

WiSLAM: improving FootSLAM with WiFi

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Abstract—We address Simultaneous Localization and Mapping (SLAM) for pedestrians by means of WiFi signal strength measurements. In our system odometric data from foot mounted Inertial Measurements Units are fused with received signal strength (RSS) measures of IEEE 802.11. To do this, we assign a probabilistic model to RSS measures, and adopt the Bayesian framework on which FootSLAM and PlaceSLAM are based. Simulative and experimental examples for the main components in WiSLAM are shown to validate the effectiveness of our solution.

Keywords — SLAM, Received Signal Strengths, Inertial Measurements Units, Bayesian algorithm

I. INTRODUCTION

Recently, Simultaneous Localization and Mapping (SLAM) for pedestrians has been shown to be an effective way to improve the localization accuracy indoors. Human users are typically not equipped with sensors like lasers or cameras and it is more likely to exploit step measurements collected by a foot mounted Inertial Measurement Unit (IMU). The residual cumulative error in heading over time leads to instability and could be mitigated by using map information [1]–[3]. When the map is not available, as we are assuming in this paper, it should be estimated, according to the SLAM paradigm.

FootSLAM and PlaceSLAM are two SLAM algorithms for pedestrians [4], [5]. However, convergence is not guaranteed, especially in open areas.

In this paper, we present the WiSLAM algorithm which integrates the Received Signal Strength (RSS) measures within a IEEE 802.11 (WiFi) network in FootSLAM. RSS-based indoor localization has been widely addressed in the past, and accuracies down to 2 meters are typically showed. The most used approaches are mainly based on fingerprinting (whose first implementation was RADAR [6]): 1) in a previous off line stage a radio map of the environment is built up with measures collected over a set of known points and 2) in the localization stage the new RSS is compared to the stored ones to guess the user's position. Other more recently approaches space from probabilistic techniques [7] to more complex models, e.g. support vector machines [8].

Our goal is to show that RSS measures from *unknown* APs are helpful in mitigating the IMUs' heading error, thus speeding up FootSLAM convergence and improving robustness.

A. FootSLAM

FootSLAM [4] uses a Bayesian estimation approach, where the state is the user's pose \mathbf{P} (position and heading) and step measurements allow the updating of both the user trajectory

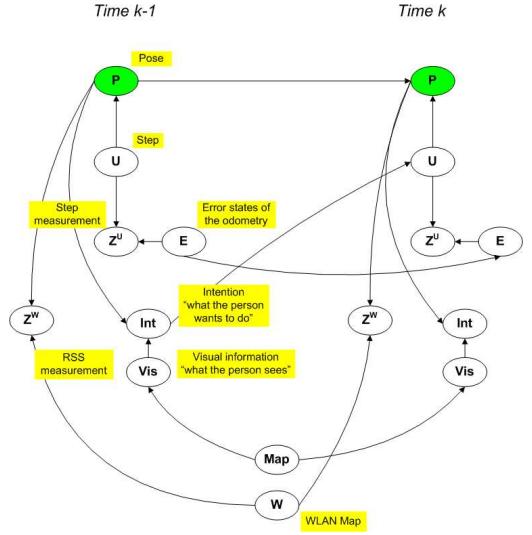


Fig. 1. DBN for WiSLAM showing two time slices. The Map can include any features and information to let the pedestrian choose Int, while \mathbf{W} is the WiFi map.

and the environment map over time. The implementation employs a Rao-Blackwellized Particle Filter (RBPF), where each particle is composed of both a user trajectory instance and its related map. This latter is obtained by partitioning the environment into hexagonal cells and estimating all the transitions probabilities. Extensive experiments show that convergence of both mapping and localization occurs when the user walks on closed loops and up to 10000 particles are used.

