Cooperative Multipath-Aided Indoor Localization

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Abstract—To obtain good position accuracy with state-of-the-art indoor localization algorithms, multiple anchors must be within radio range of the user. However, anchor placement and maintenance is expensive. By reducing the number of anchors per room, overall costs are reduced. In [1], an algorithm that can estimate the position of a user using only one anchor and a priori floor plan information. However, performance for static localization was poor due to the presence of ambiguities. This paper describes a *cooperative* positioning algorithm that utilizes a single anchor and provides both the position and the position uncertainty for multiple users, by letting the users exchange their position information. The problem is represented with a factor graph, and belief propagation (BP) is used to extract the positions and their accuracy. The proposed cooperative algorithm leads to a significant improvement of the positioning accuracy compared to the non-cooperative method from [1].

I. INTRODUCTION

With the advent of ultra-wide bandwidth transmission technologies, the possibility of performing highly accurate positioning in an indoor environment becomes more and more realistic [2]. The list of potential applications is long and includes asset tracking, health care monitoring, and robotics. Most methods for positioning require the presence of multiple reference nodes (called anchors) at known positions to make ranging measurements with the user. Assuming there is a line-of-sight (LOS) between the anchors and the user, these range measurements can be used to perform multilateration to obtain the user's absolute position. Multilateration requires at least three anchors for two dimensional localization. However, placing and maintaining anchors is expensive and therefore methods that reduce the number of anchors have been considered. In [3] it was observed that not only the LOS signal component carries useful information about the user position, but also the signal reflections. With the use of floor plan information, these reflections could be interpreted as originating from so called *virtual anchors*, which can be used for localization [4]. Utilizing these virtual anchors, localization was demonstrated with a single anchor [1]. Still, the performance was rather poor because, with the use of virtual anchors, ambiguities are added to the system so that at times no unique solution can be found.

In cooperative localization, users not only make range measurements with the anchor nodes but also with their neighboring user nodes. These additional measurements provide information about the relative position of each user, which

can be used to increase the overall positioning accuracy and coverage of the system. In [5], [6] and [7] this idea is explored through optimization techniques, which give point estimates for the users' positions. Another class of techniques relies on Bayesian inference such as belief propagation [8] or variational message passing [9]. The latter class of techniques has the advantage that it can work with a wide variety of statistical models and that can easily represent multimodal distributions.

In this paper, we reconsider the single anchor problem for indoor multipath localization from [1] and rewrite it as a Bayesian inference problem. This formulation allows us to include information from neighbors, naturally leading to a cooperative algorithm, by means of belief propagation. Through Monte Carlo simulations, we show the potential performance gains of cooperation for both static and mobile scenarios.

II. PROBLEM FORMULATION

We consider a room with one anchor and N mobile users that are wirelessly connected. At every time step k, every user i makes measurements $\mathbf{z}_{\mathrm{mp}}^{k,i}$ with the anchor and ranging measurements $\mathbf{z}_{\mathrm{coop},ij}^{k}$ with its neighbors j. The measurements $\mathbf{z}_{\mathrm{mp}}^{k,i}$ depend on the direct LOS signal between the anchor and the user, as well as signal reflections, while the measurements $\mathbf{z}_{\mathrm{coop},ij}^{k}$ depend only on the direct LOS signal. Details will be provided in Section III-B. The measurement are aggregated into the vector $\mathbf{z}_{\mathrm{mp}}^{k} = \left\{ \mathbf{z}_{\mathrm{mp}}^{k,i} \right\}_{i=1}^{N}$ and $\mathbf{z}_{\mathrm{coop}}^{k} = \left\{ z_{\mathrm{coop},ij}^{k} \right\}_{i,j=1}^{N}$, respectively. The state of user i at time k is denoted by $\boldsymbol{\theta}_i^k = \left[(\mathbf{x}_i^k)^T, (\mathbf{v}_i^k)^T \right]^T$, and contains both the position $\mathbf{x}_i^k$ and velocity $\mathbf{v}_i^k$. We focus on a two dimensional scenario, but extension to three dimensions is straightforward. We will assume that the users move independently according to a first order Markov chain, with transition probability $p\left(\boldsymbol{\theta}_i^k \mid \boldsymbol{\theta}_i^{k-1}\right)$. The goal of user i at time step k is to determine $p\left(\boldsymbol{\theta}_i^k \mid \mathbf{z}_{\mathrm{mp}}^{1:k}, \mathbf{z}_{\mathrm{coop}}^{1:k}\right)$, given the distribution of the states at the previous time step $p\left(\boldsymbol{\theta}_j^{k-1} \mid \mathbf{z}_{\mathrm{mp}}^{1:k-1}, \mathbf{z}_{\mathrm{coop}}^{1:k-1}\right)$, $\forall j$.

