Collaborative Indoor Localization of Mobile Nodes

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ABSTRACT

In this paper, we firstly survey start-of-the-art indoor localization methods which have been extensively studied in recent years. Most of the existing localization methods for indoor people have mainly focused on localization supported by infrastructure. However, considering new applications such as in-room navigation with a people crowd (like in exhibition halls and shopping malls) or social and business activity support that often needs interaction among people, we may reach a different solution that leverages mobile devices of surroundings for more cost-efficient, accurate positioning. Then we seek such a possibility, *collaborative indoor localization of mobile nodes*, and discuss technical challenges that have not been unsolved so far. Finally, we introduce our two indoor localization approaches that are based on mobile node collaboration. We address their benefit and discuss future research directions.

Keywords: Collaborative Localization, Indoor Positioning, Mobile Nodes

1 Introduction

Localization and tracking of indoor mobile clients (like people) has been studied extensively for the last decade, and is still a hot topic[1]–[3]. It has attracted a lot of researchers and developers since it contains a lot of scientific and technical challenges that cannot be solved easily.

Those approaches have solved very challenging problems with which we face in developing indoor positioning systems. However, one concern is infrastructure cost. Since most of those approaches have mainly focused on localization supported by infrastructure, they need a massive investment in reference points like embedded active RF beacon tags (like SpotON[4], LANDMARC[5] and others like SherLock [6]) for identifying object locations or recent pseudo GPS signal transmitters (*e.g.* Indoor MEssaging Systems (IMES) where maximum separations of transmitters are a few tens of meters [7]) for better coverage). Although highly-accurate positioning may be achieved, they do not provide general solutions for ad-hoc, on-the-fly (or instant) localization of mobile people without requiring physical space to locate reference points and related maintenance effort like continuous power supplement or battery replacement.

One efficient solution for such a problem may be to let clients participate in the localization process (collaborative localization). Let us consider peer-to-peer (P2P) computing systems. Clients simultaneously produce and consume resources for distributed, self-organized operations of file sharing, content distribution and distributed computing. Clients are motivated to provision their own resources by the availability of shared resources and contents. Similar collaboration may be expected in location services where people join the services and provide their location information to obtain more valuable, collective information.

In collaborative localization, clients may act as reference points in addition to a role of clients. Recent penetration of highly-capable mobile phones into consumers will bring this concept into shape since those phones are equipped with several wireless devices (Bluetooth, WiFi and even NFC) and users may develop, install and run any programs they want to use. Also due to emerging enhancement of MEMS technology, wearable devices are becoming smaller and more invisible, which also have a lot of possibilities for collaboration with surroundings. On the other hand, there are not a few issues that should be taken into account, like location privacy issues, battery limitation and robustness to low node density.

Collaboration of nodes has been normally assumed in Wireless Sensor Networks (WSNs). However, the situation is quite different from the case of collaboration for people tracking since in WSNs nodes are stationary, homogeneous and densely deployed. Also battery consumption should be optimized to maximize "network lifetime", not in per-node basis.

In this paper, we pursue the possibility of mobile node collaboration in indoor localization. We discuss the benefit in terms of accuracy and costs and challenges to be solved. Then we introduce our two indoor localization approaches [8], [9] that leverage collaboration among mobile nodes instead of installing high-cost infrastructure. We demonstrate the effect of collaboration in localization and finally discuss future research directions.

2 Brief Survey of Indoor Localization

Indoor localization has been widely studied (see surveys [2], [3]). They employ different types of ranging methods such as ToA and TDoA for triangulation, or assume training to build prior dataset in area of interest to cope with more complex architecture where Lines of Sight (LoS) are not ensured. Self-localization such as Pedestrian Dead Reckoning (PDR) has also been well-investigated and recently phone-based PDR that fully utilize self-contained sensors and wireless devices is a growing tread.

