HIPS: A Calibration-less Hybrid Indoor Positioning System Using Heterogeneous Sensors

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***Abstract*—Positioning is a crucial task in pervasive computing, aimed at estimating the user's positions to provide location-based services. In this paper, we study an interesting problem: when we wish to obtain hybrid positioning granularities in an office environment, how can we incorporate heterogeneous sensors to build an indoor positioning system with minimal human calibration effort? We propose a calibration-less solution by incorporating the ultrasound sensors with the radio-frequency sensors. In our solution, we use these two different types of sensors to satisfy the different granularities requirement; and meanwhile, we use the ultrasound sensors to help calibrate the radio-frequency sensors for positioning, so that we can minimize, or even eliminate the labeling effort for the radio-frequency positioning. Finally, we develop a system prototype with real-world sensor networks, and verify the feasibility and effectiveness of our proposed solution.**

I. Introduction

As the pervasive environments become more common, determining a user's position is crucial for providing location-based services [6]. In this paper, we consider a real-world application scenario known as *security table*, which requires hybrid positioning granularities at different areas in an office. As shown in Fig. 1, the security table application is for a meeting scenario. It requires that only those meeting participants at the table can access certain confidential files; while once a participant travels outside the table's range, the files' access will be denied. In this case, a user's position is regarded as physical key to guarantee the security. We consider the table area as interested area where we need a highly accurate positioning module. For example, we can use the ultrasound sensors for positioning, which can reach a high resolution at centimeter level[9]. In the area outside of the table range, we can afford to have a lower positioning resolution for other location-based services. So we may choose to use the radio-frequency (RF) sensors, which are cheaper than ultrasound sensors and with a larger signal coverage [1].

We develop a hybrid indoor positioning system (HIPS), which is a calibration-less solution for this security-table application. In our HIPS, we just hold a target sensor equipped with ultrasound and RF components to walk across the RF coverage area through the ultrasound coverage area. Then our HIPS system can automatically build a positioning system for RF signals. This process involves very little human effort (essentially, the effort to walk through the areas), and thus we call this solution *calibration-less*. If we wish to improve the positioning accuracy in RF coverage areas, we can additionally label a few RF data at some landmark points such as room corners, as shown by green stars in Fig. 1.

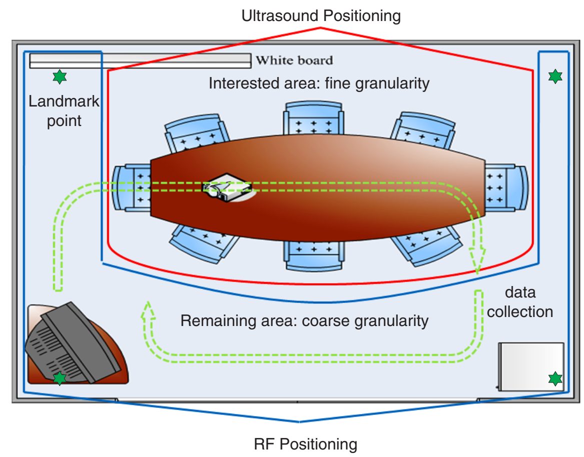


Fig. 1. Application: security table.

The major contributions of this work are as follows:

1) *We introduce a novel application of positioning with hybrid granularities*. We use a few specialized sensors such as ultrasound to provide high resolution coverage, while using lower-cost RF sensors for a larger area where positioning resolution needs not be that high.
2) *We provide a calibration-less solution for positioning*. RF positioning, using either fingerprinting[10], [15] or propagation models [11], may require much human calibration effort. We use ultrasound sensors to provide calibration for the RF sensors, thus reducing or even eliminating the human effort. We also organize the ultrasound sensors in a structural topology to minimize the human effort in building the ultrasound positioning module.
3) *We develop a system prototype with real sensor network to verify the feasibility and effectiveness of our design*.

The rest of the paper is organized as follows. In Section II, we introduce our sensor network components. In Section III, we introduce our hybrid indoor positioning system. We give the details of the positioning modules in Section IV. Empirical

[1]Please refer to http://www.xbow.com.

study is reported in Section V. Section VI discusses the related work. The work is concluded in Section VII.

