An energy-efficient strategy for combined RSS-PDR indoor localization

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***Abstract*—We propose an optimization-based framework to minimize the energy consumption in a sensor network when using an indoor localization system based on the combination of received signal strength (RSS) and pedestrian dead reckoning (PDR). The objective is to find the RSS localization frequency and the number of RSS measurements used at each localization round that jointly minimize the total consumed energy, while ensuring at the same time a desired accuracy in the localization result. The optimization approach leverages practical models to predict the localization error and the overall energy consumption for combined RSS-PDR localization systems. The performance of the proposed strategy is assessed through simulation, showing energy savings with respect to other approaches while guaranteeing a target accuracy.**

I. Introduction

The capability of tracking the position of people and objects is nowadays fundamental within numerous pervasive computing applications. In indoor environments, where GPS cannot be used, radio-frequency localization techniques [1] have become very popular, due to the wide-spread use of wireless networks. In particular, as current off-the-shelf equipment can easily collect information about the Received Signal Strength (RSS), it has become the basis for localization in pervasive wireless networks.

RSS-based localization systems often feature a fixed infrastructure of wireless devices (anchors) to collect the RSS measurements from the radio transmissions of the wireless device to be localized. Such measurements are then fed into localization algorithms to estimate the current position of the device. The localization accuracy depends in general on the accuracy of the RSS measurements, on the number and relative positions of the nodes, and on the physical characteristics of the environment.

In order to improve the localization accuracy, hybrid localization systems have been proposed, combining RSS localization with measurements provided by inertial sensors, such as accelerometers and gyroscopes [2], [3], [4], [5]. To this end, these devices are mounted on the object/person to be tracked to implement dead reckoning systems, which provide continuous estimates of the position, speed and orientation of the object. Pedestrian Dead Reckoning (PDR) systems are especially attractive for localization in unprepared environments, as they do not rely on any available infrastructure. However, as the new positions are calculated from the previous estimations, measurement errors are cumulative and may produce an unbounded increase in the localization error.

In addition to localization accuracy, also energy efficiency has to be considered when designing localization systems, as wireless devices involved in the localization process may often be battery-operated. To this extent, the localization system has to be designed to achieve a desired localization accuracy while limiting the consumed energy due to processing and wireless communication.

This paper targets the design of accurate and energy efficient hybrid localization systems based on RSS measurements and dead reckoning. Within this field, the simplest approach in the related literature is to use RSS localization periodically, whilst using dead reckoning techniques between consecutive RSS localization rounds. As in plain RSS-based localization, the energy consumption can be reduced by (adaptively) setting the RSS localization frequency according to heuristic criteria on the estimated current localization error and/or on the mobility characteristics of the mobile devices. Differently, we introduce in this paper an optimization-based framework which properly sets, besides the RSS localization frequency, also the number of RSS measurements used at each localization round. The optimization approach leverages practical models to capture/predict the localization error and the overall energy consumption for localization systems featuring RSS-based and dead reckoning based approaches. The performance of the proposed method is assessed through simulation and compared against well-known approaches available in the literature.

The structure of the paper is as follows. Section II reviews related work on energy-efficient localization. Section III defines the models that have been developed to capture the localization accuracy of combined RSS-PDR localization systems, while their energy consumption is analyzed in Section IV. A strategy to minimize energy consumption while achieving a target accuracy in the localization result is proposed in Section V and its performance is evaluated numerically in Section VI. Section VII concludes the paper.

II. Related work

A conventional approach to optimize the accuracy-consumption tradeoff adopted in RSS-based localization varies the periodicity at which the localization is performed: more frequent localizations lead to a more precise position tracking, at the cost of a higher radio consumption. The very same approach can be easily extended to hybrid RSS-PDR systems, with the advantage that inertial measurements can be used to find enhanced inter-localization periods.

