# Ultra-Low-Power Quantized-RSSI-based Localization Using Wake-Up Receivers

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***Abstract*—Localization capability is a key feature within the developing Internet of Things. This paper proposes an optimal and efficient system solution, based on ultra-low-power wake-up receiver hardware. To that end, a beacon-based quantized-RSSI maximum likelihood approach is employed. Measurements leading to an adapted log-distance path loss model are presented for an exemplary warehouse test environment, forming the basis for the statistical derivations. It is further shown that the hardware-imposed quantization of input power measurements does not significantly impair localization accuracy, while enabling efficient integration of the algorithm. Measurements confirm a mean error of 0.86 meters, with 80 % of distance errors below 1 m.**

***Index Terms*—Localization, Receivers, Indoor navigation, Received signal strength indicator, Low-power electronics, UHF propagation**

## I. Introduction

Wireless Sensor Networks (WSNs) and wireless asset tracking have gained significant importance over the past years. Objects within industrial, home and entertainment contexts are being integrated into the so-called Internet of Things (IoT). To facilitate all these connections, different efficient and robust wireless technologies are available on the market, including ZigBee and Bluetooth Low Energy (BLE) solutions. The main design goal often is to reduce energy consumption effectively, without adversely affecting transmission and network capabilities. In the context of this paper, a logistics and supply chain management viewpoint is pursued, although findings are translatable to other areas and applications as well. A thorough overview on the IoT is given for example in [1].

Many typical wireless modules provide information on received signal strength (RSSI). RSSI-based localization techniques may thus be implemented straightforwardly, as no additional costly hardware is necessary. While works on these techniques are numerous [2]–[4], their majority neglects the energy efficiency of the applied algorithms themselves, most of which have to be carried out on energy-intensive microcontrollers. A cheap and efficient silicon-integrable solution directly on the transceiver IC would thus be preferable.

Common standards and ICs currently face a second problem: they rely on extensive sleep periods to reduce mean receiver power consumption. This inevitably introduces a high latency when trying to wirelessly contact these network nodes, up to the length of their full sleep cycle. As is shown in detail in [5], sleep cycles may range up to ten seconds to achieve acceptable energy consumption ranges. To break this seeming dilemma between long battery lifetime and latency, a so-called wake-up receiver IC was presented in [6] and [7]. The IC allows to continually monitor the wireless channel on 868 MHz, while drawing only 7 µW off the battery. Upon reception of a special wake-up sequence, the IC may go ahead and activate further, more demanding circuitry on the transceiver module. Depending on the set operation mode, wake-up latency may for example be 30 ms. Due to a multi-branch receiver design, the chip also delivers a quantized estimate of the received signal strength with, at the moment, seven configurable power levels.

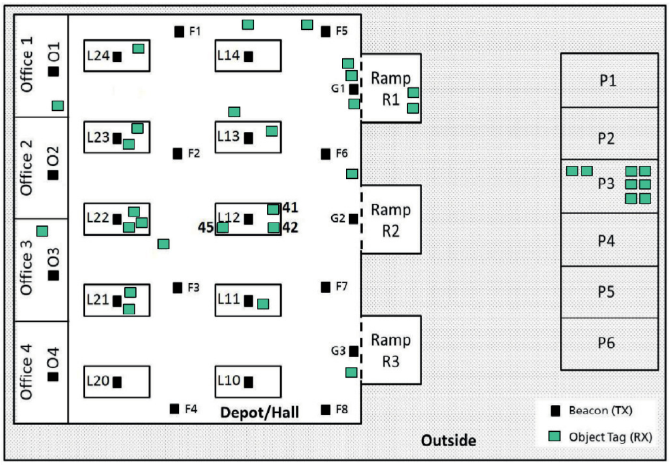


Fig. 1. Warehouse example for a beacon-based localization system. Numbered beacons are placed within offices (Ox), the warehouse area (Fx) and key positions, such as loading ramps (Lxx, Gx).