II. Our Sensor Network

In this section, we introduce our sensor hardware and some terminologies. Our sensor network consists of two types of sensors: the *ultrasound sensors* and the *RF sensors*. The ultrasound sensors are capable of sending/receiving both ultrasound and RF signals. The RF sensors can only send/receive RF signals. The positioning system uses both types of sensors. Our *target sensor* is an ultrasound sensor, which is attached to the mobile object and sending out both ultrasound and RF signals. After looking into the specifications of different available sensors, we chose to use inexpensive, off-the-shelf, simple hardware components to construct our network. Basic parameters of our ultrasound sensors are shown in Table I. An ultrasound sensor includes a micro-controller (e.g. ATMEL 128 processor), a set of ultrasound receivers, and a RF transceiver for time synchronization and object ID recognition. In particular, a Complex Programmable Logic Device (CPLD) is used to setup a single clock for each ultrasound receiver. Our RF sensors are implemented using the same hardware components as ultrasound sensors, but without ultrasound transmitters.

TABLE I
ULTRASOUND SENSOR'S PARAMETERS

Name	Value
RF chip	CC1000 [2]
RF frequency	433MHz
RF data rate	19.2Kbps
RF transmission distance	30m-60m
Ultrasound transducer	255-400SR12/ST12 [3]
Ultrasound frequency	40KHz
Ultrasound propagation dist.	10 meters

III. Hybrid Indoor Positioning System

As shown in Fig. 2, our HIPS system consists of two modules: an ultrasound positioning module, called *POD*[4], denoted by a set of ultrasound sensors in the green box. A RF positioning module is denoted by a set of RF sensors. A target sensor to be localized is moving in the environment, which keeps sending out both ultrasound and RF signals.

A. Our Design's Work-flow with Two Types of Sensors

Our system works in two phases: a setup phase and a predicting phase. The setup phase has three steps (*Step 1*∼ *Step 3*), which tries to set up the system before use. The predicting phase has one step (*Step 4*), which uses the set system to do positioning.

- *Step 1: Set up an ultrasound positioning module.* This is done by using trilateration method based on the ultrasound Time of Arrival measurements as discussed in Section IV-A.

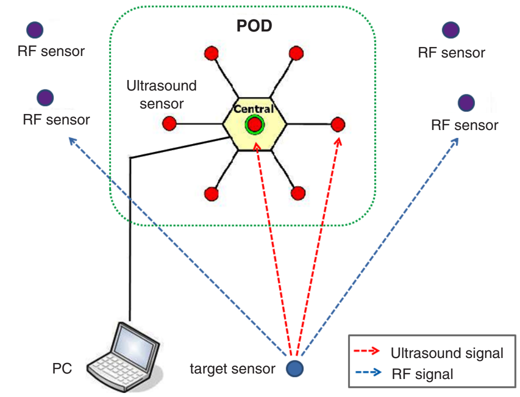


Fig. 2. System overview of HIPS.

- *Step 2: Collect the RF data for training a RF positioning module.* We carry a target sensor to walk across the RF coverage area through the ultrasound coverage area. The target sensor can send out both ultrasound and RF signals simultaneously. We use ultrasound positioning results to calibrate the RF sensor signals, so as to minimize the human effort. If the ultrasound signals are heard by at least three ultrasound sensors, the corresponding RF signal vector is labeled with the ultrasound positioning result; otherwise, it is left unlabeled. Optionally, we can manually label a few RF signal vectors at some landmark positions, *e.g.* corners. Consequently, we have both labeled and unlabeled RF data.
- *Step 3: Train a RF positioning model from the collected RF data.* In training, a manifold learning technique is used. Note that in previous work [7], the data labels for manifold learning are labeled by human; but in our solution, the labels are automatically derived from ultrasound sensors, in a calibration-less way. Details are discussed in Section IV-B.
- *Step 4: Incorporate the ultrasound positioning module and RF positioning module to do positioning*. At this step, the HIPS system is ready for use. When a user attached with a target sensor walks into the office, his/her target sensor can send out both ultrasound and RF signals. If there are at least three ultrasound sensors hearing the sent ultrasound signal, the HIPS system returns the ultrasound positioning result to the server; otherwise, it returns the RF positioning result. Hence in both case, the server can know the user's position so as to determine which kind of service to provide. We argue that a more sophisticated approach to combine different sensor positioning results can be beneficial [12], [5], and we leave it as our future work.

