On-Line Training of the Path-Loss Model in Bayesian WLAN Indoor Positioning

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Abstract—Received signal strengths have been widely exploited in indoor positioning due to the massive presence of wireless local networks in buildings. Theoretical propagation models such as the path-loss model can be used in order to avoid long training phases as in fingerprinting approaches. The main issue concerning the employment of the path-loss model is that the values of some parameters, i.e., the transmit power and the decay exponent, depend on many factors, such as the device, building structure and other environmental features.

In this paper, we propose a Bayesian positioning algorithm based on the Rao-Blackwellized particle filter, where the parameters of the path-loss model are estimated independently for each AP in addition to localizing the user. Both parameters are described by discrete random variables with uniform priors. We validate our proposal by means of simulations and two different experiments; finally, some remarks on complexity are also given.

I. INTRODUCTION

Reliable indoor localization techniques are required to provide Location Based Services in buildings and urban canyons, e.g., navigation in airports and malls and support of first-aid units [1], [2]. Satellite navigation systems are inaccurate indoors due to multipath, therefore techniques based on local and low cost sensors are needed [3]. As a consequence, the sensors which are already available in a mobile phone, like accelerometers, compass, magnetometers, and radio receivers, are gathering a growing interest, both in scenarios where they are employed alone and when their measurements are fused, e.g. according to a probabilistic paradigm [4].

We focus on wireless local area networks (WLANs), which are increasingly spreading indoors. WLAN based localization makes use mainly of Received Signal Strengths (RSSs) of the beacon signals which are periodically sent by the Access Points (APs); it does not require any sensitive information exchange between user and network, in agreement with privacy issues [5].

Limits to RSS based localization are usually imposed by the characterization of the radio channel, that is still an open issue due to multipath and blockage yielded by the building structure, the materials of walls and furniture and the presence of metallic objects and people. Furthermore, it has been widely shown how propagation features can harshly change within short and long term intervals [6].

Fingerprinting techniques avoid radio propagation modeling and rather rely on extensive measurement campaigns across the area under test [7]. Hence, a radio map (RM) is built as a collection of RSS vectors associated to known positions and during the localization stage the vectors in the RM are compared to the upcoming RSS vectors: the user’s position is then estimated based on a clustering algorithm. RADAR, presented in [7], is still today a popular fingerprinting algorithm: the RM contains only the average of the RSS vectors collected in each position and clustering is based on the minimization of the Euclidean distance. Fingerprinting achieves localization accuracy down to 2-3 meters if the RM covers sufficiently the area under test. The algorithm stability is, however, affected by the environmental changes, that are usually approached by map corrections. To do so, [8] proposes the RM correction by means of a linear transformation under the arbitrary assumption that the change is uniform across the area, while the algorithm in [9] makes use of Model Trees to adapt the RM online without assuming explicit transformation functions. Both algorithms use measurements at additional reference nodes in order to detect and evaluate the changes. More recently, [10] proposed a technique based on principal component analysis to extract features from the RM without reference nodes.

An alternative approach to WLAN based fingerprinting localization employs theoretical models and resorts to geometric principles, like trilateration, to localize the user [7], [11], [12]. The theoretical approach is usually not as accurate as fingerprinting, but it avoids any RM construction; furthermore, propagation models can be stated as functions of parameters, whose calibration is used to fit environmental features. We focus on the parameters calibration in the case of the path-loss model [7], [11]. We avoid both a training phase and the use of reference nodes by developing an adaptive algorithm based on Bayesian probabilistic theory, in which the parameters are learned while performing localization. The APs are deployed in known positions and we assume independent outcomes of the path-loss parameters for each AP.