This paper presents and compares typical algorithmic localization solutions under these quantized RSSI (QRSSI) conditions. The focus is not only on accuracy, but also on complexity and integrability. Further information on WSN localization may for example be found in [8]. The following section first introduces a possible system design, while section III presents different localization strategies for wide indoor areas. Simulation and measurement results are summarized and evaluated in section IV.

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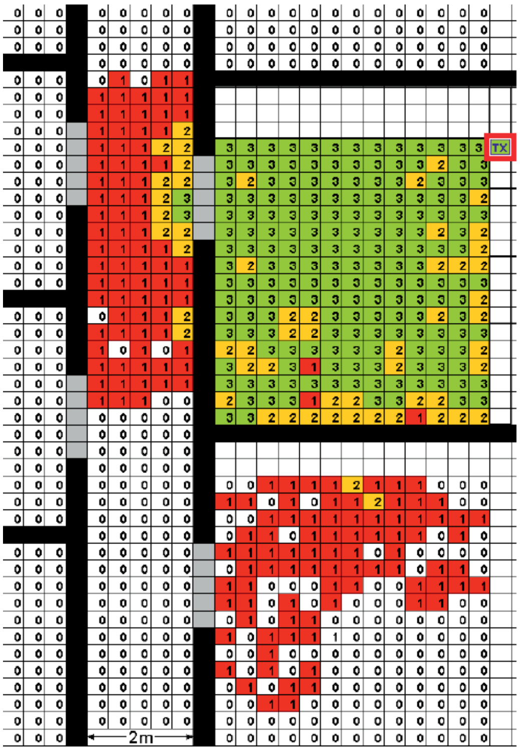


Fig. 2. Signal propagation from within the top right corner of a closed office room, measured in RSSI quantized to 4 levels (0 to 3) using a wake-up receiver.

## II. System design

As was presented in detail in [9], the proposed wake-up-based localization system relies on a number of fixed beacons (also called anchors) with known locations. These beacons periodically transmit beacon signals, combined with a wake-up preamble. These beacon frames also contain each beacons location and/or ID and are picked up by tag modules, fixed to objects of interest. These tags then use the gathered beacon information to localize themselves and may subsequently transmit their findings or act upon them. This, for example, may include geofencing applications or warehouse logistics. A sample warehouse scenario is shown in Fig. 1. An advantage of this self-localization scheme is, that the wireless channel is not blocked by network chatter. The only signals emitted are the periodic or requested transmissions of beacons, which also saves on tag energy.

For indoor localization the system proposes to distinguish two different types of environments. The first type is called confined areas, which are dominated by small rooms, hallways and walls, as is typical for office scenarios (compare Fig. 1). In confined areas signal propagation is dominated by wall shadowing effects from room to room. Equipping all rooms of interest with beacons, tagged objects may be localized with room-scale accuracy, which is often enough for typical applications. Due to shadowing, a simple maximum decision of the strongest beacon already provides quite reliable tracking: Fig. 2 presents a measured signal propagation map of

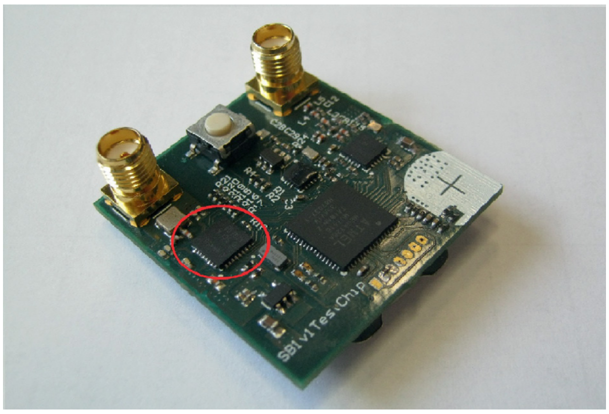

Fig. 3. Wake-up receiver test module, with wake-up IC (encircled), microcontroller and additional CC1101 transceiver chip by Texas Instruments. (Antennas not shown.)

a ”tagged” office room, showing reliable signal dampening by walls. Simple maximum decision beacons are also typical for gateway scenarios, where goods are to notice their passing through designated focus areas, such as loading ramps or gates. The gateway approach is also typical for passive RFID systems, which lack the ability to communicate over greater distances.

