RSSI localisation with sensors placed on the user

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***Abstract*—We examine the indoor single-room localisation problem while using multiple fixed transmitters (anchors) and multiple mobile receivers placed on the user (mobiles). Anchors transmit a periodic beacon that the mobiles receive and of which they measure the received power level value (RSSI). Using this information only, which requires no specialised hardware, the mobiles estimate the position and orientation of the user. Many methods have been proposed to tackle this problem. In this paper we describe a purely theoretical procedure that aims to evaluate the maximum attainable performance of any real methods using RSSI for localisation purpose. Our analysis we present is based on a fine grid of RSSI values in a room, which are computed via ray-tracing, and a maximum-likelihood approach to localisation. Here we illustrate the performance gains of using multiple mobiles versus using a single one and and the attainable performance of user orientation estimation.**

I. INTRODUCTION

The presence of prospective high number of wireless transmitters in indoor spaces has motivated researchers to investigate whether their built-in received signal strength indicator (RSSI) could be exploited to gain information on the relative position of a receiver with respect to a number of transmitters. For this reason the RSSI range-based localisation systems that use inexpensive, non-dedicated wireless devices have gathered great attention in the last years. Even though RSSI meters are not built to this end, but rather to give information to the higher communication protocol layers about the status of the communication link, their usage is highly attractive, because the information they give is obtained almost “for free”. As a consequence, many studies exist which, analytically, through simulations or through real measurements, analyse how a mobile can use RSSI relative to multiple wireless transmitters (*anchors*) to compute its position [1], [2]. This approach is popular because no additional hardware is required on the nodes for localisation. In [3] the authors find that range-based methods (such as RSSI-based approaches) perform better than connection-based ones under a given set of conditions. We find that these conclusions are also consistent with the results sketched in our preliminary work [4].

The basic idea in RSSI-based localisation is to compare the measured RSSI values to a model of RSSI for each position and then identify the position that gives the best match. The two most common models are the path loss model and the dedicated power map. The *path loss model* models the RSSI value in dB as a linearly decreasing function of transmitter-receiver distance. This method suffers from high ambient noise level and from multi-path effects, particularly when there is no line of sight between transmitter and receiver. The *dedicated power map model* requires to know the RSSI values in a number of points scattered in the environment and save these in a database (i.e. a map). This can be done using an off-line measurement campaign or by simulating the environment with one of several techniques (e.g. ray-tracing [4]). The set of RSSI values that are collected for each position in the map from various anchors is called a *fingerprint* of that position, and the method is also known as *fingerprinting*. Fingerprinting methods usually provide better performance than path loss model-based methods [5], [6], [7], [8].

In this paper we concentrate on evaluating what is the maximum attainable performance of a practical localisation method in a given environment. In order to provide this result, we start form a detailed two-dimensional map of an office room obtained with a 3-D ray-tracing program. The map is based on a 3 cm square grid at a height of 90 cm from the floor. The room is approximately 5 m by 7 m and contains three pieces of furniture: a low cabinet, a high cabinet and a blackboard. The map provides the RSSI measured in each node of the grid by a vertical dipole antenna. On the walls and ceiling of the room 18 transmitters are placed in different points and with various dipole antenna orientations. We assume that the receiver has a positioning standard error of 10 cm, an orientation standard error of 0.3 radians and a standard error on received power of 2 dB, all errors are Gaussian. We then place the receiver on a given position and orientation and read from the map what is the RSSI it gets from each of the anchors. More precisely, we read (with a received power error) the RSSI it receives from each of the anchor as if it were placed at a position and orientation equal to actual one plus a positioning and orientation error. Using the RSSI readings, we then evaluate the position of the mobile using a maximum-likelihood technique. We claim that the average performance of this procedure (which is too complex to be practically usable as a real localisation method) is a lower bound on the error attainable by any real localisation method [4].

