Exploiting Opportunistic Interactions for Localization in Heterogeneous Wireless Systems

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***Abstract*—This paper addresses the problem of localization in mobile networks. Our goal is to make localization possible even for off-the-shelf communication devices like smartphones or sensor nodes, not equipped with GPS or operating in areas where the GPS does not work well. In our approach, a *user* estimates its position by exploiting opportunistic exchanges with other devices (*peer* devices). The localization information provided by peers include their own position estimation and can be used even though it may be highly inaccurate. In a heterogeneous setup, peers can provide different ranging technologies (e.g. RSSI and UWB). We investigate the performance of two existing localization algorithms based on Weighted Centroid (WC) and Linear Matrix Inequalities (LMI) under different conditions of accuracy and heterogeneity. The study is performed by means of simulations that, however, make use of realistic ranging models, derived from an extensive set of RSSI and UWB measurements. The simulation results show that in most cases LMI provides a better user position estimation than WC, with an error of 1 to 4 meters for 10 opportunistic interactions, and that heterogeneity of peer positioning accuracy has a limited but positive impact on the localization performance.**

***Index Terms*—opportunistic, localization, heterogeneity, Linear Matrix Inequality, weighted centroid**

I. Introduction

Inferring the geographical location of nodes in a certain area is recognized as a fundamental service in many different contexts, from robotics to telecommunication systems, that may enable a number of applications and network optimizations strategies. The topic has been widely and deeply investigated from many different perspectives and the general conclusion is that accurate node localization requires either dedicated hardware or sophisticated software [1], or even both in particularly harsh environments [2], [3], [4], whereas simple localization schemes that make use of the received signal strength to estimate the distance between nodes are generally affected by residual localization errors in the order of meters, in particular in indoor environments [5].

In this paper, we tackle the localization problem from a different and rather new perspective: rather than searching for yet another signal processing technique or system architecture explicitly designed to provide localization services, we propose to spill out this service from the opportunistic interactions that may occur among heterogeneous wireless nodes. More specifically, we advocate that a strayed node with no self-localization capabilities can estimate its own position by exploiting the localization information provided by passing-by nodes. In practice, nodes that happen to be within opportunistic interaction range will exchange packets containing their current position estimate, together with an indication of its accuracy. Furthermore, nodes will perform some sort of ranging to estimate their mutual distance. Then, each node can use the information collected during the opportunistic interaction to estimate its own position.

The opportunistic interaction paradigm is enabled by the growing popularity of small and portable personal electronic devices, such as smart phones, PDAs, music and video players and so on, which draws a prospective scenario where a large number of mobile, heterogeneous nodes may exchange data with passing by nodes on an opportunistic basis, for different purposes [6]. In particular, some of the mobile nodes may be equipped with self-localization hardware, e.g. Cricket [7], indoor GPS [8], MEMS-based navigation, or RSSI-based. Hence, the opportunistic interactions among nodes may be exploited to enhance the localization capabilities of the different devices through opportunistic localization techniques.

A possible target scenario for opportunistic localization is, for instance, an airport, where employees and passengers may carry different devices. Employees may carry high-end positioning devices, capable of extremely accurate self-localization, whereas passengers may be given low-end localization devices as airport gadgets, with hardly any self-localization capability. Passengers' devices may rely on occasional interactions with employees' devices to improve the accuracy of their own positioning. Furthermore, dedicated localization devices may be sparsely placed in airport lounges and corridors to further help the opportunistic localization of passengers. A similar service may be offered to the visitors of large exhibitions, archaeological sites, amusement parks, museums, and so on.

