A Survey of Fingerprint-Based Outdoor Localization

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***Abstract*—A growing number of sensors on smart mobile devices has led to rapid development of various mobile applications using location-based or context-aware services. Typically, outdoor localization techniques have relied on GPS or on cellular infrastructure support. While GPS gives high positioning accuracy, it can quickly deplete the battery on the device. On the other hand, base station based localization has low accuracy. In search of alternative techniques for outdoor localization, several approaches have explored the use of data gathered from other available sensors, like accelerometer, microphone, compass, and even daily patterns of usage, to identify unique signatures that can locate a device. Signatures, or fingerprints of an area, are hidden cues existing around a user's environment. However, under different operating scenarios, fingerprint-based localization techniques have variable performance in terms of accuracy, latency of detection, battery usage. The main contribution of this survey is to present a classification of existing fingerprint-based localization approaches which intelligently sense and match different clues from the environment for location identification. We describe how each fingerprinting technique works, followed by a review of the merits and demerits of the systems built based on these techniques. We conclude by identifying several improvements and application domain for fingerprinting based localization.**

***Index Terms*—Outdoor positioning, content based image retrieval, signal based positioning, smartphone sensing, database search, pattern matching, energy efficiency.**

I. Introduction

SMARTPHONE-BASED outdoor localization has been gaining attention as increasing number of in-built sensors make it easier to locate a smartphone and its user. It is common for most location-based applications, like Poido and MapQuest Map, to use GPS on a smartphone. Although GPS is the preferred mode of outdoor localization, GPS-based techniques often do not perform well in crowded cities or in unfavorable weather, like overcast conditions. When the satellite signals are delayed due to multi-path or blocked by obstacles, GPS-based localization service can suffer. In addition, it is well-known that GPS is extremely power hungry.

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The presence of multiple sensors on smartphones has opened up new avenues for outdoor localization. Smartphones equipped with cameras and low-power sensors have enabled us to not only gather information about our surroundings, but also can detect movements to track our daily activities. The clues about our environment, or location, collected from the sensor inputs or the user activity patterns lead to an alternative way of locating a device and its user. The clues act as signatures that can be matched against pre-defined geotagged signatures. We term this fingerprint-based localization, and focus on its application for outdoor localization.

Compared to GPS and other standard positioning techniques, these fingerprint-based localization techniques have many advantages. First, the low-power sensors integrated in current smartphones draw much lower power, even when active continuously. Second, depending on the application requirement, one may wish to trade-off accuracy for energy efficiency. Fingerprint-based localization can enable such trade-off more effectively. Finally, no additional hardware or infrastructure modifications are needed in most of the fingerprint-based localization techniques.

Since different fingerprint-based localization techniques vary considerably in performance and operating environments, a summary of the techniques helps the user in selecting a suitable solution based on the various trade-offs. To this end, we present a survey that considers different fingerprint-based techniques for outdoor localization. To the best of our knowledge, this is the first study which captures usage of different sensors for outdoor localization, unlike earlier surveys on network-based mobile positioning techniques [1] or indoor localization techniques [2], [3].

The main contribution of this survey is to review fingerprint-based localization techniques and existing systems in the domain. We classify the current techniques and the systems with respect to different fingerprinting approaches. To understand the trade-offs of each approach, we present the advantages and disadvantages of each technique. Finally, we highlight the issues in existing solutions and new research directions to augment fingerprint-based outdoor localization systems.

The rest of this survey is organized as follows. In Section II, we present an overview of the concepts relevant to fingerprint-based localization techniques. We focus on visual fingerprint, motion fingerprint, signal fingerprint, and hybrid fingerprint which are the most commonly used fingerprinting modalities in literature. In Section III, we classify current fingerprint-based localization techniques according to fingerprint types, followed by a review of the existing fingerprint-based localization systems in Section IV. Section V presents a comparison of the systems along three performance objectives. Section VI presents future directions in the use of fingerprint-based localization techniques. Finally, we conclude the survey in Section VII.

II. Overview of Fingerprint-Based Localization

In this section, we first explain the concept of fingerprint-based localization and illustrate its usage using examples. Next, we present the types of fingerprints which are commonly used. Finally, we present the functional design used typically in all the techniques.

A. Fingerprint-Based Localization

Fingerprint-based localization captures signatures that are matched against a set of geotagged signatures to identify a device location. Signatures can be recorded using different in-built sensors in a mobile device, or the sensors can be used intelligently to detect users' activity pattern. For example, one can use the camera to take a picture of a landmark and match the picture against geotagged images to identify the location. Microphones can be used to detect the sound signature of different places. Even the user's daily movement pattern, namely the detection of specific WiFi access points, can indicate that the user is in office or at home. More complex cues are hidden in our environment. The goal of fingerprint-based localization is to discover these hidden cues and use them effectively to determine the location of a device, and a user where the user is carrying a device, like a smartphone.

B. Fingerprint Types

Due to the increasing number of sensors on smartphones, many types of information present around us can be sensed. This enables new opportunities for utilizing the context information as signatures for smartphone localization. Recently, various fingerprint-based localization techniques have been proposed. Three main fingerprint types used in the literature are *visual fingerprint*, *motion fingerprint*, and *signal fingerprint*. Finally, by combining multiple cues from different sensors it is possible to generate *hybrid fingerprints*.

1) Visual Fingerprint: Powerful image- and video-processing techniques equipped in modern mobile devices (smartphones or tablets) have enabled intensive research in visual-search techniques in the last decade. Many content-based image retrieval techniques have been proposed to search a query image from a large image database using visual features appearing in images such as color, texture, shape [4]. Along with these techniques, many mobile image-based retrieval applications have been introduced such as Google Goggles [5] and Vuforia Object Scanner [6]. Google Goggles is an image search application which can identify products, paintings, landmarks appearing in mobile images to provide users with useful information. Vuforia Object Scanner is an Android application that provides real-time visual feedback on the target quality, coverage, and tracking performance of the scanned objects.

Nowadays, images taken by a mobile device can be used to pinpoint the location of mobile devices. Due to the proliferation of geotagged images, many visual-based localization systems have been proposed using smartphone cameras [7], [8].

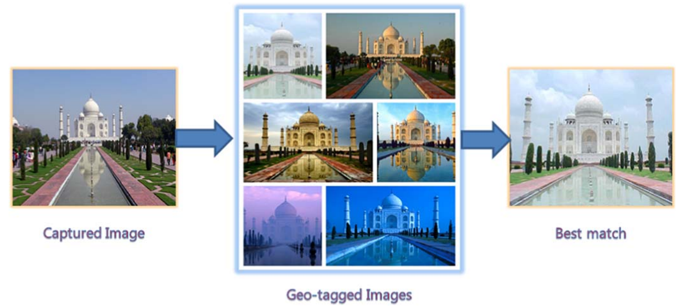

Fig. 1. Visual fingerprint-based localization uses an image captured by the user to match against geotagged images in a database to identify the location.

A typical system can be seen as shown in Fig. 1, where the user clicks an image with her smartphone camera and uses the captured image as a query input to find similar images from a database of geotagged images. The best-matched image is returned with the geo-location information as the location where the query image was shot.

2) Motion Fingerprint: With the support of motion sensors such as accelerometers and electronic compasses or gyroscopes, today's smartphones can perform sensing and user motion recognition in real-time. Recent studies show that the motion data can be used not only as a signature to locate the position of a mobile user, but also as additional inputs to improve the localization performance in other standard positioning techniques.

The basic idea is to combine the accelerometer and compass readings and match them with a map of the area of interest to estimate the location of mobile devices. Readings from the accelerometer are used to detect the traveled distance, while readings from the compass are used to estimate the orientation of the mobile devices. The traveled distance and the orientation of the mobile devices are measured periodically, and used as fingerprints and for localization.

3) Signal Fingerprint: The proliferation of mobile devices and wireless networks has encouraged a growing interest in location-aware systems and services. Several types of techniques that detect wireless signal for localization have been proposed such as signal fingerprinting, time of arrival (ToA), angle of arrival (AoA), time difference of arrival (TDoA) [9]. Among them, signal fingerprint-based localization techniques show higher accuracy in presence of complex radio wave propagations, compared to other techniques which often suffer from the effect of multipath signals in indoor environments. The basic idea of this technique is to find the location of a mobile device by comparing its signal pattern received from multiple transmitters (e.g., WiFi APs or BSs) with a pre-defined database of signal patterns. There are a variety of signal fingerprint-based localization systems in the literature [2]. RADAR system is one typical example of this technique, which employs WiFi signals for indoor localization [10]. The WiFi fingerprint is constructed using the RSSIs received from WiFi APs, which are visible to the WiFi antenna in laptops. However, it was developed to track indoor locations.

As the availability of WiFi access points (APs) and base stations (BSs) have become more pervasive in many urban areas, signal fingerprint-based localization techniques have

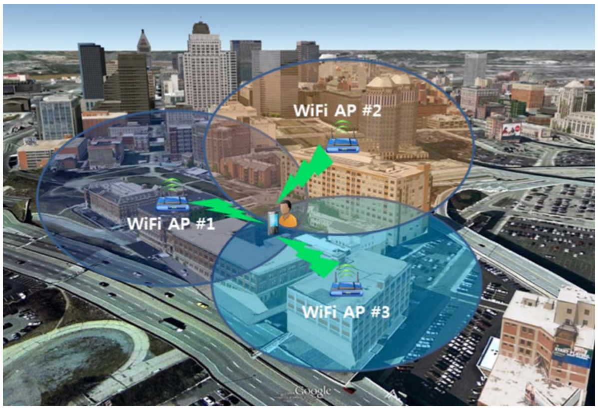

Fig. 2. Signal fingerprinting works by collecting the RSSI values from multiple WiFi access points or base stations to generate a unique signature of an area.

been proposed for outdoor environments. In general, the signal pattern is generated by observing the Received Signal Strength Indicator (RSSI) values at a mobile device. The fingerprint is a tuple comprising of RSSI value, and the AP or BS identifier [11]. It can also be a sequence of cell-IDs as proposed in [12], or combinations of RSSI values with other information such as MAC address of the APs or signal-to-noise ratio (SNR) [13]. Fig. 2 depicts the use of signal fingerprint for outdoor localization.