In a previous paper a similar framework is proposed in which only one parameter of the path-loss model is estimated per AP, namely the transmit power [13]. The parameter is stacked into the state vector and estimated by means of a particle filter together with the user’s trajectory; the path-loss exponent, which describes the decay of power with distance, is instead not estimated and the algorithm is fed with the
free-space value, that is 2. In real scenarios, however, the path-loss exponent is reported to vary in the range of 1 to 4 [11]. Although localization performance improves even by estimating only the transmit power, relevant potential lies in the determination of the path-loss exponent, as shown in the literature both in an experimental scenario [14] and according to theoretical considerations [15]. Authors in [16] propose a RSS-based localization algorithm in which the path-loss exponent is considered unknown. Although they do not estimate it in an explicit way, they implicitly account for it. In fact, the range estimations which are yielded by the RSS are combined with a spring-relaxation method: each AP-user distance is modeled by a spring, whose elasticity coefficient is made variable with the distance in order to mitigate the path-loss exponent inaccuracy. This approach is based on the claim that such a mismatch yields an error in the distance determination that is proportional to the distance itself; therefore, they propose to increase the variance of weak RSS measurements to account for the error caused by the parameter mismatch. Authors in [17] adopt the joint estimation of both transmit power and path-loss exponent by performing a training stage during which a maximum likelihood estimation is implemented by means of a Rao-Blackwellized particle filter (RBPF) whose complexity is also discussed; simulation and experimental results are instead discussed in Sections IV and V, respectively, while concluding remarks will be given in Section VI.

II. PATH-LOSS MODEL AND PARAMETERS

The path-loss model describes the decay of signal power propagating over a finite distance and it is obtained as an extension of Friis formula. According to it, the power $P(r)$ received by a mobile user at distance $r$ from the AP is given by [11]

$$P(r) = P_0 \left(\frac{d_0}{r}\right)^\alpha,$$

(1)

where $d_0$ is a reference distance, $P_0 = P(d_0)$ is a constant power representing the transmit power and antenna gains and $\alpha$ is the path-loss exponent ($\alpha = 2$ in free space). This model is valid in far field condition, as for $r \to 0$, $P(r) \to \infty$. In this paper, $d_0$ is the limit between near and far field, i.e., we assume $r \geq d_0$ and, therefore, $P(r) \leq P(d_0)$.

Restating (1) in dBm for the signal strength $h(r)$ (square root of power) we find:

$$h(r) = h - 20\alpha \log_{10} \left(\frac{r}{d_0}\right),$$

(2)
where $h = 10 \log_{10} P_0$ is the transmit power in dBm. RSS measurements in dBm are corrupted by a Gaussian white noise with mean given by (2) and variance denoted by $\sigma_y^2 > 0$, i.e.:

$$y \sim \mathcal{N}(h(r), \sigma_y^2).$$

(3)

The Gaussian probabilistic model is used in the literature in environments where slow fading is prevalent; it is shown that it corresponds for the signal strength in Watt to a Lognormal probability density function (pdf) \cite{7}, \cite{11}, \cite{13}.

The path-loss parameters are, in our case, the transmit signal strength $h$ and the exponent $\alpha$ in (2). We here consider them unknown but static, at least over a sufficiently short time interval (our experiments last few minutes). Their joint estimation, combined with inaccuracy on the user’s position and with RSS noise, could be prevented by ambiguity. As an example, we refer to simulation scenarios where $k$ independent measurements are sampled according to the model (3), with $\sigma_y = 3$ dBm and $r$ randomly chosen between $d_0 = 1.6$ m and 15 m. In Fig. 1 we show the likelihood function of the measurements conditioned on the distance $r$ and on the parameters $h$ and $\alpha$; in this case $r$ is exactly known and we compute the likelihood function over a wide range of parameter values. The panels of Fig. 1 show the likelihood function depicted against the parameters at different $k$, $k = 1$ in panel (a), $k = 5$ in (b) and $k = 20$ in (c), respectively. The representation is in terms of contour plots (the lines are at 1%, 50%, and 90% of the maximal value, the red cross indicates the values adopted to generate the measurements). After just one measurement, in (a), the likelihood function is symmetrical around a straight line, meaning ambiguity among infinite pairs of values. The following measurements bring relevant information and even at $k = 5$ the likelihood function is an oval centered on a section of the previous line. After 20 measurements most ambiguity has vanished and the accurate estimation of the parameters is possible by, i.e., maximizing the likelihood function. The fact that the maximum of the likelihood function does not coincide exactly with the values used in the RSS generation is a consequence of the RSS noise and represents the estimation error.

