PinMe: Tracking a Smartphone User around the World

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Abstract—With the pervasive use of smartphones that sense, collect, and process valuable information about the environment, ensuring location privacy has become one of the most important concerns in the modern age.

A few recent research studies discuss the feasibility of processing sensory data gathered by a smartphone to locate the phone's owner, even when the user does not intend to share his location information, e.g., when the user has turned off the Global Positioning System (GPS) on the device. Previous research efforts rely on at least one of the two following fundamental requirements, which impose significant limitations on the adversary: (i) the attacker must accurately know either the user's initial location or the set of routes through which the user travels and/or (ii) the attacker must measure a set of features, e.g., device acceleration, for different potential routes in advance and construct a training dataset.

In this paper, we demonstrate that neither of the above-mentioned requirements is essential for compromising the user's location privacy. We describe PinMe, a novel user-location mechanism that exploits non-sensory/sensory data stored on the smartphone, e.g., the environment's air pressure and device's timezone, along with publicly-available auxiliary information, e.g., elevation maps, to estimate the user's location when all location services, e.g., GPS, are turned off. Unlike previously-proposed attacks, PinMe neither requires any prior knowledge about the user nor a training dataset on specific routes. We demonstrate that PinMe can accurately estimate the user's location during four activities (walking, traveling on a train, driving, and traveling on a plane). We also suggest several defenses against the proposed attack.

Index Terms—Air pressure, auxiliary information, elevation map, navigational map, privacy, sensor, smartphone, tracking.

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1 Introduction

With widespread use of smartphones that can sense and collect environment-related data and process them to extract valuable information about the environment, ensuring privacy has become one of the most important challenges in the modern era. Indeed, rapid technological advances in electronics and mobile devices have led (and will continue to lead) to serious concerns about privacy in general, and location privacy in particular [1].

Modern smartphones are equipped with many compact sensors, e.g., accelerometers and barometers, and powerful communication capabilities in order to offer a variety of services. Although the numerous smartphone applications make the user's life convenient, they can also intentionally/unintentionally reveal personal or corporate secrets [2]–[9]. In particular, they can leak valuable data about the user's whereabouts, which can be processed to extract contextual information about his habits, regular activities, and even relationships [10], [11]. Moreover, disclosure of the user's location may expose him to location-based spams, scams, and advertisements, or make him a victim of blackmail or violence [1], [12].

With the emergence of enormous privacy concerns in the last decade, several privacy policies have been put in place to force organizations to take their users' privacy into account. In particular, the U.S. Congress introduced the Geolocation Privacy and Surveillance Act in 2011 to provide a legal framework for giving government agencies, commercial entities, and private citizens clear guidelines for when and how geolocation information can be accessed and used [13]. As a result, in all modern smartphones, an application must explicitly ask for the user's permission if it wants to access location services, e.g., GPS [14], [15].

A few recent research efforts have demonstrated the feasibility of locating smartphone owners without accessing GPS [9], [16]–[18]. For instance, Michalevsky et al. proposed PowerSpy [17], a mechanism that locates the user by processing the power consumption of the smartphone, when the user travels through a known set of routes. PowerSpy was able to detect 45% of driving trajectories in the best-case scenario. Han et al. showed that accelerometer readings can be used to estimate the trajectory and starting point of an individual who is driving [19]. They were able to return two clusters of possible starting points (each including five points) such that the starting point was within one of the clusters.

The successful demonstration of such attacks against location privacy suggests that revealing the user's location by processing presumably non-critical data is feasible. However, all previously-suggested attacks against location privacy mainly rely on at least one of the three following fundamental requirements.

- **Req. 1:** The attacker must either know the user's initial location (the exact GPS coordinates) or has *substantial prior knowledge* of the area through which the victim is traveling, e.g., the attacker assumes that the victim is traveling through a small set of known

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routes.

- **Req. 2:** The attacker must measure a set of features, e.g., power consumption [17], for different *potential routes* in advance and construct an attack-specific training dataset.
- **Req. 3:** The sensory data must be continuously collected at a *high sampling rate*, e.g., $30Hz$ [19], [20], which is significantly higher than the sampling rate needed for a majority of benign applications.

The first two requirements significantly limit the attacker's ability to locate the user in realistic scenarios, and the third can raise suspicion, making it easier to detect the attack [21]. Even with these requirements, previous attacks offer a rough estimation of the user's trajectory, as discussed later in Section 6.

This paper aims to demonstrate that none of the above-mentioned requirements is needed to accurately track the user when all location services, e.g., GPS, are off. We propose an attack on location privacy in which: (i) the attacker needs neither the user's initial location nor a small set of potential travel routes, (ii) he is not burdened with the construction of an attack-specific database, and (iii) he does not collect data at a high sampling rate, e.g., as demonstrated later, a sampling rate of $0.1Hz$ is sufficient to track the user when he is driving. The first two characteristics of the proposed scheme enable an attacker to launch an attack on a large scale, when he has no prior knowledge about users' initial locations or the set of routes through which he travels. The third one makes the attack invisible to known defenses that detect the maliciousness of an application based on its high sampling frequency, e.g., the defense in [21].

Our main contributions can be summarized as follows:

1) We develop PinMe, a location mechanism that enables an attacker to accurately locate the user using sensory/non-sensory data along with publicly-available auxiliary information.
2) We demonstrate how different types of seemingly-benign non-sensory data, e.g., the smartphone's timezone and network status, and sensory data, e.g., air pressure and heading, can offer sensitive information to the attacker who aims to locate the user.
3) We introduce five sources of publicly-available auxiliary information (public maps, transportation time tables, airports' specification databases, weather reports, and trains' heading dataset) that can be used in conjunction with smartphone's data to develop an attack against location privacy.
4) Unlike previously-proposed attacks [17], [19] that are focused on a single activity, e.g., driving, we demonstrate how a user can be located when he is: (i) traveling on a plane, (ii) walking, (iii) traveling on a train, and (iv) driving. As far as we know, PinMe is the first smartphone-based user location mechanism that aims to locate the user while undertaking different activities.
5) In order to evaluate the accuracy of the proposed location mechanism, we collect real-world data using three devices (iPhone 6, iPhone 6S, and Galaxy S4 i9500).

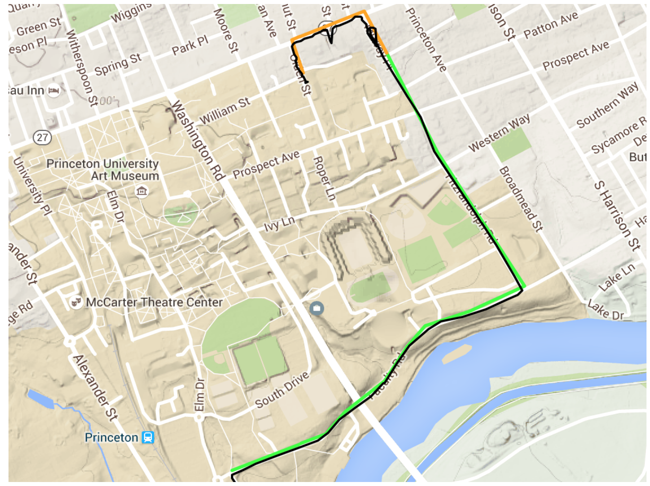

Fig. 1. PinMe could find and return the user's trajectory without accessing GPS data. The green and orange lines demonstrate the estimated paths traversed by the user during driving and walking, respectively. The black line is the actual user trajectory reported by GPS data.

6) We evaluate the accuracy of PinMe for estimating the user's location using two real-world datasets. We demonstrate that, unlike previous attacks, PinMe is able to accurately and uniquely return a trajectory that is comparable to GPS-based trajectory (Fig. 1).
7) Finally, we discuss defenses against the proposed attack.

To sum up, PinMe aims to offer a comprehensive (i.e., covering multiple activities) attack that minimizes the need to have prior knowledge about the user, removes the need for building attack-specific datasets, and uses the interdependence between seemingly-independent activities to obtain an accurate user trajectory. Our end-to-end evaluation demonstrates that PinMe works accurately (comparable to GPS) in real-world scenarios. As discussed in Section 5, protecting the user against this attack can be very challenging due to its robustness against potential sources of noise and the low sampling rate required for the attack.

The remainder of this paper is organized as follows. Section 2 provides the problem definition and discusses how the attacker can acquire the data needed for the proposed attack. Section 3 discusses PinMe comprehensively and describes different sources of information and algorithms used to implement the attack. Section 4 describes how we collected real-world data for evaluating PinMe and examines the accuracy of the proposed location mechanism. Section 5 suggests several countermeasures for mitigating the risks of the proposed attack. Section 6 summarizes related work. Section 7 discusses the limitations of PinMe and describes how we used the interdependence between activities to facilitate (and enhance the accuracy of) our proposed attack and how PinMe can be used as an alternative to GPS in autonomous cars to enhance their security. Finally, Section 8 concludes the paper.