The authors of [6] compare three different methods to set the localization frequency: 1) Using a fixed frequency, 2) Using an adaptive localization frequency: the next localization is scheduled when the node is supposed to have traveled a predefined distance, and it is calculated by estimating speed from two previous position estimations, 3) Dead reckoning is also used to estimate position: if this estimated position is similar to the position obtained through localization, localization frequency is decreased; otherwise, the localization frequency is increased. The simulations reported in [6] show that the energy consumption due to communication is lower for methods 2) and 3) when the mobility pattern is predictable (low speed, infrequent changes). On the other hand, the localization errors for these strategies increase proportionally to the node speed.

Similarly, the authors of [7], [8] propose to modify the localization frequency depending on the mobility level of the node. In particular, the estimated speed of the mobile node is used to adapt the localization period so that the localization error does not exceed a given error tolerance. Four different methods are compared to estimate the mobile node speed: 1) The mobile node is assumed to move at a constant speed (the maximum possible speed in the application), 2) The speed is calculated from the two previous position estimations, 3) Accelerometers are used to indicate if the node is moving; then, if it is static the position is not calculated, if it is moving, speed is calculated from the two previous position estimations, 4) Speed is estimated by counting the number of steps and multiplying them by the average human step length. The results show that methods 3) and 4) have a lower energy consumption (due to communications), specially for low mobility, but a bit higher non-conformance rate (exceeding desired localization error).

In general, these methods try to optimize only the localization frequency in order to achieve a desired accuracy while keeping as low as possible the energy consumption. However, the localization accuracy can also be traded for energy consumption by optimizing the number of RSS measurements used at each localization round. The work in [9] leverages this trade-off by optimizing the transmission power of the packets from which the RSS measurements are collected, as well as the number of RSS samples which are averaged to run the localization algorithm in order to obtain a given localization accuracy while minimizing energy consumption. Along this line, we propose in this paper a new method to jointly optimize the localization frequency and the number of radio measurements at each localization period in order to minimize the energy consumption while achieving a desired accuracy in the localization results.

III. RSS-BASED AND PDR LOCALIZATION ERRORS

In the following, we propose simplified models of the localization error for RSS-based and PDR techniques, which will be leveraged to develop the optimal localization strategy.

A. RSS-based localization error

A popular technique for RSS-based indoor localization, due to its ease of deployment and simplicity, is the use of the log-normal shadowing path loss model [10] to establish a relation between the RSS and the distance between two nodes. The location of a node can then be determined from a set of pairwise distances using proper positioning algorithms, such as the ones in [11]. According to this model, the relation between the received power (P_{RX}) and the distance (d) between transmitter and receiver is given by:

$$P_{RX}\,[dBm] = A - 10\eta \log \frac{d}{d_0} + N \tag{1}$$

where A is the received power at d_0 meters, η is the path loss exponent, and $N \sim \mathcal{N}(0,\sigma^2)$ is a zero-mean Gaussian random variable with standard deviation σ. This model describes RSS measurements as Gaussian random variables [1], thus, their standard deviation can be reduced by a factor of $\sqrt{n}$ if n measurements are averaged, provided the measurements are independent.

The Cramer-Rao lower bound for the localization error with RSS measurements is derived in [12] and indicates which is the minimum variance an unbiased estimator of the position can achieve. Assuming the log-normal channel model, its expression for a network composed of M reference nodes (with positions (x_i, y_i), i=1,...,M) and one mobile node with unknown position (x, y) is given by:

$$\sigma_{crlb}^2 = E\left[(\hat{x}-x)^2 + (\hat{y}-y)^2\right] \geq \frac{1}{b} \frac{\sum_{i=1}^{M} d_i^{-2}}{\sum_{i=1}^{M-1} \sum_{j=i+1}^{M} \left(\frac{d_{\perp ij} d_{ij}}{d_i^2 d_j^2} \right)^2} \tag{2}$$

where d_i is the distance between the mobile node and reference node i, d_{ij} is the distance between reference nodes i and j, $d_{\perp ij}$ is the shortest distance from the mobile node to the line segment connecting nodes i and j, and $b = \left(\frac{10\eta}{\sigma_{RSS} \ln 10} \right)^2$, where η is the pathloss exponent and σ_{RSS} the standard deviation of the RSS measurements. If the average RSS value from n packets is used to perform each localization, $\sigma_{RSS} = \sigma/\sqrt{n}$, where σ is the standard deviation due to shadowing in the log-normal model (1).