B. PlaceSLAM

In PlaceSLAM [5], proximity information relative to some well recognizable places, e.g. doors, is assumed. The places' locations are initially unknown and thus formally included in the map. The complexity increase with respect to FootSLAM is light, but convergence is showed to become remarkably quicker. WiSLAM is different from PlaceSLAM since RSS measures provide distance instead of proximity information. This is why better accuracy is expected. Furthermore, in WiSLAM the measures are fully automatic, while PlaceSLAM requires the user to detect the places manually.

II. WiSLAM FORMULATION

A. Dynamic Bayesian Network

We represent the pedestrian behaviour through a dynamic Bayesian Network (DBN) similar to FootSLAM's and PlaceS-

LAM's ones (see Fig. 1 for two adjacent time slices). The pedestrian is assumed to be guided by his intention **Int** (e.g. to reach a room or to exit the building), that is influenced by the human visual system **Vis** and thus by the environment **Map** (**M**). The intention, neither measurable nor processed in our algorithm, determines the step \mathbf{U}_k that leads to the new pose \mathbf{P}_k given the past one \mathbf{P}_{k-1} . The step measure \mathbf{Z}_k^U is observable and is affected by IMU's correlated errors encoded in the state variable \mathbf{E}_k . In WiSLAM there is the RSS vector \mathbf{Z}_k^W as well, that is basically a noisy measure of the current distance between the user and the AP. Note that the length of \mathbf{Z}_k^W is variable, since the user can either enter or exit APs' ranges of activity. This is easily handled since the RSS measures are always labeled because the APs transmit their MAC address.

B. RSS measures

Some definitions and assumptions about the RSS measures are now in order.

Our main assumptions are that RSS from different APs are independent given the user's position and, furthermore, the APs' maps **W** are also independent. This allows us to compute the contribution of each AP in a separate way and to fuse them at the end. Moreover, different measures from the same AP are also conditionally independent. Given the current Euclidean distance \mathbf{D}_k^W of the user from the AP, located in \mathbf{W}_P the RSS likelihood is assumed Gaussian with variance σ^2 and mean given by the simple model [6]

$$h(\mathbf{D}_k^W) = \mathbf{h} - 20\alpha \log_{10}(\mathbf{D}_k^W/d_0), \quad (1)$$

where \mathbf{h} is the reference signal strength emitted by the AP, accounting also for the antenna orientation and gain, α is the propagation exponent, varying from 2 (free space) up to 4 and d_0 is a known reference distance. Note that both \mathbf{h} and α are usually unknown, and mainly \mathbf{h} is found to vary strongly for different APs with dramatic effects on the mapping, unless it is learnt. This is why we introduce both \mathbf{W}_P and \mathbf{h} in the WiFi map **W**. We found less sensitivity to α inaccuracies and thus for simplicity we set $\alpha = 2$.

Finally, we found it convenient to model \mathbf{h} as a discrete random variable, independent from AP to AP, drawn among N_h equally spaced values $\{h_h^t\}_{i=h..N_h}$.

C. Derivation of the Bayesian filter

In a Bayesian formulation, we are interested in the joint posterior $p(\mathbf{P}_{0:k}\mathbf{U}_{0:k}\mathbf{E}_{0:k}, \mathbf{W}, \mathbf{M}|\mathbf{Z}_{1:k}^U, \mathbf{Z}_{1:k}^W)$ of both the state histories and the maps given step and RSS measures, which factorizes into

$$p(\mathbf{M}|\mathbf{P}_{0:k}) \cdot p(\mathbf{W}|\mathbf{P}_{0:k}, \mathbf{Z}_{1:k}^W) \cdot p(\mathbf{P}_{0:k}\mathbf{U}_{0:k}\mathbf{E}_{0:k}|\mathbf{Z}_{1:k}^U, \mathbf{Z}_{1:k}^W). \quad (2)$$

