CrowdWatch: Pedestrian Safety Assistance with Mobile Crowd Sensing

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Abstract
Pedestrians distracted by smartphones are easy to meet with various dangers when crossing or walking on the street. To help them, we propose CrowdWatch, a system that leverages crowd-powered smartphone sensing to make fine-grained characterization of the sensing field and provides context-aware alerts to pedestrians for their safety. The crowd data including acceleration, orientation, and GPS reflects the behavior of the crowd in three different situations: crossing roads, waiting traffic lights, and encountering obstacles. We present details about applying the behavior of the crowd into the system in this paper. What's more, under different contexts/situations, different reminders are delivered. Experiment results indicate that CrowdWatch is effective in safety dynamics detection.

Author Keywords
Mobile crowd sensing; pedestrian safety; obstacle; crowd mobility patterns; mobile applications.

ACM Classification Keywords
H.4.m. Information System Applications: Miscellaneous.

Introduction
Smartphone distracted walking has been a rising concern for pedestrian safety. It is reported that the number of pedestrians injured from being distracted

Figure 1: Alert of obstacle

Figure 2: Alert of traffic light

while using smartphones has more than doubled since 2004. In this paper, we propose CrowdWatch, an MCS [1] system that uses crowd behavior patterns and personal sensory data aggregation to protect pedestrian safety while crossing the street or walking on the sidewalk. Rich information regarding pedestrian safety are learned from crowd contributed data, including fine-grained urban infrastructure and sidewalk dynamics. Particularly, we have made the following contributions:

1) Crowd urban-infrastructure context sensing. By learning from crowd contributed data, CrowdWatch can learn fine-grained urban infrastructure contexts (e.g., traffic light status, overpasses) for crossing-road safety estimation and route recommendation.

2) Crowd sidewalk-obstacle sensing. There are often static/dynamic obstacles (e.g., car parking) on sidewalks, particularly in developing countries. We leverage crowd movement patterns to infer the existence as well as the size of sidewalk obstacles.

3) Context-aware reminding. By learning surrounding contexts, we measure the dangerous level and prompt suitable reminders to pedestrians.

Related Work

There have been a number of studies regarding pedestrian safety protection. Most of them are based on built-in sensors of smartphones for ambient sensing and danger warning. For example, You *et al.* [4] used cameras to detect obstacles and vehicles. Wen *et al.* [3] used attached ultrasonic sensors for pothole and stair detection. However, it is clear that one device can only obtain information of a quite limited area (e.g., the sensing range of a phone camera or an ultrasonic sensor is restricted by its position and direction).

Crowd urban-infrastructure context sensing

In order to detect urban infrastructure, we first need to understand the activity context of each pedestrian. We thus collect accelerometer data from pedestrians, extract the features (MintoMax, average of wavelength, standard deviation and correlation coefficient), and train a decision tree using WEKA to classify four pedestrian activities: stop, walk (walking on a relatively flat surface), upstairs, and downstairs.

Overpass and underpass

In this section, we meet with two difficulties. First, we should determine whether there is an overpass or underpass, and update the map. Second, we need to find pedestrians who cross the street.

Leveraging the decision tree above, we can obtain the status sequences of each pedestrian which consist of constant activities. 1) If the pedestrian status sequence is *<upstairs, walking, downstairs>*, then the pedestrian is crossing the street using a pedestrian overpass. 2) If the pedestrian status sequence is *<downstairs, walking, upstairs>*, then the pedestrian is crossing the street using a pedestrian underpass. 3) If the pedestrian does not have upstairs or downstairs status during the time period, the pedestrian is crossing the street in mid-block. In the process of detection, there may be some errors. For example, there may be a few downstairs activities among a sequence of upstairs activities. We use the first-order Markov model [2] to improve the classification accuracy.

Traffic Light Detection

Besides overpasses and underpasses, traffic lights are another part of urban infrastructure. People distracted by smartphone always ignore traffic light. To assist

Figure 3: Alert of mid-block crossing

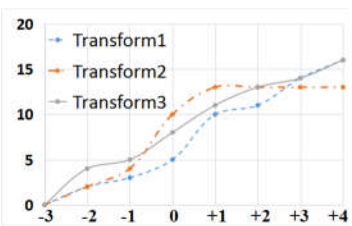

Figure 4: The growth curve of green light changing

these pedestrians, we analyze crowd movements to detect when a traffic light changes. According to observations, we find three rationales about traffic light in intersection: First, One direction is green light while the other should be red. Second, pedestrians change their status when traffic light changes. Third, number of pedestrian status change is noticeable in the red-to-green case but not in the green-to-red case.