III. BAYESIAN FILTER AND RBPF IMPLEMENTATION

The user’s state at the time instant $k = 0, 1, \ldots$ is composed of both its position $\theta_k \in \mathcal{A} \subset \mathbb{R}^2$ and its velocity

$$x_k = \begin{bmatrix} \theta_k^T, \dot{\theta}_k^T \end{bmatrix}^T,$$

(4)

where $\mathcal{A}$ is the two dimensional indoor area under test and the coordinates are expressed according to a local Cartesian reference system. A number $N_{\text{AP}}$ of APs are deployed in known locations of $\mathcal{A}$, namely, the $j$-th AP is in $\theta_{\text{AP},j}$. The RSS measurement $y_{j,k}$ from AP $j$ at time instant $k$ is drawn from a Gaussian pdf, conditioned on state and parameters. By explicating time dependence and user’s state in (2) and (3) we find:

$$y_{j,k} = h_j - 10\alpha_j \log_{10} (||\theta_k - \theta_{\text{AP},j}||/d_0) + n_{j,k},$$

(5)

where $h_j$ and $\alpha_j$ are the $j$-th AP parameters and $n_k$ is a white zero-mean Gaussian process

$$n_{j,k} \sim \mathcal{N}(0, \sigma_y^2).$$

(6)

Finally, independence is assumed among measurements of different APs, given the user’s state. Our aim is to estimate the user’s state $x_k$ and the path-loss parameters $h_j$ and $\alpha_j$ for all APs based on the RSS measurements.

A. Bayesian Filter

The Bayesian filter computes the posterior pdf of user’s state and path-loss parameters:

$$p \left( x_{0:k}, \{ h_j, \alpha_j \}_{j=1:N_{\text{AP}}} \mid \{ y_{j,1:k} \}_{j=1:N_{\text{AP}}} \right),$$

starting from suitable independent prior distributions that we will indicate, with a little abuse of notation, with $p_0(x)$ and $p_0(h_j, \alpha_j)$, respectively. The posterior pdf (7) can be decomposed in order to split the parameter estimation terms from the localization term:

$$p \left( x_{0:k}, \{ h_j, \alpha_j \}_{j=1:N_{\text{AP}}} \mid \{ y_{j,1:k} \}_{j=1:N_{\text{AP}}} \right) =$$

$$\prod_{j=1}^{N_{\text{AP}}} p \left( h_j, \alpha_j \mid x_{0:k}, y_{j,1:k} \right) \cdot p \left( x_{0:k} \mid \{ y_{j,1:k} \}_{j=1:N_{\text{AP}}} \right).$$

Let us focus on the localization term, the last on the second line of (8). A further factorization yields the recursive formulation

$$p \left( x_{0:k} \mid \{ y_{j,1:k} \}_{j=1:N_{\text{AP}}} \right) =$$

$$\prod_{j=1}^{N_{\text{AP}}} p \left( y_{j,k} \mid x_{0:k}, y_{j,1:k-1} \right) \cdot p \left( x_{0:k-1} \mid \{ y_{j,1:k-1} \}_{j=1:N_{\text{AP}}} \right) \cdot p \left( x_{0:k-1} \mid \{ y_{j,1:k-1} \}_{j=1:N_{\text{AP}}} \right),$$

(9)

The first term on the right hand side of (9) is the product of measurement likelihood functions, one per AP, which are conditionally independent. Each factor requires a marginalization over the path-loss parameters of the same AP, i.e., for the $j$-th factor:

$$p \left( y_{j,k} \mid x_{0:k}, y_{j,1:k-1} \right) =$$

$$\int_{h_j, \alpha_j} p (y_{j,k} | h_j, \alpha_j, x_{0:k}, y_{j,1:k-1}) \cdot p (h_j, \alpha_j | x_{0:k-1}, y_{j,1:k-1}) \, dh_j \, d\alpha_j,$$

(10)

where the likelihood function conditioned on the path-loss parameters, based on independence assumptions, results in

$$p (y_{j,k} | h_j, \alpha_j, x_{0:k}, y_{j,1:k-1}) = p (y_{j,k} | h_j, \alpha_j, x_k),$$

(11)

and is given by (3).

