Enhancing RSSI-Based Tracking Accuracy in Wireless Sensor Networks

GADDI BLUMROSEN, BRACHA HOD, TAL ANKER, and DANNY DOLEV, The Hebrew University of Jerusalem
BORIS RUBINSKY, The Hebrew University of Jerusalem and University of California, Berkeley

In recent years, the demand for high-precision tracking systems has significantly increased in the field of Wireless Sensor Network (WSN). A new tracking system based on exploitation of Received Signal Strength Indicator (RSSI) measurements in WSN is proposed. The proposed system is designed in particular for WSNs that are deployed in close proximity and can transmit data at a high transmission rate. The close proximity and an optimized transmit power level enable accurate conversion of RSSI measurements to range estimates. Having an adequate transmission rate enables spatial-temporal correlation between consecutive RSSI measurements. In addition, advanced statistical and signal processing methods are used to mitigate channel distortion and to compensate for packet loss. The system is evaluated in indoor conditions and achieves tracking resolution of a few centimeters which is compatible with theoretical bounds.

Categories and Subject Descriptors: C.2.1 [Computer-Communication Networks]: Network Architecture and Design Systems—Wireless communication

General Terms: Algorithms, Experimentation, Performance

Additional Key Words and Phrases: Wireless sensor network, received signal strength indicator, tracking

ACM Reference Format:
DOI: http://dx.doi.org/10.1145/2480730.2480732

1. INTRODUCTION

Precise motion and location tracking in an indoor environment using Wireless Sensor Networks (WSNs) plays an important role in sports, medicine, and many other fields. In sports, the tracking system can give information about the movement of different body parts during activity. In medicine, a precise tracking system can be deployed at the clinic or at patients' homes for analyzing abnormalities in gait or in motion, and for rehabilitation of injured persons [Jovanov et al. 2005; Alemdar and Ersoy 2010]. Applications in these fields estimate body parts displacements over time and use it to classify motion patterns to different pathologies. The performance of such applications highly depends on the accuracy of the tracking system. Consequently, many efforts have been taken recently to improve the tracking resolution to scale of centimeters.
WSN is composed of spatially distributed autonomous sensor nodes equipped with a radio transceiver. Systems designed for indoor object tracking based on WSNs [Liu et al. 2007; Gu et al. 2009; Seco et al. 2009; Xia et al. 2010] can be classified by technology, measurement metrics, and processing methods. The main technologies are inertial sensors technology, infra-red technology, ultrasound technology, and radio technologies. Common measurement metrics are: Angle-of-Arrival, Time-of-Arrival, and Received Signal Strength Indicator. The main processing methods are based either on statistical approaches or on geometrical techniques of triangulation or trilateration.

WSN tracking systems that utilize radio technology can be based on Received Signal Strength Indicator (RSSI) measurements. RSSI is a measurement of the signal power on a radio link [Rappaport 2001] and can be used for localization, link-quality estimation, and power control. It is part of the IEEE 802.11 protocol family and the 802.15.4 standards and it is supported by most of the existing transceiver chipsets with no extra cost. RSSI measurements are very simple to use and have a lower power consumption compared to other methods. Therefore, RSSI is widely used in various applications, including tracking.

RSSI-based tracking systems usually consist of several mobile nodes and a set of static nodes, referred to as anchor nodes. The tracking algorithm tries to continuously estimate the mobile nodes’ location from the RSSI measurements [Sichitiu and Ramadurai 2004; Bertinato et al. 2007; Chung 2007; Lee et al. 2008]. RSSI-based tracking algorithms [Wang et al. 2010] are usually composed of two steps. In the first step, RSSI measurements are used to estimate the range between pairs of nodes using known channel model characteristics or by calibration methods used offline. The calibration methods either find channel model parameters or produce a conversion table among RSSI measurements and distances, for example, Helen et al. [2001], Alippi and Vanini [2006], and Patwari and Agrawal [2009]. In the second step, statistical or geometrical methods are applied to obtain the instant location from the range estimation [Zanca et al. 2008].

The design of RSSI-based tracking systems has numerous challenges that are related to the nature of RSSI. First, RSSI measurements are highly affected by the variation in the wireless medium [Stoyanova et al. 2007]. Reflections of the transmitted signal from walls or from scatterers in the medium result in severe multipath interference at the received signal. The interference causes range estimation errors that can lead to large tracking errors. Second, an accurate conversion of RSSI measurements to range requires a precise calibration process which reflects the channel model. In many cases, changes in the medium during tracking with a calibration process that does not reflect the dynamic channel can cause severe conversion errors. Third, RSSI measurements are very sensitive to interference at relatively high distances. The RSSI measurements attenuate in distance with a power decay factor [Hara et al. 2005]. This implies that when the distance between the nodes is not proximate, that is, in range of a few meters, the range approximation is sensitive to small interference which can result in high range estimations errors.

The sensitivity of RSSI measurements to the medium and to distance can be mitigated using a priori knowledge. Prior knowledge about the target application or the relevant environment settings leads to improved tracking accuracy. For example, prior information about the environment dimensions enables an optimized transmission power setting of the nodes and a better conversion of RSSI measurements to range as nonrelevant range can be truncated. Information about the range of possible velocities enables an adjustment of the transmission rate. An appropriate transmission rate implies effective use of the correlation among consecutive RSSI measurements in order to reduce noisy measurements. Existing RSSI-based tracking systems usually do not exploit such a priori knowledge and so their accuracy is measurable in the scale of a
In this work, we present a novel idea of an RSSI-based tracking system that exploits existing a priori knowledge. The tracking system is tailored to the area of Body Sensor Networks (BSN) [Yang and Yacoub 2006] and can be used in many sport and health-care applications. In BSN applications, the set of sensor nodes is deployed over a human body in proximate Line-of-Site (LOS) conditions and in a distance of less than one meter from each other. The position estimation and tracking are performed relative to the anchor nodes. The anchor nodes can be either placed on reference locations in the room or attached to the relatively static torso. The mobile nodes can be attached to any other body part, such as the legs or arms, for relative motion analysis. The sensor nodes can be charged every few days to enable continuous tracking during daily life activities.

