LookUp: Enabling Pedestrian Safety Services via Shoe Sensing

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ABSTRACT

Motivated by safety challenges resulting from distracted pedestrians, this paper presents a sensing technology for fine-grained location classification in an urban environment. It seeks to detect the transitions from sidewalk locations to in-street locations, to enable applications such as alerting texting pedestrians when they step into the street. In this work, we use shoe-mounted inertial sensors for location classification based on surface gradient profile and step patterns. This approach is different from existing shoe sensing solutions that focus on dead reckoning and inertial navigation. The shoe sensors relay inertial sensor measurements to a smartphone, which extracts the step pattern and the inclination of the ground a pedestrian is walking on. This allows detecting transitions such as stepping over a curb or walking down sidewalk ramps that lead into the street. We carried out walking trials in metropolitan environments in United States (Manhattan) and Europe (Turin). The results from these experiments show that we can accurately determine transitions between sidewalk and street locations to identify pedestrian risk.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous

General Terms

Design, Experimentation, Algorithms, Performance

Keywords

Pedestrian Safety; Smartphone; Localization; Inertial Sensing; GPS; Accelerometer; Gyroscope

1. INTRODUCTION

Evidence is mounting that technology distractions have a negative impact on pedestrian traffic safety. In the last decade, from 2003 to 2012, American streets have witnessed more than 676,000 pedestrians injured in traffic accidents, 47,025 of them fatally [1]. Pedestrians account for nearly 14% of all traffic fatalities in the US [2] and about 22% worldwide [3]. While motorist fatalities have declined, pedestrian fatalities have been rising at an annual rate of 4.9% from 2009-2012 [3, 4] (the 2013 estimates look more positive, fortunately). Econometric analysis has shown that at high densities of cell phone use, the life-taking effect due to distractions outweighs the life-saving effect of improved emergency medical response times [5]. According to a study, 26% of pedestrians text or email, 51% talk on the phone and 36% listen to music while crossing the street [6]. While the evidence is not yet fully conclusive, it is significant enough that municipalities have started stenciling "LOOK" signs at crosswalks in an attempt to alert pedestrians who text while crossing the street (see Figure 1).

Figure 1: Signage at crosswalks in Delaware and New York City [7, 8].

We believe that a technology solution would be more effective for the problem at hand. Smartphones and future wearable devices, which are part of the problem, can also be part of the solution by suppressing distractions or alerting pedestrians to dangers. Smartphones could also be integrated with the emerging wireless road traffic management and safety infrastructure (e.g., DSRC [9] [10]) to provide information about pedestrian behaviors and positions to vehicles and vice versa. If they could sense potentially dangerous situations, they could generate much more targeted and noticeable alerts. Achieving targeted notifications and accurate suppression of distractions, however, requires a sensing technique that can identify when more attention is required from the pedestrian.

In prior work, the Walksafe project has presented preliminary results on using cameras on pedestrians' smartphones for detecting oncoming vehicles [11]. Even if further significant improvements in accuracy will make this approach feasible, the energy consumption of continuous camera operation is likely to remain

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a challenge. Smartphones can also sense when they are being used while walking using existing activity recognition techniques [12], but this information is not sufficient to precisely target an alert. If pedestrians' smartphones and in-car devices can communicate (e.g. DSRC[9], [13]), they can determine when they are in close proximity. This can be useful for generating alerts in select scenarios but in busy urban areas pedestrians that are safe on a sidewalk are frequently very close to passing cars.

Pedestrian safety improvements, however, do not necessarily require such near-collision detection. Since the majority of pedestrian fatalities occur during road crossing at intersections or mid-block locations [14], safety improvements could also be achieved by supporting good crossing habits or by alerting distracted pedestrians who enter the roadway.[1] Phones can easily monitor when they are being used for texting and other potentially distracting purposes. The challenge, however, is to determine when pedestrians are crossing and to distinguish this from walking in relatively safe areas on a sidewalk. Existing localization technologies such as cellular, WiFi, and satellite positioning do not consistently achieve the accuracy necessary to discriminate sidewalks and roadways. The Global Positioning System may come close under ideal open-sky conditions but cannot achieve the same accuracy in many urban centers, where it would be most needed for pedestrian safety.

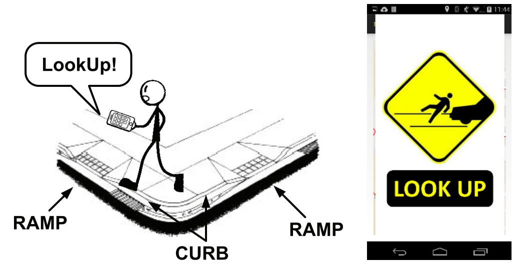
In this work, we address this challenge through a shoe-based step and terrain gradient profiling technique that can detect transitions between sidewalks and streets. This approach exploits the trends toward wearable sensing in shoes for health and fitness [16, 17]. While prior research and products have used sensors in shoes for tracking a person's movements (exercise tracking, posture analysis, and step counting), we show that similar inertial sensors can also sense properties of the ground. This allows constructing ground profiles which are useful in a pedestrian safety context and potential other applications such as localization. We note that sidewalks in urban environments (at least in more developed regions) follow relatively consistent design guidelines [18] with curbs separating roadways from sidewalks and increasingly ramps leading into dedicated crossings. These features are specifically designed to let even visually impaired pedestrians distinguish relatively safe sidewalk areas from street crossings.

We leverage these design features and develop a sensing system that can automatically detect transitions from a sidewalk into the road. This includes stepping over a curb, which often occurs when crossing a street. More importantly, however, our solution can track the inclination of the ground and detect the sloped transitions (ramps) that are installed at many dedicated crossing to improve accessibility. We focus on ramps because they are common in urban environments and we believe that the smoother transition makes it more likely that a distracted pedestrian fails to recognize the transition into the street. We have developed a prototype sensing system based on an inertial device affixed to a shoe to evaluate the effectiveness of this approach, both in laboratory experiments and in approximately 80 hours of walking, spread over the downtown area of a small city, the European city of Turin, and the midtown area of Manhattan.

In summary, the major contributions of this work are as follows:

- Proposing the use of shoe-mounted inertial sensors for step and ground profiling, and not just for step counting.

[1]Indeed, after a sharp 2012 uptick in traffic fatalities in New York City, the Transportation Commissioner blamed it in part on distracted walking and lamented: "I don't think that the iPhone has invented an app yet that will ping you when you hit a crosswalk." [15].



(a) Sidewalk-street transitions. (b) LookUp screenshot.

Figure 2: Virtual Look Up.

- Designing step and slope profiling algorithms that identify when a pedestrian enters the street by sensing changes in the step and ground profile due to typical sidewalk design features such as ramps and curbs.

- Prototyping a LookUp safety feature to demonstrate the feasibility of alerting distracted pedestrians when entering the street.

- Experimentally analyzing the performance of the detection algorithms across pedestrian environments including major cities on two continents with different sidewalk designs (Manhattan, NY and Turin, Italy). The total distance walked during these experiments was 112.5 miles and this experimental dataset included 1670 street crossings.

2. APPLICATIONS

There are multiple applications that could benefit from a sensing technique to detect the transitions from sidewalks to streets. These applications impose different requirements based on the timeliness of detections, the need for online processing of gradient data, the target environment and the tolerance to false positives. We enumerate selected applications with their requirements in Table 1 and detail them in the remainder of this section.

Virtual Look Up. Rather than relying on signs painted on the roadway, which may lead to warning fatigue, smartphones could issue a much more targeted electronic alert when an apparently distracted pedestrian is about to step into the street (illustrated in Figure 2).

The exact mode of alert or notification could range from visual (for texting users) to auditory, and might differ based on the robustness of detection. More intrusive alerts might be desirable when the system can attain high confidence that the user is at risk; more peripheral warnings may be suitable when there is lower confidence. We leave the exact design of such alert mechanisms to user experience designers and focus our discussion and effort on the robustness of the underlying sensing techniques. A sensing technique to support this application would need to be accurate in entrance detections and exhibit low false positives to be effective (and not cause warning fatigue). It will also need to determine detections online and with high timeliness requirement, since a distracted pedestrian should be alerted when entering the street. Note, however, that many accidents do not occur on the very first step into the street. They often occur after several steps, when emerging behind a parked car, for example. This means that short detection delays of 1-2 steps are often tolerable. This application is best suited to urban environments where car traffic is relatively dense and the likelihood of being struck when inattentive is higher.

Application	Online Processing	Timeliness	Target Environment	Tolerance to False Positives
Virtual Look Up	Yes	High	Urban	Low
Driver Pedestrian Awareness	Yes	High	Urban/Suburban	Low-High
Reducing In-street Notifications	Yes	Medium	Urban	Medium
Feedback on Crossing Habits	No	–	Urban/Suburban/Rural	Low

Table 1: Applications of street entrance detection for safety services.

