dedicated bikes lanes to urban trails [15] [16] [17] [18]. Factors that influence the speed such as the grade and the cyclist attributes have been identified [19] [20]. Table 1 summarizes the results of some recent studies on the subject. It is important to note that the majority of the surveyed studies are based on manual speed measurements by field or video observations. Attempts to use computer vision techniques are still primitive. The manual methods currently used in practice for the collection of cyclists’ data lack the ability to capture microscopic changes in position and speed. Automated video analysis is becoming more popular as it overcomes the shortcomings present in manual methods that are commonly used. Table 1 covers only relevant results in the past two decades, pointer to earlier studies can be found in [8] as well as the AASHTO Guide [21] of development of bicycles facilities, which reported recommended speed design based on cyclists expertise population. According to a study by the FHWA, a design speed of 32 km/h is sufficient for most cyclists to travel at their desired speeds [22] [8].

Cyclists Detection and Tracking

For automatic tracking of cyclists, moving road users must be detected and tracked frame-by-frame and classified into cyclists and non-cyclists [23] [24]. Common problems in this challenging task include global illumination variations, shadow handling, and multiple object tracking [25]. Road-user classification is undertaken during the video analysis, in order to aid the tracking of the moving objects. CV based classification has found applications in traffic monitoring and the activity recognition [25] [26]. Typical sequence of analysis steps start with object detection, hypothesis generation, classification, and finally tracking. Classification relies in general on descriptive or discriminative features identified in the analysis. In several instances, the classification relies on library information from previously learned models. Bicycles don't have a precise shape and their classification inherits many of the challenges. A blend of methods based on shape detection has been proposed in a series of papers ( [24], [27]). The authors in [28] described a vision-based bicycle classification. The algorithm relies on features detection around the wheels regions. Relying on particular features as wheel detection can be challenging especially when the camera field of view or traffic occlusion limits access to such features. The authors in [29] examined the performance of different types of texture-based and motion features for the discrimination between bicycles and pedestrians. In [29], the study used shape based and background subtraction to identify and classify pedestrians and cyclists. They proposed using the distributions of typical velocity along geometric information (width to height ratio values). In summary, velocity values are hence more suitable to be used in conjunction with the appearance based classifier. Reported count accuracy was around 81 percent [29].
Table 1: Relevant Studies on the Cyclists’ data collection

