Cooperation among Smartphones to Improve Indoor Position Information

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***Abstract*—Accurate indoor location information remains a challenge without incorporating extensive *fingerprinting* approaches or sophisticated infrastructures within buildings. Nevertheless, modern smartphones are equipped with sensors and radios that can detect movement and can be used to predict location. Dead reckoning applications on a smartphone may attempt to track a person's movement or locate a person within an indoor environment. Nevertheless, smartphone positioning applications continue to be inaccurate. We propose a new approach, CRISP - CoopeRating to Improve Smartphone Positioning, which assumes that dead reckoning approaches have inaccuracies, but leverages opportunities of the interaction of multiple smartphones. Each smartphone computes its own position, and then shares it with other nearby smartphones. The signal strengths of multiple radios that are used on smartphones estimate distances between the devices. While individual smartphones may provide some positioning (possibly inaccurate) information, accuracy may improve when several smartphones cooperate and share position information through multiple iterations. Via indoor experimentation and simulation, we evaluate our approach and believe it is promising as an inexpensive means to improve position information and possibly lead to better results for a number of applications, including exercise profiling.**

I. Introduction

Accurate indoor position and movement information of devices enables numerous opportunities for location based services [1] and emerging personalized exercise monitoring applications. Services such as guiding users through buildings, highlighting nearby services within shopping malls, or tracking the number of steps taken or climbed by a user in order to profile daily exercise are some of the opportunities available when accurate positioning information is computed by devices. GPS [2] provides accurate localization results in an outdoor environment, such as navigation information for vehicles. Presently, accurate indoor location information remains a challenge without the incorporation of expensive devices or sophisticated infrastructures within buildings. Traditional indoor localization approaches can be categorized into two types: 1) users required to carry special devices or deploying some infrastructures (specialized access points, antenna arrays, acoustic beacons) to assist the localization [3]–[7]. The costs of such systems are expensive and the users have to be bonded with extra devices 2) for device free localization approaches [8]–[11] user do not carry extra devices, but fingerprints (or other machine learning) algorithms are often needed to train the off-line signal strength for certain environments or via crowdsourcing to achieve ideal accuracy. Data collection and training are exhaustive and time consuming.

Modern smartphones or tablets are equipped with sensors, such as accelerometer, gyroscope, rotation vector, and orientation sensors, and multiple types of radios, which can detect movement and can be used to predict location. Dead reckoning [13] can calculate a person's current positions by using a previously determined position. The parameters that dead reckoning needs are obtained by the accelerometer and orientation sensors on the smartphones. The performance of dead reckoning relies on the measurement accuracy of these sensors. In fact, the accumulative errors caused by the inertial sensors are difficult to avoid. As a common sensor used for localization, UM6 [21], small errors of the orientation estimate causes serious deviation of the computed location. With only 0.5 degree error of the orientation sensor, an error of 308 meters can occur within a minute.

Furthermore, new devices are introduced regularly for health monitoring and exercise profiling, which include detecting the movement of people for the purposes of counting the number of steps a person takes on a daily basis. It is said that walking 10,000 steps a day is important exercise that the human body needs to stay fit. Therefore, by building a pedometer using the accelerometer on the smartphones, the application on smartphones can provide health and medical information to users, such as number of steps and burning calories [14]–[17]. These pedometers count users' steps by using their own algorithms. However, since the data obtained from accelerometers are not accurate and the algorithms are not perfect, the accuracy of such pedometers is not ideal. Smartphones may be paired with such pedometers, or may use their internal sensors.

We propose a new approach, CRISP - CoopeRating to Improve Smartphone Positioning, which assumes that dead reckoning approaches have inaccuracies, but leverages opportunities of the interaction of multiple smartphones to improve accuracy. Each smartphone computes its own position, and then shares it with nearby smartphones. Furthermore, the signal strengths of multiple radios are used on smartphones to estimate distances between the devices. The idea is that while individual smartphones may provide some positioning (possibly inaccurate) information, opportunities of accuracy improvement occur when several smartphones cooperate and share position information. Accuracy may improve as multiple iterations of information sharing and computations are made. Via indoor experimentation and simulation, we evaluate our approach and believe it is promising as an inexpensive means to improve position information and possibly lead to better

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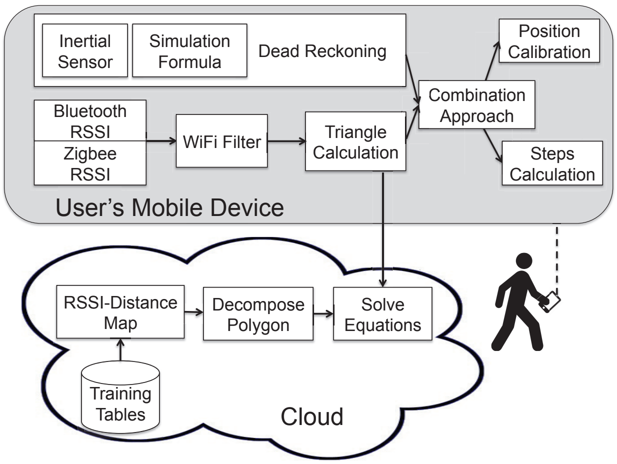


Fig. 1: Framework of CRISP.

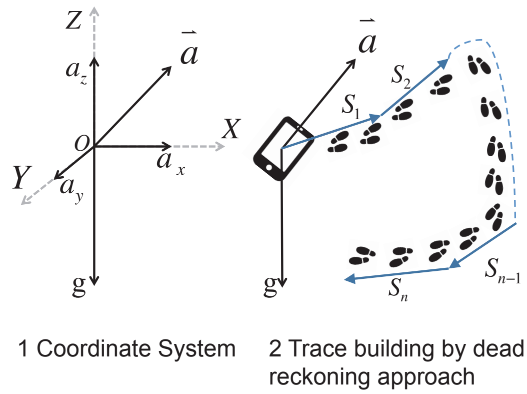


Fig. 2: Dead reckoning approach.

results for exercise profiling.

