UniLoc: A Unified Mobile Localization Framework Exploiting Scheme Diversity

Wan Du†, Panrong Tong§, and Mo Li§
† Department of Computer Science and Engineering, University of California, Merced, USA
§ School of Computer Science and Engineering, Nanyang Technological University, Singapore
wdu3@ucm.edu; tong0091@e.ntu.edu.sg; limo@ntu.edu.sg

***Abstract*—Current localization schemes on mobile devices are experiencing great diversity that is mainly shown in two aspects: the large number of available localization schemes and their diverse performance. This paper presents *UniLoc*, a unified framework that gains improved performance from multiple localization schemes by exploiting their diversity. UniLoc predicts the localization error of each scheme online based on an error model and real-time context. It further combines the results of all available schemes based on the error prediction results and an ensemble learning algorithm. The combined result is more accurate than any individual schemes. With the flexible design of error modeling and ensemble learning, UniLoc can easily integrate a new localization scheme. The energy consumption of UniLoc is low, since its computation, including both error prediction and ensemble learning, only involves simple linear calculation. Our experience with extensive experiments tells that such easy aggregation incurs little overhead in integrating and training a localization scheme, but gains substantially from the scheme diversity. UniLoc outperforms individual localization schemes by 1.6× in a variety of environments, including >89% new places where we did not train the error models.**

I. Introduction

In the past decade, various localization schemes [1]–[29] have been developed for mobile devices using different sensors, e.g., GPS, Wi-Fi RSSIs (Received Signal Strength Indicator) [1]–[6], and inertial sensors (i.e., accelerometer, gyroscope and magnetometer) [7]–[13]. However, as sensor data quality[1] changes accoridng to environmental conditions, the performance of an individual scheme varies spatiotemporally [7]. To provide more stable performance, some works fuse the raw data of multiple sensors, e.g., Wi-Fi RSSIs are used to refine the results of motion-based Pedestrian Dead Reckoning (PDR) by particle filtering [11]–[13]. With predefined types of sensors, it is hard for a fixed fusion algorithm to automatically adapt to all possible environmental conditions. For instance, in some regions with weak Wi-Fi signals (due to high wireless interference or sparse deployment of access points), Wi-Fi RSSIs may not be able to help the default motion-based PDR, or even make the estimated location depart from the user's true location. As a consequence, there does not yet exist a one-size-fit-all mobile localization system that can cover all the places in people's daily life.

In this paper, we propose *UniLoc*, a unified framework that exploits the diversity of existing localization schemes to achieve accurate and robust positioning across variant environment. Different localization schemes use different sensors and they may provide complementary information for estimating the user's location. UniLoc adopts a novel fusion methodology that without going into the details of individual schemes, only processes the final outputs to exploit the complementary information of all available schemes and provide better result than any individual schemes. Based on such a design principle, UniLoc provides three features.

- **General**. UniLoc is not constrained to any specific localization schemes or sensor data. Any localization scheme can be easily integrated into UniLoc.
- **Adaptive**. UniLoc can automatically adapt to the spatiotemporal variation of sensor data at every location.
- **Scalable**. UniLoc can be used in new unknown places without pre-training.

It is challenging to transform such a framework into a practical system. First, we need an online error prediction method that can estimate the localization error of any schemes (*general*) at every location (*adaptive*) and in any places (*scalable*). Although some error models have been proposed [28]–[33], they are dedicated to special localization schemes and do not consider the real-time context either, but just assign a constant accuracy level to a scheme in an entire place. Second, it is hard to integrate the complementary information of multiple schemes only based on their final outputs without knowing the details of specific localization algorithms. Moreover, such an integration should also adapt to real-time context.

We tackle the above challenges from the perspective of sensor data. All factors (e.g., sensor specifications and environmental conditions) that implicitly impact the localization accuracy take effect by changing the sensor readings. We find some potential data features for each sensor type. The relation between localization error and data features is only determined by specific localization algorithms. We can quantify the deterministic relation by training a regression model. In such a way, the implicit influence factors are captured by a set of explicit data features, and the regression model of one localization scheme is consistent at different places and *scalable* to new places without training. The confidence in each localization scheme's output can be calculated online according to the real-time sensor data at every location

[1]In this paper, we refer the quality of sensor data as its capacity in labeling and distinguishing different locations. It is determined by both sensor specifications and instant environmental conditions, e.g., Wi-Fi AP (Access Point) deployment or visible GPS satellites.

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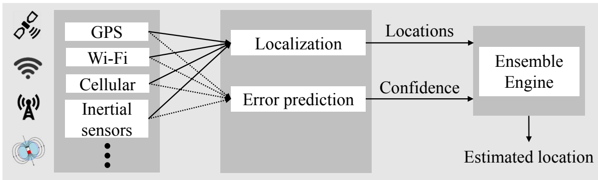


Fig. 1: UniLoc framework.

adaptively. Furthermore, since the data features are quantified directly by sensor data, we do not require the details of specific localization algorithms. The outputs of all available schemes are combined using an ensemble learning algorithm. Any localization schemes can be easily added into our *general* framework. For example, sensor data fusion based localization schemes, like Travi-Navi [11] and UnLoc [12], can also be treated as an individual scheme in our framework.

In UniLoc, as depicted in Figure 1, multiple *localization schemes* run in parallel. An *error model* is used to online estimate the accuracy of each scheme according to the real-time context. A probabilistic confidence in the output of each localization scheme is calculated. Both the output and confidence of all available schemes are processed in an *ensemble engine*. UniLoc combines the outputs of all schemes using a locally-weighted Bayesian Model Averaging (BMA) algorithm. Our work differs fundamentally from previous BMA-based approaches [29] in that we adapt the weight of each scheme at every location according to the real-time context. In UniLoc, the optimal weight of each scheme is approached by the confidence in its result at every location. Such a weighted averaging can better tolerate the uncertainty in online error prediction, and the combined result is more accurate than the output of any individual schemes. In addition, the locally-weighted BMA-based algorithm offers UniLoc high flexibility. UniLoc can temporarily exclude one localization scheme by simply setting its confidence as zero, if it is not available in some regions, e.g., no Wi-Fi signal.