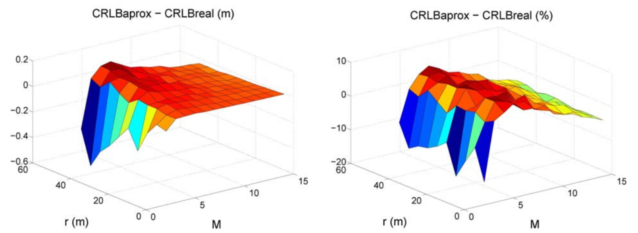
Therefore, the accuracy of the RSS-based localization depends on the position of the reference nodes, the position of the mobile node, the channel parameters η and σ and the number n of packets used to obtain the RSS measurement.

In practice, we are interested in the average value of σ_{crlb} over the area of interest. In order to find an approximate expression, we evaluated σ_{crlb} for different realizations of M randomly distributed nodes inside the coverage area of a node (a circular area with radius r and area $S = \pi r^2$ m^2). We found that the following model:

$$\bar{\sigma}_{crlb} \approx \frac{\sigma}{\eta\sqrt{n}} a\sqrt{S} M^b \tag{3}$$

fits quite well the theoretical average value of σ_{crlb} for a = 0.34 and b = -0.84. The intuition behind this expression comes from the fact that for a given number of reference nodes, the CRLB should increase with the size (proportionally to the square root of the area, due to dimensionality reasons) and that for a given area, the CRLB should diminish when more reference nodes are added (therefore, we expect a M^b-type trend, with a negative value of b).

For the extreme case of 3 reference nodes in a 50m-radius coverage area the difference between the real and the approximated value of σ_{crlb} is 0.58 m. For more realistic parameters, the deviation is even lower (see Fig. 1). For example for 4 or more reference nodes in the area the difference only reaches 0.14 m in the worst case. Thus, this expression can be used as an approximate lower bound of the RSS localization error.



(a) Difference in m (b) Difference in %

Figure 1. Difference between the approximated CRLB and the real average value of the CRLB for a topology with M reference nodes randomly distributed inside the coverage area (circular with radius r) of a node.

B. PDR localization error

As previously said, dead reckoning consists in estimating the trajectory of an object by continuously adding its displacements from a given starting point. The main disadvantage of using inertial sensors, in particular accelerometers and gyroscopes, for dead reckoning is that the integration of their noise results in cumulative errors. The errors are even bigger for pedestrian dead reckoning, i.e., when the object to be tracked is a person, as the inertial sensors are attached to the body and, therefore, may move with respect to the person during walk. When inertial measurements are integrated to track the position of a user the main error contributions are the following [13], [14], [15]:

- Accelerometer noise produces an error in the position whose RMS value increases with $t^{1.5}$

$$\sigma_n = \frac{1}{2}\frac{\sigma_d}{\sqrt{f_s}} t^{1.5} \tag{4}$$

  where f_s is the sampling frequency and σ_d the standard deviation of the accelerometer noise.

- Accelerometer bias, when double integrated, produces a position error that grows with t^2

$$\sigma_{abias} = \frac{1}{2} A t^2 \tag{5}$$

  where A is the accelerometer bias.

- Gyroscope bias produces a position error that grows with t^3

$$\sigma_{gbias} = \frac{1}{6} aBt^3 \tag{6}$$

  where B is the gyroscope bias and a the acceleration that affects the sensor (typically, the acceleration due to gravity g).

