RFID-based centralized cooperative localization in indoor environments

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***Abstract*—We demonstrate the effectiveness of a cooperative scheme to improve the positioning accuracy of four users moving in a building, by using the received signal strength (RSS) measurements from a number of known location RFID tags (anchors) and combining it with RSS measurements of mobile tags carried by themselves. The method is based on a centralized particle filter approach over the joint state of all users. Due to a relatively small number of anchor nodes (7 tags for an area of 1600 m^2), individual localization is not very accurate (median error of 6.2 m), but this improves to 5.1 m when cooperative measurements are taken into account. When PDR estimates of user displacement are incorporated to the particle filter, the median positioning error is further decreased to 4.0 m (individual localization) and 3.5 m (cooperative localization).**

I. Introduction

Localization of people in indoor environments is a very interesting and challenging research topic (as this IPIN conference can attest) for which so far no standard technological solution exists. Most indoor positioning systems are based in the transmission of signals to, or from, the user's location to a set of beacons in the infrastructure, and then measurement of a physical parameter such as time-of-arrival, received signal strength, and so on. This estimate can be improved if the user has access to a self-carried sensor information about his or her movement, by use of Pedestrian Dead Reckoning (PDR) methods. Both kinds of sensory information are available if the user carries a smartphone, in which he runs the location engine as a software application.

When we consider several users in a given scenario, this localization scheme can be *individually* replicated for each user, or users can exchange signals and share information between themselves to produce joint estimates of their positions *cooperatively*. Cooperative localization techniques can succeed in situations where individual localization does not, for example, when users do not have access to enough reference modes to estimate their location.

There already exists considerable literature on cooperative localization techniques, as shown in reference [1]. Basically, methods can be classified into deterministic algorithms, which use range measurements and techniques such as multilateration, least squares minimization [2] or multidimensional scaling [3]; and Bayesian techniques, based upon probabilistic estimates of the position of users from measurements with an intrinsic uncertainty [4]. Bayesian techniques, such as particle filters, are powerful methods for localization and tracking of persons and mobile vehicles [5], and it's the approach we will follow in the present work.

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II. Theory

In cooperative localization of a set of users, each individual has access to a number of beacon points (or anchors) at known locations in the environment, but is also able to detect RF signals from other users in their proximity. While a given individual may not be able to localize himself only from the RF signals from the anchors, it is possible that all users can do it by combining their joint information.

We will use a centralized localization method, in which the sensory information retrieved by all users through their smartphones is transmitted to some nearby processing unit, and computation of users' positions is later distributed back to them through a communication network. Future work will be oriented towards distributed information processing methods which are more practical for cooperative positioning.

The cooperative localization technique is comprised of several elements, which are discussed now.

A. Particle filter

Consider a number of N_u persons moving in a displacement area, each of which has access to up to N_a fixed position RF beacons or anchors. Let $\mathbf{x}_j^t = (x_j^t, y_j^t, \theta_j^t)$ be the 2-dimensional position and spatial orientation (heading) of the j-th user at time t. In Bayesian estimation techniques [6], our knowledge about the state of the j-th user at time t is represented as a probability distribution function (PDF) $p(\mathbf{x}_j^t)$. In our collective localization scheme, we will assume a single PDF for all users, which has the form:

$$p(\mathbf{x}_1^t, \mathbf{x}_2^t, \ldots, \mathbf{x}_{N_u}^t), \tag{1}$$

while in individual localization we would consider separate PDFs $p(\mathbf{x}_1^t)$, $p(\mathbf{x}_2^t)$, etc, for each user.

In this work, we will use a particle filter (PF) approach for localizing and tracking the users. Of all possible Bayesian

methods for estimating the probability distributions $p(\mathbf{x})$, PFs have the advantage of being methodologically simple and flexible; they are not subject to any particular PDF shape for $\mathbf{x}$. Furthermore, in our case they permit to control the effects of the increased number of dimensions of the state space associated with cooperative positioning.

The state of all users is represented by a set of N_p particles, each of which expresses a hypothesis about the joint position and orientation of all users:

$$p_i = \{x_{1i}, y_{1i}, \theta_{1i}, \ldots, x_{N_u i}, y_{N_u i}, \theta_{N_u i}\}, \quad i = 1, \ldots, N_p, \quad (2)$$

(therefore being of dimension $3N_u$) and has an associated weight w_i representing the estimated probability of this hypothesis. At initialization, all particles are assigned random positions and orientations, and their weights taken as equal ($w_i = 1/N_p$). The positions and weights of the particles evolve in time as RF measurements are received and motion from the users is detected. We will consider this now.

