Video-Based Monitoring of Pedestrian Movements at Signalized Intersections

Yegor Malinovskiy
Graduate Research Assistant
Department of Civil and Environmental Engineering
University of Washington
Seattle, WA 98195
Tel: (206) 543-7827
Email: yegorm@u.washington.edu

Yao-Jan Wu (Corresponding Author)
Graduate Research Assistant
Box 352700
Department of Civil and Environmental Engineering
University of Washington
Seattle, WA 98195-2700
Tel: (206) 685-6817
Email: yaojan@u.washington.edu

Yinhai Wang
Associate Professor
Box 352700
Department of Civil and Environmental Engineering
University of Washington
Seattle, WA 98195-2700
Tel: (206) 616-2696
Fax: (206) 543-5965
Email: yinhai@u.washington.edu

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ABSTRACT

Pedestrian and cyclist crossing characteristics are important for the design of urban intersections and signalized crossings. Parameters, such as waiting time, crossing time, and arrival rate are key variables for describing pedestrian characteristics and improving crossing design and signal timing plan. Manually collecting such data is often extremely labor intensive. Therefore, we introduce an automated computer-vision based approach for collecting these parameters in real-time using ordinary video cameras. Broadly defined pedestrian objects including bicyclists and boarders are extracted via the background subtraction technique and tracked through an inherent cost characteristic function in conjunction with an $\alpha-\beta$ filter. The waiting zone concept introduced in this paper helps provide robust pedestrian tracking initialization and parameter extraction. The proposed approach is implemented in a Pedestrian Tracking (PedTrack) system using Microsoft Visual C#. Tested with real video data from three study sites, this system was proven to be effective and about 80% of pedestrian crossing events were successfully detected. PedTrack shows a potential to be a great data collection tool for non-motorized object movements at intersections.

1. INTRODUCTION

Pedestrian and cyclist behavior dictates the design of numerous facilities, including urban intersections, as stated in the Transportation Equity Act for the 21st Century (TEA-21) *(1)*. The need for non-motorized traffic data has been highlighted in a recent report by the Bureau of Transportation Statistics *(2)*. This report ranks information regarding the "number of bicyclists and pedestrians by facility or geographic area" as a high priority, while noting the sparseness of available data. There has been much work done in the field of pedestrian and cyclist behavior *(3,4)*. Nevertheless, most of the data collection techniques rely on labor intensive manual operations. In the case of large and widespread data set collection, manual methods remain fairly impractical and expensive.

Automatic detection and tracking of pedestrians and cyclists is still a largely open question. In terms of transportation applications, much work has been done for motorized vehicle detection and tracking *(5-9)*. However, bicycle and pedestrian tracking is substantially different from automobile detection and often much more intricate. One of the differences is the freedom of motion pedestrian and cyclist objects have with respect to motorized vehicles. Pedestrians and bicyclists are often not constrained by lane markings and pre-specified movements. The relatively complicated inner motion of human objects compared to the rigidly-connected components of a vehicle is yet another complication. Many practical locations contain mixed modes of transit, resulting in further difficulties. A significant problem arises as the smaller objects, such as pedestrians and bicyclists, disappear behind the larger objects that are of no interest, resulting in frequent occlusions. Total occlusions are defined as the complete disappearance of one object behind a static element in the scene or another object.

Numerous automatic remote sensing technologies have been implemented for Intelligent Transportation System (ITS) applications in recent years. Although mostly vehicle-oriented, these technologies are primarily based on inductance, electromagnetic, microwave, infra-red, video or sonic signal interpretation. A recent study funded by the Federal Highway Administration *(10)* reviews a comprehensive list of available bicycle and pedestrian detection systems, but none of them offers complete tracking capabilities for pedestrian and bicycle movement data collection. The lack of practical systems for non-motorized transport data collection motivates further research and development of pedestrian and bicycle detection technologies. Several approaches using infra-red sensors have been attempted with encouraging results *(11, 12),* yet the relatively high cost, narrow focus area, and mounting restrictions of infra-red sensors make video-imaging techniques comparatively appealing. Video information is already available in many urban intersection locations from surveillance cameras and temporary cameras can be easily mounted on or in nearby structures for temporary data collection purposes.