\footnote{The notation $j = a : b$ stays for $j = a, a+1, \ldots, b$ and is used across the paper for shortness.}
The second term on the right hand side of (9) is the user’s movement model; by assuming the Markov property, we simplify it in

\[ p\left( x_{i,k-1} \mid \{ y_{j,k-1}\} \right) = p\left( x_{i,k-1} \right). \tag{12} \]

The user’s movement model depends on the type of user, e.g., a pedestrian or a robot, and two examples will be provided when discussing the results.

As for the parameter pdf, the update formula is obtained by means of the Bayes theorem, i.e., for the j-th AP:

\[ p(h_j, \alpha_j \mid x_{o,k}, y_{j,k}) = \frac{p(y_{j,k} \mid h_j, \alpha_j, x_{o,k}) \cdot p(h_j, \alpha_j \mid x_{o,k}, y_{j,k-1})}{p(y_{j,k} \mid x_{o,k}, y_{j,k-1})}, \tag{13} \]

where (11) is employed and

\[ p(h_j, \alpha_j \mid x_{o,k}, y_{j,k-1}) = p(h_j, \alpha_j \mid x_{o,k}, y_{j,k-1}). \tag{14} \]

### B. Path-Loss Parameter Model

The model of the path-loss parameters should represent a fair compromise between accuracy and mathematical tractability. Our choice is to discretize the variables by defining a finite set of \( N_S \) hypotheses for each AP, e.g., for the j-th AP:

\[ H_{j,s} = \{ h_j, \alpha_j \}, s = 1, \ldots, N_S. \tag{15} \]

The values of the parameters can be sampled on either a suitable grid or according to some prior information. Their pdf is therefore represented by the set of probabilities of each hypothesis, whose update is found by means of the Bayes theorem, as in (13):

\[ \Pr \left( H_{j,s} \mid x_{o,k}, y_{j,k} \right) = \frac{p(y_{j,k} \mid H_{j,s}, x_{o,k}) \cdot p(H_{j,s} \mid x_{o,k}, y_{j,k-1})}{p(y_{j,k} \mid x_{o,k}, y_{j,k-1})}, \tag{16} \]

for all \( j \) and \( s \). Finally, the integral in (10) results in the finite sum

\[ p(y_{j,k} \mid x_{o,k}, y_{j,k-1}) = \sum_{s=1}^{N_S} p(y_{j,k} \mid H_{j,s}, x_{o,k}) \cdot \Pr \left( H_{j,s} \mid x_{o,k}, y_{j,k-1} \right) \cdot p(H_{j,s} \mid x_{o,k-1}, y_{j,k-1}) \cdot \Pr \left( H_{j,s} \mid x_{o,k-1}, y_{j,k-1} \right). \tag{17} \]

**Algorithm 1** WLAN localization with path-loss parameter estimation

1. Initialization: \( \triangleright \) Initialize user’s state and particle weights
2. for \( i = 1 \) to \( N_P \) do
3. Draw the initial user’s state \( x_i^0 \sim p(x_0) \)
4. \( w_i^0 = N^{-1}_P \)
5. Select a set of \( N_S \) hypotheses \( H_{j,s} \)
6. for \( j = 1 \) to \( N_{AP} \) do
7. \( \triangleright \) Initialize parameter distributions
8. \( \Pr \left( H_{j,s} \mid x_i^0 \right) = N^{-1}_S \)
9. end for
10. end for
11. end for
12. Iterations:
13. \( k = 1 \)
14. while ( New measurement available ) do
15. for \( i = 1 \) to \( N_P \) do
16. Draw the user’s state \( x_i^k \sim p(x_i^k \mid x_i^{k-1}) \)
17. for \( j = 1 \) to \( N_{AP} \) do
18. Compute \( I_{j,k}^i \) like in (20)
19. \( \triangleright \) Update the particle weights
20. for \( s = 1 \) to \( N_S \) do
21. Compute \( \Pr \left( H_{j,s} \mid x_i^k, y_{j,k} \right) \) like in (21)
22. Normaliz \( e \Pr \left( H_{j,s} \mid x_i^k, y_{j,k} \right) \) over \( s \)
23. end for
24. \( \triangleright \) Update the particle weights
25. end for
26. \( W = \sum_{i=1}^{N_P} w_i^k \)
27. \( w_i^k = w_i^{k-1} \cdot \prod_{j=1}^{N_{AP}} I_{j,k}^i \)
28. \( k = k + 1 \)
29. end while
30. Termination: compute MMSE or MAP trajectory.