III. STATISTICAL DESCRIPTION

A. Global description

Given the Markovian nature of the system, we can write the joint posterior distribution as follows

$$p\left(\boldsymbol{\theta}_{1:N}^{k}|\mathbf{z}_{\mathrm{mp}}^{1:k},\mathbf{z}_{\mathrm{coop}}^{1:k}\right) \qquad (1)$$

$$= \int p\left(\boldsymbol{\theta}_{1:N}^{k}|\mathbf{z}_{\mathrm{mp}}^{k},\mathbf{z}_{\mathrm{coop}}^{k},\boldsymbol{\theta}_{1:N}^{k-1}\right) p\left(\boldsymbol{\theta}_{1:N}^{k-1}|\mathbf{z}_{\mathrm{mp}}^{1:k-1},\mathbf{z}_{\mathrm{coop}}^{1:k-1}\right) \mathrm{d}\boldsymbol{\theta}_{1:N}^{k-1}$$

where

$$p\left(\boldsymbol{\theta}_{1:N}^{k}|\mathbf{z}_{\mathrm{mp}}^{k},\mathbf{z}_{\mathrm{coop}}^{k},\boldsymbol{\theta}_{1:N}^{k-1}\right)$$
$$\propto p(\mathbf{z}_{\mathrm{mp}}^{k},\mathbf{z}_{\mathrm{coop}}^{k} \mid \boldsymbol{\theta}_{1:N}^{k}) p(\boldsymbol{\theta}_{1:N}^{k} \mid \boldsymbol{\theta}_{1:N}^{k-1})$$
$$= \prod_{i=1}^{N} \underbrace{p\left(\mathbf{z}_{\mathrm{mp}}^{k,i} \mid \mathbf{x}_{i}^{k}\right)}_{\text{single anchor}} \underbrace{p\left(\boldsymbol{\theta}_{i}^{k} \mid \boldsymbol{\theta}_{i}^{k-1}\right)}_{\text{tracking}}$$
$$\times \underbrace{\prod_{j \in \mathcal{N}(i)} p\left(z_{\mathrm{coop},ij}^{k} \mid \mathbf{x}_{i}^{k},\mathbf{x}_{j}^{k}\right)}_{\text{cooperation}}. \qquad (2)$$

Here, $\mathcal{N}(i)$ is the set of users within radio range of user i. We have assumed that measurements only depend on positions, but not on velocities. Substitution of (2) into (1) yields

$$p\left(\boldsymbol{\theta}_{1:N}^{k}|\mathbf{z}_{\mathrm{mp}}^{1:k},\mathbf{z}_{\mathrm{coop}}^{1:k}\right) \qquad (3)$$
$$\propto \prod_{i=1}^{N} \int p\left(\mathbf{z}_{\mathrm{mp}}^{k,i} \mid \mathbf{x}_{i}^{k}\right) p\left(\boldsymbol{\theta}_{i}^{k} \mid \boldsymbol{\theta}_{i}^{k-1}\right)$$
$$\prod_{j \in \mathcal{N}(i)} p\left(z_{\mathrm{coop},ij}^{k} \mid \mathbf{x}_{i}^{k},\mathbf{x}_{j}^{k}\right) p\left(\boldsymbol{\theta}_{i}^{k-1}|\mathbf{z}_{\mathrm{mp}}^{1:k-1},\mathbf{z}_{\mathrm{coop}}^{1:k-1}\right) \mathrm{d}\boldsymbol{\theta}_{i}^{k-1}.$$