Driver Pedestrian Awareness. Government transportation departments are working with car makers towards a vehicle communication network that can be used to provide vehicles with better situational awareness [19]. To support safety applications and increasingly automated driving, over time all vehicles are expected to announce their current position and other vehicle dynamics information to vehicles in the vicinity. While this network was initially planned only for vehicles, prototype smartphones now exist that can participate in such an 802.11p based network [10]. Including smartphones would not just enable pedestrians' devices to learn about oncoming cars, but they could also potentially announce the presence of the pedestrian to nearby vehicles. These announcements would need to be generated on the go and processed online, while restricting timeliness requirement to be high for rendering usefulness. In suburban areas, where vehicles are rare, a pedestrian need not be warned at every crossing, but only if a vehicle is approaching; which makes this scenario resilient to false positives. However, owing to the high density of pedestrians and vehicles in urban areas, such announcements would have to be more selective, so that the system can distinguish pedestrians that are safely walking on the sidewalk from pedestrians that may be at risk. This system could be more forgiving to false positives if an additional layer of filtering is added to the vehicle, that can identify true alerts based on added information. Consequently, this application finds use over a wide range of target scenarios, which also alter its tolerance to false positives.

Reducing In-street Notifications. Smartphones could silence distractions emanating from incoming calls, texts, or app notifications while the pedestrian is crossing a street. Since a crossing usually lasts no more than a few tens of seconds, the phone can simply delay the call/text (e.g. by disabling vibration or ringing) till the pedestrian exits the street. Such delays should be acceptable for most messages or notifications and if a call is missed, it can simply be returned when the pedestrian reaches the sidewalk. This application is more tolerant to false positives than the prior applications because even in case of a false detection the notification or call is delayed by only a small duration. The timeliness requirement is also slightly lower, since many distractions can still be suppressed even if the pedestrian is already several steps in the street when the system realizes this. This application could be an asset for urban environments where fatalities due to distracted walking are a rising concern.

Feedback on Crossing Habits. Not all applications require distinguishing pedestrian walking locations in near real-time. Offline analysis of historical walking traces can also be useful to monitor and provide feedback on good crossing-habits. For example, our proposed technique can be a very useful component of a sensing system that could allow parents to monitor whether children that walk to school are stopping (to look) before an intersection or whether they dash into the street. While this system would work in all kinds of environment, it would still need to be precise in detections, with few false positives.

Other Applications of Gradient Sensing. Besides these safety applications that benefit from a technique for detecting when pedestrians enter the street, we believe that a variety of other applications can also gain from this work. In particular, the shoe-based ground gradient sensing techniques are more generally applicable. By leveraging the slope traces and crowdsourcing them from a large number of people that walk the same path almost everyday, we can create a unique terrain profile for each sidewalk. Using the rough position estimate from the GPS and the sidewalk profile, we can improve localization in urban canyons by matching the terrain profile of the currently observed walking trace to this database of sidewalks. Additionally, we can also use these sidewalk profiles to monitor sidewalk status (surface health monitoring) as well as to identify the level of accessibility in an urban area to people with mobility impairments (e.g., surface smoothness, availability of ramps).

3. GPS LIMITATIONS FOR PEDESTRIAN SAFETY

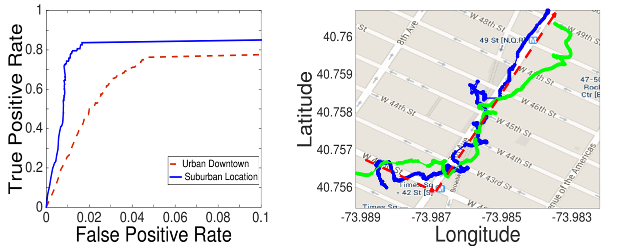
Consider a straw-man approach that attempts to localize the pedestrian using existing methods and distinguish sidewalks and roadways by comparing the position coordinates with the location of known roadways on a map. The requirements and challenges for GPS-based crossing detection assume different meanings across scenarios.

In out-of-town environments such as rural roads or highways, walking along the roads, which typically do not have sidewalks, can be particularly hazardous. Since pedestrians are sparse and tend to walk along roads for extended periods, the accuracy requirements on a positioning system are relatively low, in the order of tens of meters. It thus suffices to know if a pedestrian is walking along a street and a GPS-based approach can be expected to work.

In suburban or residential areas, there may or may not be sidewalks, and one may expect occasional pedestrians, walking in the street (when no sidewalks are present) or on the sidewalk. For the latter case, solely detecting that there is a pedestrian walking along the street would result in generating alerts uselessly. It is thus beneficial to identify the events when this person may be stepping into the street, putting himself at a higher risk of being hit by car. This requires the ability to distinguish the pedestrian's location as street or sidewalk.

Most urban downtowns and cities are well developed and have sidewalks, with a large number of pedestrians walking along the street. Just knowing that a pedestrian is walking along a street would create far too many alerts and cause warning fatigue. In such a scenario, more fine-grained differentiation of pedestrians at risk is not only beneficial but necessary. Since a pedestrian is usually safe when walking on the sidewalk, our approach is to identify pedestrians that are in the roadway. Accurate detection of street entrance therefore becomes a key concern.

Typical GPS accuracies are in the order of a few meters under good conditions and the accuracy can quickly degrade to tens of meters in urban canyons. Through experiments conducted in environments ranging from suburban to small and metropolitan cities, it is evident that the performance of GPS-based detection of pedes-



(a) In-street detection performance for urban and suburban testbeds.

(b) Sample GPS traces from Manhattan experiments and actual walk (dashed trace).

Figure 3: GPS based approach.

trian's transitions from sidewalk to street is limited even in a relatively benign suburban environment.

Using the location coordinates of the pedestrian and the heading, both obtained from the GPS, we can extrapolate a person's path of motion to approximate his position in the next d meters. We can then check this extended path for intersection with a nearby street. Such an intersection of the pedestrian's predicted path and the street would indicate that the pedestrian might be purposed to cross the street. The distance d is fixed to roughly half the width of the street. The underlying street network data can be accessed from OpenStreetMap [20], an open-source map database, which provides information about street orientations and locations. Figure 3(a) shows the performance of the GPS-based crossing detection in a suburban environment compared to an urban environment (e.g., downtown New Brunswick, NJ). The suburban environment exhibits a better performance with a detection rate of 85% than that of the urban environment (i.e., 78%). The maximum rate at which we can sample GPS is approximately once per second. It is evident from the performance curves that GPS does not suffice for applications with a stringent timing and fine grained localization requirement, such as pedestrian safety applications. More details on the limits of GPS-based pedestrian risk detection can be found in our earlier works [21, 22].

Figure 3(b) presents our best GPS traces collected in the urban environment of Manhattan, using a Nexus 5, held in hand. The green and blue lines are two separate GPS traces collected on different days. The red dashed line is the actual walked path. It is further evident from these results that GPS alone cannot serve the purpose for fine-grained localization such as detecting transitions from the sidewalk to street. Cellular and WiFi positioning could provide little help in such scenarios. Since sidewalks are often only a few meters wide, this level of accuracy makes it extremely challenging to distinguish a pedestrian on the sidewalk from one in the street, let alone determine the event when a person transitions from the sidewalk to the street.

Other Challenges. Even with accurate positioning, the GPS-based system would have to compare the position coordinates with a map to distinguish sidewalks from streets. Unfortunately, road maps such as those available from OpenStreetMap [20] record only road centerlines. Whether a sidewalk is present along the roadway is not always stored. Even if it were, the boundary between street and sidewalk would need to be estimated based on assumptions of typical road width. This further limits accuracy or requires additional effort in constructing such a map.

To overcome these challenges, we explore a sensing-based approach that detects events in a local frame of reference for the pedestrian, instead of relying on absolute positioning.

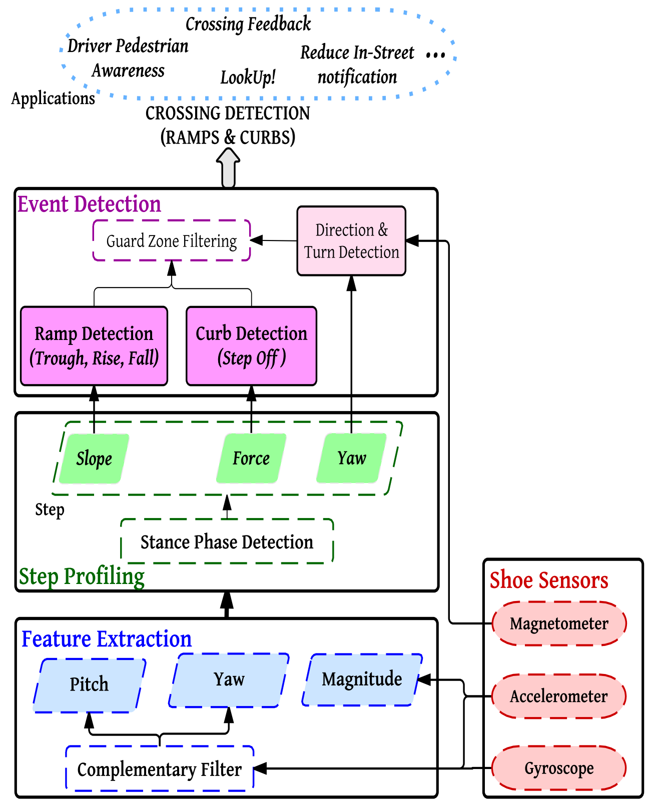


Figure 4: System overview of crossing detection.