In this paper, we introduce an automated computer-vision based approach for real-time pedestrian (and cyclist) detection and tracking using ordinary video cameras. Presently, we set the scope of this research to daylight conditions with good visibility. Nighttime and foul-weather conditions associated with poor visibility are not considered in this study. We feel that fair-weather, daytime conditions are most relevant for pedestrians and bicyclists and thus are of primary concern. The proposed approach significantly enhances the Pedestrian Tracking (PedTrack) system, first developed at the University of Washington Smart Transportation Applications and Research laboratory

(STAR Lab) in 2006 *(13)*. We will retain this name for convenience. PedTrack has been modified and enhanced to track and record pedestrian and cyclist movements at intersections. Three pedestrian parameters that describe a complete crossing event - waiting time, crossing time and arrival time are now automatically recorded for pedestrians appearing in live or stored video samples. These pedestrian parameters can also be retrieved and further analyzed to demonstrate the characteristics of pedestrian crossing movements at different intersection locations.

2. LITERATURE REVIEW

Video-based pedestrian/cyclist detection and tracking is a sophisticated field with many open questions. Numerous algorithms and techniques have been proposed. A feature-based algorithm is implemented by Abramson et al. *(14)*. Learning of the features is done using AdaBoost and genetic-like algorithms. Even though it provided fairly good performance, the algorithm is complicated and cannot be executed in real-time on typical computing devices today. Satoh et al. *(15)* proposed a color based probabilistic tracking method. However, the method may not be always practical since a significant portion of deployed surveillance cameras are still mono-color cameras. Point-feature detection and tracking techniques, such as Harris or SUSAN corner detector *(16)*, are promising techniques, as they are not reliant on background image quality and extensive sample library. Nevertheless, these point-feature detectors are best suited to the tracking of rigid objects, such as vehicles, when the structural relationships between the points remain constant. Pattern matching, as described in *(17)*, requires an extensive library of positive and negative samples in order to train the algorithm to recognize desired objects. Computation cost is also a serious concern for pattern matching algorithms. The larger and more complete the library, the longer the matching process takes and thus may not be performed in real-time. In a recent study, Gavrila *(18)* presented a robust system combining shape-based and texture-based tracking algorithms. This system worked well as a driving assistance method. In our study, background subtraction, a region based approach, is used in our system since the intended applications typically maintain a stable background and it is a very common and straightforward method for real-time applications as demonstrated by *(5, 19)*.

Regardless of the approach used, object tracking typically involves three steps: acquisition of moving objects, tracking, and classification *(20, 21)*. Acquisition of moving objects can be done through a number of techniques and most of these techniques focus on the comparison of either consequent frames or a derived background image with the current frame. Once the objects are acquired, tracking them through a complicated environment can be very difficult due to occlusions and inconsistence in obtaining the same object throughout a sequence of frames *(22)*. A Kalman filter is often used to clean the inconsistencies involved with tracking. The Kalman filter, however, is computationally expensive and Blackman *(23)* suggests the use of an α –β filter as a lighter alternative. Classification can occur before or after tracking, depending on the approach used. Static approaches that rely on inherent characteristics of the objects can classify them without path analysis *(13)*. Harmonic motion approaches to pedestrian tracking rely on some prior history of the object being tracked, which is not always available if the object is motionless, for example, a pedestrian waiting to cross.