2 Threat Model

In this section, we first describe several consequences of launching an attack against location privacy, and provide a brief description of our proposed attack. Then, we discuss how attackers can acquire the data that are required to launch the proposed attack.

2.1 Problem definition

Today's smartphones are equipped with several low-power high-precision sensors and powerful processors that enable them to continuously collect and process environment-related data. As a result, a modern smartphone carries several types of valuable data. Such data can be processed to reveal sensitive information about the phone's user. For example, the contextual information attached to movement traces conveys much about the user's interests, activities, and even relationships [1].

Launching an attack against location privacy can expose the user to unwanted advertisement, spams, or scams. Moreover, it can lead to several consequences, ranging from the uncomfortable feeling of being monitored to unwanted disclosure of personal activities or even actual physical harm [22]. For example, it may be embarrassing for a user if his/her relatives find out that he/she went to certain places, e.g., an HIV clinic or an abortion clinic. While these consequences are a direct result of manual inspection of leaked location-related information, several recent research efforts have investigated the feasibility of extracting other valuable information from the user's location-related information. For example, early research work in this area [23] explored the possibility of inferring information about the user's habits and detecting places important to him, e.g., his home and office, from GPS traces.

Although the importance of preventing location services, e.g., GPS, from leaking unwanted information has become clear, the extent of location-related information that can be inferred from presumably non-critical data, such as movement-related data, e.g., acceleration and heading, and environment-related data, e.g., air pressure, is neither well-known nor well-understood. This paper aims to demonstrate the possibility of accurately locating the smartphone's user using such presumably non-critical data stored on the phone.

2.2 Acquiring data

The attacker can obtain the smartphone's non-sensory and sensory data, which are required for the proposed attack, using one of the two following approaches:

Approach 1: Utilizing a malicious application

Smartphones are characterized by their ability to run third-party applications. Both Android and iOS offer hundreds of thousands of applications through their application markets. Such markets benefit developers by simplifying application sales and distribution. The existence of huge application markets might also enable cyber criminals to distribute a malicious application in an attempt to steal personal information stored on the phone, e.g., credit card numbers and personal photos. Fortunately, such critical information is commonly protected by the smartphone's operating system, and users are also very careful about sharing their personal information with third parties. However, several types of non-sensory/sensory data, which are stored on the smartphone, are either loosely-protected or not protected at all, e.g., gyroscope, accelerometer, barometer, and magnetometer measurements are accessible by an application installed on the smartphone without requiring user's approval. As a result, a malicious application that is installed on the smartphone and runs in the background can continuously capture such data without arousing suspicion.

Approach 2: Accessing a presumably trusted application server

Several trusted applications upload their data to the cloud. For example, the majority of fitness monitoring applications continuously collect and upload the user's data to the cloud. The collection of the data in the cloud enables the user to access and share his fitness statistics with his family, friends, and peer groups. A recent report by the mHealth development industry [24] estimates that there are about 100,000 applications dedicated to health and fitness. Such applications can, without arousing suspicion, collect and upload a significant amount of valuable non-sensory/sensory data, which can be post-processed to infer critical information about the user. In particular, as we demonstrate later, an attacker, who can access such application databases, e.g., the application development company or an individual who has access to the data shared by the user, can post-process such data to estimate the past locations of the user.

Our approach: In this paper, we assume that the proposed location mechanism obtains the required non-sensory/sensory data using the first approach. In fact, we installed an application on the smartphone that continuously collects the required data. We assume that the application does not have access to GPS. Moreover, the application has no permission to query the identity of visible cellular base stations or the service set identifier (SSID) of visible WiFi networks. To sum up, we assume that the attacker only uses presumably *non-critical data collected by a malicious application along with publicly-available auxiliary information to reveal the user's location.* The proposed attack does not rely on careless behaviors of the user (e.g., a careless user may just accept all permission requests, including a request to access GPS data, without carefully reviewing them). In fact, PinMe aims to demonstrate the feasibility of a privacy attack against careful users (for example, a user who checks what he shares with third-party applications, minimizes the access level of untrusted applications, and even turns off all location services when he travels through sensitive routes to ensure his location privacy). The introduction of this attack sheds light on the possibility that a third party, which has an application on the user's smartphone, can potentially extract his sensitive location information without asking for any permission (except Internet connectivity that is needed for sending either raw data or inferred location to the third party).

3 The Proposed Location Mechanism

In this section, we describe PinMe, the proposed location mechanism. First, we introduce the main sources of information that are given to PinMe as inputs. Second, we describe various algorithms that we have designed and implemented to locate the user in scenarios involving different activities.

TABLE 1
Smartphone's Non-Sensory Data

Non-sensory data	Description
Timezone (TZ)	Specifies the device's current timezone (i.e., a region including the cities/states that have the same time)
Device's address (IP)	Provides the phone's IP address when it is connected to the Internet
Network status (NS)	Specifies whether the smartphone is connected to a WiFi or a cellular network

TABLE 2
Smartphone's Sensory Data

Sensor	Sensory data
Accelerometer	Magnitudes of the acceleration in three-dimensional space
Magnetometer	Angle between device's actual orientation relative to true north (heading)
Barometer	The environment's air pressure

3.1 Sources of information

PinMe exploits two main sources of information: (i) non-sensory/sensory data collected by the smartphone, and (ii) publicly-available auxiliary information. Next, we describe each source in more detail.

3.1.1 Smartphone's non-sensory/sensory data

An application installed on the smartphone can obtain several types of non-sensory and sensory data without requesting user's approval. Non-sensory data provide general information about the device, e.g., the version of the device's operating system, current timezone, IP address, the amount of available storage, and network status. Table 1 summarizes different forms of non-sensory data that PinMe uses to locate the user during different activities, along with a short description of each.

In addition to the non-sensory data, sensory data collected by the smartphone's built-in sensors provide valuable information about the user's movements and the environment in which the smartphone is located. Table 2 includes different sensors that are accessed by PinMe and sensory data provided by each sensor.

3.1.2 Publicly-available auxiliary information

The proposed user location mechanism uses several types of auxiliary information to narrow the area of interest. In particular, it utilizes five main types of information: (i) public maps, (ii) weather reports, (iii) airports' specifications database, (iv) trains' heading dataset, and (v) transportation timetables. Next, we describe each information type.

Public maps: The proposed mechanism uses two widely-known map types:
1. Navigational map: A navigational map mainly depicts roads, highways, and transportation links. Such a map can specify a large set of possible routes through which the user can travel. PinMe uses OpenStreetMap (OSM) [25] maps. OSM maps can be downloaded as Extensible Markup Language (XML) files that can be easily processed and modified.
2. Elevation map: An elevation map contains the elevation, i.e., the height above or below the Earth's sea level, of all points on the Earth's surface. Several commercial, e.g., Google Map API [26], and governmental services, e.g., U.S. Geological Survey Maps [27], provide comprehensive elevation data of the world surface. For instance, the Google Map API offers a free and publicly-available interface that can be used by developers to fetch the elevation of a point of interest, given its longitude and latitude.

Weather reports: Weather reports offer different types of information collected by weather stations. We use weather reports provided by The Weather Channel [28]. They include temperature, humidity, and air pressure readings at weather stations, and the actual elevation of the weather station. PinMe uses weather reports to estimate the elevation of the smartphone using its air pressure reading. The use of weather reports is essential for accurately estimating the elevation of the smartphone since the air pressure readings are highly dependent on both elevation and weather conditions.

Airports' specifications databases: PinMe uses OpenFlights [29], the most comprehensive freely-available airports' specifications database, which includes elevation information, GPS coordinates, and timezone of 9541 different airports around the world.

Trains' heading databases: Trains' heading database is a simple database that includes the trains' directions at each station. We have constructed this database based on Google Map [30]. For each train station considered in our experiments, we extract different potential movement directions based on the illustration of the stations' tracks on Google Map. Note that each track in a station can have two possible headings corresponding to a train entering and leaving the station.

Transport timetables: Transport timetables contain information about service times to assist passengers in planning their trip. A timetable lists the times when a service is scheduled to arrive (depart) at (from) specified locations[1]. The two most common types of transport timetables are flight and train timetables. These timetables are often available in a variety of electronic formats, e.g., PDF files, and are commonly posted on airports'/stations' websites. They are also accessible through various APIs.

3.2 Main Algorithms

Next, we describe the main algorithms that we have designed and implemented for estimating the user's location. PinMe is implemented using Python and Matlab, and our prototype implementation includes about 2000 lines of code. It has three main steps: (i) pre-processing, (ii) activity classification, and (iii) location estimation. *Algorithm I: PinMe* provides a simplified pseudo-code of the proposed location mechanism. Next, we describe each step in more detail.