<table>
<thead>
<tr>
<th>Study</th>
<th>Locations</th>
<th>Reported 15th Percentile Cycling Speed</th>
<th>Reported 85th Percentile Cycling Speed</th>
<th>Mean speed (SD)</th>
<th>Number of Subjects</th>
<th>Method¹</th>
<th>Significant Attributes²</th>
<th>Insignificant Attributes²</th>
</tr>
</thead>
<tbody>
<tr>
<td>[16]</td>
<td>Signalized Intersection</td>
<td>8.19 Km/Hr.</td>
<td>20.41 Km/Hr.</td>
<td>11.44 Km/Hr. (3.01)</td>
<td>561</td>
<td>1.2</td>
<td>2.3, 2.4</td>
<td>2.1</td>
</tr>
<tr>
<td>[30]</td>
<td>6 Signalized Intersections</td>
<td>-</td>
<td>-</td>
<td>8.4 to 14 Km/Hr. (crossing) and 14.3 to 26.6 Km/Hr. (rolling starts)</td>
<td>550</td>
<td>1.1</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>[18]</td>
<td>16 Signalized Intersections</td>
<td>10.8 Km/Hr.</td>
<td>-</td>
<td>12.7 Km/Hr.</td>
<td>442</td>
<td>1.2</td>
<td>2.5, 2.7</td>
<td>-</td>
</tr>
<tr>
<td>[31]</td>
<td>Citywide</td>
<td>-</td>
<td>-</td>
<td>16 Km/Hr.</td>
<td>8</td>
<td>1.5</td>
<td>2.1, 2.6</td>
<td>-</td>
</tr>
<tr>
<td>[32]</td>
<td>2 Signalized Intersections</td>
<td>10.62 Km/Hr.</td>
<td>-</td>
<td>11.92 Km/Hr.</td>
<td>122</td>
<td>1.2</td>
<td>2.1, 2.9</td>
<td>-</td>
</tr>
<tr>
<td>[33]</td>
<td>Road Segment</td>
<td>-</td>
<td>-</td>
<td>14.8 Km/Hr. (4.18)</td>
<td>152</td>
<td>1.6</td>
<td>-</td>
<td>2.1, 2.7</td>
</tr>
<tr>
<td>[34]</td>
<td>Citywide</td>
<td>-</td>
<td>22 Km/Hr.</td>
<td>21.6 Km/Hr. (6.01)</td>
<td>16</td>
<td>1.5</td>
<td>2.9</td>
<td>2.1</td>
</tr>
<tr>
<td>[17]</td>
<td>2 Trails</td>
<td>-</td>
<td>-</td>
<td>21.42 Km/Hr. (7.56)</td>
<td>140</td>
<td>1.1</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>[35]</td>
<td>7 Different Sites</td>
<td>-</td>
<td>-</td>
<td>16.5 Km/Hr.</td>
<td>1557</td>
<td>1.3</td>
<td>2.2, 2.7, 2.1</td>
<td>-</td>
</tr>
<tr>
<td>[20]</td>
<td>10 Signalized Intersections</td>
<td>9.77 Km/Hr.</td>
<td>-</td>
<td>14.76 Km/Hr. (5.29)</td>
<td>2097</td>
<td>1.2</td>
<td>2.5</td>
<td>-</td>
</tr>
<tr>
<td>[19]</td>
<td>Signalized Intersection</td>
<td>-</td>
<td>-</td>
<td>15.84 Km/Hr.</td>
<td>&gt;150</td>
<td>1.4</td>
<td>2.9, 2.8, 2.6</td>
<td>-</td>
</tr>
<tr>
<td>[37]</td>
<td>Trail</td>
<td>11 Km/Hr.</td>
<td>22 Km/Hr.</td>
<td>17 Km/Hr. (6)</td>
<td>367</td>
<td>2</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

²Attributes: 1) Gender 2) Helmet Usage 3) Turn/Through 4) Group 5) Standing/Roll Crossing 6) Trip environment 7) Age 8) Light condition 9) Grade
Research Procedure

The Computer Vision System

The automated cyclist data collection is performed using a computer vision system developed at the University of British Columbia [12] (See Figure 1). The backbone of the system is the detection and tracking of moving features based on the standard Kanade-Lucas-Tomasi (KLT) features tracking algorithm [38]. Follow up to the tracking step is the grouping of features sharing spatial proximity and dynamical similarities. The grouping suggests the trajectory of a moving object (e.g., a road-user). Objects are subsequently classified based on the analysis of their trajectories and speed profiles [39]. In such way, only cyclist trajectories are identified and kept for further data collection analysis. Further details of the computer vision system can be found in [12]. Initialization of the CV system consists of setting tuning parameters to ensure proper tracking under different environment conditions.

An important process in the generation of the road-users trajectories is to create a mapping from world coordinates to image plane coordinates using a homography matrix (camera calibration). The positional analysis of road users requires accurate estimation of the camera parameters. During video recording, the three-dimensional real-world is captured on a two-dimensional image space. This mapping enables the recovery of real-world coordinates of points that appear in the video. In such way, the trajectory information such as positions and velocities are recorded in real-world coordinates rather than pixel based coordinate. The camera calibration procedure consists primarily of the estimation of certain camera parameters. In [40], this is set as an error minimization problem between selected projected geometric features (e.g., points, lines) onto world plane space and the actual measurements of these entities in projection (video image) space. The parameters are obtained by minimizing the difference between the projection of geometric entities, e.g. Corresponding Points, Distances, Angles, Global Up Directions points and lines, onto world or image plane spaces and the real-world measurements of these entities. Camera calibration is performed at the beginning of the data collection procedure [40]. Details of the adopted mixed-feature camera calibration approach are presented in [40].