That being covered, this work concentrates on the second type of indoor environment: large-scale areas. Signal propagation in halls or warehouses is dominated by path loss and multipath propagation effects. It is necessary and reasonable to use more sophisticated algorithms to estimate tag positions within these open environments, relying on an infrastructure of beacons, scattered throughout the area. In fact, a large number of cheap beacons with long battery lifetime can be used to counteract the fading-induced information loss, as their propagation paths can be assumed to be independent (coherence distance $\Delta x_c = \lambda/4 \approx 8\,\mathrm{cm}$ [10]). Open area indoor strategies are also applicable to outdoor localization, where multipath fading if far less obtrusive.

## III. Localization algorithms for open areas

Apart from achieving the best possible accuracy, applicable algorithms are expected to be highly integrable in terms of necessary operations and memory requirements as well as scalable with the number of beacons and objects. They should also be robust against multipath and interferers and execute quickly. Demanding schemes like fingerprinting (e.g. [11]) are thus not discussed here.

### A. *Propagation model*

Algorithms are, among many other criteria, separable into range-free and range-based schemes [12], [13]. The second group performs statistical or geometrical calculations based on the measured, uncertain distances from the tag to each received beacon. With RSSI these distances are calculated via a propagation model (path loss model). The advantage of range-based algorithms is thus the potentially optimal use of

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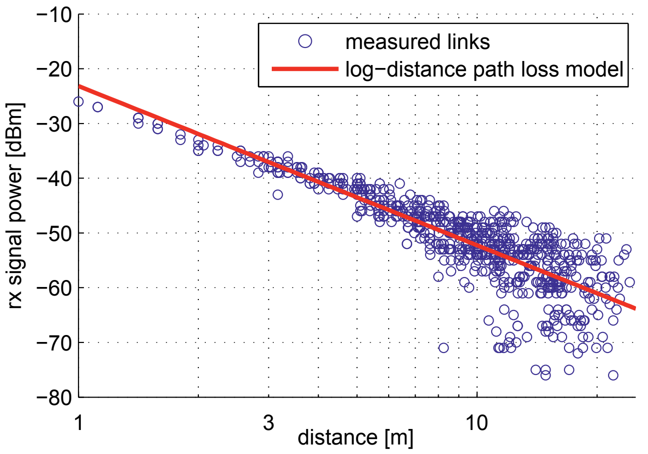


Fig. 4. Scatter plot and least squares approximation of measured wireless links within the test hall.

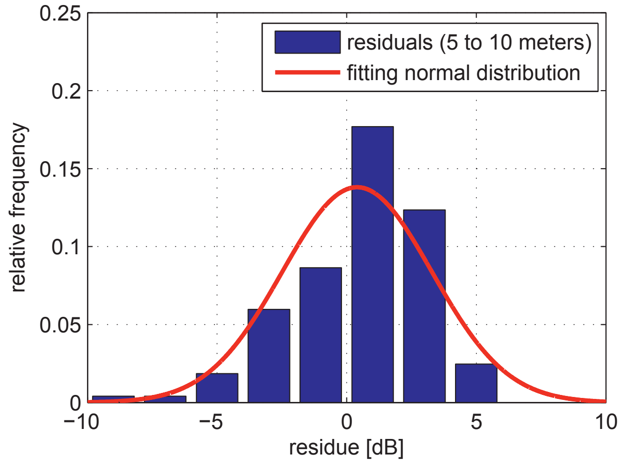


Fig. 5. Example for the residual distribution between 5 and 10 m with according normal distribution model.