To solve the problems, we take into consideration movements of all people within a monitoring area at the intersection. We divide pedestrians at the same intersection into two groups, P and V, by their orientations. People in group V are with a perpendicular orientation to that in group P. If the number for group P (or V) exceeds a threshold F, we estimate that the traffic light for group P (or V) c. Correspondingly, the traffic light for the other group, turns from green to red. To decide the value of the threshold *F*, we collect numbers of pedestrian status changes when the traffic light turns from red to green at three different locations. The results are shown in Figure 4. To ensure that the threshold *F* captures the right moment of traffic light change, we set its value to '4'.

Crowd Sidewalk Obstacle Dynamics Sensing

To overcome the shortages of the limited range of cameras, CrowdWatch leverages the traces of the crowd to analyze whether an obstacle exists and how big it is. We meet several challenges in this section. First, it is not easy to extract useful information to detect an obstacle because different people make different traces to avoid an obstacle. Second, if an obstacle exists, we should estimate the size of the obstacle. Third, timely updating is an important part to upgrade the digital map according to obstacle dynamics.

To overcome the challenges above, we observe behaviors of pedestrians when they take avoidance measures. We find that pedestrians make a detour (avoidance distance) around the obstacle instead of walking straightly. With the crowd avoidance distances, we calculate the confidence interval which is then taken as the estimated obstacle size. The avoidance distance can also be used to update the existence of an obstacle, with the help of our sliding-window-based rapid change detection algorithm.

Context-Aware Reminding

We want to alert the user only when necessary so as not to be annoying and also to reduce energy overhead. We find that only when the screen is on and the *z*-axis points to the direction of gravity, the user is focusing on the phone. We then enable the alert system.

Risk Levels. Different situations have different risk levels. We define three different risk levels {*A1*, *A2*, *A3*}. *A1* has the lowest risk while *A3* has the highest risk. Under different risk levels, we use different alert methods.

A1: Obstacles on the side walk, such as temporary parking, repair shielding, and so on. Because of the low risk of such obstacles, we alert the user by displaying the size of obstacle and which side can be taken through the phone as shown in Figure 1.

A2: Red traffic light is more dangerous than obstacles. When a user tries to cross the street when the traffic light is red, we show the color of the traffic light on the screen and vibrate the phone and dim the screen to remind the user to pay attention to the traffic light as shown in Figure 2.

	total	accuracy
over-pass	59	83.050%
under-pass	43	81.395%

Table 1: Table 1: Accuracy of overpass and underpass detection

Cross no.	TD	AD	CD
Green1	-2s	60s	64s
Green2	0s	60s	62s
Red3	-2s	30s	35s
Red4	+10s	35s	29s

Table 2: accuracy of traffic light detection.
TD:Time difference.
AD:Actual duration.
CD:Calculated Duration

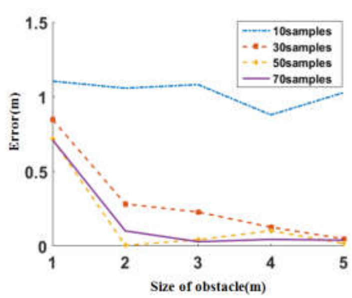

Figure 5: Errors of obstacle size estimation

A3: When mid-block crossing happens, we vibrate the phone and show the user the closest overpass, underpass, or crosswalk as shown in Figure 3.

Evaluation

Accuracy of overpass and underpass detection.
The accuracy of overpass and underpass detection determines whether mid-block crossing reminder is effective. 21 subjects were recruited for data collection. Each participant passed the overpass and the underpass less than 3 times. Finally, we collected 59 samples of overpass and 43 samples of underpass. We present the results in Table 1. The accuracy of detecting an overpass or underpass is over 80%.

Accuracy of traffic light detection. We conducted the experiment at four crossroads. There were 20 to 30 users at each crossroad. Table 2 shows the accuracy of our traffic light detection results. The first two rows are for green light detection. The third row is for red light detection with help of green light as CrowdWatch does. The forth row is without help of green light. We see that our calculated traffic light durations in the first three rows are very close to the actual durations. In contrast, the latency of Red4 is too long. It indicates that it is necessary to detect red light with the help of green light in the perpendicular direction.

Accuracy of obstacle detection. Five kinds of obstacles were tested in the experiments. The obstacle lengths varied from 1 to 5 meters. 70 samples were collected for each obstacle. Then we estimated the obstacle lengths by calculating the confidence intervals. The results are shown in Figure 5.Generally, the errors are bigger when the obstacle is smaller and when fewer samples are available.

Conclusion

By applying mobile crowdsensing to pedestrian safety, this paper explores a new direction of using crowd data. We have presented CrowdWatch, a pedestrian auxiliary system that uses acceleration, orientation, and GPS data on smartphones to enrich the map with overpasses or underpasses, and detect traffic light and dynamic barriers to alert pedestrians about dangers regarding the risk level. We plan to deploy the system and make a long-term study to improve the danger detection and reminding methods.

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