Key Contributions

1) While many researchers have used RSSI as a means to measure distances between positions [7], [8], [10], [11], to the best of our knowledge, CRISP is the first of its kind to interact with other scanned mobile devices held by other users in order to improve a user's own localization accuracy.
2) We design and evaluate an approach to improve the accuracy of a pedometer application on a smartphone by RSSI measurement rather than only judging accelerometer data.
3) We combine the RSSI from Zigbee and Bluetooth detected on mobile devices, and design a WiFi filter to reduce the noise.

The rest of the paper is organized as follows: Section II presents the system design. Experiments and simulations are shown in section III and further discussions are provided in section IV. Related work is given in section V. Section VI provides the conclusions and a discussion of future work.

II. System Design

A. System Overview

Before introducing details about our design, we provide a short overview of the components used in design. Figure 1 shows the overall architecture.

Our system has two mechanisms on a user's mobile device: 1) periodically measures the accelerometer on user's mobile device, by simulating user's walking mode as a formula, we compute the user's position by dead reckoning, and 2) when a user encounters other users, CRISP periodically broadcasts Bluetooth, Zigbee and WiFi signals to the other users' devices that are nearby. By receiving the RSSI values from other detected devices, a mobile analyzes the variation of the RSSI in each period. Since the WiFi signal is sensitive to interference, if the variation of the WiFi RSSI is beyond a threshold, we assert that the RSSI values received in this period are invalid because of interference and recompute using historical data.

A practical challenge is that how to use RSSI values to help a user locate himself accurately without any extra devices. In our system, after obtaining RSSI from detected devices, the user uses the mapping relation between RSSI and the Euclidean Distance to estimate the distance between these devices. These relations of different mobile devices are trained off-line and can be accessed on the cloud. After obtaining the distance between each pair of devices, all devices in the detected range can form a triangle or polygon. The initial position of each vertex is generated by dead reckoning. The user computes its own position by using the distances to other devices and other devices' locations. By iteration, the errors of estimated positions decrease effectively. A mechanism of choosing the estimated positions between dead reckoning and geometry computation is executed in each period. CRISP also designs a model for counting the user's walking steps. This model can reduce the errors caused by common pedometers on the smartphones.

B. Dead Reckoning Approach

We develop a dead reckoning approach first. An accelerometer is an inertial sensor that is suitable for a user's activity recognition. Mobile devices sense the acceleration on three axes orthogonal to one another periodically. We set the time length of each period to be 1 second. The formula to compute acceleration is in equation (1). The symbol g refers to the earth gravity, a_x, a_y and a_z refer to the acceleration received on the Ox, Oy and Oz. By the obtained acceleration in each period, the movement distance of a mobile device in time period n is based on the equation (1). v_{n-1} and a_{n-1} refer to the velocity and acceleration from previous time period, t_n refers to the time length of current period. S_n refers to the vector of movement distance in current period. As shown in Figure 2, if the application on smartphone computes movement distance in each segment by (1) continuously, it can obtain the whole trace of mobile device. However, the accelerometer on a mobile device records the acceleration of the mobile device rather than a human's body. Therefore, if a person's body movement is different from a mobile device's movement, dead reckoning will cause serious distance deviation.

$$\vec{a} = (a_x, a_y, a_z - g),\ \vec{S}_n - \vec{S}_{n-1} = \frac{1}{2}\vec{a}_{n-1}t_n^2 + \vec{v}_{n-1}t_n \tag{1}$$

C. Distance and RSSI

Received Signal Strength Indicator (RSSI) is a common measurement of the power present in a received radio signal, with "dBm" as the unit of RSSI. RSSI is easy to collect on most mobile devices. Although the RSSI values often vary due to interference and path loss, RSSI values obtained from the other

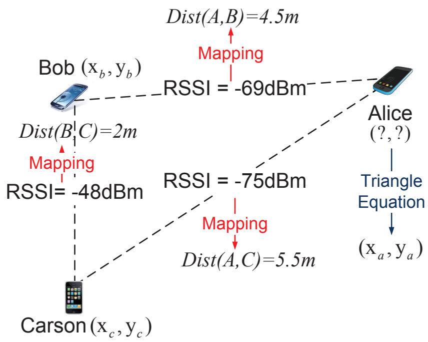


Fig. 3: Triangulation model.

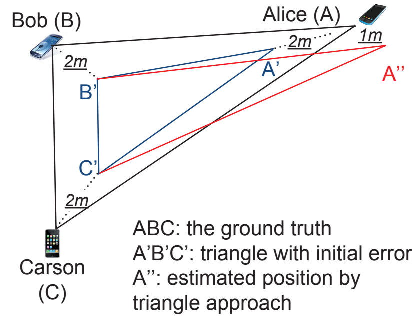


Fig. 4: Triangulation calibration example.

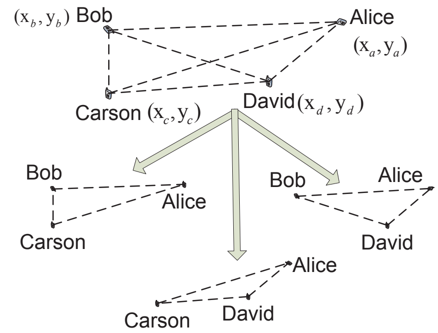


Fig. 5: Decompose quadrilateral to triangles.

devices are highly related to the distance between the devices. Shorter distances often represents stronger RSSI. In CRISP, we build the RSSI-distance mapping relation by collecting the data that represents the distances and RSSI values for different types of popular mobile devices.