We observe that $p\left(\boldsymbol{\theta}_{i}^{k-1}|\mathbf{z}_{\mathrm{mp}}^{1:k-1},\mathbf{z}_{\mathrm{coop}}^{1:k-1}\right)$ was computed in the previous time slot, so that when $N = 1$, (3) leads to a simple recursive algorithm. The function (2) factorizes into three major factors: the first factor is responsible for providing absolute positioning information using only a single anchor; the second factor is related to the mobility model and is used for tracking over time steps; the third factor provides relative position information among users. In the following sections, we will derive expressions for the three factors from (2) and provide additional details regarding the models.

B. Single anchor localization

We will consider a rectangular room where one anchor node is placed. Every signal reflection the user receives can be considered as a wave coming from some virtual anchor (VA) behind the walls. A set of virtual anchors can be obtained by mirroring the anchor's position at each reflecting surface. In this paper we will only focus on single and double reflections, as well as the line-of-sight component, which gives a total number of (virtual) anchors $N_{\mathrm{VA}} = 9$. An example room is shown in Fig. 1. Note that for this example room, the set of anchors is independent of the user's position and only depends on the anchor's position. For different room geometries this may no longer be true and the effect of this is subject to further research.

Using ultra-wideband technology, it is possible to accurately distinguish the different multipath components in a received waveform due to the fine time-resolution [2]. If we assume
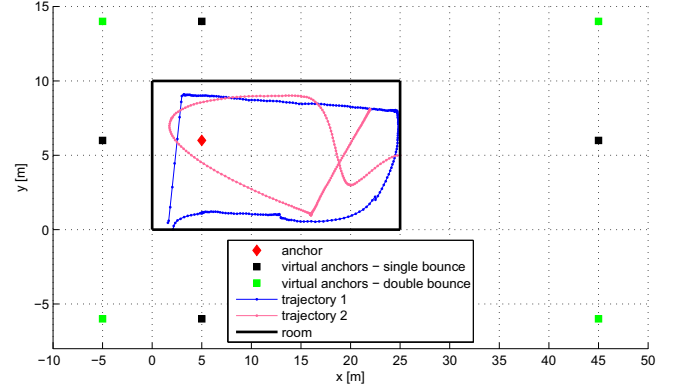

Figure 1. Example room with one anchor and corresponding virtual anchors.

a synchronized system, the time of arrival (TOA) for all multipath components can be converted to range estimates.[1] Let $\mathbf{z}_{\mathrm{mp}}^{k,i}$ be the measurement vector containing M_{i}^{k} range estimates obtained in the measurement phase. In general, this vector will contain range measurements corresponding to some of the virtual anchors,[2] as well as reflections corresponding to other scatterers. Furthermore, it is unknown which range estimate corresponds to which virtual anchor. Because we do not know this mapping, we cannot use standard multilateration techniques. Therefore, a probabilistic approach, where every measurement has a certain chance of coming from a certain virtual anchor, is an appropriate alternative. If we now consider all range measurements to be independent,[3] we can write the joint likelihood function for $\mathbf{z}_{\mathrm{mp}}^{k,i}$ as follows:

$$p\left(\mathbf{z}_{\mathrm{mp}}^{k,i} \mid \mathbf{x}_{i}^{k}\right) = \prod_{m=1}^{M_{i}^{k}} p\left(z_{\mathrm{mp},m}^{k,i} \mid \mathbf{x}_{i}^{k}\right). \qquad (4)$$