Applying the a priori knowledge about the target application and the relevant environment settings leads to an improved tracking accuracy. The proximate LOS condition, that is, where there are no massive scatterers between the nodes, results in a relatively static channel which promises that the calibration process will be relevant to real-time scenarios. In close proximity, where the distance between the nodes is small, for example, around a meter, we can adopt an adequate transmission power level so the RSSI dynamic range is higher and the conversion of RSSI measurements to range is more accurate. With an adequate transmission rate, we can further exploit the knowledge about the continuity of the movement. In a continuous movement, consecutive RSSI measurements refer to proximate locations of the mobile sensor node and can compensate for channel interference distortion.

The proposed RSSI-based tracking first derives a constrained Minimum Mean Square Error (MMSE) criterion for tracking based on the RSSI measurements. The constraints are tailored to the a priori knowledge about the system settings. In order to solve the criterion, a transmission power level that maximizes the RSSI dynamic range is used. An advance calibration scheme that uses prior knowledge about the channel conditions and the environment dimension is applied. Effective processing of the RSSI measurements that exploits their spatial-temporal correlation are then performed. The processing stage includes preprocessing of the RSSI measurements, estimation of the range between each pair of nodes, mobile node location estimation based on the range estimation, and advanced filtering based on the constrains is applied to the location estimations. The localization algorithm used in this system tries to derive the mobile node’s location from the RSSI measurements using maximum likelihood estimation that is based on geometrical properties. This implementation might not be optimal in MMSE sense for all channel realizations, but it is simpler than other statistical algorithms, such as Kalman filter [Paul and Wan 2009] or particle filter [Seshadri et al. 2003]. This algorithm clearly demonstrates the exploitation of the constraint to improve tracking accuracy.

A series of experiments were conducted in a real-world indoor environment for performance evaluation of a tracking system. Two anchor nodes were deployed in known locations and a single mobile node was moving continuously in a range of less than a meter from the other two nodes. In a first set of experiments, the mobile node was attached to a toy car that was moving different predetermined tracks. The first set evaluates the proposed processing methods and algorithms. The properties of the system are demonstrated using manual measurements as a reference. In a second set, the mobile node was attached to a human hand that was moving randomly on a 2D plane. The second experiment set presents the capability of the system to give location estimations in a real environment with dynamic channel conditions. Body reflections affect the RSSI measurements, and therefore the location estimation is more challenging.
The hand was arbitrarily chosen, and the experiments can be extended in the future to other body parts and to 3D plane.

A performance bound per path was derived to evaluate the performance of the system. The bound is based on the theoretical Cramer-Rao Bound (CRB) for RSSI-based location estimation in static conditions [Patwari and Hero 2003b] and on the numerical simulation of the Maximal Likelihood Estimator (MLE), which corresponds to the experimental conditions. Experiment results show that the accuracy of our proposed tracking scheme in terms of location, mean error, and standard deviation is in the range of a few centimeters.

This work makes a twofold contribution. First, we employ a new RSSI-based tracking system that exploits an a priori knowledge about the system settings to improve the tracking accuracy. The calibration technique utilizes constraints on the environment’s physical dimensions and on channel conditions. The transmit power was selected to maximize the RSSI dynamic range. The filters were adopted to exploit the spatial-temporal correlations between consecutive RSSI measurements. The tracking accuracy achieved in this work is in a scale of centimeters and can be used by BSN applications. Existing tracking systems for an indoor environment are usually designed for general applications and therefore present an accuracy in the scale of one meter. Second, we derive a bound that is tailored to the path shape and uses the static channel conditions. Preliminary results were provided in Blumrosen et al. [2010], where the location of a mobile node moving in a circular trail based on RSSI measurements was calculated.

The article is organized as follows. Section 2 describes the system model and the problem formulation. The data processing and the calibration process are described in Section 3. Section 4 presents the theoretical bounds of RSSI-based localization. Section 5 introduces the experimental setup and Section 6 describes the experiment’s results. Conclusion and discussion about future work are presented in Section 7.

2. SYSTEM MODEL

2.1. System Description

The basic system consists of a single mobile node with a location of \( L_0 = (x_0, y_0, z_0) \) in Cartesian coordinates and \( N \) static nodes, referred to as anchor nodes, placed at \( L_1 = (x_1, y_1, z_1), L_2 = (x_2, y_2, z_2), \ldots, L_N = (x_N, y_N, z_N) \), respectively. The goal of our work is to continuously estimate the mobile node’s location \( L_t = (x_t, y_t, z_t) \) at any given time \( t \). The mobile node transmits a data packet with a known transmission power to the anchor nodes every \( T \) ms. The anchor nodes, located in the transmission range of the mobile node, calculate the received power values \( P_{r_1}, P_{r_2}, \ldots, P_{r_N} \). Each transmitted packet is labeled with a time stamp which is used for recovering possible packet loss. No synchronization is assumed among the nodes.

2.2. Wireless Channel Model

The most common wireless channel model is the channel pathloss model [Miluzzo et al. 2008]. The received power for anchor node \( i \) at time \( t \) in the channel pathloss model is

\[
P_{r_i}^t = P_t + G_r G_t + A - q 10 \log_{10} d_i^t + \alpha^t,
\]

where \( G_r, G_t \) are the receive and transmit antennas’ gains and \( A \) is a constant that is a function of the transmission wave length [Mao et al. 2007]; \( q \) is the channel exponent that varies between 2 (free space) and 5 (indoor with many scatterers); \( d_i^t \) is the distance between the anchor node \( i \) and the mobile node; and \( \alpha^t \) is additive noise that accounts for the random effect of multipath and for channel model inaccuracy.