In our preparation phase, we evaluate the RSSI-distance mapping relation for the Samsung Galaxy S5 smartphone, Samsung Tablet 4, and Google Nexus 5 tablet. The RSSI is obtained from the Bluetooth Adapter. For example, if the distance between Samsung S5 smartphone and Samsung Tablet 4 is 5 meters in an empty room, the RSSI is -66 dBm. The training relation does not consider interference and other factor fading the RSSI values. These noises and exceptions will be handled by the WiFi filter. These mapping relations are stored in the database on a cloud server. In addition, even if training the mapping relation may bring labor and time costs, since the types of mobile devices in our work are popular, the obtained relations can serve common Android based mobile devices.

D. Triangular Calculation Localization

1) Triangular Calculation Model: In CRISP, the goal of triangular calculation is to locate a user's position by knowing other detective devices' locations and RSSI values. To illustrate this idea, we provide an example: as shown in Figure 3, three users (Alice, Bob, and Carson) hold mobile devices that have Bluetooth adapters. In each time period, we assume they form a triangle. After turning on the Bluetooth option, each receives Bluetooth RSSI values from the other two users. Then, we can obtain the length of the three sides of the triangle by the distance-RSSI mapping relation. If Alice hopes to locate herself and she knows positions of Carson and Bob (Bob and Carson's positions are computed by the dead reckoning approach and sent to Alice when they encounter), Alice can compute her position by the equations (2), (x_a, y_a) denotes the the device a's position on a two dimension plane. AB and AC denotes the distances between Alice and Bob, Alice and Carson. This example explains how the triangulation calculation model helps one user to locate his/her position. In our design, because the range of Bluetooth detection is 10 meters, the upper bound of each slide in a triangle is 10 meters.

$$\begin{aligned} Mapping(RSSI_{AB}) = |AB| = \sqrt{(x_a - x_b)^2 + (y_a - y_b)^2} \\ Mapping(RSSI_{AC}) = |AC| = \sqrt{(x_a - x_c)^2 + (y_a - y_c)^2} \end{aligned} \tag{2}$$

Since the dead reckoning approach is not enough to provide satisfactory location information, another case is proposed in Figure 4. There are three users (**A**lice, **B**ob, and **C**arson) carrying smartphones. The vertices on triangle ABC refer to the real positions of the three users. We assume the three users evaluate their initial locations by the dead reckoning apps, which are not accurate. The estimated positions are A', B', and C'. The distances between A and A', B and B', and C and C' are two meters. By using the triangular calculation, Alice obtains RSSI values from Bob and Carson, and by the RSSI-distance mapping relation, Alice evaluates the estimated distance from Bob and Carson.

Then, by the two computed distances (AB' and AC') and the distances between B' and C' (B'C'), we can compute the position A"- which is the estimated position of A computed by the equations as (1). A is closer to A" rather than A'. We can also compute the position B" and C". Thus, the new formed triangle A"B"C" is able to reduce the distance errors caused by dead reckoning.

We apply the triangle calculation to a dynamic scenario. The preliminary observation is: user Alice carries the mobile device and enters an empty room; Bob and Carson are already in the room. The three people walk freely. In the beginning, we assume they do not have any initial error of distance. Then, we record the Alice's distance error, which is caused by dead reckoning in the next 14 seconds.

As illustrated in Figure 6 and Figure 7, since there are inaccurate values obtained from accelerometer, the distance errors due to dead reckoning increase rapidly. However, the localization errors of the triangle approach stay at a low level because the triangle calculation errors are caused by the differences between estimated mapping distances and the real distances.

The above analysis is from the perspective of Alice. We turn focus to all three devices in the triangle. We also execute the experiment as above. The only change is that we set each user to an initial deviation from their real starting position (the deviation is 2 meters). The initial deviations of their locations are caused by the dead reckoning application on the smartphone. Then, we use the triangle calculation to compute the users' locations. As Figure 8, after running the triangle computation for 600 seconds, the distance errors of A, B and C are all reduced effectively. To validate this conclusion, we repeat the same experiment 3 times. Then, we simulate the experiments 47 times. As the Figure 9 shows, the data samples on the two

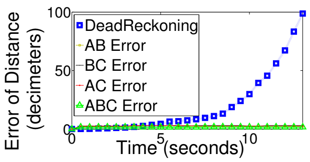


Fig. 6: Distance errors of dead reckoning and triangle computation approaches.

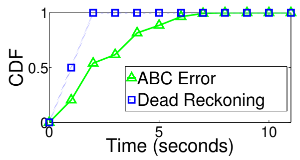


Fig. 7: CDF error of dead reckoning and triangle computation approaches.

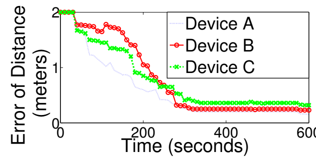


Fig. 8: Distance errors of triangle computation by three cooperating devices.

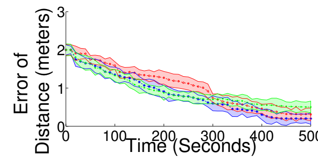


Fig. 9: Repeated triangle computation by three cooperating devices.

dimensional plane refer to the average values of distance errors of the 50 experiments (or simulations) at different time points. The shadow areas refer to the confidence interval for each data point. In this paper, confidence intervals are typically stated at the 95 percentage confidence level. Although it is a preliminary observation, by adopting triangle computation, with the time increasing, errors of distance can be reduced within 1 meter, which is reasonable and acceptable for many indoor positioning applications.