B. Measurement model

In the indoor environment, the RF reader carried by the j-th user is continuosly registering signal strength measurements (RSS) both from fixed position (anchors) and mobile RF emitters. We use notation $\{\mathrm{RSS}^a_{jk}\}$, where $k \in \{1, \ldots, N_a\}$ for the measurements from the anchor nodes, and $\{\mathrm{RSS}^m_{jl}\}$, where $l \in \{1, \ldots, N_u\, l \neq j\}$ for the measurements from other users (superscripts a and m stand for anchor nodes and mobile nodes, respectively). Note that, in general, $\mathrm{RSS}^m_{jl} \neq \mathrm{RSS}^m_{lj}$, experimentally.

In order to incorporate these measurements to the particle filter, we need a measurement model that relates RSS readings to the user positions. Determining this model exactly is impossible due to the complex characteristics of RF propagation in indoor environments, so some simplifications have to be made. The simplest is the well-known path loss law [7]:

$$\mathrm{RSS}^{(a,m)}(d) = \mathrm{RSS}^{(a,m)}_0 - 10\alpha^{(a,m)} \log_{10} \frac{d}{d_0} + e_{\mathrm{RSS}}, \quad (3)$$

where d is the distance between user j and anchor node k or between users j and l, d_0 is a reference distance, RSS_0 is the signal strength at distance d_0, and α is the path loss exponent. Note that different path loss law parameters $\{\mathrm{RSS}^a_0, \alpha^a\}$, $\{\mathrm{RSS}^m_0, \alpha^m\}$ are considered for RSS readings from anchor nodes to users, and between users themselves, respectively. Finally, e_{RSS} is fading noise corresponding to the unmodeled effects of indoor propagation of RF signals; we will consider that it is Gaussian distributed, $e_{\mathrm{RSS}} \sim \mathcal{N}(0, \sigma^2_{\mathrm{RSS}})$. Parameters RSS_0, α and σ_{RSS} are estimated from a set of calibration measurements taken at sample locations in the displacement region.

The assumption that the signal strength depends exclusively on the range between emitter and receiver is certainly an oversimplification of the real phenomenon. More accurate two-dimensional models can be produced by fingerprinting techniques [8] or regression techniques [9]; however, the calibration effort required by these methods is higher.

C. Update stage

The particle weights are updated with the RSS readings received by all users during the time interval between instants t and $t+1$, considering RF signals from anchors as well as between users as:

$$w^{t+1}_i = w^t_i \times \prod_{j=1}^{N_u} \prod_{k=1}^{N_a} p(\mathrm{RSS}^a_{jk} \mid \|\mathbf{x}^t_{ji} - \mathbf{x}_{ak}\|) \times \prod_{j=1}^{N_u} \prod_{\substack{l=1 \\ l \neq j}}^{N_u} p(\mathrm{RSS}^m_{jl} \mid \|\mathbf{x}^t_{ji} - \mathbf{x}^t_{li}\|), \quad (4)$$

where the first product corresponds to RF measurements between users and fixed beacons at positions $\mathbf{x}_{ak}$ ($k = 1, \ldots, N_a$), and the second to RF measurements between the users themselves. Due to the assumption on RSS noise distribution of the PLL model above, all probabilities in equation 4 are Gaussian.

The PF operates in time steps t, which are not fixed time intervals but rather depend on the time instants where a step by one of the users is detected by the PDR algorithm, or well when a specified time has passed without any step being detected.

D. Particle motion and resampling

The state of motion of the j-th user can be determined with Pedestrian Dead Reckoning (PDR) algorithms [10] by accessing the smartphone inertial sensor's accelerometer and gyroscope signals. For each user j, the PDR module produces a sequence of steps of the form [11]: $\{l^t_j, \Delta\theta^t_j\}$, where t is the time where a step is completed, l^t_j is the step length from the previously estimated position (x^{t-1}_j, y^{t-1}_j) and $\Delta\theta^t_j$ the change of orientation with respect to previously estimated orientation θ^{t-1}_j.