RSSI information, with the disadvantage of being sensitive to model errors. A further benefit of having a correct propagation model is the possibility to setup simulations for algorithm test and optimization.

To analyze the propagation conditions, various measurements were conducted in a test warehouse with dimensions of about 45 x 30 x 12 m, using wake-up receiver test modules. To minimize the antenna impact on path loss measurements, custom ground-plane antennas were used in conjunction with Texas Instruments' CC1101 transceiver chip (Fig. 3).

Fig. 4 shows a scatter plot of the measured wireless links. The added trend of path loss versus distance (red) clearly shows the typical log-distance relationship. However, in contrast to high reflector density environments, like for example woods [14], the spread of values in dB scale around the deterministic part is not constant over distance. The classical log-normal fading model (e.g. [15]) is thus extended to reflect this observation to

$$\begin{aligned} P_{RX} &= P_0 - 10n \cdot \log_{10}(d/d_0) + \mathcal{N}(0, \sigma^2(d)) \\ &= \mathcal{N}(P_{det}(d), \sigma^2(d)) \;. \end{aligned} \quad (1)$$

$P_0$ and $d_0$ are defined as reference received power (in dBm) and distance respectively. $\sigma(d)$ denotes the distance-dependent standard deviation of the Gaussian random model abbreviated by $\mathcal{N}(\mu, \sigma(d))$.

This behavior is likely to be caused by the high average distance of communication partners to reflectors, i.e. walls. With greater distance and thus weaker line-of-sight (LoS) path components, the influence of multipath fading increases. As the exemplary residuals in Fig. 5 show, the statistical distribution of multipath fading effects may be approximated by a normal distribution. In contrast to this popular approach, it is also possible to model these via Rician fading [16]. The normal distribution nevertheless also encompasses further, independent effects, such as uncertain received signal power measurements and is thus used here. According to Fig. 6, the standard deviation in dB may be modeled as a linear

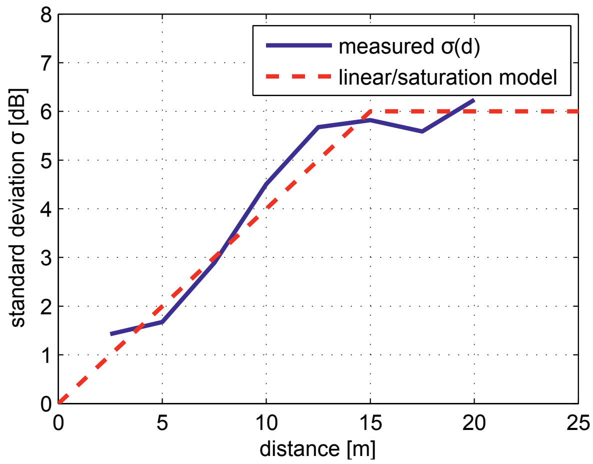


Fig. 6. Measured standard deviation $\sigma$ of residuals over distance with model approximation.

increase from 0 dB to 6 dB within the first 15 meters. This easy, empirical model also allows for closed form solutions in statistical calculations, shown in section III-C. Measurements in other environments may however differ to these findings. An extensive simulation environment for localization algorithms in static and dynamic situations was implemented in Matlab, where different propagation models may be set as a basis.

## *B. Weighted Centroids Algorithm*

A popular and intuitive approach to WSN localization is the weighted centroids scheme, for example used in [17] and [18]. This algorithm simply calculates the weighted mean of the $J$ received beacons' coordinates. This equals the center of gravity, according to:

$$\hat{\vec{z}} = \frac{1}{\sum_{j=1}^{J} w_j} \sum_{j=1}^{J} w_j \cdot \vec{z}_j \;. \quad (2)$$

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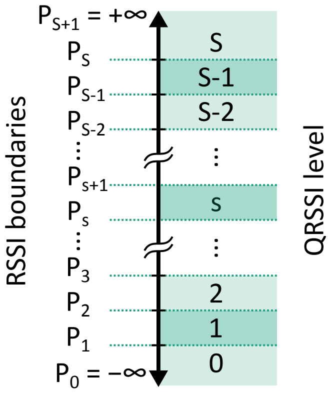


Fig. 7. Nomenclature of QRSSI levels with according RSSI input power thresholds $P_0$ to $P_{S+1}$.