2) Extension from Triangle to Polygon: Based on the above example that includes three users, Alice can obtain her position by triangle computation. In a real scenario, there might be more than three devices in a room or in a hallway. As the above example, if David enters the room, we can form a quadrilateral. User devices can be treated as the vertices of a quadrilateral. Then, three are three triangles in the quadrilateral including the node Alice, namely, triangles ABC, ABD, ACD as shown in Figure 5. The new location of Alice is defined as the mean value of estimated Alice's locations from the three triangles: x_a= $(x_{a(abc)} + x_{a(abd)} + x_{a(acd)})/3$, y_a=$(y_{a(abc)} + y_{a(abd)} + y_{a(acd)})/3$, where $x_{a(abc)}$, $y_{a(abc)}$ are the Alice's (a's) x and y values computed from triangle ABC. If the room contains more than 4 devices, all the devices can be abstracted as the vertices of a polygon. For each of the devices, we can use the triangles that are in the polygon to help localize itself. Then, by computing the mean value of the position obtained from different triangles, the user of a device can compute its position. If one user encounters more mobile devices and forms more complex polygons, the localization results may be more accurate.

E. Combine Different Types of Signals: Bluetooth, Zigbee, WiFi

1) The Features of Three Types of Signals: Most smartphones and tablets support applications of Bluetooth and WiFi. Bluetooth RSSI is not only sensitive to interference but also sensitive to the distance between two detective devices. Bluetooth RSSI values often vary from maximum to minimum within its 10 meters' range. Shorter distance reflects stronger signal strength. WiFi RSSI values are sensitive to interference such as the human body or wall between the sender and receiver, but for most wireless routers that provide WiFi for mobile devices, the RSSI values do not vary much by changing the distance from 1 to 10 meters.

A Bluetooth adapter operates using a procedure of scanning and inquiring. It often costs 5-15 seconds for current mobile devices. Therefore, the sampling frequency of Bluetooth RSSI is limited. Sometimes, if mobile devices move rapidly, the user might lose the chance to record the Bluetooth RSSI values from them. To remove this defect, we introduce the RSSI received from the Zigbee Protocol. The feature of RSSI using Zigbee is similar to Bluetooth RSSI, but Zigbee does not require a long time to scan and connect to other devices. Also, Zigbee is able to set the RSSI sampling frequency by the programmer, with 1HZ or 0.5HZ as common RSSI sampling frequencies. Although most current smartphones are not integrated with Zigbee, we consider adding Zigbee to have more RSSI samples to improve the localization accuracy, and consider that future generations of smartphones may have similar capabilities.

2) WiFi and Direct-WiFi Filter: RSSI is known to perform poorly in indoor environments. Some variations of RSSI values may cause errors in RSSI-distance mapping. For example, if a moving object is between the two Zigbee sensors (or Bluetooth adapters), the received value of RSSI will decrease. Then, if we use a RSSI-distance mapping in training datasets, the corresponding distance will increase.

Therefore, we need to filter this interference (noise). As mentioned in the previous section, although WiFi is not sensitive to the distance, WiFi is sensitive to the interference. By this feature of WiFi, we design a filter to reduce the effect of noise caused by interference.

Since a user's movement cannot change abruptly, if the received WiFi RSSI varies each 10 seconds more than 5dBm, we assume such obvious change of RSSI is caused by interference. We define the 10 second time period as a "Noise Period (NP)". We use the average RSSI value in the closest previous period that is not a NP to replace the RSSI values in the NP. As shown in Figure 10, when the WiFi signal encounters interferences at two NPs (116-119 seconds, 166-169 seconds), the values of RSSI decrease sharply. After using the WiFi filter to detect NPs, the noise samples of Bluetooth and Zigbee RSSI are corrected by the average RSSI value in the closest previous time periods.

In most of indoor scenarios, people receive WiFi signals by wireless routers. However, some indoor environments do not have such infrastructures. Wi-Fi Direct is a Wi-Fi standard that is adopted on most of popular mobile devices, such as iPhone, iPad, and Android smartphones. This technology enables devices to connect with each other without requiring a wireless access point, such as a wireless router. Each smartphone/tablet can open the WiFi-direct option, which means each mobile device can detect others by WiFi and receive the RSSI values from these devices. If the WiFi values obtained by Directed-WiFi changes sharply, it is also seen to be a NP and be handled by the WiFi filter.

F. Combine Triangle Calculation and Dead Reckoning

Although triangle calculation is close to the ground truth, it still has the errors caused by the mapping. In fact, for dead reckoning, its errors are caused by the variation of accelerometer. It is difficult to predict the range of error. Therefore, the ideal situation is to select the better localization result from both of the two approaches in each time period. To achieve this goal, we define following two events to indicate when the dead

Algorithm 1 WiFi-Filter Algorithm

Input:
The RSSI samples collected from Bluetooth, Zigbee, WiFi adapters, threshold of WiFi filter
Output:
Filtered RSSI values of Bluetooth, Zigbee

for i=1;i < num of periods; i++ **do**
  if variation of WiFi RSSI value > threshold **then**
    // Find RSSI values of the closest previous period
    call WiFi-Filter(i-1);
    // Replace the abnormal RSSI values in the NP
    for j=1; j < number of Bluetooth samples in i (n_b); j++ **do**
      $BluetoothRSSI[i][j] = \frac{\sum_{j=1}^{n_b} BluetoothRSSI[i-1],[j]}{n_b}$
    end for
    for k=1; k < number of Zigbee samples in period i (n_z); k++ **do**
      $ZigbeeRSSI[i][k] = \frac{\sum_{k=1}^{n_z} ZigbeeRSSI[i-1][k]}{n_z}$
    end for
  else
    Return *BluetoothRSSI*[i][n_b];
    Return *ZigbeeRSSI*[i][n_z];
  end if
end for

Algorithm 2 Algorithm of Combination Approach

Input:
The computed location by dead reckoning approach and triangle calculation at time period i: $(x_i, y_i)_d$, $(x_i, y_i)_t$,
Output:
The combination location results at time period i:$(x_i, y_i)_c$

while each time slot i **do**
  if time period i is Noise Period (NP) **then**
    Call WiFi-Filter(i);
    Recompute the $(x_i, y_i)_t$ by updated BluetoothRSSI$[i][n_b]$ and ZigbeeRSSI$[i][n_z]$
  else
    $(x_i, y_i)_c$=$(x_i, y_i)_d$
    if event1 or event2 **then**
      $(x_i, y_i)_c$=$(x_i, y_i)_t$
    end if
  end if
  Return $(x_i, y_i)_c$
end while

reckoning approach is not reliable:

Definition: Event 1: In a certain time period i and in comparison to the previous time period i-1, the accelerometer changes sharply, a_x or a_y or a_z changes more than $1m/s^2$.