![Figure 1: Computer Vision System Architecture](image-url)
Data collection consists of providing accurate speed measurements as well as counts for the cyclists. A screen line count procedure will identify the cyclist tracks crossing a predefined screen lines at a selected location. The sum of the counts represents the final output of the process, which are the automatic count of cyclists crossing the screen line. The object trajectory tracks from the tracking algorithm are used directly as an input for mean speed measurements. Two parallel screen lines with a known distance apart are specified on the screen, and the time elapsed for each track to pass through the two lines is recorded. Dividing the known distance by the elapsed time generates the mean speed of that particular track.

The performance of the computer vision tracking system can be assessed by its ability to accurately detect cyclists. This can be measured by the validation of counts made with screen lines. The results of the automatic counting process are validated with manual counts made for the same screen line and same footage. Another important measure is the ability to track cyclists accurately in space and time. This can be achieved by the validation of average speed measurements taken from the extracted trajectories. To validate the results of the speed measurement, a specific length on the image with known physical distance is used. This section of road space is selected such that there is a high degree of overlap with the section defined by the screen lines in the automatic speed calculations. This ensures that the results of the speed measurements are comparable. A number of cyclist tracks are selected, and the time it takes for them to transverse the specific distance is obtained. By dividing the length of the known distance by the time elapsed, the average cycling speed is obtained for the selected cyclists. The manually calculated speed is compared to the automatically measured speed. Given an $n$ cyclists, $x_{\text{man}}$ is a vector of their manually calculated mean speeds and $x_{\text{aut}}$ is a vector of the automatically calculated speeds. The Root Mean Square Error (RMSE) is defined as follows: $RMSE(x_{\text{man}}, x_{\text{aut}}) = \sqrt{\frac{\sum_{i=1}^{n} (x_{\text{man}}^i - x_{\text{aut}}^i)^2}{n}}$. After the validation, the mean speed calculated from the automatic tracking can be used for further analysis. Cyclists are classified based on their attributes, and statistical tests are used to test for significant differences between the classes.

**Case Study**

**Site Characteristics**

Following a surge in roundabout designs in North America, several initiatives to build modern roundabout have been undertaken in greater Vancouver [41]. The case study in this paper is a recently built roundabout in the University of British Columbia main campus. The roundabout of interest is situated in the south eastern entrance to the campus at the intersection of Wesbrook Mall and West 16th Avenue. This is a mixed traffic, yield controlled roundabout comprised of four approaches as defined by Sakshaug et al [42]. Prior to entering the carriageway, the bicycle lane merges with the sidewalk. Therefore, it can be confusing for cyclists when entering into the ring. Cyclists can either merge with the motor vehicle traffic in the carriageway entry bay or continue onto the sidewalk to merge with the pedestrian traffic. Because cyclists can be grouped with either the motor-vehicle or the pedestrian traffic, they have two alternatives to get to their destination. Data collection on this location is applied as a predecessor for a traffic safety study conducted at the same location. The goal is to provide information necessary to tackle concerns related to cyclists behavior in general and at roundabouts in particular [43], [44]. During the study, the weather conditions varied over the selected days. Out of these days, March 16, 2011, and March 17, 2011, were selected to be analyzed. The first day consisted of cloudy and overcast conditions with occasional sunny breaks throughout the morning. It was observed that it was mostly sunny around noon and consistently cloudy for the remainder of the day. The second day had similar cloudy and overcast conditions in the morning with a surprise rain shower for a very short period between
11:15 AM to 12:00PM. The day continued to have long periods of overcast conditions with sunny breaks in between.

**Data Collection**

A video camera was used to record the activities that occurred over a time period of two days. It was placed in a position to capture the southern and eastern approaches of the roundabout. The length of each recording was 12 hours per day, beginning at 9:00 AM and ending at 9:00PM. For ground truth data, the videos were manually observed to log the behavioural characteristics of cyclists’ activities, assign attributes to gather information of riders, identify possible conflict events, and manually count the number of cyclists. The assigned classification and attribution was completed manually with excellent accuracy due to the quality of the recording.