It is easy to realize that the effectiveness of the opportunistic localization paradigm is determined by four major features: i) the likelihood of opportunistic interactions; ii) the initial accuracy of nodes' localization; iii) the ranging accuracy; iv) the algorithm used to process the information obtained through opportunistic interactions, i.e., the so-called *opportunistic localization algorithm*. The aim of this study is to shed some light on the way these different features affect the opportunistic localization performance. We focus on the three last features, studying what happens when the contacts have occurred. To this end, we define a simple but realistic system model that makes it possible to control each feature by opportunely setting some system parameters. More specifically, we consider two opportunistic localization algorithms, namely the Weighted Centroid (WC) [9] and the Linear Matrix Inequality (LMI) [10], which have been recently proposed for the opportunistic scenario [11]. We then study the localization accuracy attained by these algorithms when varying the number of opportunistic interactions, in two scenarios with complementary characteristics in terms of native nodes' localization and ranging accuracy. To give practical significance to the study, the ranging models considered in our analysis have been experimentally characterized. More specifically, we consider two ranging techniques, one based on the Received Signal Strength Indication (RSSI) measures obtained with ZigBee sensor nodes, and the other one based on the Time of Arrival (ToA) measures, provided by PulsON'220 UWB devices. Note that these technologies are complementary in terms of popularity and ranging accuracy: the RSSI circuitry is in fact a mature technology, natively supported by basically all wireless devices, but provides extremely noisy ranging estimates, whereas UWB technology is still in a prototyping phase, though it can achieve extremely accurate ranging [12], [13], [14]. Hence, the experimental characterization of the ranging accuracy with RSSI and UWB technologies can actually be considered as a side contribution of this work.

The remaining of the paper is structured as follows. In Sec. II we formally state the opportunistic localization problem and describe the system model. In Sec. III, we present the experimental characterization of the RSSI and UWB ranging techniques. The opportunistic localization algorithms considered in this work are presented in Sec. IV. Then, Sec. V reports the analysis of the localization performance obtained through simulations. Finally, Sec. VI draws conclusions.

II. System model

We address a scenario where a number of mobile nodes, equipped with a common communication device (Bluetooth, WiFi or ZigBee), can exchange data on an opportunistic basis, when they happen to be in coverage range. We focus our attention to the worst case, where one node, called *user*, is not equipped with any self-localization module. The other nodes, named *peers*, can instead perform some form of self-localization, with some level of accuracy. The opportunistic localization problem consists in estimating the user's position from the positioning and ranging information provided by mobile and static peers through direct opportunistic data exchange.

A. Communication model

The opportunistic interactions between the user and the peers occur through the common wireless interface. We consider the classic path loss and shadowing RF channel model, according to which the signal power $\Gamma_r(d)$ received at distance d from the transmitter is given by:

$$\Gamma_r(d) = \Gamma_t + K - 10\eta \log_{10}\left(\frac{d}{d_0}\right) + \psi \,, \tag{1}$$

where Γ_t is the transmission power [in dB], K is a unitless constant that depends on the environment, d_0 is the reference distance for the antenna far field model, and η is the so-called path loss coefficient that, once again, depends on the environment. Finally, ψ is a Gaussian-distributed random variable, with zero mean and variance σ^2_ψ, that describes the long term fading (or shadowing) effect.

We assume that opportunistic interaction is enabled only if the received signal strength is above a certain threshold Γ_{th} that, according to (1), yields a *nominal opportunistic range* R_{targ} given by:

$$R_{targ} = d_0 10^{(\Gamma_t + K - \Gamma_{th})/10\eta} \,. \tag{2}$$

Clearly, in a real scenario the opportunistic range cannot be considered fixed, since the shadowing term ψ in (1) makes the actual communication range R_{opp} a log-normal distributed random variable, given by:

$$R_{opp} = R_{targ} 10^{\psi/10\eta} \,. \tag{3}$$

B. Self-positioning model used by peers

We assume that peer nodes can self-localize with some level of accuracy, e.g., using a dedicated (non opportunistic) localization infrastructure (as indoor GPS). The position estimation is modeled as a 2-D Gaussian random variable, with zero mean and variance σ^2_{loc}, therefore the error distance between the estimated ($\widehat{P}_i$) and the actual position (P_i), is a Rayleigh random variable with parameter σ_{loc}. We note that the probability distribution of the localization error obtained by practical self-localization schemes may not be necessarily Gaussian. Nonetheless, the gaussian model condenses the accuracy of the native self-localization mechanism in a single parameter, namely σ^2_{loc}, thus making it possible to better control the scenario characteristics and greatly simplifying the investigation. In any case, the qualitative results provided by our analysis are preserved even for more realistic error models, as we observed in some experiments (not reported here for space constraints) where the self-localization information of the peers was generated using practical localization schemes.