Definition: Event 2: In certain time period i and in comparison to the previous time period i-1, the position of mobile device changes sharply, x or y changes more than 5 meters.

When the WiFi filter detects the Noise Period, the triangle calculation approach is not reliable. Therefore, we provide the mechanism for selecting best approach between dead-reckoning and triangle computation in Algorithm 2.

G. Step Benefits

Steps are counted by the pedometer applications on smartphones, however, most pedometers are highly inaccurate [15], [23], [24]. One intuitive reason is that the pedometer integrated on the smartphone relies on the accelerometer. The accelerometer values on smartphone do not equal to human bodies' accelerations, it is difficult to identify an acceleration signature in human walking pattern without errors.

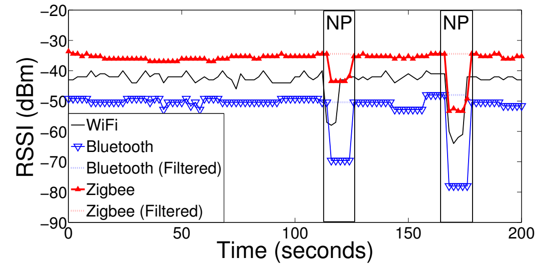


Fig. 10: WiFi filter.

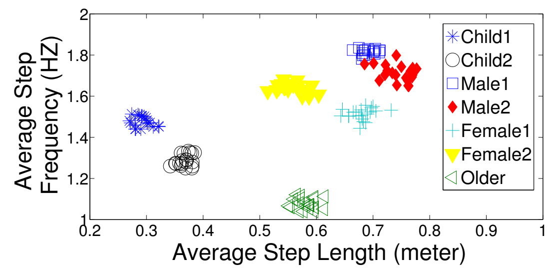


Fig. 11: Relation between step length and step frequency.

Different people have different lengths of steps. To enable CRISP to count steps, it is necessary to estimate the length of the step for each user. We employ a linear step-frequency model as equation (3), which is described by Li [23] and Hilsenbeck [24]. The symbol f_k denotes the step frequency that can be counted manually in a short training period k, its minimum time length is 20 seconds. The symbol d_k is the length of the step. Then, we develop a two dimension data set containing the average step length and average step frequency of different people as illustrated in Figure 11. Seven groups of volunteers present their own features. We fit the linear model by using the least square to set a and b. Thus, by conducting a lightweight training phase, the user can get his/her own step length for counting steps.

In our approach, users obtained the location information continuously in different periods. Within a short time period i, we may assume people walk straight. Computing by equation (4), it is simple to count steps a user have walked within a certain time period. By adding the number of steps that have recorded in each time period, the user can determine the number of steps they walked in total.

$$d_k = a \times f_k + b \tag{3}$$

$$number\ of\ steps = \frac{\sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2}}{d} \tag{4}$$

H. Running CRISP in the Cloud

CRISP is a light weight application. Users upload their received RSSI and location messages from other cooperating devices periodically. Thus, the prepared distance-RSSI maps stored on the server transfer received RSSI values to distances continuously. Besides, because we deploy the tasks 1) forming polygons of devices, 2) decomposing polygons to triangles, 3) solving equation (3) to compute the location of a user's device

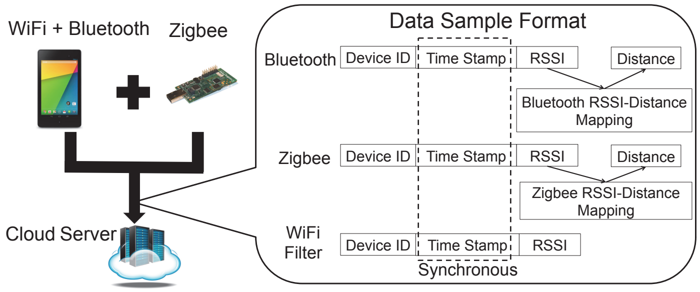


Fig. 12: The equipment structure and data sample format in our experiment.

on the server instead of running it on a mobile device.

III. Evaluation

A. Experimental Setup

We built a prototype of CRISP on Android mobile devices using the version KitKat. In the experiments and simulations on each device, we combine Bluetooth, Zigbee and Direct-WiFi Filter together to do the triangle calculation. Although current mobile devices, such as the Samsung Galaxy and the Google Nexus smartphones do not integrate Zigbee on them, in our experiment, we bound the Telosb Zigbee sensors on these mobile devices and run the application programs on TinyOS [25]. Since the Zigbee model is not supported by Android OS, we record the Zigbee and Bluetooth data synchronously by sharing the timestamps. The frequencies of Zigbee and direct WiFi samples are 1HZ and 0.25HZ. The sampling frequency of Bluetooth RSSI is around 0.1 to 0.2 HZ. The format of the data sample is shown in Figure 12. For each data sample, after receiving Bluetooth and Zigbee RSSI values translated by the trained mapping relation, the estimated distance between each pair of devices is determined.

The dead reckoning approach is implemented as follow: we set each slot period to be 1 second. Then, we use equation (1) to compute the movement direction and the movement distance in each segment. By collecting the computed segments in each time period, we generate the user's trace. The users carry the devices and walk freely in rooms or hallways.