The motion update is combined with a resampling stage in which the particles are moved to new positions and their weights reassigned to a constant value $1/N_p$. If we assume that we have detected a step for the j-th user, the i-th particle's position and orientation coordinates for this user are chosen as:

$$\begin{aligned} x^t_{ji} &= x^{t-1}_{ji'} + (l^t_j + \delta_l)\cos(\theta^{t-1}_{ji'} + \Delta\theta^t_j + \delta_{\Delta\theta}) \\ y^t_{ji} &= y^{t-1}_{ji'} + (l^t_j + \delta_l)\sin(\theta^{t-1}_{ji'} + \Delta\theta^t_j + \delta_{\Delta\theta}) \\ \theta^t_{ji} &= \theta^{t-1}_{ji'} + \Delta\theta^t_j + \delta_{\Delta\theta}, \end{aligned} \quad (5)$$

where i' is drawn from the set $i \in \{1, \ldots, N_p\}$ with probability w_i. δ_l and $\delta_{\Delta\theta}$ are Gaussian modelled disturbances on both the step length and change of orientation, which are distributed according to $\delta_l \sim \mathcal{N}(0, \sigma^2_{l\mathrm{PDR}})$ and $\delta_\theta \sim \mathcal{N}(0, \sigma^2_{\Delta\theta\mathrm{PDR}})$. The particle components corresponding to the remaining users $l \neq j$ are resampled, but not displaced:

$$x^t_{li} = x^{t-1}_{li'} \quad y^t_{li} = y^{t-1}_{li'} \quad \theta^t_{li} = \theta^{t-1}_{li'}, \quad \forall l \neq j.$$

In the case that the analysis of the IMU signals of user j by the PDR module does not result in any step estimate for a sufficient long time (T_{max}), we consider that the user is standing still or that his motion has not been detected for some reason, and equation 5 is replaced by:

$$\begin{aligned} x_{ji}^{t} &= x_{ji'}^{t-1} + \delta_x \\ y_{ji}^{t} &= y_{ji'}^{t-1} + \delta_y \\ \theta_{ji}^{t} &= \delta_\theta, \end{aligned} \tag{6}$$

where (δ_x, δ_y) are sampled from a uniform distribution in the circle defined by $\delta_x^2 + \delta_y^2 \leq v_{\text{max}}^2 T_{\text{max}}^2$, and δ_θ in the interval $[0, 2\pi)$. In the experiments described later, we take $v_{\text{max}} = 2$ m/s as a maximum displacement speed, and $T_{\text{max}} = 2$ s as the maximum time that we allow the PF to proceed without resampling for any user. Thus, equation 6 models an unknown displacement in a given range and a random change of orientation that went undetected by the PDR algorithm. The motion/resampling of equation 6 is also used in experiments where PDR is not considered as a way to follow the user's motion. Particle i' is drawn in the same way as in equation 5.

A further precaution is needed to detect the circumstance of particle degeneracy, in which the number of particles with significant weights is reduced. In our implementation, we check for the number of effective particles (as defined in [4]), and perform a resampling step (without motion), if this number falls below threshold $N_p/10$. This event occurs rarely in our experiments.

E. Position estimate

The position estimates for each user are given by the minimum mean square error (MMSE) estimator, defined as:

$$\mathbf{x}_{j,\text{MMSE}}^{t} = \sum_{i=1}^{N_p} w_i \mathbf{x}_{ji}^{t}. \tag{7}$$

Next we will demonstrate the effectiveness of the cooperative approach for position estimation and tracking in some experiments carried out in our building.

III. Experimental device

The RF signals for positioning are obtained with active RFID tags, although the principle is the same for other equivalent technologies such as wifi, since only the received signal strength (RSS) is used for positioning estimation. Some tags are placed at fixed positions in our building, while others are carried by each user in their pockets. RFID technology is low cost and is easy to deploy, permitting to cover a large area in a simple way.

We have placed a large number of RFID active tags (model M100 from RFCode) in our building, attached to the walls at a height of 2 m, and covering a total area of 1600 m^2 (55 different rooms), which permits positioning in our building, and even in a limited area in the exterior (with degraded accuracy). The tags are factory set to emit their identification code every second, and the RF digital signals are modulated at 433 MHz. We have used RFID technology extensively in previous works [12], [13], [14], [15] for individual localization of users in indoor environments.

