Opportunistic Localization: Modeling and Analysis

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***Abstract*— Localization and tracking functionalities can benefit a number of applications. Despite the large number of algorithms and technologies that have been proposed in this context, the literature still lacks a widely accepted solution, capable of cutting a tradeoff between service quality (i.e., localization accuracy) and device/architecture cost and complexity. In this paper, we tackle the problem from a different and rather new perspective: we investigate how the localization accuracy of nodes can be ameliorated by opportunistically exchanging localization information among heterogeneous nodes that occasionally happen to be in proximity. To this end, we define a simple though accurate opportunistic meeting model and, then, we develop a mathematical framework that permits to analyze the performance of an opportunistic localization strategy based on a Maximum Likelihood argument.**

I. Introduction

The problem of locating and tracking of mobile users in a given area has been deeply studied in several different contexts, from robotics to telecommunications systems, thanks to the large set of possibilities and optimizations that might be enabled by knowing the geographical position of the nodes in a communication system. Whereas most of the solutions proposed in the literature consider homogeneous devices, an emerging research trend aims at improving the localization accuracy by exploiting the device heterogeneity through cooperative strategies. This type of systems are usually designed in order to facilitate nodes cooperation, so that the cooperative interactions occur in a rather controlled and/or pre-planned manner. A totally different approach consists in enabling the cooperative interaction between nodes on an occasional basis only. In this case, instead of cooperative interactions we shall better talk of *opportunistic interaction*. A typical example of an opportunistic interaction scenario is the seamless data exchange between portable devices carried by people in public areas, such as malls, theaters, hotel lounges and so on[1]. In this case, people move in a rather uncoordinated manner, each person following her personal purpose, so that data exchange between devices carried by people can occur on occasional basis only.

In this paper, we address the problem of providing accurate self-localization service in such an opportunistic scenario. We envision a number of mobile nodes with different mobility patterns and equipped with heterogeneous communication devices and self-localization hardware, e.g. Cricket [2], MEMS [3], indoor GPS [4], RSSI-based or none. Nodes are capable of performing seamless and opportunistic data exchange to attain certain goals and, in particular, to improve their positioning estimate. More specifically, we investigate how the localization accuracy of nodes can be ameliorated by opportunistically exchanging localization information with other nodes that occasionally happen to be in proximity.

This scenario offers a number of research challenges that include the definition of efficient nodes discovery and link establishment algorithms for opportunistic data exchange between multi-interface devices, the design of suitable opportunistic data exchange protocols, the devising and analysis of localization enhancing schemes based on opportunistic data exchange. Prior to afford any of such problems, however, it is desirable to gain some insights on the actual potentialities of the opportunistic paradigm in the context of nodes localization and to get a first understanding of the tradeoffs between the different performance indexes, such as localization accuracy versus protocol overhead/channel occupancy/energy consumption. Here we provide a first contribution in this direction which is articulated in the following two items.

1) We propose a mathematical model of the opportunistic information exchange that takes into account some important design parameters, such as the coverage range, the frequency of scan/query phases by which nodes look for opportunistic interactions and the amount of time dedicated to such a process.
2) We apply the model to an opportunistic localization scheme based on a Maximum Likelihood argument and investigate the improvements in nodes' position estimate enabled by the opportunistic paradigm for different settings of the system parameters.

The rest of the paper is structured as follows. In Section II we present the state of the art on nodes localization, dwelling upon cooperative localization in the specific. Section III presents the mathematical model for the opportunistic data exchange. Section IV describes how the information obtained by the opportunistic interactions is used to improve the location estimate of the nodes. In Section V we investigate the impact of some system parameters on the performance of the opportunistic localization scheme. Finally, in Section VI we conclude with some final remarks.

II. Related Works

As mentioned, the self-localization and tracking problems have been investigated in a number of papers. Range-based

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localization algorithms require that non-localized nodes get an estimate of their distance from some reference nodes, called beacons or landmarks, in order to perform lateration and triangulation techniques [5], [6] or to apply statistical estimation methods [7]. In this case, the most critical phase is the ranging estimate, which can be obtained by measuring the power of the Received Signal Strength (RSS) or the Time of Arrival (ToA) of the RF signals sent by the beacons [8], [9], [10]. Other techniques consisting in multi-step localization with a refinement phase have been proposed by Savarese [11] and Savvides [6].