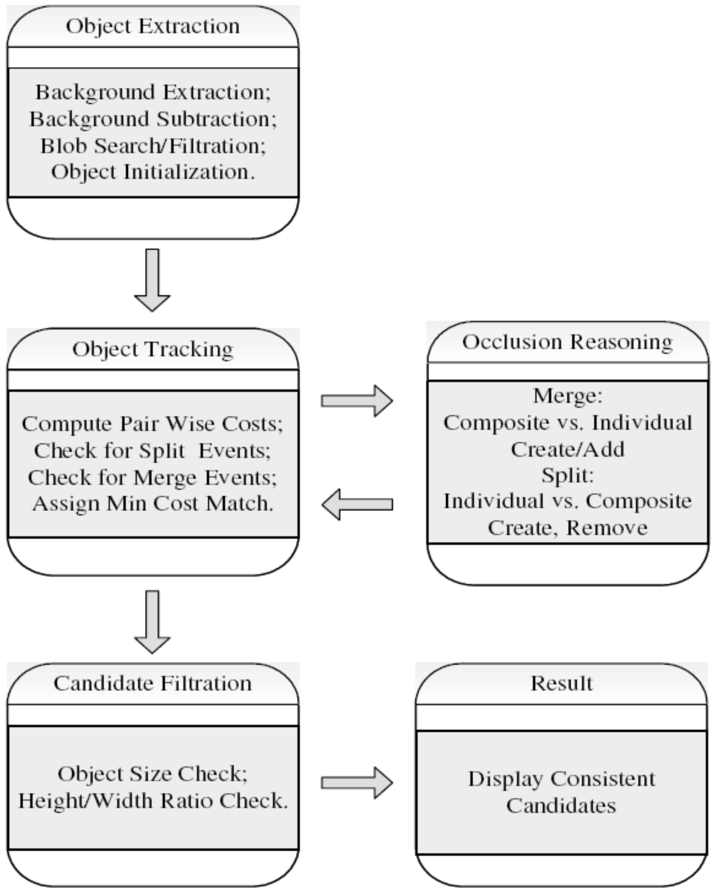
There are still numerous challenges in pedestrian detection and tracking applications. The studies mentioned above help guide our efforts in further exploration of this field.

3. METHODOLOGY

The approach used to obtain pedestrian and bicyclist objects is based on our previous work with PedTrack *(13).* Since then, significant improvements and modifications have been made, including a broader orientation towards non-pedestrian objects such as bicyclists and boarders, by being less restrictive for size and proportion characteristics. This allows for multi-mode analysis as will be shown in the results section. Therefore, the term "pedestrian" hereafter refers to not only regular pedestrian object, but also bicyclist and boarder objects for simplicity. The following section is a review of the PedTrack system introduced in our earlier work. Improvements made to the original algorithm follow, along with the application-specific configurations introduced.

PedTrack Review

As in PedTrack, our approach begins with simple background subtraction to extract foreground objects. As potential pedestrian objects are determined by their characteristics, such as the size and proportion, an inherent cost function is adopted to track subsequent potential objects based on their attributes of size, height, width, and grayscale color distribution. Occlusions are dealt with by watching and reasoning through splitting and merging. When two objects merge, a composite object is created and tracked as one. When an object splits, an attempt is made to recognize the resulting smaller objects as those that merged earlier to create the larger object. Finally, the output is shown as the trajectory of each successful candidate tracked. The details of the PedTrack algorithm can be found in *(13)* and are summarized in Figure 1 below:



FIGIRE 1 Review of basic PedTrack algorithm

Object Tracking

For most unobstructed angles of overhead observation, PedTrack is fairly robust. Failures arise when the scene becomes complicated and pedestrians are occluded frequently by other foreground objects, such as wires and utility posts. As mentioned earlier, occlusion problems are tough challenges for image processing. In order to handle these issues, a filter mechanism is incorporated into the PedTrack system. We choose to use an alpha-beta (α–β) filter because it is easy to implement and quick in computation due to its fixed parameters for filter gains. In our implementation, every single coordinate output is smoothed or predicted by this filter. The following equations show an example of how the filter handles output data points in x-direction *(22)*:

$$x_s(k) = \hat{x}(k \mid k) = x_p(k) + \alpha_x \left[x_o(k) - x_p(k) \right] \tag{1}$$

$$v_{sx}(k) = \hat{\dot{x}}(k \mid k) = v_{sx}(k-1) + \frac{\beta_x}{qT} \left[x_o(k) - x_p(k) \right] \tag{2}$$

$$x_p(k+1) = \hat{x}(k+1 \mid k) = x_s(k) + T \cdot v_{sx}(k) \tag{3}$$

where $x_o(k)$ is the observed target position in the x direction at the k_{th} frame;

$x_p(k)$ is the predicted target position in the x direction at the k_{th} frame;

$x_s(k)$ is the smoothed target position in the x direction at the k_{th} frame;

$v_{sx}(k)$ is the smoothed target velocity in the x direction at the k_{th} frame;

T is the sampling interval;

q is the number of scans since the last measurement;

α_x, β_x fixed-coefficient filter parameters in the x and y direction.