The computation of UniLoc, including both error modeling and BMA-based averaging, is light-weight, as they only involve simple linear calculation. To make UniLoc a general framework that can integrate some energy-consuming localization schemes, two techniques are adopted, i.e., GPS downsampling and offloading. First, GPS is turned off when its error is predicted to be large at some locations. Second, to avoid some localization schemes consuming much energy on smartphones, we move their computation to a server. By intelligently processing some raw sensor data on smartphones, the transmitted data and the energy consumed by data transmissions are both minimized. Even with five schemes running in parallel, according to our experiments, UniLoc only increases the energy consumption of the most energy-efficient scheme (i.e., the motion-based PDR) by 14%.

Our experience shows that instead of studying new localization algorithms, easy aggregation of the end results from state-of-the-art schemes can already gain substantial extra performance improvement. Such experience indicates stretched design space considering the enormous availability of existing localization solutions. We implement a UniLoc framework that aggregates five existing localization schemes. We evaluate its performance in a variety of environments. Most of the experiments, >89%, are conducted in new places where we did not conduct any experiments to train the error models. The experiments demonstrate that UniLoc incurs little overhead in energy consumption and model training, but gains substantial performance improvement from scheme diversity (i.e., 1.6× error reduction against individual localization schemes).

II. Motivation

To investigate the performance diversity of existing localization schemes, we run five typical localization programs[2] independently on a smartphone (Google Nexus 5X) along with a daily walking path from our laboratory to a restaurant. The path is 302 meters and composed of different segments, including indoors (office, basement passageway, semi-open corridor and car park) and outdoors.

- **GPS**. We use the results reported from the default GPS module on smartphones.
- **Wi-Fi RSSI**. We adopt RADAR [1] for its simplicity and effectiveness. We first build an offline fingerprint database by collecting RSSIs from all audible APs at different locations. We calculate the Euclidean distances between an online measured RSSI vector and all offline fingerprints, and find the location with the shortest RSSI distance.
- **Cellular RSSI**. We use the same fingerprinting algorithm of RADAR on cellular GSM signals like in [22].
- **Motion-based PDR**. Inertial sensors (i.e., accelerometer, gyroscope and magnetometer) on smartphones have recently been exploited for PDR [7], [8]. We implement the system proposed in [7] which infers the walking model (i.e., step count, step length and walking orientation) from the readings of inertial sensors and uses a particle filter to incorporate the map constraints (e.g., path edges and walls). We also detect more landmarks (e.g., turns, doors and Wi-Fi signatures) [12] for calibration.
- **Sensor data fusion**. Some recent solutions perform sensor fusion across Wi-Fi RSSI and motion-based PDR [11], [13]. We adopt the approach in [11] and assign different weights to the particles of motion-based PDR according to the Wi-Fi RSSI distances between the online and offline RSSI vectors.

Figure 2 depicts the measured errors of these localization schemes. At every location, each scheme reports an estimated location of the user independently. Since we know the user's true location, the localization error can be calculated. At some locations, the Wi-Fi and cellular based schemes provide identical result, because they use the same fingerprinting

[2]The parameters of each scheme are set to be the optimal empirically, e.g., for the motion and fusion based schemes, 3000 particles are generated and maintained every step. In this work, we focus on the localization schemes that are ready to implement on commercial off-the-shelf smartphones. The schemes using other sensors (e.g., bluetooth [34], camera [23] and sound [25]) are not considered, as they require customized hardware devices, such as iBeacon transmitters, programmable LEDs or high-end microphones.

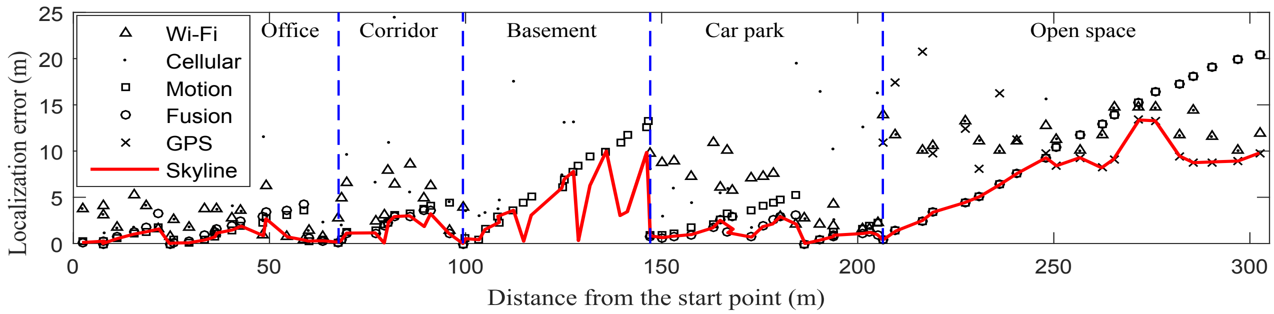


Fig. 2: Localization error of different schemes along a daily path on our campus.At each location, as we know the ground truth in the experiment, Skyline chooses the best scheme as its result.

algorithm and the same offline fingerprint layout. From the experiment results, we find the following two observations.

First, none of these schemes can cover the path with stable performance. Such a conclusion is also partially supported by some indoor experiments [6]. One reason may be that the existing schemes do not explicitly handle the variation of sensor data quality. Even for the fusion-based scheme, Wi-Fi RSSIs cannot always help reducing the localization error of the motion-based PDR. At some locations, e.g., ∼180 m, the low-quality Wi-Fi RSSIs make the estimated location depart from the user's true location. The existing fusion-based schemes [11], [13] process the Wi-Fi RSSI data in the same way at different locations, but do not consider the quality variation of Wi-Fi RSSI data.

Second, different localization schemes complement with each other at different locations. The performance of each scheme changes spatiotemporally, as the data quality of different sensors varies, caused by the natures of physical sensors (e.g., error accumulation of gyroscope) or variation of environment conditions (e.g., variant Wi-Fi AP density or interference [35]). It is hard for a single scheme to overcome the intrinsic limitations of sensor data; however, at each location, it is possible that at least one localization scheme is able to provide good performance. For example, among the total 91 locations of the path, the cellular-based localization scheme provides the highest accuracy at 14 locations (15.4% of the total locations), in which 10 locations (11.4% of the total locations) are in the basement segment, where Wi-Fi and GPS are not available and the error of the motion-based PDR scheme increases accumulatively.

Design space. If we can predict the localization error of each scheme at every location, we may choose the most-accurate scheme as our result. Figure 2 shows that the performance of Skyline is more stable than any individual schemes. For the Skyline, as we know the true location of the user in experiments, we can calculate the localization error of each scheme; however, in reality, it is hard to predict the localization error online and in turn find the best scheme. Additionally, we want to further ask a question: can we go beyond the Skyline? Can we combine the outputs of all schemes such that the combined result may exceed the Skyline?