A more recent research trend addresses the localization problem in cooperative scenarios, which have been extensively studied, in particular, in the robotic area. A typical reference case consists in teams of mobile autonomous robots equipped with different sensors that cooperate one another and, occasionally, interact with simple sensors placed in the environment to achieve a given goal, such as node localization and tracking. Motion tracking algorithms generally leverage on Extended Kalman Filter [12] or Particle Filter [13], [14] for exploit the correlation among different measurements. In [15] the authors utilize Markov localization in order to self–localize nodes and then probabilistic methods to synchronize each robot's estimates when two of them have a contact. A distributed Kalman Filter is performed for collective localization in [16], avoiding a centralized data fusion, that is not so feasible in a cooperative scenario. An anchor-free approach is proposed in [17], where robots infer their position only using the information exchanged among them. Similar approaches are proposed for very specific applications as in [18] for video surveillance and in [19] for autonomous vehicles in mining.

The literature on the opportunistic interaction paradigm, instead, is mainly focused on routing and scheduling issues, whereas, to the authors' knowledge, the opportunistic localization problem has not been yet considered.

III. Opportunistic meeting model

In this section, we define a mathematical model of an opportunistic interaction. The model is based on a simplified scenario that, although idealized, includes some of the most interesting design parameters, such as the maximum range of an opportunistic communication, the fraction of time devoted to the opportunistic interactions, and the relative speed between the nodes. Then, the model permits to investigate the impact of these parameters on some performance indexes that are of interest for the opportunistic localization scheme, namely the probability of occurrence of an opportunistic interaction and the statistical distribution of the distance between the nodes when such an opportunistic data exchange occurs.

Assumptions

In our model, we take into account only a couple of nodes, say A and B, both equipped with a common wireless communication interface that is used for (opportunistic) data exchange. Radio propagation is described by means of a simple unit-disk model, according to which the radio transmission is always correctly received within a distance R (*coverage range*) from the transmitter, whereas it is not received at longer distances. Although the unit-disk model is known to be over-simplified, it permits to isolate the performance analysis from the characteristics of the radio interface that, at this stage of the work, is left generic. (In any case, the mathematical framework derived in the following section can be easily adapted to include more sophisticated radio-propagation models.)

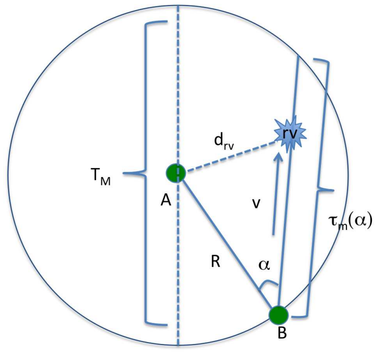

Fig. 1. Fly-by model

Following independent mobility patterns, nodes can occasionally find themselves in mutual coverage range, an event that we call *fly-by*. In this study, we limit our attention to the events that may occur during the fly-by of nodes A and B. The duration of the fly-by clearly depends on the trajectory and the mobility pattern of the two nodes. For simplicity, we suppose that nodes' trajectory are straight and uniform, at least during the fly-by. Hence, centering the reference system on node A, we can describe the relative trajectory of node B during the fly-by by means of two parameters, namely the (relative) speed v and the angle of incidence α of B's trajectory into the circle of radius R centered in A. With reference to Fig. 1, we define the following parameters whose inter-relations can be easily obtained by basic trigonometry:

- τ: time since the beginning of the fly-by event;
- $s(\tau) = v\tau$: distance covered by B at time τ;
- $d(\tau, \alpha) = \sqrt{R^2 + s(\tau)^2 - 2Rs(\tau)\cos(\alpha)}$ Euclidean distance between A and B at time τ;
- $\tau_m(\alpha) = 2R\cos(\alpha)/v$: overall fly-by duration;
- $T_M = 2R/v = \tau_m(0)$: maximum fly-by duration.

We assume that opportunistic interaction can occur only during a fly-by and under the condition that both nodes are in the so-called *Scan Phase*, which may correspond to an interlaced Inquiry/Scan phase of Bluetooth or to the Active Scanning procedure of IEEE 802.11 systems. When such conditions occur, the nodes immediately perform the opportunistic data exchange in negligible time. We call this event *rendezvous* and we denote by t_{rv} the instant when it occurs with respect to the beginning of the fly-by.