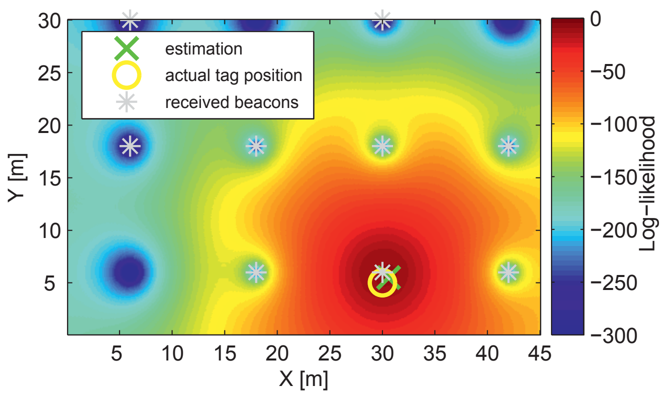


Fig. 8. Example log-likelihood over a 30 x 45 m search area. Beacons here have a mutual distance of 12 meters to each other.

The weights $w_j$ may be calculated with or without usage of a propagation model. It is for example possible to assign weights directly according to QRRSI input:

$$w_j = RSSI_j^k \ , \tag{3}$$

or apply an inverse distance scheme:

$$w_j = d_j^{-k} \ . \tag{4}$$

In both cases, $k$ denotes an exponent increasing or decreasing the influence of high RSSI values. This oftentimes has to be tuned to the beacon setup to get the best results. Here a value of $k = 2.4$ is used with (3). As no distances are required, the algorithm using expression (3) is distance-free. In both cases it is computable on integrated hardware, as the weights can be precalculated and the needed $J$ multiplications may be carried out with fixed precision. However, due to the nature of the averaging operation of coordinates, the result may only lie within the convex hull of the placed beacons. In addition, the perceived average weight of the beacon field may bias results from the edges of the field to be closer to the center. This behavior decreases with higher $k$ or lower sensitivity of the tag, yet this contradicts the idea of countering multipath effects by averaging. This scheme is often chosen for its good accuracy vs. complexity ratio in situations where beacons are mostly placed on the borders of the area of interest.

### C. Maximum Likelihood Estimation

A correct propagation model assumed, statistical approaches yield the best possible solution to a given static situation, i.e. with a tag remaining in one position. From a statistical point of view, the localization problem is one of parameter estimation. The following derivations are related to [19], [20], where the focus is on the derivation of the according Cramér-Rao-Bound (CRB). Given is the just-received vector of QRSSI values $\vec{r}_Q = (P^Q_{RX,1}, P^Q_{RX,2}, \ldots, P^Q_{RX,J})^T$ at the true tag position $\vec{z} = (x, y)^T$ from beacons $1 \ldots J$ at their respective positions $\vec{z}_1 \ldots \vec{z}_J$, where $J$ is the number of beacons deployed. The desired estimated position is $\hat{\vec{z}} = \hat{\vec{z}}(\vec{r}_Q)$, minimizing a certain performance metric. A typical approach is that of maximum likelihood (ML) [21], formulated as:

$$\hat{\vec{z}}_{ML} = \arg\max_{\vec{z}} \Pr(\vec{r}_Q | \vec{z}) \ . \tag{5}$$

Referring to the aforementioned model, the probability density distribution of the yet unquantized received signal power (RSSI) $P_{RX,j}$ from beacon $j$ perceivable at a position $\vec{z}$ may be expressed as:

$$p(P_{RX,j} | \vec{z}, \vec{z}_j) = p(P_{RX,j} | d_j) = \mathcal{N}(P_{det,j}, \sigma^2(d_j)) \ , \tag{6}$$

$$\text{with} \quad P_{det,j} = P_0 - 10n \cdot \log_{10}\left(d_j/d_0\right) \tag{7}$$

$$\text{and} \quad d_j = \| \vec{z} - \vec{z}_j \|_2 \ . \tag{8}$$

Note that the dependency on the two positions $\vec{z}$ and $\vec{z_j}$ reduces to a dependency on the distance between these coordinates alone. This applies to two-dimensional and three-dimensional considerations as well.