Besides these conventional signal fingerprint-based localization techniques, an alternative approach has been introduced using the signal subspaces obtained by array antennas [14]. The basic idea is that the signal subspaces, which consist of information about the signal strengths and angle of arrival of impinging signals on the array antenna, can be used as the fingerprint to estimate the location of the mobile device.

4) Hybrid Fingerprint: There is a tradeoff between accuracy and power consumption in most of the techniques. However, combining multiple fingerprint types can lead to more robust hybrid fingerprint-based localization systems with better performance. For instance, to minimize the impact of inherent noise from motion sensors, SmartLoc has proposed the use of landmarks (e.g., bridges, traffic lights) or the driving speed of mobile users as signatures to calibrate the localization result [15]. This can maintain high accuracy when GPS signals are temporarily disrupted.

Incorporating the use of fingerprinting approaches along with standard positioning techniques can also improve performance. For instance, motion fingerprint has been used in association with GPS module as auxiliary signatures to increase energy efficiency [16], [17]. The motion data are analyzed to recognize the user's current activity state, such as stationary or mobile. This gives the hint to switch on or off location sensors, which can reduce power consumption. When a user is stationary, the activity detected using accelerometer readings can prevent activating GPS, thus saving energy spent.

C. Functional Design of Fingerprint-Based Localization

A fingerprint-based localization system typically comprises of two key modules; fingerprint sensing module and fingerprint matching module. We present a description of the functional blocks of a typical fingerprint-based localization system. Fig. 3 shows the sequence of steps in the workflow.

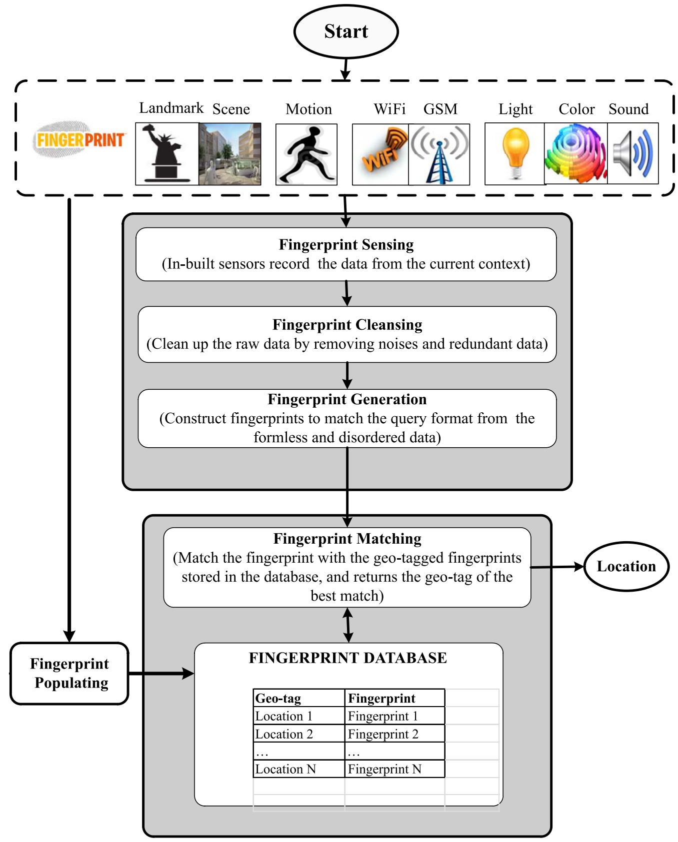

Fig. 3. Functional design of fingerprint-based localization systems showing the sequence of activities for fingerprint generation and matching, as well as populating the fingerprint database with geotagged signatures.

1) Fingerprint Sensing: Fingerprint sensing is the first step in any fingerprint-based localization. When a fingerprint-based system starts, the necessary sensors are activated to record the data continuously or periodically.

In many image-based localization applications, for instance, the smartphone camera is activated to enable the user to take a picture used as the input to the location query. On the other hand, motion fingerprint-based localization techniques activate the motion sensors, accelerometer and gyroscope for continuous recording.

2) Fingerprint Cleansing: The raw data received from sensors often contain noise. Utilizing these raw data directly for localization process would degrade the performance of the whole system in terms of accuracy, energy efficiency, and latency. To avoid this problem, a filtering process is required to clean the data before forwarding it to the next step.

In image-based localization techniques, transmitting the entire image over the network or performing image processing steps for the entire image takes more time and may consume more energy than just performing the steps over the relevant parts of the image. Therefore, to minimize the energy cost of the whole system, it is necessary to select only the relevant parts of an image for the localization process.

3) Fingerprint Generation: The fingerprint generation step organizes the inputs from different sensors into a structure that can be easily parsed during the matching step. After eliminating noise, fingerprint-based localization approaches construct a fingerprint query which is sent to the matching process. Data captured by the sensors are usually disordered or sometimes it is formless compared to the pre-recorded fingerprints in the database.

Different types of fingerprints have different ways to construct signatures. For example, the order of RSSIs from respective APs or BSs is important in constructing a fingerprint. Thus, the raw signal received at the smartphone must be processed to obtain the RSSIs fingerprints in the form that matches the structure of the stored signatures.

4) Fingerprint Matching: Although different types of fingerprints require different matching techniques, they all consider the size of the search space in order to increase the matching performance in terms of power consumption and processing time. As the size of the reference fingerprints in database increases, the matching performance notably decreases. Therefore, limiting the search space to a confined area is the prior knowledge integrated in most fingerprint matching processes.

Various techniques have been employed to direct the matching process to only fingerprints which exist within the area of interest. Most of them employ approximate coarse localization techniques available on most mobile devices, such as using Cell-ID of the network provider to restrict the search space to only the region inside the cell [7], [8].

After limiting the search space, a pattern matching algorithm is used to figure out the location of the mobile device by comparing the query fingerprint to the pre-recorded fingerprints in the database. The pattern matching process returns the closest match with a location coordinate.

5) Populating the Fingerprint Database: Fingerprint-based localization systems require a database of fingerprints with geotags that must be constructed a priori. It requires a war-driving to collect the signatures from different areas. Alternatively, crowdsourcing geotagged information, like images posted with geotags, can be used to populate the database [18].

III. Characterization of Fingerprint Types for Outdoor Localization

There are various fingerprint-based outdoor localization techniques proposed in the literature. Depending on the fingerprint type, each technique varies in implementation details, as well as, localization performance in terms of accuracy, energy efficiency, and latency. Fig. 4 shows a classification of different fingerprint types used in literature, as well as the performance objectives for the systems. Although all the fingerprint-based localization schemes follow a similar workflow, as shown in Fig. 3, note that the details and the complexity of each function block varies considerably. This section presents the generic approach for each fingerprinting modality. Finally, different techniques used in each function block are summarized in Table I.

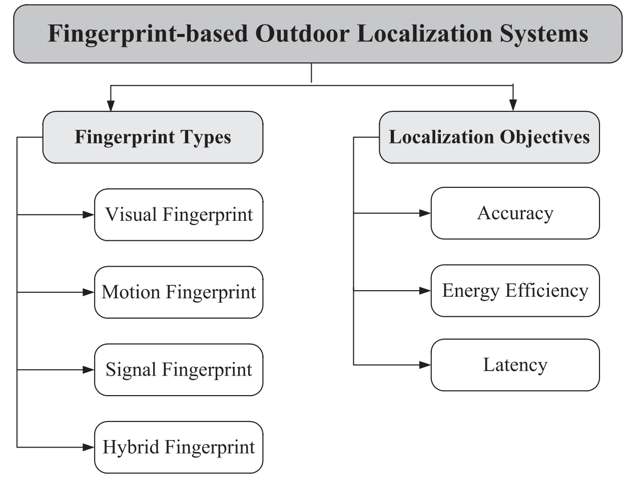

Fig. 4. Different modes and performance objectives for outdoor fingerprint-based localization.

A. Visual Fingerprint-Based Localization

The basic idea of visual Fingerprint-Based localization is to analyze the contents of an image and extract visual features which can be used to construct a fingerprint for searching similar images from a database of geotagged images. This image search technique, known as content-based image retrieval (CBIR), has been an area of extensive research in computer vision for the past few decades [4], [19].

The main challenge of CBIR technique is the accuracy rate and speed of searching for digital images in large databases. By representing an image using bag-of-words (BoW) model with the aid of the *k*-means algorithm, each image can be treated as a document. One constructs a codebook by clustering each visual feature of training images into different visual words, and then represents each image by a histogram of the visual words for classification [20]–[22].

Fig. 5 shows a functional design for visual fingerprint-based localization. The techniques used in each function block are presented next.

1) Visual Fingerprint Generation: As a first step, visual features extracted from the taken image are analyzed to generate a visual fingerprint for recognizing the landscape (or a prominent building) in the image. In general, visual features can be categorized into global and local features. Global features refer to image's overall properties such as color, edge, and texture. Local features aim to represent the image content which describes points of interest extracted from salient regions or patches within the image. Most landmark recognition systems use global features in conjunction with local features to improve the performance of the recognizing process.

The points of interest (PoI) are captured using feature descriptors, which are useful for comparing variations in objects across images. A feature descriptor is a high-dimensional feature vector of each region in an image, and uniquely characterizes PoI of the image. With respect to illumination conditions, scale changes, and affine transformation, Scale-Invariant Feature Transform (SIFT) [23] has been introduced as a well-known algorithm, which detects PoI in a scale-invariant way. Several variants of the SIFT algorithm have appeared in the last decade, trying to improve the PoI extraction or the feature descriptor [24]–[26]. For instance, the Speeded-Up Robust Features (SURF) algorithm [25] improves the PoI extraction.