Following the FootSLAM derivation, the last term in eq. (2)

admits a recursive formulation based on the DBN:

$$\begin{aligned} p(\{\text{PUE}\}_{0:k}|\mathbf{Z}_{1:k}^W, \mathbf{Z}_{1:k}^U) &\propto \\ &p(\mathbf{Z}_k^U|\{\text{UE}\}_k) \cdot p(\mathbf{Z}_k^W|\mathbf{P}_{0:k}, \mathbf{Z}_{1:k-1}^W) \cdot \\ &p(\{\mathbf{E}_k|\mathbf{E}_{k-1}\}) \cdot p(\{\text{PU}\}_k|\{\text{PU}\}_{0:k-1}) \cdot \\ &p(\{\text{PUE}\}_{0:k-1}|\mathbf{Z}_{1:k-1}^U, \mathbf{Z}_{1:k-1}^W). \end{aligned} \quad (3)$$

The novelty in WiSLAM with respect to FootSLAM is the RSS likelihood term. From the DBN it is clear that the **W** map has a strong influence on the posterior. We define

$$\begin{aligned} I_W &\hat{=} p(\mathbf{Z}_k^W|\mathbf{P}_{0:k}, \mathbf{Z}_{1:k-1}^W) \\ &= \int_{\mathbf{W}} p(\mathbf{Z}_k^W|\mathbf{W}, \mathbf{P}_k) \cdot p(\mathbf{W}|\mathbf{P}_{0:k-1}, \mathbf{Z}_{1:k-1}^W) d\mathbf{W} \\ &= \sum_{h=1}^{N_h} \Pr(h_h^t|\mathbf{P}_{0:k-1}, \mathbf{Z}_{1:k-1}^W) \cdot \\ &\int_{\mathbf{W}_P} p(\mathbf{Z}_k^W|\mathbf{W}_P, h_h^t, \mathbf{P}_k) \cdot p(\mathbf{W}_P|h_h^t, \mathbf{P}_{0:k-1}, \mathbf{Z}_{1:k-1}^W) d\mathbf{W}_P. \end{aligned} \quad (4)$$

D. WiFi map learning

The last point to consider is map learning. Of course **M** is evaluated like in FootSLAM. With the factorization

$$p(\mathbf{W}|\mathbf{P}_{0:k}, \mathbf{Z}_{1:k}^W) = p(\mathbf{W}_P|\mathbf{h}, \mathbf{P}_{0:k}, \mathbf{Z}_{1:k}^W) \cdot p(\mathbf{h}|\mathbf{P}_{0:k}, \mathbf{Z}_{1:k}^W), \quad (5)$$

we split the **W** estimation in two separate tasks. To determine the probabilities for h_h^t and assuming a suitable prior, e.g. uniform, we apply Bayes rule to express:

$$\begin{aligned} \Pr(h_h^t|\mathbf{P}_{0:k}, \mathbf{Z}_{1:k}^W) &\propto p(\mathbf{Z}_k^W|h_h^t, \mathbf{P}_{0:k}, \mathbf{Z}_{1:k-1}^W) \\ &\Pr(h_h^t|\mathbf{P}_{0:k-1}, \mathbf{Z}_{1:k-1}^W). \end{aligned} \quad (6)$$

More insight instead is needed in learning AP's position \mathbf{W}_P , given \mathbf{h} . In Fig. 2 we show the results of a simulative experiment which makes our analysis clearer: a user walks along the dotted path and collects RSS from an AP, drawn according to the models in Sect. II-B (a standard deviation of 5 dB is assumed for the noise). Finally, a density plot (higher values are darker) is used to depict the pdf. At $k = 1$ the updated pdf is simply (see Fig. 2.a)

$$p(\mathbf{W}_P|h_h^t, \mathbf{P}_{0:1}, \mathbf{Z}_1^W) \propto p(\mathbf{Z}_1^W|h_h^t, \mathbf{W}_P, \mathbf{P}_1),$$

that is a donut-shaped function centered on the user and whose radius is related to the distance from the AP (it is easy to prove that the radius is a Lognormal variable). For $k > 1$, we find

$$p(\mathbf{W}_P|h_h^t, \mathbf{P}_{0:k}, \mathbf{Z}_{1:k}^W) \propto \prod_{s=1}^k p(\mathbf{Z}_s^W|\mathbf{W}_P, h_h^t, \mathbf{P}_s), \quad (7)$$

that is the product of k non concentric donut-shaped functions, properly normalized. As the user walks along a straight line, the initial donut evolves into two peaks, one centered on the AP and the other in its symmetrical position (Fig. 2.b-c). After a corner, only the correct peak survives, that is further sharpened by subsequent RSS measures (Fig. 2.d-f).

