Joint Estimation of Indoor Position and Orientation from RF Signal Strength Measurements

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***Abstract*—In personal indoor guidance and navigation applications, it is desirable to determine both the user's position and spatial orientation, since this enables to provide him with directions in a more natural way. The common method for estimation of orientation uses the magnetic compass included in numerous portable devices; this approach becomes unreliable when the device's own orientation relative to the user is unknown, or if the environment contains metallic structures which disturb the magnetic field. In this work we propose an alternative approach for estimation of personal position and orientation which requires no additional sensors and is based solely in the attenuation of radiofrequency signal strength (RSS) introduced by the user's own body. The physical system consists in a set of emitting RF nodes located at known positions in the environment, and two RF receivers placed in the front and back parts of the user's body (alternatively, a single receiver with two antennas). We show how the position of the user can be inferred from the average received signal strength, while his orientation is estimated from the difference of signal strengths from the two receivers, by adapting two commonly used techniques in indoor localization: least-squares minimization and Bayesian filters. We have validated experimentally both techniques with an RFID-based localization system arranged in a typical building, showing that orientation can be determined with a mean error of 0.3 radians, sufficient for most applications.**

I. Introduction

It is well established that the position of a person in indoor environments can be estimated from the Received Signal Strength (RSS) of radiofrequency (RF) emitters placed at known positions in the environment [1], [2]. The typical positioning accuracy lies in the range of 1 to 3 meters, depending on the characteristics of the environment, and the density of RF beacons.

While most of the research in indoor positioning concentrates in determining the position of the user, the estimation of his or her spatial orientation is also important; for example, in guidance systems it permits to transmit directions to the user in a natural way. If the user is moving in a decided manner, the orientation can be produced from the heading of his deduced trajectory. However, due to the uncertainty inherent to RSS-based positioning, orientation estimates produced in this way tend to be noisy. Furthermore, this simple method does not work if the user is standing still or walking in an erratic manner.

For positioning methods based in dead reckoning, the use of the magnetometer readings from the inertial motion unit worn by the user gives his spatial orientation in an absolute frame reference [3]. This method, however, requires an additional sensor, and is subject to local magnetic perturbations caused by large metallic objects, power lines, etc, present in some buildings.

The impact of the user's spatial orientation on the estimation of position was noted right away in the first works on RF RSS-based localization systems [4]. Variations of the signal strength of up to 5 dBm caused by the body, led to a "fairly significant degradation in the accuracy of location estimation". For fingerprinting-based approaches to localization, other researchers [5] found that particular body orientations caused a large drop in RSS from a given RF transmitter, making it go undetected, and producing large positioning errors. The conclusion of these authors was that the orientation of the user should be taken into account in the calibration process.

The influence of body orientation on RF signal attenuation depends mostly on its frequency. It is most perceptible at the typical 2.4 GHz band used in wifi systems, since this corresponds with the resonance of the water molecules which comprise a large part of the human body. The effect is less notorious, but perceptible, at lower frequencies. The attenuation introduced by the body in several frequency bands has been quantified in [6] both through computer simulations and experimental tests; the RSS drop is up to 19 dB in the 2.4 GHz band, and descends to 13 dB at 900 MHz, the lowest frequency studied. These results are translated through simulations to ranging errors equivalent to a few meters. For handheld devices like smartphones, the grip of the hand can produce signal attenuations of the same order as those caused by blocking by the body, as shown in [7].

Although in principle the user could carry the RF signals receiver (or emitter) in a way such that his spatial orientation became irrelevant (for example, the top of his head, or carried in a pole), such arrangements are not practical in real world usage.

At the present, the most popular way to tackle the problem of mitigating the effect of body orientation on positioning accuracy is through fingerprinting methods. This approach consists in producing RSS fingerprints at the sample positions with a number of fixed orientations (usually four) during the calibration stage. At estimation, the system uses an onboard digital compass to measure the body orientation and select the convenient fingerprint(s). Variants of this technique are found in references [8], [9], [10], employing either a laptop computer with an external magnetometer, or a smartphone

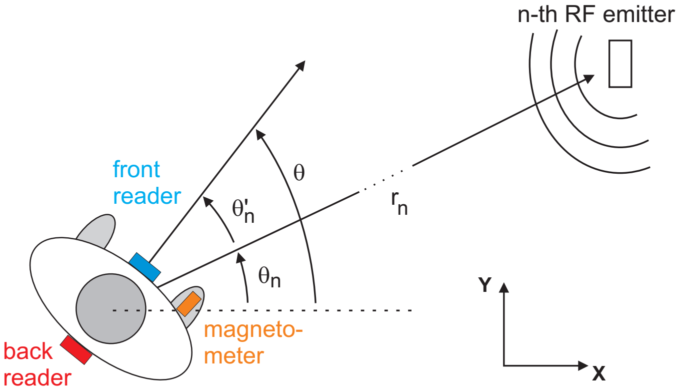

Fig. 1. Problem setup: a user receives an RF signal from an emitter with two readers placed in his front and back sides, and estimates its absolute angular orientation (θ).

with the embedded magnetic compass. The reported accuracy improvements (with respect to disregarding the user's orientation) lie between 10-30 %, at the expense of prolonging the calibration stage.