B. Generalization of Our Design to Multiple Types of Sensors

We have shown our design by using two types of heterogeneous sensors in hybrid positioning, and we will also show our calibration-less solution can easily generalize to more than two types of sensors. For example, we may use ultrasound, infrared

[2] http://www.chipcon.com/
[3] http://www.mouser.com/kobitone/
[4] Abbr. for *Positioning on One Device*. We will discuss it in Section IV-A.

[13], Bluetooth [1], *etc.*, which are with higher positioning resolutions, to calibrate the low-resolution sensors such as RF sensors. The workflow of using multiple types of sensors can be similar to our current system by using two types of sensors. Analogous to Section III-A, we also have 2 phases with 4 steps: (1) Set up the positioning modules for ultrasound and/or infrared and/or Bluetooth sensors and/or other sensors; (2) Collect the RF data for training a RF positioning module, and utilize the step 1's positioning modules to help labeling part of the data; (3) Train a RF positioning model from the collected RF data; (4) Incorporate all the positioning modules to do positioning.

IV. Positioning Modules

A. Ultrasound Positioning

We develop an easy-to-install, calibration-less ultrasound positioning module, called *Positioning on One Device* (POD), attached at the room ceiling. As shown in Fig. 2, the POD integrates single RF receiver and multiple ultrasound receivers in one device, and organizes these receivers in a structural topology. By measuring the distances among the target sensor and the POD ultrasound receivers based on Time of Arrival (TOA), we use a structural trilateration algorithm for positioning [16]. Note that more sophisticated trilateration methods can be used to replace our structural trilateration algorithm in ultrasound positioning, without any harm to our calibration-less solution.

- *Step 1: Use a TOA reliability filter to eliminate the outliers from the TOA measurements*. Assume the minimal survived TOA measurement as the most reliable one. We calculate the transmitter-receiver distances from TOA measurements and check the minimal and the maximal distances by triangle inequalities:

$$\left\{ \begin{array}{l} d_{max} - d_{min} < E_{i,j} \\ d_{max} + d_{min} > E_{i,j} \end{array} \right. , \quad (1)$$

  where d_{max} and d_{min} are the maximal and minimal distance, $E_{i,j}$ is the distance between receiver i and receiver j. If the condition is satisfied, the maximal distance is regarded as a direct-path signal, *i.e.* a reliable TOA measurement, and all the TOAs are accepted; otherwise, the maximal distance is rejected as an outlier. Such checking process repeats until this condition is satisfied.
- *Step 2: Select three of the reliable TOAs according to the Max Separation criterion*. It is stated that more separated the selected TOAs' corresponding receivers are, the better the positioning result will be [16]. Hence, we define the max separation criterion as selecting the three most separated receivers, *i.e.* with largest distance sum among them.
- *Step 3: Use standard trilateration to infer the location from the three selected TOA measurements*. This step is involved with solving a set of linear equations.

B. RF Positioning

In RF positioning, we use a semi-supervised learning technique, called *manifold learning* [7]. We should note that our calibration-less solution can also use other learning techniques, since the idea of utilizing other more accurate sensors to provide labels is independent of the learning techniques.