2.1 Range-based Technologies

Time of Arrival (ToA) is a ranging technology between two time-synchronized nodes. Since the distance between two nodes is proportional to the time of flight (ToF) of signals, the receiver calculates ToF and estimates the distance based on the speed of light [1]. Instead of using RF, sound is also a reasonable solution whose propagation speed is much slower than light. TDoA can be performed using RF and ultrasound of two different propagation speeds in like the cricket system [10] or the reception time of a single RF signal transmitted by a mobile target is compared among time-synchronized multiple receivers (stations) to calculate time-of-flight difference. Angle of Arrival (AoA) can be observed by some directional antennas or sensors like position sensitive detector [11].

The precision of distance measurement depends on wireless technologies. UWB is robust to NLoS (Non-Lines of Sight) which often happens in indoor space since time resolution of UWB is precise enough to exclude signals delayed by reflection [12]. Exploiting such a feature, some location systems like Ubisense[13] have been in market. Ultrasound-based location system provides fine-grained position information. ActiveBat [14] and Cricket [10] are early and well-known methods, and recently wideband ultrasound has been developed in [15]. BeepBeep [16] takes an interesting approach that achieves accurate ranging between mobile phones using propagation delay of sound signals.

RSS-based ranging has been used in both lateration and fingerprinting. Most of the lateration-based methods assume RSS decrease is proportional to log-scale distance increase (the pathloss exponent is a linear coefficient) and perform the least squares method. Zero-configuration localization [17] performs on-line calibration using both AP-to-client and AP-to-AP RSS measurement to take physical characteristics into account. Recent interesting approach called EZ localization [18] attempts to locate APs and multiple clients with assistance of GPS positioning near windows, where off-the-shelf device localization without any prior knowledge is the primary objective. Fingerprinting exploits dataset obtained by training where RF fingerprints are generated in the area of interest and a signal strength map is pre-built. Then a vector of on-line measurement RSS from different APs is compared, and the point in the map that minimizes the Euclid distance (or some other metrics) is the estimate. The well-known WiFi-based methods like RADAR [19] and Horus [20] take such an approach.

We note that the concept of fingerprinting is utilized by not only WiFi-based approaches but also by other approaches such as GSM signal fingerprinting [21], Geomagnetic fingerprinting [22] and even ambient (light, sound etc.) fingerprinting like SurroundSense [23].

2.2 Self-Localization Technologies

The definition of "self-localization" is somehow ambiguous, but this term is mostly used to represent autonomous robot control like Simultaneous Localization And Mapping (SLAM) [24]. Due to difficulty of pose estimation in human activity which is usually assumed and employed in SLAM of robots, pedestrian dead reckoning [25], [26] that estimates the trace of pedestrians using accelerometers, digital compasses and gyro sensors is still a big challenge. While most previous PDR methods have assumed dedicated sensor devices attached to human bodies, some methods such as CompAcc [27] have utilized commercial mobile phones. Escort [28] combines PDR with proximity sensing via sound beaconing to estimate relative positions, assuming such services that guide users to their friends in unknown places. [29] enhances the quality of PDR by deriving proximity information from Bluetooth visibility of devices.

3 Motivation and Our Approach

3.1 Why Collaboration?

Accurate ranging is usually achieved only in close distance using some dedicated hardware. Due to its range limitation like UWB and ultrasound, dense deployment of reference points is mandatory to track mobile targets in large space like a hall and exhibition space. On the contrary, long-range measurements are easily affected by noise, interference and multipath due to signal attenuation and reflection. Instead of deploying stationary reference points, using mobile reference points is a reasonable approach. WiFi-based approaches are cost-effective by use of COTS clients and reuse of existing stations. However, most of them do not provide sufficient precision. Generally, the positioning error ranges from a few meters with training data [20] or from 4-5m without training data [18], both of which are largely dependent on configuration of physical environment (interference, floor architecture, location of APs and so on). Additionally, considering promising mobile, context-based applications that support social activities like automatic detection of people interaction, we often need to estimate relative positions, *i.e.* position relationship. Utilizing direct distance or proximity measurement among clients will contribute to increase relative position accuracy, which is also a strong benefit.