### C. RBPF Implementation

The Bayesian filter described in the previous Sections has been implemented by means of the RBPF [20] and is summarized in the algorithm box. Initialization is done by sampling the user’s state from the prior pdf \( p(x_0) \) and by setting all the hypothesis probabilities to \( N_S^{-1} \) for all \( N_P \) particles. Then, for the i-th particle at the time instant \( k > 0 \), the user’s state is drawn according to

\[ x_i^k \sim p(x_i^k \mid x_i^{k-1}), \tag{18} \]

and the weight is computed from the RSS likelihood function

\[ w_i^k = w_i^{k-1} \cdot \left( \prod_{j=1}^{N_{AP}} p(y_{j,k} \mid x_i^k, y_{j,k-1}) \right) \cdot \left( \prod_{j=1}^{N_{AP}} p(y_{j,k} \mid x_i^k, y_{j,k-1}) \right), \tag{19} \]

in which the parameter pdf is involved like in (17)

\[ I_{j,k}^i = p(y_{j,k} \mid x_i^k, y_{j,k-1}) \cdot \Pr \left( H_{j,s} \mid x_i^{k-1}, y_{j,k-1} \right). \tag{20} \]

Fig. 2. Testbed adopted in the simulations; in the figure \( L_x = 40 \) m and \( L_y = 20 \) m and the APs are in the positions denoted by red circles.
As the last step of the iteration, the hypothesis probabilities
are updated according to (16), with
\[
\Pr \left( H_{j,s} \mid \mathbf{x}_k, y_{j,1:k} \right) \propto p \left( y_{j,k} \mid H_{j,s}, \mathbf{x}_k \right) \cdot p \left( H_{j,s} \mid \mathbf{x}_{k-1}, y_{j,1:k-1} \right),
\]
for all hypotheses and APs, and then normalized over \( s \).
When the algorithm terminates, the estimated trajectory can be computed either by averaging over the particles to obtain the Minimum Mean Square error (MMSE) estimator or by considering the best particle trajectory (Maximum A-Posteriori - MAP - estimator). The estimation can be done at each time instant when real-time tracking is needed.

The computational complexity required by the proposed algorithm is linearly proportional to the number of particles, \( N_P \), to the number of APs, \( N_{AP} \), and to the number of hypotheses, \( N_S \). The advantage of applying RBPF is that the state sampling, that is the heaviest operation, refers only to the user’s state, whose dimensionality does not depend on the number of APs and parameters. These latter are only involved in the evaluation of the conditional RSS likelihood functions, which can be efficiently done in logarithmic domain.

**IV. SIMULATIONS**

We propose a preliminary validation of the algorithm by means of simulations. The synthetic testbed is depicted in Fig. 2 and is a \( 40 \times 20 \) m open area where 5 APs are denoted by red circles and they emit a beacon signal with a constant period \( \tau \).
Fig. 5. Experiment in a 65 × 20 m office floor with 4 APs: the trajectory in dashed blue line is obtained by applying FootSLAM [19] and is here considered the ground truth, while the estimated trajectory is denoted by a red continuous line; the AP’s true positions are denoted by green triangles and they are employed by the algorithm; the trajectories are arranged in the floor layout, that is not known by the algorithm. Here, 1000 particles and $\sigma_y = 5$ dBm are employed.

The user’s state transition (18)

$$p(x_k|x_{k-1}), \ k = 1, 2, \ldots,$$

is described in this simulation by means of the popular Nearly Constant Velocity Model (NCVM) sampled at time instants $kT$ [21]

$$x_{k+1} = Fx_k + v_k, \ k = 0, 1, 2, \ldots,$$

where $x_k$ is a zero mean white Gaussian process. In (22) the 4 × 4 matrix $F$ is defined like

$$F = \begin{pmatrix} 1 & \tau \\ 0 & 1 \end{pmatrix} \otimes I_2,$$

where $h_0 = -40$ dBm and $\alpha_0 = 2$, and diagonal covariance matrices; in all the simulations the standard deviation of the prior distributions are set to $\sigma_h = 3$ dBm and $\sigma_v = 0.3$, respectively, and 1000 particles are employed.