The contribution of this paper with respect to our previous work is that here we evaluate how much the lower error bound on position estimation is improved when we place multiple receivers on the mobile. Also, we evaluate the attainable precision of orientation estimation, something that can only

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be done when using multiple receivers. As we just said, this study does not lend itself to practical implementation of a localisation method, but rather provides insight into performance assessment by using either one or more sensor nodes placed on the user. In other words, this study aims at answering the following questions: *How does the localisation performance increase by using multiple sensors placed on the user?* and *Is it possible to estimate the direction where the user is facing?* We answer these questions by comparing configurations with one to five sensors on the mobile. We present our simulation results along with remarks on Wireless Sensor Networks (WSNs), which is the illustrative case study for this research. However, the qualitative results of our study should equally apply to other types of networks since the proposed approach meet the requirements of most location-dependent applications.

This paper is organised as follows. Section II recalls the main localisation systems, the maximum-likelihood procedure is summarised in Section III. Its performance is illustrated in Section IV. Conclusions are drawn in Section V.

II. Related work

Many of the indoor positioning systems proposed in the last years extract the location-dependent parameters such as time of arrival, time difference of arrival and angle of arrival [9] from the received radio signal transmitted by the mobile station. Such measurement needs to be estimated accurately and it requires line of sight between the transmitter and the receiver. Furthermore, it requires specialised and generally expensive hardware integrated into the sensor communications equipment. Because of these reasons and because of the ever more widespread deployments of WLAN infrastructures and the fact that RSSI readings are available in all wireless interfaces, RSSI-based positioning system promise to be a cheaper solution.

The fingerprinting based RSSI approach is one of the most widely found in the literature [5], [6], [7], [8]. Fingerprints are generated during an off-line calibration phase where RSSI data is collected at a set of training locations. The most challenging aspect of the fingerprinting based methods is to formulate a distance calculation that can measure similarity between the observed RSSI and the known RSSI fingerprints. Various machine learning techniques can be applied to the location estimation problem [10]. Probabilistic method [11], k-nearest-neighbour [5], neural networks [12], and support vector machines [7] are popular positioning techniques based on the location fingerprinting.

Euclidean distance based calculation has been used in [13] to measure the minimum distance between the observed RSSI and the mean of the fingerprints collected at each training point. RADAR [5] uses a k-nearest-neighbours method in order to find the closest match between fingerprints and RSSI observation. Recently, research efforts have concentrated on developing a better distance measure that can take into account the variability of the RSSI training vectors. These methods estimate probability density for the training RSSI and then compute likelihood/a posteriori estimates during the tracking phase using the observed RSSI and the estimated densities [6]. User localisation is performed using a maximum-likelihood (ML) or maximum a posteriori (MAP) estimate of position. Kernel canonical correlation analysis [8] is used to construct a more accurate mapping function between RSSI and radio map. Although these recent developments improve position estimates compared to simple k-nearest-neighbours, they often require a larger training set and greater computational resources. Chai [14] proposes a learning-based approach to reducing the calibration effort. A uncorrelated transformation can be found in [15]. Recently, some approaches utilise sensor network to assist location system for adapting the radio dynamics [16]. The unstable factors such as open/closed doors and humidity are detected by the sensors and thus a collaborative positioning system is provided by such context-awareness radio map [17]. Yin [18] proposes a learning approach where the radio map is temporally updated depending on the current environment. In Moraes's work [19], a dynamic RSSI mapping architecture is investigated. The dynamic noise problem is in some sense reduced in such mechanisms where the environmental changing is monitored. However, the short-term dynamic multi-path is difficult to detect and several difficulties are faced such as a site survey on environmental factors and additional hardware installation in these techniques.