C. Joint localization error

In the reference system, the RSS-based localization is done periodically and inertial sensors are used between consecutive RSS-localizations to track the position of the user. The total localization error will have two contributions, one due to the RSS-localization and the other due to PDR-localization:

$$RMSE^2(t) = RMSE_{RSS}^2 + RMSE_{PDR}^2(t) \tag{7}$$

where t is the elapsed time from the last localization reset.

The RSS-localization error does not depend on the time t, but only on the positions of the nodes and on the characteristics of the channel. In order to simplify this term, we can use the approximate equation (3), which depends on the number of reference nodes and the size of the deployment area.

The PDR localization error depends on the integration time t. The maximum value of the PDR localization error appears at the end of the integration time, i.e. at the end of each RSS localization period (i.e. when $t = T$). At this moment, the RMS error can be written as:

$$RMSE(T)^2 \approx \left(\frac{\sigma}{\eta\sqrt{n}} a\sqrt{S} M^b\right)^2 + \left(\frac{1}{2}\frac{\sigma_d}{\sqrt{f_s}} t^{1.5}\right)^2 + \left(\frac{1}{2} At^2\right)^2 + \left(\frac{1}{6} aBt^3\right)^2 \tag{8}$$

It can be seen that the localization accuracy depends on the values of n and T. On one hand, increasing n will diminish the RSS localization error. On the other hand, diminishing T will diminish the PDR localization error. Thus, a desired localization error (e.g. a given RMSE(T)) yields a relationship between n and T. Clearly, the different combinations n - T will have a different energy consumption (the energy consumption increases with n and diminishes with T), so it would be interesting to find a method to calculate their optimum values.

IV. ENERGY CONSUMPTION

In the following, we analyze the dependence of the energy consumption on the parameters n and T, which will serve to formulate our optimization strategy. We are interested in minimizing the energy consumption at the mobile nodes, as they are battery-supplied. During the localization activity, the mobile node must communicate with the reference nodes to obtain RSS measurements, perform some processing operations and use its inertial sensors to obtain additional measurements. We will consider here the energy consumption during the communication activities. The energy consumption due to processing is neglected, since it can be optimized separately. On the other hand, the inertial sensors should be active all the time to perform the PDR localization, so their energy consumption will be constant (independent of n and T) and will not have any effect in the minimization of the energy consumption.

The radio energy consumption depends on how the message exchange is performed. We consider here the case in which the RSS-based localization is performed uplink, i.e. the anchor nodes measure the RSS from the beacons sent by the mobile node and send these measurements to a central node, which performs the localization. For a single RSS-localization the mobile node sends n beacons and a total of m neighbor reference nodes will measure their RSS and send them to the central node. The central node estimates the position of the mobile node and sends back to the mobile node a message with the calculated position. Taking this position as a starting point, the mobile node tracks its own trajectory with the inertial sensors for a time T, after which a new RSS-localization is performed and the whole procedure is repeated. The position information between two consecutive RSS-based localization remains at the mobile node, therefore, the mobile node may send periodically (with a period $T_n<T$) a message with its position to the central node. The energy consumption over a time interval $T_{tot} >> T$ in this case will be:

$$\begin{aligned} E_{radio} &= E_{TXbeacon} + E_{RXpos} + E_{TXpos} = \\ &\frac{T_{tot}}{T}\left(V_{cc} I_{TX} t_{TXb}\right) + \frac{T_{tot}}{T}\left(V_{cc} I_{RX} t_{RXp}\right) + \frac{T_{tot}}{T_n}\left(V_{cc} I_{TX} t_{TXp}\right) \end{aligned} \tag{9}$$

where V_{cc} is the voltage supply, I_{TX} and I_{RX} are the current consumptions in transmission and reception modes, t_{TXb} is the time in transmission mode required to send the beacons, and t_{RXp}/t_{TXp} are the times in reception/transmission modes required to receive/send the position packet. These time are given by: $t_{TXb} = nt_b$, $t_{RXp} = t_p + t_{wait}$ and $t_{TXp} = t_p$, where t_b is the duration of a beacon, t_p is the duration of the position information packet and t_{wait} is the time during which the mobile node remains in reception mode in order to receive the position packet.