4. STEP AND SLOPE PROFILING

Our primary idea is to distinguish street and sidewalk locations of the pedestrian through inertial sensing of ground features, particularly by sensing the sidewalk design features that demarcate roadways and sidewalks. In more developed regions, engineers are required to follow increasingly precise and consistent sidewalk design guidelines [18, 23] to improve accessibility. Typically, sidewalks and roadways are separated by curbs, which are lowered at designated crossings through a ramp. These features make sidewalk-roadway transitions and special crossings detectable by the visually impaired yet do not pose significant barriers for wheelchair users. We recognize that the same features can also be sensed for pedestrian safety services. The proposed approach therefore addresses the aforementioned challenges because it does not rely on absolute localization from GPS or maps and achieves robustness by taking advantage of unique sidewalk design features.

Shoe-based Step and Slope Sensing. More specifically, we propose a pedestrian safety system that acquires inertial data from a shoe-mounted sensor, to detect changes in step pattern and ground patterns caused by ramps and curbs. In particular, a salient feature of this work is that it senses small changes in the inclination of the ground, which are expected due to ramps and the sideways slope of roadways to facilitate water runoff. The shoe-mounted sensor has the capability to measure the foot inclination at any given point in time and reflects the slope of the ground when the foot is flat on the ground. We chose inertial sensors because they allow us to infer information about the ground with a very modest power budget, compared to GPS or camera-based approaches.

We selected a shoe placement of the sensors because they are closer to the ground than other wearable or smartphone sensors and move along with the foot. They can therefore trace the exact movement of the foot at each step and provide accurate information about ground features. Note that the trend towards wearable shoe sensors for fitness purposes [16, 17] has already made such sensors available in some shoes. With continuing technology advances, we envision that such shoe sensors will be increasingly available for other emerging tracking [24], fitness [16] and healthcare monitoring [25, 26] applications. They could first be embedded in shoes for especially vulnerable traffic participants (e.g., children) and eventually most shoes.

System Overview. The system comprises inertial sensor modules on both shoes that share their measurements with a smartphone over a wireless Bluetooth connection. While a sensor on one foot can also achieve most of the ramp detections, sensors on both feet substantially improve the detection of stepping over a curb. It allows us to detect foot movements over the curb, irrespective of the foot the pedestrian uses for the action. A smartphone can serve as a hub for processing the shoe sensor data and implementing any of the aforementioned applications. The key processing steps of our sensing system are depicted in Figure 4. The core components of our system are *Feature Extraction, Step Profiling* and *Event Detection*.

The *Feature Extraction* block processes raw accelerometer and gyroscope readings (sampled at 50 Hz in our implementation) through a complementary filter, and extracts traces of pitch, yaw, and acceleration magnitude features from these measurements (see Figure 5 for an illustration of key features). While it primarily relies on this inertial data, it also collects magnetometer readings to assist with the Guard Zone filtering step in the Event Detection component.

The *Step Profiling* component divides these traces into distinct steps and for each step cycle extracts the period when the foot is flat on the ground, which we refer to as *Stance Phase Detection*. It then estimates the slope of the ground from the pitch readings and the relative rotation of the foot from the yaw readings, during the stance phase. It also extracts peak acceleration magnitude over an entire step cycle as an indication of foot impact force.

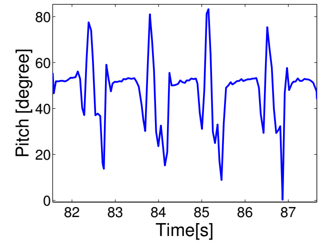
Finally, *Event Detection* layer aims to detect stepping into the roadway through ramp and curb detection. Ramps manifest themselves through characteristic changes in slope, while steps over a curb usually show higher foot impact forces. These candidate detections can then be filtered through a guard zone mechanism. It helps to remove spurious events caused by uneven road surfaces. Since many cities feature somewhat regular intervals between road crossings (especially so for cities that are laid out in a grid shape), it is rare for a pedestrian that walks straight to encounter a crossing immediately after previous crossing. The guard zone mechanism tracks whether a pedestrian walks straight and then suppresses detections that come to soon.

5. CROSSING DETECTION

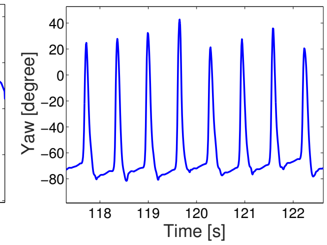
Below, we detail the feature extraction, step profiling, and event detection layers depicted in Figure 4 and outlined in the previous section.

5.1 Feature Extraction

This component extracts changes in pitch, yaw and acceleration magnitude for each sample from the tri-axis accelerometer and tri-axis gyroscope measurements. For simplicity, let us assume that the inertial sensor unit is oriented such that the x axis points approximately forward in the direction of motion, the y axis points sideways, and the z axis points opposite to the direction of gravity, as shown in Figure 6. Note, that the sensor orientation does not need to be precisely calibrated; small discrepancies can be tolerated since we only track changes in pitch, yaw, and magnitude from step to step. For arbitrary mounting positions, the system can also be extended to include a complete coordinate system calibration step similar to [27].



(a) Pitch vs. Time.



(b) Yaw vs. Time.

Figure 5: Pitch and Yaw traces.

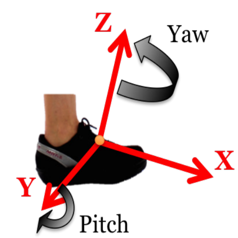


Figure 6: Shoe mounted sensor with axis orientation.

Pitch. Pitch is the rotation of the foot along the sideways y axis (see Figure 6), which represents the inclination of the ground during the stance phase. We measure changes in pitch relative to the first step, to account for mounting offset. Changes in pitch can be determined from the accelerometer readings, since the change leads to a different projection of the gravity force on the accelerometer axes. These estimates can suffer from vibration errors, however. An alternative way of obtaining changes in pitch angle is by using the gyroscope data. Since the gyroscope directly measures angular velocity around all axes, integrating the angular velocity around the y axis will yield the change in pitch. While the gyroscope allows tracking small changes more precisely, the integration process accumulates error over time, leading to significant errors for longer integration intervals. To overcome the drawbacks of the individual sensors, we borrow a popular technique from robotics, for accurate pitch measurement. This technique involves combining the accelerometer and gyroscope data using a complementary filter [28, 29]. To obtain the pitch from raw accelerometer and gyroscope readings, we use a second order complementary filter.

The second order complementary filter takes the following inputs: the accelerometer readings along x and z direction, A_x and A_z, and the gyroscope rotations along the y axis, G_y. The filter also needs two parameters, k - the bandwidth of the filter and T - the sampling rate. For our system, the sampling frequency is 50 Hz, i.e. T is 0.02 and we empirically set k=13.5. The filter is given by the following set of equations, where i is the generic sampling step and $\alpha(i) = atan(A_x(i)/A_z(i))$ represents the angle between the accelerometer readings along the x and z axis.

$$v(i) = Tk^2[\alpha(i) - pitch(i-1)] + v(i-1) \quad (1)$$
$$w(i) = v(i) + 2k[\alpha(i) - pitch(i-1)] + G_y(i) \quad (2)$$
$$pitch(i) = Tw(i) + pitch(i-1) \quad (3)$$

In (1), a low-pass filter is applied to the difference between the current angle and the previous pitch so as to only let long-term changes through, filtering out short-term fluctuations. The output of the filter is integrated over the sampling step T. Equation (2) sums the output of (1) to the output of a low-pass filter and gyroscope rotation G_y. Finally, (3) performs an integration over the sampling step and adds the result to the pitch. A typical pitch trace is shown in Figure 5(a).

Yaw. Yaw is the change in rotation of the foot around the vertical axis, the z axis. We measure yaw relative to the previous step. We can obtain the yaw from the complementary filter in the same way as the pitch, by only changing the axis. Note, however, that the yaw information primarily stems from the gyroscope since the accelerometer tends to convey less information about yaw. In fact, if the accelerometer z axis is aligned with the gravity axis, then a change in yaw will yield no measurable difference in the $x - y$ plane, since there is no gravity component on these axes. A typical yaw trace is shown in Figure 5(b). Yaw gives information on whether the pedestrian is walking straight or turning, which we use for turn detection and in the Guard Zone Filtering, as described later.