In our model, we suppose that all nodes enter the scan phase periodically, every T seconds, though in an asynchronous and independent manner, so that the offset between the scan phases of two nodes can be modeled as a random variable with uniform distribution in the interval $(0, T)$. The duration of the scan phase, normalized to the scan period T, is called *duty* *cycle* and denoted by δ. Whereas all nodes have equal scan period T, the duty cycle may differ, depending on the specific requirements and management policy of each node. Without loss of generality, in the sequel we consider $\delta_A \geq \delta_B$.

Let τ_o denote the instant at which the scan phases of the two nodes overlap for the first time, measured with respect to the beginning of the fly–by, and let $F_{\tau_o}(\cdot)$ and $f_{\tau_o}(\cdot)$ be the corresponding probability distribution and density functions, respectively. Note that, due to the periodicity of the scan phases, we have $\tau_o \in [0, T]$. When $\delta_A + \delta_B \leq 1$, there is a positive probability that the scan phases do not overlap. In this case, $F_{\tau_o}(\tau)$ is a defective distribution with upper limit given by $F_{\tau_o}(T) = \delta_A + \delta_B$, which corresponds to the probability of overlapping before T. After some easy algebra, the probability density function (pdf) $f_{\tau_o}(\tau)$ turns out to be

$$f_{\tau_o}(\tau) = \begin{cases} \delta_A \delta_B \delta(t) & \scriptstyle \tau=0 \\ (\delta_A + \delta_B)/T & \scriptstyle 0<\tau\leq T(1-\delta_B) \\ 2(T-\tau)/T^2 & \scriptstyle T(1-\delta_B)<\tau\leq T \end{cases} \tag{1}$$

where $\delta(t)$ is the Dirac delta function, which accounts for the case in which the two nodes enter the communication range when their are both scanning for opportunistic interaction, so that communication can immediately take place and $\tau_o = 0$. When $\delta_A + \delta_B > 1$, the scan phases always overlap at some point in the interval $[0, T]$ and the pdf, not reported here for space limits, can be obtained following the same rationale explained above.

Given α, a rendezvous occurs when $t_{rv} \leq \tau_m(\alpha)$, so that the cumulative distribution function (cdf) $F_{t_{rv}}(t, \alpha)$ of the rendezvous time t_{rv}, conditioned on α, can be expressed as

$$F_{t_{rv}}(t, \alpha) = \begin{cases} F_{\tau_o}(t, \alpha) & \text{for} \quad 0 \leq t < \tau_m(\alpha) \\ F_{\tau_o}(\tau_m(\alpha), \alpha) & \text{for} \quad t > \tau_m(\alpha) \end{cases} \tag{2}$$

We note that $F_{t_{rv}}(a, \alpha)$ is a defective distribution. The upper limit of $F_{t_{rv}}(a, \alpha)$ gives to the so-called *hit probability*, that is the probability of observing a rendezvous during a fly-by, which will be denoted by

$$P_H(\alpha) = F_{\tau_o}(\tau_m(\alpha)) \tag{3}$$

Averaging over the distribution $f_\alpha(\theta)$ of α we get the expected hit probability

$$P_H = \int_{-\pi/2}^{\pi/2} P_H(\theta) f_\alpha(\theta) d\theta \tag{4}$$

The hit probability P_H is an important performance index, since it conveys the possibility of enabling any opportunistic algorithm in a given scenario. The other performance index of interest for the localization scheme is the so-called “hit-distance” d, ie., the distance at which the hit occurs. Applying simple geometric arguments, we can easily realize that, given α, the nodes are at exactly at distance x during the fly-by in the two instants

$$t_{1,2}(x, \alpha) = \left(\frac{R\cos(\alpha) \mp \sqrt{x^2 - R^2 \sin^2(\alpha)}}{v} \right)$$

Then, the probability that the hit-distance $d \leq x$ is equal to the probability that the rendezvous occurs in the time interval $[t_1(x, \alpha),\ t_2(x, \alpha)]$. Averaging over α, we hence get

$$F_d(x) = \int_{-\pi/2}^{\pi/2} \left[F_{t_{rv}}(t_2(x, \theta)) - F_{\tau_o}(t_1(x, \theta)) \right] f_\alpha(\theta) d\theta \tag{5}$$

which provides the cdf of the “hit-distance”. This distribution is of great interest in the analysis that follows because the performance of range-based localization schemes closely depend on the quality of the ranging that, in turn, is a function of the real distance between the two communicating devices.