The function $p\left(z_{\mathrm{mp},m}^{k,i} \mid \mathbf{x}_{i}^{k}\right)$ can be written as follows [1]:[4]

$$p\left(z_{\mathrm{mp},m}^{k,i} \mid \mathbf{x}_{i}^{k}\right)$$
$$= \frac{P_{\mathrm{VA}}}{P_{\mathrm{v}}} \sum_{p=1}^{N_{\mathrm{VA}}} P_{\mathrm{v},p} \mathcal{N}(z_{\mathrm{mp},m}^{k,i}; \|\mathbf{x}_{i}^{k} - \mathbf{x}_{p}\|, \sigma_{p}^{2}) + \frac{(1 - P_{\mathrm{VA}})}{R_{\max}}.$$

We made the following assumptions: A measurement $z_{\mathrm{mp},m}^{k,i}$ has probability P_{VA} of coming from a VA and $(1 - P_{\mathrm{VA}})$ of not being related to any VA. In the latter case, $z_{\mathrm{mp},m}^{k,i}$ is uniformly distributed between 0 and the maximum range $R_{\max}$.[5] In the former case, we have a weighted sum of N_{VA}

[1]The assumption of synchronization can be removed by considering a two-way ranging protocol.

[2]Due to obstructions, not every reflection will always be present, leading to an invisible virtual anchor.

[3]It should be noted that this independence assumption is a simplification of reality since all reflections are more or less correlated depending on the environment. This correlation however is prohibitively complex and therefore not taken into account.

[4]We write $\mathcal{N}(x; \mu, \sigma^2)$ to denote a Gaussian distribution with variable x, mean μ, and variance σ^2.

[5]The maximum range $R_{\max}$ is the maximum distance between any one virtual anchor, and one of the corners of the room.
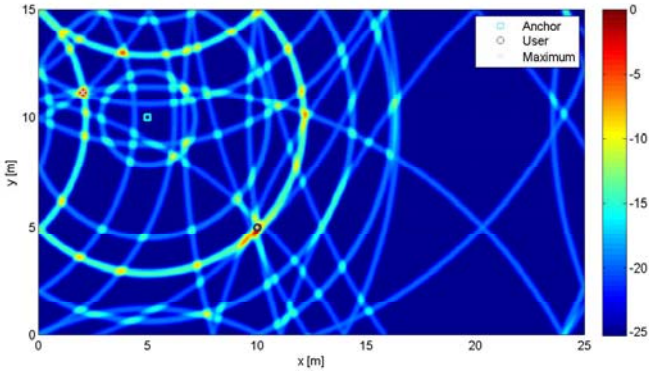
Figure 2. Plot of $\log p\left(z_{\mathrm{mp}}^{k,i} \mid \mathbf{x}_i^k\right)$. It can be seen that this function has many local maxima, and that the global maximum is located almost 10m away from the true user position. The anchor is located at (5,10), the user at (10,5), and the global maximum at (2.1, 11.3).
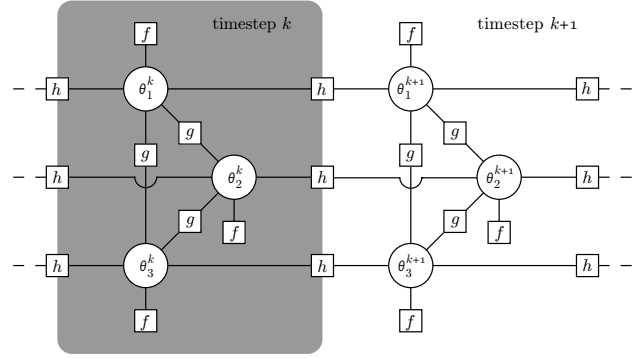

Figure 3. Factor graph representation of the posterior likelihood function for 3 users. Here, $f(\boldsymbol{\theta}_i^k) = p\left(\mathbf{z}_{\mathrm{mp}}^{k,i} \mid \boldsymbol{\theta}_i^k\right)$, $g\left(\boldsymbol{\theta}_i^k, \boldsymbol{\theta}_j^k\right) = p\left(z_{\mathrm{coop},ij}^k \mid \boldsymbol{\theta}_i^k, \boldsymbol{\theta}_j^k\right)$ and $h\left(\boldsymbol{\theta}_i^k, \boldsymbol{\theta}_i^{k-1}\right) = p\left(\boldsymbol{\theta}_i^k \mid \boldsymbol{\theta}_i^{k-1}\right)$.