The basic idea for manifold learning is that, if two data samples (RSS vector) are similar, then their labels (positions) should be similar. Given some labeled data $\{\mathbf{x}_i, y_i\}_{i=1}^{l}$ and unlabeled data $\{\mathbf{x}_i\}_{i=l+1}^{l+u}$, where $\mathbf{x}$ denotes a received RSS vector with each dimension as the RSS value from a RF sensor, and $y \in \mathbb{R}$ denotes the corresponding location's $l^{(1)}$- or $l^{(2)}$-coordinate[5]. Standard manifold learning solves the following minimization problem:

$$\begin{array}{c} f = \arg\min\limits_{f \in H_k} \frac{1}{l} \sum_{i=1}^{l} (f(\mathbf{x}_i) - y_i)^2 \\ + \gamma_A \|f\|_{\mathcal{K}}^2 + \frac{\gamma_I}{(l+u)^2} \mathbf{f}' L \mathbf{f}, \end{array} \quad (2)$$

which finds the optimal function f^* in the reproducing kernel Hilbert space (RKHS) $\mathcal{H}_k$. In Eq.(2), the first term is a square loss function over the labeled data, the second term controls the complexity of f in the ambient space, and the third term controls the complexity of f in the intrinsic geometry of the data's marginal distribution. In the third term, $\mathbf{f} = [f(\mathbf{x}_1), ..., f(\mathbf{x}_{l+u})]'$ is over all the data. L is the graph Laplacian. Both γ_A and γ_I are regularization parameters. From the extended Representer Theorem [3], the optimal function should be expressed as

$$f^*(\mathbf{x}) = \sum\nolimits_{i=1}^{l+u} \alpha_i K(\mathbf{x}_i, \mathbf{x}), \quad (3)$$

where K is an $(l+u) \times (l+u)$ kernel matrix over all the data, and the optimal solution $\alpha^* = (\alpha_1^*, ..., \alpha_{l+u}^*)'$ is

$$\alpha^* = (JK + \gamma_A l I + \frac{\gamma_I l}{(l+u)^2} LK)^{-1} Y, \quad (4)$$

where Y is an $(l+u)$-dimensional label vector given by $Y = (y_1, ..., y_l, 0..., 0)'$. $J = diag(1, ..., 1, 0, ..., 0)'$ is an $(l+u) \times (l+u)$ diagonal matrix with the first l diagonal entries being ones and the rest being zeros.

After getting the optimal positioning function f^*, we can use it to estimate the position for any new input RF signal vector. Note that all the manifold learning parameters (*e.g.* kernel K, γ_I, γ_A) used in our HIPS are set similar to [3].

V. Empirical Study and Discussion

We develop a system prototype for the room-size security table application. The test bed is built in a lab office with size of $750cm \times 750cm$, as shown in Fig. 3. We have a table area ($320cm \times 200cm$), denoted as a blue dash box. Let it be our interested area, and we set up a POD consisting of 5 ultrasound sensors (denoted as red dots) for it. The POD is attached to the ceiling at a height of $275cm$, and the POD nodes are organized in a cross topology with each edge as $50cm$. In this topology, we tested the ultrasound coverage area

[5]Consider 2-D positioning, with position as ($l^{(1)}$,$l^{(2)}$).

with at least 3 ultrasound sensors available as 32% of the room size. Different topologies can be discussed, but we leave it as future work. The blue triangles denote the RF sensors. The green stars at the four corners denote the landmark points. A user carries a target sensor at a chest height of $150cm$, and moves in the room for positioning.

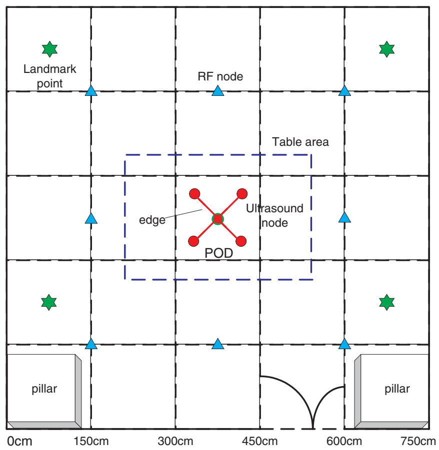


Fig. 3. Test bed in lab office.