Note that only the first two terms of (9) depend on the localization interval T and the number of packets n that are used to measure the RSS. Therefore, the component of energy consumption that should be minimized is given by:

$$E(n,T) = \frac{1}{T} f(n) \tag{10}$$

where, for the considered uplink localization scenario:

$$f(n) = V_{cc} I_{TX} n t_b + V_{cc} I_{RX}\left(t_p + t_{wait}\right) \tag{11}$$

A similar expression can be derived under different localization strategies (e.g., RSS samples measured at the mobile nodes).

V. PROPOSED STRATEGY

As we explained previously, increasing the number of RSS measurements n that are averaged for each radio-localization will diminish the RSS localization error. On the other hand, diminishing the localization period T will diminish the PDR localization error. Hence, in order to achieve a given localization accuracy, we can either modify n, or T or both. As this two variables also have an impact on the energy consumption, we propose to find the combination n - T that yields a lower energy consumption. The objective is to minimize the energy consumption at the mobile node while, at the same time, maintaining a certain degree of accuracy in the localization result. Therefore, the optimization problem can be written as:

$$\begin{aligned} &\min E(n,T) = \frac{1}{T} f(n) \\ &s.t. \begin{cases} RMSE(n,T) \le Acc \\ T_{\min} \le T \le T_{\max} \\ n \ge 1 \end{cases} \end{aligned} \tag{12}$$

where T_{min} and T_{max} are the minimum and maximum values allowed for the localization period, Acc is the accuracy we would like to achieve and $RMSE$ can be calculated according to (8). Note that we have decided to impose as a constraint that the expected accuracy at the end of each localization interval does not exceed a given value, but other constraints could be reasonable depending on the application (e.g. fixing the average value over time of the expected accuracy).

VI. PERFORMANCE EVALUATION

In this section we evaluate the performance of the proposed technique in terms of energy efficiency and accuracy of the localization results through detailed simulation. We compare these results with those obtained with different strategies aimed at reducing the energy consumption during the localization. Namely, the strategies adopted for comparison are:

- **Periodic localization** [6], [7]: RSS localization is performed periodically with a fixed period, equal to the maximum localization error divided by the maximum expected speed. At a given time, the node is considered to be located at the position of the last localization.
- **Periodic localization + PDR**: Inertial sensors are added to the previous strategy to perform PDR and reduce the localization error between RSS localizations.
- **Localization period controlled by mobile node speed**: The frequency of the RSS localization is modified according to the speed of the mobile node. The objective is to put an upper bound on the distance that the node can travel without updating its position (d_{max}), so that the localization period can be obtained as $T=d_{max}/v$. The speed of the mobile node can be calculated in different ways:
  - *RSS-estimated speed* [6], [7]: Speed is estimated from the two previous localizations and the time that has elapsed between them.
  - *Measured speed* [8]: Speed is measured with the inertial sensors. As inertial measurements need to be integrated to calculate the speed, they can be also used to obtain PDR position estimations that can be used between two consecutive RSS localizations to reduce the error.
- **Localization period controlled by PDR accuracy** [6]: Dead reckoning is used to track the position of the mobile node between RSS localizations. When a new RSS localization is obtained, the PDR position is compared with that of the RSS (which is supposed to be accurate). If the two positions are similar, the PDR is assumed to be performing well, so the localization period is increased. Otherwise, the localization period is reduced.

The simulation environment comprises a sensor network composed of M reference nodes deployed on a rectangular grid covering an area of $x_{max} \times x_{max}$ m^2. Two different trajectories have been simulated for the mobile node: a uniform circular motion and a trajectory generated with the random waypoint mobility model [16].