Algorithm I: PinMe

Given: The smartphone's sensory data (D), non-sensory data (IP, NS, and TZ), and all sources of publicly-available auxiliary information (allAux: public maps, weather reports, airports' specifications databases, trains' heading databases, transport timetables)

//Step 1: Pre-processing
  $lastWiFiIP \leftarrow findLastWiFiIP(NS, IP)$
  $city \leftarrow IPGeolocation(lastWiFiIP)$
  $aux \leftarrow getAux(allAux, city)$
  $chunks[] \leftarrow streamPartitioning(D)$
//Step 2: Activity classification
  $acts[] \leftarrow activityClassifier(chunks[])$
//Step 3: Location estimation
  for each activity in $acts[]$
    $[city, loc[i]] \leftarrow Estimator(chunks[i], acts[i], aux, city)$
  end
  $return\ loc[]$

3.2.1 Pre-processing

In this step, PinMe first recognizes the last city in which the user was connected to a WiFi network and gets the required sources of auxiliary information for the potential city of interest. Second, it breaks the sensory data into several chunks so that each chunk is associated with a single activity.

1. Inferring the city: When the smartphone is connected to a WiFi network, IP geolocation techniques can process the device's current IP address and return the city in which the smartphone is located. Although such techniques can accurately locate the smartphone when it is connected to a WiFi network, they usually fail to locate it when connected to a cellular Internet network [31], [32].

Both iOS and Android allow an installed application to determine whether the smartphone is connected to a WiFi or a cellular network. In order to find the last city in which the user was connected to a WiFi network, PinMe processes the previous readings of smartphone's Network Status (NS) and IP address to find the last IP address of the smartphone when it was connected to a WiFi network, and feeds that IP address to $IPGeolocation(...)$. Then, PinMe obtains different types of auxiliary information about the city, e.g., its maps. *PinMe does not assume that the user remains in the same city*. However, it starts tracking the user from that city. In fact, the user's current city becomes regularly updated based on his past movements.

2. Data stream partitioning: In the pre-processing step, PinMe also breaks the long data stream collected over a long time period, e.g., a day, into data chunks so that each chunk only includes the data associated with one activity. Based on our empirical analyses, a simple pattern in the acceleration data can indicate that a new activity has commenced: in the transition from one activity to another, the accelerometer measures a series of large absolute acceleration readings (larger than 25 m/s^2) in a short time frame due to the fact that there is always a transition from standing (sitting) position to sitting (standing) position between two activities. This is the pattern PinMe uses to break the data stream into small data chunks. Unfortunately, a similar pattern might be present in the acceleration data collected during a single activity, e.g., when the user suddenly moves or falls. Therefore, it is possible that PinMe falsely detects the start of a new activity even when the user's activity has not changed. However, this does not negatively impact the accuracy of the location mechanism because as described later, for all activities, the activity classifier accurately detects the user's activity and PinMe can merge consecutive data chunks into one data chunk when the user's activity has not changed.

3.2.2 Activity classification

In this step, the activity classifier aims to specify the user's activities. Throughout the paper, we assumed that the user takes part in one of the four activities mentioned earlier: driving, traveling on a plane, traveling on a train, and walking. To classify these activities, we have implemented two classification methods: (i) a traditional machine learning-based method that relies on building models to label the user's activities, and (ii) a tailored algorithm designed to deduce the user's activities based on the physical characteristics of each activity.

To the best of our knowledge, the activity classifiers utilized in PinMe are the first activity classification mechanisms that use air pressure data as a primary source of data for activity classification, and the first to use macro-level features, e.g., the number of turns and the rate of change during a turn, of heading data. Our examination of real-world data shows that air pressure and heading can offer valuable discriminatory information for activity classification.

Fig. 2 illustrates how the smartphone's heading changes in four data chunks collected during different activities. Among all activities, traveling on a train is the only one in which the smartphone observes *no significant change in heading data*. Note that heading data are measured clockwise from true north and vary from 0° to 359°.

1. The actual destination/departure time may vary from the scheduled destination/departure time due to transportation delays. However, accurate information about the service is added to transport timetables after departure.

Fig. 3 shows how air pressure changes during different activities. Traveling on a plane is the only activity in which *a fast significant drop in the environment's air pressure* was noticed.

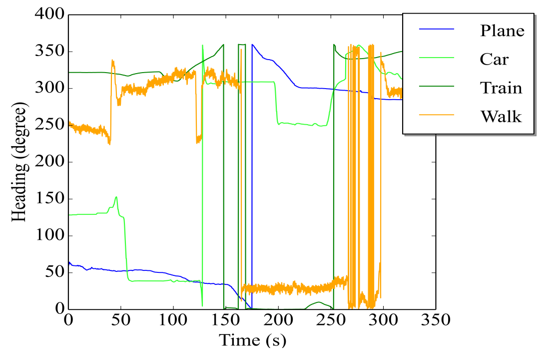

Fig. 2. Heading data collected during four different activities. Heading data are measured clockwise from true north and varies from 0° to 359°. The smartphone's heading only slightly changes when the user is traveling on the train (within a 30-degree range).

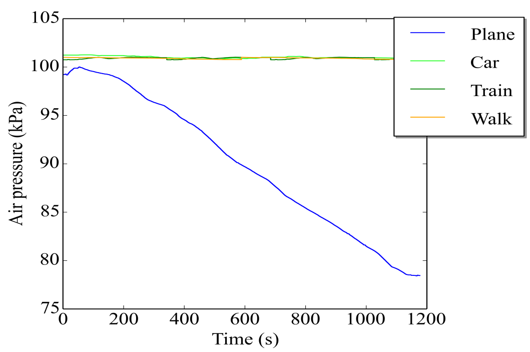

Fig. 3. Air pressure data collected during four different activities.

Next, we describe each of the above-mentioned methods.

Method 1: Machine learning-based classification

A classical approach to implementing an activity classification mechanism is to devise a scheme based on a supervised machine learning algorithm, which builds a model using labeled training data. The training dataset used for activity classification is not attack-specific (attacker can collect the required data using his own smartphone while traveling through unknown paths). This mechanism consists of three steps: feature extraction, binary classification, and decision making. Upon receiving a data chunk, the feature extraction step generates a feature vector. This vector is then sent to four binary classifiers, each trained to only detect a single activity. Finally, the decision making step returns the user's activity based on the outputs of the binary classifiers. Next, we discuss how each of these steps is implemented in our proposed scheme.

1. Feature extraction: Previous research efforts [33]–[37] have suggested a variety of features that can be extracted from acceleration data and be used to classify various user activities. In our mechanism, we use several features extracted from heading and air pressure data along with a few previously-proposed acceleration-related features. Each feature vector includes: time-domain features (mean, median, and standard deviation) and frequency-domain features (principal frequency and spectral energy) extracted from each dimension of acceleration readings, time-domain features (mean, median, and standard deviation, and range) from air pressure, and macro-level features (number of turns and maximum rate of change in heading over 1-second windows) from magnetometer readings.

2. Binary classifiers: In order to implement binary classifiers, we use Linear Support Vector Machine (LSVM) [38]. LSVM is one of the simplest, yet powerful, binary classification methods. The basic concept behind an LSVM is to find a hyperplane that separates the n-dimensional data into two classes. When no prior knowledge about the dataset is available, LSVMs usually demonstrate promising results and generalize well. They construct a decision boundary with the largest possible distance to data points. As described later in Section 4.2.1, our LSVM-based activity classification algorithm accurately distinguishes different activities, which are discussed in this paper, from each other. Therefore, we did not consider more advanced classification algorithms (for example, neural networks [39]). The binary classifiers used in the proposed scheme are trained so that each classifier can only recognize a single activity.

3. Final decision making: The final decision making step receives the classifiers' outputs, and returns an output as follows: if only one classifier detects the activity, it returns the activity associated with that classifier, otherwise, it returns a message stating that the activity is not recognized.

Method 2: Tailored algorithm

In addition to the machine-learning based method, we have developed a simple, yet accurate, classification algorithm. The simple tailored algorithm classifies the user's activities based on each activity's physical characteristics. We examine several data streams collected by the smartphone during different user activities. For each activity, we extract a set of characteristics that only pertains to that activity. Table 3 summarizes these characteristics.

3.2.3 Location estimation

In order to estimate the user's location, we have implemented four algorithms, referred to as location estimators. Upon detection of the user's activities ($acts[]$) using the activity classifier, for each activity, PinMe calls $Estimator(...)$ that executes one of the four location estimators to find the user's locations. For each location estimator, Table 4 summarizes the required non-sensory/sensory data and auxiliary information given to it and the outputs provided by each algorithm. Next, we describe the four proposed location estimators in more detail.