TABLE I
SUMMARY OF TECHNIQUES APPLIED IN DIFFERENT FUNCTIONS FOR FINGERPRINT-BASED LOCALIZATION

Fingerprint Type	Fingerprint Generation	Fingerprint Matching	Fingerprint Population
Visual Fingerprint	• Scale-Invariant Feature Transform (SIFT) • Speeded-Up Robust Features (SURF) • Gradient Location and Orientation Histogram (GLOH) • Bag-of-Words (BoW) Model	• Coarse Localization Techniques • Content Based Image Retrieval (CBIR) • BoW-based Location Retrieval • Nearest-Neighbor Search (NNS)	• Crowdsourcing-based Fingerprint Populating Techniques
Motion Fingerprint	• Dead Reckoning Algorithm • Distance Estimation Techniques • Direction Estimation Techniques	• Digital Map Matching Techniques	• Digital Map Construction Techniques
Signal Fingerprint	• RSSI-based Techniques • Multiple Signal Parameters-based Techniques • Signal Subspace-based Techniques	• Euclidean Distance-based Matching Algorithm • Received Signal Strengths Ordering	• War-driving Techniques • Grid-based War-driving Techniques • Crowdsourcing-based Fingerprint Populating Techniques • Signal Subspace Interpolation Method

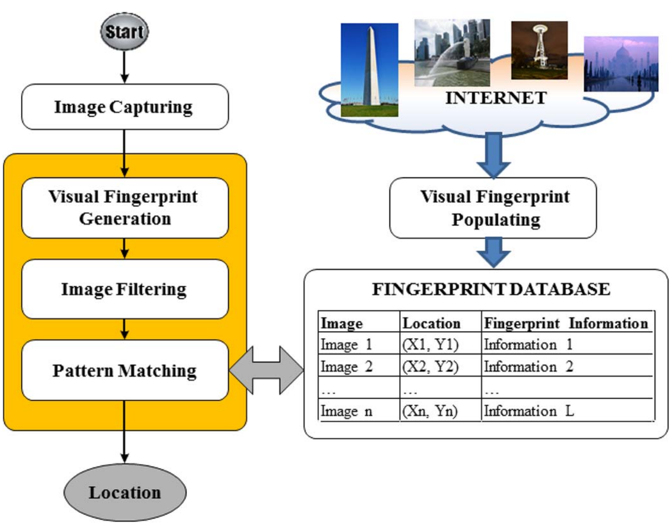

Fig. 5. Functional design for visual fingerprint-based localization.

For those trying to improve the feature descriptor, the Gradient Location and Orientation Histogram (GLOH) [26] has been considered as a robust image descriptor.

By quantizing the high-dimensional feature descriptors into the so-called visual words using the *k*-means algorithm, an image can be represented by a visual word frequency histogram (or BoW vector) [27], which can be used as fingerprints for large scale image search. In other words, images are translated into textual documents, also known as inverted files, which are then indexed and retrieved in the same way as the text-based search. Various extensions have been proposed to improve the performance of the quantization [28]–[30].

2) Visual Fingerprint Matching Technique: Using *k*-means clustering algorithm, the image retrieval problem is reformulated into a text retrieval one. The similarity between the query image and each reference image in the database can be computed efficiently using inverted files. However, the size of the inverted files scales linearly with the number of reference images. The visual fingerprint matching technique suffers from high power consumption and high latency, as the size of the inverted files increases. This happens due to the fact that the CBIR technique has to match the query image against the entire large database of geotagged images.

Similar to other fingerprint-based localization systems, the CBIR-based techniques first limit the search space to only images which have geo-tags within the neighbor area of the mobile device using an anchor. This anchor can be computed using coarse localization techniques available on most mobile devices, such as via cell tower triangulation or the location of the current cell that the mobile device is connected to [31]. Using this anchor, various techniques have been proposed to search for the neighbor area. Divide and conquer algorithm-based approaches segment the search area into several overlapping subregions and use the anchor to search for the approximate coarse area [7], [8].

After reducing the size of the search space, a visual fingerprint matching technique is used to find the spatially closest image from a database of geotagged images. Most CBIR-based matching techniques employ the Nearest-Neighbor Search (NNS) algorithm, which computes the distance between two images, to calculate the similarity of two images. Using the PoIs and feature descriptors of the query image, NNS technique selects candidate images in the search space and groups them into different sets of features. One candidate image can appear in more than one result set. Finally, the candidate images are merged together, and sorted by the number of occurrences in the respective result sets [31]. For example, if an image has very similar color and edge features in comparison to the reference description, then the same image will probably occur in both result sets: color and edge set. During this merging process, images are ranked based on the number of times they occur in different result sets.

3) Visual Fingerprint Populating Technique: Geo-tagging has become a popular function in cameras recently. A picture can be tagged with the geolocation information while it is clicked using GPS. Since many landmarks and prominent locations already have their geotagged images on the Internet, comparing an image captured by a mobile device with these geotagged images can help identify the location of the mobile device.

There are a large number of geotagged images accessible from the Internet such as Flickr, Pinterest, Instagram, Photobucket, or Picasa. Many visual fingerprint populating techniques have been proposed to collect geotagged images from these image-sharing websites for constructing visual databases. For instance, Chen *et al.* [32] released a large set of street-level images organized together with hundreds of geotagged query images. Other localization systems also use 360° panoramic images with geotags, which can be accessible from many web mapping services like Google Street View from Google or Bing Maps from Microsoft, to construct visual fingerprint databases [7].

B. Motion Fingerprint-Based Localization

Motion fingerprint-based localization is a positioning technique that detects a mobile user's location using movement data of that user. The movement data is collected from motion sensors in mobile devices, such as accelerometer and gyroscope. In general, a motion fingerprint-based localization consists of two main processes: movement tracing and map matching, as shown in Fig. 6. The movement tracing process is mostly done by using Dead Reckoning (DR) algorithm, which traces the moving speed and direction of a mobile user. DR algorithm uses sensed data from motion sensors in mobile devices and generates motion fingerprints periodically. The current location is estimated using the previous location and the latest motion fingerprint.

However, due to the fact that motion sensors can be noisy, localization accuracy of the estimation is often low. Therefore, a map matching process is often required to refine the user's location by adjusting the estimated location to the correct location in a digital map. Alternatively, some motion fingerprint-based systems are integrated with other fingerprints (e.g., visual fingerprint and signal fingerprint) or other standard positioning techniques, to calibrate the location.

1) Motion Fingerprint Generation: DR algorithm is used for generating motion fingerprints. DR algorithm periodically records the data from the accelerometer and gyroscope to estimate the travel distance and the direction of movement of a mobile user. Typically, there are two estimates required in the DR algorithm: travel distance estimate and travel direction estimate.

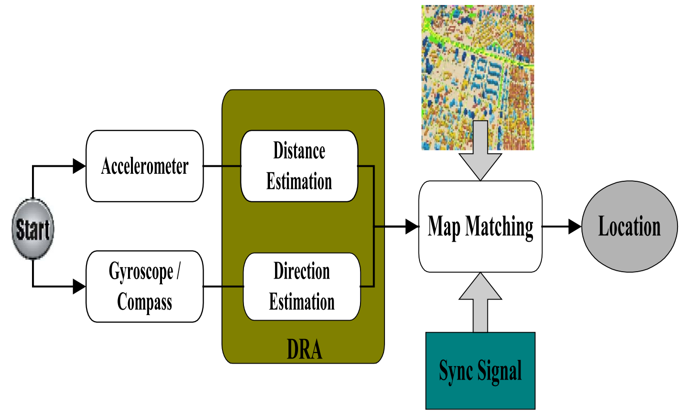

Fig. 6. Workflow describing motion fingerprint-based localization. A sync signal is often used as a reference point that allows the phone to recalibrate its location when the map matching process has deviated. This sync signal is created using other standard positioning techniques, such as GPS or cellular infrastructure supported localization.

Estimating Travel Distance: In general, a travel distance can be calculated by taking the double integral of acceleration data collected by the accelerometer readings. However, cheap accelerometers in mobile devices are highly noisy. Therefore, estimating travel distance for mobile devices using the integration of acceleration would require corrections, especially for pedestrian tracking.

It is possible to use a person's gait to estimate travel distance. While walking, gait has a repeating pattern that provides a uniform step length. Several ways to estimate travel distance are proposed for pedestrians as follows:

- Distance Estimation Techniques: There are two ways to estimate a travel distance: step-based distance estimation and walking pattern-based distance estimation.

  Step-Based Distance Estimation: Travelled distance can be estimated by counting the number of walking steps and then multiply it by the step length, as described in the following simple formula.

$$d = n_s . l_s \tag{1}$$

  where d is the travel distance estimated, n_s is the number of walking steps, and l_s is the step length trained beforehand. The challenge is to detect a step based on accelerometer readings. This is done by using step detection technique, which detects one's walking step pattern using motion data. To detect one step, continuous readings received from accelerometer in one walking step are analyzed and mapped to a pre-defined walking step pattern [33].

  Walking Pattern-Based Distance Estimation: Research in [34] shows that the different placement of the phone impacts the accuracy of each step counter due to the nature of walking. For instance, having the phone in hand correctly produces desired data, which contain 6 recurring patterns, while keeping the phone in the pocket produces only 3 recurring patterns.

  [34] also found that no matter how the phone is placed, the acceleration data always shows some recurring

patterns. For convenience, they refer to a pattern as a period. By relaxing "human step" to "period", they propose a similar but more accurate formula to estimate the travel distance as following:

$$d = n_p . l_p \tag{2}$$

where d is the travel distance, n_p is the number of periods, and l_p is the travel distance within one period trained by experiments. A travel distance within one period is referred as one step length in the step detection technique.

- Step Detection Technique: While the mobile user is walking, the step detection technique keeps sensing and analyzing the sensed data received from the accelerometer. Let's assume that a series of acceleration magnitudes has a form of $a_1, a_2, \ldots, a_n$; where a_n is the most recent data received and mapped to a bit according to

$$Q(a_n) = \begin{cases} 1 & \text{if } a_n > \mu_n + \sigma_n \\ 0 & \text{if } a_n < \mu_n - \sigma_n \\ \wedge & \textit{otherwise}, \end{cases}$$

where μ_n is the average of the series, σ_n is the corresponding standard deviation, and $\wedge$ is an undefined state. The two thresholds $\mu_n + \sigma_n$ and $\mu_n - \sigma_n$ are the levels for characterizing "up" and "down" patterns respectively. This mapping yields a sequence of bits. The technique then merges consecutive 1 s into a single bit 1, 0 s to 0, and $\wedge$s into $\wedge$ to form a step with a pattern of "10" or "$1 \wedge 0$". Whenever a step is detected, it will be reported to the map matching process for enhancing the localization accuracy.

Estimating Travel Direction: Orientation of mobile devices can be estimated using an embedded magnetic digital compass. However, it is influenced by the environment and especially the ways of holding the phone. Nowadays, applications tend to use gyroscopes for direction estimation. Gyroscope data is with respect to the Cartesian frame of reference of the phone itself. The frame is represented by the orthogonal xyz axes with the x-axis pointing to the right side of the phone, the y-axis pointing to the top of the phone, and the z-axis leaving the screen. Though the angular velocity varies over time, but the value at each axis follows a recurring pattern. Therefore, integrating these three angular velocity values along time may reduce the fluctuation. In addition, when a pedestrian walks in a straight line, the average acceleration in any axis does not fluctuate much.