The interference factor \( \alpha^t \), which accounts for the random effect of shadowing and for channel model inaccuracy, is sometimes not stationary due to the random effect...
of multipaths and shadowing. Some channel models divide the interference into two components: a Gaussian distributed random variable, with zero mean and standard deviation $\sigma$, and a component that reflects the strong reflections from walls [Andersen et al. 2002]. The component of the reflection factor can sometimes be estimated and partially filtered over time with advanced processing [Guvenc et al. 2003]. With many scatterers in the medium and no dominant reflectors or in LOS conditions, $\alpha$ can be modeled just by its Gaussian part, with zero mean and standard deviation $\sigma$.

Each antenna has a distinct radiation pattern. The antenna can radiate greater power in one direction compared to its other directions. An antenna that radiates power uniformly in one plane with a directive pattern shape in a perpendicular plane is called an omnidirectional antenna [McDonald 1999]. In this work we will use omnidirectional antennas for the anchor and mobile nodes.

For the case of omnidirectional antennas and a constant transmit power, the received power in Eq. (1) can be written as a function of only three parameters:

$$P_r = B_i - q10 \log_{10} d_i^2 + \alpha^t,$$

where $B_i$ is the power offset that consists of the transmit power $P_t$, the receive and transmit antenna gain factors $G_r, G_t$, and the system constant $A$.

2.3. Problem Formulation

In order to track the mobile node, we need to continuously estimate, using the set of $N$ power measurements, the location of the mobile node. The Minimum Mean Square Error (MMSE) optimal transformation of the measurement matrix $Pr$ can be obtained by solving the following criterion:

$$\hat{f} = \arg\min f E(L_0 - f(Pr))^2$$

subject to $|L_{t+1} - L_t| < \delta$,

where $L_0$ consists of $M$ consecutive coordinates of the mobile node; $M$ refers to the size of a frame; $Pr$ is the $N \times M$ power measurement matrix that contains the $N$ anchor nodes’ power measurements over $M$ measurements; $f$ is a transformation of the power measurements to location; $E[\cdot]$ is the expected value over all stochastic sources; and $\delta$ is a bound on the difference between consecutive location estimations, which are a function of transmission rate and mobile node velocity. With high RSSI transmission rate or low mobile node velocity, consecutive RSSI measurements imply proximate locations.

The problem is neither linear nor convex [Papamanthou et al. 2008], thus the criterion in Eq. (3) can only be solved numerically. Furthermore, an optimal transformation requires accurate statistical knowledge [Awad et al. 2007] which is not always available. Since the mobile node moves during observation time, the channel is not stationary so frequent new updates of the transformation are needed for accurate approximation.

3. METHODS

The goal of the processing methods is to estimate from the RSSI measurements the instant mobile node location. Our RSSI-based tracking algorithm is composed of two phases: an offline phase, which includes finding the optimal transmit power and calibration process, and a tracking phase in which we track the mobile node location in real time.

In the offline phase, we perform a set of offline tests of the system that attempt to match system parameters to the experiment’s environment by using different RSSI measurements at predetermined locations. First, we find the optimal transmission power for the environment. Then we perform a calibration process in which we find
the channel model parameters for translating the RSSI measurements to range estimations.

The tracking phase is comprised of the following four stages.

1. Preprocessing of the RSSI measurements obtains the received power. This stage includes conversion of the RSSI measurements to power measurements, interpolation missing samples, and filtering out the channel noise.

2. Range estimation between the mobile node and each anchor node is done according to the power measurements and calibration.

3. We combine the information from all the nodes and MMSE estimation of the mobile node’s location.

4. Filtering out estimation errors with statistical methods is based on the continuity of the mobile node’s movement.

3.1. Transmit Power Selection

Distance estimation accuracy is highly affected by the transmission power level [Lymberopoulos et al. 2006]. Insufficient transmission power may lead to high packet loss while high transmission power can lead to saturation of the RSSI measurements and distort the distance estimation. As an increase in the RSSI measurements’ dynamic range for a given environment can improve the distance estimation accuracy [Hara et al. 2005], we would like to maximize the dynamic range of the RSSI measurements. Adaptive transmission power has been investigated in several papers, such as Lin et al. [2006], and was considered in Blumenthal et al. [2007] and Ren and Meng [2009] in the context of distance estimation. A transmit-power adjustment is feasible for most existing off-the-shelf transceivers in WSNs, for example, CC2420 [Chipcon 2004].

We suggest a different, simpler method to find the optimal transmit power level. The new method can be incorporated into the calibration process and therefore does not require any additional overhead. In our method, the mobile node is placed at different locations along the indoor tracking environment. For each location, the mobile node transmits different packets with different transmission power levels, and the corresponding RSSI measurements are stored in a table. RSSI measurements with high packet loss, for example, more than 10%, are excluded from the table. For each transmission power level between each pair of nodes, we calculate the RSSI quality and the RSSI dynamic range. RSSI quality can be estimated by the inverse of RSSI standard deviation, \( \sigma(P_t) \). The criterion to obtain the optimal transmit power level which tries to maximize RSSI dynamic range on both anchor nodes under the constraints of low packet loss and small RSSI standard deviation is

\[
\hat{P}_t = \arg\max_{P_t}(\Delta P_t(P_t)),
\]

s.t. \( \sigma(P_t) \leq T_{\sigma\text{RSSI}} \) and \( PL \leq T_{PL} \).

In this equation, \( \Delta P_t(P_t) \) is the RSSI dynamic range of the transmitted power \( P_t \) in the environment dimensions and is calculated by \( \Delta P_t(P_t) = P_{\text{max}}(P_t) - P_{\text{min}}(P_t) \). \( T_{\sigma\text{RSSI}} \) is a threshold over \( \sigma\text{RSSI} \) and has typical values between 0.5–2 dBm. \( T_{PL} \) is a threshold over packet loss and has typical values of 10%.

The optimal power level can be found by numerical methods such as a binary search. In a binary search, the range of transmission power is divided at each iteration into two sections. For each interval the two boundary transmission power levels are calculated according to Eq. (4). A transmission power level with high packet loss rate can be excluded from the search.