III. Error modeling

The experiments in Section II have demonstrated that the error of one localization scheme is mainly determined by the online sensor data. For one localization scheme, given a series of measurements, error modeling is to learn the quantitative relation between the localization error and corresponding sensor data. It can be formulated as a regression problem. In this section, we introduce a general error modeling workflow and learn the error models of five typical localization schemes.

A. General workflow

We adopt a general 2-step error modeling workflow, which is applicable for all localization schemes.

Step 1: Data collection. We treat all localization schemes as black boxes and execute them on smartphones independently. At every location, we measure some data, including the estimated locations of all underlying schemes and the data from all available sensors. As we know the user's true location, the localization error of each scheme can be calculated. As a result, for each scheme, we build a database that records the localization errors and the corresponding sensor data at different locations.

According to our experiments, also confirmed by many previous works [28], most localization schemes has distinct characteristics in indoor and outdoor environments. To minimize uncertainty in error modeling, we perform the studies in indoor and outdoor environments separately. In this work, we treat all the places with roofs (e.g., corridors on the edges of buildings) as indoor environment, since they have similar error characteristics. IODetector [36] is used to automatically identify the indoor and outdoor environments. It is very energy-efficient, as it only uses some low-power sensors, including light sensor, magnetism sensor and cellular signals.

Step 2: Regression modeling. This step is to learn a regression model based on the collected data. We categorize the existing localization schemes into several classes according to the sensor data they use. For each data source, we find some factors that may influence the localization accuracy, according to the experiences learned from some existing works on specific localization schemes. Table I summarizes the potential influence factors of some typical data sources.

TABLE I: Influence factors of typical localization models.

Models	Schemes	Influence factors
GPS	GPS on smartphones	Number of visible satellites Geometric positions of visible satellites
Wi-Fi RSSI	RADAR [1] Horus [2] EZ [4]	Spatial density of fingerprints (β_1) RSSI distance deviation (β_2) Number of audible APs
Cellular RSSI	Otsason et al. [22]	Spatial density of fingerprints (β_1) RSSI distance deviation (β_2) Number of audible cell towers
IMU	Li et al. [7] Travi-Navi [11] UnLoc [12] Constandache et al. [8]	Distance from the last landmark (β_1) Width of the corridor (β_2) Orientation changing frequency Step count error

The set of influence factors is the same for all the schemes using the same data sources. Different schemes of specific localization algorithms may have different coefficients for the same factor. The fusion-based localization schemes have the influence factors of all involved data sources. We use multiple linear regression model to learn the coefficients. For one scheme, assume we have N entities in the training database. The localization error y_i can be calculated as the follows.

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_p x_{pi} + \epsilon_i, \qquad (1)$$

where x_{1i} is the first factor of the ith entity, β_1 is the coefficient of the first factor, β_0 is the intercept term and ϵ_i is the residual term after regression. One localization scheme has p influence factors. The residual ϵ of all entities should follow a normal distribution with a deviation σ_ϵ.

B. *Error models*

We learn the error models for those five localization schemes implemented in Section II. We adopt the procedure suggested in [37] to conduct our regression analysis. We estimate the coefficients and check the model appropriateness in this section. We conduct experiments in an office of 56×20 m^2 and an open space of ∼1000 m^2 on our campus. In each place, we perform location estimation at 300 locations. Table II presents the coefficients of error models for four localization schemes, except GPS.

Checking the model appropriateness. The intercept term β_0 is zero for all schemes, since the localization error is zero if all coefficients are zero. The results in Table II suggest that multiple linear regression can approximately capture the variability in localization error. 1) For every localization scheme, we find more than two data features that have a pValue less than 0.05. The pValue evaluates the hypothesis that the coefficient is equal to zero. Normally, a pValue less than 0.05 indicates that the feature is significant given the other features in the model. 2) The residuals of all error models follow a normal distribution with a mean in the vicinity of zero (μ_ϵ) and a small deviation (σ_ϵ). 3) The R^2 values of the motion and fusion localization schemes are as high as 85%. It means that the derived model can explain (approximately larger than 85% of) the variability in localization error. Although the R^2 values of the Wi-Fi and cellular schemes are low, the experiments in Section V will show that these error models are sufficient, because UniLoc does not need the absolute errors of each localization scheme, but just the relative errors to distinguish the accuracy of different schemes.

Wi-Fi and Cellular RSSI fingerprinting. Spatial density of fingerprints (β_1) is measured by the average distance between two fingerprints around the location under consideration. The localization error is likely to be high if the fingerprint distance is large. Therefore, the coefficient is a positive number. RSSI distance deviation (β_2) is the deviation of RSSI distances for the first k location candidates (k=3 in our setting) that have the lowest RSSI distances. If the deviation is small, the fingerprints at these locations are more similar, and in turn the estimated location is more likely to be wrong.

The experiments are done in an indoor office (56×20 m^2). The distance between two fingerprints is 1∼3 m. For larger fingerprint distances (e.g., 5 m, 10 m, and 15 m), we down-sample the fine-grained fingerprint data. The spatial density is not uniformly-distributed in a large place, due to the physical constraints during fingerprint collection. We use the density around the user's location as the value of factor β_1. During the training phase, we know the user's true location. For online localization, to calculate the value of factor β_1, we estimate the user's location based on the existing location prediction methods [24], like Hidden Markov Model (HMM) or Kalman filter. In our current implementation, we use a second order HMM, which can provide an acceptable estimation accuracy.

Our experiment results suggest that the number of audible APs is not a significant factor. When the number of audible APs is less than 3, it is unlikely for the RSSI fingerprinting scheme to provide a meaningful result; as the number increases, however, it does not present a strong correlation with localization accuracy.

Horus [2] handles the temporal variation of Wi-Fi signals by learning a distribution of RSSIs for every audible AP. However, it requires hundreds of samples to capture an accurate distribution at one location. Each path (2.78 km in total) or each place (e.g., shopping mall and office) in our evaluation (Section V) requires tens of days to collect fingerprints with a resolution of 3×3 m^2. Like some previous works [6], we assume that a RSSI fingerprint database is updated by service providers or crowdsourcing [9], [10]. In our experiments, each offline fingerprint has one sample from each audible AP. The online localization is made within half an hour after the offline fingerprints are collected.