As has been shown in this brief introduction, the current point of view seems to be that the body orientation of the user is a disturbing factor in the process of estimating his position, to be compensated by using more sophisticated positioning techniques. We propose an alternative approach, in which personal position and orientation are jointly estimated, precisely by employing the RSS attenuation introduced by the human body on the RF positioning signals.

This work is organized as follows: section II introduces measurement models for the estimation of position and orientation in both least-squares minimization and Bayesian approaches. Section III describes the experimental setup and the calibration process of the system, while section IV offers the experimental results on static and dynamic situations. Some final conclusions are given in section V.

II. Measurement models for the estimation of orientation

The main idea of this work is to use the attenuation caused by the human body on the RF signals propagating through it, to estimate the absolute orientation of a person. The setup for this purpose is shown in figure 1, where the person is wearing two RF readers, one in his front part and other in the back. The differential RSS of the signals coming from a given RF emitter, as measured by the two readers, depends on the relative angle θ'_n between his spatial orientation and the line that connects the positions of the person and the n-th RF emitter.

We will provide a method for producing orientation estimates for two common techniques used in indoor positioning: least squares minimization and Bayesian positioning [11]. Orientation estimation techniques for fingerprinting-based localization have already been offered in the works cited in section I.

In both cases, we will consider that the person to be located stands at absolute position (x, y), with absolute angular orientation θ with respect to some reference frame, and that, in a given time interval, he is able to detect a number N of RF emitters placed at known positions (x_n, y_n) through his front and back RF readers, producing signal strength measurements $(\mathrm{RSS}_n^{\mathrm{front}}, \mathrm{RSS}_n^{\mathrm{back}})$, respectively.

A. *Least squares-based model for orientation*

The least squares model for joint estimation of position and orientation builds on the well known log path-loss law that models generically the received signal strength from an RF emitter in indoor environments [12]:

$$\mathrm{RSS}^{\mathrm{PL}}(r_n) = \mathrm{RSS}_0 - 10\alpha \log_{10} \frac{r_n}{r_0} + e, \tag{1}$$

where $r_n^2 = (x - x_n)^2 + (y - y_n)^2$ is the distance between the n-th RF emitter and the person, $\mathrm{RSS}_n^{\mathrm{PL}}$ is the signal strength in logarithmic scale (measured in dBm), r_0 is a reference distance at which the signal strength equals RSS_0, and the loss exponent α depends on the environment and is determined empirically. The term e is a random variable which takes into account statistical fluctuations in the signal strength caused by multipath propagation, presence of obstacles, etc; it is usually assumed to follow a normal distribution with zero mean and variance σ_n^2.

During the calibration stage where parameters RSS_0 and α are fitted to the experimental data, the orientation between the RF emitter and the current position is usually either disregarded, or averaged over several random orientations. In consequence, equation 1, as commonly used in indoor localization problems, does not contain any reference to the spatial orientation θ of the user.

We propose to include the effect of orientation on the received signal strength by adding a correction term to equation 1, such as:

$$\mathrm{RSS}^{\mathrm{PL}}(r_n, \theta'_n) = \mathrm{RSS}^{\mathrm{PL}}(r_n) + \mathrm{RSS}^{\mathrm{PL}}(\theta'_n), \tag{2}$$

with

$$\mathrm{RSS}^{\mathrm{PL}}(\theta'_n) = \mathrm{RSS}_1 \left(1 - \frac{2|\theta'_n|}{\pi}\right), \tag{3}$$

with $\theta'_n = \theta - \theta_n$ being the relative angle between the absolute orientation of the person (θ) and the line that connects receiver to emitter ($\theta_n = \angle(x_n - x, y_n - y)$), and RSS_1 an empirically determined constant which stands for the RF strength shadowing provided by the human body. For simplicity, we have assumed that deviations of the RSS from the ideal PL law are linear with relative angle θ'_n.

The dependence of signal strength and angle of equation 3 is symmetric about the line that connects the user's current position with the RF emitter (i.e., θ'_n can only be determined in the range $(0, \pi)$). When the angle θ'_n is converted from a relative to absolute value and measurements from two or three different beacons are combined, this ambiguity is resolved.

Following this, we can build the cost function that permits to estimate position and orientation simultaneously as:

$$
F(x,y,\theta) = \\
\sum_n \left[\mathrm{RSS}_n^{\text{front}} - \mathrm{RSS}_0 + 10\alpha\log_{10} r_n - \mathrm{RSS}_1 (1 - \frac{2|\theta'_n|}{\pi}) \right]^2 + \\
\sum_n \left[\mathrm{RSS}_n^{\text{back}} - \mathrm{RSS}_0 + 10\alpha\log_{10} r_n + \mathrm{RSS}_1 (1 - \frac{2|\theta'_n|}{\pi}) \right]^2 , \tag{4}
$$

where the index n runs over all detected RF emitters. The least squares estimate of position and orientation is the set $(\widehat{x}_{\mathrm{LS}}, \widehat{y}_{\mathrm{LS}}, \widehat{\theta}_{\mathrm{LS}})$ which minimizes $F(x,y,\theta)$. Conventional Gauss-Newton or Levenberg-Marquardt methods [11] can be used for that purpose.