Travel direction can be estimated using the angular displacement based on gyroscope readings. The angular displacement around all three axis are monitored to determine straight walking. Within a time window, the user is believed to be walking along a straight line if all three angular displacements do not exceed a pre-determined threshold. During the duration when the user walks in a straight line, the acceleration readings are averaged in each direction and the adjusted angular displacement for an incoming turn is calculated as

$$AD = \frac{(\alpha\mu_x + \beta\mu_y + \gamma\mu_z)}{\sqrt{\mu_x^2 + \mu_y^2 + \mu_z^2}}, \tag{3}$$

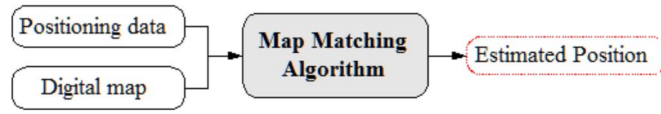

Fig. 7. Map Matching to estimate the position of the mobile device.

where α, β, γ are the angular displacements computed in the first step, and μ_x, μ_y, μ_z are the acceleration readings averages in each direction, respectively.

2) Motion Fingerprint Matching Technique: When a new step or a new turn is reported from the DR algorithm, the map matching is performed to incorporate this new information for refining the user's location. This is done by merging the positioning data according to pre-defined digital map, which estimates the user's location in the best match to the digital map.

Map matching helps in correcting errors due to DR algorithm. For instance, when the location of a moving car is unexpectedly estimated at somewhere inside a certain building, the map matching process will correct this estimated position to the nearest road.

Fig. 7 shows a general block diagram of a map matching process. Two inputs are required to pinpoint the position: positioning data and digital map. The digital map is often generated in the form of a list of polylines in a graph. Due to errors in the positioning system, the positioning data are often not on any polyline provided by the digital map. Therefore, the map matching is required to lay the estimated position on the polyline.

3) Digital Map Construction: In order to improve localization accuracy, a digital map is often used as a constraint on the possible user positions. The returned location from the DR algorithm, can be correlated with the map to estimate the location of the user. The map is generated by using a subset of points in 2D Euclidean space [34], or a set of segment markers with the latitude and longitude tagged [35]. The combination of continuous segment markers or points represents the roads and paths in the map.

C. Signal Fingerprint-Based Localization

The basic concept of signal fingerprint-based localization is to estimate the location of the mobile devices by matching the received signal fingerprint against a previously recorded database of known signal-location information. As a fingerprint technique, the database of signal fingerprints needs to be constructed in advance. Therefore, this technique requires two main phases: signal fingerprint populating phase (also known as training phase or offline phase) and signal fingerprint matching phase (also known as online phase). In the training phase, a signal map is generated by exploring the signal fingerprint at each reference location inside the area of interest. During the matching phase, the location of the mobile device is estimated by comparing the signal fingerprint generated one the device with the pre-defined signal map. Fig. 8 summarizes the workflow of a signal fingerprint-based localization.

1) Signal Fingerprint Generation: When the mobile device enters the area of interest, a signal fingerprint matching technique uses the currently observed signals and previously

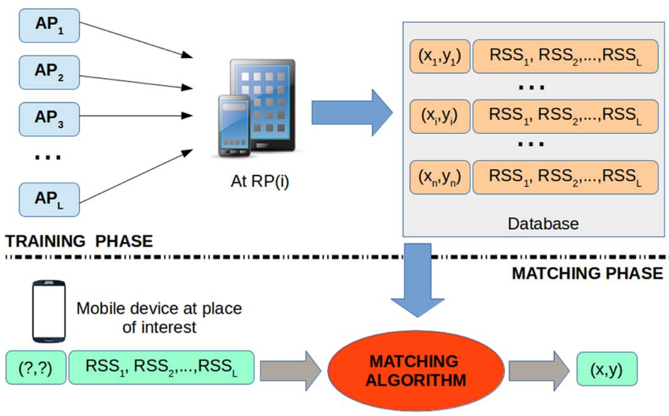

Fig. 8. Signal fingerprint-based localization.

collected fingerprints in the signal map to figure out an estimated location. Originally, the signals are observed in disorder ways, they must be organized to form a signal pattern in a conventional structure like the pre-defined fingerprints in the signal map.

The most common signal fingerprint used in conventional techniques has a form as following:

$$F_i(x, y) = [RSSI_1, RSSI_2, \ldots, RSSI_N] \tag{4}$$

where $F_i(x, y)$ is the signal fingerprint generated at the i^{th} location of the mobile device with geo-coordinate (x, y), $RSSI_k$ is the received signal strength indicator value at the i^{th} location from the k^{th} WiFi AP or GSM BS, and N is the number of the WiFi APs or GSM BSs.

Besides using RSSI values, several systems also use extra parameters to construct the signal fingerprint. For instance, LifeTag is a personal location-logging system based on the PlaceEngine location platform [13], [36]. It estimates the location of mobile devices by utilizing signal fingerprint including MAC addresses and the RSSI of nearby APs as following:

$$F(x, y) = ([MAC_1, RSSI_1], \ldots, [MAC_N, RSSI_N]) \tag{5}$$

where $F(x, y)$ is the signal fingerprint at location (x,y), MAC_i is the MAC address of AP_i, and $RSSI_i$ is the received signal strength indicator value from the AP_i.

Also, the RADAR system [10] proposed by Microsoft constructs the fingerprint using a tuple of the form as:

$$F(x, y) = (d, [RSSI_1, SNR_1], \ldots, [RSSI_N, SNR_N]) \tag{6}$$

where $F(x, y)$ is the signal fingerprint at location (x,y), d is the direction of measurement, N is the number of the audible WiFi APs or GSM BSs, $RSSI_i$ and SNR_i are the received signal strength indicator value and the signal-to-noise ratio from the i_{th} BS, respectively. The main challenge of these signal fingerprint types is that the received signal could be affected by diffraction, reflection, and scattering in the propagation environments.

While these conventional localization systems use signals received at the mobile device to construct fingerprints, the signal subspace-based techniques alternatively use the signals received by an array antenna at the BS to generate fingerprints. The array antenna receives signals from direct path and many reflected multipath components simultaneously due to obstacles in the propagation environments. The received signal $\mathbf{x}(t)$ at an L-element array antenna from AOA θ_i with noise is modeled as

$$\mathbf{x}(t) = \sum_{i=0}^{M} \mathbf{a}(\theta_i)s_i(t) + \mathbf{n}(t) = \mathbf{A}s(t) + \mathbf{n}(t), \tag{7}$$

where M is the total number of direct and multipath components, $\mathbf{a}(\theta)$ is a steering vector denoting a phase shift of a received signal at each antenna, and $\mathbf{A}$ is the steering matrix of $L \times M$. By using the received signal, the signal subspace is constructed as the fingerprint for estimating the location of the mobile device. This technique has been developed in both indoor and outdoor localization [37], [38].

2) Signal Fingerprint Matching Technique: This is often done by using Euclidean Distance-based Matching algorithm, which consists of measuring Euclidean distances between the recorded signal fingerprint and each reference location in the database. The Euclidean distance between two fingerprints is defined as:

$$dist = \sqrt{\sum_{i=1}^{N} (RSSI_{RL}(i) - RSSI_{ML}(i))^2} \tag{8}$$

where N is the number of WiFi APs or BSs, $RSSI_{RL}$ and $RSSI_{ML}$ are the RSSI vector at one reference location and the measurement location, respectively.

The Euclidean distance indicates how close a fingerprint at one reference location to the query fingerprint at the measurement location. After the distances between the query fingerprint to each fingerprint in the database are calculated, the Nearest Neighbor algorithm is called to select the closest fingerprint. Among the fingerprints in the database, the selected fingerprint has the smallest distance to the query fingerprint.

Signal Fingerprint Filtering: As the size of the surveyed area in the training phase get larger, the size of the database of signal fingerprints quickly increases. Every time when a location is requested, matching the query signal fingerprint to all the fingerprints existing in the database is too inefficient. To improve the matching performance, it is necessary to reduce the search space by keeping only signal fingerprints which may affect to the localization result.

Several efficient methods have been used to accomplish this idea. The simplest method is to select the AP which has the strongest signal in the query signal fingerprint, and find all the fingerprints in the database which contain this AP. Instead of selecting only the strongest signal AP, an alternative method is to select several APs in the query, and finds all the pre-defined fingerprints which contain all these APs. For example, if the user sends a query fingerprint which contains two APs X and Y, with signal strengths $RSSI_X$ and $RSSI_Y$, respectively. The search space can be reduced by searching for all the fingerprints that contain both APs A and B, and where the signal strengths are "close" to $RSSI_X$ and $RSSI_Y$. However, in order not to eliminate the correct fingerprint, Quader *et al.* also showed that this method must not be too restrictive [39].

3) Signal Fingerprint Populating Techniques: There are two techniques mostly used to create a signal map: War-driving technique and Grid-based War-driving technique.

- War-Driving Technique: War-driving technique, also called war-sensing, is the most common approach that creates a signal map by war-driving an area of interest and records signal fingerprints for reference locations in the area. At each reference location, the technique collects the location coordinates and respective RSSIs from the APs or BSs. The collected RSSIs at each reference location are then used to construct a signal fingerprint which is unique to that location.
- Grid-Based War-Driving Technique: The purpose of this technique is to construct the signal strength histogram for the RSSI received from each base station at each location in the fingerprint. Using the war-driving technique, however, requires the mobile user to stand at each location for a certain time in order to collect enough samples for constructing the RSSI histogram. This increases the fingerprint construction overhead, as the war-driving car has to measure the RSSI at each location for a certain time.

  To avoid this overhead, the grid-based war-driving technique divides an area of interest into cells using a gridding approach with a floor plan. The histogram is then constructed for each AP/BS in a given cell using all fingerprint locations inside the cell, rather than for each fingerprint point [11].