3.2 Challenges in Collaborative Indoor Localization

Nevertheless, we have to overcome both operational issues and technical challenges for collaborative localization of mobile clients (mobile phones in particular). As for operational issues, the most important ones are privacy and incentive issues. That is, how to protect privacy when we transmit position information and how to encourage users to join the collaboration are two major concerns. Untracablity should be guaranteed for privacy protection, and it is generally achieved by introducing temporally-variant ID in localization of mobile nodes in untrusted party (strangers) like in public space. Similar issues have been discussed in privacy protection of probing cars where each vehicle transmits every 100ms second information about precise location and motion. Incentives have been discussed in client-based systems such as P2P-computing systems. Recently it has become clear that in promising cloud-based location services like recent car navigation systems (and service provides like Apple/Google), most people provide their location information to join the services and valuable information are rewarded in return. Although we become more nervous in direct communication with neighboring strangers, attractive services themselves are potentially strong incentives. We note that in some extreme situation like in emergency sites, or in some closed indoor space like museums and exhibitions, we may expect every node is collaborative as in a trusted party even though they do not know each other.

As for technical challenges, (i) *reference node selection* is a critical issue. Since everybody may become a virtual reference point in collaborative localization, more careful design is needed. Meanwhile, they are all mobile, which potentially decreases accuracy and increases frequency of localization. Therefore, How to choose an appropriate set of virtual reference nodes considerably affects the performance. Intuitively, as surrounding nodes increase, the amount of information increases and accordingly we may obtain more precise location by localization using all these nodes. However, with mobility, at each moment error variances are not uniform among nodes. That is, some mobile nodes will contain large errors since the elapsed time from the last localization. This is closely related with tracking frequency. (ii) *Energy efficiency* is also an important issue. Unnecessary communication and localization attempts will waste batteries. Space and time of localization attempts should be optimized in this viewpoint. We investigate these issues (i) and (ii) in details in our stop-and-go localization [8] in the following section. Finally, (iii) *self-localization to fill sparse space* is important. Different from the assumptions made in many WSN researches, node distribution is not uniform and time-variant, meaning that clients may not always expect the presence of neighboring nodes. In this context, the collaborative localization should also be tolerant to stand alone operations, and incorporation of PDR technology is a reasonable approach. On the other hand, as we demonstrated in our work [9], PDR using self-contained devices still suffers from large errors. Therefore, we need some calibration mechanisms. Although anchor-assisted PDR error correction has been investigated [30], it will be the best option that calibration is done within the framework of collaborative localization.

3.3 Our Approach

Based on the above discussion, we introduce our two collaborative indoor localization approaches.

Stop-and-go localization [8] assumes each mobile node is equipped with a ranging device to measure distance between nodes based on TDoA (like RF and US (ultrasound)). It performs collaborative lateration but aims at *energy efficient* tracking of mobile nodes by performing stop-and-go activity detection *to select appropriate set of reference nodes*. All these operations are naturally integrated into the localization process, meaning that all we need is accurate ranging devices between

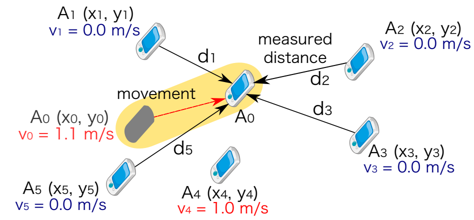


Figure 1: Concept of the Proposed Algorithm.

neighboring nodes and particular processing and devices for such motion detection are not necessary.

People-Centric Navigation [9] introduces the concept of mobile node collaboration into Pedestrian Dead Reckoning (PDR). PDR is an important technology to allow self-navigation without reference points, but accumulation of errors is a critical issue. We introduce a concept of group activity clustering for collaborative PDR. Basically each mobile node provides its own trajectory information to let the others know the "group-averaged" trajectory. Based on prior knowledge on similarity of people's movement (speed and directions) that can be observed in many situations, the erroneous trajectories can be adjusted.