To facilitate the evaluation, we divide the room into 5×5 grids, each with $150cm \times 150cm$ size. We will evaluate the positioning results at the 23 available grids[6]. Generally, we have two data sources: (1) *Source 1*: At each grid, we collect around 90 samples on average, with each sample is a vector of 8-dimensional RF signal strengths and 3-dimensional ultrasound positioning results. Note that some grids may not be covered by the ultrasound positioning module, so the corresponding samples at these grids would have $Null$ values for those 3 ultrasound-related dimensions. (2) *Source 2*: We move in the ultrasound coverage area to collect samples, of which the 3 ultrasound-related dimensions are filled by ultrasound positioning results. In experiments, to reduce the statistical variability, results reported are all based on averages over 10 repetitions.

A. Accuracy

We study how accurate our HIPS can be in positioning. In the following experiments, we employ at each repetition: (i) 20 samples at each landmark point grid from source 1, (ii) 50 samples in the ultrasound coverage area from source 2, (iii) 20 samples at each grid in the remaining area from source 1, for learning a RF-positioning module. We have 20 samples at each grid for all the 23 grids for test.

First, we show the hybrid granularities by our HIPS positioning. As shown in Fig. 4(a), we plot the average error distances over the grids for HIPS predictions. As expected, the central (interested) area has lower average error distances by using ultrasound positioning. In our study, this area (central 9 grids) can have a $10.5 \pm 0.2cm$ resolution on average, and the remaining area (14 grids) has a $216.1 \pm 10.8cm$ resolution.

[6]Except the 2 unavailable grids with pillars.

The error distance increases when a user is farther from the room center, since there are few labeled data in the remaining area. We may additionally label some RF data at landmark points so as to improve the accuracy.

Second, we set different error distance thresholds for ultrasound coverage area and remaining area. A prediction is counted as correct if the predicted position is in a distance smaller than the error distance threshold to the ground truth position. The cumulative probability of correct predictions over all the predictions is then accuracy. As shown in Fig. 4(b), our HIPS can reach a $20cm$ ultrasound positioning granularity and a $200cm$ RF positioning granularity with accuracy over 71%.

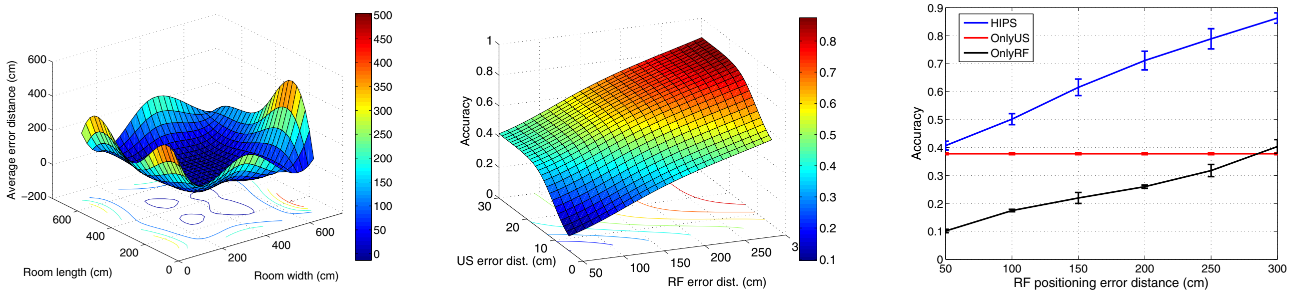
Third, we show the effectiveness of our HIPS in incorporating both ultrasound and RF sensors for positioning in Fig. 4(c). The *OnlyUS* curve denotes the positioning accuracy by using ultrasound positioning module POD. Since the POD is limited in coverage, it can only predict part of the test data, and its performance is invariant to the change of RF error distance. The *OnlyRF* curve denotes the positioning accuracy by using RF positioning module. Because the RF positioning module is limited in positioning granularity at central interested area, its accuracy is low. Our HIPS incorporates both sensors in prediction, and thus keeps outperforming the two baselines.