Fig. 1. Experimental device, formed by an RFID portable reader from RFCode (left) and a mobile phone (right) with dedicated software for data collection. Processing of the PF position estimation is performed offline.

Each user carries an RFCode model M220 portable reader in his belt clip, equipped with two 1/4 wave articulated helical antennas (see figure 1). The reader decodes the RF message transmitted by tags and, for every detection event, reports the tag ID, the measured RSS at both antennas and a timestamp to an Android-based mobile phone through a Bluetooth link. Additionally, the program running on the mobile phone samples the three-axis accelerometer, gyroscope and magnetometer signals from the inertial motion unit at an average rate of 50 Hz, which is high enough for PDR algorithms. GNSS data (when available) is also acquired by the program, but not used in our experiments.

For the experiments on cooperative positioning described in this paper, we will use only 7 fixed position RFID tags (or anchors); additionally, each user carries one RFID tag in his pocket. We have kept the number of anchor nodes deliberately low so the effects of cooperative positioning stand out more clearly. With our setup, a user has access to an average 2.1 RSS readings from anchor tags, and 0.99 RSS readings from other users at every time instant. Furthermore, 3 or more anchors tags (the minimum number for position estimation by trilateration) are available to a user for only 34% of time on average, making position fixing difficult individually (see figure 2). Logically, it would be very convenient if the combination of RSS measurements from both anchor and mobile tags can improve the position estimate of each user.

IV. Experimental results and discussion

A. Calibration

The goal of the calibration process is obtaining suitable parameters for the path loss law models of equation 3. As

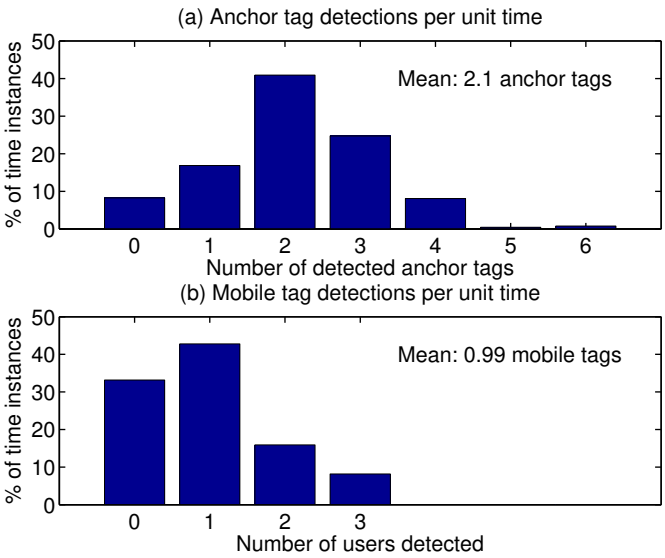

Fig. 2. Histograms with the number of detections of (a) anchor tags and (b) mobile tags per unit time in the evaluation trajectories. On average, at each time instant a user receives 2.1 RSS readings from fixed tags, and 0.99 RSS readings from different users close to him.

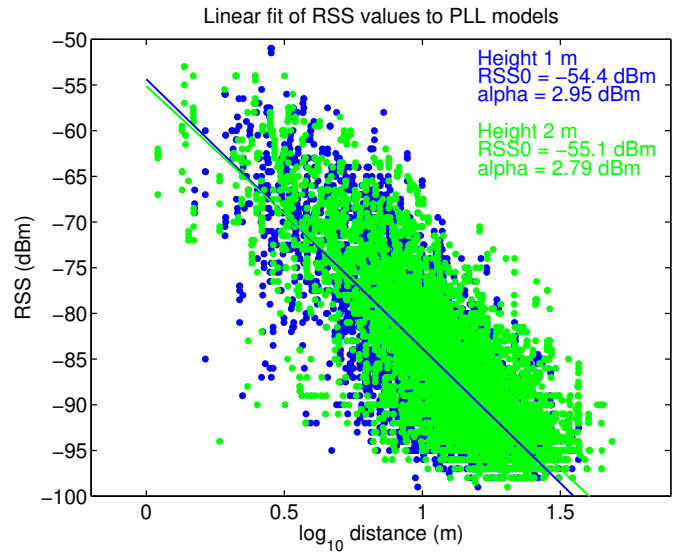

Fig. 3. Results of calibration process for the PLL model, for RFID tags placed at two different heights (2 m for anchor tags, 1 m for mobile tags).