A usual initialization process for the filter is defined by:

$$x_s(1) = x_p(1) = x_o(1) \text{ and } v_{sx}(1) = 0 \tag{4}$$

$$v_{sx}(2) = \frac{x_o(2) - x_o(1)}{T} \tag{5}$$

The above equations are used for conditions under which an object is consistently detected. If the object is missed in a frame, the values of the coordinates are predicted as follows:

$$x_o(k) = x_s(k) = x_p(k) \text{ and } v_{sx}(k) = v_{sx}(k-1) \tag{6}$$

The optimal relationship between α_x and β_x is known to be *(23):*

$$\beta_x = 2 \cdot (2 - \alpha_x) - 4\sqrt{1 - \alpha_x} \tag{7}$$

Note that the y-direction follows a set of similar equations as shown above. Therefore, 2-D tracking can be fulfilled.

Extended Application of the $\alpha - \beta$ Filter

During the execution of the algorithm whose flow chart is shown in Figure 1, each input frame is first subtracted from the background. The regions (silhouettes) obtained from background subtraction are further filtered for size information. Then they are matched to existing objects. If no matching object is found, they are assigned as new ones. The matching process relies on a cost function that attempts to maintain the lowest cost for the correctly matched object-silhouette pair. Previously, the cost function was entirely based on inherent characteristics. The current version of PedTrack has the α–β filter incorporated into this process. This filter allows us to compare the predicted values for a particular object with those observed for each silhouette. The difference vector of a silhouette – object pair O_i and S_j is thus calculated as follows:

$$d(O_i, S_j) = \left(\left|A_i - A_j\right|, \left|H_i - H_j\right|, \left|W_i - W_j\right|, \left|G_i - G_j\right|, \left|PR_i - P_j\right|\right) \tag{8}$$

Where A_i and A_j are object/silhouette areas, H_i and H_j are heights, W_i and W_j are widths, G_i and G_j are grayscale histograms, and PR_i is the object's predicted position and P_j is current position of the silhouette to be matched to the object. The grayscale histogram difference $\left|G_i - G_j\right|$ is calculated as follows:

$$\left|G_i - G_j\right| = \sum_{k=0}^{255} | f_{k,Oi} - f_{k,Sj} | \tag{9}$$

where $f_{k,\,Oi}$ and $f_{k,\,Sj}$ are the frequencies for grayscale value k in the histogram of object i and silhouette j, respectively. In order to be able to compare the object and silhouettes, a cost is computed between each current object and its potential match. The cost function is the normalized difference of the parameter vectors of the object-silhouette pair, and it is calculated as follows:

$$c(O_i, S_j) = \sum_{n=1}^{4} \frac{d_n(O_i, S_j)}{R_n(O_i)} \tag{10}$$

where $d_n(O_i, S_j)$ is the n^{th} element of $d(O_i, S_j)$ and $R_n(O_i)$ is the n^{th} element of $R(O_i)$. $R(O_i)$ is the attribute vector of object O_i, which is calculated as follows:

$$R(O_i) = \left(A_i, H_i, W_i, G_i\right) \tag{11}$$

where

$$G_i = \sum_{k=0}^{255} f_{k,O_i} \tag{12}$$

By means of comparing predicted object positions and those of the current silhouette, the cost function can determine the relative movement of multiple objects. In this manner, the confusion between objects with different velocities can be reduced, e.g. pedestrians crossing in opposing directions.

By integrating such a new tracking and matching approach to the previous system, a more robust PedTrack system is now presented. However, before using this system, some configuration is necessary for collecting pedestrian movement data at intersections.

Detecting Pedestrian Movement

In order to detect pedestrian movements at intersections, a proper configuration of the PedTrack system should be made in advance. The idea of waiting zone is proposed to collect pedestrian waiting time for crossing. The waiting zone not only provides additional restrictions on where the objects can be initialized, but also further filters the incoming objects which are more likely to use the crosswalk. The proposed waiting zone is defined by a polygon at an entrance of a crosswalk in order to ensure that only pedestrian objects are initiated and tracked. The time the object spends in its original initial zone counts as time waited prior to crossing. It should be noted that while the waiting time can be used to estimate pedestrian delay caused by the signal, the two may not always be identical. Pedestrian arrival rate and headway can be calculated by using the number of initialized objects in waiting zones over a time period and the recorded timestamps of the initializations.