The nomenclature for the configurable input power quantization to QRSSI at the receiver side is depicted in fig. 7. In our case the number of bins is $S + 1 = 7$, including level $s = 0$ if no connection could be made. The discrete probability to receive a certain level $s$ may thus be calculated via integration of equation (6) from lower to upper quantization level boundary:

$$\begin{aligned} \Pr(P^Q_{RX,j} = s | d_j) &= \int_{P_s}^{P_{s+1}} p(P_{RX} | d_j) \, \mathrm{d}P_{RX} \\ &= \frac{1}{2} \left[ \operatorname{erf}\left( \frac{P_{s+1} - P_{det,j}}{\sqrt{2}\sigma(d_j)} \right) - \operatorname{erf}\left( \frac{P_s - P_{det,j}}{\sqrt{2}\sigma(d_j)} \right) \right] \ . \end{aligned} \tag{9}$$

As the fading on the different paths from each beacon j to the tag can be considered independent, the resulting overall likelihood for position $\vec{z}$ to receive a certain power signature $\vec{r}_Q$ is given by multiplication as

$$\Pr(\vec{r}_Q | \vec{z}) = \prod_{j=1}^{J} \Pr(P^Q_{RX,j} | d_j) \ . \tag{10}$$

The optimal point $\hat{\vec{z}}$, satisfying equation (5) may now be found using a searching scheme over the coordinates $x$ and

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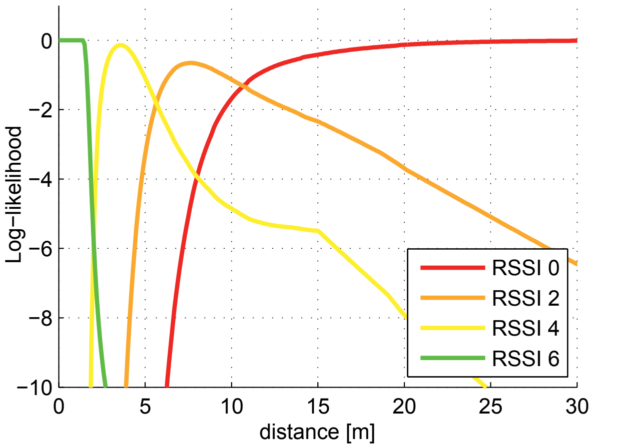


Fig. 9. Example for the precalculated partial log-likelihoods over distance $d_j$ with the model parameters assumed above. (not all shown for clarity)

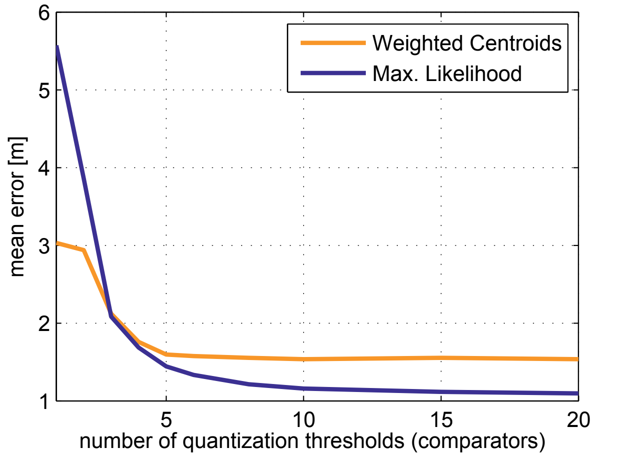


Fig. 10. Simulated mean distance error over number of quantization thresholds $S$. The beacon distance was 12 meters.