D. Hybrid Fingerprint-Based Localization

Hybrid fingerprinting combines multiple fingerprint types to achieve better accuracy [40]. There are several types of integrations in hybrid fingerprint-based localization. Some systems combine multiple fingerprints, some are integrated with standard positioning techniques. In some hybrid systems, in addition, ambient characteristics of the surrounding environment (e.g., temperature, light, sound, humidity, and barometric pressure), are also used as signatures for localization. Continuous observation of such information can provide cues to identify where a user is. For instance, the ambient sound recorded by using a smartphone microphone can tell whether the user currently is at home or market, on a bus or subway. Also, the temperature and light together can indicate whether the user is indoor or outdoor.

In practice, various types of environmental context information are combined and integrated with other fingerprints to give a robust localization result. Multiple sensors (e.g., thermometers, hygrometers, pressure, light sensors) are activated simultaneously to capture a rich set of ambient characteristics for localization. SurroundSense system [41] is one example of this trend. The system proposes four localization modes across multiple sensors. Each mode comprises a different combination of sensors such as WiFi-only mode, Snd-Acc-Lt-Clr mode (which stands for sound, accelerometer, light and color mode), Snd-Acc-WiFi mode (which stands for sound, accelerometer, and WiFi mode), and SurroundSense mode (which is the combined scheme with all modes of ambience fingerprinting). Evaluation results show that the SurroundSense system can achieve an average accuracy of 87% when all sensing modalities are used.

IV. Review of Outdoor Localization Systems Based on Fingerprinting Modes

There exist many fingerprint-based localization approaches that vary greatly in localization accuracy and energy consumption. When selecting one localization approach, several key aspects are considered such as mode of fingerprint as well as localization performance in different environmental contexts. This section classifies fingerprint-based outdoor localization systems existing in the last decade based on fingerprint types. A comparison of these systems is summarized in Table II.

A. Visual Fingerprint-Based Localization Systems

The basic idea of visual fingerprint-based localization is to match a user generated query image against a database of geotagged images for localization. One of the main challenges of this is performance degradation as the size of the visual fingerprint databases grows. As the size of the database grows, the performance of this technique decreases in terms of localization accuracy, energy efficiency and high latency. Many solutions have been proposed to address this problem. For instance, Zhang *et al.* introduced an approach for large scale image retrieval for user localization [8]. The idea is to segment the large database of geotagged images for a large area into a number of overlapping cells, and take advantage of coarse position estimates available on modern mobile devices (e.g., via base station triangulation) to reduce the search space. The CBIR technique then matches the query image to only the images located inside the area of interest (e.g., a region of a cell tower), which helps improving the matching performance. For datasets in Berkeley and Oakland, CA, made of tens of thousands of images, this approach achieves 90% image retrieval accuracy and 67% experiments within 50 m.

However, similar to [8], techniques such as randomized kd-trees [42] and locality sensitive hashing [43], which segment a large environment like a city into several overlapping subregions may lead to redundant retrieval result. Also, a major challenge of visual-fingerprint localization is the transmission data between the client and sever. Schroth *et al.* have proposed an approach to avoid the redundant images and the network delay [7]. By exploiting the statistics of the database, only relevant features, which provide most information about the location of the device, can be identified and downloaded. The authors experiment the system using Google Street View panoramas. By tracking the system every 3 s using realistic video recording, a new set of tracked query features is uploaded to the server. The set of tracked features is used to query the full vocabularies to retrieve the visually most similar locations. About 5000 selected visual words and their associated inverted files are downloaded to the client within 3 s. Experiment results show that at least one panorama is retrieved within 20 m for 82.3% of the track, and within 40 m for 91.0% of the track. By eliminating the network delay, the authors facilitate a close to real-time pose estimation on the mobile device.

TABLE II
COMPARISON OF FINGERPRINT-BASED OUTDOOR LOCALIZATION SYSTEMS

Fingerprint Type	System Name	Sensors	Accuracy	Power Consumption	Note
Visual	J.Zhang [8]	Camera	67% experiments within 50m		Result match 96% of the time
	G.Schroth [7]	Camera	Less than 20m for 82.3%, and 40m for 91.0 of the track%		Close to real-time pose estimation
Motion	GAC [44]	Compass, Accelerometer	Up to 97% within intra-city roads	Less energy consumed than GPS	GPS is infrequently used
	CompAcc [35]	Compass, Accelerometer	Less than 11m	Around 0.1W	Require AGPS for fallback mechanism
	APT [34]	Gyroscope, Accelerometer	Error is less than 5m	Less energy consumed than GPS	GPS is infrequently used
Signal	Place Lab [45]	WiFi antenna, GSM antenna	Median accuracy of 15-20m		
	PlaceEngine [36]	WiFi antenna	From 5 to 100m		Response time is less than 1 second
	P. Cherntanomwong [38]	WiFi antenna	Mean error is less than 5m even under non line-of-sight conditions		
	CAPS [12]	GSM antenna	Mean error is less than 20% of the cell tower-based triangulation	Improve energy efficiency by more than 90% compared to GPS	
	CellSense [11]	GSM antenna	Mean errors are 42.43 meters and 27.86 meters in rural and urban areas, respectively		More than 5.4 times savings in running time, compared to other signal fingerprint-based techniques
Hybrid	M. Anisetti [31]	GSM antenna, Camera	Mean error of 25.08m with standard deviation of 38.33m		
	WheelLoc [46]	Accelerometer, Magnetometer, GSM antenna	About 40m	Only 240mW consumed	Estimated location returned within 40ms
	Dejavu [47]	WiFi antenna, GSM antenna, Accelerometer, Magnetometer	Within 8.4m median error in city roads and 16.6m on highways	Extend the battery lifetime by 347%	Providing both accurate and energy-efficient
	EnLoc [48]	WiFi antenna, GSM antenna	Average localization errors are around 12m	Around 25% of the energy budget per 24-hours	
	RAPS [16]	Accelerometer, GSM antenna		Phone life-times increased by more than a factor of 3.8, compared to GPS	GPS is activated manually
	LocationStudy [17]	Accelerometer		Reduces GPS energy-consumption up to 27 %	
	SmartLoc [15]	Gyroscope, Accelerometer	Less than 20m for more than 90% roads		Landmarks and special driving patterns are used when the GPS signal is weak
	A. Hallquist [40]	Camera, Accelerometer, Compass	Within 10m for 92% of queries		An extension of [8]

B. Motion Fingerprint-Based Localization Systems

Although motion sensors in smartphones can be used to detect movements of a mobile user, these sensors are highly noisy. This leads to poor traveling distance and speed estimation in standalone motion fingerprint-based localization systems. To address this challenge, many solutions have been proposed with the integration of the GPS module.

GAC system introduced a low-energy localization technique using the readings from motion sensors and the brief support of GPS for synchronization [44]. Using Newton's laws of motion, the travel distance is calculated by taking the double integral of accelerometer readings. However, due to the noise in the accelerometer, error accumulates as time goes on. The main idea is to reduce the accumulated error by turning on the GPS briefly and infrequently to obtain an accurate location estimate. Depending on the frequency of synchronization with the GPS, there is a trade-off between accuracy and energy consumption in this system. Experimenting the GAC system in both highways and intra-city driving environments show that the proposed system has exponential saving in energy, with a linear loss in accuracy compared to GPS.

On the other hand, CompAcc employs DR algorithm and Assisted-GPS (AGPS) to build an infrastructure-independent localization system [35]. The walking speed and the orientation of a mobile user are measured using accelerometer and electronic compass in smartphones. Using these readings and dead-reckoning technique, CompAcc calculates the user's walking pattern or a directional trail. This direction trail is then matched against possible path signatures, which are pre-generated within an area of interest. Using infrequent AGPS readings, CompAcc can periodically recalibrate the phone location, and use it as a reference for further position estimation. The evaluation results show that CompAcc could provide a location accuracy of less than 11 m in regions, where today's localization services are unsatisfactory or unavailable. Although this technique is considered as a simple localization method without war-driving, but it needs time-consuming calibration, and therefore it is not suitable for large scale area.

APT proposed an outdoor pedestrian tracking system with higher accuracy compared to the built-in GPS on smartphones [34]. By using several useful observations such as the regular movement patterns of pedestrians, the ability in distinguishing between distant routes of GPS, and the simplicity of generating augmented maps on smartphones, APT introduces a robust DR algorithm and an error-tolerant algorithm for map matching. Instead of detecting walking steps as usual, the proposed DR algorithm finds the user's acceleration patterns which can reflect travel distance. The algorithm also estimates the walking directions without requiring the user to hold the phone flat out. While matching motion fingerprints against a digital map, the proposed error-tolerant map-matching algorithm tolerates possible errors of the DR algorithm. Using this tolerance and the support of GPS, APT can eliminate ambiguous routes and determine the correct route. The evaluation results show that APT can achieve a localization accuracy within 5 meters, while GPS-based approaches have error up to 15 meters.

C. Signal Fingerprint-Based Localization

There are many research and commercial systems that have been built using both WiFi APs and base stations as beacons for fingerprint localization. Place Lab is one of well-known examples of this technique for both indoor and outdoor positioning [45]. In this system, the authors address both maximizing coverage across people's daily lives and the high-cost of infrastructure of previous localization approaches. They employ radio beacon sources which all have unique or semi-unique IDs (i.e., MAC addresses), and can be mapped appropriately to maximize the coverage in most people's daily lives. The authors evaluate the localization performance by experimenting the Place Lab system in three distinct neighborhoods of Seattle with different densities of beacons like urban, residential, and suburban. The result shows that Place Lab can achieve a median accuracy of 15–20 meters in downtown Seattle where at least three distinct beacons are seen during a 10 second window. Compared to GPS, this accuracy is much lower, but unlike GPS, the location covers almost 100% of users' daily lives. In the suburban area, such as Champaign, IL, and Durham, NC, the experiment results in median accuracy just over 30 meters.

Another commercial WiFi-based location platform service, called PlaceEngine, have been proposed using MAC addresses and the RSSI of nearby APs [36]. This is a web service that enables any device equipped with WiFi can determine its current location, using a database consisting of more than half a million estimated access point (AP) locations. Besides War Driving, the signal database is constructed by combining different methods such as (i) Warwalking—the WiFi signal fingerprint is collected by walkers, (ii) End User Register—the end users of the system explicitly register locations by using a map interface, and (iii) Access Log Analysis—analyzing end users' query logs. However, the WiFi signals can be sensed differently at a given time and place. Thus, it is difficult to determine the precise accuracy of the PlaceEngine server. The rough estimation of the accuracy is on the order of 5 to 100 meters. In addition, many PlaceEngine clients, such as web service or mobile applications, have been created using the PlaceEngine platform. Among them, LifeTag has been known as a personal location-logging system that continuously and precisely records one's location history [13]. By sending WiFi information to the PlaceEngine server, LifeTag can detect a user's location even indoors or underground, where it might normally not be possible with GPS. Since the WiFi signal recording is quick (typicall less than one second), the entire logging phase takes 3 seconds to record the location of the mobile device.