stated in the introduction, we allow for different values of parameters RSS_0 and α for the case of anchor tags (placed at a height of 2 m) and mobile tags (carried by users at a height of 1 m). For this purpose, we moved to 44 different positions in our building, and collected the RSS values from a set of anchor and mobile tags. The linear fit results are shown in figure 3. As can be seen, the PLL model values are similar for both anchor and mobile tags: $\text{RSS}_0^a = -55.1$ dBm, $\alpha^a = 2.79$ dBm; $\text{RSS}_0^m = -54.4$ dBm and $\alpha^m = 2.95$ dBm. This indicates that the non-line of sight (NLOS) effects on the propagation of RF signals are more important in our case that the height of the tags over the floor. The standard deviation of the signal strength is found to be relatively constant, $\sigma_{\text{RSS}} \simeq 10$ dBm, regardless of range d. It is convenient to use a conservative (i.e., large) value for the measurement noise variance, so the particle filter does not become overconfident on some RSS values. We have also found that using a somewhat larger value for the standard deviation of the RSS measurements from the mobile tags provides better results for cooperative positioning if PDR is employed (we used $\sigma_{\text{RSS}}^a = 10$ dBm and $\sigma_{\text{RSS}}^m = 15$ dBm).

B. Pedestrian reckoning estimation of trajectories

We optionally fuse the RFID measurements with displacement motion estimates obtained from a Pedestrian Dead-Reckoning (PDR) algorithm using the accelerometer, gyroscope and magnetometer sensors of the inertial motion unit (IMU) contained in each user's smartphone. We process the IMU signals with a step and heading system (SHS) which produces a sequence of step lengths and step changes of heading which can be added to reconstruct the trajectory followed by the user [11]. This approach is more robust than full inertial navigation system (INS) methods, and works well even when the IMU is low-grade and handheld.

Following the empirical method in [16], the step length l_j^t of a walking person is considered proportional to the vertical motion (bounce) of the upper body. This can be estimated by measuring the amplitude swing of the vertical acceleration as measured by the phone IMU, which is previously low-pass filtered to remove noise. The last operation necessary to estimate the step length is calibrating a constant of proportionality that links vertical bounce with step length; this is done separately for each user. The change in heading at each step is measured directly with the IMU's gyroscope and magnetometer [14].

Although the described approach is not as accurate as zero velocity update (ZUPT) methods (which require a foot-mounted inertial unit), it can provide reasonable estimates of a walking person's trajectory moving in a steady way. However, as all PDR techniques, the SHS trajectory estimation method described is subject to drift, and will gradually separate from the actual trajectory, as shown in figure 4. Note that, in this figure, the correct value for the heading has been provided to the PDR algorithm; however, in our actual trajectory estimation experiments in section IV-C, the particle filter is initialized with random orientation values.

In our implementation, the information passed by the PDR to the particle filter consists in a series of steps for each user, given as the sequence $\{t_j, l_j^t, \Delta\theta_j^t\}$. This information is used to displace the hypotheses on the position (particles) for each use. Standard deviations for the noise affecting the step length and change of heading estimates (see section II-D) are taken as $\sigma_{l\text{PDR}} = 0.2$ m and $\sigma_{\Delta\theta\text{PDR}} = 0.1$ rad, respectively.

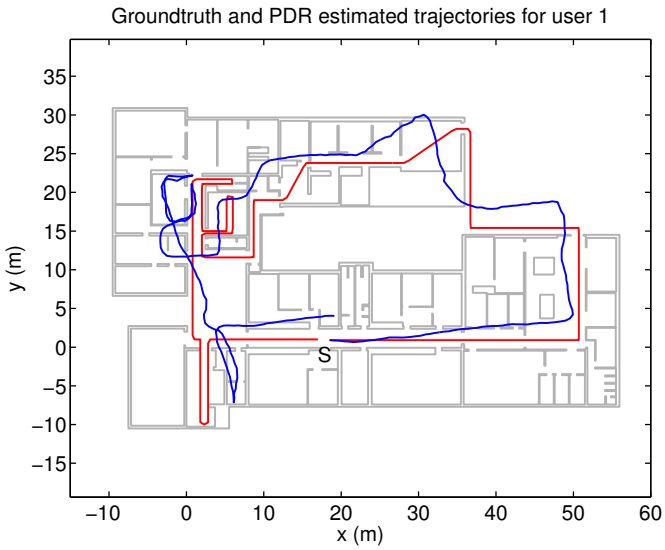

Fig. 4. The PDR estimated trajectory (blue) resembles the groundtruth trajectory (red), but is subject to drift. In order to produce this figure, the starting point and heading for the PDR trajectory were set to the correct values.