IV. Opportunistic localization algorithm

In our model, we assume that nodes have “native” self-positioning capabilities, provided by some (non opportunistic) scheme. Accordingly, we denote by $\mathbf{s}$ and $\hat{\mathbf{s}}$ the real and the estimated node’s position in the area, expressed in polar coordinates. For simplicity, we assume that the estimation error $\mathbf{e} = \mathbf{s} - \hat{\mathbf{s}}$ can be modeled as a 2–dimensional Gaussian random variable with zero mean and variance σ_i^2. Accordingly, $||\mathbf{e}||$ is a Rayleigh-distributed random variable with parameter σ_i, having pdf

$$f_{\epsilon_i}(x) = \frac{x \exp\left(\frac{-x^2}{2\sigma_i^2}\right)}{\sigma_i^2} \ ; \quad x \geq 0$$

We assume that nodes can be classified in different “*classes*” according to the variance σ_i^2 that characterizes their self-localization accuracy. During a rendezvous, nodes exchange packets containing their estimated positions $\hat{\mathbf{s}}_A$ and $\hat{\mathbf{s}}_B$, and the variance associated to the localization class they belong to. Furthermore, the nodes make an estimation $\hat{d}$ of their by using some ranging technique, e.g. RSSI or ToA based [8]. Then, each node refines its own position estimate to $\tilde{\mathbf{s}}$ using a Maximum Likelihood (ML) argument. In our opportunistic localization scheme, the ML equation can be written as

$$\begin{aligned} \tilde{\mathbf{s}}_{A,B} &= \arg\max_{\mathbf{s}_A, \mathbf{s}_B} \Pr\left[\hat{d}, \hat{\mathbf{s}}_A, \hat{\mathbf{s}}_B | \mathbf{s}_A, \mathbf{s}_B\right] \\ &= \arg\max_{\mathbf{s}_A, \mathbf{s}_B} \Big\{ f_{\epsilon_A}\left(\|\hat{\mathbf{s}}_A - \mathbf{s}_A\|\right) f_{\epsilon_B}\left(\|\hat{\mathbf{s}}_B - \mathbf{s}_B\|\right) \cdot \\ &\qquad\qquad \cdot f_r\left(\hat{d} \| \mathbf{s}_A - \mathbf{s}_B\|\right) \Big\} \end{aligned} \tag{6}$$

where $\hat{\mathbf{s}}_A$, $\hat{\mathbf{s}}_B$ and $\hat{d}$ are the new estimates of nodes’ position and distance, $\|\cdot\|$ denotes the Euclidean norm, whereas $f_r(\cdot)$ is the pdf of the ranging, which depends on the specific ranging technique used by the nodes. In our study, we use an RSSI-based ranging technique which provides a distance estimate given by

$$\hat{d} = d \cdot 10^{\frac{\psi(t, \mathbf{x})}{10\gamma}}$$

where d is the real distance between transmitter and receiver, γ is the path loss coefficient and $\psi(t, \mathbf{x})$ is a gaussian variable that models the shadow fading [20]. Hence, the ranging estimate turns out to be biased, with a lognormal distribution. Unfortunately, the ML equation (6) cannot be solved in closed form, so that we resort to Monte Carlo simulations.

The first interesting scenario can be node A with perfect knowledge of his position, node B with gaussian position error on the estimation $\hat{B}$ and perfect ranging.