For crossing time data collection, two registration lines are configured to specify the beginning and end of pedestrian crossing movements. Once a pedestrian object crosses one registration line, a timer is started to count the crossing time of this object until the second registration line is crossed. The time an object spent between the two registration lines is defined as the crossing time for the object. For each pedestrian object, its path and time counts are displayed to show the progress of pedestrian crossing movements.

4. TESTING AND DATA RETRIVEAL

Study Sites

In order to obtain a variety of crossing characteristics and fully test the PedTrack system in diverse scenes, three signalized crossings were selected around the University of Washington in Seattle, where a large population of students resides. These three study sites are: the Brooklyn crosswalk, the Campus Parkway crosswalk, and the 15th AVE crosswalk.

As shown in Figure 2, the Brooklyn crosswalk is located at the southbound approach of the Brooklyn Avenue NE next to the Pacific Street. This crosswalk has a relatively high bicyclists' usage since it is a part the Burke Gilman Trail biking corridor. As can be seen, the light post between the two registration lines makes observation of the scene more challenging. The Campus Parkway crosswalk is located at the eastbound approach of NE Campus Parkway. Several trolleybus routes pass by and create a complex scene due to prolonged occlusions. The 15th AVE crosswalk is located at the intersection of the 15th Avenue NE and the NE 41st Street. Several trolleybus wires hanging over the street may create occlusion cases in addition to the occlusions caused by the buses themselves.

Defining Waiting Zones

All of the locations tested had an overhead angle view of the crosswalk to be examined. Such an overhead angle view helps reduce occlusion and obtain a broader observation on the entire crossing region and approaches. Figure 2 shows the three test sites together with the waiting zones and registration lines plotted for each crosswalk.

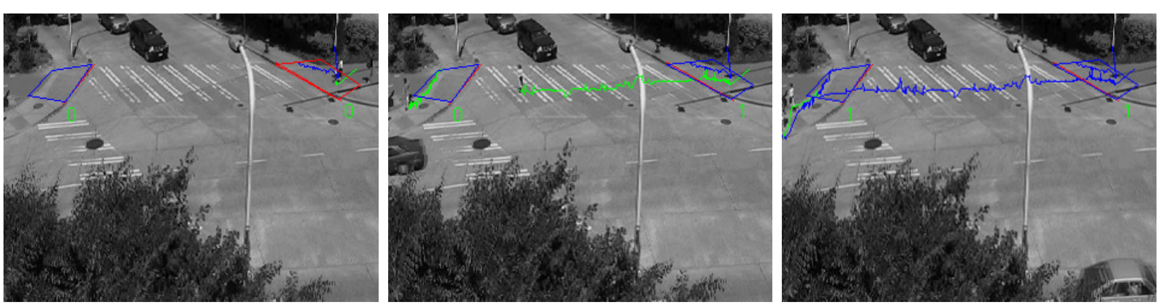
(a) Brooklyn Crosswalk (b) Campus Parkway Crosswalk (c) 15th Ave Crosswalk

FIGURE 2 Crossing location setup for the three test crosswalks, Brooklyn AVE, Campus Parkway, and 15th AVE

Testing

Of the above test locations, the Brooklyn crosswalk is the most favorable due to less frequent occlusions caused by large vehicles. The 15th AVE crosswalk hosts numerous bus routes, and upon passing in front of the vantage point, the buses often block the entire intersection creating a total occlusion lasting throughout the entire crossing event. Thus, the Brooklyn crosswalk was tested for a total of 60 minutes, including morning, midday, and late afternoon sections. The other two sites were tested for 10 minutes each at midday. The detection and tracking rate of complete crossing events (waiting and completing the crossing from one registration line to another) was about 80%, providing sufficient data for analysis.

Figure 3 shows a complete crossing event. In Figure 3(a), the object arrival is detected and initialized at the right waiting zone (as represented by the polygon in the upper-right corner of this figure). Figure 3(b) displays the crossing stage of the event. The object has been registered at right-hand registration line and is moving toward the left-hand registration line. Even though this object was occluded by the light post, it is still tracked through successfully. Finally, Figure 3(c) displays the completed crossing event, the tracked object has past the left-hand registration line and its track has been cleared from the screen. As soon as a crossing event is complete, its crossing time is recorded. This sequence constitutes the necessary steps to obtain complete arrival, waiting, and crossing times for a pedestrian's approach-crossing movement.