For our evaluation and discussion, we mainly seek to answer four questions: 1) Does our approach improve the mobile devices' localization accuracies in different environments? 2) Does our approach count walking steps for users effectively? 3) How does the Zigbee model and WiFi filter assist the Bluetooth model? 4) For one user, does encountering a greater number of users who also use CRISP improve his/her own position accuracy?

B. Metric of Measurements

Two metrics are introduced in the evaluation: 1) *error of accumulative steps* indicates the different number of steps counted between third-party application and CRISP 2) *error of distance* is the distance (in meters) between the ground truth and the estimated position.

C. Scenario Measurements

As shown in Figure 14, we conduct the experiments for 45 minutes in a room of the Engineering College at Michigan State University. There are three users who carry mobile devices and walk freely. All use CRISP and interact with others frequently. As illustrated in Figure 14(b), the X axis refers to the time of the experiment. the Y axis refers to the error of distance of a user A. The blue line, red line, green line refer to the distance errors of dead reckoning, triangle approach and the approach combining both of them. As shown in Figure 15, we conduct the similar experiment in a hallway. From the two types of experiments, after cooperating with the triangle computation, the combination approach performs best. The average deviation from dead reckoning is reduced to 0.5 meters.

We repeat our experiments 200 times by simulations. When simulating the dead-reckoning approach, we adopt equation (1) and obtain the acceleration values from the accelerometer on the smartphone periodically. Then, we add random errors of acceleration on the x, y, z axes, the error range is from $-1m/s^2$ to $1m/s^2$. For the triangle computation, we add -10 to 10 percentage distance errors for each side of the triangle, randomly. The time of each experiment group is reduced from 45 minutes to 1000 seconds. As Figure 14(c) and Figure 15(c) display, at a specific time point, the data samples on the each line refer to the average values of distance errors obtained in 50 times of simulations. The shadow of each line is the confidence interval of computed values. The two figures indicate that after many simulations, the combination approach has more accurate results than the dead reckoning and triangle calculation. It achieves the error range that is within 1 meter.

We extend our experiment from one place to an indoor building with multiple rooms and hallways: a user walks with the mobile device and communicates with other devices. All devices are installed and running CRISP. As depicted in Figure 16, the dash lines refer to the time points when the user changes their room. For example, at the 50th second, a user leaves a room and enters the hallway. The localization results of the combination approach are more accurate than the other two approaches, especially for the dead reckoning approach. The errors of localization using CRISP are still within 1 meter. Figure 13 provides the overview of the two estimated traces in our floor plan.

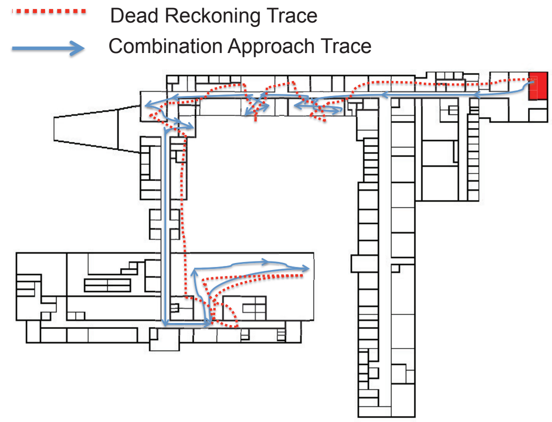
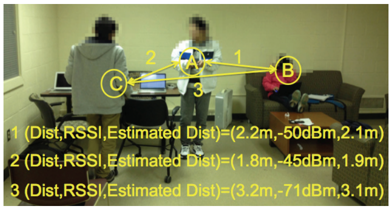
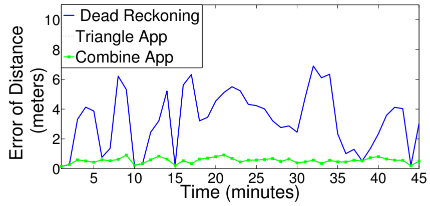


Fig. 13: Traces comparison in real floor plan.

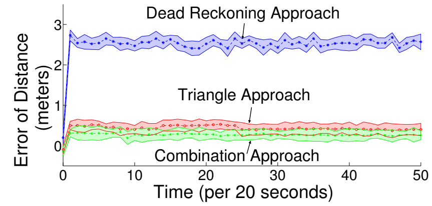
We also focus on step counting in this experiment. Figure 17 illustrates the step counting and two pedometers on the smartphones. The stems refer to the accumulative error of the number of walking steps computed by the combination approach in CRISP. The remaining two lines refer to the accumulative error of number of walking steps caused by two



(a) Room environment

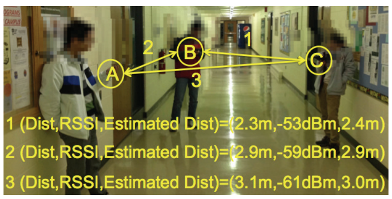


(b) Room measurement for one time

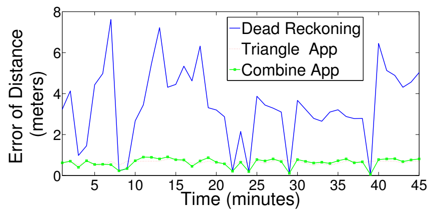


(c) Room measurement repeated 200 times

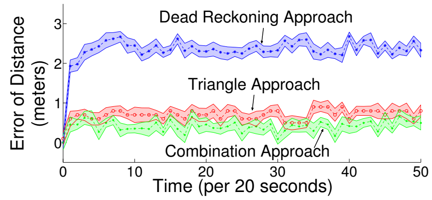
Fig. 14: Experiment measurement in a room.