As we will see empirically in section III, the term RSS_1 is relatively small with respect to typical RSS values; therefore, estimation of position $(\widehat{x}_{\mathrm{LS}}, \widehat{y}_{\mathrm{LS}})$ is not largely affected by the orientation-dependent terms. However, differences between $\mathrm{RSS}_n^{\text{front}}$ and $\mathrm{RSS}_n^{\text{back}}$, even if relatively small, give significant information on the angle θ.

B. Bayesian model for estimation of orientation

Bayesian models are powerful and flexible and are amongst the most popular techniques for indoor position estimation [13]. We have previously used Bayesian estimation of indoor position (without orientation), as reported in [14]. Here we present an extension of such models to include a Bayesian estimate of orientation which is the equivalent of the one shown in section II-A.

Consider the event z_n defined as the detection of the RF signal from the n-th emitter by the readers carried by the user, in the setup of figure 1. The following three mutually exclusive events are possible: the RF emitter is detected by the front reader only, is detected by the back reader only, or is detected by both. Assuming that the probability of each event is dependent only on the relative angle θ'_n between the absolute orientation of the body and the line between him and the RF emitter, a Bayesian model for an RF detection can be posed as:

$$
p(z_n \,|\, \theta'_n) = \begin{cases} p(\text{front reader only} \,|\, \theta'_n) \\ p(\text{back reader only} \,|\, \theta'_n) \\ p(\text{both readers} \,|\, \theta'_n) \cdot p(\Delta\mathrm{RSS}_n \,|\, \theta'_n), \end{cases} \tag{5}
$$

where $\Delta\mathrm{RSS}_n = \mathrm{RSS}_n^{\text{front}} - \mathrm{RSS}_n^{\text{back}}$. Adding up the events from all detected emitters, the maximum likelihood estimation of absolute orientation θ is given as:

$$
\widehat{\theta}_{\mathrm{MLE}} = \arg\max L(\theta \,|\, z_1, \ldots, z_N), \tag{6}
$$

where the likelihood L, considering conditional independence, is given as:

$$
L(\theta \,|\, z_1, \ldots, z_N) = \prod_n p(z_n \,|\, \theta'_n), \tag{7}
$$

and index n runs over all detected emitters. Note that, given the implicit relationship with position (x,y) of relative angle θ', both position and orientation should be jointly estimated in a rigorous Bayesian treatment. However, in practice we have found that it is possible to decouple the problem and use a range-based RSS positioning model $p(\mathrm{RSS}|r_n)$ [14] with the averaged value of signal strengths, $(\mathrm{RSS}_n^{\text{front}} + \mathrm{RSS}_n^{\text{back}})/2$, to produce an estimate of position $(\widehat{x}, \widehat{y})$ and then use maximization of the likelihood in equation 6 to estimate the orientation.

III. Experimental setup and calibration

This section discusses the experimental device, the process of gathering RSS calibration data, and the creation of the least-squares minimization and Bayesian models.

A. Experimental device

Empirical tests are carried out with an indoor localization system based on active radiofrequency identification (RFID) technology, as described in previous works [14], [15]. The advantages of RFID technology are its low cost and maintenance requirements and ease of deployment, achieving a large covered area in a simple way.

In our system, a total of 71 active tags (model M100 from RFCode) are deployed 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). Positioning is also possible in outer areas surrounding our building, but accuracy is degraded. The tags are factory set to emit their identification code every second, and the RF digital signals are modulated at 433 MHz.

The user carries two RFCode model M220 portable readers in his belt clip (one in front of him and another in the back), equipped with two 1/4 wave articulated helical antennas each. The readers decode the RF message transmitted by tags and, for every detection event, report the tag ID, the average measured RSS at both antennas and a timestamp to a Android-based mobile phone through a Bluetooth link.

Additionally, the user also carries an Xsens inertial motion unit, model MTi placed in his right foot. This sensor provides three-axis accelerometer, gyroscope and magnetometer readings to the recording device through a USB bus at a frequency of 100 Hz, and is used in this work for estimating the absolute spatial orientation of the user [3].

Data collection and processing are done in the Matlab environment.

B. Calibration data

To gather the RSS calibration data, a person stood at 12 different points in our building, facing for 20 s in each of 4 orthogonal directions, and collecting RSS signals from all detected RFID tags through both front and back readers. In total, 30,700 different tag detections were collected, and the whole calibration process took about 20 minutes, including noting down the calibration positions, and saving the data. Results at one sample position are shown in figure 2. The values for $|\mathrm{RSS}_n^{\text{front}}$ and $\mathrm{RSS}_n^{\text{back}}|$ correspond to the averaged values over all readings in each time interval.

C. Empirical results for the LS model for orientation

Figure 3 shows the log path loss law (Eq. 1) fitted to the experimental data, and disregarding the spatial orientation.