C. Ranging model

We assume that, during opportunistic interactions, nodes perform ranging estimation using either Radio Signal Strength Indication (RSSI) or Time of Arrival (ToA) measures. The two ranging techniques are briefly explained below.

1) RSSI ranging: The RSSI-based ranging provides an estimate $\hat{d}$ of the actual distance d between transmitter and receiver by maximizing the likelihood of the received signal power Γ_r, according to the propagation law (1). In practice, for a received signal strength Γ_r, the RSSI ranging results in:

$$\hat{d} = d_0 10^{(\Gamma_t + K - \Gamma_r)/10\eta} = d \; 10^{-\psi/10\eta} \,. \tag{4}$$

From (4) we clearly see that short distances have smaller ranging error, $\widehat{d}$ being proportional to the actual distance d.

2) ToA ranging: The ToA-based ranging provides an estimate $\hat{d}$ of d by using the time T that an RF impulse takes to propagate from sender to receiver and back. This time, thus, includes the transmission and propagation time of the RF impulse, plus the processing time at sender and receiver. Since the transmission and processing time intervals are all known and deterministic, they can be easily removed from the measure T, thus obtaining an estimate of the sole propagation time τ of the RF impulse over space. Ideally, τ is equal to the distance d between transmitter and receiver divided by the propagation speed v_p of the electromagnetic wave. In practice, however, this measure is affected by noise, due to the difficulty of discriminating the first propagation path from reflections. Furthermore, in absence of line of sight (LOS) between transmitter and receiver, the ranging estimate may be unreliable. However, in LOS condition, the measured time delay can be fairly well modeled as a Gaussian random variable with mean d/v_p and variance σ_τ^2, according to what stated in [15]. The ML distance estimate is thus given by:

$$\hat{d} = \tau v_p \,, \tag{5}$$

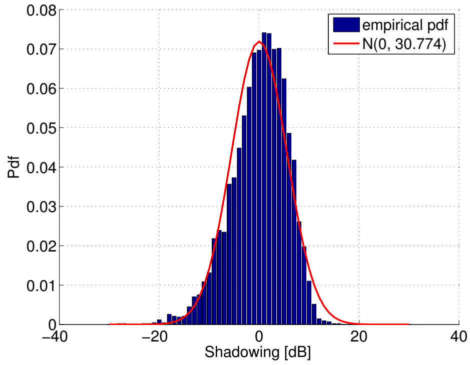
where v_p is the propagation speed of electromagnetic waves in air. Note that, conversely to RSSI-based ranging, the probability distribution of the ranging error provided by ToA does not depend on the actual value of d.

III. Experimental characterization of the ranging models

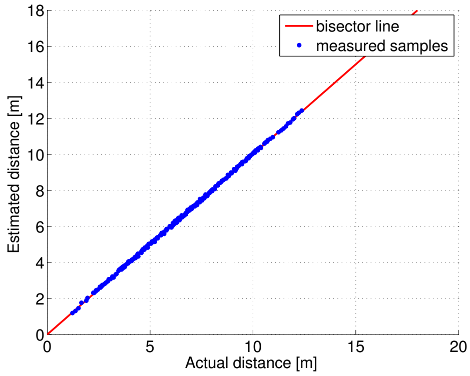
In order to give practical meaning to the results provided by our analysis, we characterized the ranging-error models defined in Sec. II-C by using real measurements, collected within the FP7 Network of Excellence in Wireless COMmunications NEWCOM++. More specifically, we collected both RSSI measures, using ZigBee sensor nodes, and ranging samples provided by PulsON'220 UWB devices. The measures were performed using a Lego robot, equipped with ZigBee and UWB devices, that moved along a predefined L-shaped path in a corridor at a constant speed (6 m straight, a quarter of circle curve and then another 8.2 m straight). During its motion, the robot communicated with the static nodes deployed both in the same corridor and inside adjacent rooms. (See [16] for more details.)