In contrast with fingerprinting, model-based positioning techniques express the RF signal attenuation using a physics-based path loss model [20], [21]. Starting from the RSSI observed by a mobile relative to at least three anchors, these methods estimate the distance of the mobile from the anchors and triangulate its position. However, the relationship between distance and RSSI is highly complex due to multi-path, metal reflection, and interference noise. Thus, the signal propagation mechanism on which the distance computation is based may not be adequately captured by a fixed invariant model. A number of variants on probabilistic Bayesian inference approaches have appeared in the literature [11]. Bayesian inference is a probabilistic framework which sequentially estimates the unknown state from noisy observations using a dynamic predictive model and an observation likelihood. Bayesian methods can estimate a person's velocity and acceleration in addition to position, and can also provide an uncertainty measure of the estimates. Recently, Letchner et al. [22] introduced a sensor measurement model in the particle filter framework that combines a Wi-Fi signal propagation model and fingerprinting technique for localisation. The method assumes radially symmetric attenuation of wireless signals and also requires large training data sets for fingerprinting. Several other algorithms assume an empirical path-loss-based radio signal propagation map to compute the likelihood of RSSI observation [20]. The performance of these algorithms, however, may degrade in practice due to RSSI variability over time and location. For this reason, research efforts have been recently directed towards developing a localisation algorithm that automatically calibrates the propagation model parameters [21].

A survey on indoor radio location algorithms can be found

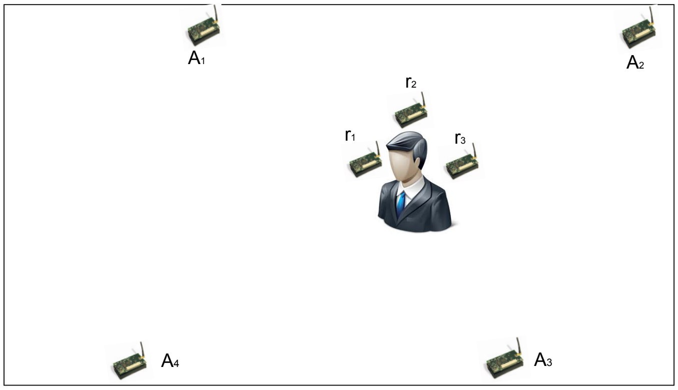

Fig. 1. Scenario: single-room localisation with 3 mobiles placed on the user and 4 anchors deployed in the environment.

in [23], where an experimental platform has been deployed to compare various positioning techniques. Differently from what is done in [23], we used numerical data obtained through accurate propagation modelling instead of measurements, which allows for a greater number of field values. In our case, we considered a dense grid and different scenarios as far as anchors positioning and antenna orientations are regarded, with up to five mobile nodes on the user.

Propagation modelling represents a useful tool during the deployment phase of indoor wireless propagation systems; more recently, it is going to be also used to validate and develop efficient radio location algorithms. Although deterministic models are relatively time-consuming, they remain an attractive approach for those cases where a site-specific approach appear to be more suitable than stochastic ones, as it happens in small indoor environments made of one or few rooms. In this context several efforts are focused on developing fast deterministic models, by using computer graphics techniques to speed up ray-tracer algorithms or by adopting novel approaches as those based on the multi-resolution frequency domain parflow technique [24].

In this paper, a deterministic propagation model combining effective ray-tracing algorithms and high-frequency expressions for the reflected/diffracted fields is used. Since we are focused on deriving accuracy bounds for existing location algorithms, we are interested in obtaining field maps as close as possible to those that could be measured in the reference indoor scenario, without any concern about time required for numerical simulations.

III. Lower bound on localisation error

In the scenario depicted in figure 1 a user is located in a room, wearing a number M of receivers (the *mobiles*). A number N of transmitters (the *anchors*) placed in well known positions transmit beacon packets. Each mobile r registers the corresponding RSSI which form a fingerprint vector of RSSI values y^r, defined as

$$y^r \triangleq [y_1^r, y_2^r, \cdots, y_N^r] \qquad \forall r \leq M. \tag{1}$$

TABLE I
Performance obtained with variable number of transmitters and a single receiver.