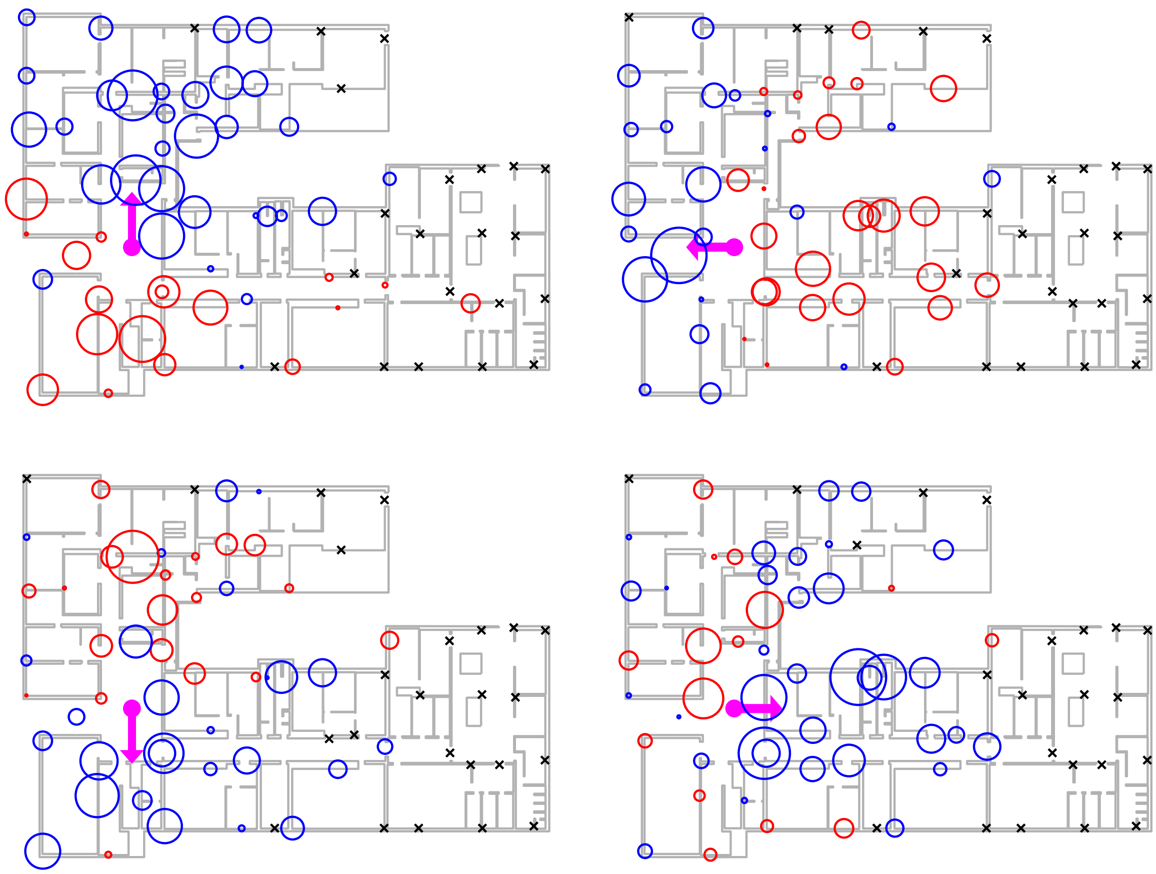

Fig. 2. Representation of calibration results when the user stands at one particular point (magenta full circle) with four different orientations (magenta arrows). The open circles represent the position of the tags and their sizes are proportional to the difference $|\mathrm{RSS}_n^{\mathrm{front}} - \mathrm{RSS}_n^{\mathrm{back}}|$; they are coloured blue if the signal from the front reader is stronger, and red otherwise. Undetected tags are plotted as small black crosses.

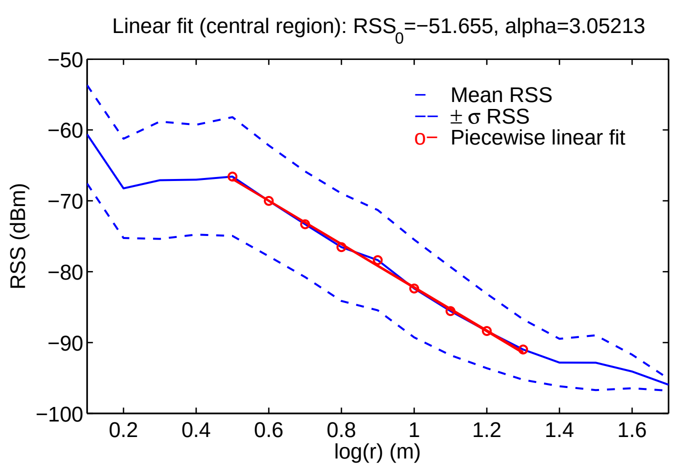

Fig. 3. Path loss law for for the calibration data of section III-B, without considering orientation.

The experimentally determined values of RSS_0 and α are -51.7 dBm and 3.05 dBm, respectively.

The data for $\mathrm{RSS}^{\mathrm{PL}}(\theta')$ of Eq. 3 is obtained by subtracting from the experimental RSS data the path loss law model results from figure 3, leaving the angle-dependent data of figure 4. $\mathrm{RSS}^{\mathrm{PL}}(\theta')$ is modeled as a Gaussian variable:

$$\mathrm{RSS}^{\mathrm{PL}}(\theta') = \mathcal{N}(\mathrm{RSS}; \mu_{\mathrm{RSS}}(\theta'), \sigma^2_{\mathrm{RSS}}(\theta')),$$

where the slope of $\mu_{\mathrm{RSS}}(\theta')$ is about -1.7 dBm/rad, the maximum swing from 0 to π radians is $2 \cdot \mathrm{RSS}_1 = 5.3$ dBm, and $\sigma_{\mathrm{RSS}}(\theta') \simeq 6.6$ dBm.