Gaussian rings centered around every virtual anchor (with position $\mathbf{x}_p$) with radius $z_{\mathrm{mp},m}^{k,i}$ and standard deviation σ_p. The pth virtual anchor is visible with probability $P_{\mathrm{v},p}$. To ensure proper normalization, we introduce $P_{\mathrm{v}} = \sum_p^{N_{\mathrm{VA}}} P_{\mathrm{v},p}$.

An example of $p\left(\mathbf{z}_{\mathrm{mp}}^{k,i} \mid \mathbf{x}_i^k\right)$ is shown in Fig 2. As we do not know the mapping between ranges and VAs, $p\left(\mathbf{z}_{\mathrm{mp}}^{k,i} \mid \mathbf{x}_i^k\right)$ has many local maxima and might even have a global maximum far away from the user position. Estimating $\mathbf{x}_i^k$ from $p\left(\mathbf{z}_{\mathrm{mp}}^{k,i} \mid \mathbf{x}_i^k\right)$ will thus lead to poor performance. By introducing cooperation or tracking, many of the false maxima will disappear due to the added constraints, leading to better estimates. On a side note, we mention that for this room geometry, the average number of local maxima greatly increases whenever the anchor is placed on the bisectors of the walls. This is due to symmetry reasons and in this case performance is always expected to be low, even with tracking or cooperation, and should be avoided.

C. Tracking

Secondly, the factor from (2) corresponding to the tracking of the user states is considered. We assume that the movement of the user can be described by the following linear time-invariant model for 2D movement:

$$p\left(\boldsymbol{\theta}_i^k \mid \boldsymbol{\theta}_i^{k-1}\right) = \mathcal{N}\left(\boldsymbol{\theta}_i^k; \mathbf{F}\boldsymbol{\theta}_i^{k-1}, \sigma_{\mathrm{a}}^2 \mathbf{G}\mathbf{G}^T\right), \quad (5)$$

with

$$\mathbf{F} = \begin{bmatrix} 1 & 0 & \Delta T & 0 \\ 0 & 1 & 0 & \Delta T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad \text{and} \quad \mathbf{G} = \begin{bmatrix} \frac{\Delta T^2}{2} & 0 \\ 0 & \frac{\Delta T^2}{2} \\ \Delta T & 0 \\ 0 & \Delta T \end{bmatrix}.$$

Here, ΔT is the time between successive measurements and σ_{a} denotes the standard deviation of the user's acceleration.[6]

[6] Assuming the 3-sigma point for the acceleration equals the maximum acceleration, the standard deviation for the acceleration equals $\sigma_{\mathrm{a}} = \frac{\Delta L_{\mathrm{max}}}{3\Delta T^2}$, where ΔL_{max} is the maximum distance a user is able to cross during time ΔT.

D. Cooperation

The factor $p\left(z_{\mathrm{coop},ij}^k \mid \mathbf{x}_i^k, \mathbf{x}_j^k\right)$ from (2) is derived as follows: we assume that between users we perform a ranging protocol and collect only the distance estimates corresponding to the LOS signal. Multipath information is discarded, since no fixed set of virtual anchors can be identified for the cooperating users when they have position uncertainty. We assume a standard Gaussian model: $p\left(z_{\mathrm{coop},ij}^k \mid \mathbf{x}_i^k, \mathbf{x}_j^k\right) = \mathcal{N}(z_{\mathrm{coop},ij}^k; \|\mathbf{x}_i^k - \mathbf{x}_j^k\|, \sigma_{\mathrm{n}}^2)$.