Number of transmitters	3	5	7	12	18
Error (third quartile) [cm]	356	300	267	145	73

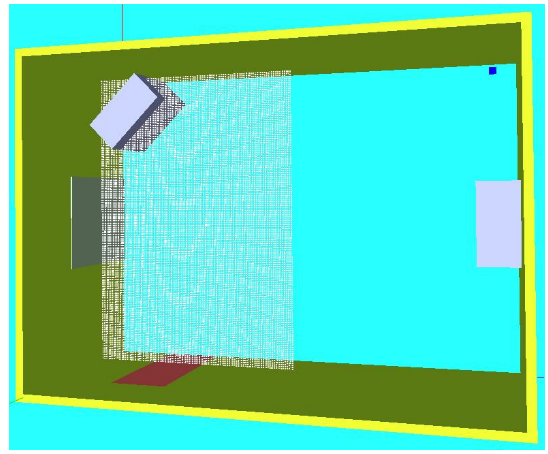

Fig. 2. The room environment. Only half of the grid is shown.

For each point on the map i and for each receiver r, the RSSI database h is populated by means of a ray-tracing simulation run with data:

$$h^{i,r} \triangleq [h_1^{i,r}, h_2^{i,r}, \cdots, h_N^{i,r}] \qquad \forall r \leq M. \tag{2}$$

Note that each fingerprint vector $h^{i,r}$ is composed of the expected RSSI values at position i for receiver r. We assume that the probability of measuring y^r given the RSSI vector $h^{i,r}$, that is $\mathrm{P}(y^r|h^{i,r})$, is a multivariate Gaussian random variable $\mathcal{N}(h^{i,r}, \Sigma)$, where $Sigma$ accounts for the errors relative to the spatial coordinates and to the received power level RSSI, which are independent random variables. The estimated position $\hat{i}$ is then evaluated using a maximum likelihood estimation (MLE) criterion i.e.

$$\hat{i} = \arg\max_i \mathrm{P}(y^r|h^{i,r}). \tag{3}$$

In [4] we show that the localisation error for a single mobile decreases by increasing the number of anchors (Table I) and found a lower bound of the median error for 18 anchors equal to 21 cm. In this paper we want to examine if performance can be further increased by using multiple mobiles.

IV. Simulation results

A. Simulation environment

We consider an office room at our lab at ISTI, CNR, in Pisa. Its size is 7 by 4.95 meters, its height is 3.12 meters. The room has two doors, a magnetic whiteboard, a low metallic cabinet in the top-left corner and a high one on the right wall. The walls are made of gasbeton, the floor is wooden and there is a lightweight dropped ceiling (Figure 2). Both the mobiles and the anchors are modelled as a $\lambda/2$ dipoles

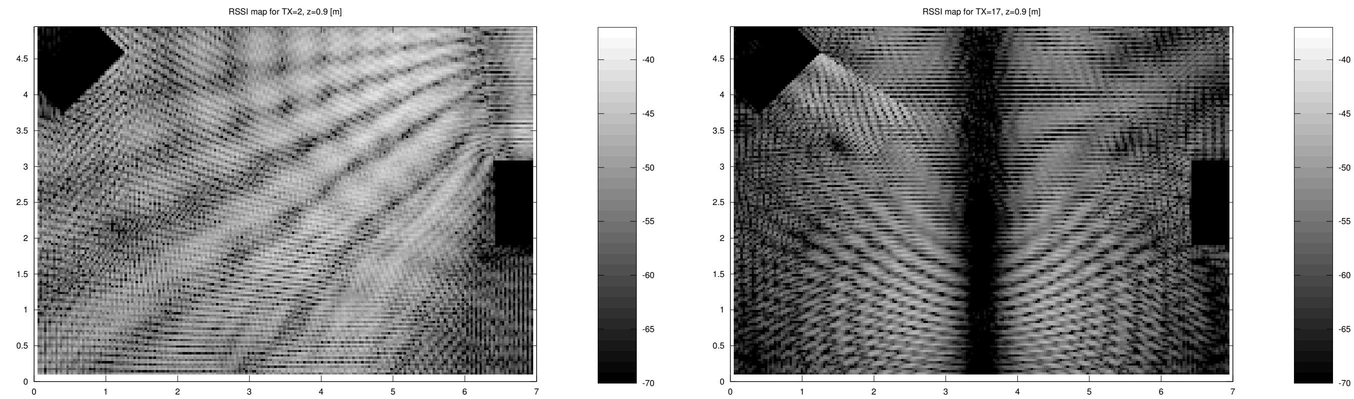

Fig. 3. RSSI behaviour when a single anchor is placed in a corner and on the centre of the room.