(a) Hallway environment



(b) Hallway measurement for one time



(c) Hallway measurement repeated 200 times

Fig. 15: Experiment measurement in a hallway.

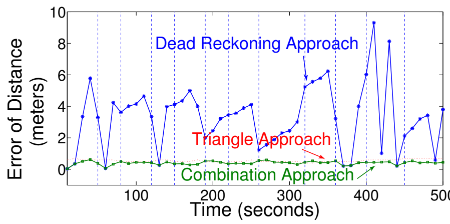


Fig. 16: CRISP measurement in the complex indoor environment.

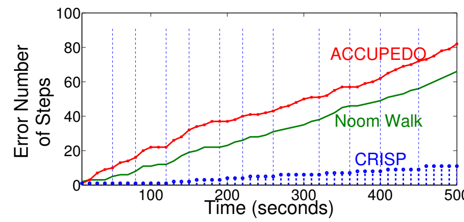


Fig. 17: Comparison of accumulative step errors for three applications.

popular pedometer applications (Noom Walk, ACCUPEDO) from Google Play [16], [22]. CRISP maintains less errors than the other two pedometers in the whole procedure.

IV. Discussion

A. Compare different types of signals

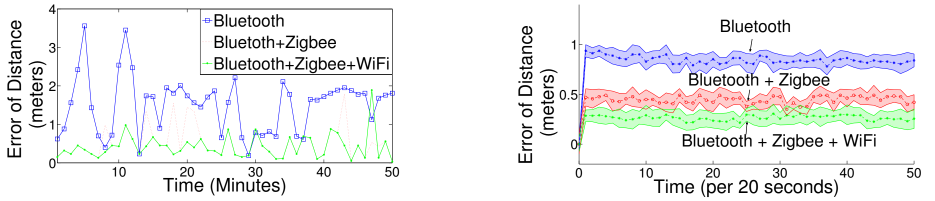
CRISP integrates Bluetooth, Zigbee and WiFi filter to implement triangle calculation for measuring users' locations. To analyze the effectiveness of each technology, we conduct the following evaluation: while maintaining the same experimental environment, as given in Figure 18(a), first, we use Bluetooth RSSI without the Zigbee sensor and the WiFi filter to collect RSSI. Second, by adding the Zigbee approach to the Bluetooth approach, we observe the indoor localization results. Third, the green line on the figure denotes the experimental results by combining all the three technologies. Then, we simulate our experiments 100 times. The simulation is generated as in the single room evaluation section. The time period is reduced from 45 minutes to 1000 seconds. Figure 18(b) presents the localization results by the repeated simulations. As shown in Figure 18, we believe that 1) adding more RSSI samples from Zigbee model and 2) filtering the interferences in the Noise Period by the WiFi filter are helpful for improving the indoor positioning results.

B. The number of mobile devices encountered influence the localization accuracies

In this section, we discuss whether the number of mobile devices a user encounters can influence the localization accuracy. First, we assume that Alice carries a smartphone and walks freely in one room within 500 seconds. Then, other people help Alice to locate herself by CRISP. When we start this experiment, we set two control groups: 1) the group includes Bob and Carson, who will help Alice to apply triangle computation, and 2) the group contains Bob, Carson, and David to do triangle computation after using "polygon decomposition." According to our observation in Figure 19(a), the "3+1" control group has less errors than the "2+1" group. Then, we repeat our experiments 500 times of simulation, shown in Figure 19(b). We draw the same conclusion as what we had in the physical experiments.

To further support the above conclusion, a more complex experiment is conducted: a user of CRISP walks in an indoor building. Three traces are generated: 1) a user does not meet any other users (a user's location is computed by dead reckoning), 2) a user always has other two users assisting him to locate himself by the combination approach 3) a user always has three to four users to help him to locate himself. The trace continues 1000 seconds and we simulate such traces 100 times. In Figure 19(c), trace 1) only uses dead reckoning and often has a serious deviation (around 3 meters) from the ground truth. The trace 3) uses a combination approach and encounters more people to achieve the best performance.

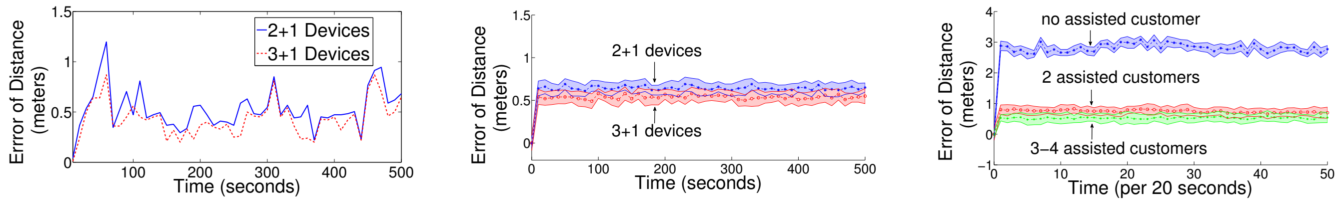
Based on the above evaluations, if all users run CRISP on their mobile devices, the localization accuracy of each user can be improved.



(a) Comparison of different types of signals

(b) Repeated comparisons of different types of signals

Fig. 18: Shows Bluetooth RSSI, Zigbee RSSI, and WiFi filter to improve the experiment results, respectively.



(a) Observation of different number of devices encountered

(b) Repeated observation of different number of devices encountered

(c) Control groups comparison

Fig. 19: Number of devices encountered to differentiate localization accuracies.