Besides fingerprinting, Wi-Fi RSSI localization can also use propagation models, e.g., EZ [4] adopts the log-distance path loss model to estimate the distances between multiple users and APs. The distances are further processed to infer the users' location by trilateration. The model-based Wi-Fi localization is not considered in this work, because it only works for multiple users and requires a large number of APs, which may not be practical in some places.

TABLE II: Error model coefficients for four typical localization schemes, i.e., RADAR [1], the cellular-based localization scheme [22], the motion-based localization scheme [7] and Travi-Navi [11].

Wi-Fi, Cellular, Motion, Fusion		Estimate	pValue	μ_ϵ	σ_ϵ	R^2
Indoor	β_1	1.27, 2.08, 0.06, 0.06	0, 0, 0, 0	0, 0, -0.23, -0.27	3.46, 4.37, 0.49, 0.81	0.26, 0.42, 0.85, 0.85
	β_2	-0.02, -0.16, 0.04, 0.05	0, 0, 0.01, 0			
	β_3	n/a, n/a, n/a, 0.13	n/a, n/a, n/a, 0			
Outdoor	β_1	1.01, 2.49, 0.10, 0.10	0, 0, 0, 0	0, 0, -0.07, -0.07	2.57, 15.17, 0.6, 0.6	0.31, 0.53, 0.88, 0.88
	β_2	-0.12, -0.2, 0.03, 0.03	0, 0.09, 0, 0			

Motion-based PDR. The motion-based PDR [7] leverages the map to impose constraints on the user's possible locations. The localization error increases as the distance from the last landmark (β_1) increases, because the step error accumulates. If a corridor or path is wider (β_2), it has looser constraint and the localization error is likely to be higher.

Orientation changing frequency does not have significant influence in localization accuracy. The trembling of the user hand may cause inaccurate orientation inference. However, the random error of orientation readings is averaged to almost zero, as 50 orientation readings are made per second and an average orientation is calculated every 3 s.

Step count error is not a significant factor either. Trembling may cause some jitters in the accelerometer trace, which result in errors of step count inference. We add a compensation mechanism into the localization system [7]. The normal period of one human walking step is from 0.4 s to 0.7 s. If the time duration of one step is less than 0.4 s or larger than 0.7 s, the system will infer a false positive or false negative step, and delete or add one step in the user's trajectory. Our experiments show that such a mechanism can well mitigate the localization error caused by trembling.

When the phone is put in different positions, like on hand or in pockets, it infers different orientations of users. Many existing works [7], [13], [19] handle the measurement offset caused by different phone positions. They normally target at imperceptible tracking. We do not consider the impact of smartphone positions. As a localization system, UniLoc provides real-time positioning service. It is reasonable to assume that users hold their phone on hand for updated location result.

Different persons have different gait patterns, like step frequency and step length. Personalization of step model is considered in [7]. Dynamic time warping is applied during the inference of step count from the accelerometer traces, and the step length are adaptively updated by particle filter. We test with 6 persons, including both females and males with different ages (from 20s to 50s). Benefitting from the personalization of step model [7], the individual difference does not impact the localization accuracy much.

Fusion-based scheme. It has all influence factors of the motion-based PDR (β_1 and β_2). Spatial density of Wi-Fi RSSI fingerprints (β_3) is also significant, since fine-grained fingerprints have tighter constraints to the particles of motion-based PDR. RSSI distance deviation becomes insignificant, as the particles of the motion-based PDR may not be located in the grids of the first k location candidates of RADAR.

In outdoor environments, the physical distance between two fingerprints is large (e.g., 10$\sim$20 m), as we may not be able to access some regions (e.g., in the middle of roads or blocked by buildings). The coarse Wi-Fi RSSI information cannot refine the motion-based PDR scheme. Therefore, the fusion-based scheme has the same error model with the motion-based scheme in the outdoor environments.

GPS. The results provided by the GPS module of current smartphones include the user's coordinate, Horizontal Dilution of Precision (HDOP) and the number of visible satellites. HDOP measures the confidence of the reported location, based on the number of visible satellites and their geometric positions. A reliable location estimation requires that the number of visible satellites is larger than 4 and HDOP is less than 6 [28]. Through a series of experiments, we find that the number of visible satellites is $\sim$10.9 and the average HDOP is $\sim$0.9 in the outdoor environment. Moreover, based on our measured data (400 locations in two urban open spaces), the GPS error follows a Gaussian distribution with a mean of 13.5 m and a deviation of 9.4 m. Therefore, the intercept β_0 is 13.5 and the deviation of residual σ_ϵ is 9.4 for the GPS error model.

Impact of device heterogeneity. Two devices may have different RSSI measurements from the same wireless signal, due to hardware heterogeneity. If a person uses a phone that is not the device used for fingerprinting, the localization accuracy may be impacted. There are many works handling the problem of device heterogeneity, like online offset calibration [6], [38]. UniLoc is orthogonal to these algorithms. In our experiments with two smartphones, Google Nexus 5X (Qualcomm QCA6174 802.11ac Wi-Fi 2x2 MIMO Combo SoC) and LG G3 (BroadcomBCM4339 5G Wi-Fi combo chip), we also find an offset between the measured RSSIs. We transfer their RSSI readings of device A and B by an online-learned offset: $RSSI_A = \alpha * RSSI_B + \delta$, where α is close to 1 [38]. We also conduct many experiments for GPS and the motion-based localization. The results show that device heterogeneity does not impact the error modeling in these schemes.

Modelling Overhead. Since the relation between localization error and sensor data is only determined by the localization algorithm and does not change according to environment variation, the offline error modeling only needs to be performed once when one localization scheme is first intergraded into UniLoc. The learned error models can be used in new places without retraining. Moreover, multiple schemes can be learned at the same time. The data collection of five localization schemes in two places can be accomplished by one person within one day. According to the experiments in a variety of environments (Section V), 300 measurements are sufficient to learn an acceptable error model that can be used in new places to provide substantial performance gain in UniLoc.

IV. UniLoc

In this section, we present two versions of UniLoc and the techniques to reduce the energy consumption.