TABLE II
POSITIONS OF THE EIGHTEEN ANCHORS. θ IS THE INCLINATION AND ϕ IS THE AZIMUTH OF THE DIPOLE ANTENNA. WHERE MORE TWO ANGLES ARE GIVEN, TWO ANCHORS WITH DIFFERENT ORIENTATION ANTENNAS ARE USED IN THE SAME PLACE.

Position	x	y	z	θ	ϕ
POS01	6.65	4.6	2	0/45	0
POS02	6.4	3.0	2	0/45	0
POS03	6.95	0.1	2	0	0
POS04	1.9	0.1	2	0	0
POS05	0.8	3.85	2	0	0
POS06	0.1	4.9	2	0	0
POS07	2.333	2.525	2	90	0/90
POS08	4.663	2.525	2	90	0/90
POS09	3.5	2.525	2	90	0/90
POS10	3.5	4	2	90	0/90
POS11	3.5	1.05	2	90	0/90

TABLE III
POSITIONS AND ANTENNA ORIENTATION OF THE FOUR BEST ANCHORS OUT OF THE TOTAL EIGHTEEN.

Position	x	y	z	θ	ϕ
POS01	6.65	4.6	2	45	0
POS03	6.95	0.1	2	0	0
POS07	2.333	2.525	2	90	0
POS09	3.5	2.525	2	90	90

(being λ the wavelength at the second channel of the IEEE 802.15.4 standard), which is about 62 mm.

Eighteen anchors are placed in different positions on the walls and ceiling (see Table II), with different antenna orientations, while the mobiles are placed on or around the user with vertical antennas. When multiple mobiles are present, they are equally distributed on a horizontal circle around the user, with a radius of 25 cm. The radius was chosen so that two mobiles could be placed on the user's shoulders. We also made simulations with radii of 12.5 cm (to be placed on a hat) and of 50 cm (on the corners of a wheelchair), but we do not report those results as they are not significantly different from the ones at 25 cm.

B. Ray-tracing simulation

In order to simulate the behaviour of the transmitted signal and evaluate the RSSI estimated at the receivers, we use a three-dimensional deterministic propagation model based on an inverse ray-tracing algorithm which accounts for contributions up to third order reflections. The model evaluates first-order edge diffractions through heuristic UTD (Uniform Geometrical Theory of Diffraction) dyadic diffraction coefficients, valid for discontinuities on impedance surfaces, and accounts for conductivity and permittivity of the wall materials. The grid of the map is narrow enough (3.1 cm) that we can assume we have most of the information about RSSI on the considered plane. Let's now look at reflections inside the room, and how much they affect the RSSI pattern. Figures 3 represents the RSSI behaviour when a single anchor is placed in the indoor environment, specifically in the top-right corner at 2 m height with a vertical antenna in the figure on the left and at the centre of the roof with a horizontal antenna in the figure on the right. One can see that the RSSI patterns are very complex, and even displacements of a few centimetres can change the received value significantly. At the same time, for each given RSSI value, there are many, even far-apart locations in the room where the same RSSI value is observed. We can draw the following conclusions:

- Since reflections dominate the RSSI distribution, the use of a simplified path-loss models introduce significant errors in this type of environment.
- The accuracy of positioning during off-line measurements for calibration should be a primary concern; in fact, errors of few centimetres can significantly change the fingerprint at a given location.
- Positioning errors can be caused by incorrect measurements in real environments, incorrect modelling in simulated environments, small changes in the environment itself after calibration, and so on.
- Fingerprinting methods using interpolation of grid values assume that the RSSI distribution in the area of interest is somewhat continuous, but by looking at figure 3, one