D. Empirical results for the Bayesian model for orientation

The results of the Bayesian model for the detection probability and the ΔRSS are shown in figures 5 and 6, respectively. Figure 5 shows that it's most likely that both readers detect a given tag (73% of events) than only the front (16%) or the back (11%) do it (the difference between these last two probabilities might be due to unequal receiver sensitivities). As expected, probability $p(\text{front reader only} \,|\, \theta')$ is maximum at $\theta' = 0$ and $p(\text{back reader only} \,|\, \theta')$ at $\theta' = \pi$, and both are approximately symmetrical with respect to $\theta' = \frac{\pi}{2}$. With respect to ΔRSS, it shows an approximate linear dependence with relative angle θ': the slope is about -3.7 dBm/rad, and the maximum swing is 11.6 dBm from 0 to π radians, which is approximately twice as large as that of the LS model, as expected. The standard deviation of the difference of RSS values is $\sigma_{\Delta\mathrm{RSS}} = 6.4$ dBm.

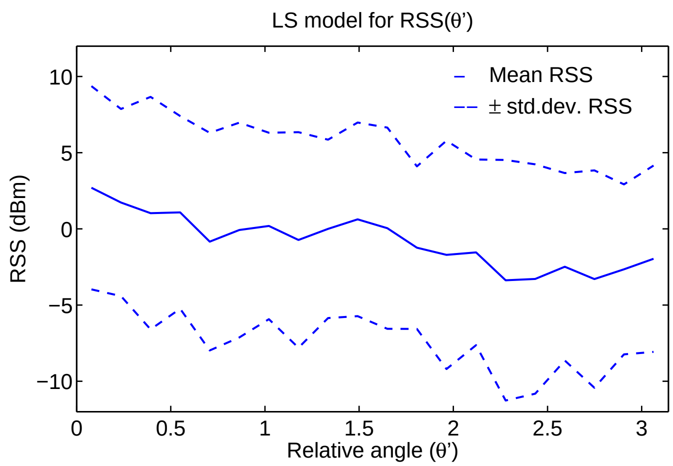

Fig. 4. Least squares model for the term $\text{RSS}^{\text{PL}}(\theta')$ of Eq. 3, obtained from the calibration data.

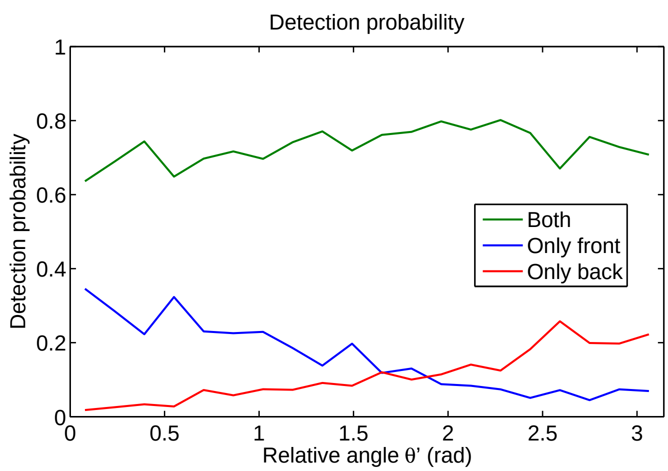

Fig. 5. Bayesian model for the detection probability of a given tag by the front, back, or both, antennas.

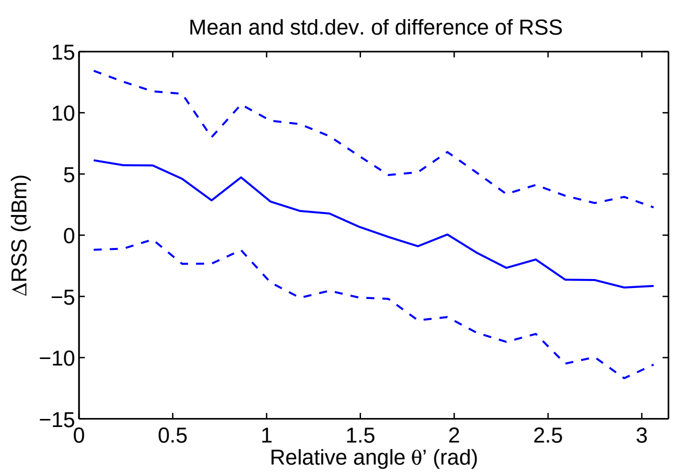

Fig. 6. Bayesian model for the ΔRSS probability of a given tag between the front and back antennas.

IV. Estimation of Personal Orientation in Static and Dynamic Situations

In this section we will carry some experimental tests to determine the spatial orientation of a person with the setup described previously.

A. *Estimation of orientation in static positions*

The effect of body orientation on the position estimates is shown in figure 7, where the user stands at a given point in the entrance hall, but changes his orientation to four different directions (the same ones used in the calibration process). Position estimates are produced by ordinary least squares minimization with Eq. 1 from the RSS readings received in intervals of one second, by a single RF reader in the front part of his body. The results of the estimated position, shown in part (a), appear as if the user was in four different positions, which are separated up to 7 m. Besides showing a systematic error of 1.7 m, the area of the 90% confidence ellipse is 38.5 m^2 (we have chosen this as a particularly bad case of body orientation-induced positioning error). Positioning results using only the back reader are similar (part (b)), with a confidence ellipse of area 20.2 m^2. This is the effect noted by previous researchers mentioned in section I [4], [5] and that greatly degrades position estimates.