![Bicycles Trajectories](image)

**Figure 2: Bicycles Trajectories**

**Counting Validation**

For counting purposes, screen lines were strategically placed to capture the movements of the cyclists entering and exiting the roundabout as shown in Figure 3. A screen line was installed to capture cyclists using the eastern sidewalk facility. A second screen line was placed spanning midway across the southern approach to count the number of cyclists entering the roundabout from this approach. A third screen line captures the two lanes within the roundabout. A final screen is installed to capture cyclists leaving the roundabout (leaving the university campus) eastward to 16th Avenue. The counting validation was performed by comparing the manual counts with the automated counting performed by analyzing the trajectories coordinates. The results of the comparison indicated that the automated counts provided accuracy above 84 percent for the four selected screens as detailed in Table 2. The maximum resulting classification error of the counts of around 15% is considered fairly acceptable. The error is generally related to errors involving the object tracks. These errors can include over-segmentation, over-grouping and missed detection. Over-segmentation occurs when more than one trajectory is attributed to a single cyclist. In terms of counting, the effect of this is an inflation of counts in the case that both the tracks will pass the

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1 Installation and placement referred to the designation of the coordinates of a virtual screen so it can be used in the counting algorithm and superimposed on the video for the manual count. 

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Paper revised from original submittal.
A main cause for this is when a cyclist along with its shadow are detected and considered as road-users rather than a single one. Over-grouping occurs when a trajectory is attributed to several cyclists. This happens when group of cyclists are traveling at nearly the same speed and fairly at closed proximity with each other. The effect of this is a deflation of actual counts. Some tracks may not be complete and may have not passed the screen lines to be accounted for. The main factor that contributed to such inaccuracy is occlusion caused by other road-users. Another reason may be due to the selected location of the screen line. It should be noted that the higher accuracy for screen S4 is likely due to the clear camera angle that limited the effect of partial occlusions. This is in contrast to other screens positions at which trajectories were susceptible to interruption. For example, at screen S3, cyclists in the inner lane suffered greatly from occlusion due to vehicles traveling at the outer lane. At screen S2, the number of missed detection of cyclists is less than at the other screens. There is a low volume of traffic going through the roundabout exit (near the camera), therefore occlusion from that traffic is very low reducing the chance of misdetection. On the other hand, miss-detection at screen S1 is due to the distance of that screen from the camera.

Figure 3: Counting Screens

Table 2: Counting Validation

<table>
<thead>
<tr>
<th></th>
<th>s1</th>
<th>s2</th>
<th>s3</th>
<th>s4</th>
<th>Average Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manual Count</td>
<td>211</td>
<td>82</td>
<td>315</td>
<td>296</td>
<td></td>
</tr>
<tr>
<td>Automated Count</td>
<td>182</td>
<td>89</td>
<td>276</td>
<td>286</td>
<td></td>
</tr>
<tr>
<td>Count Difference</td>
<td>29</td>
<td>-7</td>
<td>39</td>
<td>10</td>
<td></td>
</tr>
<tr>
<td>Count Accuracy</td>
<td>0.862559</td>
<td>0.914634</td>
<td>0.87619</td>
<td>0.966216</td>
<td>0.90490002</td>
</tr>
<tr>
<td>Undercount (UC)</td>
<td>39</td>
<td>3</td>
<td>69</td>
<td>34</td>
<td></td>
</tr>
<tr>
<td>Overcount (OC)</td>
<td>10</td>
<td>10</td>
<td>30</td>
<td>24</td>
<td></td>
</tr>
<tr>
<td>Actual Auto. Count</td>
<td>172</td>
<td>79</td>
<td>246</td>
<td>262</td>
<td></td>
</tr>
<tr>
<td>UC Error</td>
<td>0.184834</td>
<td>0.036585</td>
<td>0.219048</td>
<td>0.114865</td>
<td>0.13883299</td>
</tr>
<tr>
<td>OC Error</td>
<td>0.047393</td>
<td>0.121951</td>
<td>0.095238</td>
<td>0.081081</td>
<td>0.08641594</td>
</tr>
</tbody>
</table>
Speed Validation