Algorithm 1: carTracker: Unlike the method in [20] that uses barometer measurements sampled at *a very high frequency* ($30Hz$) to provide *a rough estimation* of the user's trajectory, this algorithm can process heading and air pressure readings collected at a very low sampling rate ($0.1Hz$, as shown in Section 5.1) to provide an accurate tracking mechanism. It has three main steps:

Step 1: Map construction: Prior to tracking the user, PinMe constructs a labeled directed graph G using both elevation and navigational maps of the city so that its vertices and edges represent the intersections and roads between intersections, respectively. Labels of vertices are the elevation of

TABLE 3
Discriminatory characteristics of each activity

Activity	Characteristics
Driving	Irregular positive (negative) accelerations as the driver accelerates (brakes) Specific changes (around 90 degrees) in the smartphone's heading as the car turns
Traveling on a plane	Rapid changes in the timezone Significant increase/decrease of air pressure in a short time frame
Traveling on a train	Regular positive (negative) accelerations in one direction as the train leaves (reaches) a station No significant changes in the smartphone's heading
Walking	Very frequent periodic acceleration changes in one direction, no matter how the device is held

TABLE 4
The required non-sensory/sensory data and auxiliary information given to each location estimator and the outputs provided by each algorithm

Location estimator	Inputs	Outputs
Algorithm 1: carTracker	Air pressure, heading, public maps, and weather reports	The initial and last locations and cities, and the car's estimated trajectory
Algorithm 2: planeTracker	Air pressure, acceleration, TZ, weather reports, airports' specifications databases, and flight timetables	The destination and departure airports
Algorithm 3: trainTracker	Acceleration, heading, train timetables, and trains' heading databases	The destination and departure stations
Algorithm 4: walkingUserTracker	Air pressure, acceleration, heading, weather reports, and public maps	The user's last location and trajectory

the intersections extracted from the navigational map and the angle between roads connecting to that intersection.

Step 2: Pruning set of probable candidates: At each moment of time, the algorithm has an array of trees (the set of probable paths with different starting points, referred to as P) where each tree represents a sequence of intersections on the navigational map. Prior to the attack, this array contains all vertices of G, indicating that the first turn can be at any intersection. Upon the detection of a turn (e.g., an almost 90-degree change in the heading data), the algorithm prunes and updates the set of trees as follows. For each probable path (each tree in set P), it drops the path if all neighbors of its last vertex do not meet the following conditions: the elevation or relative changes in the heading direction of all neighbors (represented as labels of vertices in graph G) do not match their values extracted from sensory data.

Step 3: Updating the remaining candidates: At each turn, if a tree is not dropped from the set, the algorithm adds all neighbors (intersections) that meet the above-mentioned conditions to the tree. Eventually, it sorts paths in P based on their error, defined as the weighted sum of absolute differences between the extracted features from the sensory data and their actual values reported in navigational/elevation data, and returns the most probable path from the set (the path with the lowest error).

Although the number of intersections of a city is large, we observe based on experimental results that *the number of intersections that can be a part of a candidate path drops extremely fast from thousands to only a few after the first few turns*. As a result, the size of set P is reduced quickly as the algorithm removes many impossible candidates when they become inconsistent with new data. This is demonstrated later in Section 4.

Note: Although there is a well-known physics equation [40] for estimating elevation (relative to sea level) based on air pressure measurements alone, it does not provide an accurate estimation of the elevation in practice since barometer measurements significantly depend on weather conditions. To accurately estimate the elevation (H_{turn}) of a turn point, given the air pressure measured at the point (P_{turn}), PinMe first extracts the air pressure ($P_{station}$), elevation ($H_{station}$), temperature information (T), and humidity (indicated by a constant C) at $city$'s weather station, provided by its weather report, and then uses the following physics equation [41]:

$$H_{turn} = H_{station} + \frac{T}{C} ln(\frac{P_{turn}}{P_{station}}) \quad (1)$$

Algorithm 2: planeTracker: *planeTracker* first extracts three features from the raw data provided by the smartphone: (i) flight time data (takeoff and landing times and flight duration), (ii) TZ and elevation of the departure airport, and (iii) TZ and elevation of the destination airport. In order to extract these features from the raw data, the algorithm first recognizes different aviation phases of the flight (pre-flight, takeoff, cruising, descending, landing, and taxiing to the gate) by processing acceleration and elevation data collected by the smartphone during the flight. Then, it calculates the flight duration as the time difference between the pre-flight phase (i.e., when the plane leaves the gate at the departure airport) and taxiing phase (i.e., when the plane reaches the gate at the destination airport). Moreover, it stores the device's air pressure and TZ in both the pre-flight and taxiing phases. Afterwards, it calculates the elevations of both departure and destination airports, given the weather report (including the air pressure reading at $city$'s weather station and its elevation data). Then, it searches through the airports' specifications database to find the flight routes, which have the following characteristics: (i) the TZ of both destination and departure airports reported by the smartphone matches the ones reported in the database, (ii) the difference between elevation measured from air pressure data and elevation extracted from the database is less than a small threshold, e.g., $T_{elevation} = 5m$, and (iii) the difference between flight duration measured from acceleration data and flight duration extracted from the database is less than a certain threshold, e.g., $T_{duration} = 1h$.

Given timetables of probable departure/destination airports, *planeTracker* returns the routes for which both takeoff time and landing time almost match their corresponding times provided by timetables, e.g., $\Delta T_{landing}, \Delta T_{takeoff} < 1h$, where $\Delta T_{landing/takeoff}$ is the difference between landing/takeoff times extracted from sensory data and their expected values in timetables.

Algorithm 3: trainTracker: Acceleration data can reveal different transportation phases, e.g., when the train leaves or approaches a station, and the combination of acceleration and heading data provides an approximation of the train's heading. This algorithm has two main steps:

Step 1: Extracting features: It first extracts three features from the raw acceleration and heading data: (i) travel intervals (an array T), defined as the difference between the time the train leaves a station and the time it reaches the next station, (ii) departure time $T_{departure}$ that represents when the train left the first station, and (iii) train's heading, i.e., an approximation of the direction of the train's movement at the first station.

Step 2: Searching through the timetable: After extracting the above-mentioned features from the raw data, this algorithm searches the timetables of $city's$ stations to find the most probable route. It first constructs T_{train} for all trains that already left or will leave the current city around the departure time (within $T_{departure} - 1h$ to $T_{departure} + 1h$) as follows: each T_{train} is itself an array including travel intervals for a single train. Then, for each T_{train} in the list, it computes the difference between travel intervals extracted from the sensory data (T) and T_{train}, i.e., $D = \sum_{n=1}^{length(T)} |T[i] - T_{train}[i]|$. If the difference between T and T_{train} is below a certain threshold (i.e., $D < 2mins \times length(T)$), the route corresponding to T_{train} is added to the set of probable routes (P). Then, the algorithm prunes P by removing routes for which the difference between the trains' heading extracted from the sensory data and the actual value of heading reported in trains' heading database is above a certain threshold (30 degrees). Finally, from the remaining routes, it returns a single route corresponding to the lowest D in the set.

Algorithm 4: walkingUserTracker: This algorithm assumes that the user walks through the walking areas (roads or sidewalks) of the navigational map. We have implemented two different versions of the algorithm. The first version searches through the whole map to find the user's trajectory. However, to find the initial location of this activity, the second version only considers a small area ($300m \times 300m$) on the map around a given location (in real-world scenarios, this location is determined by a previous activity). Next, we describe the first version that has three steps (the second version is similar, however, it only considers a smaller set of nodes to find the initial point).

Step 1: Map construction: Prior to the attack, *walkingUserTracker* constructs a graph G similar to the one generated for *Algorithm 1: carTracker*, with a slight difference: the graph also has a label on each edge that represents the length of the corresponding road extracted from the navigational map. Similar to *carTracker*, the algorithm maintains an array of trees (the set of probable paths with different starting points, referred to as P) where each tree represents a sequence of intersections on the navigational map.

Step 2: Pruning the set of probable candidates: The algorithm extracts the steps and their directions from the raw acceleration and heading data and elevation of intersections from air pressure readings. Upon the detection of a turn (e.g., an almost 90-degree change in the heading), the algorithm updates the set of trees as follows. For each probable path, it drops the path if all neighbors of its last vertex do not meet at least one of the following conditions: (i) all labels of edges that connect the last vertex to it neighbors ($D[i]$s) do not match the estimation of the traveled distance calculated based on the number of steps (for example, all $D[i]$s are not within the range of $0.4m \times \#steps$ to $1.2m \times \#steps$), or (ii) the elevation or relative changes in heading direction of neighbors do not match their values extracted from sensory data.

Step 3: Updating the remaining candidates: At each turn, if a tree is not eliminated, the algorithm extends it by adding all neighbors (intersections) that meet the above conditions. This algorithm sorts paths P based on their error, defined as the weighted sum of absolute differences between the extracted features from the sensory data and their actual values given by maps, and returns the path with the lowest error.

Note: Although this algorithm uses an estimation of the distance walked by the user to find the trajectory, it can also accurately estimate the user's step size upon the detection of a unique path. It uses the information gathered in the last sidewalk/road (e.g., total number of steps) along with information offered by the navigational map (e.g., the total length of the last sidewalk/road) to adaptively estimate the user's step size. Upon the detection of a unique trajectory, the estimation of the step size enables the algorithm to accurately estimate the user's location on the road.

4 Evaluation of the Proposed Mechanism

In this section, we first describe our data collection procedure. Then, we examine the accuracy of PinMe using real-world data.

4.1 Data collection procedure

We start with the description of the data collection procedure.