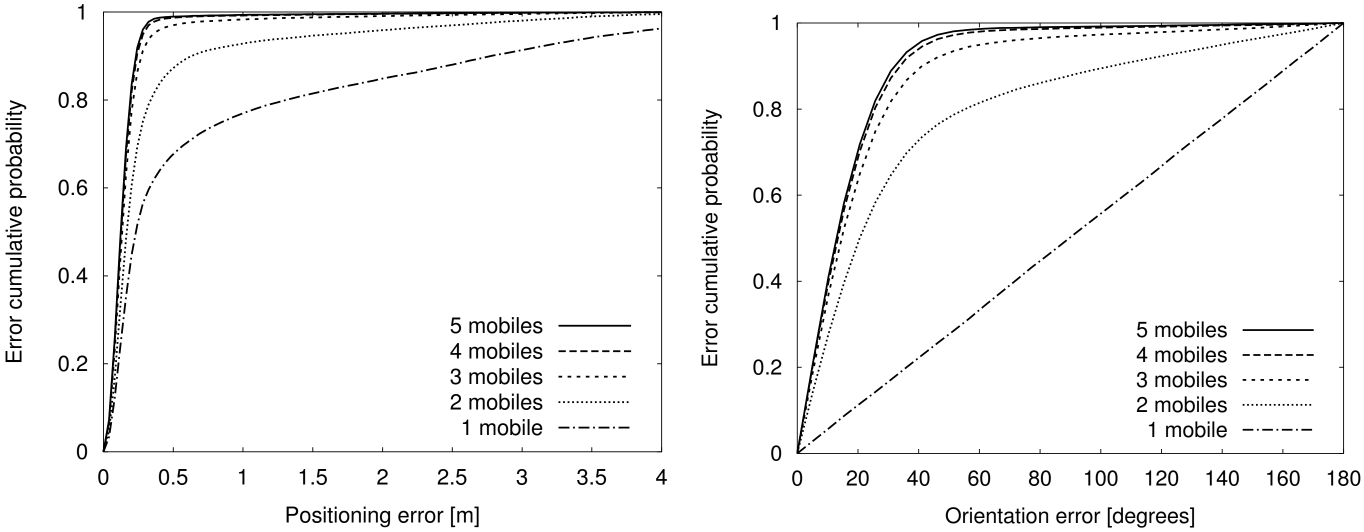

Fig. 4. Cumulative distribution functions of errors for up to five mobiles when all 18 anchors are used. Errors decrease with increasing number of mobiles.