3.2. Calibration

Calibration is required to find the system parameters for translating the power levels’ measurements between each pair of sensor nodes to the corresponding distance.
Calibration schemes [Helen et al. 2001] often use an a priori knowledge about the channel or perform offline measurements at a grid of points in the area of interest. The result of the calibration process is either a mapping table between RSSI measurements and distances or an estimation of the channel propagation model parameters. Inaccurate calibration or using a channel propagation model that does not reflect the channel may lead to range and tracking estimation errors.

For multidimensional location tracking, multiple sensors deployed in different planes are necessary. The calibration process should be performed between the mobile node and each of the other anchor nodes. In the case where the sensor nodes’ antennas are not fully isotropic, the RSSI measurements can vary in different planes. As a result, the calibration is not uniform in space and should be performed in a multidimensional grid [Stoyanova et al. 2007]. The calibration procedure usually requires human intervention and is sometimes tedious and inaccurate. Self-calibration methods were proposed recently in order to avoid this procedure [Lim et al. 2005; Barsocchi et al. 2009] by exploiting other sensors’ data or by an advanced online processing of all node information.

In this work, we use a calibration scheme that is based on log fitting of the RSSI measurements and approximating the power offset and the channel exponent using the a priori knowledge of the environment physical dimensions and the range of the channel exponent values. The range of channel exponent values can be determined by the channel conditions in the environment. This method is an extension to the methods of logarithmic fitting in Blumrosen et al. [2010]. This calibration method can provide a relatively accurate distance estimation with few RSSI measurements.

A MMSE criterion to derive the power offset \( B_i \) and channel exponent \( q_i \) from the measurements with a constraint on the channel exponent range is

\[
(\hat{B}_i, \hat{q}_i) = \arg\min_{B_i, q_i} \sum_{k=1}^{K} ((B_i + q_i 10^{\log_{10} d_k}) - P_{rk})^2
\]

s.t. \( d_{\text{min}} \leq d_i \leq d_{\text{max}} \), \( q_{\text{min}} \leq q_i \leq q_{\text{max}} \),

where \( K \) is the number of calibration points, \( d_{\text{min}} \) and \( d_{\text{max}} \) are the minimum and maximum distances, and \( q_{\text{min}} \) and \( q_{\text{max}} \) are the minimum and maximum range of the channel exponent which can be obtained by the channel conditions. As an example, for channel conditions without many scatterers and walls in the area of the mobile object, \( q_{\text{min}} \) has the minimum value of 2 and a reasonable choice for \( q_{\text{max}} \) can be 3. For channel conditions with many scatterers, a reasonable value of \( q_{\text{max}} \) would be 4. A possible implementation of the algorithm is by linear programming methods [Avriel 2003].

### 3.3. Processing Stages

#### 3.3.1. Preprocessing of RSSI Measurements

Preprocessing of the RSSI measurements is necessary for synchronizing the RSSI measurements obtained at the different anchor nodes, to recover lost packets, and to exclude the channel noise from the measurements.

Synchronization between the measurements can be obtained by two key methods. The first one is clock synchronization of all nodes in the system. In clock synchronization, for example, Patwari et al. [2005] and Sivrikaya and Yener [2004], all measurements are measured at the same time. Clock synchronization algorithms in WSN have overhead in computation and battery consumption and suffer clock drift. This may affect the synchronization. The second synchronization method is obtained by a global time reference. In our system, it can be implemented by using data frames and time stamps of the mobile node (which is the global time reference in each anchor node). The synchronization is performed at the beginning of each frame. The frame size is in
the range of one second. The delay induced to the system is measured in the scale of the frame size. This delay is acceptable for most tracking applications.

After the synchronization of the different nodes, lost packets can be recovered using interpolation that relies on the spatial and temporal correlation obtained by the high sampling rate and the continuous movement of the mobile node [Jain and Chang 2004]. When the packet loss is caused by a long burst due to inefficient power or shadowing, the interpolation will only partially recover the signal distortion.

Following the nodes’ frame synchronization and packet loss recovery, we can filter the channel interference with a Low Pass Filter (LPF). The signal after preprocessing is

\[ \tilde{P}_r^t = P_r^t * h, \]  

where * denotes the convolution operation and \( h \) is an LPF that smoothes the additive noise and eliminates fast-fading. The LPF filter can also be implemented by auto regression moving average or with Kalman smoother [Paul and Wan 2009].

3.3.2. Range Estimation. A continuous estimation of the distance between the mobile node and an anchor node \( i \) can be derived analytically from the filtered received power according to Eq. (1).

\[ \tilde{d}_i^t = 10^{\frac{\eta + \frac{L_0^t}{10}}{10}}, \]  

This range approximation requires a priori knowledge of channel parameters, channel exponent value, and receive and transmit antenna gains that determine the exponent offset. Using the common channel exponent for an indoor environment in a range of 2–4 will not provide accurate results and will not compensate for specific channel conditions such as shadowing.

3.3.3. Location Estimation. Let us denote by \( \tilde{D} \) the \( N \times M \) matrix of approximated distances between the mobile nodes and the \( N \) anchor nodes over \( M \) measurements.

The following criteria can estimate the mobile node’s location.

\[ \hat{g} = \arg \min E(L_0 - g(\tilde{D}))^2 \]  

\[ s.t. |L_{0}^{t+1} - L_{0}^{t}| < \delta \]  

There are several methods for solving Eq. (8). The most common one is trilateration. Trilateration is a positioning technique [Moore et al. 2004] which estimates the mobile node’s location by the intersection of the circles, each centered on the anchor node position with a radius equal to the estimated distance between the mobile node and the anchor node. The number of anchor nodes required for localization is \( N = p + 1 \) anchor nodes in a \( p \)-dimensional space. The estimated location is defined by the center of the region formed by the intersection of the circles. Another approach [Liao and Lee 2006] utilizes only \( N = p \) anchor nodes and estimates the location by only one of the intersection points. It records several intersection points in consecutive times and estimates the intersection location by the closest distance.