4.1.1 Device characteristics and experimental configurations

The proposed location mechanism is evaluated on three smartphones (Galaxy S4 i9500, iPhone 6, and iPhone 6S). Each device is equipped with an internal GPS device and several high-precision sensors including, but not limited to, a 3/6-axis accelerometer, magnetometer, and barometer.

As mentioned earlier in Section 3, PinMe processes various types of sensory data (air pressure, heading, and acceleration) and non-sensory data (the device's TZ, IP, and

NS). In order to collect the required data using Galaxy S4 i9500, we developed an Android application that continuously records the non-sensory/sensory readings of the device. Moreover, we installed a sensor data logger application on both iPhone 6 and iPhone 6s, called SensorLog [42], which continuously records the required non-sensory/sensory data. In our data collection procedure, sensory data are collected at the sampling frequency of $5Hz$. In addition to the above-mentioned data, the applications installed on the smartphones also collect GPS readings. GPS data are only used to evaluate the accuracy of PinMe in estimating the user's location (PinMe does not access GPS data).

4.1.2 Datasets

We constructed two datasets using real-world data. The first dataset consists of several data chunks, i.e., sequences of consecutive readings of non-sensory/sensory data collected during one activity. The second dataset includes three non-sensory/sensory data streams collected by the three under-experiment smartphones for a whole day. Next, we briefly describe each dataset. During the collection of each data chunk, the smartphone's orientation was almost fixed, however, the actual orientation of the smartphone was unknown in all cases.

Dataset #1: This dataset consists of 405 data chunks collected during different user activities where each data chunk contains consecutive readings of air pressure, heading, acceleration, and the device's TZ, IP, and NS during each activity. Table 5 shows the number of collected chunks for each activity. Next, for each activity, we briefly describe how we collected real-world data.

TABLE 5
Number of data chunks in Dataset #1 for each activity

Activity	Number of data chunks
Driving	271
Traveling on a plane	4
Traveling on a train	30
Walking	100

1. Driving: A user, carrying an iPhone 6, drove in three different cities. 271 data chunks were collected, where each chunk contains the smartphone's data during one driving period. Table 6 shows the cities in which the user drove, their population, the state in which each city is located, the number of collected data chunks, total traveled distance, and the average traveled distance for each city. To provide a fair evaluation, we tried to collect data chunks from different areas (both dense and sparse) of these cities.
2. Traveling on a plane: We collected four data chunks when the user traveled on four different airplanes on four different flight routes: (i) from Philadelphia to Dallas, (ii) from Dallas to New York, (iii) from College Station to Dallas, and (iv) from Dallas to College Station. All four data chunks were collected using iPhone 6S.
3. Traveling on a train: We collected 30 data chunks using an iPhone 6s when the user traveled on a train (10 chunks for Princeton Junction Station to New York, 10 chunks for Baltimore Penn Station to New York, and 10 chunks for Washington D.C. Union Station to New York).
4. Walking: We collected 100 data chunks when the user walked carrying an iPhone 6. These data chunks were gathered in Princeton.

TABLE 6
Cities, their populations and state, and the number of driving chunks, total traveled distance, and the average traveled distance for each city

City name	Population	State	Chunks	Total distance	Average distance
Princeton	12307	NJ	105	327km	3.11km
Trenton	84308	NJ	111	293km	2.63km
Philadelphia	1.5M	PA	55	157km	2.85km

Dataset #2: This dataset includes three data streams collected by three users while going through their regular daily activities. Two users were located in Princeton, NJ and one user was located in Baltimore, MD. In order to construct this dataset, we asked the users to choose and carry one of the three under-experiment smartphones (Galaxy S4 i9500, iPhone 6, and iPhone 6S).

4.2 Accuracy evaluation

In the following, we first evaluate the accuracy of the two main steps of PinMe (activity classification and location estimation) using Dataset #1. Then, we use Dataset #2 to provide an end-to-end evaluation.

4.2.1 Step-by-step evaluation

Next, we evaluate the accuracy of the activity classifier and location estimators using Dataset #1.
Evaluating the activity classifier
We evaluated the two activity classification methods discussed in Section 3 using Dataset #1. In the machine-learning based approach, we used 50% of the collected data chunks for training the binary classifiers, and tested the accuracy of the scheme using data not used in the training phase. In the other approach, we used all data chunks to test the accuracy of the tailored algorithm. Both methods provided a classification accuracy of 100%, where classification accuracy is defined as the ratio of correctly recognized activities to the total number of activities processed by the activity classifier. A high classification accuracy was expected since each of the supported activities (driving, traveling on a plane, traveling on train, and walking) has unique physical characteristics that differentiate it from other activities.
Evaluating the location estimators
Next, we examine how accurately the four location estimator algorithms discussed in Section 3 can estimate the user's location.
Algorithm 1: carTracker: In order to evaluate the accuracy of *carTracker*, we used 271 data chunks from Dataset #1, which were collected in three different cities (Table 6). Next, we examine how accurately this algorithm can locate the user when it returns the most probable driving path from the set of probable driving paths and how the size of the set

changes with respect to the number of turns in the driving path.

Fig. 4 shows the average approximation error with respect to the number of turns. The approximation error is defined as the distance between the actual location (as provided by GPS sensor) and the estimated location (as estimated by PinMe) of the user, divided by the total traveled distance (computed by processing GPS readings). In our experiments, the number of turns varies between 4 and 17. As can be seen from this figure, as the number of turns increases, the approximation error of the estimator typically decreases.

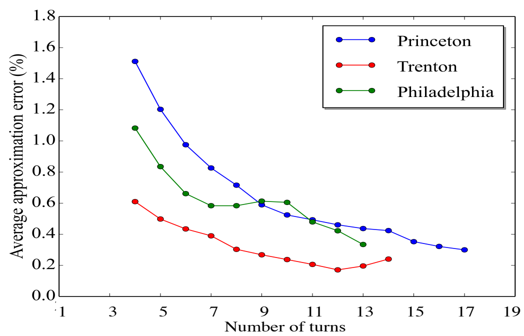

Fig. 4. Average approximation error with respect to the number of turns. The average approximation error is less than 1.5% in all cases.

We examined how the number of possible driving paths decreases when the number of turns in the driving path increases. Fig. 5 illustrates the number of possible driving paths with respect to the number of turns. As can be seen, the number of possible driving paths drops rapidly as the number of turns increases.

To sum up, as the number of turns increases, PinMe collects more information about the user's environment, and as a result, it is more likely to find a unique driving path on the map.

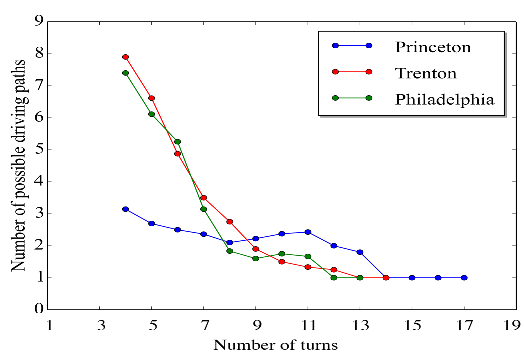

Fig. 5. Number of possible driving paths with respect to the number of turns.

Algorithm 2: planeTracker: We examined the accuracy of *planeTracker* in finding departure and destination airports using Dataset #1. As shown in Table 5, we collected four data chunks while traveling on a plane. Despite the existence of potential differences between the approximated values of takeoff time, landing time, and elevation, and their expected values reported in airports' specification database and flight timetables, *planeTracker* was able to *accurately and uniquely* return both departure and destination airports for all four flight routes.

For each of the four data chunks, we examined how much the approximated takeoff time, landing time, and elevation readings extracted by processing the smartphone's sensory data differ from their expected values calculated by processing publicly-available auxiliary data (airports' specification database and flight timetables), and noticed that: (i) the average difference between estimated elevation reported by the smartphone and the elevation extracted from airports' specification database was $2.3\ m$, (ii) the average difference between the estimated flight duration and the actual flight duration was 4% of the actual duration, (iii) the difference between approximated takeoff time and the takeoff time reported in the flight timetable (flight delay) was 17 minutes.

In addition to the above-mentioned analyses, we also examined the discriminatory power of the features extracted by *planeTracker* (flight duration, TZs, and elevations of both destination and departure airports) using Monte Carlo simulation methodology [43]. We considered two scenarios: (i) similar to above-mentioned real-world cases, both departure and destination airports are unknown and *planeTracker* returns the flight route (departure and destination airports), and (ii) attacker knows the departure airport from a previous activity, e.g., driving to the airport, and he only wants to identify the destination airport. For each scenario, we generated 500 random flight routes assuming that (i) for each route, the difference between the estimated flight duration and actual flight duration varies between 0% and 10% of the actual duration, and (ii) the difference between the estimated elevation reported by the smartphone and the elevation extracted from airports' specification database varies between $0\ m$ and $5\ m$. We slightly modified $planeTracker$ so that it returns the three most probable flight routes using the extracted features (without even using flight timetables). After finding a set of probable flight routes, it sorts the routes based on their error, defined as the weighted sum of absolute differences between the features (elevation and flight duration) calculated from sensory data and their expected values extracted from airports' specifications database.