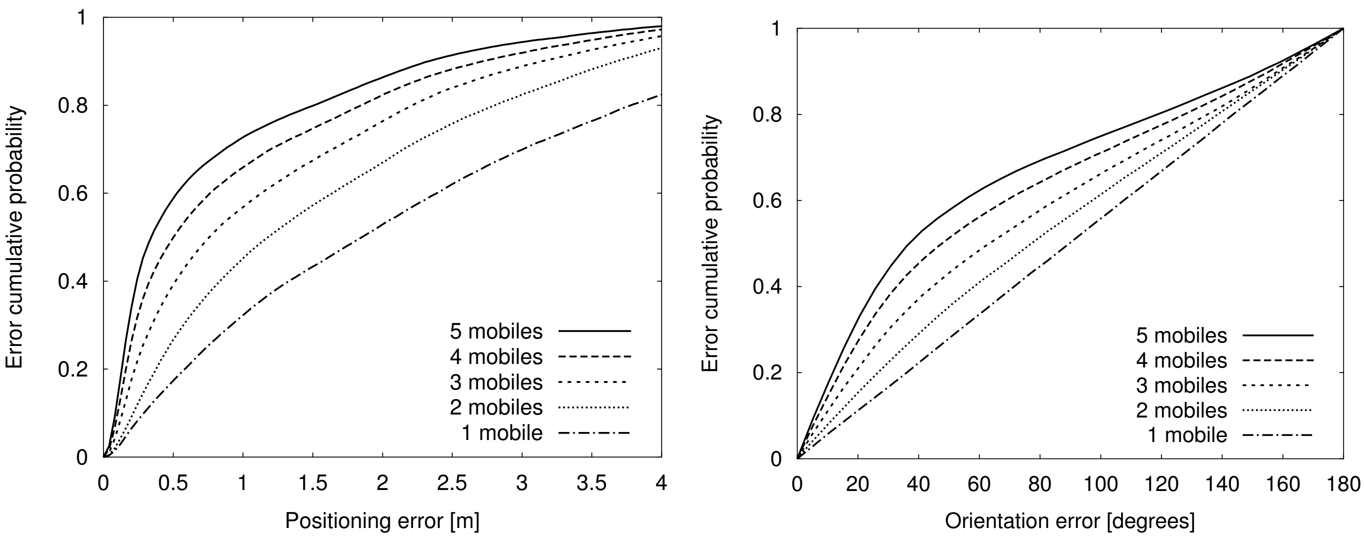

Fig. 5. Cumulative distribution functions of errors for up to five mobiles when the best four out of all eighteen anchors are used. Errors decrease with increasing number of mobiles.

would say that this is clearly not the case. Even when some kind of interpolation is used, the strongly non-linear distribution of RSSI will make this process prone to significant localisation error.

- For any method used, errors both in RSSI measurement at the mobile and power strength at the anchor should be kept into account, since both random and systematic non-negligible errors will occur.

C. Single versus multiple mobiles

For each scenario, the mobile receives RSSI information from a number of anchors, and for each grid of the map we compute the likelihood for the mobile to be located at this position. Performance is computed as the positioning and orientation errors for a given configuration. We generated 40 000 points inside the room, with uniformly random positioning and orientation. For each generated point (the *actual* point, we perturbated its position and orientation to simulate imprecise positioning measurements and perturbated the RSSI readings at the perturbated position to simulate incorrect RSSI measurement at the mobile. We did not introduce any sort of error to account for the anchors incorrect transmission power. For the resulting vectors (one per mobile) of RSSI readings (one per anchor), the likelihood of being at each position and orientation on the map was evaluated and the maximum was sought. For the estimated position and orientation, the distance from the *actual* position and orientation was computed.

The distributions of these distances are plotted in figure 5: the first two plots are computed when considering the RSSI received from all 18 anchors we placed in the simulated environment, while the second two plots only consider the best 4 anchors (Table III), that is, the anchor quartet that gives the best results.

The primary purpose of this work is to answer the two questions: does attainable performance increase when using multiple mobiles placed on the user rather than a single one? do multiple mobiles allow to estimate orientation with reasonable accuracy? When considering the already good results attainable with 18 anchors, we observe that improvements are significant only up two mobiles, with a modest improvement at three mobiles, and no significant further improvement with 4 and 5 mobiles. On the other hand, when starting from the bad attainable performance we have with 4 anchors and a single mobile, each increase in the number of mobiles brings a significant advantage.

The resulting numbers indicate that in the 18-anchors case a localisation method can potentially be devised that gives a good estimate of the positioning and orientation of the user. In the 4-anchors case, on the other hand, a (memoryless) purely RSSI-based localisation method could potentially give reasonable positioning estimates only using five mobiles, but will not be able to give usable orientation estimates. These results are valid for the specific positions that we adopted for the anchors and for the specific environment that we analysed: more thorough investigation is needed to obtain widely-applicable conclusions.

V. Conclusions

We analysed the maximum performance attainable by a localisation system based exclusively on RSSI measured by one or multiple receivers placed on a user in an office room. The signals are sent by a number of fixed transmitters placed on the walls and ceilings. The system has no memory and uses no other information than RSSI readings. We find that using multiple mobile receivers has the potential of increasing both the positioning and the orientation capabilities of localisation systems based on RSSI measurements. However, more than just a few transmitters may be needed to obtain usable estimates.

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