We choose a variant of Liao and Lee [2006] to estimate the mobile node’s location using the Maximum A Posteriori (MAP) criterion. Assuming the range estimations have the same statistical distribution and the mobile node location has Gaussian distribution, the MAP criterion coincides with the MMSE criterion [Van Trees 2001]. The solution is performed with the following steps.

1. Derive the intersection of the circles formed by the estimated distance for each anchor node.
2. Choose the intersection that minimizes the MAP criterion.
3.3.4. Deriving Circles’ Intersections Points. The mobile node’s location can be estimated from the intersection of the circles described in the previous section. For 2D with two anchor nodes, the two circles formed by the distance estimation are

\[ (x - r_x)^2 + y^2 = (\hat{d}_t^r)^2 \]
\[ x^2 + (y - r_y)^2 = (\hat{d}_t^i)^2, \]

where \( r_x \) and \( r_y \) are the anchor nodes’ locations in the \( x \) and \( y \) axes. One of the two intersection points is the estimated mobile node location, as illustrated in Figure 1.

3.3.5. Optimal Intersection Points Selection. We use a trellis diagram to select the intersection points that represent the mobile node location estimation and minimize Eq. (8) in MMSE sense. We define a state as a possible location estimation. In 2D with two anchor nodes, the two states at time interval \( t \), \( S_t^1 \) and \( S_t^2 \), represent the two intersection points. A path in the diagram is a transition between states at consecutive discrete time intervals. Each possible transition represents a possible motion of the mobile node from one position to another. The transition between the states is relatively low due to the high transmission rate and the continuity of the mobile node motion.

Each legal transition between states can be defined as a branch with a branch metric \( S \) which is a function of the distance between consecutive states. We use a branch metric that reflects the continuity constraint in Eq. (8). A branch metric can be based on the proximity of consecutive location estimations and is defined by

\[ BM_t^d = \| d(S_t^{i+1}) - d(S_t^j) \|, \]

(10)

where \( \| \cdot \| \) is a Euclidian norm. Another branch metric, which is based on continuity of the mobile node’s motion, is defined by

\[ BM_t^v = \| v(S_t^{i+1}) - v(S_t^{j+1}) \|. \]

(11)

The velocity \( v \) can be either linear or angular in polar coordinates. The most likely path in the trellis diagram minimizes the criteria in Eq. (8). A path metric is the sum of the branch metrics for constraint length \( W \) location estimations.

\[ PM^t = \sum_{t'=t-W}^t BM_t^{r} \]

(12)
The constraint length is relatively small, $W \ll M$, and usually includes location estimations that relate to the same state. The MAP criterion selects the minimum path metric out of all the possible paths. A more efficient algorithm would be to use the Maximum Likelihood (ML) criterion which can be implemented by the Viterbi algorithm [Forney 1973]. If we assume that the distance distribution is identically and independently distributed, both MAP and ML solutions minimize the error criterion in Eq. (8) [Van Trees 2001]. Figure 1(b) illustrates a selection of the intersection point that estimates the mobile node’s location.

3.3.6. Postprocessing. We use additional filtering to exclude location estimations that are not likely due to the continuous movement and in order to smooth the results. The filtering at this stage is more effective as it is performed on the combined estimation obtained by all anchor nodes, unlike the filtering in the preprocessing stage which is performed on each anchor node separately. Furthermore, the locations are continuous, and the constraint in Eq. (3) can only be applied at this stage. Mean filter and median filter [Tukey 1977] are both effective filtering techniques that exploit statistical information of the data. Mean filter [Wu et al. 2010] is a variant of a moving average that operates only on measurements in which their standard deviation is above a predetermined threshold. The median filter is a nonlinear filtering technique that uses the median value instead of the mean. The median filter and the mean filter performances depend on the window size and threshold value. With zero thresholds, the mean value coincides with the LPF simple moving average. With Gaussian noise, the mean and median filters display a similar performance [Liu et al. 2010]. When the data is corrupted by spike noise, the median filter can exclude the spikes better than the mean and the LPF filter [Bednar and Watt 2003]. We use the median filter to apply the continuity constraint on location estimations which can be caused either by error in combining the anchor nodes’ distance estimations or by imperfect compensation for packet loss due to burst noise. We exploit the spatial and temporal diversity by using the LPF that averages proximate location estimations.

The filters’ length should reflect the spatial-temporal correlations of the RSSI measurements. It can be small with high measurement correlations due to low mobile node velocity, high transmission rate, or small channel deviations. The filters’ length should be higher with an increase in the mobile node velocity, a low transmission rate, or distortion of the signal due to multipath fading and packet loss burst.

4. THEORETICAL BOUNDS

RSSI-based location and tracking estimations in WSNs have been studied in many papers, for example, Lowton et al. [2006] and Patwari and Hero [2003a, 2003b]. The accuracy of the mobile node location estimation is affected by many factors, such as the number of nodes, the channel conditions, inaccuracies in estimation of channel model parameters, and imperfect nodes synchronization. The location estimation accuracy and the effect of system parameters on the location accuracy are essential for system evaluation and for the sensor nodes’ deployment. The Cramér-Rao Bound (CRLB) [Rao 2002] provides a lower bound on the variance achievable by unbiased Maximum Likelihood Estimator (MLE). This bound computes the minimal attainable variance of an unbiased sensor location MLE as a function of system parameters like the channel exponent and the number of nodes. The work in Patwari and Hero [2003a] quantifies the (CRLB) and the work done by Patwari and Hero [2003b] expands it by examining the RSSI measurements’ quantization effect on the CRLB bound. The experimental approach, such as in Lowton et al. [2006], provides a location bound of 10 cm using 802.15.4 RSSI measurements in close proximity and static channel conditions.
The location MLE is defined as

\[ \hat{L}_0 = \arg\min_{L_0} (Pr \mid L_0). \] (13)

The MLE can be obtained by substituting Eq. (1) and solving the criterion. In the case where the power measurements from the sensor nodes are independent and the channel is stationary, as we assume, the CRLB bound is also the bound of the unbiased Bayesian estimators.