Fig. 6 demonstrates how accurately $planeTracker$ is able to find the actual flight route without knowing the departure airport, where accuracy is defined as the number of cases in which the actual flight route was among the three returned flight candidates divided by the total number of trials (500). Similarly, Fig. 7 shows how accurately $planeTracker$ can find the destination airport, given the departure airport. Despite the presence of potential differences between the approximated duration and elevation and their expected values, in the majority of cases, *planeTracker* was able to find a set of three routes/destination airports that includes the actual flight route/destination airport, as illustrated in Fig. 6 and Fig. 7, respectively.

Algorithm 3: trainTracker: As mentioned earlier, *trainTracker* returns both departure and destination stations. We examined the accuracy of the tracking mechanism in finding actual traveling routes using the 30 data chunks collected by the smartphone (10 chunks for Princeton Junction Station to

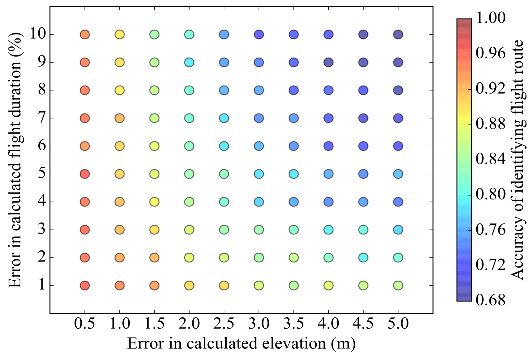

Fig. 6. Accuracy of $planeTracker$ in providing a set of three potential candidates so that the actual flight route is in the set.

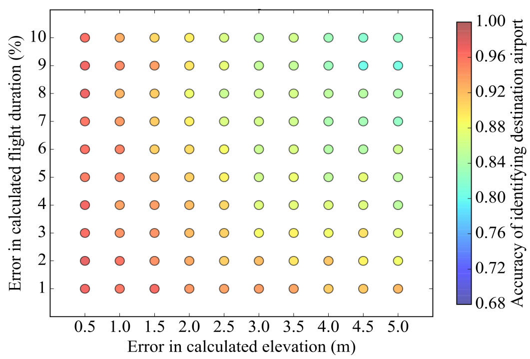

Fig. 7. Accuracy of $planeTracker$ in providing a set of three potential destination airports (given the departure airport) so that the actual destination airport is in the set.

New York, 10 chunks for Baltimore Penn Station to New York, and 10 chunks for Washington D.C. Union Station to New York). Our experimental results demonstrated that *trainTracker* was able to accurately identify the user's travel route in all trials.

Algorithm 4: walkingUserTracker: As mentioned earlier, two different versions of *Algorithm 4: walkingUserTracker* have been implemented: one that searches the whole map, and the other one that assumes the initial location is within a small area ($300m \times 300m$) around the final location of the last activity. Fig. 8 shows how the number of possible walking paths will change with respect to the number of walking steps for the first version of the algorithm. Based on our empirical results, although the possible number of candidates is reduced quickly, the possibility of each of them at each moment of time is similar to the others (i.e., when the number of steps is small, uniquely distinguishing the actual path is not feasible). As shown in Fig. 8, in order to return a unique accurate path, the first version of the algorithm requires a long stream of sensory data (i.e., the user should walk over 2500 steps). We observed that, in real-world scenarios, users usually walk shorter distances (including only a few different roads) preceded by other activities (commonly driving). Thus, to accurately track the user in real-world scenarios during multiple activities, we suggest using the second version of the algorithm that utilizes the data provided by the previous activity.

We examined how accurately the second version of *walkingUserTracker* estimates the user's location. Fig. 9 shows the approximation error for all walking trials with respect to the number of steps, where approximation error is defined as the distance between the user's actual location (as provided by GPS sensor) and the user's estimated location (as estimated by PinMe), divided by the total walking distance. As shown in the figure, the approximation error was less than 2.5% for all data chunks.

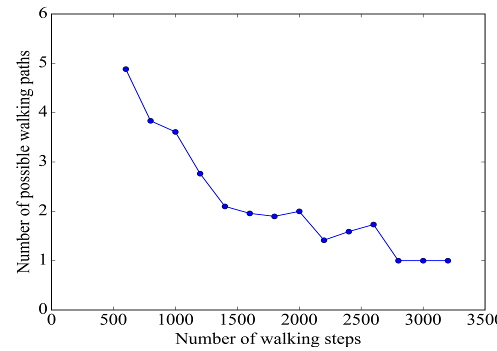

Fig. 8. Number of potential candidates with respect to the number of walking steps

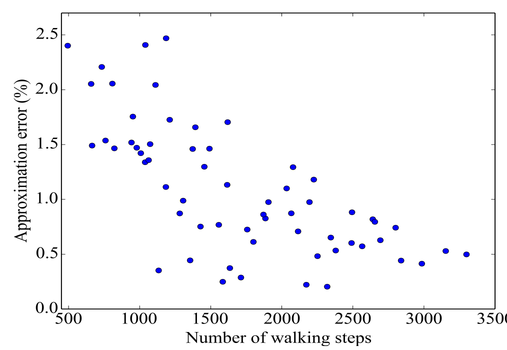

Fig. 9. Approximation error with respect to the number of walking steps.

4.2.2 End-to-end evaluation

In order to provide an end-to-end evaluation, we evaluated the accuracy of PinMe using Dataset #2. As discussed in Section 3.2.3, we have implemented two different versions of *walkingUserTracker*. For this evaluation, we used the second version, which assumes that the user is within a small area around his vehicle after he leaves the vehicle. Fig. 10 demonstrates the actual trajectories of the users' movements (as provided by GPS sensor) along with the estimated trajectories (as provided by PinMe). As illustrated in this figure, for all three data streams, which were collected by three different users while carrying three different smartphones, the actual trajectories of the users' movements were very similar to the estimated ones provided by PinMe. However, we observed four mismatch areas (bounded by red/blue boxes in Fig. 10). In the first and last areas ($M1$ and $M4$), the starting point of the actual driving path was slightly different from the point discovered by PinMe due to the similarities between two nearby intersections marked on the map. In two other mismatch areas, PinMe more accurately located the user than GPS. The GPS trajectory shows that the user's vehicle was off the road ($M2$). Furthermore, it

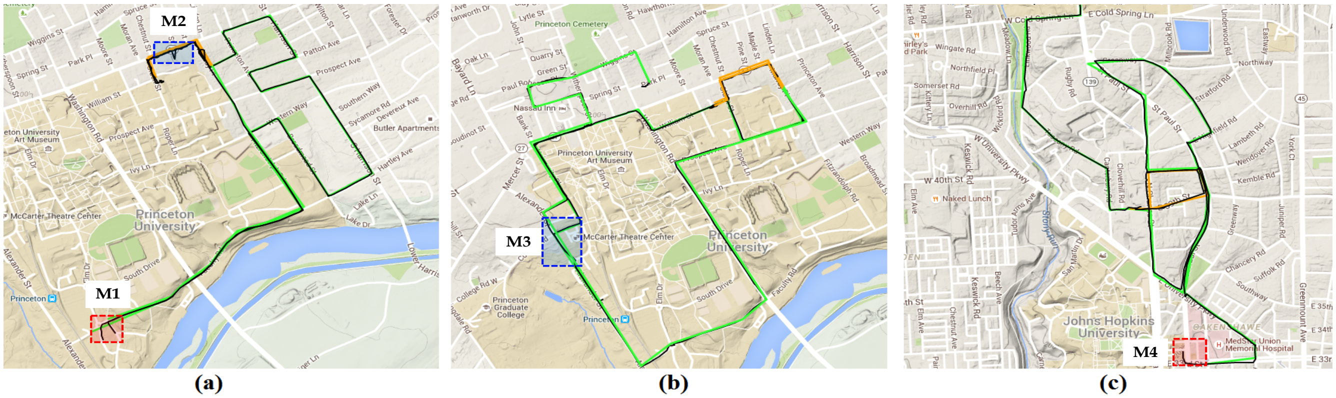

Fig. 10. Trajectories of three different users. Starting from the left and moving to right: (a) the first user was located in Princeton and carried a Galaxy S4 i9500, (b) the second user was located in Princeton and carried an iPhone 6, and (c) the third user was located in Baltimore and carried an iPhone 6S. The green and orange lines demonstrate the estimated user's paths during driving and walking, respectively. The black line is the actual user's trajectory reported by GPS data.

indicates that the user was off the sidewalk when he was walking ($M3$). In these two cases, we checked the validity of PinMe's trajectories with the users, and they confirmed that the results provided by PinMe show the actual trajectory in $M2$ and $M3$.