Different from the above WiFi-based approaches, Paek *et al.* presented a new energy-efficient localization technique, called Cell-ID Aided Positioning System (CAPS), that provides better accuracy than cell tower-based localization for various location-based services [12]. With respect to energy efficiency, the authors proposed a novel cell-ID sequence-matching algorithm to estimate the location based on the history of cell-ID and GPS position sequences that match the current cell-ID sequence. The basic idea is based on the observation that, mobile users have consistent routes and the cell-ID transition point that each user experience can often uniquely represent the current location of that user. By using a modified Smith-Waterman algorithm, CAPS searches a matched cell-ID sequence with geotag in the user's history to extract accurate position information, without activating GPS. The evaluation results show that CAPS can improve energy efficiency by more than 90%, compared to GPS-only approaches, while providing position accuracy comparable to that of GPS, and with errors less than 20% of the cell tower-based triangulation.

However, most signal fingerprint-based systems, including [36], [45], use deterministic techniques to construct signal fingerprints for these localization systems. Such techniques can be piggybacked on these systems due to extra overhead. By using a probabilistic fingerprint-based technique for GSM localization, CellSense presents an alternative way to construct fingerprints without incurring any additional overhead [11]. To address this challenge, instead of measuring the signal strength histogram at each fingerprint location for a certain amount of time, the authors of CellSense divide the area of interest into a grid and construct the histogram for each grid cell. This, not only removes significantly the extra overhead of standing at each location for a certain time, but also increases the scalability by increasing the grid cell size, which can reduce the fingerprint size. Moreover, to further reduce the computational overhead of CellSense, the authors also proposed a hybrid technique, called CellSense-Hybrid, that combines probabilistic and deterministic estimations to achieve both high accuracy and low computational overhead. The result shows that the median errors of CellSense are 42.43 meters and 27.86 meters in rural and urban areas, respectively. On the other hand, the positioning accuracy of CellSense is better than other signal fingerprint-based localization techniques with at least 108.57% in rural areas and at least 89.03% urban areas, and with more than 5.4 times savings in running time.

Although there are many researches on signal fingerprint-based positioning techniques, the advantages of the spatial information were not utilized effectively. Nezafat *et al.* proposed a subspace fingerprint localization, which localizes non-cooperative transmitters in a micro-cellular environment dominated by non line-of-sight (NLOS) propagation, using the signals received by an array antenna at the BS [14]. This fingerprint-based technique also requires construction of the database in advance. The finer the spatial resolution of the database, the more accurate the estimate of the localization. However, the signal subspace for discrete measurement points in this technique has a coarse spatial sampling interval of 100 m used for interpolation, leading to big errors in location estimation. To address this problem, Cherntanomwong *et al.* proposed a method of the signal subspace interpolation to construct a continuous fingerprint database[38]. By using the interpolation of the signal subspace for discrete measurement points with spatial sampling intervals of 5 m and 10 m, a continuous spatial signature is regenerated. The authors constructed one database which composes of the signal subspaces for every 5 m, and another composes of the signal subspaces for every 10 m. The experimental results show that the finer sampling interval could achieve the more accurate location, with the estimation error is less than 5 m for most locations.

D. Hybrid Fingerprint-Based Localization

Compared to standalone positioning techniques, the hybrid schemes have better performance in terms of accuracy and energy efficiency. However, hybrid fingerprint-based approaches always require a fingerprint generation process, which combines multiple sensed data collected from multiple sensors to construct the hybrid fingerprints. The rest of this section categorizes localization system based on types of hybrid fingerprints.

1) Use of Multiple Fingerprint Modes: Anisetti *et al.* presents a robust localization approach that could enhance the accuracy in areas with poor signal and low accurate geolocation [31]. This is done by mixing the location information acquired with the RSSI fingerprint and a landmark matching obtainable using the smartphone camera. This work proposed a geolocation approach based on a time-forwarding algorithm using a database correlation technique over RSSI data. Then, they integrate the geolocation approach with a landmark recognition to improve the signal-based geolocation approach. The performances of the geolocation algorithm are carefully validated by an extensive experimentation, carried out on real data collected from the mobile network antennas of a complex urban environment.

Also, in order to improve the positioning accuracy of the image-based localization system presented in [8], Hallquist *et al.* present a sensor fusion approach which estimates the pose of a mobile device in urban environments using readings from GPS, accelerometer, and compass [40]. There are two steps in this approach. In the first step, a city-scale image database is used to find an image that matches the query image captured by the mobile device. This technique, presented in [8], achieves 90% image retrieval accuracy for a database of tens of thousands of images in Berkeley and Oakland, CA. This database contains three dimensional (3D) information, including the full pose of each image and 3D point clouds corresponding to the depth map of each image. In the second step, the matching image retrieved in the first step and its associated pose in the global world coordinates are used to recover the pose of the query image, by taking into account the input from the accelerometer and compass on the mobile device. The full orientation and the planes of the mobile device are first detected, then the pose of the mobile device is computed by estimating a homography transformation matrix between the query image and the matching image, constrained by the knowledge of the change in orientation obtained from the mobile device gyro and augmented with 3D information from the database. Characterizing the performance of this approach for the dataset in Oakland, CA shows that 92% of the queries are localized within 10 meters.

Unlike previous localization schemes, WheelLoc is presented as a continuous location service using an indirect approach which seeks to capture user mobility trace and obtain point locations through interpolation or extrapolation [46]. WheelLoc records simultaneously both the base station IDs and the user movements (e.g., the velocity and direction) estimated from accelerometer and magnetometer readings. While the base station IDs are used to obtain a map of the searching area, the readings from these motion sensors are used to build the user mobility trace. The mobility trace is then used as a sequence of estimated distance and turns, which is afterward matched to the most likely road segments on the map via a Hidden Markov Model and Viterbi decoding-based matching process. Depending on when the location query is issued, the point location is obtained via time- and speed-aware interpolation or extrapolation. The effectiveness of WheelLoc has been confirmed through experimental results. Due to the use of low-power sensors, the results from the experiments show that WheelLoc could return a location with an accuracy about 40 m, and consumes only 240 mW energy. Compared with GPS and cellular-based localization, WheelLoc is able to provide instant location fix with significantly improved energy-accuracy tradeoff.

While the other approaches attempt to improve either localization accuracy or energy efficiency, Dejavu has been proposed as a system capable of providing both accurate and energy-efficient outdoor localization [47]. The idea is based on the fact that different roads have different sets of clues such as bumps, bridges, and even potholes, which all affect the inertial sensors of mobile devices as a unique signature to distinguish the roads. Although Dejavu mainly employs a dead-reckoning approach using the low-energy profile inertial sensors, but different from other dead-reckoning-based techniques Dejavu also identifies unique signatures in the environment, i.e., landmarks or anchors, and uses them to reset the error accumulation in the dead-reckoning displacement. The experimental results show that Dejavu could provide a median accuracy of 8.4 m in city roads and 16.6 m in highways. This is 42.9% better in median localization error than GPS in city driving conditions. In addition, compared to GPS, Dejavu can extend the battery lifetime by 347% due to the use of only low-power sensors or sensors that are already running for other purposes, e.g., GSM and opportunistic WiFi signal strength.

2) Augmenting Standard Positioning Techniques With Fingerprints: Realizing the battery shortage problem of GPS-based localization systems, various solutions have been proposed to save energy using motion fingerprint. Rate-adaptive positioning system (RAPS) is one example of the techniques which explore the energy-accuracy trade-off by introducing novel techniques for cheaply inferring when GPS activations are necessary [16]. RAPS estimates user velocity from the location-time history of previously measured velocities, and adaptively turn on GPS only if the estimated uncertainty in position exceeds the accuracy threshold. By using a duty-cycled accelerometer, RAPS also efficiently estimates user movement and employs Bluetooth communication to reduce position uncertainty among neighboring devices. And finally, RAPS delays GPS activation if the identifier and the signal strength from the current active base station indicates that previous activation attempts at locations with comparable identifier and signal strength information failed frequently. In other words, if RAPS detects locations where GPS is unavailable, it avoids turning on GPS in these cases. The evaluation results from experimenting RAPS through real-world show that it has over 3.8× longer battery lifetime as compared to continuous GPS sampling.

Similar to the RAPS system, LocationStudy focuses solely improving the energy-efficiency of GPS using an accelerometer based architecture [17]. Using the embedded smartphone accelerometer, LocationStudy proposed a user mobility context detection algorithm which could differentiate between subtle activities with high accuracy such as being stationary (lying down or sitting) and in-motion (walking or jogging). The results of the proposed algorithm then can be used to manage the process of turning-on and off location sensors (such as GPS) embedded in smartphones on purpose of reducing energy consumption. Evaluation of LocationStudy shows that it could save the energy up to 27% in typical circumstances. Recently, motion fingerprint-based localization systems have exploited the possibility of using inertial sensors such as accelerometer and compass, to measure the walking speed and direction of a mobile user, and then estimate the location using a dead-reckoning algorithm [34], [35]. However, these sensors are highly noisy and could make the naive distance estimation based on Newton's Law unavailable because the error is accumulated. Recently, a metropolis localization system, called SmartLoc [15], has been proposed to improve the localization accuracy in metropolises by leveraging these sensors and the GPS module of smartphones. To reduce the impact of inherent noise and accumulated error, SmartLoc constructs a predictive regression model to estimate the trajectory using linear regression. Also, it detects the road conditions (e.g., bridge, traffic light, uphill and downhill), and recognize the user's driving status (e.g., turns, stops) as landmarks to calibrate the localization result. By using the user's driving status (e.g., turns, stops) and the road conditions (e.g., bridge, traffic light, uphill and downhill) as landmarks, SmartLoc proposed a self-learning driving model which could calibrate the localization result. This calibration strategy reduces the speed and trajectory distance estimation error brought by the inherent noise and dead-reckoning, and therefore the localization accuracy is improved even when the GPS signal is weak. The evaluations show that SmartLoc can improve the localization accuracy to less than 20 m for more than 90% roads in Chicago downtown, while the known mean error of GPS is 42.22 m.