The CRLB matrix of the mobile node location \( \hat{L}_0 \) for one set of measurements is

\[ \text{CRLB} = E\left[ -\nabla_{L_0} \left( \nabla_{L_0} \ln(Pr \mid L_0)^T \right) \right]^{-1}. \] (14)

Here \( E[\cdot] \) indicates the expected value, \( \nabla_{L_0} \) is the gradient operator over the mobile node location, and the superscript \( T \) indicates matrix transpose. The covariance estimation of the mobile node location must satisfy

\[ \text{CRLB} \leq \text{var}(\hat{L}_0). \] (15)

The location variance bound of the mobile node is given by the trace of the covariance matrix in Eq. (14). For one mobile node, the estimator variance is bounded by

\[ \sum_{i=1}^{N} \text{CRLB}(i, i) \leq \sigma_{L_0}. \] (16)

Estimators can be biased and then their variance is not bounded by the CRLB. The total variance of any estimator with a given bias gradient (i.e., the gradient of the estimation bias) is bounded by the biased CRLB [Van Trees 2001]. To reach this bound, a particular bias gradient must be chosen, a task that is not always achievable. A lower bound on the attainable variance using any estimator with bias gradient whose norm is bounded by a constant is the uniform CRLB (UCRLB) [Hero et al. 2002].

Analysis of the solution of Eq. (16) in Patwari and Hero [2003a] implies that the CRLB is proportional to the path-loss model interference \( \sigma \) and that it is inversely proportional to the channel exponent \( q \). The CRLB bound increases with the environment’s physical dimensions. When the anchor nodes and the mobile node are in close locations, the estimation variance is smaller. This increase can be explained by the sensitive region in the log-normal distribution which is related to the path-loss channel model for proximate locations.

Figure 2 shows the estimation error variance of one mobile node location in the 2D space with LOS conditions of \( \sigma = 1.9 \) dBm, \( q = 2.3 \), and ratio of \( \sigma/q = 0.82 \). Figure 2(a) and Figure 2(b) show the CRLB bound at different scales for two nodes, located at (0, 40) and (40, 0) cm. Figure 2(c) and Figure 2(d) show the variance at a different scale for four nodes, located at (0, 0), (0, 40), (40, 0), and (40, 40) cm. The first observation from the graphs is that the estimation quality improves with the number of sensor nodes. The minimal variance in the case of two sensor nodes is around 10 cm, while the minimal variance for four sensor nodes is around 5 cm. This observation can be explained by the additional information that each sensor node contributes to the estimation. The second observation is that the estimation variance decreases inside the inner area defined by all sensor nodes, but it increases on the lines that connect the anchor nodes. The locations with high estimation errors are explained by a bias in the MLE [Patwari and Hero 2003a].

A map of the bias gradient is produced in the work done by Patwari et al. [2002] and shows that for the case of four sensor nodes, the bias gradient and the estimation bias are high near each anchor node and on the lines that connect the anchor nodes. When the mobile node is very close to one anchor node and far away from the others,
the measurements from the other nodes provide relatively little information regarding the location of the mobile node. As a result, the location estimator in these conditions is biased and the CRLB is less informative.

There are two main methods to obtain a bound on error variance that will be adequate for biased and unbiased MLEs for all mobile node locations. The first one is to calculate the bias gradient norm and use it to derive the UCRLB. This can be achieved by some bias-reduced MLE [Eldar 2004]. The second method is to derive the MLE for the channel conditions of interest either analytically or by numerical methods [Patwari et al. 2002] and to obtain the estimation boundaries for the specific channel. An MLE with a pathloss model, interference, a standard deviation of 0.9, and a channel exponent of 2.3 was simulated with two anchor nodes located similar to the location in Figure 3 at (0, 40) and (40, 0) cm. Ten points were chosen along a pear-shape path. For each location, 50 experiments were performed with a noise having zero mean value and a standard deviation of 0.9. The minimization of the likelihood function in Eq. (13) was performed numerically by the method of Fletcher-Reeves-Polak-Ribiere [Jacobs 1977].

Figure 4 shows the standard deviation and the location estimations obtained by MLE compared to the CRLB standard deviation and the real locations. The estimation bias is relatively small; it is between 1 cm to 9 cm with an average near 5 cm.

Figure 4 describes the estimation bias compared to the standard deviation of the MLE. As the bias is small, the CRLB is a relatively good bound to the biased MLE variance. The biased MLE variance is more accurate than the CRLB as is seen near the line that connects the two anchor nodes, corresponding to the location points between
Fig. 3. The MLE standard deviation and mean value compared to the CRLB standard deviation and the real locations along the pear shape trail.

Fig. 4. The MLE standard deviation compared to the CRLB standard deviation along the pear shape trail.

20 and 30. This can be explained by the sensitivity of the CRLB bound to bias in the unbiased MLE.

We can conclude that in most of the locations which are not near the line connecting the anchor nodes nor near one anchor node, the bias for the path-loss model is relatively small and the CRLB bound can be used. As a result, the minimal unbiased estimation (15 cm for the path, 10 cm for all of the locations) can serve as a rough bound for the MLE.

It is important to emphasize that these bounds do not exploit the spatial and temporal diversity of the RSSI measurements obtained from continuous measurements of the mobile node while moving. Using algorithms that exploit this diversity is expected to provide superior tracking accuracy compared with the CRLB or biased MLE bounds.

5. EXPERIMENTAL SETUP

Two sets of experiments in a small-scale indoor environment were conducted. The first set tracked a toy car moving over a plastic trail. The second set of experiments tracked the movement of a human hand. In both experiments the setup included two anchor nodes, a mobile node, a base station, and a notebook. RSSI measurements were derived at the anchor nodes located at known separate locations and then sent through the base station to a notebook for further analysis. For the first experimental set, a reference to the tracking application was obtained by interpolating predetermined points marked in advance on the plastic trail. The reference was synchronized to the tracking according
The experiment setup of the mobile car tracking consists of a plastic trail, 2 anchor nodes, located in x and y axes, a car model that functions as a mobile node, a base station, and a notebook that functions as a processing unit.