$y$ (and $z$ if three dimensions are desired). An example Log-likelihood as goal function over the whole search area is shown in fig. 8. In order to find the maximum, not all points of the search space need to be evaluated though. A typical approach, commonly found in video compression, is that of applying a test pattern, e.g. nine points in a square grid, around a given starting point. The starting point may be selected by a simpler algorithm, for example by WCL (as done here), or may be the strongest beacon's position. Upon evaluation of the likelihood at all test points, the pattern center is moved to the best point or the pattern search size is reduced if already centered correctly. The advantages of this scheme are the possibility of following a likelihood gradient indefinitely and scalability in terms of final accuracy vs. number of points evaluated. This two-dimensional optimization routine is however limited to finding the closest local maximum from the starting point. As of now, observed likelihoods over the search area proofed to only have one global optimum (compare Fig. 8). It is possible to extend this scheme to three dimensions as well. However, this was not part of the preliminary investigations presented here.

Iterating over the logarithm of the likelihood yields the advantage of not changing the optimum

$$\arg\max_{\vec{z}} \Pr(\vec{r}_Q|\vec{z}) = \arg\max_{\vec{z}} \log\left(\Pr(\vec{r}_Q|\vec{z})\right) \ , \qquad (11)$$

while reducing the product in (10) to a sum over the partial log-likelihoods. Also it can be observed that these partial logarithmic probabilities are dependent only on their distances $d_j$ and the corresponding QRSSI level $s$. Fig. 9 shows these log-likelihoods using the model parameters shown above. Notice the inconstancy at distance 15 m, where the model standard deviation saturates in Fig. 6. It is thus possible to precalculate and tabulate these $S+1$ curves into on-chip lookup tables. Assuming 1 Byte per entry, and 10 values per meter over 30 m, we here have $10 \times 30 \times 7 = 2.1\,\text{kB}$ memory requirement. Convergence speed depends on the set final search accuracy, as well as the individual received pattern. Each test point's Log-likelihood $log(\Pr(\vec{r}_Q|\tilde{\vec{z}}))$ is then merely a sum of $J$ lookup values, significantly saving on chip area and energy consumption. This maximum likelihood estimation may thus be calculated on-chip, only using iterators (for the search pattern), memory accesses and sums. It is also possible to evolve this scheme to a maximum a posteriori (MAP) approach, without significant increase in complexity, by adding a priori knowledge to the goal function.

## IV. Results

Along with a number of other, e.g. geometric, approaches, the algorithms were tested through simulation and experimental validation. One particularly interesting find from simulation is the trend of the mean localization error in dependency of the number of quantization thresholds $S$. As shown in Fig. 10, the accuracy does not improve significantly beyond seven to eight quantization intervals. It can be concluded that, while making the calculations feasible to be carried out on-chip, a rough quantization above this threshold does not significantly impair accuracy. The derived maximum likelihood approach on the given hardware is therefore almost optimal and energy-efficient.

Another important system property for open areas is the distance between beacons, arranged in a regular grid. This distance influences the mean reliability of beacon signals by reducing the mean distance. Clearly the grid also specifies the overall number of beacons needed to cover a certain area and thus system setup effort. Simulations using the presented algorithms show an almost linear behavior of mean error to beacon distance, which also matches the preliminary expectations obtained via CRB. This result may be used to tailor system performance to applications at hand.