It is simple to see that in this case the error after the heuristic opportunistic localization depends only on the angle $\widehat{BA\hat{B}}$ following this equation

$$P[\epsilon < K] = 2 \cdot F_\alpha \left(2 \cdot \arcsin\left(\frac{K}{2d_{AB}}\right)\right) \tag{7}$$

where the distribution of the angle, given the distance d_{AB} between A and B and σ_B, is

$$\begin{aligned} f_\alpha(\alpha) &= \int_{-D}^{+\infty} p_x(x)p_y((D+x)\tan(\alpha)) \cdot (D+x)dx \qquad (8) \\ &= \frac{1}{2}\frac{e^{-\frac{d^2}{2\sigma_B^2}}}{2\pi}\left(2+\frac{e^{\frac{d^2\cos(\alpha)^2}{2\sigma_B^2}}\sqrt{2\pi}\cdot d\cos(\alpha)}{\sigma_B}\cdot(1-Erf(\frac{d\cos(\alpha)}{\sqrt{2}\sigma_B}))\right) \\ &= \frac{e^{-\frac{D^2\tan^2(\alpha)}{2\sigma^2(1+\tan^2(\alpha))}}}{2\sqrt{2\pi}\sigma\sqrt{1+\tan^2(\alpha)}}\left[1-Erf\left(\frac{-D-2D\tan^2\alpha}{\sqrt{2\sigma^2}\sqrt{1+\tan^2(\alpha)}}\right)\right] \qquad (9) \end{aligned}$$

or

$$\begin{aligned} F_\alpha(\alpha) &= P[\widehat{BA\hat{B}} < \alpha | \alpha < \pi/2] \qquad (10) \\ &= \int_{-D}^{+\infty} p_x(x) \int_0^{(D+x)\tan(\alpha)} p_y(y)dydx \end{aligned}$$

where $p_x(x)$ and $p_y(y)$ are gaussian pdf with zero mean and the same variance σ_B^2.

If the ranging is affected by an error, the previous equation becomes more complicated. The total position error is given by ϵ_α, the error due to the angle between A and $\hat{B}$, and ϵ_ρ, the error due to the erroneous estimation of ranging. We have that $\epsilon_\alpha = 2d\sin(\alpha/2)$ and given ϵ_{range}, then the total estimation error is $\epsilon^2 = \epsilon_\rho^2 + \epsilon_\alpha^2 + 2\epsilon_\rho\epsilon_\alpha\sin(\alpha/2)$

Therefore we can write the distribution of position error as

$$P[\epsilon<K]=\int_{-d}^{+\infty} f_{\epsilon_\rho}(\delta)\cdot 2\cdot F_\alpha\left(2\cdot\arccos\left(\frac{d^2+(d+\delta)^2-K^2}{2d(d+\delta)}\right)\right)d\delta \tag{11}$$

where δ is the ranging error.

or, equivalently

$$P[\epsilon < K] = \begin{cases} 2\int_0^{\hat{\theta}} f_\alpha(\alpha)(F_\rho(p_2) - F_\rho(p_1))d\alpha & K \le d \\ 2\int_0^{\pi} f_\alpha(\alpha)F_\rho(p_2)d\alpha & K > d \end{cases} \tag{12}$$

where $p_{1,2} = d\cos(\alpha) \mp \sqrt{K^2 - d^2\sin^2(\alpha)}$ and $\hat{\theta} = \arcsin(\min(\frac{K}{d}, 1))$

Then it is possible to add the last random effect: the node A has a position error, so the estimated angle between the two nodes is affected also by the imperfect position of A.

The geometric situation is explained in figure 2

Therefore it is necessary to explain the behaviour of $\tilde{d}$ in order to exploit the previous model.

Hence, the distribution of the complete model is

$$\int_0^{+\infty} P[\epsilon < K | d = s] f_{\tilde{d}}(s)ds \tag{13}$$

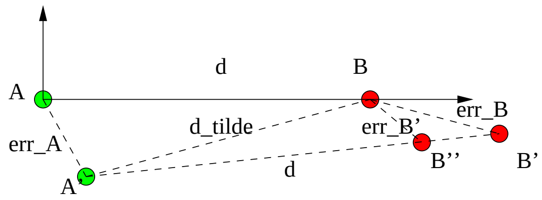

Fig. 2. Geometric model of the problem

where

$$f_{\tilde{d}}(s) = \frac{2}{\pi}\frac{s}{\sqrt{s^2 - d^2\sin^2(\alpha)}}\int_0^{\arcsin(\min(\frac{s}{d},1))}(f_\rho(p_2)+f_\rho(p_1)) \tag{14}$$

with $f_{\tilde{d}}$ is a Rayleigh random variable with parameter $\sigma_A\sqrt{\frac{\pi}{2}}$ The maximization of this equation needs some complexity that is not good in a scenario with low–cost devices and mobile nodes.