The mobile node on the toy car consists of a BSN node and a dipole antenna.

Hand tracking setup with a Polaris camera as a reference. The anchor nodes, base station, and processing unit are the same as in the mobile car tracking’s setup.

to a starting point using a relatively constant car velocity. For the second set, an optical real-time motion tracking system Polaris (Northern Digital, Inc.) [Polaris 2004] was used as a reference. The Polaris tracking system provides an accurate orientation and positioning information with an update rate of up to 60 Hz and accuracy of around 0.35 mm. The Polaris affective coverage is limited to 1 square meter. The system model of the mobile car tracking and the hand movement is demonstrated in Figure 5, Figure 6, and Figure 7. Table I summarizes the default parameters used during the experiments.
Table I. Default Parameters Used in the Experiments

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Default Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Anchor nodes location</td>
<td>(0,40), (40,0)</td>
</tr>
<tr>
<td>Distance between mobile and anchor nodes</td>
<td>10–95 cm</td>
</tr>
<tr>
<td>Transmission power level</td>
<td>–11dBm</td>
</tr>
<tr>
<td>Transmission rate</td>
<td>50Hz</td>
</tr>
<tr>
<td>Car velocity</td>
<td>33 cm per second</td>
</tr>
</tbody>
</table>

The two anchor nodes and the mobile node included a BSN node [Lo et al. 2005] and a dipole antenna. A BSN node includes a processing unit (TI MSP430) and a transceiver for the wireless communication (Chipcon CC2420) [Chipcon 2004]. The transceiver has a built-in RSSI that provides a digital value in the range of –127 to 128 dBm. The RSSI value is always averaged over 8 symbol periods (128 ms). The conversion of the RSSI measurements to the received power is done by an addition of –45 dBm. The transceiver offers an additional mechanism for transmission power selection in a desired range from –25 dBm to 0 dBm. Using the TinyOS operating system [Levis et al. 2005], we set the transmission power in real time, according to the power selection algorithm. An omnidirectional antenna was added to each node to increase the transmission range. The antenna was made by bending and winding together a 10-cm wire and forming a dipole antenna of 5 cm, which is equivalent to half the length of the 802.15.4a wave length. The antenna was connected to a dedicated connector in the BSN node’s board. The anchor nodes were placed at x and y axes and attached to a wooden cube giving them the same height as the mobile node and forming a 2D plane that maximizes performance. The mobile node was attached to the car or to the human hand. The base station was implemented by a sensor node (TelosB) [Polastre et al. 2005]. The communication between the base station and the anchor nodes was implemented by 802.15.4. The notebook processed the data (IBM T43) and was used to program the sensors.

The first set of experiments was performed in an indoor environment in stationary conditions without significant reflection from walls and without metal reflectors. There was a direct path between the sensor nodes approximating LOS conditions. The maximal range among the sensor nodes was less than a meter. The anchor nodes were located in the x and y axes, in coordinates of (40;0) and (0;40) centimeters, respectively. We examined three different trails in the shapes of a circle, a pear, and a heart, as shown in Figure 8. The circular trail was with radius of 26 cm and the two other trails were in the range of 10 to 68 cm from the origin. Each trail had a reference of marked points. Using an interpolation process could have provided a description of the trail with 1 cm error. To compare the tracking results with the reference, we matched each reference point with a time stamp. For the circular trail, the matching was accurate with a resolution of 2 cm due to the nearly constant velocity of the toy car.

Fig. 8. Trails used in the experiments.
The calibration between the mobile node and each of the anchor nodes was performed at 12 different locations along the trail. The two anchor nodes received packets transmitted from the mobile node with a known power level. They calculated the received power level and then sent it to the processing unit for analysis. For the optimal transmit power-level selection we used the two extreme locations and found the optimal transmit power for each sensor node as described in Eq. (4). The 32 different transmit power levels of Chipcon CC2420 were changed in a loop by commands sent from the base station. The packet loss ratio and the RSSI measurements were continuously recorded and stored in the notebook. For the tracking phase, the car model traveled over the trail having a constant velocity of 0.33 m/s. The sensor node was attached to the top of the car and periodically transmitted data packets with time stamps in a cycle of 20 ms. Each anchor node computed the received power and transmitted it to the processing unit via the base station.

The second set of experiments was performed in the same environment as in the first set, but with a presence of a human body. With the human body, the channel was not fully LOS as the body reflected part of the transmitted signal to the medium and, due to body movements, the channel was not fully stationary. The calibration process between the mobile node and each of the anchor nodes was performed at 8 different locations. The measurements were at a distance of 20 cm to 85 cm from the nodes. During the tracking phase, the hand arbitrarily moved in the area at different speeds.

6. EXPERIMENTS’ RESULTS
We conducted a series of experiments with the different trails. The experiments for each trail had a separate calibration process. We analyzed the tracking system performance accuracy and the effect of the processing stages.

6.1. Omnidirectionality Assumption Verification
Before the calibration phase, we verified the assumption of omnidirectionality. The anchor node was placed in the center of the 26 cm circular trail and the mobile node was placed at 12 different locations along the circular trail. Figure 9 shows the verification results. Figure 9(a) shows the power level obtained at the sensor node x. The average received power was $-18.94$ dBm with a standard deviation of 0.31 dBm. The radiation pattern of the sensor node is nearly omnidirectional as shown in Figure 9(b).