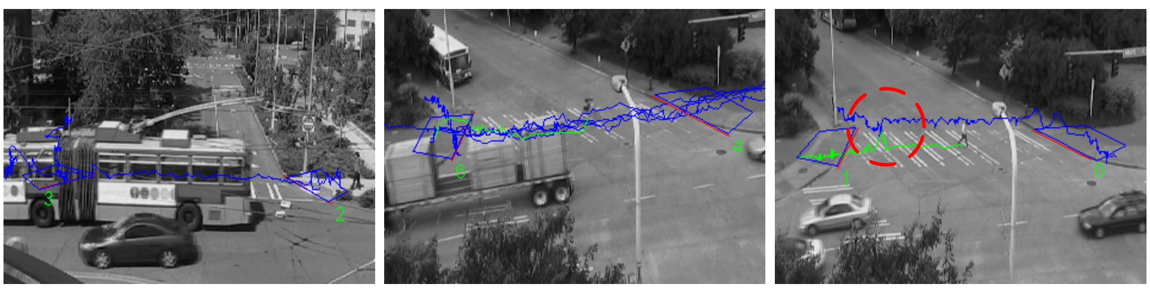


(a) Object Initiated (b) Object Crossing (c) Object Data Recorded

FIGURE 3 Complete crossing event

Issues Encountered

As mentioned before, occlusion is a key issue in data collection. PedTrack can handle most occlusion issues, such as light posts and wires, to some extent. Figure 4 displays some of the typical occlusions encountered in our study sites. Figure 4(a) shows a complete occlusion resulting in a failure – the slow-moving bus blocked the object (and the crosswalk) completely for a significant portion of time resulting in a miss of the pedestrian. Figure 4(b) displays a partial occlusion case. PedTrack was successful in tracking the partially occluded object. The success shows the robustness of the proposed tracking algorithm. Through the field tests, we encountered vehicle-pedestrian, pedestrian-pedestrian, and pedestrian-static object occlusions that are all challenging to video-based pedestrian detection and tracking. If two or more tracking objects move too close to each other, they are likely to merge into one composite object. An example of this type of occlusion can be seen in Figure 4(c). As circled in a dashed line, a person-person occlusion occurred. PedTrack successfully reasoned between the two pedestrians and properly projected the movements of both pedestrians, although the upper pedestrian missed the left registration line because they walked beyond the crosswalk marking. In this case, crossing time for this pedestrian will not be calculated and the crossing is considered incomplete.



(a) Complete Occlusion (b) Partial Occlusion (c) Person-Person Occlusion

FIGURE 4 Various occlusion types

5. PEDESTRIAN BEHAVIOR ANALYSIS

As described in Highway Capacity Manual (HCM) 2000 *(24),* pedestrian characteristics highly depend on different factors, such as their activity areas. The 80-minute long testing video sequence collected from three study sites contained 126 complete crossing events. From these 126 events, crossing times, waiting times, and arrival rates are analyzed and compared. These parameter analyses reveal distinctive movement characteristics of pedestrians and cyclists around the university district. Data associated with incomplete events, such as pedestrian waiting time, were not used because the intentions of the pedestrians could not be determined.

Crossing Time

The crossing time can be used to calibrate the green time for the pedestrian phase. The average crossing times for the 15th Avenue NE, Campus Parkway, and the Brooklyn

Avenue NE were 9.2s, 8.4s, and 4.5s, respectively. Brooklyn's short crossing time is probably best described as a result of a much higher cyclist percentage, as well as a shorter length. In Figure 5, one can see that the Brooklyn crossing data contains two peaks, one high peak at about 4 seconds and the other smaller peak at 10 seconds. The higher peak centered at about 4 seconds represents crossing times for bicyclists and the lower peak represents regular pedestrian crossing times. This bi-modal feature of crossing time enables further classification between pedestrians and bicyclists. However, it is important to note that although the average crossing time for bikes is shorter than that for pedestrians, the difference may vary depending on location and volume of bikes and pedestrians. Thus, more data are needed to implement this feature. The current version of PedTrack cannot classify pedestrians from bicycles. It is also worth mentioning that the overall average crossing time of 4.4s could be misleading because it does not reflect the expected crossing time for pedestrians. Special attention must be paid when using the PedTrack system to collect pedestrian crossing data for signal timing purposes.