V. Results

In this section, we first investigate the impact of the system parameters on the hit probability on the hit-distance. This first analysis allows us to reduce the parameters space by fixing some values. Then, we forget put temporarily aside the opportunistic model to focus on the opportunistic location update algorithm only. In this case, we assume that a rendezvous occurs at a given point during the fly-by and analyze the potential improvements tat can be obtained from such an interaction. Finally, we put all the pieces together and show the overall performance of the opportunistic localization scheme in different scenarios.

A. Opportunistic interaction analysis

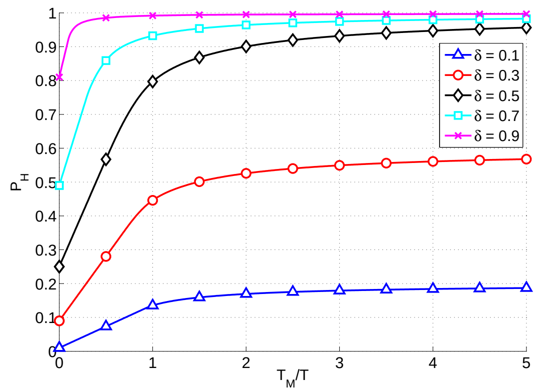

Fig. 3. Hit probability P_H when varying the duty–cycle $\delta_A = \delta_B = \delta$

Fig. 3 shows P_H versus T_M/T, for different duty cycles, assuming $f_\alpha(\theta) = 1/(2\pi)$ with $\theta \in [-\pi/2, \pi/2]$. The ratio T_M/T gives the *maximum* number of scan periods that the two nodes can perform during a fly-by. Note that $T_M/T > 1$ does not guarantee that the nodes always perform an entire scan phase during the fly-by, since the actual duration of each fly-by depends on α. We note that P_H grows rather rapidly till $T_M/T < 2$ after which the curves tend rather slowly to their asymptotic value $P_H = \min(1, 2\delta)$, which corresponds to the hit probability when each fly-by lasts more than T. On the light of these results, in the following we set $T_M/T = 2$.

Fig. 4 shows the distribution $F_d(x)$ of the hit-distance, as given by (5), when varying the duty–cycle δ. First of all, we

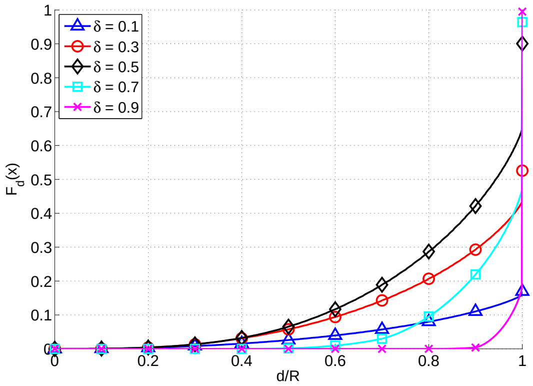

Fig. 4. CDF of the hit-distance d when varying the duty-cycle δ

observe that the curves show a discontinuity when $d/R = 1$, which depends on the Dirac impulse observed in (1). We also observe that the curves do not reach 1, since the distribution is defective, the upper limit corresponding to the hitting probability. Recalling that RSSI-based ranging techniques usually perform better at short distance, the best setting for δ is 0.5. Smaller values of δ would reduce the hit probability, whereas larger value would increase the probability that the $rendezvous$ occurs at the border of the coverage range (we consider only the first rendezvous during the fly–by).

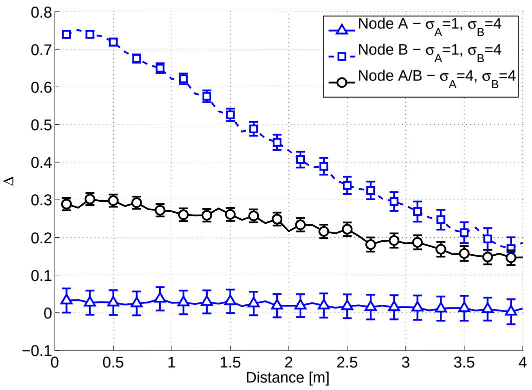

Fig. 5. Relative localization error gain after an opportunistic update varying the hit distance