In addition, many research and commercial localization systems attempted to find the trade-off between energy consumption and localization accuracy. EnLoc is one such system which quantifies this important trade-off and underlies a range or emerging services [48]. From the preliminary experiments, EnLoc proved that when power consumption is translated to net battery life, GPS allowed for 9 hours, while WiFi and GSM sustained for 40 and 60 hours, respectively. However, the corresponding localization accuracies are rapidly dropped from 10 m, 40 m to 400 m. To optimize the localization accuracy for a given energy budget, the authors of EnLoc developed a dynamic programming solution to determine a schedule with which the location sensors (GPS, WiFi, or GSM) should be triggered such that the average localization error is minimized. By using an anonymous student's mobility profile for their experiment for 30 days, the results showed that for the given energy budget of 25% per a day the average localization errors are around 12 m.

V. Comparison of Fingerprint-Based Outdoor Localization Systems Based on Performance Objectives

Most of the existing fingerprint-based localization techniques have focused primarily on either accuracy and complexity. It is critical to achieve a good balance between accuracy and complexity on mobile platforms. However, due to the limited battery and computing power of mobile devices, several challenges exist when developing fingerprint-based localization systems on mobile devices. For instance, multimedia processing consumes high computational power and memory, which

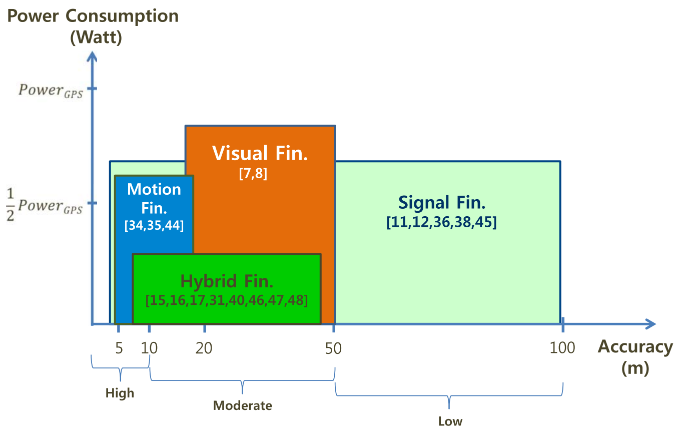

Fig. 9. Comparison of different Fingerprint-Based localization system with respect to accuracy and energy efficiency.

makes it difficult to perform on mobile devices. In this section, we compare the performance of the various fingerprint-based localization systems with respect to positioning accuracy, energy efficiency, and latency, as shown in Fig. 9.

A. Positioning Accuracy

Positioning accuracy across standalone fingerprint-based techniques are lower compared to hybrid techniques. For instance, standalone visual fingerprint-based systems often result lower accuracy compared to the other techniques [8]. However, by using visual fingerprint in conjunction with readings from the GPS, accelerometer, and compass, Hallquist *et al.* improve the positioning accuracy in the previous work [8] to less than 10 meters for 92% of queries [40].

Compared to visual fingerprint-based techniques, motion fingerprint and signal fingerprint-based techniques are often better in accuracy. However, due to the errors accumulated from inertial sensors during the tracing process, motion fingerprint-based techniques are often used in conjunction with standard positioning techniques such as GPS, to recalibrate the estimated location. For example, APT presents a signal fingerprint-based technique which can achieve a localization accuracy less than 5 meters using the support from GPS infrequently.

Also, the accuracy of signal fingerprint-based techniques is degraded due to the limit of WiFi signals or cellular signals in outdoor environments. The positioning error varies depending on the spatial resolution of signal fingerprints in the database. For instance, the positioning accuracy of the PlaceEngine service is on the order of 5 to 100 meters, depends on the WiFi signal density at a given time and place [36].

B. Energy Efficiency

Fig. 9 shows that all of the fingerprint-based localization systems consume less power than the GPS-based systems, due to the use of low-power sensors embedded in mobile devices. Among them, hybrid fingerprint-based techniques consume less power. Many hybrid fingerprint-based systems such as RAPS [16] or Dejavu [47], can increase the phone lifetime by more than a factor of 3.8, compared to GPS.

On the other hand, visual fingerprint-based techniques on mobile devices consume more power than the others. The power consumption is high due to the use of compute-intensive methods from computer vision and image processing on mobile devices. Considering the limited processing power and battery life of mobile device, recent visual fingerprint-based techniques use client-server architecture to reduce the work at the mobile devices [20]. The mobile device works as a client, capturing images and sending each image to the server via a network connection. At the server side, the content of the captured image is analyzed to extract visual features as a fingerprint for the image retrieval. The server performs the image retrieval, then returns the result to the mobile client.

C. Latency

The latency of the localization process, or response time to a query, plays a very important role in many location-based applications. The response time is measured from the time when the fingerprint is sensed until the estimated location is returned. Depending on the types of the fingerprints, the localization processes may take different amounts of time to respond with the location information. Among them, localization techniques using motion fingerprints or hybrid fingerprints have less response time compared to the others. For instance, WheelLoc can return a location fix within 40 ms over 99% of time [46].

On the other hand, visual fingerprint-based techniques on mobile devices often need more time to identify the location. This happens due to the fact that the mobile devices have limited processing power and the visual feature quantization is a time-consuming process. Recent visual fingerprint-based techniques adopt a client-server architecture to speed-up the localization process. However, network transmission is time-consuming as the amount of data transmitted to the server increases. To address this problem, Schroth *et al.* propose an approach that eliminates the network delay by sending only features tracked from images to the server, and downloading only the relevant information as a database features for localization [7].

VI. Future Directions in Use of Fingerprint Based Localization Techniques

In this section, we take a close look at the applications that can be enabled using fingerprint-based localization. We identify the challenges that can be addressed and improvements that can further enhance the capabilities of fingerprint-based localization.

A. Applying Cross-Domain Techniques

Existing fingerprint-based localization can be improved if they are augmented with cross-domain techniques from computer vision, signal processing, machine learning. Examples include solutions which reduce the complexity of the matching process in visual fingerprint-based localization, such as [49]. By incorporating computer vision techniques, the processing time and the complexity in image matching process can be reduced, which would increase the performance and the feasibility of visual fingerprint-based localization technique.

Use of techniques from machine learning research for faster and more accurate pattern matching can also benefit the solutions. For instance, genetic algorithms and game theoretic techniques can help in balancing the trade-offs between conflicting performance objectives.

B. Moving Towards Fingerprint-Based Navigation

Navigation applications can be a logical extension of the fingerprint-based localization. Currently, motion fingerprint-based localizations are employed in many navigation systems. The challenge of applying other Fingerprint-Based approaches for navigation are still being investigated, as shown in [50], [51].

C. Augmented Reality With Fingerprint-Based Localization

One of the important requirements for an Augmented Reality positioning system is that it should work indoors and outdoors. Standard localization techniques using GPS can fail in indoor settings. Therefore, as the fingerprint-based localization become feasible, many augmented reality techniques try to use fingerprints for localization [52]. For instance, one augmented reality system may want to access information related to some remote objects (e.g., building, restaurants, hotels). The system first identifies the location of the remote object of interest, then uses location-based services to acquire the information of that object, such as "how expensive the rooms in that hotel" or "the closing time of a coffee shop within view".

D. Seamless Indoor and Outdoor Location Systems Using Fingerprints

Use of different fingerprints, like FM signals, has been explored for indoor localization [53]. Unifying fingerprint-based techniques for indoor and outdoor localization can lead to seamless tracking of user. Lau *et al.* had shown that RSSI based signatures can be used effectively to track a user across indoor and outdoor environments [54]. Adopting a single location sensing technology, or switching between different fingerprinting technologies transparent to the user, can lead to a truly pervasive location sensing solution.

VII. Conclusion

Outdoor localization is an essential service used in many location based applications. With the growing number of inbuilt sensors on smartphones, several techniques have exploited these sensors for to capture signatures of the environment, and matched against these geotagged signatures to determine location. In this survey, we present a review of fingerprint-based outdoor localization. We explain the concept of fingerprint-based localization and show how different techniques using various ambient cues fit into the general idea of fingerprint-based localization. We classify the existing techniques for localization based on different fingerprint modes, namely visual fingerprint, motion fingerprint, signal fingerprint, and hybrid fingerprint. Existing outdoor localization systems are reviewed based on the use of fingerprint types and the performance of the systems are summarized along the three performance objectives—accuracy, energy efficiency and latency of localization. We also highlight the use of fingerprint localization for enabling new applications and related research opportunities.

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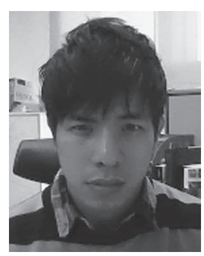
References