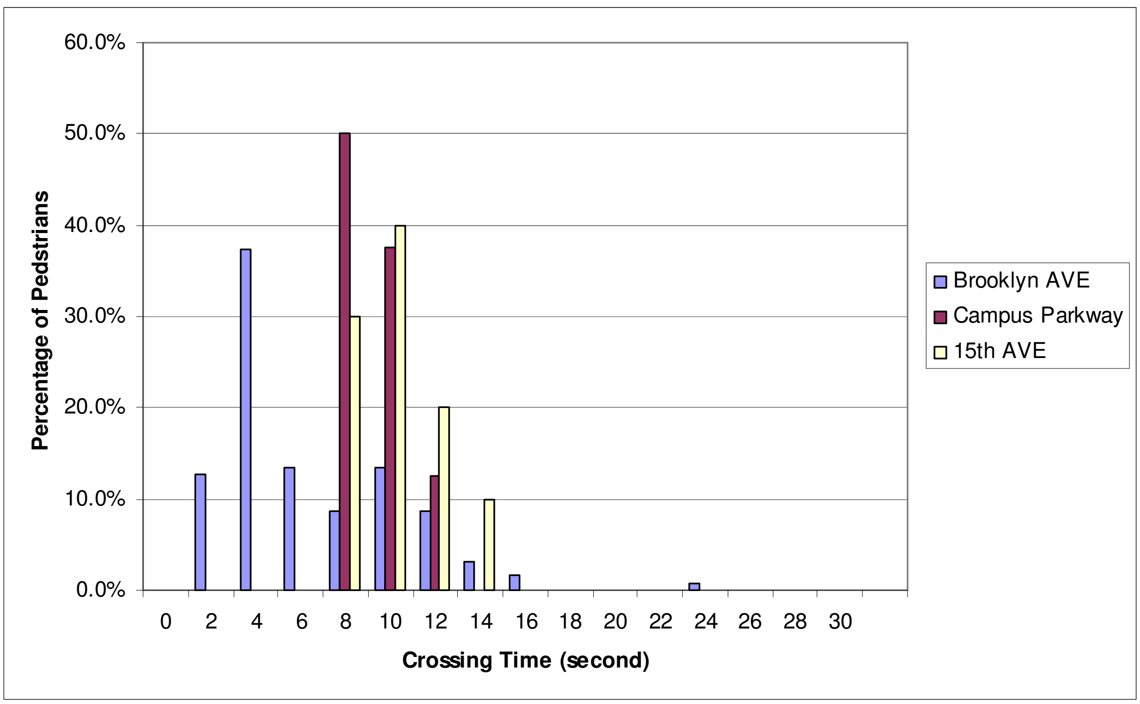


FIGURE 5 Crossing time statistics for each study site

Waiting Time

Along with the crossing time, waiting time is also an important measure for designing signal timing plan and evaluating the performance of signalized intersections. If the delay, or average waiting time, is too long, the pedestrian's likelihood of violating the signal will increase. In fact, if the average delay is higher than 60 seconds, then the likelihood of non-compliance will be "very high" according to HCM 2000 *(24)*.

Figure 6 shows the waiting time distribution for each study sites. The average waiting time for the Brooklyn Avenue NE, the 15th Avenue NE, and Campus Parkway are 1.4s, 6.6s and 5.0s, respectively. Brooklyn has the shortest waiting time. This is partly due to the long green time for the Brooklyn crosswalk. Most pedestrians are likely to arrive at the crosswalk in green signal indication, resulting a prompt crossing without waiting. Nevertheless, several extreme values obtained at other sites still deserve further investigations in follow-up studies. For example, 30 % of pedestrians on the 15th Avenue NE site waited over 20 seconds. On the Campus Parkway site, 12.5% of pedestrians were waiting for 30 seconds, which is the exact length of the pedestrian red phase of the pedestrian signal.