The parameter hypotheses, $\{H_s\}$, $s = 1 : N_S$, are
represented by all the couples \( \{ h_j^s, \alpha_j^s \} \) obtained by the combinations of the values \( h_j^s \) from -50 dBm up to -30 dBm with step 1 dBm and \( \alpha \) from 1.5 up to 3.5 with step 0.1.

The black curves in both panels of Fig. 3 refer to the localization error achieved in the simulation scenario of Fig. 2. The RSS measurements have been generated with variance \( \sigma_j^2 = 5 \) and the walk lasts \( K = 500 \) seconds at the pace of \( \tau = 1 \) s (that is 500 measurements per each AP). We compute the Minimum Mean Square Error (MMSE) estimator of the whole trajectory, averaged on \( I = 100 \) independent realizations. For simplicity, we depict the root MSE (RMSE), since its dimensions are in meters; panel (a) shows the localization RMSE against time while panel (b) reports on its empirical cumulative density function (CDF).

In Fig. 3 we draw two other set of curves. The red dashed ones refer to performance of the algorithm with perfect knowledge of the parameters, i.e., only one hypothesis is considered, \( N_S = 1 \), which corresponds to the values adopted in the generation of data. This case is equivalent to apply the Sampling Importance Resampling (SIR) algorithm where the state space is composed only of the user’s state [22]. Also the blue dotted curves are obtained by assuming only one hypothesis, but the values here are the prior means \( h_0 \) and \( \alpha_0 \). In this latter case the mismatch on the parameters will be on the same order of magnitude as the prior pdf’s standard deviations, 3 dBm for \( h \) and 0.3 for \( \alpha \). Although such deviations are not that large, we can see in Fig. 3 how big the produced error can be, and in panel (a) we notice that the blue curve diverges. On the other hand our proposal is very close to the red curve, since the model mismatch is highly mitigated by the parameter estimation. This latter is explicitly reported in Fig. 4 for the same simulation: panel (a) refers to the transmit signal strength and shows the average, maximum and minimum absolute error of the estimation, further averaged on all 5 APs. The same is done for \( \alpha \) in panel (b) and in both cases we notice that after an initial transient the absolute errors clearly decrease; at the end of the simulation the average absolute error is reduced by 60%-70% with respect to the maximum in both cases.

V. EXPERIMENTS

Two experiments have been carried out in different buildings and configurations in order to validate our algorithm. The user’s state model (18) is here provided by the output of a foot-mounted IMU: the raw inertial measurements are filtered by a ZUPT algorithm and the resulting step measurements are then used to sample the new user’s state [18], [19]. The RSS measurements are collected by means of either a laptop or a mobile phone. The use of an expensive and invasive foot mounted IMU is realistic in a professional application, like a Disaster Management scenario, but not for commercial mass-market services; in the latter case it can be replaced by the inertial sensor available in most smartphones: their inaccuracy will be a challenge to afford in the close future.

The first experiment takes place in an office floor which is about 65 m long and 20 m wide, where the user walks for about 3 minutes back and forth the hallways and some rooms. The user equipment is composed of a foot mounted IMU and a hand-held smartphone which logs the RSS measurements from 4 APs, within a IEEE 802.11 (WiFi) b/g network; the processing has been done off-line. We notice that RSS measurements from different APs are usually not synchronous and this is accounted for in the algorithm by assigning dummy values to the weights \( I_{i,k} \) of (20), for all \( i \), in the case of missing measurements. The parameter hypotheses, \( \{ h_s \}_s \), \( s = 1: N_S \), are obtained by the combinations of the values \( h_j^s \) from -46 dBm up to -30 dBm with step 2 dBm and \( \alpha \) from 1 up to 4 with step 0.5. The standard deviation of the RSS measurements is set to \( \sigma_\theta = 5 \) dBm.