4 Stop-and-Go Localization of Mobile Nodes: Concept and Results

4.1 Preliminaries

2-dimensional localization requires distance information from at least three reference points. As we discussed in the previous part, it is sometimes hard to find those reference points, and therefore we use estimated positions of neighboring nodes as reference points. We will refer to such semi-mobile reference points as *semi-anchors*. We assume that three or more anchors are deployed at known positions in a target area, and that all nodes have ad hoc communication and range measurement faculties. For range measurement, we assume a Time Difference of Arrival (TDoA) technique as provided by ultrasound devices. A node simultaneously transmits RF and ultrasound signals to allow a receiver node to calculate the time difference of two signals to estimate the distance. On account of its accurate ranging capability, ultrasonic ranging provides precise, robust indoor positioning, and thus has been commonly-used in indoor localization methods such as DOLPHIN[31] and Cricket[10]. Since an ultrasound transmitter has a directional range pattern, we assume that each node has several ultrasound transmitters and receivers which are arranged radially to achieve the omni-directional range pattern.

4.2 Algorithm Overview

For localizing a node, our algorithm identifies "temporarily stopping nodes" from its neighbors to choose appropriate semi-anchors. This is also effective to reduce localization frequency, because such nodes are not necessary to be localized

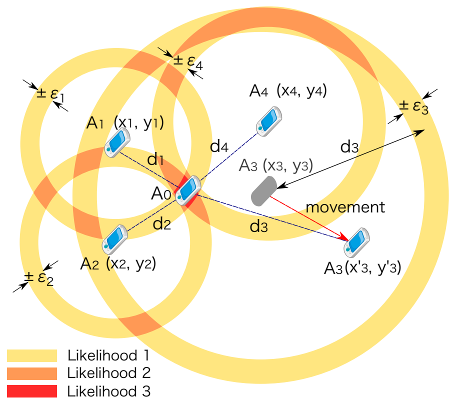


Figure 2: Likelihood Distribution

unless they move. Each node A_i holds position, speed and "state" information (*static*, *moving* or *unknown*). A_i starts localization by transmitting TDoA distance estimation request. Neighboring node A_j immediately sends a response to tell the estimated distance and A_j's current position to A_i *only if A_j is in static state*. A_i performs localization referring to the *static* neighboring nodes. However, since state information is just an estimation, moving nodes may regard themselves as *static*. To exclude such inappropriate nodes, A_i validates A_j's state information using the received distance and position information. Once three or more anchors or semi-anchors are found, A_i estimates its position by the least squares method. If node A_i finds A_j is moving, A_i lets A_j change the state information to *moving* and perform localization immediately. Fig. 1 shows the localization process of A_0. Based on its estimated speed, A_0 innovates its localization process by range measurement signal. Then nodes A_1, A_2, A_3 and A_5 in *static* state reply with distance and position information.

Considering the error range of the estimate position (ϕ_j) and distance (d_j), the solution space of A_i's position is assumed to be a circular ring with inner radius ($d_j - \epsilon_j$) and outer radius ($d_j + \epsilon_j$) where we define $\epsilon_j = \sigma_{p_j} + \sigma_{r_j}$, which is the sum of the expected position error (σ_{p_j}) and range measurement error (σ_{r_j}) of A_j. σ_{p_j} is calculated by A_j in its localization process. If the error of measured distance follows the Gaussian distribution, the error linearly increases as two nodes are distant and can be estimated as $\sigma_{r_j} = \sigma_0 d_j$ where σ_0 denotes the standard deviation of distance errors when the distance is 1m, which can be given by some preliminary measurement. Using ϕ_j, d_j and ϵ_j, the circular ring of A_j can be determined, and the solution is likely to be contained in the intersection of the largest number of circular rings. We choose the initial solution from a point in the region and A_j is regarded as in *moving* state if its circular ring does not include the point. In Fig. 2, node A_0 selects the initial solution from the intersection of circular rings of A_1, A_2 and A_4, and regards A_3 in *moving* state.

After choosing the initial solution θ_0, we calculate distance denoted by $d_j^{(0)}$ between θ_0 and the estimated position ϕ_j. Then we regard that $d_j^{(0)}$ are correct since it is derived from confidence by multiple nodes, and exclude such A_j that causes inconsistency between $d_j^{(0)}$ and original measurement d_j from the set of semi-anchors.