Based on our experimental results, we can say that the location estimation accuracy of *carTracker* was independent of the user's smartphone and vehicle. This was expected for two reasons. First, PinMe utilizes sensory data, which do not correlate with the smartphone model (air pressure, heading, and acceleration), as opposed to PowerSpy [17] that uses power consumption, which highly correlates with the smartphone model. Second, as described in Section 3, *carTracker* mainly relies on air pressure and heading to track the vehicle when the user is driving – these data are not correlated with the vehicle model, as opposed to acceleration data that are correlated with the vehicle model due to the existence of vibrations caused by the engine of the running vehicle [19].

5 Countermeasures

In this section, we briefly describe several countermeasures (along with their shortcomings) for mitigating the risks of attacks against location privacy.

5.1 Adaptive sampling rate

Limiting the sampling rate of sensors can potentially limit the amount of information leaked by the smartphone. In order to briefly discuss how the accuracy of PinMe might be negatively impacted if the sampling rate decreases, we examined *carTracker* using sensory data collected at different sampling rates. Fig. 11 shows how the average approximation error of *carTracker* changes with respect to the sampling rate. As we decrease the sampling rate, the approximation error only slightly increases for this algorithm (even when the sampling rate is around $0.1Hz$). However, based on our empirical results, the accuracy of *carTracker* suddenly drops when the sampling rate becomes very low (i.e., below $0.02Hz$) since the algorithm cannot detect the intersection (when the car turns) anymore. Many benign applications

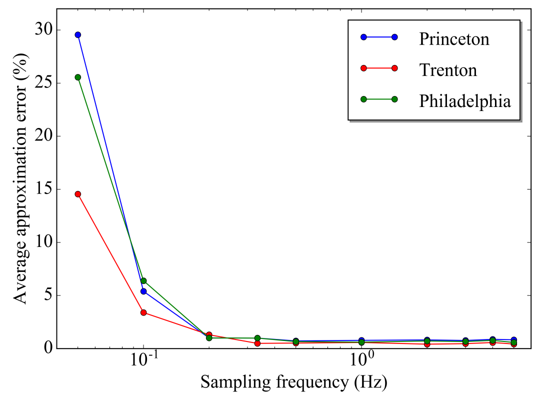

Fig. 11. Average approximation error of *carTracker* with respect to the sampling frequency.

(for example, fitness tracker [44] and fall detection [45]) require a sampling frequency larger than $0.1Hz$, and thus decreasing the sampling rate of sensors below $0.1Hz$, to prevent a PinMe attack, would reduce the efficiency, efficacy, and utility of trusted applications as well.

Utilizing context-aware sampling mechanisms, which can adaptively control sensor sampling rates, may be an alternative approach to maximizing utility and minimizing information leakage. For example, consider a mechanism that changes the maximum allowable sampling rate of the sensors based on user's current activity. Such a mechanism can allow a fitness tracking application to obtain very frequent samples from the accelerometer when the user is running and only allow infrequent sampling when the user is driving.

5.2 Risk-evaluation mechanism

Generally, a risk-evaluation mechanism aims to share the smartphone's data in such a way that certain kinds of inferences cannot be drawn. It examines if a set of sensory/non-sensory data collected by an application can leak sensitive information about the user, and blocks an application upon the detection of a potential information leakage. A few recent research efforts have been geared towards risk-evaluation mechanisms that can be implemented on the smartphone to ensure user privacy [21], [46], [47]. For instance, Chakraborty et al. [47] have proposed ipShield, a framework to control the sensory data that are accessible by various applications installed on a smartphone. Their risk-evaluation mechanism continuously examines what inferences can be made from the shared sensory/non-sensory information.

Zhang et al. [21] proposed a defense against runtime-information-gathering attacks in which a malicious app runs side-by-side with a target application (a victim) and performs runtime information gathering (RIG). They suggested temporarily stopping the applications that are potentially able to collect data from a sensitive application or killing applications that may be collecting side-channel information in the background while the foreground application performs sensitive tasks. They discuss two suspicious activities that can reveal maliciousness of an application: (1) a high sampling rate needed for continuous monitoring, (2) the presence of a correlation between an application's activity and the activity of a sensitive application. The location estimation algorithms described in our paper need a much lower sampling frequency (for example, as shown earlier, $0.1Hz$ led to accurate results for *carTracker*) than the frequency used in many previous attacks (for example, ACComplice [19] uses a sampling rate of $30Hz$). Therefore, sampling rate cannot be solely used to reveal the malicious activity of PinMe. Furthermore, PinMe does not require any data from other applications since it directly collects permission-free data, therefore, there is no correlation between its activity and other applications' activities. Finally, their defense relies on monitoring application-specific files, which are no longer accessible in Android M [48]. Thus, the approach discussed in [21] does not address PinMe.

5.3 Sensor data manipulation

Sensor data manipulation enables the user to manipulate or add noise to the content of collected sensory data when he is apprehensive about sensor data abuse in certain sensing applications. Typical data manipulation approaches include rounding the values in the sensory data to approximate values, replacing particular sensor readings by previously-recorded readings, and adding random noise to the sensory data. However, as mentioned earlier, unlike many previous attacks, PinMe relies on several macro-level features extracted from sensory data. As a result, it is robust against several potential sources of noise. For example, for *planeTracker* described in Section 3.2.3, it only extracts the aviation phases of the plane from noisy acceleration readings (as apposed to the actual displacement) from which it estimates the flight duration. As shown in Fig. 6 (Fig. 7), *planeTracker* was able to find a set of three routes (airports) that includes the actual flight route (destination airport), with a high level of accuracy, even when the approximated duration and elevation are assumed to be inaccurate due to the presence of noise (up to 10% for flight duration and $5m$ for elevation).

Adding significant noise to sensory readings or replacing data with previously-recorded data may significantly reduce the utility of trusted applications relying on such sensory data.

5.4 Turn-off switch

A hardware turn-off switch that lets the user quickly and easily turn off all sensors or a sensor-free mode implemented in the operating system in which no application can obtain sensory information enables the user to easily stop information leakage when he suspects that there might be privacy risks. For example, the user can turn off all sensors when he is driving to ensure that no application can track him.

6 Related Work

Several prior research studies have demonstrated the use of smartphone sensors in diverse application domains. The use of accelerometer for activity monitoring has been widely discussed in the literature [49]–[52]. Furthermore, recent research articles have discussed the feasibility of using air pressure measurements for indoor positioning [53], [54], in particular, floor detection.

Moreover, as briefly mentioned in Section 1, a few recent research efforts have demonstrated the feasibility of obtaining valuable information about the smartphone's location without accessing the GPS. In the following, we discuss them in more detail.

PowerSpy [17] demonstrated that an adversary can estimate the user's location by processing the power consumption information of the device when he is driving through a known set of routes. As mentioned in [17], this user location mechanism has the following limitations: (i) it requires a massive training dataset of power profiles associated with GPS coordinates, (ii) since the power profiles of different smartphones vary significantly from each other, in order to construct the training dataset, the attacker needs to measure the power consumption of many devices while driving, (iii) it assumes that there is enough variability in the device's power consumption along a route such that it exhibits unique features, (iv) it is only applicable to Android devices, and (v) it is able to detect the complete driving path in only 45% of the trials in the in the best-case scenario using HTC Desire for data collection and a small set of possible routes (the estimation accuracy significantly worsened when other smartphones were used in the experiment).

ACComplice [19] showed that continuous measurements of acceleration in smartphones can reveal user location while driving. It has four main limitations: (i) it requires a training dataset that contains data on multiple car trips through each potential traveling route, with the smartphone constantly collecting motion sensor data, (ii) since it mainly relies on smartphone's acceleration data, the noise in sensor readings, e.g., due to different road conditions, can significantly affect its accuracy, (iii) it returns several (usually more than 10) potential driving paths, and (iv) device acceleration needs to be measured at a relatively high frequency ($30Hz$). In [19], ACComplice is evaluated using only two driving paths. When the initial point was not given to the algorithm, for each test, it was able to return two clusters of possible starting points (each including five points) such that the starting point was within one of the clusters. Knowing the initial location, it could only partially find the driving paths (it correctly found 18 out of 23 routes for one test case and 9 out of 12 routes for the other).

TABLE 7
Comparison of different user-tracking mechanisms

Tracking mechanism	#Activity	Prior info.	Training	OS	Sampling freq.	Device/Vehicle dependence
PowerSpy [17]	1	Y	Y	Andorid	N/A	Y
ACComplice [19]	1	Y	Y	Android and iOS	$30Hz$	Y
Tracking Metro [18]	1	Y	Y	Android and iOS	$10Hz$	N/A
From Pressure [20]	1	Y	N	N/A	$30Hz$	N
RIG [9]	1	Y	N	Android	$50Hz$	N
PinMe	4	N	N	Android and iOS	$5Hz$ ($0.1Hz$ for driving)	N

Zhou et al. [9] discussed an attack based on acoustic information leakage from another application. Their approach processes the sequence of acoustic data generated by the smartphone's speaker when the user is driving and using a navigational application. This attack does not depend on the vehicle and device, and constructing real-world attack-specific dataset (it constructs a dataset based on simulations). However, they assume that attacker knows the user's start location or a place on his route and the rough area he goes (e.g., city) to find some points of interest and implicitly ignore the possible loops/rerouting. Furthermore, if the user goes to unlabeled places that is not likely to be included in the constructed dataset of points of interest (for example, if he parks his vehicle far from a point of interest), the approach discussed in [9] is unable to return the user's trajectory. In addition, since this attack requires a very high sampling rate ($50Hz$), their applications can be easily marked as "malicious" using the approach described in [21]. Finally, if the user simply turns off the speech guidance mechanism of the navigation application, this attack is not applicable anymore.