A. RSSI ranging model

The RSSI experiment was performed using 21 ZigBee devices CC2430 that communicated with the mobile device every 50 ms. Overall, more than 4000 samples were collected in the experiment. These data have been used to characterized the parameters of (1). Using a Least Square method, we estimated $\eta = 3.31$ and $P_0 = \Gamma_t + K = -29.03$ dBm at distance $d_0 = 0.1$ m. Furthermore, the shadowing term was found to be approximately Gaussian-distributed (in dB), with zero mean and standard deviation $\sigma_\psi = 5.55$, as plotted in Fig. 1(a).



(a) Empirical pdf of the shadowing term ψ in (1)



(b) Estimated vs. actual distance for UWB LOS measurements

Fig. 1. Experimental measurements

B. UWB ranging model

High time resolution is one of the key benefits of ultra-wideband signals for precision ranging. Due to the extremely short duration of transmitted pulses, UWB receivers are able to discriminate individual multipath components, thus achieving high accuracy [17].

The ToA experiment was performed using PulsON'220 UWB devices [18], placed in 12 different positions. Each pair of nodes communicates every 500 ms, collecting more than 1000 measurements. Among these values, we considered only the line of sight (LOS) samples that were singled out from the dataset by using the geometric information and observing the correlation of consecutive measures. Fig. 1(b) shows the estimated distance returned by PulsON'220 devices vs the actual distance, confirming the very high ranging accuracy provided by the device in LOS condition. The empirical distribution of the ranging error obtained from the collected data can be fairly well modeled as Gaussian, with zero mean and standard deviation $\sigma_d = 0.029$ m.

IV. Opportunistic localization algorithms

During an opportunistic interaction, the peer node sends to the user its current position estimate $\widehat{P}_i$ along with an estimate of its maximal positioning error ϵ_{loc}^{max}. Note that, according to the Gaussian self-localization model described in Sec. II-B, the localization error is unbounded, at least in principle, so

ϵ_{loc}^{max} is set to the 0.9-quantile, i.e., such that:

$$P\left[\epsilon \leq \epsilon_{loc}^{max}\right] = 0.9\,. \tag{6}$$

In addition to receiving $\widehat{P}_i$ and ϵ_{loc}^{max} from peers, the user also performs an estimate $\hat{d}$ of its distance from each transmitting peer. Once again, the error that affects this estimate is unbounded, in principle. However, we cut the maximum ranging error to:

$$\epsilon_{rang}^{max} = d_{max} - \hat{d}\,, \tag{7}$$

where d_{max} is such that:

$$P\left[\hat{d} \leq d_{max}\right] < 0.9\,. \tag{8}$$

The probability distribution of $\hat{d}$ depends on the particular ranging technique used by the nodes, as specified in Sec. II-C.

We assume that the user performs N opportunistic interactions with different nodes, while staying in the same position. With the collected data, it runs one of the opportunistic localization algorithms described below.

A. WC localization algorithm

The Weighted Centroid (WC) algorithm, derived from [9], estimates the user's position $\widehat{P_u}$ simply as a weighted average of the peers' estimated coordinates:

$$\widehat{P_u} = \frac{\sum_{i=1}^{N} w_i \widehat{P}_i}{\sum_{i=1}^{N} w_i}\,, \tag{9}$$

where each coefficient w_i is inversely proportional to the estimated distance from the i^{th} peer and its position accuracy, i.e.:

$$w_i = \frac{1}{\hat{d}_i(1+\sigma_{loc,i})}\,. \tag{10}$$

B. LMI localization algorithm

Another localization scheme, proposed in [10], is based on the solution of Linear Matrix Inequality (LMI) problems. For each peer i involved in an opportunistic interaction, the user writes the following inequality:

$$\|P_u - \widehat{P}_i\| \leq R_i\,, \tag{11}$$

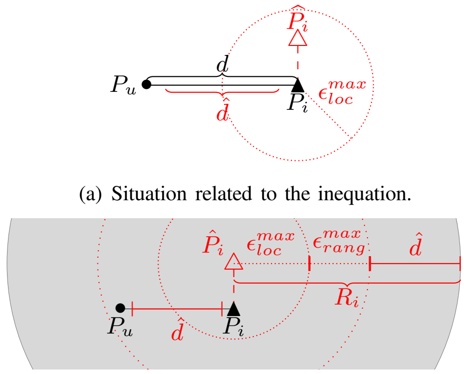
where $||\cdot||$ denotes the Euclidian distance, and R_i is the maximum admissible distance between the user and peer i, given by:

$$R_i = \hat{d} + \epsilon_{rang}^{max} + \epsilon_{loc}^{max}\,. \tag{12}$$

This situation is illustrated in Figure 2. In the figure above, the dotted circle delimits the area that will likely contain the estimated position $\widehat{P}_i$. In the figure below, the gray disc represents the area that will likely contain P_u. Note that the circle is centered on $\widehat{P}_i$ rather than P_i and that its radius R_i takes into account the ranging error.

The chosen user's estimated position $\widehat{P_u}$ is the center of the rectangle that tightly encloses the *intersection area* of N circles centered in $\widehat{P}_i$ with radius R_i, for $i = 1, 2, \ldots, N$, as illustrated by Figure 3(a).

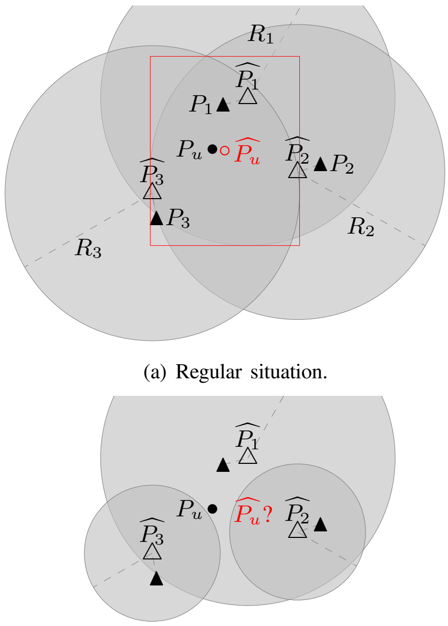
We observe that, due to the approximated upper bounds in (8) and (6), it is actually possible that some of the peers



(a) Situation related to the inequation.

(b) Circle used in the inequation.

Fig. 2. Illustration of a single LMI inequation.



(a) Regular situation.

(b) Unsolvable situation.

Fig. 3. LMI estimation.

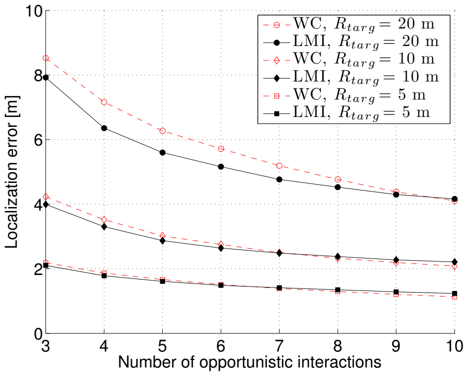
can communicate with the user even when their distance is larger than R_i. In this case, the LMI problem may be unsolvable, because the intersection of circles is empty, as in Figure 3(b). When this event occurs, we relax the LMI problem by increasing progressively the value of R_i until a solution is found.