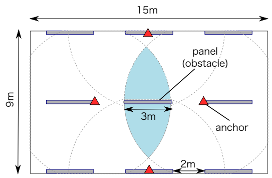
Each node estimates its speed whenever it performs localization. We let $\theta(t')$ and $\theta(t)$ denote the estimated positions at time t' and time t ($t' \leq t$), respectively. Speed v_i of A_i is estimated by $v_i = \frac{||\theta(t)-\theta(t')||}{t-t'}$. If this speed is substantially low, A_i is expected to be stopping. Hence, when $||\theta(t) - \theta(t')||$ is less than $\sigma_{p_i}(t) + \sigma_{p_i}(t')$, which means the sum of expected errors of $\theta(t)$ and $\theta(t')$, A_i is regarded to be stopping and v_i is set to zero. If not, A_i is regarded to be moving and A_i performs localization at every $I_v(v_i)$ sec which is updated in each localization process as $I_v(v_i) = \frac{1}{cv_i}$ with a certain upper bound. c is the number of localization attempts per moving distance.

Finally, to prevent contention among TDoA measurement, we have designed a collision avoidance mechanism similar to the RTS/CTS mechanism in CSMA/CA-based protocols. When a node performs localization, it broadcasts a *Request To Measure (RTM)* message before sending TDoA measurement signals, and occupies the frequency for measurement signals for a while. Also, each node has a timer to hold the time when the bandwidth for measurement signals is occupied by other nodes. We call the time *Network Allocation Vector (NAV)*. Whenever a node receives an RTM message, it sets NAV timer for T_{cycle} sec., which can be determined considering the maximum propagation time of ultrasound. Then, it decrements NAV timer over time. While NAV timer is more than zero, a node postpones localization. A node which has delayed localization can perform it when NAV timer reaches zero. To consider fairness, we let each node wait for backoff time before sending an RTM message. The backoff time $T_{backoff}$ is determined such that a node which has been delayed for longer time can have shorter backoff time using the following formula; $T_{backoff} = CW \cdot \exp(-at)$ where t is the delay time, CW is the maximum backoff time and a is a parameter to define the characteristic of the backoff time, respectively. Larger CW can reduce collision probability of RTM messages, but requires longer time to perform localization.

4.3 Experimental Results

We assume that a conference poster session with 9 poster panels held in a 9m × 15m hall as shown in Fig.3. Each node is equipped with three pairs of ultrasound transmitter and receiver. We also assume that poster panels and human bodies obstruct propagation of measurement signals. We model a human body as a 30cm line which is 30 cm away from the terminal. Thus, nodes can measure the distance to the neighboring nodes in the directions except backward by TDoA techniques.

On account of high directionality of ultrasound signals, they depend on angle of departure (θ) and angle of arrival (ϕ) in addition to distance d between nodes. We assume that the range measurement error follows a Gaussian distribution with a mean defined by a function $\mu(d, \theta, \phi)$ and variance defined by $\sigma(d, \theta, \phi)$, and that the ranging success rate is determined



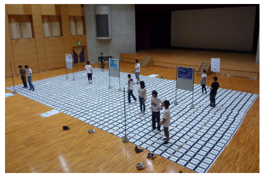


Figure 3: Poster Session Scenario

Figure 4: Field Experiment

by a function $\rho(d, \theta, \phi)$. We define these functions based on measurements using MCS410CA (Cricket Mote [10]). As a result, we confirmed that in all the cases of ϕ, the maximum range of measurement signals in mobile nodes were about 2m shorter than those in static nodes. Hence, in the simulation, we calculated the mean and variance of the range measurement error and the ranging success rate based on measurement results of static nodes by assigning $(d+2, \theta, \phi)$ instead of (d, θ, ϕ). We also conducted field experiments as shown in Fig. 4 to obtain actual mobility traces of presenters and audiences. 12 students behaved as audiences and presenters in a 9m $\times$ 15m hall where 9 poster panels were arranged as Fig.3. We laid out 1,500 markers which are made of 0.3m-square papers printed with their coordinate on the ground. Each student moved over the markers recording the coordinate with a video camera for 5 minutes. After we conducted such experiments 8 times, we obtained 72 traces of audiences and 24 trajectories of presenters.