Ho et al. [20] presented an approach that uses dynamic time warping (DTW) algorithms (i.e., a time-series alignment algorithm in which two signals are compared against each other by means of a cost matrix) to track a vehicle using air pressure readings sampled at $30Hz$. DTW is used to compare the sequence of air pressure data samples with that of different candidate paths. However, in real-world scenarios, unfortunately, the search space of all candidate paths can be very large. If path loops are included, the search space may be infinite. They assumed that the path does not contain any loop and examined two DTW-based methods. For the first one, the median error is reported to be around $800m$ (when median error for a random walk was only $1600m$). Considering prior knowledge about the user to limit the area of interest and reduce search complexity, the second algorithm offers a median error of $60m$. However, as mentioned in [20], the second approach does not scale well for large maps.

Hua et al. [18] demonstrated that acceleration data can provide valuable location-related information when the user is traveling on a train. As mentioned in [18], the tracking method has two main limitations: (i) similar to the above-mentioned methods, it requires a large training dataset collected by the attacker while traveling through different potential paths, and (ii) it is difficult to provide a high level of location estimation accuracy due to various types of noise in the training data.

Table 7 compares different location mechanisms and highlights the advantages of PinMe. Our experimental results indicate that, without knowing the initial location, PinMe was able to return a single accurate driving path that is very similar to the trajectory provided by GPS readings. We believe that PinMe is able to return very accurate results since it mainly relies on noise-robust features extracted from barometer and magnetometer measurements. Moreover, unlike previously-proposed mechanisms, PinMe does not require measurements on a set of possible routes in advance. Therefore, our proposed attack is also more scalable. Unlike PinMe, the above-mentioned attacks only estimate the user's location during a single activity. Moreover, they commonly assume that the adversary has substantial prior information about the user's initial location. This knowledge is required because the attacker needs to collect a set of sensory data for different potential routes in advance and construct an attack-specific training database (e.g., in [17]) or the location estimation algorithm does not scale well for a large area of interest (e.g., in [20]).

7 Discussion

In this section, we discuss three items not yet explained in detail. First, we discuss limitations of the proposed mechanism. Second, we describe how we took advantage of the interdependence between activities in our algorithms. We then discuss how PinMe can also be used as a stand-alone location mechanism, and how it can be used to enhance the security of autonomous vehicles.

7.1 Limitations

Next, we briefly discuss four potential limitations of PinMe.

PinMe uses the history of smartphone IP addresses to infer the last city in which the user was connected to a WiFi network. In fact, it assumes that the user is directly connected to the Internet. Thus, if the user utilizes an anonymous communication service, e.g., Tor [55], PinMe may fail to locate the user. However, as mentioned later, the interdependence between activities can be used to resolve this limitation.

In addition, PinMe (in the end-to-end implementation) assumes that the initial location of the user when he starts walking is within a small area ($300m \times 300m$) around the latest location of the user estimated by the previous activity. Thus, if PinMe cannot roughly (i.e., within the $300m \times 300m$ area around the actual location) estimate the location of the user from the previous activity, it also fails to track him when he is walking.

Moreover, PinMe relies significantly on the variability of elevations and route directions. Therefore, PinMe might be unable to estimate the user's location if the user only moves in grid routes, e.g., some parts of Manhattan, NY, in which the roads are almost flat and parallel to each other.

Furthermore, since PinMe relies on publicly-available datasets, the existence of erroneous data in auxiliary datasets given to PinMe may reduce the location estimation accuracy. For example, OSM navigational maps do not typically include very recent constructions/detours. Therefore, if the user travels through a new road that has not been added to the map, PinMe may fail to track the user.

Despite the above-mentioned limitations, PinMe presents a significant advance in state-of-the-art smartphone-based user location, since it enables an attacker to scale up the attack against location privacy by minimizing attack requirements and offers a high location estimation accuracy.

7.2 Interdependence of activities

As described earlier in Section 3.2.3, we designed four different independent algorithms for tracking the user during four different activities. Although the user's activities may seem independent of each other at first glance, there exists an interdependence between them due to physical constraints imposed by the world and the user's movement.

In particular, we make two observations. First, the users always walk between other activities (driving, traveling on a train, and traveling on a plane), and therefore, certain sequences of activities are not feasible. For example, the user cannot get on a plane as soon as he stops driving. This helps our tailored classifier algorithm to remove impossible cases.

Second, the final location of the user after performing each activity *roughly* determines the initial location of the next activity. However, since the precision of the estimated location determined by different algorithms might differ from each other, combining the results from different algorithms to get an accurate trajectory is not usually straightforward. For example, consider the following scenario: a user takes a flight that lands at airport A, then walks for a few hundred meters to reach his car, and eventually drives to his home from the airport. In order to track the user, PinMe utilizes *flightTracker*, *walkingUserTracker*, and *carTracker*, respectively. *flightTracker* returns departure and destination airports, whereas *carTracker* and *walkingUserTracker* return a trajectory with an accuracy comparable to GPS. If PinMe relies on the assumption that the initial location for each activity is *accurately* determined by the previous activity, then it fails to provide an accurate estimation of the user's trajectory in the above-mentioned scenario since the location returned by the first activity provides an inaccurate initial point for *carTracker* (the whole airport area is marked as a single point with fixed GPS coordinates on navigational maps). However, the interdependence between activities still provides valuable pieces of information in this scenario. First, *flightTracker* returns the destination airport from which the current city can be identified even if the user has not connected to any WiFi network yet or is using an anonymous communication service, e.g., Tor [55]. Second, the final location of the user after performing each activity can significantly bound our area of interest. This has been used in our end-to-end evaluation, where the *walkingUserTracker* algorithm assumes that the user's initial location, when he starts walking, is within a small area around the final location of the user estimated by *carTracker*.

7.3 PinMe as an alternative to GPS

Next, we first describe drawbacks of traditional GPS systems. We then describe why PinMe can offer a more secure navigation mechanism for autonomous vehicles.

With the widespread use of GPS receivers in modern vehicles, ranging from yachts to autonomous cars, the security of GPS has garnered ever-increasing attention in recent years. GPS receivers compare timestamped signals from a constellation of satellites, inferring their position through computations on the lightspeed lag from each signal. Several research studies [56]–[58] have demonstrated the feasibility of faking the satellite signals needed for positioning and mentioned that security attacks against the GPS signals used in autonomous vehicles may lead to disastrous consequences.

Unfortunately, protecting GPS signals against spoofing is difficult for three reasons. First, the computational load associated with cryptographic signatures on the signal is high. Second, it is impossible to use a challenge-response protocol since the communication channel between the satellites and GPS receiver is unidirectional, i.e., the receiver cannot transmit data to the satellites. Third, the implementation of new algorithms/mechanisms, which need modifications to the GPS infrastructure, is difficult and costly.

As demonstrated in Section 4, PinMe was able to accurately (comparable to GPS) locate the user during different activities. A slightly modified version of PinMe can be implemented on autonomous vehicles, e.g., driverless cars, as a stand-alone in-vehicle positioning system. For example, air pressure and heading sensors can be added to driverless vehicles, enabling sensory data to be processed by on-vehicle processing units. Odometer readings are easily accessible to in-vehicle processing units and can be used to further improve the accuracy of PinMe. Since PinMe does not collect sensory data from any remote sources, it is resilient against remote attacks, assuming that navigational/elevation maps provided by Google [26] and weather reports given by The Weather Channel [28] are accurate.

8 Conclusion

This paper highlighted the unintended consequences of letting third-party applications access smartphone's presumably non-critical data. We proposed an attack on location privacy in which the attacker (i) needs no prior knowledge of the area of interest, (ii) does not need to construct an attack-specific training dataset, and (iii) does not collect data at a high sampling rate.

We demonstrated that there is no need to construct an attack-specific dataset to compromise location privacy. Evaluation of the proposed user-location mechanism demonstrated that it is feasible to gain sensitive information about the user's location without accessing location services, e.g., GPS. It suggests that the threat of unintended information leakage on the location of smartphone owners is far beyond what is currently thought possible. Indeed, even seemingly benign sensory/non-sensory data gathered by a smartphone can leak critical information about the user. Therefore, they should be proactively protected from third-party applications.

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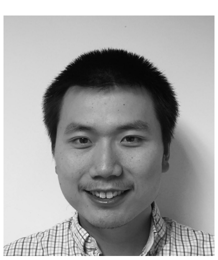

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