When the simulation starts, the mobile node performs a RSS localization and schedules the next localization T seconds later. Then it starts moving and the initial localization result is used as the starting point for the PDR algorithm. After T seconds a new RSS localization is performed, which will reset the PDR positioning error, and the procedure will continue. The localization period T and the number of packets (n) are chosen according to the proper strategies.

RSS localization is simulated in the following way. The log-normal channel model (1) is used to transform the real distances between the nodes into RSS measurements. Once n values of the RSS for each mobile-reference node pair are obtained, those RSS values below the sensitivity threshold are discarded and those above the threshold are averaged and used to obtain the pair-wise distance estimations. Finally, these estimated distances are used to estimate the position of the mobile node using the weighted hyperbolic positioning algorithm [11]. The message exchange strategy for the RSS-based localization is simulated as described in Section IV.

On the other hand, from the simulated trajectory of the node, the real accelerations and angular rates in the mobile reference system are obtained (with a sampling rate of f_s). Noise and bias are then added to generate the simulated inertial measurements, which are then integrated to obtain the estimated position using the equations in [15]. Since the initial position, speed and orientation are needed when the PDR is started, the PDR is reset after each RSS localization using the estimated position as the initial position. The initial speed and orientation are ideally initialized with their true values.

In the following figures we present the performance of the considered methods for a simulation environment with M = 9 anchor nodes in a 20 × 20 m^2 area, where a mobile node follows a circular trajectory during 500 s. The inertial measurements are affected by acceleration noise (σ_d = 5.7575·10^{-2} m/s^2) and gyroscope bias (B = 10°/h) and are taken at a sampling frequency f_s = 50 Hz. The propagation channel is modeled using the log-normal model, with parameters $\eta = 2.5$, $\sigma = 5$ dB and A = -60 dB (coverage radio around 25 m, as the sensitivity was set to S = -95 dBm). The maximum localization period was set to 30 s for all the strategies.

Fig. 2 shows how the proposed strategy adapts T and n depending on the desired accuracy. As expected, when the desired accuracy is lower, T is allowed to be higher and n smaller. The sharp behavior is due to the fact that n must be an integer, so if n decreases by 1, the accuracy of the RSS-based localization decreases significatively and, thus, T should be reduced with respect to its previous value in order to increase the accuracy of the PDR system. The relation between the final localization accuracy and the energy consumption of the proposed strategy is shown in Fig. 3, where the different points were obtained for different values of the desired accuracy.

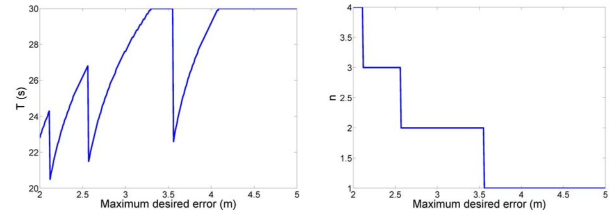


Figure 2. Values of T and n given by the proposed strategy as a function of the desired accuracy.

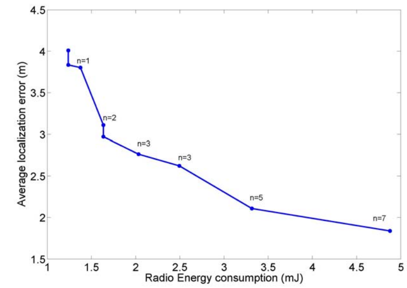


Figure 3. Error-Consumption curve for the proposed method. Each point was obtained for a different desired accuracy (from 2 m to 6 m). The average value of n corresponding to each point is also represented.

Fig. 4 represents the relation between the radio energy consumption and the average accuracy of the localization for the considered strategies, obtained for a target accuracy of 3 m and for different values of n. Note that the value of n determines the accuracy of the radio localization. Only the proposed strategy calculates its optimum value, together with the localization period. The other strategies should decide *a priori* the number of packets whose RSS should be averaged to get each localization. This figure highlights the importance of properly choosing its value: smaller values of n yield in general lower energy consumption but also lower localization accuracy. Obviously, for the proposed strategy, as n is calculated automatically, the values of energy consumption and accuracy do not change.