IV. BELIEF PROPAGATION FOR LOCALIZATION

The factorization of (2) can be represented graphically by a factor graph on which message passing algorithms, such as belief propagation, can be applied [10]. The factor graph is created by drawing square vertices for every factor of the joint probability and circular vertices for every variable. Every factor vertex is connected by an edge to a variable vertex when the factor is function of this particular variable. The factor graph in case of three users ($N = 3$) and at time step k is shown in the shaded area in Fig. 3. From the previous time step, every user has the input $p\left(\boldsymbol{\theta}_i^{k-1} \mid \mathbf{z}_{\mathrm{mp}}^{1:k-1}, \mathbf{z}_{\mathrm{coop}}^{1:k-1}\right)$. Towards the next time step, the user generates $p\left(\boldsymbol{\theta}_i^k \mid \mathbf{z}_{\mathrm{mp}}^{1:k}, \mathbf{z}_{\mathrm{coop}}^{1:k}\right)$. The distributions $p\left(\boldsymbol{\theta}_i^k \mid \mathbf{z}_{\mathrm{mp}}^{1:k}, \mathbf{z}_{\mathrm{coop}}^{1:k}\right)$ are computed using belief propagation, which is a message passing algorithm over the factor graph. The messages are computed as follows, assuming a variable that appears in 3 factors:[7]

1) Given a x_i that appears in factors $f(x_i, x_j)$, $g(x_i, x_l)$ and $h(x_i, x_m)$, the message from x_i to x_j is given by

$$m_{i \to j}(x_j) = \int f(x_i, x_j) \prod_{n \in \{l,m\}} m_{n \to i}(x_i) \, \mathrm{d}x_i.$$

2) The a posteriori distribution of x_i is given by

$$b(x_i) \propto \prod_{n \in \{l,m,j\}} m_{n \to i}(x_i). \quad (6)$$

[7] The generalization to more than three factors is straightforward.

Algorithm 1 Cooperative multipath localization at time step k

Initialization:

$$m_{i \to j}(\mathbf{x}_j^k) = 1 \qquad \forall i, j \in \mathcal{N}(i) \tag{7}$$

$$b(\boldsymbol{\theta}_i^k) = 1 \qquad \forall i \tag{8}$$

$$b(\boldsymbol{\theta}_i^{k-1}) \qquad \text{from previous time step, } \forall i \tag{9}$$

Calculate non-cooperative belief:

$$b_{\mathrm{nc}}(\boldsymbol{\theta}_i^k) = p\left(\mathbf{z}_{\mathrm{mp}}^{k,i} \mid \mathbf{x}_i^k\right) \int p\left(\boldsymbol{\theta}_i^k \mid \boldsymbol{\theta}_i^{k-1}\right) b(\boldsymbol{\theta}_i^{k-1}) \mathrm{d}\boldsymbol{\theta}_i^{k-1} \tag{10}$$

For all users

  Calculate all outgoing messages:

$$m_{i \to j}(\mathbf{x}_j^k) = \int p\left(z_{\mathrm{coop},ij}^k \mid \mathbf{x}_i^k, \mathbf{x}_j^k\right) \frac{b(\boldsymbol{\theta}_i^k)}{m_{j \to i}(\mathbf{x}_i^k)} \mathrm{d}\boldsymbol{\theta}_i^k \tag{11}$$

  Calculate updated belief:

$$b(\boldsymbol{\theta}_i^k) \propto b_{\mathrm{nc}}(\boldsymbol{\theta}_i^k) \prod_{j \in \mathcal{N}(i)} m_{j \to i}(\mathbf{x}_i^k) \tag{12}$$

until stopping criterion is reached.