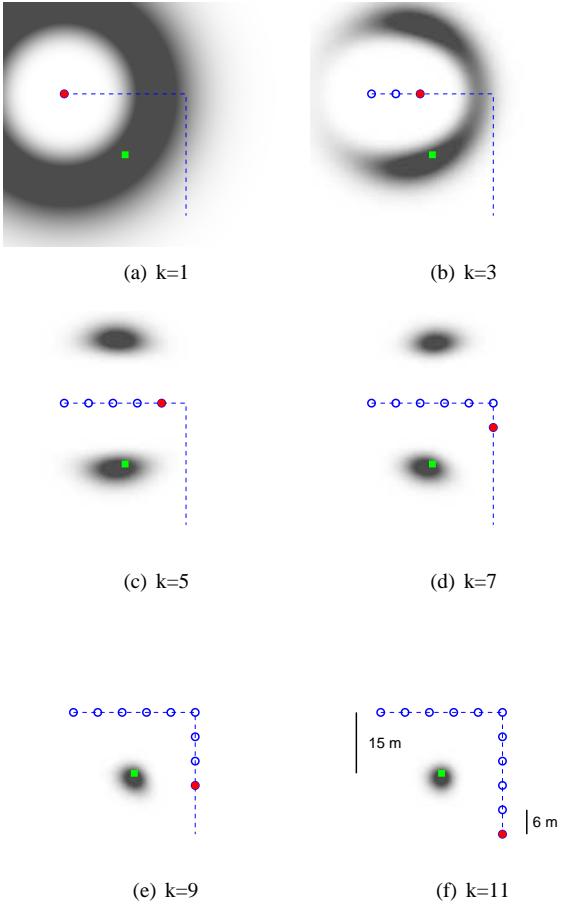


Fig. 2. Simulative results: a user walks along the dotted blue path and collects RSS from the AP (denoted by a green square) in the points marked by empty circles. The red full circle denotes, instead, its current position. The pdf of the AP's position is depicted through a density plot (high values darker) at the instants $k = 1, 3, 5, 7, 9, 11$. We assumed known \mathbf{h} , RSS standard deviation 5 dB.

The cutting off of the specular peak can however take some time because the RSS measures are noisy.

The complete $p(\mathbf{W}|\mathbf{P}_{0:k}, \mathbf{Z}_{1:k}^W)$ is thus a mixture of N_H 'donuts' products, in which the weights, the probabilities for h_h^t , also evolve over time.

E. Particle Filter implementation

Like in FootSLAM, for a PF implementation of the Bayesian filter, we sample from the 'likelihood PF' proposal density [9]

$$p(\mathbf{U}_k | \mathbf{Z}_k^U, \mathbf{E}_k^i) p(\mathbf{E}_k | \mathbf{E}_{k-1}^i). \quad (8)$$

The RSS contribution is a multiplying factor in the particle weights

$$w_k^i \propto w_{k-1}^i \cdot I_M^i \cdot I_W^i \quad (9)$$

where I_M^i is relative to \mathbf{M} estimation [4] and I_W^i is a numerical approximation for I_W in eq. (4). The easiest way to compute I_W^i is to sample the 2 dimensional space of \mathbf{W}_P over a static grid in the area of interest, and to compute the pdf in eq. (7) for the samples. Further research will also deal with more effective sampling techniques.