Magnitude. The magnitude of the acceleration helps us detect the event of stepping off a curb. We notice that during step off events, the accelerometer records a peak in acceleration along the axis on which the gravity is acting. Therefore we calculate the magnitude of acceleration along the z axis and the y axis, for every sample. We remove the x axis from consideration to filter out significant acceleration in the walking direction.

5.2 Step Profiling

The foot mounted inertial sensors are used to obtain the slope of the ground at each step the walker takes, hence the measurement of the ramp inclination. This algorithm proceeds in three steps. First, it tracks the pitch angle 50 times a second. Second, it uses this pitch trace to extract the slope from the stance periods of a walking cycle, the period when the foot is flat on the ground. A sequence of these slope values corresponds to the slope profile of the ground that the pedestrian is walking on. Third, in addition to the slope, each step also has yaw and force attributes, that are derived from the yaw and magnitude features. Therefore, at the end of the profiling algorithm, we obtain a sequence of steps, where each step has a slope, yaw and force attribute. While the slope is acquired by sensing the terrain gradient, the yaw and the force attributes are particular to the walking style. Below, we provide further details on the stance phase detection algorithm.

Stance Phase Detection. We use the pitch trace to identify the different phases of a person's walk. Figure 7 shows one such trace and the corresponding phases of walking. We require the *stance* phase of the walk, which is when the foot is flat on the ground. The inclination measurement obtained in this phase results from the slope of the ground at that spot, in addition to the initial pitch due to mounting.

As a person walks, the inclination of the foot changes continuously, varying rapidly during the swing phase but maintaining a small amplitude during the stance phase. Thus, the stance phase detection algorithm identifies the large negative peaks in the trace and isolates the samples between consecutive peaks. This is one walking cycle. By tracking the variation of the pitch during each cycle, the stance phase is identified as the interval in which the foot is stationary implying very small or no changes at all to the pitch. The samples making up each stance phase are determined as the collection of at least *count* number of pitch values within a few degrees of each other. Here *count* depends on the sampling rate of the sensor and the duration for which the foot is in contact with the ground. For our analysis we assume that the foot remains in contact with the ground for at least one-third of a second, during normal walking. At a sampling rate of 50 Hz, this implies that the stance phase should have approximately 15 samples. The mean of

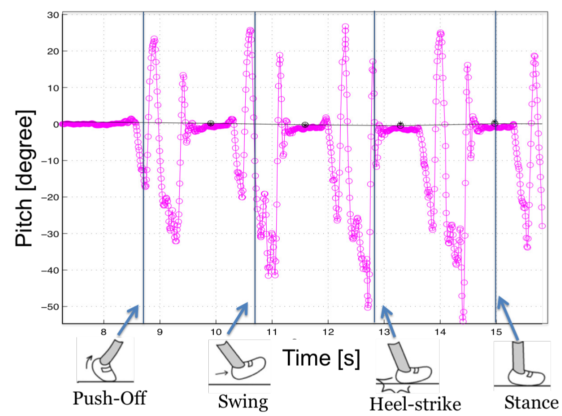


Figure 7: A pitch trace identifying different phases of a walking cycle.

the inclination values (pitch) during the stance phase provides us with the slope of the ground at that step.

By repeating this calculation for each stance phase, we acquire a sequence of slope values, the slope trace, where each slope corresponds to a step. From this slope trace, we obtain an estimate for the slope of the ground by subtracting the initial tilt of the accelerometer, caused by the shoe mounting.

We assume that pedestrians walk in the forward direction and not backwards. However, if a person halts and only stamps his feet without moving, the pitch trace does not record a complete walking cycle. The swing phase of the stamping activity is distinct from the swing phase of the walking activity and thus these spurious steps are easily filtered out.

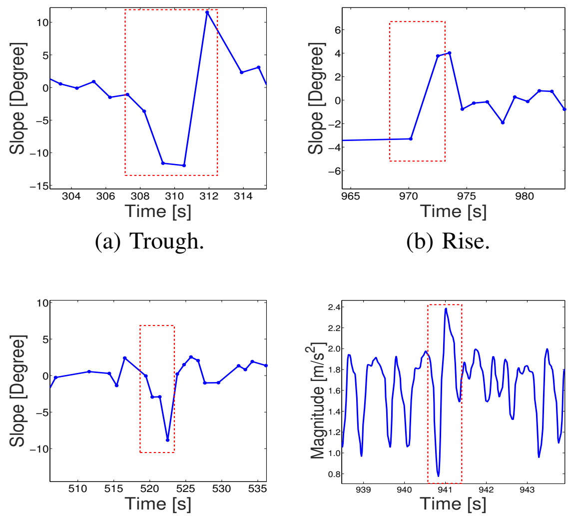
5.3 Event Detection and Classification

The pitch computation and stance phase detection discussed above are performed independently for each foot. After these procedures, we obtain the slope measurement of the ground at each step from both feet. Each time a walking cycle is completed, we compare the slope of the current step to the slope acquired in the past 3 steps. We determine the 3-step window by observation. Events are detected by applying a threshold to the slope change in this window. This threshold reflects the typical ramp inclination and is determined empirically.

The force at each step is also evaluated against a step off threshold to detect steps with a force significantly higher than past 3 steps, likely implying stepping-off curbs. The events detection and classification details are provided in Algorithm 1. To ensure robust detection, not only do we identify events that exceed the threshold, but we further process them as explained below. First, we categorize the detected events as follows.

Trough. A trough is typical of a street entrance via a ramp. As a pedestrian walks from the sidewalk to the street, there is a negative slope measured off the descending sidewalk ramp. As the person steps into the street, the sensors measure a positive slope, due to the street curvature. A combination of the negative slope of the sidewalk ramp and the positive incline of the street edge forms a trough, if the detected change in slope is significant (higher than a given threshold). Figure 8(a) shows an example *trough* event. While this is the ideal measurement case, we do not observe this ideal pattern at all crossings, due to measurement errors and surface invariations.

Rise. A rise is an event detected due to a sharp increase in the measured slope of the ground, i.e. a positive incline. This occur-



(a) Trough. (b) Rise.

(c) Fall. (d) Step Off.

Figure 8: Event patterns.

rence is most common when the pedestrian just steps into the street. This is due to the fact that streets have a convex curvature to facilitate water to drain off to the sides. When walking from sidewalk to street, this curve is measured as the positive incline. Figure 8(b) shows an example *rise* event.

Fall. A fall is an event detected due to a sharp decrease in the measured slope of the ground. This event is most commonly detected when a pedestrian is walking down the sidewalk ramp, which shows up as a negative incline. Figure 8(c) shows an example *fall* event.

Step Off. A step off event occurs as a sudden increase in the accelerometer magnitude along the vertical direction. This signifies the force associated with that step. If the force at a step is higher than the person's average force over the past 3 steps, we flag this event as a step off event. This event is very important for detecting street entrances where a person steps off the curb instead of walking down a ramp. Figure 8(d) shows an example *step off* event.

We then classify a combination of these events as *high confidence* and *low confidence* events. A pair of trough events, one from each foot, constitutes a high confidence event. Similarly, a pair of step off events is also classified as high confidence event occurrence. All other events are classified as low confidence events. A low confidence event could also be triggered by various obstacles on the sidewalk or unexpected discrepancies in the pedestrian's movement.

An example of low confidence event is a fall event, which can occur at both, entrances (when walking down a sidewalk ramp) and exits (at the edge of the road, when leaving). However, the algorithm can identify an entrance based on the spatial and temporal occurrence of the events. If the events occur close to each other, they denote an entrance and the following exit. Also, as detailed later, when a high confidence event allows the detection of an entrance, the guard zone is set and the exit event can be easily discarded.