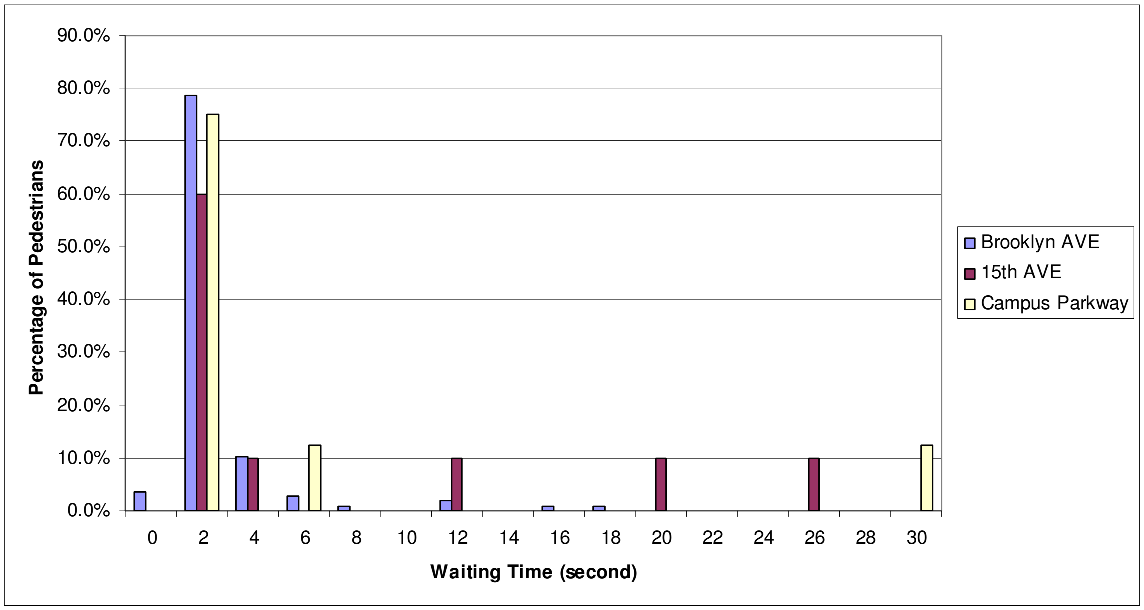


FIGURE 6 Waiting time statistics for each study site

Arrival Rate

Arrival rate data has several important applications, such as predicting how many people will be queuing in a waiting zone, predicting expected delays, calculating green time for the pedestrian phase, etc. Pedestrian arrival rate depends on time of day. To investigate how pedestrian arrival rate changes with time of day, samples retrieved from the Brooklyn crosswalk were further divided into a morning group and an evening group. The results show that evening samples have a slightly lower arrival rate, 2.35 pedestrians per minute (p/m) than the morning one, at 2.78 (p/m). However, they are still lower than the arrival rate at the 15th Avenue NE site, 6.93 (p/m) and the one at the Campus Parkway site, 6.45 (p/m). These two study sites are major walking passes frequently used by students walking between campus and residential areas.

6. SUMMARY

In this paper, an automated computer-vision based approach for real-time pedestrian detection and tracking is proposed. This proposed approach uses images from an ordinary un-calibrated video camera to detect complete crossing events at designated roadway sections. The waiting zone concept introduced in this paper help provide robust pedestrian tracking initialization and parameter extraction. The entire approach has been implemented in the PedTrack system and tested at three signalized crosswalks near the

University of Washington campus. About 80% of pedestrians and cyclists were successfully detected and tracked at the three challenging study sites. PedTrack has proven its potential to be a feasible alternative to manual pedestrian data collection.

Using the pedestrian crossing data recorded by the PedTrack system, several statistical analyses were conducted to demonstrate how PedTrack can help traffic engineering practice and research. Pedestrian waiting time, crossing time, and arrival rate data collected by PedTrack are potentially valuable inputs for intersection geometric design, signal timing, and safety studies.

However, the PedTrack system is still in its early research and development stage. Plenty of work needs to be done to make it a practical tool for automatic pedestrian data collection. Further enhancements in the detection and tracking algorithm will definitely help improve the accuracy of the proposed approach. The PedTrack system may serve as an example that shows how video image processing can help collect data automatically for traffic engineering practice and research.

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