A. UniLoc1: selecting the "best" localization scheme

To predict the accuracy of one localization scheme online, besides the absolute error, we also consider the uncertainty in the prediction. When a scheme provides a location estimation at time t, its localization error (y_t) can be predicted as a variable with Gaussian distribution, $Y_t \sim \mathcal{N}(\mu_t, \sigma_\epsilon)$, where $\mu_t = \beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + \cdots + \beta_p x_{pt}$ and σ_ϵ is determined by the residual of the regression model (ϵ). Each β is an error model coefficient learnt offline and x_t is calculated online by the real-time sensor data at every location. We estimate the confidence of one localization scheme (c_t) in its results at time t as the probability that its localization error is less than a threshold τ.

$$c_t = P(Y_t < \tau) = \int_{x=0}^{\tau} \frac{1}{\sigma_\epsilon \sqrt{2\pi}} e^{\left\{ -\frac{x^2}{2\sigma_\epsilon^2} \right\}} dx \tag{2}$$

In our implementation, τ is set adaptively at different locations, as the average predicted error of all available schemes. For every location estimation, we choose the scheme with the highest confidence as our final result. If a scheme is not available at some locations, it just sets its output to zero and UniLoc will exclude it in calculation temporarily.

B. UniLoc2: locally-weighted BMA-based localization

Let s_t be the sensor readings measured at time t, and l be one location. A place is divided into I locations, corresponding to l_1 to l_I. Assume we have N localization schemes integrated into UniLoc. These schemes are N models, i.e., M^1 to M^N, in BMA. We calculate the joint probability that the user is at location l_i as:

$$P(l = l_i|s_t) = \sum_{n=1}^{N} P(l = l_i|M^n, s_t) \times P(M^n|s_t), \tag{3}$$

where $P(l = l_i|M^n, s_t)$ is the probability estimated by the M^n localization scheme, and $P(M^n|s_t)$ can be considered as the weight ($w_{n,t}$) of the M^n scheme given the real-time sensor data s_t. For a place with I locations, we can estimate the user's location at time t as:

$$L_t = \sum_{i=1}^{I} l_i \times \frac{P(l = l_i|s_t)}{\sum_{i=1}^{I} P(l = l_i|s_t)} \tag{4}$$

There exists an optimal weight for each localization scheme ($w^*_{n,t}$) that minimizes the distance between the user's true location L_t^{true} and the estimated location L_t. An optimal weight assignment ensures that one model will have a higher weight, if its estimated result ($P(l = l_i|s_t)$) is closer to the true $P^{true}(l = l_i|s_t)$ for all possible locations l_i. Therefore, we approximate the optimal weight of one localization scheme ($w^*_{n,t}$) according to its confidence in its result. Among all N localization schemes, the weight assigned to the scheme M^n at time t is calculated as:

$$w_{n,t} = \frac{c_{n,t}}{\sum_{i=1}^{N} c_{i,t}} \tag{5}$$

We use $w_{n,t}$ to approximate $P(M^n|s_t)$ in Equation 3. In a 2D space, we estimate the user's location by calculating her X and Y coordinates independently with Equation 4.

Discussion. Although BMA is widely used in many applications [39] and similar weighted combination is used to fuse the results of multiple Wi-Fi localization algorithms [29], the proposed locally-weighted BMA localization approach differs from the previous works in two aspects. 1) Our approach is locally weighted. Instead of assigning a fixed weight for each scheme globally in a large place [29], we calculate a unique weight for each localization scheme at every location. The spatial environment variation is thus considered. 2) In our approach, the weight of each scheme is determined by the real-time sensor data at every location. The temporary environment variation is also taken into account.

According to our experiments, compared with UniLoc1, UniLoc2 provides better results. UniLoc1 is a simple solution based on our online localization error prediction proposed in Section IV-A. It is mainly used for evaluating the performance of online localization error prediction.

GPS reports the absolute coordinate (i.e., latitude and longitude) in the geographic coordinate system. Wi-Fi and the motion-based PDR use the local map coordinate. To combine the results of multiple schemes, we convert the result of GPS to the map coordinate by the public digital map information.

C. Energy consumption

The error modeling of UniLoc is conducted offline; thus, it does not consume any energy for online localization. Mobile localization systems consume the energy of smartphones by two operations, i.e., sensor reading and data processing. UniLoc minimizes the energy consumption of both operations.

Most sensors on smartphones, e.g., Wi-Fi, cellular modules and inertial sensors, are energy-efficient [36]. The most energy-consuming sensor is GPS. In UniLoc, GPS is turned off indoors. In outdoor environments, the error of GPS is predicted as a constant (i.e., β_0, 13.5 m) for all locations based on the error model learnt in Section III-B. The error model does not need any input parameters from the GPS sensor; thus we can predict GPS error without enabling GPS sensor. At every location, UniLoc compares the GPS error with the other schemes. If its predicted error is the smallest one, GPS will be enabled; otherwise, GPS will be disabled.

The computation of UniLoc, including error modeling and Bayesian model averaging, is light-weight, since they only involve simple linear calculation. However, the computational overhead of the motion and fusion based schemes is high, since they need to update the statuses of 3000 particles every 0.5 s. According to our implementation, the updating cannot be accomplished within 0.5 s on Google Nexus 5. We move the particle status updating computation to a server. Sensor data are transmitted to the server via Wi-Fi. If Wi-Fi is not available in some regions, cellular network is used instead, which is pervasively available. The computation of individual schemes and UniLoc is performed on the server.

To avoid data transmissions consuming much time and energy, the raw sensor data are first processed on smartphones. For the motion and fusion based schemes, only small-size intermediate results are transmitted to the server. In our implementation, the high-frequency raw data (50 Hz) from inertial sensors are pre-processed on smartphones to infer the user's step model. The locally-processed results (including moving direction and distance between two updates) are represented by four bytes and transmitted to the server every 0.5 s. GPS transmits the user's coordinate (latitude and longitude) to the server only if the number of visible satellites is larger than 4 and HDOP is less than 6. Wi-Fi and cellular localization schemes send their online RSSI measurements to the server for fingerprint matching.

V. Evaluation

We aggregate the five localization schemes mentioned in Section II into the UniLoc framework for testing. All the computation of UniLoc is implemented in C++ running on a workstation with 16GB memory and Intel Xeon E5-1650 v3 processor of six cores. We conduct extensive experiments to evaluate the performance of UniLoc in in different environments, including a campus and urban areas, $\sim$44047 m^2 in total. The error models learned in Table II are used. Most of the testing environments (>89%) are different from the places where the data were collected for training the error models. The urban areas include a floor (95$\times$27 m^2) of a shopping mall and an urban open space ($\sim$5700 m^2). In these two places, 10 different 30-m trajectories are studied for the motion and fusion based localization schemes; at the same time, the other localization schemes is performed every 3 m along the trajectories. Each place has thus $\sim$100 tested locations.