The average speed validation was performed in a similar manner as count validation. To capture the mean speed of cyclists, two adjacent screen lines, with a known physical distance between them, were placed in the center of a relatively straight sidewalk segment as shown in Figure 4. If the screen lines were placed within a curved section, the calculated speed would not be representative because of the physical wavering nature of cyclist’s direction of travel. Therefore, the sidewalk was selected since the direction of travel is more predictable and the object tracks would be approximately linear. The time it took a track to cross both lines is recorded and divided by the distance in order to measure average speed.

Seventy cyclists with good tracking (continuous throughout) were selected. The length between the two screens lines was determined to be 14 m. The time it took for the 70 cyclists to travel across this distance was timed manually through the video footage. The manual calculated average speed of a sample of 70 cyclists over the two days was 14.1 km/hr. The automated system yielded an average speed of 13.41 km/hr. The results of the validation showed an acceptable agreement between the manual and automated calculations in Figure 5.a (RMSE = 0.374 m/s, $R^2 = 0.8647$). Cumulative distributions of the speeds for both manual and automated techniques are shown in Figure 5.b. Sources of residual errors include the assumption that the cyclists follow the shortest path between two check lines, potential camera calibration inaccuracy, and cyclist tracks noise.

Figure 4: Speed Screens for Speed Validation
Cyclist Speed Analysis

It is reasonable to assume that the average speed of cyclists will vary according to their location in the facility as well as their interaction with other road-users. Figure 6 shows a partial speed distribution of the cyclists as they traverse the roundabout. From the heat map variation, it is shown that the speed is smaller before entering the roundabout from the southern approach. Also, the average speed is low when cyclists choose to use the sidewalk. On the other hand, the average speed tends to be higher when leaving the roundabout as well as within the main facility. It is also interesting to note that the speed of the cyclists is reduced as they move northward and come merging with vehicles entering the roundabout from the eastern side.

Figure 5: Speed Validation
Comparison between Travel Speed among different Cyclist Attributes

Further analysis was carried out on the data to characterize the behaviour of cyclists as they entered and exited the roundabout. 753 cyclists were selected for the attributes analysis. Several attributes were identified to gain further understanding of the cyclist behaviour. Factors such as direction of travel, group size, helmet usage as well as travel routes can affect the behaviour of cyclist and may provide some insight to their decision making. The attributes that have been assigned to each cyclist were considered accurate due to the high quality of the video segments. For example, the trajectory of each cyclist within the intersection is manually observed and a labeling decision is made based on the cyclists’ position in a lane. A maximum of 4 categories for each variable was specified, either because of finite number of options, or because this was the maximum number that was considered possible for a non-intrusive classification. A summary of the classification is shown in Table 3.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Categories</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group Size</td>
<td>1 2+</td>
</tr>
<tr>
<td>Lane Position</td>
<td>Left Middle Right</td>
</tr>
<tr>
<td>Helmet Use</td>
<td>With Without</td>
</tr>
<tr>
<td>Travel Path</td>
<td>Street Sidewalk</td>
</tr>
</tbody>
</table>

Table 3: Chosen Attributes and their Corresponding Categories
Table 4: Classification Groups Summary