F. Summary of the algorithm

- 1) Initialize all N_P particles to $\mathbf{P}_0^i = (x, y, h = 0)$ where x, y and h denote the pose location and heading in two dimensions; draw \mathbf{E}_0^i from a suitable initial distribution for the error state.
 - 2) For each AP, draw N_W points \mathbf{W}_P^j within the test area and set $p(\mathbf{W}_P^j | \mathbf{h} = h_h^t, \mathbf{P}_0^i) = 1/N_W, \forall i, j, h$, and $\Pr(\mathbf{h} = h_h^t | \mathbf{P}_0^i) = 1/N_H, \forall i, h$.
- Then, for each time step increment k :
- 1) Draw $\mathbf{U}_k^i, \mathbf{E}_k^i$ from the proposal density in (8), compute \mathbf{P}_k^i by adding the vector \mathbf{U}_k^i to \mathbf{P}_{k-1}^i .
 - 2) Update and normalize the particle weights (eq. (9)) with I_M^i like in FootSLAM and with a multiplying contribution I_W^i per each detected AP.
 - 3) Update the map \mathbf{M} like in FootSLAM.
 - 4) Compute $p(\mathbf{W}_P^j | h_h^t, \mathbf{P}_{0:k}^i, \mathbf{Z}_{1:k}^W)$, $\forall j, h, i$ (eq. (7)) and any APs.
 - 5) Update $\Pr(\mathbf{W}_h = h_h^t | \mathbf{P}_{0:k}^i, \mathbf{Z}_{1:k}^W)$, $\forall i, h$, following eq. (6) for any APs and normalize.
 - 6) Resampling can be performed if required.

III. EXPERIMENTS WITH REAL DATA

Extensive real data measurements were carried out to validate our algorithm in an indoor area sized about 20×40 m and occupied by offices (refer to Fig. 4). We used a laptop equipped with an internal network device Link 5100, compliant with IEEE 802.11 a/b/g, and carried by a human operator. We employed one AP (green square in Fig. 4), which was a Cisco Aironet 1130 also IEEE 802.11 a/b/g compliant. Nevertheless, a previous statistical analysis led us to avoid the 802.11.a standard because at higher frequencies the effects of walls are pronounced. To test a realistic scenario we took 10 datasets relative to the same path during office hours, with the AP fully operative. Finally, all the processings and graphs were made off-line.

In the first experiment we try just to map the AP, taking note of the actual user's positions. The reference signal strength is estimated like in Sect. II-D, considering 7 values in the range $[-35, -5]$ dB (5 dB spaced), while the standard deviation is set to 5 dB. In Fig. 3.a we see that the \mathbf{W} pdf after the first RSS, depicted on the floor map is very spread, due to the mixture of several donut-shaped pdf, and only at $k = 5$ a better resolution is shown (Fig. 3.b). Interestingly, after the first turn some ambiguity holds (Fig. 3.c), and a second turn is required (Fig. 3.d-e). The reason for this is visible in Fig. 3.f, where the corresponding h_h^t probabilities are presented: the mapping is well performed when a likely reference strength (in this case -25 dB) wins over the others (about $k = 10$ steps). This is the price paid for the \mathbf{h} estimation.

Mapping is just a crucial part of SLAM, but not the only one. Our final goal is to show that RSS measures are able to distinguish between the real user's path from a competing one, affected by the heading error typical of odometry. As a figure of merit we use the product of the weights I_W over time, normalized for simplicity. The results are averaged on all the