4 anchors are deployed at (4.0, 4.5), (7.5, 0.0), (11.0, 4.5) and (7.5, 9.0) as shown in Fig.3. The shaded area represents the area where nodes can refer to three or more anchors in case of $r = 5$m where r is the maximum range of measurement signals. We assumed that anchors are deployed on the wall or poster panels, where ranging signals are not obstructed by human bodies. We selected 12 trajectories of presenters to place a presenter for each poster and 38 trajectories of audiences to conduct simulations for 5 minutes. In Table 1, we compared the performance of the proposed method with two conventional cooperative approaches. In the first method (referred to as *const.*), each node updates its location every 2 seconds using all the neighboring nodes as semi-anchors. Second one (referred to as *recursive*) is based on DOLPHIN[31], in which anchors and semi-anchors transmit ranging signals in random order while the other nodes immediately perform localization and turn into semi-anchors after they collect distance to a sufficient number of anchors or semi-anchors. Since DOLPHIN is a cooperative method for static sensor networks, we discarded the estimated position every 2 seconds and repeatedly performed localization to track mobile nodes. For *recursive*, errors are remarkably large since moved semi-anchors seriously degrade localization accuracy. As for *const.*, the deterioration caused by bad semi-anchors happens to be relaxed by averaging observations from all the neighboring nodes, whereas relatively large errors still remain. On the other hand, the proposed method improved localization accuracy by 73% compared to *const.* and by 95% to *recursive* as a benefit of semi-anchor selection

Table 1: Simulation Results

	proposed	**const.**	**recursive**
Estimation Error	0.23m	0.85m	4.68m
Tracking Error	0.51m	0.95m	5.03m
Localization Success Rate	0.95	0.99	1.00
Avg. Localization Interval	5.49 sec.	2.00 sec.	2.35 sec.
Movement Detection Rate	0.43	—	—

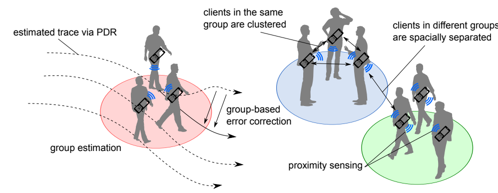


Figure 5: PCN system overview

based on movement state estimation. Furthermore, the total number of localization attempts is reduced by 64% and 57% respectively, which proves that our method achieves high localization efficiency.

5 People-Centric Navigation: Collaborative Dead-Reckoning

5.1 Overview

The concept of PCN system is shown in Fig. 5. Clients of PCN (*i.e.*, mobile phones) continuously obtain accelerometer and digital compass readings to estimate step counts and direction. They also estimate a vector of each step called *step vector*, using the direction information and stride length. Since the stride length varies between individuals, it is approximated from the body height. The clients also record RSS from the neighboring clients, which is collected through device discovery process of Bluetooth. The step vectors and RSS are transferred to a centralized server called *PCN server* via 3G or Wi-Fi, and the collected RSS is transformed into distance based on a predefined RSS-to-distance function at server side. Then the PCN server estimates relative positions among users and the results are sent back to the clients to tell the estimated situation.

Pedestrian Dead Reckoning and RSS-based distance incurs non-negligible errors. Fig. 6 shows Bluetooth RSS-distance mapping based on a real measurement using two Google Android phones (Samsung Nexus S) in our department building receiving a lot of interference from Wi-Fi. We have plotted the measured RSS at each distance (outliers have been eliminated), and indicated their maximum and average values, where error bars show the standard deviations from the average. As shown in previous literature such as [32], we can see that different RSS values were observed at the same distance due to multipath effect, interference and so on. However, we focus on a criterion to characterize this relation based on the maximum RSS values; at 7m or longer distances they never reach -70dBm, while they exceed it at 6m or shorter