C. Positioning results

In the experiments carried out to determine the performance of cooperative positioning over individual positioning, four persons traversed different trajectories in our building (remaining mostly indoors), starting from a common point in the corridor in front of our lab (point S in figure 4). Each user carries a smartphone handheld in a natural way in front of him. Synchronization between users was achieved by simultaneously pressing a button on the smartphone interface before starting to walk, which provides a common timebase to approximately one second accuracy. For reconstruction of the groundtruth, the users recorded time marks through the phone's program interface at designated points in their trajectory, including the end point. Interpolation in post-process permits to generate groundtruth values at each time and compute the positioning errors.

All trajectories are between 210 and 220 m long, and are followed at an average speed of 0.7 m/s, which remains approximately constant. The PDR algorithm is adjusted only once to calibrate for each user's typical step length, but left otherwise unmodified. Step detection is not perfect, in the sense that some steps are missed, and extraneous ones are detected, for example when a door is opened with an arm, and its motion is coupled to the opposite arm holding the phone.

In each version of the algorithm, the particle filter is initialized at the correct position (the corridor section in front of our lab), but the orientation of the particles is taken at random in the interval $[0, 2\pi)$ (i.e., PDR-estimated trajectories are not initialized to the correct heading). At the starting point, 3 anchors were within detection range of the RFID readers carried by the users. Motion of the users starts after an initial rest period of 10 s. The initialization step is probably the most critical phase of the particle filter, since insufficient anchor measurements prevent the particle filter to converge to a good initial estimate.

TABLE I
MEDIAN (50%) AND 90% POSITIONING ERRORS OBTAINED WITH INDIVIDUAL AND COOPERATIVE LOCALIZATION USING A PARTICLE FILTER.

Localization method	Without PDR		With PDR	
	50% error	90% error	50% error	90% error
Individual	6.2 m	13.2 m	4.0 m	8.6 m
Cooperative	5.1 m	10.2 m	3.5 m	7.1 m

We have used $N_p = 10,000$ particles per user for individual localization, and $N_p = 100,000$ particles for all 4 users for cooperative localization; an increase in the number of particles does not improve the positioning performance significantly.

Position estimates for all four versions of the particle filter positioning (individual positioning and cooperative positioning, without and with PDR fusion) are shown along with the groundtruth in figures 5 and 6. As simple values for comparison of the performance of each method, we provide the median and 90 % positioning error in table I. Median positioning error for the individual localization method is 6.2 m, a high value due to the low density of anchor tags available for localization. Combination with PDR information from the phones improves this error to 4.0 m. The corresponding figures for the median error for cooperative localization are 5.1 m (without PDR) and 3.5 m (with PDR).

Note that, in some occasions, the PF provides an impossible estimated trajectory which crosses the inside partitions of the building or even gets out of it altogether through the walls. Particle motion in our implementation is not constrained by the walls of the building (which is only plotted in figures 5 and 6 for reference); this is a matter for future improvement of the PF.

V. Conclusions and Future Work

In this work, we have demonstrated that a particle filter cooperative indoor localization method, based upon transmission of RF signals between the users and the infrastructure, as well as between the users themselves, exhibits superior performance when compared to individual localization where only infrastructure-based signals are available for positioning. Further improvement is obtained if a simple PDR algorithm is incorporated to the particle filter, even if the trajectory estimates are produced from the low grade IMU sensors contained in a conventional smartphone carried by hand.