A. Error model validation

Based on the derived error models, we predict the localization error of each scheme at one location as:

$$\hat{e}_i = \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p, \tag{6}$$

where the coefficients $(\beta_0, \beta_1, \cdots, \beta_p)$ are the results in Table II and the value of each factor $(x_1, x_2, \cdots, x_p)$ are calculated by the real-time sensor data. If we have M tuples of localization error and sensor data to perform validation (M=200 for each test), the normalized Root-Mean-Square Error (RMSE) of the predicted localization error is:

TABLE III: Normalized RMSE of the online error prediction for different localization schemes.

Prediction accuracy	Same places		New places	
	Same devices	Different devices	Same devices	Different devices
GPS	0.58	0.60	0.60	0.58
Wi-Fi	0.65	0.84	0.84	1.17
Cellular	0.64	1.06	1.12	1.17
Motion	0.20	0.22	0.28	0.35
Fusion	0.39	0.42	0.44	0.53
Average	0.49	0.63	0.66	0.76

$$RMSE = \frac{\sqrt{\frac{\sum_{i=1}^{M}(\hat{e}_i - e_i)^2}{M}}}{\bar{e}}, \tag{7}$$

where e_i is the groundtruth of localization error for the ith measurement, and $\bar{e}$ is the average localization error of all measurements in the test database.

Table III presents the normalized RMSE of the predicted error for the five localization schemes. On average, the prediction RMSE is less than 49%, if we use the error model derived by the same device and in the same place. We also collect the validation data with another smartphone model (LG G3) and in some new places where the error model is not trained (shopping mall and another office for the indoor test, and an urban open space). With the new device in a new place, the average prediction RMSE increases to 76%. Although the error models cannot provide perfect prediction of localization error, the results in Table II are useful in our framework. The error models learned by our approach can be used in new unknown places without re-training. Our experiments in Section V-B will show that even with imperfect error prediction, UniLoc is able to achieve significant performance gain.

B. Accuracy

We use UniLoc to provide real-time positioning service over eight paths, which are some daily paths taken by the students and staffs on our campus, e.g., from an office to a library, restaurants, bus stations, or an auditorium. Figure 4 illustrates the eight paths which have a total length of 2.78 km, including 0.8-km outdoor segments and 1.98-km indoor segments. The path studied in Section II is Path 1 in Figure 4. For Wi-Fi and cellular based schemes, the distance between two fingerprints is 1$\sim$3 m in the indoor environments and 10$\sim$20 m in open spaces respectively.

1) The daily path: We first revisit the daily path studied in Section II to analyze the gain of UniLoc in details. Figure 3 depicts that UniLoc1 can find the best localization scheme and UniLoc2 outperforms the Skyline at many locations, especially in the outdoor environments, where the localization errors of individual schemes are large. The optimal single-selection solution, noted as "Skyline", is assumed to know the true localization error of each scheme. Given the result of the best scheme, the other schemes can help moving the combined result closer to the true location.

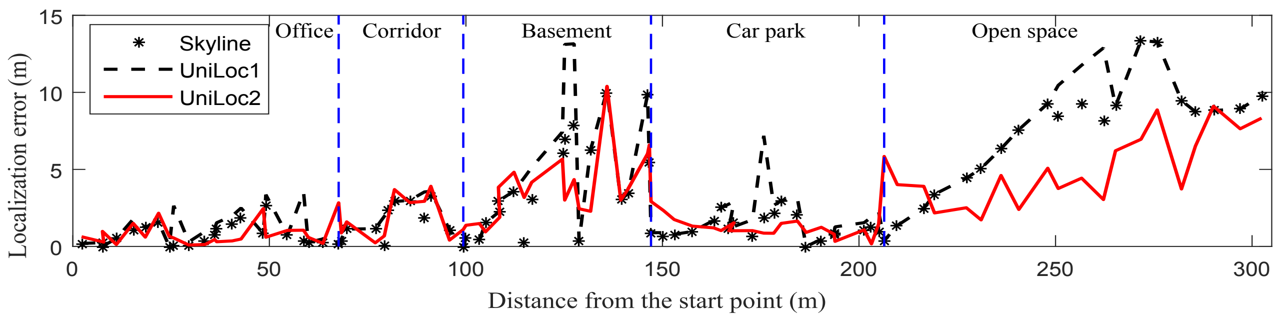


Fig. 3: Localization error of the optimal single-selection solution and UniLoc along the daily path.

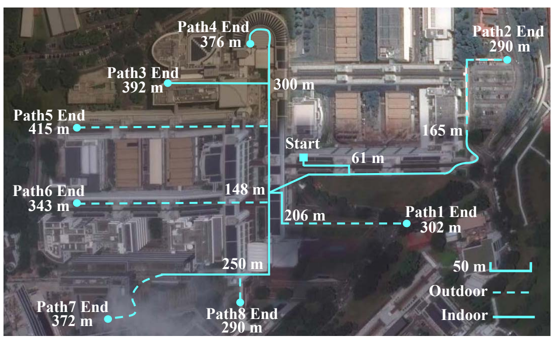


Fig. 4: Eight daily paths on our campus.

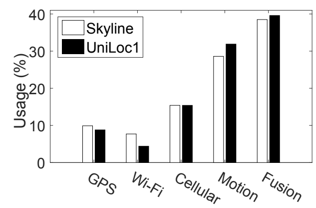


Fig. 5: Usage of different localization schemes.

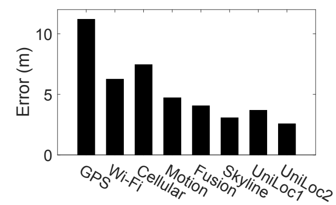


Fig. 6: Average localization error along the path.

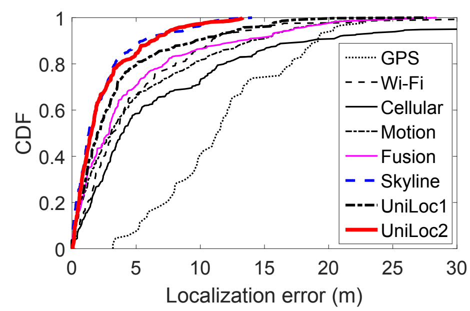


Fig. 7: Localization error on the eight daily paths.