In our case, as the factor graph has cycles, the beliefs are approximations of the true a posteriori distributions: $b(\boldsymbol{\theta}_i^k) \approx p\left(\boldsymbol{\theta}_i^k \mid \mathbf{z}_{\mathrm{mp}}^{1:k}, \mathbf{z}_{\mathrm{coop}}^{1:k}\right)$.

Applying these message update rules to the factor graph defined by (2), we obtain a sequence of updates as outlined in Algorithm 1. In this algorithm, the beliefs are calculated for one time step until convergence or until a stopping criterion is reached. Then, the beliefs are propagated forward to the next time step, when new measurements are available.

This algorithm can be employed in either a distributed or a centralized way. In a distributed way, all users calculate their own beliefs using (12) and then broadcast this belief to their neighbors. However, such broadcasting may be energy consuming, since the messages that are to be transmitted are probability functions, which need to be represented by either a dense grid or a large number of particles. It may thus be more practical to centralize all calculations in the anchor node and only send the results over the network.

V. Simulation Results

A. Static scenario

In the static scenario, the localization is performed at a single time step, without prior knowledge of the users' positions. This corresponds to the gray shaded area of the factor graph in Fig. 3. Position estimates are obtained by selecting the maximum of the beliefs after convergence. Without cooperation, the algorithm reduces to a maximum likelihood (ML) estimator. Results were obtained after 1000 independent runs where the users were randomly positioned inside the room. The parameters for this simulation are given in Table I. Note that

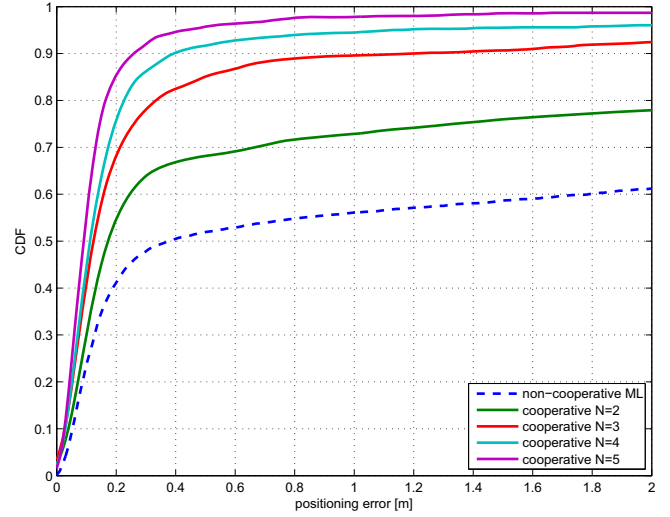| Parameter	Note	Value
σ_p, σ_{n}	Ranging std. deviation	0.1m for $\forall p$
$P_{\mathrm{v},p}$	Visibility for VAs: LOS	0.8 for $p = 1$
	single reflections	0.5 for $2 \leq p \leq 5$
	double reflections	0.3 for $6 \leq p \leq 9$
P_{VA}	Prob. that a $z_{\mathrm{mp},m}^{k,i}$ is from a VA	0.5
$w \times h$	room dimensions	10 m $\times$ 25 m
(x_1, y_1)	anchor location	(5 m, 6 m)
Δx	grid resolution	5 cm

Figure 4. CDF of the positioning error in a static scenario, for a varying number of cooperating users.

with these settings the measurement vector $\mathbf{z}_{\mathrm{mp}}^{k,i}$ will contain on average 50% completely unrelated range measurements, and there even exist a chance that not a single virtual anchor is visible to the user. For the implementation of the algorithm, beliefs and messages were represented by a grid.

In Fig. 4, the cumulative distribution function (CDF) of the positioning error is shown for a varying number of users. It is observed that the non-cooperative ML estimator performs the worst: almost half of the time this estimator cannot find the user. This is due to the false maxima in the likelihood function, and corroborates the findings from [1]. When the number of cooperating users increases, we see that the estimator achieves better performance. For 5 users, we find a positioning error smaller than 26 cm 90% of the time, compared to the ML estimator where such low errors are only achieved 44% of the time. For this static scenario no more than three or four iterations were needed for the beliefs to converge.