In part (c) we combine measurements from the front and back readers, which leads to a lower variance in the estimate of position (area of confidence ellipse: 4.0 m^2). This is due both to the compensating effect of a second reader over the body orientation, and of averaging twice as many RSS readings as in cases (a) and (b). Figure 8 shows that the absolute orientation of the user can be reliably estimated alongside with his position. Some orientation offsets between the magnetometer and the RFID-based estimations are perceptible; they are caused because the foot carrying the magnetometer was not perfectly aligned with the frontal direction of the user.

Note that, although the LS minimization method reduces the variance of the estimates of position by considering orientation, it is not enough by itself to eliminate systematic bias error in position.

Estimates of orientation are not limited to the four discrete orientations considered in the calibration. Indeed, orientation can be computed in much finer detail, as shown in the example of figure 9, where a person was standing at a fixed position and turning around himself in CCW direction at an angular speed of about 0.19 rad/s.

As we can see from the results in this section, similar results are obtained with the least squares minimization method (section II-A) and the Bayesian method (section II-B), although this last version seems to be more robust to large errors in orientation estimation.

B. *Estimation of orientation in trajectories*

Estimates of instantaneous orientation can also be produced when the user is not static. Figure 10 and table I show the results for a couple of sample trajectories.

The first route is an L-shaped trajectory along the longest corridors in our building, it is traversed 3 times at a mean speed of 1.2 m/s (total length: 436 m in 350 s). Both the user's position and orientation are successfully tracked along the route, with a median error of 0.1-0.24 radians, depending on the method. The second route is a closed-loop trajectory, in which the user traverses several rooms and even part of

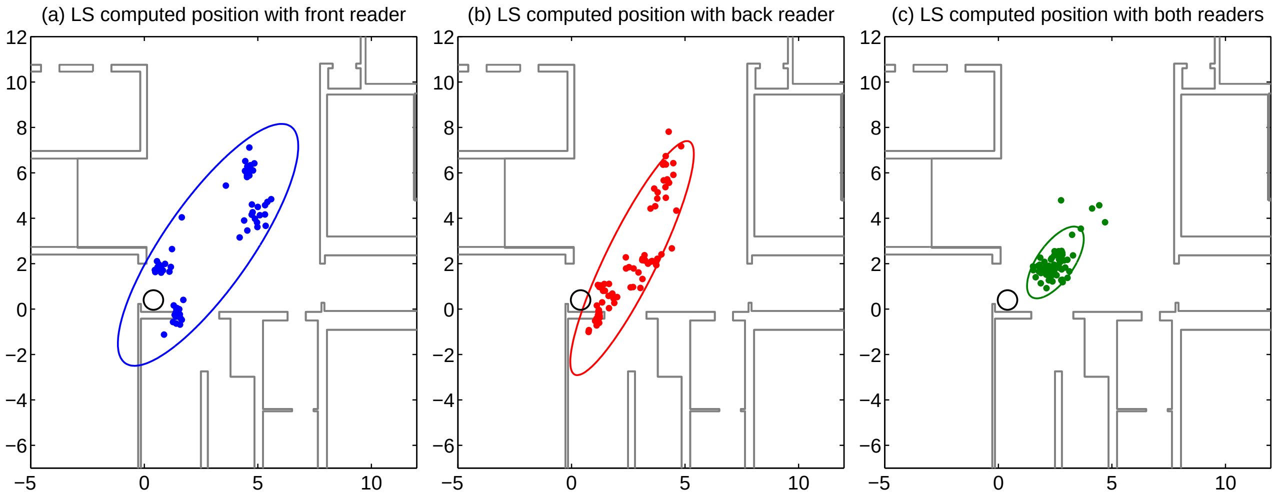

Fig. 7. The effect of orientation on the estimation of position, with only the front reader (a), the back reader (b), and both (c).

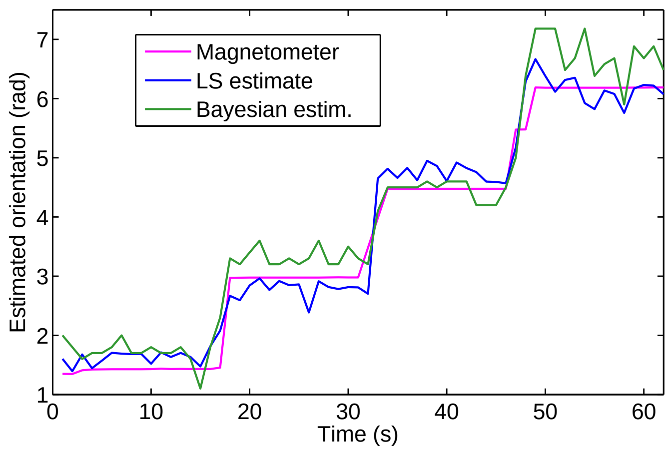

Fig. 8. Least squares- and Bayesian-based estimates of absolute orientation in the static setup described in part (c) of figure 7, compared with a foot-mounted magnetometer's readings.