Figure 5 shows that the usage of different localization schemes in UniLoc1 is close to the Skyline. Even with imperfect online error prediction, UniLoc1 can make the right selection, as long as the predicted error can distinguish the accuracy of underlying schemes. In addition, even though UniLoc1 makes suboptimal decision sometimes, the performance of the best two or three schemes are close to each other in these cases, and the misclassification between them will not impact the localization accuracy of UniLoc1 much. Along the path, the usage of the Wi-Fi based scheme is low, because the fusion-based scheme is selected instead when the Wi-Fi sensor data quality is high, especially in the indoor environment.

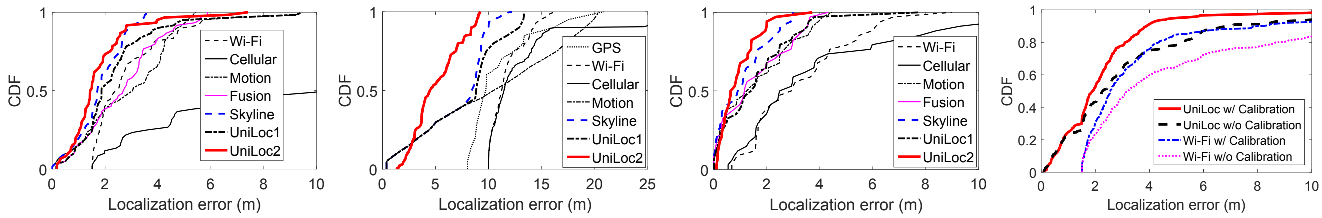
Figure 6 presents the average error of all localization schemes along the path. Among these schemes, the fusion-based scheme [7] provides the lowest localization error, i.e., 4.0 m, and UniLoc1 achieves a better accuracy, i.e., 3.7 m. By combining the results of all underlying schemes, UniLoc2 achieves an average localization error as low as 2.6 m. It reduces the localization error of the fusion-based localization scheme by 1.7× and outperforms the Skyline by 1.2×.

2) Overall performance on eight daily paths: Figure 7 presents the Cumulative Distribution Function (CDF) of the localization errors for all schemes along the eight investigated paths. UniLoc1 substantially outperforms all the individual schemes, including the fusion-based localization scheme. Although UniLoc1 cannot find the best scheme at some locations due to imperfect online error prediction, UniLoc2 can better tolerate the uncertainty in online error prediction, and achieve comparable performance with the Skyline.

For the 50th percentile value of the localization error, the fusion-based localization scheme provides the smallest error among all the schemes. UniLoc1 reduces the error of the fusion-based scheme by 1.4× and UniLoc2 further improves the reduction factor up to 1.6×.

The 90th percentile value of the localization error from RADAR (i.e., 10.6 m) is much smaller than the motion and fusion based schemes (i.e., 15.3 m), as the latter's error increase if no calibration signatures can be found, e.g., the long straight path of the outdoor segment in Path 1. Even though the Wi-Fi signatures proposed in [12] are implemented, it is hard to find sufficient signatures outdoors. By combining the results from more localization schemes, like GPS and cellular, UniLoc2 controls the 90th percentile value of the localization error as low as 5.8 m, which is 1.8× lower than RADAR.

3) Different environments: Figure 8a-8c show the CDF of the localization errors for all underlying schemes in the shopping mall, the urban open space and our office respectively. In all three places, compared with the individual schemes, UniLoc2 provides significant performance gain, i.e., ∼1.7× for both the 50th and 90th percentile values of the localiza-



(a) Shopping mall. (b) Open spaces. (c) Office. (d) Heterogeneous devices.

Fig. 8: Localization error for all underlying schemes and UniLoc in different places or with heterogeneous devices.

tion error, as it can benefit from all underlying localization schemes. Although the error models are learned in the office and our campus, UniLoc can provide comparable performance in the crowded shopping mall and the urban open space.

Comparing the performance among these places, we find two observations. 1) All these systems have better performance in office rather than shopping mall, as the office has more stable wireless signals and narrow corridors with many turns. The localization accuracy of the cellular-based scheme is low in the shopping mall, because it is at the basement floor and we can only receive the signals from two cell towers on average. 2) In the outdoor environment, the localization errors of all existing schemes are high and unstable, due to low spatial density of fingerprints or wider paths.

4) Heterogeneous devices: All the above experiments are conducted with a same smartphone model, Google Nexus 5X. We further evaluate the performance of UniLoc with heterogeneous devices. We conduct online localization experiments with another phone, LG G3. The setting of UniLoc is not modified. The error models are still the ones in Table II, which are learned with the data collected by Google Nexus 5X. For the Wi-Fi based scheme used in UniLoc, the offline fingerprint database is also collected with Google Nexus 5X.

Figure 8d shows the localization errors of UniLoc and RADAR. Benefitting from the online offset calibration, both UniLoc and RADAR significantly reduce the localization errors caused by the new device, especially when the error is large (1.9× for the 90th percentile value of the localization error). The reduction factor of UniLoc is comparable with the performance gain of RADAR. It means that UniLoc can assimilate the gain produced by the device heterogeneity handling algorithm of individual localization schemes.

C. Energy consumption

We use a Monsoon power monitor to measure the power consumed on smartphones. As the battery of Google Nexus 5X cannot be opened to connect with the power monitor, we use Samsung Galaxy S2 i9100 for power measurement. Changing the phone model does not alter the relative energy consumption of UniLoc and the underlying localization schemes.

The power and energy consumption of every localization system over the daily path 1 are presented in Table IV. Along with the 302-m path including an outdoor segment of 96 m, the average energy consumption of the individual localization schemes (except GPS as it is turned off indoors) is 172.5 J, and UniLoc consumes slightly higher energy, i.e., 191.2 J. The most energy-efficient localization scheme is the motion-based PDR. Compared with it, UniLoc only increases the energy consumption by 14%. The data transmissions with Wi-Fi or cellular network do not increase the energy consumption, as the transmission time is short.

TABLE IV: Power and energy consumption of UniLoc and all localization schemes along the daily path 1.