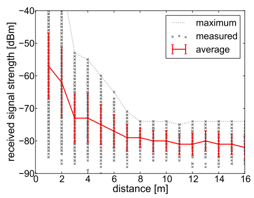


Figure 6: Distance vs. Bluetooth RSS

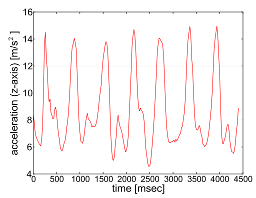


Figure 7: Acceleration in vertical direction

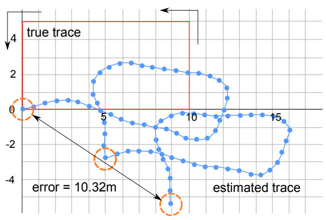


Figure 8: Trace deviation in PDR

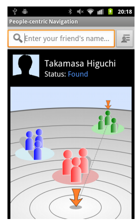


Figure 9: Prototype of PCN client

distances. We utilize this characteristic to detect "proximity" explained later, allowing some inaccuracy around the boundary of two categories.

We have also implemented a simple PDR application on the Android phones to examine the accuracy of step vectors. This application continuously monitors acceleration in the vertical direction to detect steps and the compass readings to estimate the orientation of mobile phones. As shown in Fig. 7, the acceleration in the vertical direction changes synchronously with the user's steps. Therefore we simply count up the number of steps when the acceleration exceeds a threshold where the counting interval is set to 300 milliseconds to prevent double counting. Using this application, we have analyzed the estimated trace of a user walking twice on the boundary of a 5m×10m rectangle region (Fig. 8). On the estimated trace, the true positions of the three different points highlighted by dotted circles are actually the same, and thus we can observe that the position errors grew up to 10.32m after 60m walking. We note that this is the simplest threshold-based PDR where mobile phones are assumed to be held vertically at hands. There are of course more enhanced methods such as [25], and those methods can be used to improve PDR accuracy in PCN since it just uses trace estimation results from PDR. For simplicity of discussion, we assume this simple PDR hereafter.

In order to calibrate PDR traces, we focus on general observation of human behavior; in crowded situations, the behavior can be categorized into several patterns. For example, in a party, most people stand and talk with each other. They often move around together to join the other groups or to find drinks and foods. To examine similarity of traces in a group, we have conducted the following experiment using the PDR application. We let 15 examinees with Nexus S phones freely form groups and let them walk for 30 minutes in a 10m×10m field where markers were placed with two meters spacing. The examinees also took videos of markers to record true traces as shown in Fig. 10. The obtained traces were bro-

Figure 10: Preliminary experiment

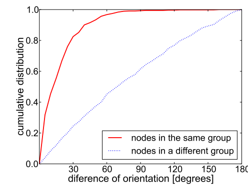


Figure 11: Deviation of moving directions

ken down into subtraces of 2 sec., and the average direction of each group was derived at each time. Then directions of the subtraces were compared to each group average to examine the deviation of orientation within and without the group. Fig. 11 shows the cumulative distribution of directional deviation from the group average. The deviation was 30 degrees or less for about 80% of subtraces in the same group, while it distributed uniformly for those in different groups.

Assuming that users in the same group have similarity of traces, PCN corrects the estimated traces that are deviated from the "group traces". Since the group information is estimated from the collected acceleration, direction and Bluetooth RSS, we do not need any additional information for the error correction. We define two criteria to recognize groups; nodes (mobile phones) currently in the same group (i) have been close to each other, and (ii) have moved similarly for some duration. Properties (i) and (ii) are called **proximity** and **trace similarity**, respectively. Based on these properties, *group likelihood* is calculated and the most likely grouping is adopted.

The estimation process of PCN is as follows. When the current traces are reported from the clients to the PCN server, deviated directions and positions are calibrated based on the trace similarity and proximity properties, respectively. For this purpose, groups are estimated using the past acceleration, direction and Bluetooth RSS information. After that, the Bluetooth RSS values are utilized to reflect the relative distance among the nodes.

Fig. 9 shows a screenshot from our PCN client on the Android platform. If group estimation is correct, the user can identify the target person in the group of three people behind the group of three people in front of him/her. This context information helps to mitigate the bad effect of position errors in recognizing the target person.