We remark that, in addition to detecting actual events, the algorithm is also equipped to handle error cases. While thresholding the slope, only relative slope change is tracked over a small window of steps. Therefore, if the sidewalk has a gradual uphill or downhill incline, the algorithm does not detect it as a ramp, since the relative slope of the ground does not change considerably in a small window. Unfortunately, obstacles in the sidewalk, such as bumps are

Data: $pitch$ - Pitch trace
    mag - Magnitude trace
    W_{step} - Step Window for comparison
    Th_r - Threshold for ramp detection
    Th_c - Threshold for curb detection
Result: $\mathcal{S}$ - Event Type
begin
  foreach $pitch, mag$ **do**
    if *walkCycleComplete(pitch) == TRUE* **then**
      $[Slope(i), Force(i)]$ =
      getStancePhaseMean($pitch$, mag);
      if *(Slope(i)− Slope(i-1)* $> Th_r$*) and*
      (Slope(i-1)− Slope(i-1-W_{step}*))* $< -Th_r$*) and*
      (range(Slope(i-1-W_{step}*:i-1))* $> Th_r$*)* **then**
        $\mathcal{S} \leftarrow$ *Trough*;
      else
        if *range(Slope(i:i-*W_{step}*))* $> Th_r$ **then**
          diff=slope(i)-slope(i-W_{step});
          if *diff* $> Th_r$ **then**
            $\mathcal{S} \leftarrow$ *Rise*;
          else if $diff < -Th_r$ **then**
            $\mathcal{S} \leftarrow$ *Fall*;
      if *Force(i)>*Th_c **then**
        $\mathcal{S} \leftarrow$ *Step Off*;
      if *inGuardZone(*$\mathcal{S}$*) == FALSE* **then**
        return $\mathcal{S}$
      else
        Discard $\mathcal{S}$;

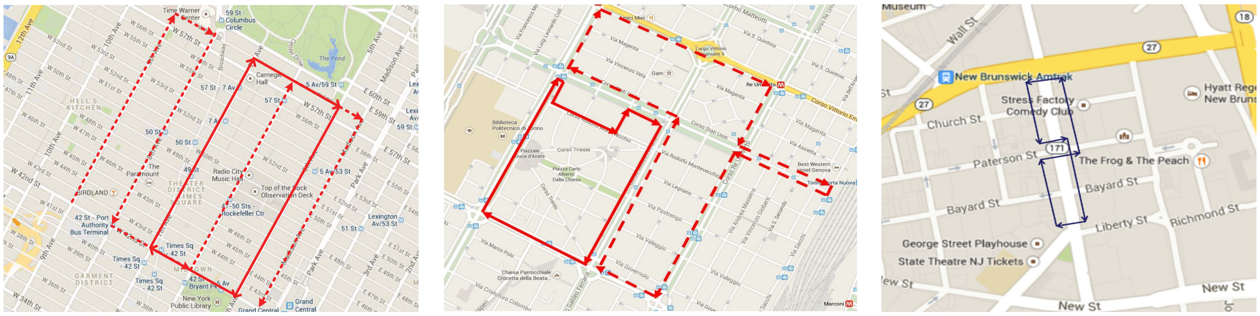
Algorithm 1: Event Detection Algorithm.

single step events and hard to filter by themselves, unless they fall in the guard zone.

5.4 Guard Zone Filtering

When a high confidence event is detected, such as a pair of *trough* events or a pair of *step off* events, the algorithm reckons this to be a definite entrance into the street and sets a *guard zone* following that entrance, until the next entrance can occur. We define *guard zone* as a stretch of the sidewalk on which true events of entering the street are unlikely to occur. Thus, any events detected within the guard zone are discarded because they can be caused by measurement noise or irregularities in the sidewalk (uneven road surfaces, potholes, bumps), and can trigger false positives. The guard zone is reset (i.e. set to zero) when a turn is detected. If a turn is made before crossing the street, the turn detection algorithm resets the guard zone. This implies that events after a turn will not be discarded, and the guard zone will be set again when a high confidence event is detected. This is done to account for pedestrians who cross a street, turn, and then cross again, shortly after the first crossing. Guard zone filtering has been primarily designed to discard false warnings due to the irregularities of the sidewalk.

Obtaining the length of the guard zone is important to reduce false positives and maintain a high rate of crossing detections. However, accurately determining this size poses several challenges. First, crossings occur not only at the ends of a street block, but pedestrians can also perform midblock crossings. Second, the complexity and varying characteristics of the road environments make it difficult to provide a generic length setting of guard zone. To overcome this issue, the guard zone algorithm takes the closeness of streets (block length) into account and sets the length of the guard zone to



(a) Manhattan Testbed. (b) Turin Testbed. (c) New Brunswick Testbed.

Figure 9: Test paths from Manhattan (New York), Turin (Italy) and New Brunswick (NJ).

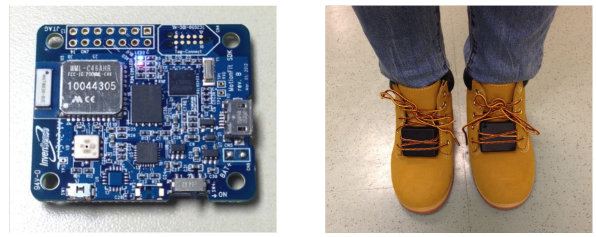
a fraction of the street block size. This setting also helps us recover in case the guard zone is incorrectly applied after a false detection. We seek to derive a sensing-based mechanism to estimate the length of the guard zone by using the pedestrian's walking direction and turning information. In this mechanism, the size of the guard zone continues to increase by accumulating the pedestrian's walking steps after the first street entrance (i.e., a high confidence event) is detected, and it resets to zero when the pedestrian makes a turn. We implement this mechanism by performing *walking direction determination* and *turn detection*, as described below.

Walking Direction Determination. This task is accomplished by leveraging magnetometer readings. Magnetometer measures the earth's magnetic field in x, y and z directions and its readings remain unique for certain direction. The magnetometer embedded in the shoe sensor can thus become a useful discriminator for the walking direction determination. Specifically, we assume $\vec{R} = (x_r, y_r, z_r)$ and $\vec{R}' = (x'_r, y'_r, z'_r)$ be the average of the real time magnetometer readings obtained from the current observation window and the previous non-overlapping observation window with a length of n walking steps, respectively. The angle between $\vec{R}$ and $\vec{R}'$ can be found using the dot product: $\theta_{\vec{R},\vec{R}'} = \cos^{-1} \frac{\vec{R}\cdot\vec{R}'}{\|\vec{R}\|\|\vec{R}'\|}$. If $\theta_{\vec{R},\vec{R}'}$ is smaller than a pre-defined threshold, the system declares that the walking direction of the user remains the same and the guard zone size increases by n walking steps.

Turn Detection. By analyzing the yaw values, we are able to detect turns made by pedestrians. A turn corresponds to a continuous change, along the same direction, of yaw readings over both feet. We develop a turn detection technique that takes the yaw value associated with each step and computes the difference between yaw at consecutive steps. Then, it sums these differences over a fixed number of steps so as to obtain the overall rotation angle. A turn is detected when such rotation exceeds an angle threshold for both feet. As mentioned before, turn detection is used to avoid discarding real entrances when guard zone filtering is applied. Indeed, we observed that most turns happen right before or after street entrance events, either at intersections or mid-block locations. Thus, if a detected event is preceded by a turn, it is likely to be a real street entrance, hence it is not discarded and the guard zone size is reset to zero. In addition to turn detection, considering both feet allows us to distinguish between actual turns and small heading variations due to the need to dodge people on a crowded sidewalk.

6. PROTOTYPE IMPLEMENTATION

Our prototype includes a shoe-mounted sensor, two Android applications for data collection and a LookUp safety feature to demonstrate the feasibility of our approach. The sensor mounted on the shoe is an Invensense MPU-9150 [30] 9-axis motion sensor, shown in Figure 10(a). It is a self-calibrating device, set to collect data at a sampling rate of 50 Hz. During our in-lab experiments we analyzed the system performance using different sampling frequencies. We chose 50 Hz considering that some people walk much faster, and this sampling frequency provided us with enough data points to extract the stance phase. The board we used comprises an accelerometer, gyroscope, magnetometer, a Bluetooth module and a battery. We chose this platform because it offers relatively high precision inertial sensing module. In order to capture all foot movements, we strapped a sensor on each of the walker's shoes, as shown in Figure 10(b). We chose a mounting position for the sensor after testing out four different positions in a controlled laboratory environment. As shown in the evaluation section (Figure 18(b)), the mounting position that was found to be consistent across separate experiments was on top of the foot. A sensor mounted on each foot ensured that stepping off the curb is detected, irrespective of the foot used



(a) MPU 9150 sensor. (b) Sensor mounting on shoes.

Figure 10: Set up for shoe-mounted sensor.

We implemented an Android application to collect sensor data on the user's smartphone via Bluetooth. The application logs the accelerometer, gyroscope and magnetometer data from the two sensors independently. Each reading is timestamped and contains raw data from the three axis. A second Android application was implemented to collect the ground truth for offline evaluation of the proposed system. This application has buttons to mark the exact time when the walker transitions between a sidewalk and a street, and whether this transition occurs via a ramp or a curb. To ensure that measurements are unbiased and the pedestrian is undistracted while crossing the street, the ground truth was entered by a second person walking with the pedestrian.

We also developed a prototype LookUp safety application on the Android platform, which alerts distracted pedestrians when entering the street. This is a shoe sensor-based crossing detection application that implements the algorithms described in Section 5. The

(a) A ramp in Manhattan. (b) A curb in Manhattan. (c) A cobblestone ramp in Turin. (d) A curb in Turin.