The performance of the algorithms described in the paper is summarized in table I and figure 7. While the improvement of cooperative over individual localization is not spectacular, it would presumably be more noticeable if a larger number of users collaborated on the positioning process; however, at present, hardware limitations stop us from going over 4 users

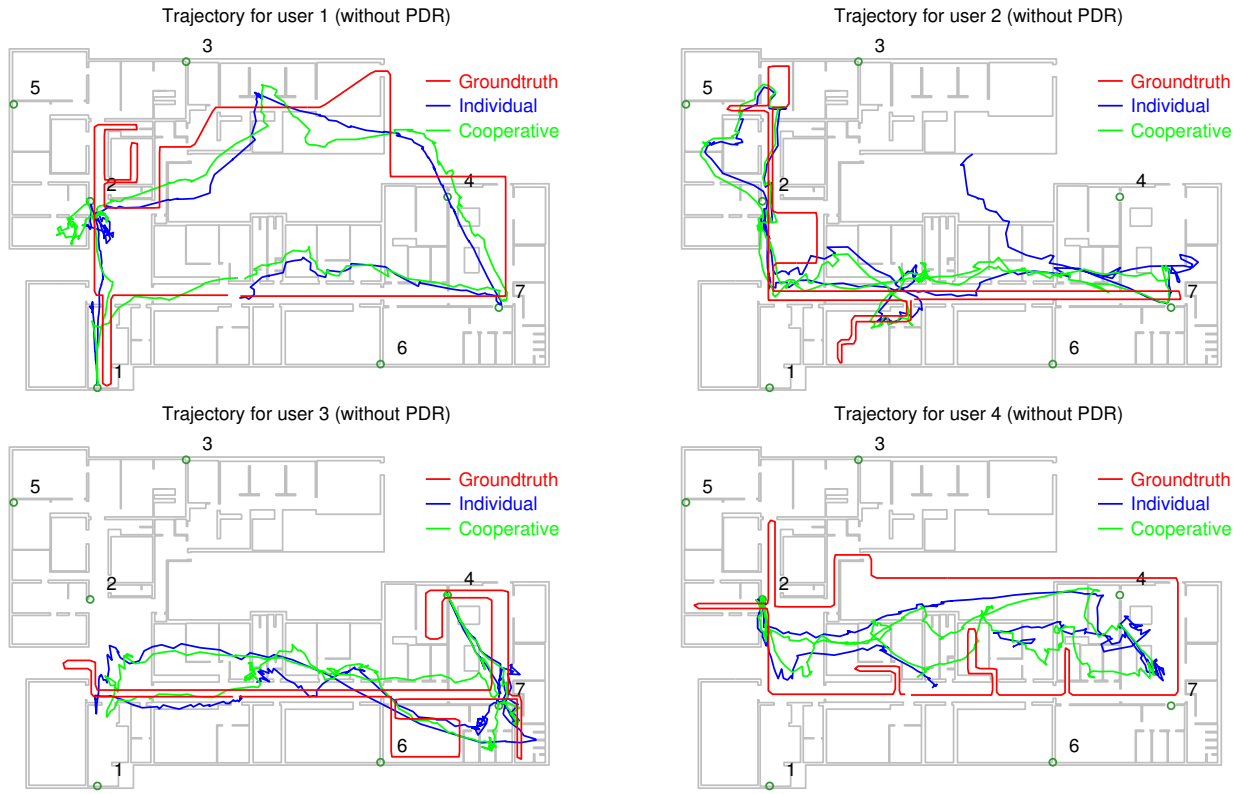

Fig. 5. Positioning results obtained for the 4 users with RFID detections and without PDR: the red trace corresponds to the groundtruth, the blue trace, to the estimated individual trajectories, and the green one to the estimated cooperative trajectories. Numbered circles correspond to anchor tags.

(we are considering alternatives to increase the number of users).

The current version of the cooperative positioning algorithm is centralized, since a common computing unit must receive and process RF and PDR readings for all users; from a practical point of view it could be convenient to adapt the particle filter methodology to a distributed version, in which information about the neighbour states is transmitted locally between users (belief propagation Bayesian approach).

Finally, a direct extension of the present work would consist in using the building map to improve the propagation of particles through the motion model. This will be considered in future work.