<table>
<thead>
<tr>
<th>Group Size</th>
<th>Categories</th>
<th>1</th>
<th>2+</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Count</td>
<td>681</td>
<td>53</td>
</tr>
<tr>
<td></td>
<td>Percent</td>
<td>92.78%</td>
<td>7.22%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Lane Position</th>
<th>Categories</th>
<th>Left</th>
<th>Middle</th>
<th>Right</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Count</td>
<td>42</td>
<td>372</td>
<td>322</td>
</tr>
<tr>
<td></td>
<td>Percent</td>
<td>5.7%</td>
<td>50.54%</td>
<td>43.75%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Helmet Use</th>
<th>Categories</th>
<th>With</th>
<th>Without</th>
<th>Can’t Tell</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Count</td>
<td>681</td>
<td>53</td>
<td>19</td>
</tr>
<tr>
<td></td>
<td>Percent</td>
<td>90.43%</td>
<td>7.03%</td>
<td>2.52%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Travel Path</th>
<th>Categories</th>
<th>Street</th>
<th>Sidewalk</th>
<th>Both</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Count</td>
<td>395</td>
<td>303</td>
<td>36</td>
</tr>
<tr>
<td></td>
<td>Percent</td>
<td>53.81%</td>
<td>41.28%</td>
<td>4.9%</td>
</tr>
</tbody>
</table>

As the location is a mixed traffic roundabout, cyclists have the option to merge with the vehicle traffic on the road or the pedestrian traffic on the sidewalk. Regardless of the cyclist’s decision to merge with a particular group, there are a set of rules that cyclists are advised to follow [45]. Table 4 shows that the majority of cyclists do stay on the road or the sidewalk. However, 5% of the cyclists observed using both the road and the sidewalk. The lane position was originally considered in the analysis of the cyclists’ routing decision. However, it was observed that cyclists entering and exiting the roundabout do not stay in a particular lane region, such as the right, middle, and left lanes. In the Bike Sense Manual published by the British Columbia Cycling Coalition, recommends cyclists to keep right and to shoulder check if lane changes are required [45]. Because of low traffic volume, cyclists have a tendency to freely choose which side of the lane they would prefer. As a result, their lane position would change constantly along the direction of travel. It is noted that the total number of cyclists varies among categories as cyclists who may be classified in more than one category (e.g. an alternating position within lanes) were excluded.

Table 5: Significance Analysis Summary

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Categories</th>
<th>Statistics</th>
<th>ANOVA/t-stat (P-Value)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group Size</td>
<td>1</td>
<td>681 4.66 (3.87)</td>
<td>0.011</td>
</tr>
<tr>
<td></td>
<td>2+</td>
<td>53 3.96 (3.5)</td>
<td></td>
</tr>
<tr>
<td>Lane Position</td>
<td>Left</td>
<td>42 4.06 (2.89)</td>
<td>0.026</td>
</tr>
<tr>
<td></td>
<td>Middle</td>
<td>372 4.5 (4.67)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Right</td>
<td>322 4.8 (2.98)</td>
<td></td>
</tr>
<tr>
<td>Helmet Use</td>
<td>With</td>
<td>681 4.73 (3.79)</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td></td>
<td>Without</td>
<td>53 3.06 (2.29)</td>
<td></td>
</tr>
<tr>
<td>Travel Path</td>
<td>Street</td>
<td>395 5.91 (2.45)</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td></td>
<td>Sidewalk</td>
<td>303 3.12 (1.24)</td>
<td></td>
</tr>
</tbody>
</table>

Table 5 shows that the travel path, helmet use, travel lane position and group size significantly affect the cyclist speed. Traveling rightmost has a slightly, but significantly higher mean speed compared to cycling in the middle of the leftmost part of the lane. Mean cycling speed was higher for cyclists travelling alone than in groups. However, this result may be valid for small group size only as other studies have shown that cycling in a group (known as peloton in group road bike
racing) may increase the speed of individual cyclists due to a decrease in wind resistance [46]. One interesting finding was that helmet usage affects the travel speed as cyclists with helmets tend to travel at higher speeds. This result is consistent with a recently published data [35], which attributed this difference in the false perception of increased safety for those utilizing helmets. Figures 7(a) and 7(b) show the cumulative speed distribution for different groups (sidewalk Vs Street as well as Helmet Usage Vs non Helmet).