Figure 11: Typical roadway features from Manhattan and Turin.

screenshot from the application is shown in Figure 2(b). When a pedestrian approaches a street, a LookUp warning flashes on his mobile screen, alerting him to pay attention to traffic. This application runs in the background and does not alter the user's interaction with the smartphone.

7. EXPERIMENTAL SCENARIOS

To evaluate the performance of our system, 21 volunteers, 16 male and 5 female, walked along predefined routes in three locations with a sensor attached to each of their shoes. Most volunteers were students from our laboratories and about 20 - 40 years old. The only instruction provided was to walk as usual along the given route. An experimenter accompanied each walker to record, through a smartphone app, ground truth information (i.e., the time when transitions occurred and whether they occurred via a ramp or a curb). Most volunteers were not aware of the objective of the experiment other than it being related to pedestrian safety. We highlight that volunteers were free to use either a ramp or a curb to cross a street (the system collected both the ground slope data as well as acceleration events for street crossing detection at the same time). The experiments in Manhattan were conducted in the months of February and early March. There were a fair number of obstacles to deal with such as icy patches, accumulated snowpiles, and street/sidewalk potholes. The data includes the movements to avoid these and volunteers may have walked faster due to cold weather. Additionally, these walking trials were performed during different times, including rush hour and weekends. At times, the volunteers had to weave around people. None of our test areas, however, included stairs or unpaved surfaces.

Midtown area of Manhattan. This location gave us the opportunity to evaluate our system in a challenging environment, with different kinds of ramps, crowded sidewalks and long paths. The experiments were performed near Times Square, which is one of the world's busiest pedestrian intersections. Five volunteers walked at different times, including rush hours and weekends. We selected two test paths. A short one that volunteers were able to cover several times (namely, 20) so as to analyze the variance of our results over the same path. Another, longer path was completed twice and allowed us to understand variations in the results depending on the different street and crossing layout. The first test path starts from Times Square (42nd Street, 7th Avenue) and goes through Central Park (58th Street, 5th Avenue) before returning to Times Square, as shown by the solid red lines in Figure 9(a). The entire path is about 2.1 miles. The average path travel time is about 60 mins, and it includes 32 street crossings. The dashed path in Figure 9(a) shows the second test path, which is about 4 mile-long. In this case, the average path travel time is approximately 120 mins, and it includes 60 street crossings. Thus, a total of nearly 25 hours of sensor data was collected. Figure 11(a) and (b) show a typical ramp and curb in Manhattan.

Turin Metropolitan Area. In order to verify the performance of our system in a different urban street layout, we selected the European city of Turin, in Italy, which has a population of about one million people. While in Manhattan most of the sidewalks are made of concrete or tiles, in Turin almost all of them are made of either asphalt or bricks. Six volunteers walked over two different test paths in the city center, as shown in Figure 9(b). The shorter path is 1.6 mile-long, includes 20 crossings and is travelled in about 30 mins. The longer one is 2.5 mile-long, includes around 40 crossings and it takes about one hour to complete it. In total, volunteers completed 10 long and 20 short paths, thus collecting a total of 20 hours of sensory data. A typical cobblestoned ramp from Turin is displayed in Figure 11(c).

New Brunswick Downtown. We conducted walking trials in the downtown area of the small city of New Brunswick. The selected area comprises only sidewalk ramps. Eleven volunteers walked over ten possible paths, each of which is 20 minute-long and covers about 800 meters. Figure 9(c) provides a map of this testing scenario and shows one of the ten possible paths, which includes 8 crossings. The number of crossings over the possible paths ranges between 8 and 12. The New Brunswick testing scenario has been used to evaluate the impact of people's walking style and speed on the performance of our system.

8. EVALUATION

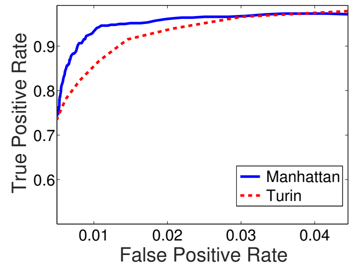
We evaluate the robustness of our crossing detection system for the three testbeds discussed earlier.

8.1 Entrance Detection

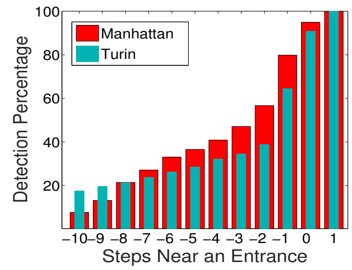
First off, we evaluate the crossing detection algorithm for delay and detection performance. This evaluation is carried out for our two main testbeds, Manhattan and Turin. These results establish that our crossing detection algorithm has very low false positives for a high detection rate, even at locations that have completely different street designs. In the second part of the entrance detection evaluation, we test the robustness of the algorithm and analyze how it is affected by the pedestrian's walking style and sensor mounting. For this evaluation we use our smaller testbed, in New Brunswick, New Jersey as well as controlled indoor experiments. We show that the detection performance is not significantly influenced by walking style and that a shoestring mounting position as used in current exercise tracking products also works well for ground sensing and entrance detection.

We use steps as the evaluation metric, which provides a comprehension of both time and distance. Due to varying speeds of walking and the time spent in waiting in differently crowded environments, the metric of time alone is insufficient without a sense of

(a) A ground truth window of 12 steps at an entrance



(b) Entrance Detection Performance for Manhattan and Turin testbeds



(c) Cumulative entrance detection in ground truth window

Figure 12: System performance evaluation.

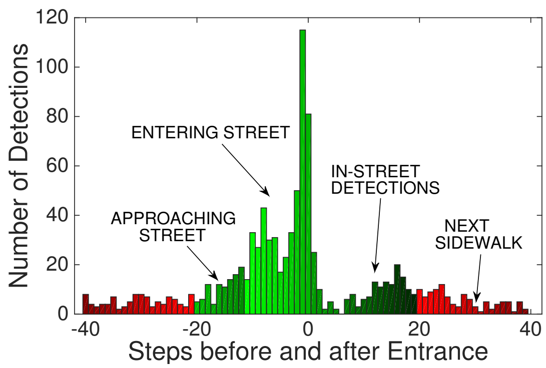


Figure 13: Detection latency for Manhattan testbed.

pedestrian motion. For example, when a person enters the street, a few seconds later we cannot tell how far the pedestrian is in the street without also tracking motion and speed. Steps help us estimate the risk to a pedestrian based on how far (how many steps) he is, into the street.

8.1.1 Detection Latency

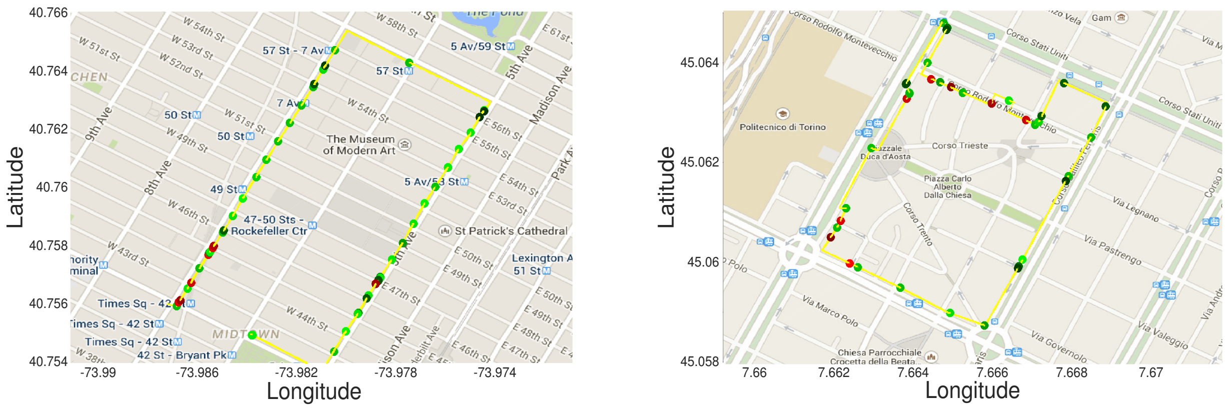
For safety applications, it is essential to understand the timeliness of event detections. To this end, we graph the delay distribution of the detections in number of steps from an actual entrance. Figure 13 shows a histogram that displays the number of detected events in a 40 step window before and after a real entrance. The negative and positive x-axis values correspond to steps before and after the entrance, respectively. Zero on the x axis marks the step when the pedestrian enters the street. We observe that the maximum number of detections occur at the step right before the entrance, followed by the first step into the street. The highest density of detected events lies in the steps before the entrance, depicted in fading shades of green to the left of zero. On either side of this window, the detections fall rapidly. The bars from 2 - 20 steps after entrance denote the detections occurring while the pedestrian is crossing the street. While these detections are late for warning the pedestrian, they are very useful for a pedestrian-2-vehicle communication scenario, where we need to know when a pedestrian is in the street to relay that information to an approaching vehicle.