V. Performance Analysis

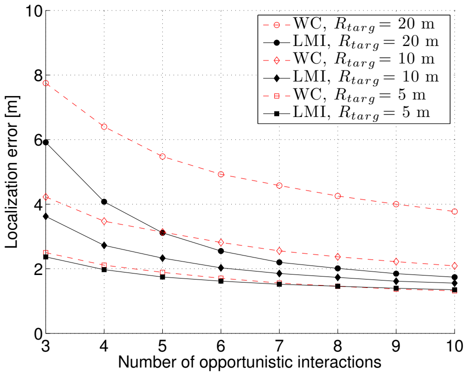
In this section we compare the localization performance of LMI and WC in different scenarios, when varying the number of opportunistic interactions. In order to study separately the impact of self-localization and ranging accuracy, we consider the following two complementary scenarios:

A All peers have very good self-localization ($\sigma_{loc} = 1$ m), but rely on quite unreliable RSSI-based ranging ($\sigma_\psi =$ 5.55 dB);

B All peers suffer rather poor self-localization ($\sigma_{loc} =$ 2 m), but perform accurate ToA-based ranging using UWB technologies ($\sigma_d = 0.029$ m).



(a) Scenario A.



(b) Scenario B.

Fig. 4. Localization error in scenario A ($\sigma_{loc} = 1$ m) and B ($\sigma_{loc} = 2$ m).

Moreover, we change the nominal coverage range R_{targ} in both scenarios in order to understand its effect on the localization accuracy.

In Fig. 4 we show the mean localization errors for the WC and LMI methods in both scenarios, varying the number of opportunisc interactions and the value of R_{targ}. Results confirm the intuitive expectations, namely:

- *The localization error decreases as the number of opportunistic interactions increases*, for all scenarios and all values of R_{targ}. In fact, as the number of interactions increases, the peers distribution around the user becomes more and more homogeneous. This is clearly beneficial for WC that estimates the user's position as the mean of the peer positions, so that the localization error asymptotically tends to zero. Similarly, the number of intersecting circles in LMI also increases, so that the intersection area progressively shrinks around the actual user position.
- *The localization error decreases as the nominal opportunistic range R_{targ} decreases.* By reducing R_{targ}, we enable opportunistic interactions only with peers that are closer to the user. The WC algorithm then computes the centroid of nodes that are closer to the user, so that the estimated position will also be closer to the user (on average). For LMI, the intersecting circles have smaller radius and, hence, the intersection area is also smaller (on average). Note that in this case, the accuracy of RSSI-based ranging improves, since according to (4), the ranging error is proportional to the distance. Clearly, the counterpart is that reducing R_{targ}, we also decrease quadratically the likelihood of an opportunistic interaction to occur, thus the localization algorithm will be performed with a much smaller number of the peers, provided that the nodes density and mobility models remain the same.
- *Results are better for scenario B than for scenario A.* In the case of WC, scenario B is using a larger σ_{loc} and therefore gives more weight to peers close to the user. In the case of LMI, the radius R_i of intersecting circles shrinks in scenario B: although σ_{loc} and consequently ϵ_{loc}^{max} is bigger, it is compensated by the tiny σ_d which makes ϵ_{rang}^{max} even smaller.

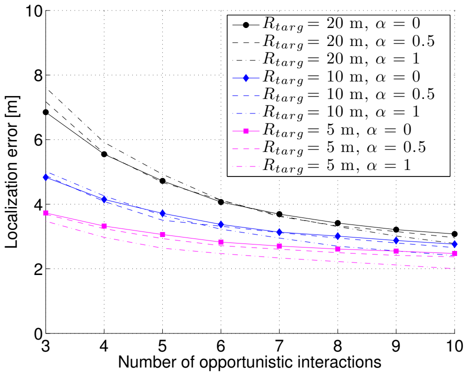
Fig. 4 also reveals that the performance of LMI is not always better than WC. In scenario A, in fact, the large ranging error will yield to wider intersecting circles in LMI and, in turn, a slower increase of the localization accuracy with the number of opportunistic contacts. This effect is less marked for small values of R_{targ}, for which the ranging error, which is proportional to the distance between user and peer, becomes less significant. In scenario B, instead, LMI exhibits better performance than WC, since the circles' radius is smaller and the intersection area shrinks faster than in the previous case.