5.2 Experimental Results

To collect sensor data and RSS logs in real environment, we conducted a field experiment in a public trade fair. As a part of a technical event named Knowledge Capital Trial 2011 (`http://www.kmo-jp.com/en/`), the trade fair was held at a 27m×40m-sized hall as shown in Fig. 12. Totally 16 industrial companies and universities exhibited their state-of-the-art technology while thousands of visitors went around the booths. We let 20 students hold Nexus S phones and asked to go around the event place with a group of four people. Finally we collected real sensor data and RSS logs which are

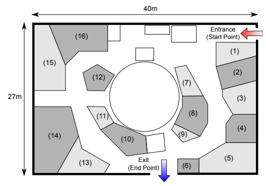


Figure 12: Floor map

Figure 13: Field experiment

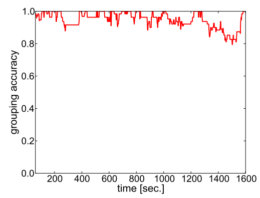


Figure 14: Accuracy of group estimation

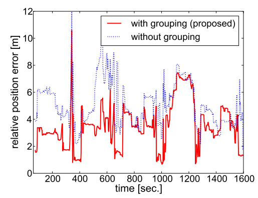


Figure 15: Relative position error

about 1,800 minutes long in total (90min. logs for 20 examinees). In the following evaluation, we used logs of 2 experiments as a learning dataset to construct group classifier (we omitted the details in this paper), and the remaining one as a test dataset to examine the performance.

We evaluated the performance of PCN from three aspects, namely, grouping accuracy and relative positioning error.

Grouping Accuracy: We applied the group classifier to all the sensor data and RSS logs in the test dataset to classify those 20 clients into activity groups. Then we evaluated the grouping accuracy by the accuracy rate of *pairwise membership test*: for each pair of nodes, we checked whether they are in the same group or not, and compared them with the actual grouping (5 groups of 4 people). As shown in the temporal change of resulting grouping accuracy in Fig. 14, we successfully achieved accuracy rate of more than 90% over most pieces of time in the experiment, with average grouping accuracy of 94.8% (1.7% false positives and 3.5% false negatives).

Relative Positioning Error: We evaluated relative positioning error to nearby nodes which are within 10m from each node A_i of interest. We represent the set of such nearby nodes at time t as $S_i(t) \subseteq S$ and define the average relative position error denoted by $err(t)$ as follows:

$$err(t) = \frac{1}{|S|} \sum_{A_i \in S} \left(\frac{1}{|S_i(t)|} \sum_{A_j \in S_i(t)} ||p_{ji,t} - \tilde{p}_{ji,t}|| \right) \quad (1)$$

where $p_{ji,t}$ and $\tilde{p}_{ji,t}$ represent the true and estimated positions of A_j at time t from a local view of A_i, respectively.

We applied our context-supported relative positioning algorithm to the test dataset, and evaluated the relative position error every 2 sec. In Fig. 15, we compared the position error with a straightforward method which performs relative positioning using RSS and plain user traces without group-based correction. As a benefit of the context-supported correction mechanism, our method achieved higher positioning accuracy over most pieces of time through the experiment. The average positioning error of our method was 3.51m, which corresponds to improvement of 31.3% compared to the plain approach.

6 Concluding Remarks

We have demonstrated that localization will perform better by fully utilizing power of people with smart devices. Considering indoor public or private space like museums, shopping malls or office space, people are always there and we may expect these people will join location services. Designing indoor location system is not a trivial task due to its variety of client devices, infrastructure, areas of interest, architectural (floor) complexity and their scale.

Two research directions can be considered. Firstly, new technologies like augmented reality is now being incorporated into mobile applications, which needs accurate indoor positioning of objects and people. Since correspondence between location information in cyber and physical objects is a key technology, it should be more studied how indoor positioning is utilized in those cases. Also some applications will become more social-aware, and indoor localization can contribute to promote social activity. We believe these two new treads are interesting to follow and study.

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