8.1.2 Detection Performance

We next evaluate our system for the Lookup application, which has the most stringent timing requirement. We classify all event detections as true positives or false positives. We define a true positive as a detected event that falls in a window around the actual entrance. We refer to this window as the *ground truth window*. It is evident from Figure 13 that most detections occur in the steps very close to the entrance, therefore we selected a long ground truth window. We define the ground truth window as a sequence of 12 steps around an entrance. Figure 12(a) shows the ground truth window at an entrance in an urban scenario. Since sidewalk ramps can be of varying lengths and early detections are helpful for warning pedestrians, we use 10 steps before an actual entrance as an appropriate window for in-time warnings. The most worrisome pedestrian accident scenarios are when the pedestrian enters the traffic lane in front of standing or stopped traffic at intersections, and when a vehicle is turning left at an intersection [14, 2]. The first is very common when a pedestrian enters the street from in between parked cars, and an approaching vehicle has no line of sight to the person. These accidents occur a few steps away from the sidewalk bounds. A warning that is triggered up to a couple of steps into the street would be beneficial, since pedestrians do not immediately put themselves in the way of a moving vehicle when they enter the street. Bearing this in mind, we consider 2 steps into the street still in time to warn a pedestrian.

Figure 12(b) shows our entrance detection performance results from the Manhattan and Turin testbeds. We use the Receiver Operating Characteristic (ROC) curve to illustrate our entrance detection results by varying the slope detection threshold from 0.1 to 15 degrees in steps of 0.1. For a large testbed such as New York City, with one of world's busiest intersections, our system achieves 90% detection rate with only 0.7% false positives in midtown Manhattan. With a 1.1% false positive rate we can reach up to 95% of crossings being detected. Occasionally, the transitions from sidewalk to street are not sharp, and the sidewalk could be at the same level as the street with no subtle inclination. In such cases our algorithm has difficulty in detecting the transitions from sidewalk to street. For the Turin testbed, our algorithm provides a true detection rate of above 90% for less than 1.5% false positives. The proximity of the two curves in Figure 12(b) demonstrates that our algorithm performance is not affected by location or by differences in sidewalk designs. Even with several walking paths of varied lengths in both testbeds, the performance of the entrance detection stays unaffected, indicating that it is not affected by the length or duration of the pedestrian's walking.

Within the ground truth window, it is interesting to study the cumulative probability of detection as the person approaches the entrance point. For all true detections, we plot this cumulative detection rate in Figure 12(c). -1 denotes the last step on the sidewalk and 0 denotes the first step into the street. With each step in the ground truth window, the y-axis marks the true detections that occurred until that step. We see that 80% of the times, the entrance was detected before entering the street, while almost all the times it was detected right after entering the street.



(a) Manhattan Testbed

(b) Turin Testbed

Figure 14: Locations of crossing detections for latency and performance analysis.

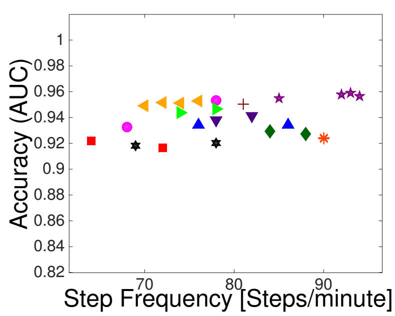
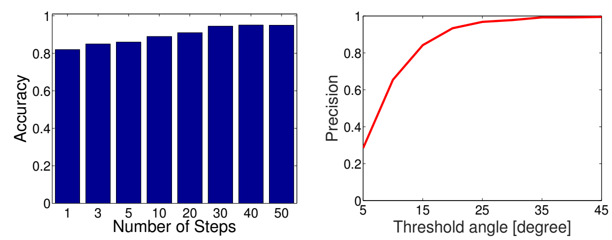


Figure 15: Performance at different walking rates for New Brunswick testbed. Each symbol represents one loop. Each person is represented by a unique symbol.

To obtain a finer perspective on where exactly these detections happen, we estimate the location for each step by interpolating location coordinates between consecutive crossings. We plot the locations of the detections from our system on maps for Manhattan and Turin testbeds as depicted in Figure 14(a) and (b). The yellow trace marks the interpolated location coordinates of each step of the path walked. The color scheme for detections on this map corresponds to the histogram in Figure 13. Fading shades of green mark the detections before an entrance, while shades of red mark detections on the sidewalk. It is evident that most detections occur close to intersections, indicating the utility for detecting pedestrian risk. The Turin map also shows few false detections. Some of these events are detected because of the guard zone being reset when a pedestrian turns, as they are likely to make another crossing.

8.1.3 *Effect of Walking Style*

Next we analyze the effect of differences in walking styles on the crossing detection algorithm. For this analysis, we use our smaller testbed in New Brunswick and conduct walking trials at different speeds and with different experimenters carrying the device. Walking speed and stride length are important metrics that distinguish walking styles. We use step frequency as a combined metric for evaluation because it accounts for the changes in speed as well as stride length. Figure 15 shows the accuracy of the algorithm for different step frequencies. We measure this accuracy in terms of



(a) Direction determination using magnetometer

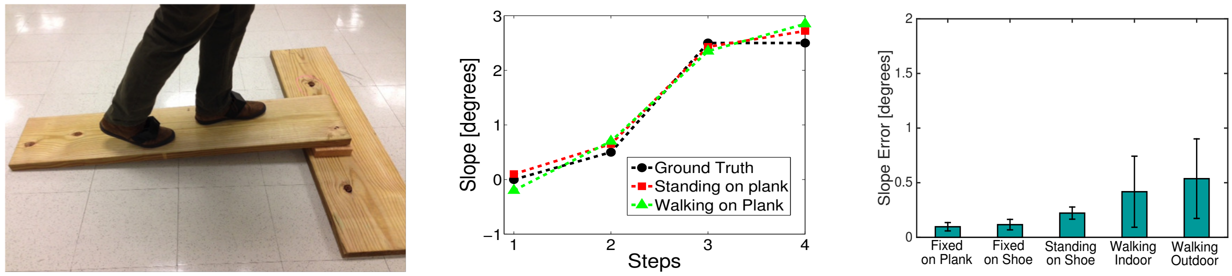
(b) Turn detection using yaw

Figure 17: Direction determination and turn detection.

the area under the ROC curve, called AUC, a metric used in machine learning to describe the performance of a classifier. The average walking speed varied between 65 and 95 steps per minute. To obtain a fair comparison in the step frequency calculation, we discarded the time during which a walker was waiting to cross an intersection. This value depends on the traffic condition and not on the walking style. The figure shows the AUC values for different walkers. Each symbol in the figure represents a loop completed by a walker. Each color and marker style correspond to a different walker. All AUC values range between 0.9 and 0.98, indicating that our system has a high accuracy irrespective of the walking speed.

8.2 Direction Determination and Turn Detection

Finally, we evaluate the effectiveness of walking direction determination using magnetometer for guard zone filtering. We use the magnetometer traces collected from the Manhattan testbed and treat the direction of the walking trajectory obtained from the map as the ground truth. We divide the whole trace into non-overlapping observation windows in terms of number of steps. An angle between each pair of consecutive observation windows is estimated using our proposed scheme in Section 5.4, based on the magnetometer readings within two windows, and then compared with a threshold to determine whether user's walking direction has changed. The accuracy is defined as the percentage of window pairs in which the determined direction matches the ground truth. Figure 17 (a) presents the accuracy of direction determination under varying lengths of observation window. We observe that the accuracy starts from 80% even with one step and exhibits an increasing trend as the number of steps increases. It is stabilized at about 95% when it



(a) Indoor ramp set up (b) Step vs. Slope at indoor ramp (c) Slope measurement error at different error placements

Figure 16: Sensor accuracy analysis.

reaches 30 walking steps. This is encouraging as it indicates that our magnetometer-based walking direction determination scheme is effective.

For the evaluation of the turn detection technique, we collected a new set of data in our laboratory. Different volunteers completed about 400 turns of various angles. During these tests, walkers marked the time instant at which they started turning, which is used as reference to evaluate the performance of the turn detection technique. Figure 17 (b) shows the turn detection precision for varying threshold angles. It is computed as the ratio between the number of true positives and the sum of true and false positives. We define a true positive as a detection event that falls within three steps after the actual turn (marked during data collection). All events detected outside this window are considered as false positives. For a threshold angle of 40 degrees we can achieve a 99% precision.