B. Calibration

We also study how well our HIPS can save the calibration effort. We employ two baselines: RADAR [2] and Horus [15]. RADAR is a k-nearest-neighbor method, which outputs the prediction by averaging the positions from top k_1 similar samples. Horus is a Bayesian method. We use its *Center of Mass Technique*, since we consider the discrete-space prediction. In Horus, we output the prediction by averaging the k_2 most probable positions, which are determined by calculating the maximum likelihoods. For data input, we use the similar setting as Section V-A, except some data's number may be changed in order to study their effects. Specific for Horus discrete space input, we will group the data from source 2 by grids.

First, we study how well our HIPS can do without any human effort in labeling RF data. As shown in Fig. 5(a), our system can still reach a 70.2% accuracy, and outperform the baselines RADAR-k_1 and Horus-k_2, with different parameters k_1 and k_2. Notice that Horus can work worse than RADAR, due to imperfect calculation of the likelihood functions with sparse data. Here, the accuracy is calculated with the ultrasound positioning error distance threshold of $20cm$ and RF positioning as $300cm$. These thresholds are used consistently in the following experiments.

Second, we study the problem that, if we can afford to label some RF data, how many labels are needed? We vary the number of labeled samples from the landmark points for input. As shown in Fig. 5(b) (denoted by black ellipses), to reach an accuracy of 75%, our HIPS only requires 2 labels, while RADAR requires 4 labels and Horus requires 10 labels. This shows that our HIPS is quite effective on reducing the

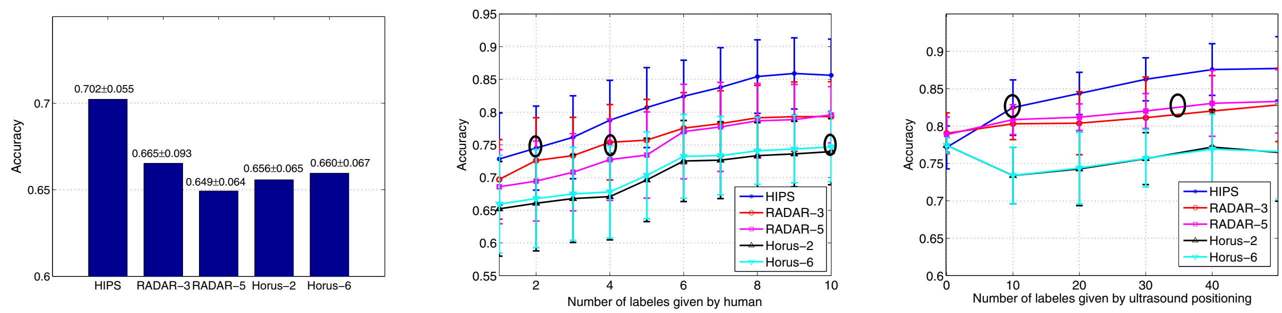


(a) Hybrid granularities for HIPS.

(b) Hybrid error distance thresholds.

(c) Benefit of using both sensors.

Fig. 4. Accuracy issues for HIPS.



(a) No human labeling effort.

(b) How many labels are needed by human?

(c) How many labels are need by US positioning?

Fig. 5. Calibration issues for HIPS.

human calibration effort. As the number of available labels increases, our HIPS can further improve its performance and also consistently outperform the baselines.

Third, we study how many labels are needed by ultrasound positioning. This question is calibration related because the user needs to carry a sensor moving in the ultrasound coverage area to get the data, although the user does not need to label them. We vary the number of labeled samples from source 2 for input. As shown in Fig. 5(c), to reach an accuracy of 82.5%, our HIPS only requires 10 labels, while RADAR requires around 35 labels and Horus has not yet reached this accuracy by 50 labels. HIPS can also reach a more satisfying accuracy of 88% by only 40 labels. With such little effort, HIPS has been able to benefit a lot from the ultrasound sensors. Note that Horus's performance may decrease due to badly modeling the signal-position likelihoods for ultrasound coverage area grids.