Road safety is a major concern for cyclists due to their vulnerability on the road. Safety programs and measures have been developed to advise cyclists to take precautions when travelling. Safety precautions that were manually observed in this study include the use of a helmet, hand signals, and dismounting while crossing at a crosswalk. It was observed that 90% of the cyclists had a helmet, 1% of cyclists on the road used hand signals to merge lanes or indicate exit, and 1.7% of cyclists who used the crosswalk dismounted and walked through. These observations illustrate cyclists’ behaviour and provide insight to the number of cyclists who abide by the road rules and use the proper safety precautions on the road. It is not surprising to see that the majority of cyclists are wearing a helmet since there have been many studies which show that wearing a helmet can reduce the number of serious head injuries [45]. It is noted that the benefit of enforcing helmet laws is still a debatable subject [47]. Missing from the abovementioned data collection is the gender and bicycle type. This information could not be properly extracted due to the camera angle limitation.

![Cumulative Speed Distribution](image.png)

(a) Sidewalk Vs Street Travel Path
Summary

The result of the automatic counting and tracking were generally acceptable in terms of their accuracy (average percentage of error). This demonstrates that automated accurate cyclist counts and tracking can be performed using computer vision techniques. This can expand the possibilities for cyclist data collection significantly. The automation of cyclist data collection can widen the range of feasible data both geographically (different locations) and temporally (for longer periods of time). Out of the 753 cyclists analyzed, the majority of cyclists exhibited predictable behaviour as some travel on the road and some on the sidewalk travelling at an average speed of around 14 Km/Hr. Another significant observation is that only a small percentage of cyclists did not use helmets when cycling (90% of cyclists were observed wearing a helmet). Several conclusions can be drawn from the analysis of cyclist speed behaviour. Group size, travel path, lane position and helmet usage were found to significantly affect the cyclist mean speed. Single cyclists had a slightly, but significantly higher mean cycling speed compared to group cycling. The mean cycling speed was highest for the cyclists using the road rather than the sidewalk. The mean cycling speed decreases for non-helmet users. The study did not consider attributes such as the cyclist gender, age and bike type classification. This limitation is related to the accuracy of the manual classification. Because this study is non-intrusive, no validation can be performed for the classification. One area of potential research is to assess a relationship between the accuracy of tracking and object density. Visual inspection reveals that some cyclists were over-segmented (multiple tracks for a single cyclist) or over-grouped and occluded, particularly when cyclist density was high.

Discussion

The results in this paper are primary findings that should be validated and refined by expending to additional data sets. Nevertheless, this study fills an important gap on the data collection for cyclists.
at roundabouts. Further data collection studies may cover speed behavior with different intersection configurations as well as free flow facilities (road segments, designated bike lanes and trails). Capacity and density estimation procedures would be developed based on the current computer vision capabilities in terms of classification, counting and data collection. Allen et al. highlight the need for research to quantify the effects of bicycles on the capacity of signalized intersections [48], a development that would enable the creation of a composite level of service for a mixed flow of intersections and eliminate the use of motor vehicle equivalents for bicyclists.

In addition to transportation applications, cyclists’ data collection can provide useful information for some health applications. Cyclists data collection involving cadence (pedaling effort per unit of time) is directly related to the effort [2]. Each cyclist’s pedal rotation is observed to introduce a periodic fluctuation in the speed profile [49], and therefore, the cadence parameter can be computed by analyzing the speed profile signal. Identifying the cadence frequency corresponds to detecting the dominant periodicity in the noisy signal of the speed profile. This is reduced to the problem of evaluating the power spectral density of the speed profile. It would be interesting to explore the significance of cyclists’ characteristics on the cadence parameters. Primarily, results showed that there is significant difference between the cadence means of cyclists using the sidewalk and those using the street. Close manual inspection of the population revealed that the majority of the street commuters are “experienced “with proper gearing and high level of fitness. On the other hand, the general population of those using the side walk facility tend to cycle in a more casual way. A thorough examination of the cadence parameters is planned for future research.

Bibliography

[11] E. Minge, S. Petersen and J. Kotzenmacher, "Evaluation of Nonintrusive Technologies for...