Fig. 5 shows the layout of the testbed with the AP’s locations, whose evaluation was based on visual inspection, and two trajectories: in blue (dashed line) the ground-truth and in red (continuous line) the trajectory estimated by our proposal. The ground-truth has been evaluated by means of FootSLAM, which is a Simultaneous Localization And Mapping (SLAM) algorithm based on the IMU only and presented in [19], [23]; FootSLAM is run with as many as \( 5 \times 10^4 \) particles and makes use of a very accurate prior map of the floor. In this conditions it provides trajectories within a sub-meter error, as the matching with the map layout confirms. From a first inspection of the results we can point out two issues of interest. On the right side of the floor the estimation is very accurate, both in the hallway and in the rooms, due to the proximity of the APs to the trajectory, especially AP 3. On the left side of the floor, instead, localization suffers from the disposition of the APs and the error increases. The black continuous curves in Fig. 6 quantify the localization error - against time in panel (a) and the corresponding CDF in panel (b). We can see that at the far ends of the walk, corresponding to the user walking in the left part of the floor, the error grows up to almost 3 meters, while it is below 1 meter in the other case. In the same figure we also depict the comparison with the result of two other algorithms: the red dashed lines refer to the SIR algorithm fed with the average parameter values, \( \alpha = 2 \) and \( h = -40 \) dBm,
while the blue dotted curves refer to the algorithm which does not make use of RSS measurements, but only of the IMU’s measurements.

The algorithm with fixed parameters has a very unstable behavior, since the localization error alternates low values to over 4-meter-peaks, due to model mismatches. Changing the parameter values yields a different disposition of the error peaks but does not improve the algorithm stability. Furthermore, using only IMU’s step measurements brings to a drift in the localization error, as widely documented in the literature [18], [19] and, in our case, the error amounts already to 6-7 meters after 3 minutes. Nonetheless, using IMU to propose the user’s state has a strong impact in mitigating inaccuracy if the user walks a short time in a part of the floor that is not well covered by the APs.

Fig. 7 presents the second experiment, performed in another office environment about 45 m long and 25 m wide, with a square hallway and 4 APs. The user walks about 7 minutes - corresponding to 3 rounds in the hallway with visits to some of the offices. In this case the RSS are collected by a hand-held laptop while the foot-mounted IMU is still used to obtain step measurements. In this scenario the results are worse than in the first experiment, due especially to a little rotation in the estimated trajectory (red curve in Fig. 7). We notice, however, that this setting is harder since, although 4 APs are still deployed, two APs - AP 2 and 3 - are located in the same position, thus reducing the area coverage and, above all, signal diversity. However, the localization error depicted in Fig. 8 highlights a performance gain with respect to the algorithm with fixed parameters - the error is below 2 meters for 80% of time.

VI. CONCLUSION

We proposed a localization algorithm for indoor environments based on RSS measurements, which are modeled by means of the path-loss model. The algorithm was developed in the framework of Bayesian probability theory and accounts for the path-loss model calibration. In detail, we dealt with the transmit power and the path-loss exponent, which are usually not known with sufficient accuracy in real scenarios. Our algorithm is able to gradually estimate such parameters together with the user’s trajectory, without any previous calibration phase.

The theoretical Bayesian filter is implemented by means of a Rao-Blackwellized particle filter, where a state transition model is assumed in order to propose the new user’s position and the RSS measurements are, then, used to weight the particles. The path-loss parameters are defined in terms of a probability distribution that is updated after each measurement. This representation has two main benefits: only the user’s state is sampled, so the complexity of this operation is not related to the presence of parameters, and, above all, the parameter estimation is not point wise but it is gradually improved, related to the quantity of information available. This avoids over-estimation issues and makes the algorithm robust.

Validation of the proposed algorithm has been carried out by means of both simulations and experiments. For the latter, two different buildings were employed and fusion with inertial data derived from a foot-mounted IMU was also discussed. Future challenges follow mainly two directions. The former is represented by a better characterization of radio propagation, above all in near field conditions, where the traditional path-loss model turns out to be increasingly inaccurate. The latter challenge is instead represented by three dimensional scenarios, which are not mere extensions of two dimensions, but offer different issues.

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