[1] Y. Pei, "A survey on localization algorithms for wireless ad hoc networks," in *Communications and Information Processing*, vol. 289, ser. Communications in Computer and Information Science. Berlin, Germany: Springer-Verlag, 2012, pp. 512–519.
[2] V. Honkavirta, T. Perala, S. Ali-Loytty, and R. Piche, "A comparative survey of WLAN location fingerprinting methods," in *Proc. 6th WPNC*, 2009, pp. 243–251.
[3] H. Liu, H. Darabi, P. Banerjee, and J. Liu, "Survey of wireless indoor positioning techniques and systems," *IEEE Trans. Syst., Man, Cybern. C, Appl. Rev.*, vol. 37, no. 6, pp. 1067–1080, Nov. 2007.
[4] T. Dharani and I. Aroquiaraj, "A survey on content based image retrieval," in *Proc. Int. Conf. PRIME*, Feb. 2013, pp. 485–490.
[5] "Google Goggles." [Online]. Available: http://www.google.com/mobile/goggles/
[6] "Vuforia Object Scanner." [Online]. Available: https://developer.vuforia.com/
[7] G. Schroth *et al.*, "Mobile visual location recognition," *IEEE Signal Process. Mag.*, vol. 28, no. 4, pp. 77–89, Jul. 2011.
[8] J. Zhang, A. Hallquist, E. Liang, and A. Zakhor, "Location-based image retrieval for urban environments," in *Proc. 18th IEEE ICIP*, Sep. 2011, pp. 3677–3680.
[9] G. Sun, J. Chen, W. Guo, and K. Liu, "Signal processing techniques in network-aided positioning: a survey of state-of-the-art positioning designs," *IEEE Signal Process. Mag.*, vol. 22, no. 4, pp. 12–23, Jul. 2005.
[10] P. Bahl and V. Padmanabhan, "Radar: An in-building rf-based user location and tracking system," in *Proc. IEEE 19th INFOCOM*, 2000, vol. 2, pp. 775–784.
[11] M. Ibrahim and M. Youssef, "Cellsense: An accurate energy-efficient GSM positioning system," *IEEE Trans. Veh. Technol.*, vol. 61, no. 1, pp. 286–296, Jan. 2012.
[12] J. Paek, K.-H. Kim, J. P. Singh, and R. Govindan, "Energy-efficient positioning for smartphones using cell-id sequence matching," in *Proc. ACM MobiSys*, A. K. Agrawala, M. D. Corner, and D. Wetherall, Eds., 2011, pp. 293–306.
[13] J. Rekimoto, T. Miyaki, and T. Ishizawa, "Lifetag: WiFi-based continuous location logging for life pattern analysis," in *Location- and Context-Awareness*, vol. 4718, ser. Lecture Notes in Computer Science, J. Hightower, B. Schiele, and T. Strang, Eds. Berlin, Germany: Springer-Verlag, 2007, pp. 35–49.
[14] M. Nezafat, M. Kaveh, H. Tsuji, and T. Fukagawa, "Subspace matching localization: A practical approach to mobile user localization in microcellular environments," in *Proc. IEEE 60th VTC—Fall*, Sep. 2004, vol. 7, pp. 5145–5149.
[15] C. Bo *et al.*, "SmartLoc: Push the limit of the inertial sensor based metropolitan localization using smartphone," in *Proc. MobiCom*, 2013, pp. 195–198.
[16] J. Paek, J. Kim, and R. Govindan, "Energy-efficient rate-adpative GPS-based positioning for smartphones," in *Proc. MobiSys*, 2010, pp. 299–314.
[17] T. Oshin, S. Poslad, and A. Ma, "Improving the energy-efficiency of GPS based location sensing smartphone applications," in *Proc. 11th IEEE Int. Conf. TrustCom, Security Privacy*, 2012, pp. 1698–1705.
[18] T. Gallagher, B. Li, A. Dempster, and C. Rizos, "Database updating through user feedback in fingerprint-based wi-fi location systems," in *Proc. UPINLBS*, Oct. 2010, pp. 1–8.
[19] R. Huitl, G. Schroth, S. Hilsenbeck, F. Schweiger, and E. Steinbach, "Virtual reference view generation for CBIR-based visual pose estimation," in *Proc. 20th ACM Int. Conf. MM*, 2012, pp. 993–996.
[20] T. Chen, K.-H. Yap, and D. Zhang, "Discriminative soft bag-of-visual phrase for mobile landmark recognition," *IEEE Trans. Multimedia*, vol. 16, no. 3, pp. 612–622, Apr. 2014.
[21] P. Bhattacharya and M. Gavrilova, "A survey of landmark recognition using the bag-of-words framework," in *Intelligent Computer Graphics*, vol. 441, ser. Studies in Computational Intelligence. Berlin, Germany: Springer-Verlag, 2013, pp. 243–263.

[22] K.-H. Yap, T. Chen, Z. Li, and K. Wu, “A comparative study of mobile-based landmark recognition techniques,” *IEEE Intell. Syst.*, vol. 25, no. 1, pp. 48–57, Jan. 2010.
[23] D. G. Lowe “Distinctive image features from scale-invariant keypoints,” *Int. J. Comput. Vis.*, vol. 60, no. 2, pp. 91–110, Nov. 2004.
[24] C. Liu, J. Yuen, and A. Torralba, “Sift flow: Dense correspondence across scenes and its applications,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 5, pp. 978–994, May 2011.
[25] H. Bay, A. Ess, T. Tuytelaars, and L. V. Gool, “Speeded-up robust features (SURF),” *Comput. Vis. Image Understand.*, vol. 110, no. 3, pp. 346–359, Jun. 2008.
[26] K. Mikolajczyk and C. Schmid, “A performance evaluation of local descriptors,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 27, no. 10, pp. 1615–1630, Oct. 2005.
[27] J. Sivic and A. Zisserman, “Video google: A text retrieval approach to object matching in videos,” in *Proc. 9th IEEE Int. Conf. Comput. Vis.*, Oct. 2003, vol. 2, pp. 1470–1477.
[28] G. Schroth, A. Al-Nuaimi, R. Huitl, F. Schweiger, and E. Steinbach, “Rapid image retrieval for mobile location recognition,” in *Proc. IEEE ICASSP*, May 2011, pp. 2320–2323.
[29] J. van Gemert, C. Veenman, A. Smeulders, and J.-M. Geusebroek, “Visual word ambiguity,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 32, no. 7, pp. 1271–1283, Jul. 2010.
[30] H. Jgou, M. Douze, and C. Schmid, “Improving bag-of-features for large scale image search,” *Int. J. Comput. Vis.*, vol. 87, no. 3, pp. 316–336, May 2010.
[31] M. Anisetti *et al.*, “Landmark-assisted location and tracking in outdoor mobile network,” *Multimedia Tools Appl.*, vol. 59, no. 1, pp. 89–111, Jul. 2012.
[32] D. Chen *et al.*, “City-scale landmark identification on mobile devices,” in *Proc. IEEE CVPR*, Jun. 2011, pp. 737–744.
[33] H.-J. Jang, J. Kim, and D. Hwang, “Robust step detection method for pedestrian navigation systems,” *Electron. Lett.*, vol. 43, no. 14, pp. 1–2, Jul. 2007.
[34] X. Zhu, Q. Li, and G. Chen, “APT: Accurate outdoor pedestrian tracking with smartphones,” in *Proc. IEEE INFOCOM*, 2013, pp. 2508–2516.
[35] I. Constandache, R. Choudhury, and I. Rhee, “Towards mobile phone localization without war-driving,” in *Proc. IEEE INFOCOM*, 2010, pp. 1–9.
[36] “PlaceEngine.” [Online]. Available: http://www.placeengine.com/en
[37] H. Tsuji, “Radio location estimation using signal subspaces of array antennas,” in *Proc. Int. Symp. ISPACS*, Jan. 2009, pp. 244–247.
[38] P. Cherntanomwong, J. C. Takada, and H. Tsuji, “Signal subspace interpolation from discrete measurement samples in constructing a database for location fingerprint technique,” *IEICE Trans.*, vol. 92-B, no. 9, pp. 2922–2930, Sep. 2009.
[39] I. J. Quader, B. Li, W. Patrick Peng, and A. G. Dempster, “Use of fingerprinting in Wi-Fi based outdoor positioning,” presented at International Global Navigation Satellite Systems Society, Sydney, NSW, Australia, 2007.
[40] A. Hallquist and A. Zakhor, “Single view pose estimation of mobile devices in urban environments,” in *Proc. IEEE WACV*, Jan. 2013, pp. 347–354.
[41] M. Azizyan, I. Constandache, and R. Roy Choudhury, “SurroundSense: Mobile phone localization via ambience fingerprinting,” in *Proc. 15th Annu. Int. Conf. MobiCom Netw.*, 2009, pp. 261–272.
[42] C. Silpa-Anan and R. Hartley, “Optimised kd-trees for fast image descriptor matching,” in *Proc. IEEE CVPR*, Jun. 2008, pp. 1–8.
[43] M. Datar, N. Immorlica, P. Indyk, and V. S. Mirrokni, “Locality-sensitive hashing scheme based on p-stable distributions,” in *Proc. 20th Annu. ACM SCG*, 2004, pp. 253–262.
[44] M. Youssef, M. Yosef, and M. El-Derini, “GAC: Energy-efficient hybrid GPS-accelerometer-compass GSM localization,” in *Proc. IEEE GLOBECOM*, 2010, pp. 1–5.
[45] A. LaMarca, “Place Lab: Device positioning using radio beacons in the wild,” in *Pervasive Computing*, ser. Lecture Notes in Computer Science, vol. 3468, H.-W. Gellersen, R. Want, and A. Schmidt, Eds. Berlin, Germany: Springer-Verlag, 2005, pp. 116–133.
[46] H. Wang *et al.*, “WheelLoc: Enabling continuous location service on mobile phone for outdoor scenarios,” in *Proc. IEEE INFOCOM*, 2013, pp. 2733–2741.
[47] H. Aly and M. Youssef, “Dejavu: An accurate energy-efficient outdoor localization system,” in *Proc. 21st ACM SIGSPATIAL Int. Conf. Adv. Geogr. Inf. Syst.* , 2013, pp. 154–163.
[48] I. Constandache, S. Gaonkar, M. Sayler, R. Choudhury, and L. Cox, “EnLoc: Energy-efficient localization for mobile phones,” in *Proc. IEEE INFOCOM*, 2009, pp. 2716–2720.
[49] T. Yeh, K. Tollmar, and T. Darrell, “Searching the web with mobile images for location recognition,” in *Proc. IEEE CVPR*, 2004, pp. II-76–II-81.
[50] H. Hile *et al.*, “Landmark-based pedestrian navigation with enhanced spatial reasoning,” in *Pervasive Computing*, ser. Lecture Notes in Computer Science. Berlin, Germany: Springer-Verlag, 2009, pp. 59–76.
[51] J. Wither, C. E. Au, R. Rischpater, and R. Grzeszczuk, “Moving beyond the map: Automated landmark based pedestrian guidance using street level panoramas,” in *Proc. 15th Int. Conf. MobileHCI Devices Serv.*, 2013, pp. 203–212.
[52] G. Takacs *et al.*, “Outdoors augmented reality on mobile phone using loxel-based visual feature organization,” in *Proc. ACM Int. Conf. Multimedia Inf. Retrieval*, 2008, pp. 427–434.
[53] Y. Chen, D. Lymberopoulos, J. Liu, and B. Priyantha, “Indoor localization using FM signals,” *IEEE Trans. Mobile Comput.*, vol. 12, no. 8, pp. 1502–1517, Aug. 2013.
[54] E.-E.-L. Lau and W.-Y. Chung, “Enhanced rssi-based real-time user location tracking system for indoor and outdoor environments,” in *Proc. ICCIT*, 2007, pp. 1213–1218.



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