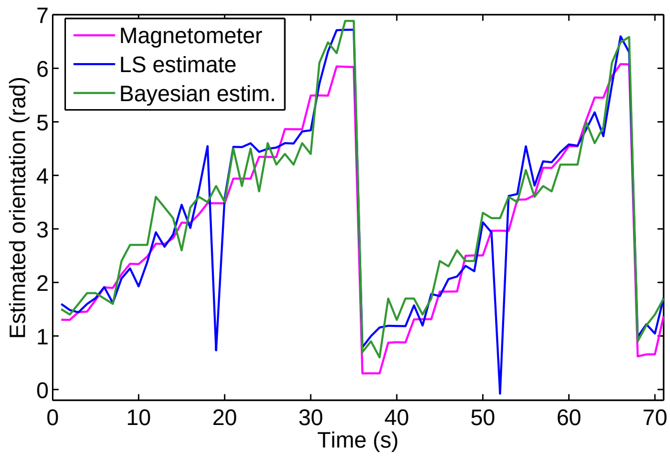

Fig. 9. A user turning around himself in counter-clockwise direction, at about 0.19 rad/s, and the estimated orientation by least squares minimization and the Bayesian method, compared with actual foot-mounted magnetometer readings.

TABLE I. ANGULAR ORIENTATION ERROR FOR THE SAMPLE TRAJECTORIES REPORTED IN FIG. 10.

Method	Angular error (radians)		
	Mean	Median	90%
Trajectory 1, length: 436 m, mean speed: 1.2 m/s			
Magnetometer	0.27	0.20	0.47
Least squares minimization	0.24	0.07	0.51
Bayesian estimation	0.37	0.26	0.71
Trajectory 2, length: 607 m, mean speed: 1.5 m/s			
Magnetometer	0.46	0.36	0.98
Least squares minimization	0.46	0.22	1.18
Bayesian estimation	0.44	0.30	0.97

the outside of the building (four loops). While position is successfully produced, there are some rather large error peaks in the estimation of orientation. They are mainly due to the dynamic response of the least squares or Bayesian filters, which in sharp turns of direction have trouble adapting to the trajectory fast enough (the trajectories have been performed at quite high walking speeds). Thus the limitation in the estimate of orientation is currently caused by the dynamic response of the filters.

Fig. 11 shows the cumulative distribution function (CDF) of the angular estimation error, in the dynamic setup described in this section. It is seen that both methods produce reliable estimates of orientation which improve slightly on the capability of the magnetometer found in the inertial sensor, although this sensor provides higher immunity against large errors on the orientation.

C. CDF of angular error and influence of the number of RF emitters

The results presented so far have been obtained with a rather large number of emitting RF nodes. Although the relatively low cost RFID technology permits to achieve high emitter densities in indoor experiments, other common setups for RF/RSS-based position estimation utilize wifi access points, where high nodes density is not feasible. Then, it is natural to discuss the question of how many independent RF nodes are necessary for reliable estimation of personal orientation. In Fig. 12 we have repeated the sample trajectories of section IV-B, and removed a set of RF emitters from the