Schemes		Localization (mW)	Time (s)	Energy (J)	
GPS		613.7	128	78.6	
Wi-Fi		433.9	403	174.9	
Cellular		415.0	403	167.3	
Motion		418.2	403	168.6	
Fusion		444.2	403	179.0	
UniLoc	w/o GPS	444.2	354	157.2	191.2
	w/ GPS	691.8	49	33.9	

The current consumption of the fusion-based scheme and UniLoc is the same. In the experiment, we assume UniLoc is used in normal cases where cellular is always enabled to mimic the normal usage of a phone as a user. The extra energy consumption of UniLoc mainly comes from GPS. UniLoc successfully minimizes the usage of GPS, i.e., turning off GPS when its error is expected to be large. In the outdoor environment, compared with the default GPS scheme, UniLoc reduce the energy consumption by 2.1×.

D. Response time

Table V shows the decomposed response time for one location estimation, including computation and data transmission. The response time mainly includes data transmissions and the computation on both the smartphone (sensor reading and pre-processing) and the server (execution of localization algorithms, error prediction of each localization algorithm and BMA). Since the algorithms of all underlying localization schemes are executed on the server in parallel, the computation time of UniLoc is the time taken by the slowest localization scheme, i.e., 50.6 ms from the fusion-based scheme.

UniLoc only needs 185.7 ms to estimate the user's location once, from the beginning of data sensing to the displaying of location result on the user's phone. It can provide real-time positioning service on smartphones. The computation added by UniLoc is only 6.1 ms, including 0.1 ms for BMA and 6.0 ms for error prediction. The data transmissions of UniLoc occupy 73% of the total response time.

TABLE V: Average response time for one location estimation, including computation and transmission.

Schemes	Time(ms)			UniLoc	Time(ms)
	Localization		Error prediction		
	Phone	Server			
GPS	1.1	0	0.1	Upload	72
Wi-Fi	8.5	25	6.0	Computation	50.6
Cellular	8.6	18	6.0	BMA	0.1
Motion	27.5	14	0.1	Download	63
Fusion	27.5	23	0.1	Total	185.7

VI. Related works

Model aggregation. BMA has been widely used in many applications [39], like health data analysis and weather prediction. It has been proven that BMA can better tolerate the uncertainty in model selection [40]. Locally-weight BMA is studied in classification [41] and applied in the analysis of urban traffic speed from multiple data sources [42]. Unlike the context-based weighting in UniLoc, these works are based on historical data for weight assignment.

Localization error. CONE estimates the error of one localization scheme by multiple measurements at the same location. However, it cannot be used if the user is moving continuously. GPS accuracy is studied according to the measurement conditions [31]. Some works analyze the localization error for Wi-Fi RSSI fingerprinting. The spatial density and number of APs are studied in [30]. Multiple regression has been used to study the impact of signal strength values [33]. The error Probability Density Function (PDF) is also studied theoretically [43]. A global error of one region is used to combine the results of multiple RF-based localization algorithms [29]. The above works only focus on Wi-Fi RSSI fingerprinting, and do not consider the real-time sensor data. CO-MAP [44], [45] leverages location information of mobile devices to improve their multiple access performance.

A-Loc [28] uses the error models of some localization schemes to select one low-cost scheme that can meet the accuracy requirement. UniLoc is different from a-Loc in two aspects. First, the error modeling and prediction in a-Loc are not scalable. A-Loc estimates a probability that the user is at one place, and then calculates the localization error of one scheme based on the pre-measured offline error records at all possible locations. As a result, it does not consider temporal variation of environment conditions and cannot be used in new places where no error record has been collected. Second, a-Loc only selects one scheme; whereas UniLoc combines the outputs of multiple schemes to achieve a better result.

Individual localization schemes. As a unified localization framework, UniLoc is orthogonal to the development of individual localization schemes. Some works [14]–[16] reduce the sampling rate of GPS by opportunistically turning on some low-energy-cost localization schemes (e.g., Wi-Fi or cellular RSSI fingerprinting) based on users' routing trajectories.

RADAR [1] is the first Wi-Fi RSSI fingerprinting localization system. Place Lab [3] extends RADAR from offices to metropolitan scale. Horus [2] handles the temporal variation of Wi-Fi signals. In some works, e.g., EZ [4] and EZPerfect [5], the log-distance path loss model is used to estimate user location based on trilateration. Some recent works, e.g., ArrayTrack [26] and SpotFi [27], exploit PHY layer information, like CSI, to provide sub-meter localization. They are not included into UniLoc, as CSI can only be accessed by software radio or special network interface cards. Otsason et al. [22] use cellular RSSIs to perform fingerprinting localization. The cell tower ID sequence is also used to estimate the user's position [17], whereas it can only be used along the users' routing trajectories.

Constandache et al. [8] first exploit the inertial sensors on smartphones to enable PDR in outdoor environments. Li et al. [7] develop a practical PDR system for indoor localization. UnLoc [12] leverages some Wi-Fi and structure signatures as landmarks for indoor PDR. Zee [9] uses Wi-Fi signatures to find the start of trajectories for PDR. LiFS [10] only processes accelerometer data to monitor walk steps, which are further used to construct indoor radio map. FOLLOWME [18] uses magnetometer to identify different indoor pathes which are further used to guide users to the right destinations.

Tsai [19] incorporates ultrasonic time-of-flight into PDR by Kalman filter. SLAC [13] and Travi-Navi [11] fuse the Wi-Fi RSSIs and motion-based PDR in particle filters. Travi-Navi also provides some techniques, like image-assisted navigation and path recommendation. The distance constraints between peers are used to adjust Wi-Fi RSSI fingerprinting [20]. Cross-modality training [46] is used for positioning in highly dynamic industrial settings. MapCraft [47] enables reliable indoor map matching for indoor localization and tracking. Geomagnetic field and motion pattern are used for indoor localization [48]. Camera images and inertial sensors are used for localization on smart glass [49].

An energy-efficient localization scheme is developed for wireless sensor networks to monitor patients in a nursing home [50]. WiFi beacons are leveraged to improve the IEEE 802.15.4 localization system [51]. A range-free localization algorithms [52] is proposed for wireless sensor networks. Based on radio frequency (RF) detection, device-free localization systems [53]–[55] are developed for residential monitoring.

VII. Conclusion

This paper presents UniLoc, a unified framework that exploits the diversity of existing localization schemes to provide accurate positioning service on mobile devices. It features a general localization error modeling workflow and a locally-weighted BMA-based localization ensemble algorithm, as well as a set of energy-saving techniques. Extensive experiments show that UniLoc significantly outperforms the existing localization schemes in accuracy across variant environment.

VIII. Acknowledgments

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