C. Discussion

There are still some other issues that are concerned. *The first issue is how many ultrasound sensors we need.* Generally, there should be at least 3 ultrasound sensors to conduct trilateration. However, in practice, the indoor environment has many obstacles, only 3 or 4 ultrasound sensors may be not sufficient in overcoming the multi-path effect and also be limited in coverage. We left for further research the problem of how many ultrasound nodes are needed, although 5 sensors have worked smoothly in our case. *The second issue is how many RF sensors are needed.* Since more RF sensors provide higher dimensionality in a data sample, the computation time spent on the setup and prediction is longer. With acceptable accuracy, we would like to select a subset of most useful RF sensors for our HIPS. We employ the information gain, as described in Section 3.1.1 of [8], for selection; and we find that it is enough to have 6 RF sensors, out of a total 8 RF sensors. Due to space limit, we do not report the figure here. *The third issue is about the running time of our system.* In our case, the ultrasound positioning costs less than $50ms$ in one prediction. Given 330 data samples, the RF positioning costs $200s$ in data collection, $685ms$ for training the model (*i.e.* setup phase), $10ms$ for one prediction. This shows that our HIPS is efficient in both setup and predicting.

VI. Related Work

There have been many positioning methods using one type of sensors for positioning [13], [2], [14], [1], [4]. And [12], [5] also show probabilistic ways to fuse different types of sensors for positioning. However, most of them do not have our new feature of using heterogeneous sensors for a calibration-less solution in hybrid granularity indoor positioning. Our calibration-less solution utilizes the ultrasound sensors to provide labeled data for the RF sensors, so as to minimize the human labeling effort. Previous works on RF positioning generally fall into two categories [2]: *Propagation Models* and *Learning-based Models*. *Propagation Models* can benefit from the knowledge of radio propagation and also the access points' locations. By using trilateration or triangulation techniques, propagation models can compute the position for the mobile target [11]. A drawback for such models is that they can't well handle the signal uncertainty. *Learning-based Models* are also known as fingerprinting models. These models benefit from mining signal-position patterns, including histogram [14], mixture of Gaussian[10], or the mean value of signal strength at different locations [2]. A drawback for such models is that they may require much human calibration effort. Our work belongs to learning-based model. Compared with propagation models, we can benefit from well handling signal uncertainty and without knowing the exact positions of the RF sensors. Compared with other learning-based models, our model is calibration-less by both employing ultrasound positioning module to help labeling RF data and utilizing unlabeled RF data in training.

From the application aspect, our design also provide an interesting and practical idea for hybrid granularity positioning. Existing positioning works do not differentiate the importance for different areas [6], [4], [8]. However, in practice, there may be the case when different positioning resolutions are needed for various areas. Utilizing only one kind of homogeneous sensors may either be expensive, limited at coverage, or unable to reach required positioning resolution in some interested areas. We address this problem by incorporating heterogeneous sensors, and thus provide a possible way for hybrid granularity positioning.

VII. Conclusions

In this paper, we study an interesting problem: when multiple positioning granularities are acceptable, how do we incorporate heterogeneous sensors to provide a calibration-less solution with minimal human calibration effort? To solve the problem, we develop a hybrid indoor positioning system HIPS, and show an example of incorporating ultrasound sensors and radio frequency sensors. We argue that our calibration-less solution can generalize to the case with multiple types of sensors. Technically, our solution employs ultrasound sensors positioning (via structural trilateration) to provide labels for the RF signal data, and trains a semi-supervised manifold learning model for RF positioning. Finally, we combine both the positioning modules in prediction. Compared with previous positioning models, our system can benefit from utilizing heterogeneous sensors in lower calibration cost and a hybrid positioning granularity. Our empirical results on a real-world sensor network confirm the feasibility and effectiveness of our system.

For future work, we will first consider the impact of RF label's reliability to our system, since there can be some errors in ultrasound positioning for labeling the RF data. Then, we will consider how to fully utilize the ultrasound signals when there are less than three receivers can hear them. We are also interested in using real-time RF data, which are labeled by ultrasound positioning, to handle the RF signal variation over time. Besides, we will consider that when multiple ultrasound positioning modules are available, how to best deploy and incorporate them for positioning, meanwhile further reducing the RF-data labeling effort for large-scale positioning.

Acknowledgment

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