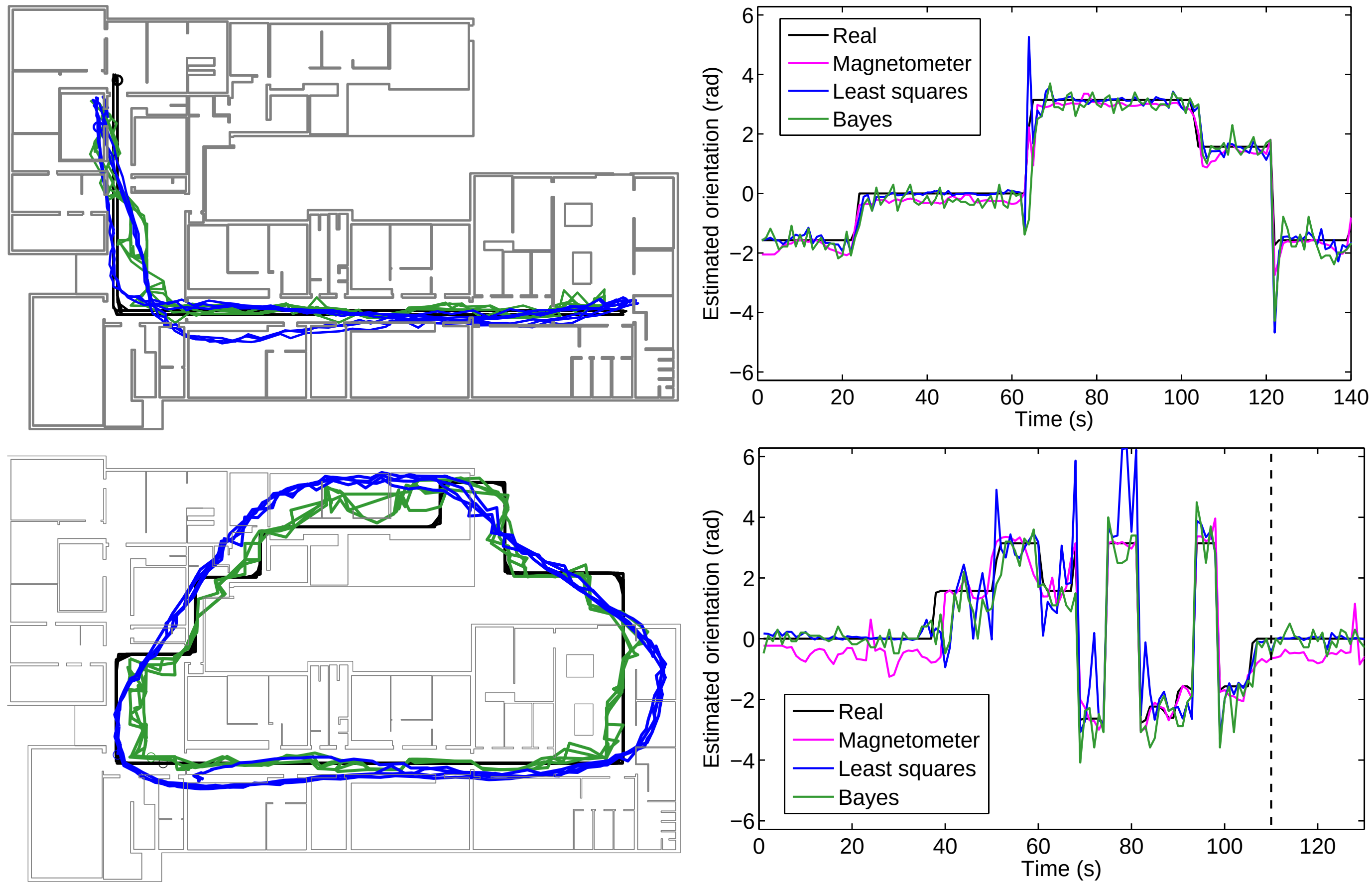

Fig. 10. Left column: two sample trajectories in our building; right column: absolute orientation determined from the heading of the trajectory, the magnetometer carried by the user, and by least-squares and Bayesian estimation (only one complete turn of each trajectory is shown).

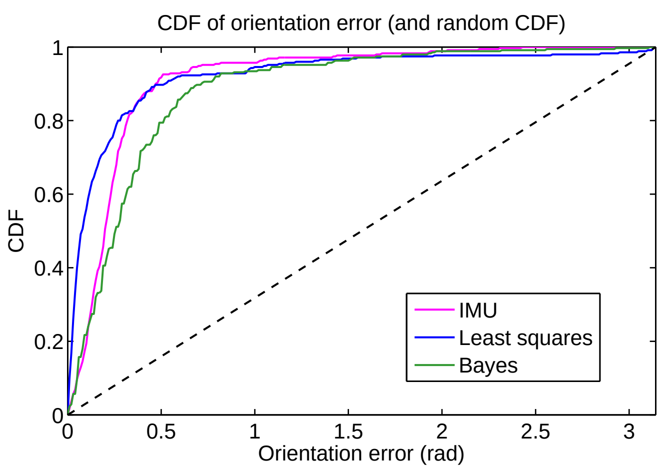

Fig. 11. CDF of angular error, as measured with the magnetometer, and computed through the least squares minimization and Bayesian estimation methods. The discontinuous line corresponds to the CDF of a purely random estimate of orientation.

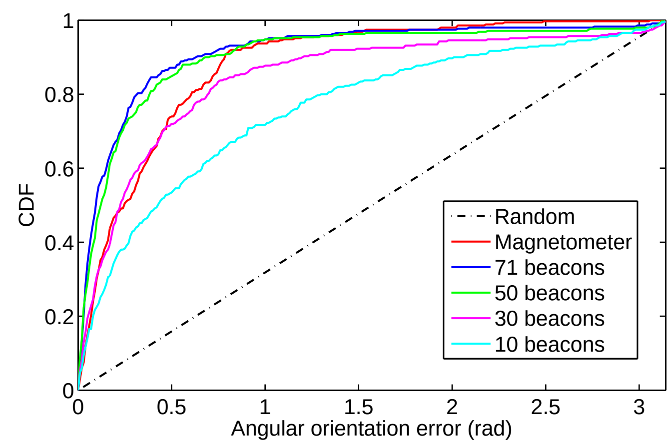

Fig. 12. CDF of angular error in dynamic trajectories versus number of active RF nodes.

total number of 71 RFID tags. It is seen that accuracy is degraded as the number of RF nodes diminishes, but even with less than half the nodes we obtain a similar result than the magnetometer sensor, and with only 10 RFID tags, the mean angular error is 0.75 radians (and 2.0 rad for 90% of measurements). We can conclude that the proposed methods are relatively robust in this sense.

V. Conclusions

In indoor positioning systems based on RF signal strength measurements, which are the vast majority, the attenuation of RF signals caused by the body of the user is generally regarded as a disturbing factor which degrades the positioning process. In this work we propose to utilize the RSS attenuation introduced by the body, with a set of two readers or antennas placed in the front and back part of his body, and estimate his spatial orientation along with his spatial position.

We introduce two techniques for estimation of orientation, valid for RSS least-squares minimization and Bayesian methods, respectively, and show experimentally that they produce reliable estimates of orientation in our building, with an RFID-based positioning system. Our results show a mean angular accuracy of 0.3 radians (0.7 radians for 90 % of cases) in both static or dynamic conditions.

The estimation techniques proposed work equally well whether the user is standing still or walking, and, unlike magnetometer-based estimations, are not affected by local magnetic field perturbations. Likewise, when compared to fingerprint-based approaches to orientation estimation, the method proposed in this communication shows a large reduction on the calibration times required before system operation.

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