B. Dynamic scenario

In the dynamic scenario all users are following a predefined trajectory inside the room. The parameters used for the movement model are $\Delta T = 0.25\mathrm{s}$ and $\Delta L_{\mathrm{max}} = 2\mathrm{m}$. Two types of trajectories were generated. The first type are independent trajectories, while the second type are parallel trajectories, corresponding to two users who are walking next to each other

through the room. Two example, independent trajectories can be seen in Fig 1. In a dynamic scenario, where the user is walking through the room, it might be that one virtual anchor is obstructed by some object or another user, such that it is not visible by the user, and that this obstruction remains for some time. This effect is captured by adding correlation to the visibilities of the virtual anchors and generating all visibilities by means of a Markov Chain as described in [1]. In [1], where no cooperation was present, it was noted that this correlation has a negative effect on performance.

In order to keep the simulations tractable, all beliefs were not represented by a fine grid, but rather by a list of particles, as in [1]. Contrary to the non-cooperative case from [1], where 2000 particles were sufficient, the cooperative algorithm required around 15000 particles. This can be explained by the fact that if a user broadcasts a belief without any particle close to the true location, this user may affect other user's belief as well. The position estimates are obtained by taking the median of the particles at every time step, as this yields the best performance.

In Fig. 5 the CDF of the estimation error is shown for a varying number of users on different trajectories. It is observed that the worst performance is obtained without cooperation. Adding a second user to the system already gives a significant performance gain, particularly for the scenario where users move independently through the room. The lower gain for the parallel tracks is due to the correlation in the users' movement. Because of this the likelihoods (4) for both users will have correlated ambiguities that cannot be eliminated with cooperation. For 5 users, we find a positioning error smaller than 20 cm 95% of the time as compared to 70% of the time with the non-cooperative particle filter of [1]. For this dynamic scenario the beliefs generally converge faster than in the static scenario, with two or three iterations being sufficient. This is due to the fact that the beliefs are already more concentrated due to the integration of the user state from the previous time step.

VI. CONCLUSIONS

In this paper we considered the problem of cooperative indoor localization using a single anchor and a floor plan, based on signals reflected from walls. We extended the work from [1] to a cooperative setting, to enable different users to help each other resolve ambiguities. We have shown that cooperation significantly improves the localization accuracy, for both static and dynamic scenarios. Our future work includes the integration of the multipath extraction step (the extraction of the localization related measurements from the signals was not considered in this paper) with the localization step, and the validation of the algorithms with real-life experiments.

ACKNOWLEDGMENTS
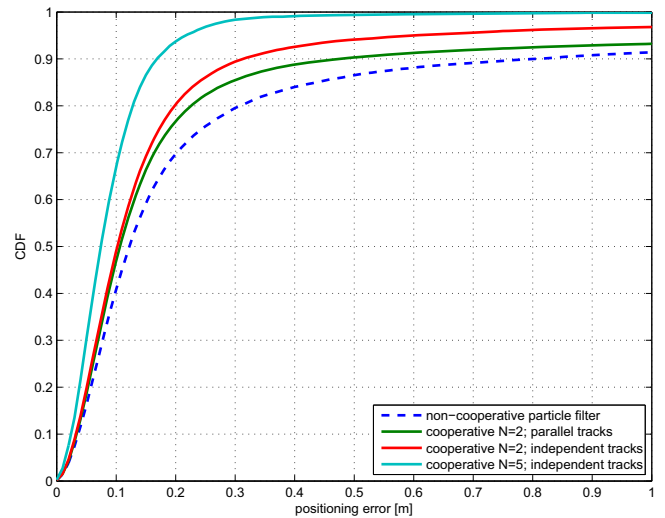
Figure 5. CDF of the positioning error in a dynamic scenario, for a varying number of cooperating users.

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