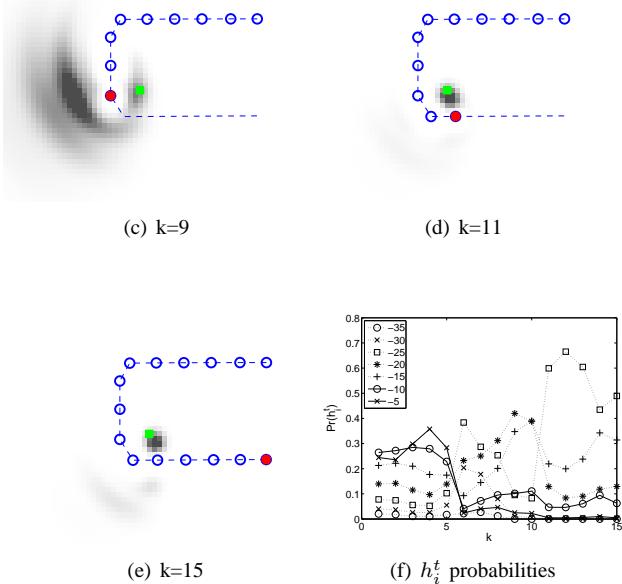
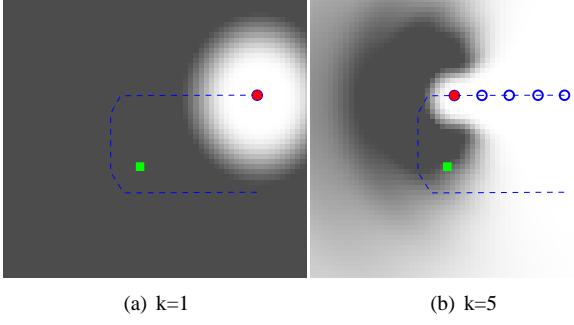


Fig. 3. Mapping: real data collected during a walk are employed to map the AP's position (a-e) and reference signal strength (f). For the meaning of the symbols see Fig. 2. The testbed is the one depicted in Fig. 4 and is here omitted for clearness.

datasets available. As an example, in Fig. 4 two competing paths (the right path is in blue with circles) are depicted along with the AP's position, and in Fig. 5 the I_W products are shown for both, highlighting the capability of our algorithm to discriminate between the two paths after few steps. In detail, the wrong path will affect the accuracy in the AP mapping, yielding lower weights. Of course the use of more APs is expected to further improve WiSLAM performance, even if such experiments are here omitted for space reasons.

IV. CONCLUSIONS & OUTLOOK FOR FINAL PAPER

We have developed a new algorithm, improving FootSLAM with RSS measures available in a WiFi network. Preliminary analysis shows the potential of our solution in improving FootSLAM. Of course, implementation of WiSLAM algorithm will let us quantify its benefits. Moreover, mismatches between real data and the model we adopt are being studied: both prefiltering, aimed at eliminating outliers, and more elaborated propagation models will be proposed in the final paper.

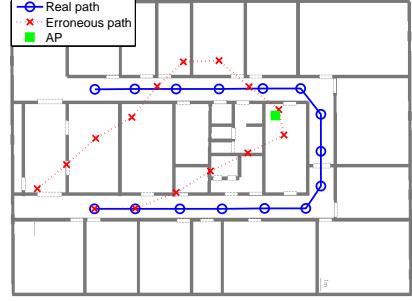


Fig. 4. Testbed for our experiments with the AP's position (green square) and two competing paths for SLAM (in blue continuous line the right path).

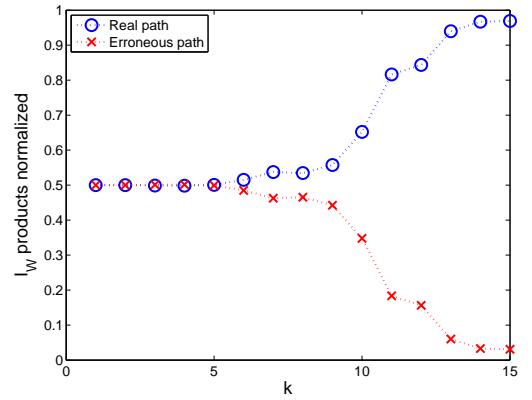


Fig. 5. Competing paths: products (normalized) of the I_W terms for both paths in Fig. 4, averaged on ten datasets. The line related to the real path is continuous with blue circles.

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