Acknowledgment

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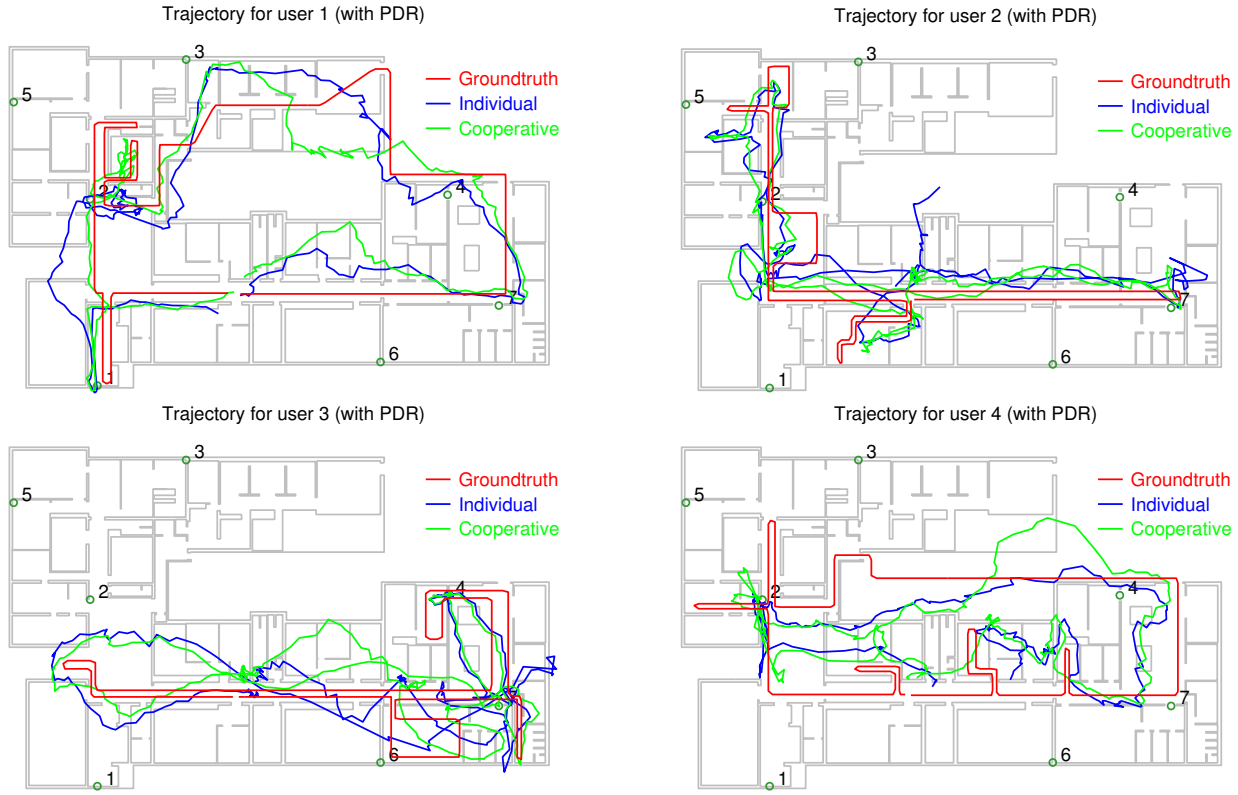

Fig. 6. Positioning results obtained for the 4 users with RFID detections and with PDR: the red trace corresponds to the groundtruth, the blue trace, to the estimated individual trajectories, and the green one to the estimated cooperative trajectories. Numbered circles correspond to anchor tags.

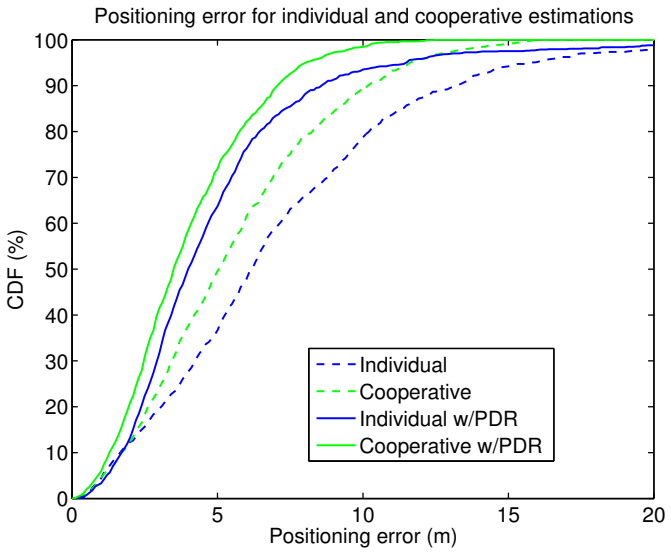

Fig. 7. Comparison of cumulative density function (CDF) of the positioning error for the trajectories of figures 5 and 6. Cooperative techniques suppose a significative increase of precision over individual estimation (dashed curves); however, the improvement is smaller if PDR corrections are incorporated to the PF (solid curves).

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