We now consider a heterogeneous version of scenario B, where the peers may have different levels of localization accuracy. To provide a fair comparison among different scenarios, we fixed a mean localization error ξ and draw $\sigma_{loc,i}$ for the i^{th} peer at random and uniformly in the interval $[(1-\alpha)\xi\sqrt{2/\pi}\ ,(1+\alpha)\xi\sqrt{2/\pi}]$, where $\alpha \in [0,1]$ is a dispersion factor. When $\alpha = 0$, all the peers will have the same localization accuracy $\sigma_{loc,i} = \xi\sqrt{2/\pi}$, which corresponds to a homogeneous scenario, whereas $\alpha = 1$ will lead to an extremely heterogeneous scenario, with some peer very well localized (like beacons) and others very poorly localized. In any case, the mean localization error is always equal to ξ.

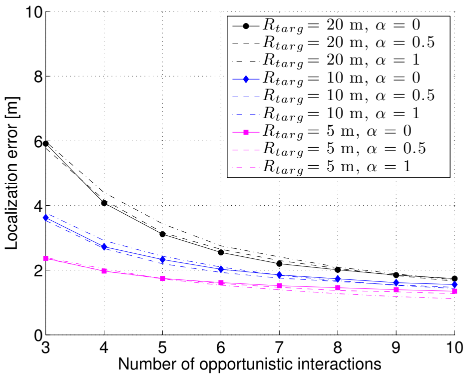
Fig. 5 reports the LMI performance in heterogeneous scenario B, with different values of σ_{loc} and, consequently, ξ. The main result here is the low impact of heterogeneity. However, we observe that, with few opportunistic interactions, better performance is achieved with homogeneous peers ($\alpha = 0$). However, as the number of contacts increases, the heterogeneity of nodes ($\alpha > 0$) turns out to be beneficial, since in the presence of even a few extremely well localized nodes with good ranging, LMI yields rather accurate localization, regardless the presence of other nodes with coarse positioning estimate. This result confirms the robustness of the LMI approach in the opportunistic scenario.

VI. Conclusions

In this paper we propose the opportunistic localization approach as a valuable solution to provide positioning information to a strayed node, called "user", by means of direct opportunistic interactions with heterogeneous wireless nodes that happen to be in spatial proximity, called "peers." Opportunistic localization can be undertaken while the user and the peers are moving, and several users can be considered. We investigated the localization error obtained by



(a) $\xi = 4\sqrt{\pi/2}$ m.



(b) $\xi = 2\sqrt{\pi/2}$ m.

Fig. 5. LMI localization error in heterogeneous scenario B.

two opportunistic localization algorithms, namely WC and LMI, when varying the number of opportunistic interactions and for various scenarios, characterized by different values of nominal opportunistic range, native positioning error of peers, and ranging accuracy. The analysis has been carried out through extensive computer simulations based on realistic ranging models validated via experimental measurements.

From the results, we observed what follows. First, as largely expected, the positioning accuracy of the user improves with the number N of opportunistic interactions and decreases with the nominal opportunistic range R_{targ}. However, all the other parameters being fixed, we expect that the time required by the user to achieve a target opportunistic localization error is roughly independent of R_{targ}. In fact, with small R_{targ}, the opportunistic interactions are less frequent, but more effective, whereas with large R_{targ}, the interactions are more frequent but less useful. Nonetheless, the LMI algorithm makes a better use of the information collected through opportunistic interactions, so that a large value of N is generally preferable. Second, the LMI algorithm benefits from accurate ranging, even in the presence of coarsely localized peers. This benefit, however, is less evident when R_{targ} is small, in which case accurate peers' localization is more effective (also considering that, over small distances, even RSSI-based ranging is rather reliable). Third, the heterogeneity of the peers localization accuracy has marginal effect on the LMI performance, though with few interactions homogeneity is preferable, whereas for larger values of N, heterogeneity brings some limited improvement.

Acknowledgments

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