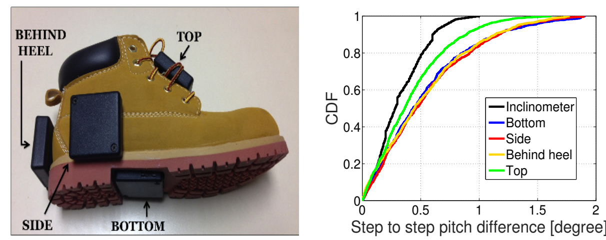
8.3 Sensor Position Comparison

One of the first challenges that we had to face was deciding the sensor mounting position on a shoe. We wanted to ensure that the performance of the gradient sensing technique is not affected by the mounting position and remains consistent over independent trials. Owing to its limited dimension, the sensor was easily mounted in different sites and setting on the shoe. As shown in Figure 18 (a), we selected four candidate positions: top, bottom, behind heel and side. The bottom location required us to dig the sole in order to avoid a direct contact between the sensor and the ground, which may damage the device and affect the data from the inertial sensors. No shoe modifications were needed for the other positions.

We conducted several walking trials in an indoor environment with a flat ground surface to determine the position that manifests consistent accuracy over time. At the start of each test, the sensors were firmly attached to the shoes and removed at the end to charge the battery. Figure 18(b) shows the cumulative distribution function of the step-to-step pitch (slope) variation for different sensor positions. The ground truth values were measured by placing an inclinometer on the floor at consecutive step positions. As expected, all sensor curves show a higher step-to-step variation compared to the ground curve, due to measurement noise. We remark that the sensor readings were collected while walking. Instead, the ground truth was collected by placing an inclinometer on the floor for few seconds. From Figure 18(b) we can infer that all sensor positions have similar performance. However the top position was found to be more consistent over independent mounting and walking trials.

8.4 Ground Slope Accuracy

To understand the accuracy of the underlying ground slope sensing technique and isolate different sources of error, we conducted the following controlled experiments. These experiments compare



(a) Alternate sensor positions (b) Sensor position analysis

Figure 18: Sensor position comparison.

the sensed slope against ground truth established with a 0.2 degree accurate inclinometer.

To remove errors from foot movement and walking, we first placed the unmounted sensor on a tilted plank and measured its slope. We then repeated this procedure with a shoe-mounted sensor. The process was further repeated for different plank inclinations. Figure 16(c) shows the mean error and standard deviation for these experiments, marked as fixed on plank and fixed on shoe, respectively. As can be seen, the errors are below the specified accuracy of our ground-truth inclinometer. We then continue the experiment with shoe that is actually worn, first by having an experimenter stand on the larger wooden plank shown in Figure 16(a), which had roughly the same length and inclination as a sidewalk ramp. In a second experiment, the experimenter walked over the plank. The results in the same figure are labeled standing on shoe and walking indoor. They show that standing results have slightly larger errors than the unworn shoe, likely due to some involuntary movements and that walking adds more noticeable but still small errors of about 0.4 degree. We further compare this with walking on an actual sidewalk ramp, where we measured the ground truth inclination at each footstep. The results show a slight increase in errors, presumably because the ground is not uniform, even within the area of a footstep. Overall, the errors are far below the expected slope variations at sidewalk ramps.

9. RELATED WORK

Pedestrian tracking using inertial sensors has been of interest to the research community for some time. Most inertial sensor- based applications use some form of dead reckoning for localization [24, 31]. They estimate the distance traveled from a known initial location, by using the stride length and implementing step count, as done by Cho et al. [32].

Robertson et al. [33] explore indoor localization for pedestrians using foot-mounted inertial sensors. Jimenez et al. [34] use ramp detection in indoor environments to provide drift correction in indoor locations. Woodman et al. [35] developed a tracking system that uses a foot-mounted inertial sensor, a model of a building, and a particle filter to track a pedestrian in an indoor environment. Skog et al. [36] developed a Kalman Filter-based zero-velocity detector for foot-mounted inertial navigation systems and evaluate their algorithm by errors in positioning. Madgwick et al. [37] develop an algorithm, which is compared to the Kalman Filter, for computing the orientation of foot mounted inertial sensors. Most of these navigation and orientation computation techniques are tested in controlled indoor environments and do not quite meet the requirements for any level of outdoor gradient sensing system.

In the pedestrian safety domain, Gandhi et al. [38] provide an overview of video, radar and laser distance measurement based approaches for active pedestrian safety. An RFID-based approach is discussed by Fackelmeier et al. [39]. Another approach that needs no line of sight and is based on 3G and WLAN is presented by Sugimoto et al. [40]. David et al. [41, 42, 43] present a radio based approach that assumes that the GPS location is precise up to 10 to 80 cm. They also add movement recognition to the radio-based solution [44]. Another pedestrian safety app by Wang et al. [11] uses the smartphone's camera to detect vehicles approaching the pedestrian when she is talking and walking. Camera-based approaches pose a challenge when it is dark and can easily drain the smartphone's battery. WiFi-honk by Dhondge et al. [13] could be a potential application for our system. They have developed a communication technique to transmit messages from pedestrian to approaching vehicles based on the pedestrian's risk level. Since our system can efficiently identify when pedestrians enter the street, their presence can be announced to approaching vehicles using this communication technique.

Pedestrian safety is now a high priority for car manufacturers. In AKTIV [45], a German road safety project launched in 2006, cameras and radar sensors installed on the vehicle are used to monitor its surrounding. Many car producers [46, 47, 48] are now integrating night vision, active breaking and automatic steering solutions in their new models to reduce pedestrian accidents. Honda is developing a Vehicle-to-Pedestrian technology that is able to detect a pedestrian with a DSRC enabled smartphone [10].

10. DISCUSSION

We have presented the design and experimental analysis of a shoe sensor-based technique, which, unlike previous work, aims at ground profiling rather than step counting. Our experiments show that foot mounted inertial sensors can be used to measure the slope of the ground and generate a corresponding slope profile, to detect when a pedestrian enters the street.

The approach does, of course, rely on instrumentation and power in shoes but it could potentially be an additional feature of existing shoe-mounted exercise tracking devices. It might also be suitable for special applications for some of the most vulnerable pedestrians (e.g., children, the elderly, people with disabilities). Furthermore, we observed that performance can be sensitive to the sensor mounting method and therefore believe that performance could be further improved with more robust mounting designs.

A convenient shoe sensing solution should also offer long battery lifetimes. Our current prototype is not optimized in this regard. To reduce the communication energy overhead, it would be desirable to move most of the sensor data processing from the smartphone into dedicated motion processor in the shoe itself. Wake-up mechanism should only activate the system when a pedestrian is walking in an urban area. Shoe sensing systems could also exploit energy harvested from walking movement. We expect that future careful circuit design with wake-up when walking and optimized low energy communications could achieve battery lifetimes of months to years, depending on the amount of walking activity.

Our current system primarily aims to reduce pedestrian-vehicle collisions that are due to the pedestrian being distracted by a smartphone. This is an increasing concern and we have focused our evaluation on a likely scenario: simply walking into the street without noticing. There are many other scenarios unrelated to smartphone distractions, such as running across a street, that put a pedestrian at risk. The shoe sensor approach may also be useful for such traditional pedestrian safety concerns, although we have not designed for or evaluated this case yet.

Similarly, we have not evaluated our framework for the elderly or children. We remark that although our user base was uniform in terms of age and walking style, our algorithm extracts the stance phase and compares users' steps to their past steps. Thus, this extraction can be adapted to various walking speed and style.

The transition detection approach also relies on consistent sidewalk designs. In the United States and the European Union, we are aware of conscious effort to follow consistent guidelines for improved accessibility, although regional customization of the algorithms may be necessary. In our experiments, we were able to detect street entrance events with high accuracy, whenever the sidewalk descends into the street either through a ramp or a curb. We encountered only one situation in which street entrances were hard to detect, i.e., the case where the sidewalk and the street are at the same level. However, the percentage of such crossing conditions was negligible in our experimental scenarios and is, in general, very low in urban environments [18, 23].

Besides safety applications such as Virtual Look Up or Driver Pedestrian Awareness, multiple applications could benefit from our approach. As an example, we have run some preliminary experiments which show that slope profiles can be matched to specific sidewalk locations, if a map of such profiles is available. While perhaps not yet robust enough on its own, the information could be combined with other positioning information to achieve more precise urban localization. Additionally, our approach could be used to create sidewalk profiles to monitor the status of the sidewalk surface and their accessibility.

11. CONCLUSION

Motivated by pedestrian safety applications, we explored how effectively shoe-mounted inertial sensors can profile ground gradients and step patterns to detect sidewalk-street transitions. We developed a sensing system to address this multifaceted problem ranging from sensory data acquisition on shoes to the development of a LookUp application. What also sets our approach apart is that we carried out walking trials in-the-wild and collected miles of data in complex metropolitan environments. Our results show a lot of promise achieving detection rates higher than 90% at 0.7% false positives, even in the intricate midtown Manhattan pedestrian environment. Not only did our approach work in the United States, we obtained similar performance from the Italian city of Turin. Overall, we hope that this work demonstrates the broader applicability of shoe-based sensing and inspires developments that go far beyond current exercise tracking applications.

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