B. *Opportunistic localization analysis*

We now focus on the performances of the opportunistic update when varying the meeting distance. We consider two different cases: an heterogeneous scenario in which nodes A and B belong to the different localization classes, with $\sigma_A = 1$ and $\sigma_B = 4$, respectively; and and homogeneous scenario where both nodes have the same localization class with $\sigma_A = \sigma_B = 4$. To better appreciate the effect of opportunistic localization, we define the *opportunistic gain* metric Δ_i, $i = A, B$, as

$$\Delta_i = \frac{\sigma_i\sqrt{\pi/2} - \tilde{\epsilon}}{\sigma_i\sqrt{\pi/2}}$$

where $\tilde{\epsilon}$ is the mean localization error after the opportunistic localization, whereas $\sigma_i\sqrt{\pi/2}$ is the mean localization error of the node obtained by using the native localization scheme. Therefore, Δ represents the relative gain in the localization error obtained by using the opportunistic scheme.

Fig. 5 shows the results for the heterogeneous scenario (solid line) and the homogeneous scenario (dashed lines). We note that the opportunistic localization can effectively provide a large performance gain, in particular if the nodes belong to different classes of accuracy and the opportunistic interaction occurs at short distances.

C. *Combined analysis*

We now investigate the performance of the complete system. Fig. 6 reports the results obtained for the heterogeneous scenario, when varying the duty cycle δ and the coverage range R. We observe that also in this case the best performance are obtained by setting $\delta = 0.5$ for every coverage range, though the performance improves for small value of R, as expected. Nonetheless, the scheme offers a 20% of gain even when $R = 4\,m$, which is a reasonable distance for this type of interactions.

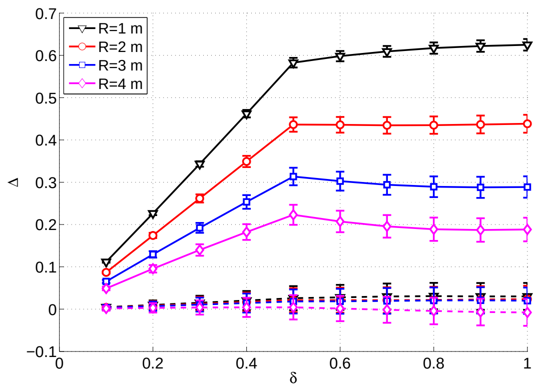

Fig. 6. Relative localization error gain after an opportunistic update for different values of range R in the heterogeneous scenario ($\sigma_\psi = 5$). Solid/dashed lines refer to node A/B.

Fig. 7 shows the same results, but for an homogeneous scenario in which both nodes have poor native self-localization capabilities. The results are substantially similar to those of the former case, though the curves are now more compacted and the relative error gain is reduced. Nonetheless, we observe that in this situation, the initial localization errors are very large, so that a gain of 25% is appreciable.

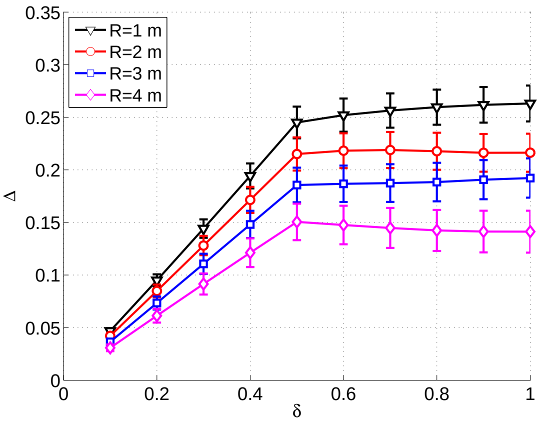

Fig. 7. Relative localization error gain after an opportunistic update for different values of range R in the homogeneous scenario ($\sigma_{\psi} = 5$)

VI. Conclusion

In this paper we propose a novel localization technique based on opportunistic data exchange between heterogeneous nodes.

The results obtained show that the opportunistic scheme can effectively improve the localization accuracy of the nodes, even though the performance strictly depends on the setting of some system parameters. In particular, the duration of the scan period and its duty cycle, as well as the maximal distance for opportunistic exchange need to be accurately set in order to attain significative gain.

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