C. Threshold of WiFi Filter

In our previous experiments and simulations, we set the threshold of WiFi filter at 5 dBm. In fact, if we set P as the threshold for filtering, if the interference that causes the value of RSSI change is less than P, the interference will be neglected. If we set the threshold of the WiFi filter too low, the normal variation of RSSI values will be judged as the interference, and hence, an optimal threshold of WiFi filter is a key factor. Based on the Samsung Galaxy S5 and Google Nexus 7 devices, we use our approach in a room in the Engineering Building and conduct the experiment as described in the previous section. The only difference is that we test different thresholds of the WiFi filter: 3dBm, 5dBm, 10dBm, 15dBm. After 5 minutes' of experiments, the successful rate of WiFi filter detection is given in the following table:

	Real Interference	**Detected Interference**	**Misjudge Interference**
3dBm	8 times	8 times	23 times
5dBm	8 times	7 times	2 times
10dBm	8 times	2 times	0 times
≥15dBm	8 times	0 times	0 times

Real Interference refers to the number of times interference was generated in the experiment; *Detected Interference* refers to the number of times interference was detected by the WiFi filter; *Misjudge Interference* is the number of false positives of interference occured. From the table, we observe when the value of the threshold equals 5, CRISP performs best.

D. Complexity of our approach

To analyze the complexity our approach, we focus on the worst and the best case of CRISP, respectively. For the worst case, we assume all devices are in a reachable range of the Bluetooth adapter (or Zigbee base station), namely, the connection should be created between each of the mobile devices. If the system contains n devices, the complexity of the system is $O(n^2)$. For the best case, a user only accesses other people in different ranges of Bluetooth adapter (or Zigbee base station), the complexity of the system is $O(n)$. Therefore, the complexity of our approach is acceptable, we can apply it in large scenarios even if the number of devices is not small.

V. Related Work

A. Indoor Localization

Traditional indoor localization can be categorized into two types:

Device-based approach: Deploying specific infrastructures or require users to carry specific devices to obtain accurate localization results. The first indoor localization system - Active Badges [3] is based on infrared technology. Each person wore an infrared beacon to report its position to a server. Ultrasonic localization systems such as Cricket [4] and Dolphin [5] were proposed later. Some localization systems obtained 3D location sensing by RFID, such as SPOT ON [6] and LANDMARC [7]. RFID Tags and measured RSSI calculated distances between objects. Although these device-based approaches often have high accuracies in certain equipped environments, it is difficult to deploy such systems in many application environments.

Device-free approach: Device-fee approaches often adopt signal fingerprinting [8]–[12] either in a training phase or via crowdsourcing. In [8], RSSI measurements are recorded at each location when a person stands at certain positions (offline training). When the system begins localization (online testing), matching is performed by using the maximum likelihood criterion. RSSI measurements are compared with the known training data and the highest probability position is chosen. In addition to RSSI, Surround-Sense [9] adds other features such as ambient sound, light, and color to construct an indoor map. It can enhance the accuracy of matching. Although these approaches reduce the cost of devices, the accuracy of device-free indoor localization depends on the size of training data. Also, the procedure of training data is a challenge for those approaches.

Smartphone approach: Dead reckoning [13] localization uses a previous determined position. The application can compute user's current position by a physical formula. However, the accumulative errors caused by sensors or algorithms are not easily reduced. Unloc [18] uses a virtual landmark to improve the accuracy, since the various manners that people carry the smartphone, the direction obtained from acceleration is not as same as the people's real direction. Although SAIL [26] employs the propagation delay of the signal traversing between single WiFi AP and smartphone to eliminate the errors caused by dead reckoning approach, but the localization results are not highly accurate. By using computer vision and sensing technologies [19], [20], [27], [28], some researchers fuse the data from accelerometer, camera sensor, and acoustic sensor to provide solutions for indoor localization, but the signal processing and recognition in indoor environments are still challenging for these systems.

B. Pedometers on Smartphones

Different from the traditional pedometers, some pedometers use smartphones sensing based architectures as a major system component to counter users' steps. Hongman et al. [14] designed a pedometer system by using the accelerometer and orientation sensors. They analyze the top (peak) and bottom (trough) of the acceleration wave and provided a configured threshold to filter the accelerometer noise. By combining the microphone and accelerometers, Inoue et al. [15] proposed a two-tier approach involving multilevel segmentation and activity recognition. On each axis, mean, frequency-domain energy, and frequency-domain entropy are extracted as the features. Then, the correlation of the combined axis was also extracted.

Besides, some applications published in Google Play or Apple Store [16], [17] can count people's steps by using accelerometer or other inertial sensing approaches. However, such pedometers have limitations: 1) although these pedometers contain some filters to reduce the noise, they can not distinguish some movements of humans' bodies from walking, such as shaking hands, 2) the algorithms to judge the steps based on the change of accelerometers are not perfect.

CRISP, compared to the traditional indoor localization technologies, does not require any extra device other than the users' smartphones or tablets, does not require the phase of training data for finger print map. Compared to other smartphone-based indoor localization approaches, just using RSSI, our approach has higher accuracies than other dead reckoning based approaches and avoids complex data fusion and analysis.

VI. Conclusion

We present a RSSI based indoor localization system called CRISP. Different from traditional indoor localization systems, a user walks in an indoor environment and opens the Bluetooth scanning option on a smartphone. The smartphone interacts with other smartphones and exchanges RSSI values. CRISP not only improves the devices' localization accuracies, but also provides the extra benefits - the number of walking steps for the user who holds a smartphone.

In CRISP, we build relations between RSSI and distances for different mobile devices. CRISP uses geometry computation to reduce the errors caused by dead reckoning. By our experiments and evaluation in the Engineering Building of Michigan State University, we show that if a walking user who carries a mobile device and uses CRISP in a building, and if he/she encounters other people using CRISP, the localization results will be more accurate. The range of error is within 1 meter. We combine the Zigbee RSSI values to the RSSI obtained from Bluetooth to collect more samples, and use a filter that is based on WiFi. Both of the two technologies improve the localization accuracy in our evaluation. With known location information, CRISP can count a walker's steps and reduce the common errors caused by smartphone based pedometers.

Acknowledgment

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