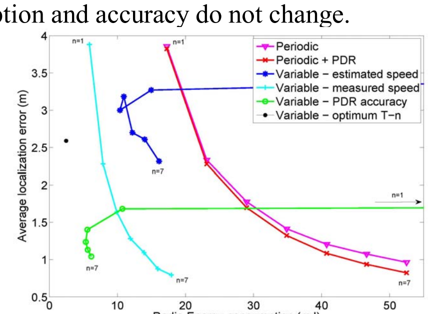


Figure 4. Error-Consumption curves for different values of n (from 1 to 7), for a speed of 1/100 rps (~0.5 m/s) and a maximum desired error of 3 m.

It can be seen that the periodic strategies consume much more energy than the proposed one. The same applies to the strategy that adjusts the localization period from the speed measured by the inertial sensors, even if this strategy has a lower energy consumption than the periodic ones, as it adapts the localization period to the real speed of the mobile node (in this case around 0.5 m/s, one third of the maximum speed -1.5 m/s- considered for the periodic strategies). Finally, the two strategies that use previous RSS localization results to adjust the localization period (either by estimating the speed from the two last localizations, or by taking the RSS-based localization as a reference to determine the PDR accuracy) are greatly affected by the accuracy of the RSS-based localization: for small values of n (not enough to make the RSS localization error smaller than the desired accuracy), their performance degrades very quickly, giving raise to an extremely high energy expenditure, as they try to reduce the error by increasing the localization frequency, which in these cases is impossible.

The proposed strategy has the lowest radio energy consumption (2.5 mJ), whereas the lowest energy consumption for the PDR-accuracy based method (the second best) is more than twice this value in the best case (5.4 mJ, for $n = 5$). Besides, the proposed method achieves an average localization accuracy below the maximum desired error. Therefore, among all the considered methods, the one proposed in this paper is able to guarantee the desired accuracy while effectively minimizing the radio energy consumption.

The previous simulation was repeated for different speeds of the mobile node, and for the random waypoint mobility model, obtaining similar results. Different target accuracies were also simulated. We noticed that for lower values of the desired localization error, the two methods that use previous RSS localization results to adjust the localization period are more affected by the value of n (leading to a very high energy consumption if n is not large enough). Therefore, in order to use these strategies, one should select the value of n carefully, otherwise, the performance could be completely unsatisfactory. With respect to the other three strategies, their energy consumption increases when the desired maximum error is lower, as expected, but their accuracy does not adapt to the desired one. Finally, the proposed strategy adapts to the desired accuracy by increasing the energy consumption in such a way that achieves a lower energy consumption than the other methods while, at the same time, obtains, in average, the desired localization accuracy.

VII. CONCLUSION

In this paper we have proposed an strategy for combined RSS-PDR localization systems that jointly optimizes the localization frequency and the number of radio measurements at each localization period with the aim of minimizing the energy consumption while achieving a desired accuracy in the localization results. The numerical evaluation has shown a good performance of the proposed approach in comparison with other approaches available in the literature, since it is able to guarantee an average final localization accuracy below the maximum desired error while effectively minimizing the radio energy consumption. Besides, the method establishes automatically the best value of n, so no attention has to be paid into tuning this parameter for an acceptable performance, as it occurs for other strategies.

Future work will address the integration of the transmission power in the optimization framework and the extension of the proposed approach to more complex RSS-PDR localization systems, as those combining RSS and inertial measurements through particle filters. On the other hand, we have deployed a testbed with MicaZ and Shimmer devices and we are starting to carry out some experimental tests, which seem encouraging. We are also planning to incorporate orientation and speed resets through practical approaches, as using GPS (outdoors) or magnetometers (indoors).

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