Fig. 11 and 12 show localization results on the basis of measured data. The signals within an area between four beacons, part of a 4x3 regular beacon grid, were measured for representativeness. Shown are the error vectors for one

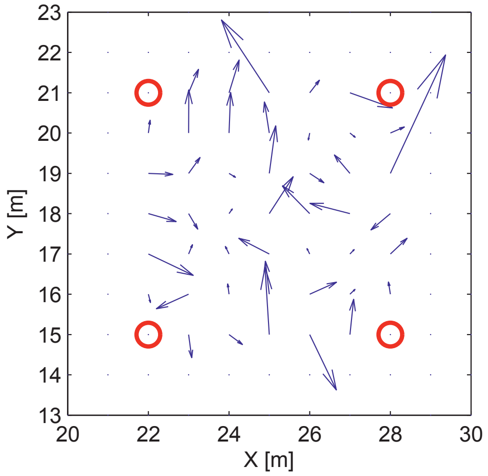


Fig. 11. Measured error vectors for max. likelihood estimation, pointing from each true measurement position to the estimation. Red circles indicate beacon positions (four out of twelve beacons within scope).

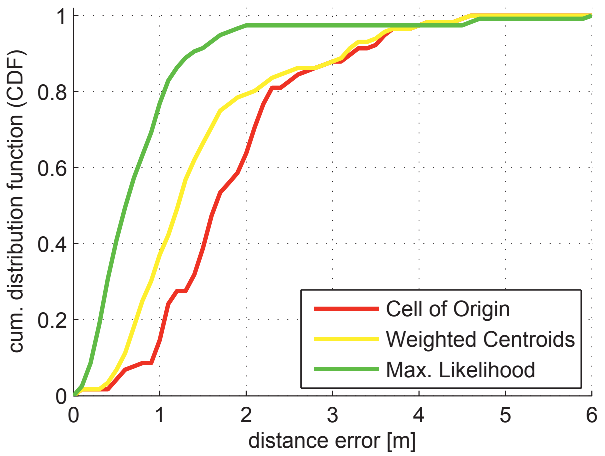


Fig. 12. Measured error distribution for a test path crossing the beacon field.

test position per square meter. These each point from the true measurement position to the according ML estimate. Error vectors allow to visually assess systematic errors within the algorithms, i.e. the bias. As can be seen in Fig. 11, errors point in random directions, indicating a low bias. Also shown is the measured cumulative probability density function for different algorithms in Fig. 12, confirming the optimality of the ML approach. With ML, 80 % of errors are below 1 meter, even under these ultra low power conditions. Overall mean errors are given in Table I, together with per-point computing times in Matlab and estimated complexities. For each test 12 beacons were distributed in a 4x3 grid with 6 m and 12 m grid spacing respectively. As expected, the ML scheme proofs to be superior. The computing times were captured on a desktop computer and are thus not representative. It is to be expected that ML on-chip computing times will largely depend on memory access delays for lookup operations.

TABLE I
EXPERIMENTAL RESULTS FOR DIFFERENT ALGORITHMS FOR 6 M AND 12 M BEACON SPACING

| | mean error (6 m) | mean error (12 m) | computation time |
|---|---|---|---|
| Cell of Origin | 1.8 m | 3.8 m | 44 µs |
| Weighted Centroids | 1.4 m | 2.0 m | 50 µs |
| Max. Likelihood | 0.86 m | 1.7 m | 2.4 ms |

## V. CONCLUSION AND FUTURE WORK

This work presents how ultra-low-power wake-up receivers may be utilized to implement an efficient, yet optimized localization system. Narrowing down the problem to wide indoor areas, a modified log-distance path loss model is introduced. Model properties however vary with number, density and distance of encountered obstructions. The applicability of Rice and/or Rayleigh models for logistics scenarios will thus be part of future research. It is shown how this simple model allows for closed solutions to the maximum likelihood approach with roughly quantized input power levels. These do not impair localization accuracy significantly, while allowing an efficient integration of the estimator through usage of lookup tables. The presented approach reaches a mean distance error of 0.86 m, with 80 % of errors below 1 m. Improved Wake-up receivers currently under development will support simultaneous monitoring of multiple ISM bands, enabling the use of frequency diversity schemes to counteract fading and are expected to significantly increase accuracy.

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