6.2. Car Tracking Offline Phase
The mapping of the power measurements to distance was performed on 12 different locations along the pear-shape path. The RSSI measurements were converted to power...
levels and then sorted according to their distance levels. Each anchor node has its own unique calibration process to reflect a possible variation in the antenna dimensions, orientation, and other manufacturer’s chipset parameters that affect the transmit and receive power. The mapping of the received power to distance of the two anchor nodes for the pear-shape trail is shown in Figure 10. Node $x$ received power almost 2 dBm lower than node $y$. This demonstrates the need for the separate calibration process for each pair of nodes. The calibration described in Section 3.2 was used and Eq. (5) was set with minimal and maximal exponent values of 2 and 3, respectively. The distance constraint for the circular and the heart-shape trails was set to minimal and maximal values of 10 cm and 65 cm, respectively; a maximal constraint of 95 cm was used for the pear-shape trail.

The optimal power was obtained to minimize the criterion in Eq. (4). The packet loss threshold was selected to be 5% and the standard deviation threshold was selected to be 2 dBm. The transmit optimal power was selected to be $-11$ dBm (power level 10 in Chipcon CC2420).

The dynamic range, as obtained from Figure 10, was around 16 for the environment dimension of 55 cm. This dynamic range represents the coarse sensitivity of the tracking system. For a standard deviation of 1 dBm, the corresponding tracking resolution per dimension would be around 4 cm.

6.3. Car Tracking Phase

6.3.1. Preprocessing. The received power measurements are stored in a synchronized frame. For each frame we performed interpolation of the measurements to recover missing measurements and to synchronize between the anchor nodes’ data. Figure 11
demonstrates the received power in $x$ and $y$ nodes on a frame with a packet loss ratio of 12% and 10%, respectively.

After the nodes’ frame synchronization and packet loss recovery, we filtered the channel interference by an LPF. We examined 3 types of filters for the received power: a standard moving average window, which is equivalent to an LPF with equal coefficients, and mean and median filters. Figure 12 shows the received power for node $x$ before and after the filters. The mean and the median filters threshold was 0.6. The window size that was used for the filters was 15 measurements which is equivalent to a time duration of nearly 0.3 s and to a distance of about 10 cm. The window size for each of the filters is a function of the received power standard deviation and the ratio between the mobile node velocity and the transmission rate. For example, for a double transmission rate, the window size must be doubled. The optimal window size can be obtained with an autocorrelation function of the RSSI measurements. The mean and the median filters replace values that divert from the mean value by more than the standard deviation with the mean and median values, respectively. These filters sometimes distort the signal and exclude fine and delicate parts of the signal. Since the RSSI interference in our system is not characterized by spikes and the received power standard deviation is low (in the range of 1 dBm), we use an LPF filter. This filter suitably exploits the correlation between successive measurements in time and space and is commonly used when there is no additional statistic knowledge on the signal.

Figure 13 shows the filter received at the anchor nodes for 3 cycles (circling the trail one time). The fluctuations, which are caused by bumps over the trail or by small variations in antenna orientation, are mostly removed by the filtering operation. The peak power in the node $y$ is about 7 dBm higher than the power in node $x$. This may be a result of the asymmetry of the path for the nodes $x$ and $y$ or from the difference in channel conditions of the two nodes, in particular a difference in the antennas’ gain. As the $x$ and $y$ axes are orthogonal, the phase shift between $x$ and $y$ is nearly 90%.
6.3.2. Range Estimation between the Sensor Nodes. The estimated range between the mobile node and the two anchor nodes in the pear-shape trail is presented in Figure 14. The distance estimation seems to represent the balance between excluding the noise and not filtering out part of the real signal. Additional filtering is applied after the location estimation where mutual information from the $x$ and $y$ nodes is combined. Subsequently, discontinuity in localization estimation is more distinguished and easier to filter out.

6.3.3. Location Estimation. We found the intersection points of the circles, which are formed by the distances between the anchor nodes and the mobile nodes, according to Section 3.3.4. Figure 15 describes the intersection of the two circles in polar coordinates. We select the intersection of the mobile node's location as described in Section 3.3.5. Since the mobile node in our experiment is inside the range defined by the two sensors, the second intersection point is usually selected.
6.3.4. Postprocessing. Figure 16(a) shows the location estimation for the $x$ and $y$ axes before the postprocessing stage. The location estimation is noisy and some of the location estimations are not continuous and have large deviations. To apply the constraint of continuity in Eq. (3), we use a median filter that excludes irregular location estimations. The median filter window size must be tailored to the specific channel similar to the preprocessing filters. For example, if the irregularity is due to a packet loss burst, the window size must be twice the size of the burst. The standard deviation threshold should be set with the window size. The threshold level should be adopted to the signal. An overly high threshold might filter out significant information while a too low threshold may not filter well part of the noise. Figure 16(b) shows the location estimation after applying a median filter with a window size of 50, which is equivalent to 1 s, and a standard deviation threshold of 0.9. The time and the spatial diversity can be further exploited by an LPF, which averages the signal and smoothes the location estimation. Figure 16(c) shows the location estimation after filtering with an LPF implemented by a moving average with a window size of 30 measurements.

The mean error and standard deviation of the approximated location before the postprocessing were 7.23 cm and 6.2 cm for the $x$ axis and 7.19 cm and 5.77 cm for the $y$ axis. After the median filter, the results were reduced to 5.72 cm and 4.74 cm for the $x$ axis and 6.79 cm and 4.56 cm for the $y$ axis. After the LPF filter, the mean error and standard deviation were further reduced to 5.35 cm and 4.3 cm for the $x$ axis and 6.14 cm and 4.06 cm for the $y$ axis. The estimation quality at different locations for $x$ and $y$ coordinates is shown in Figure 17. Inaccurate estimation can indicate a nonoptimal processing or an estimation bias as described in Section 4. The postprocessing stages are demonstrated in Figure 18. The 2D location estimation is compared with the reference path, which was obtained by markers on the trail. The location mean error and standard deviation before postprocessing were 11.21 cm and
6.3.5. Transmission Rate Effect. The transmission rate should be high enough in order to track the object motion. With a relatively high transmission rate, diverse measurements can be used to exploit spatial and temporal correlations as in Eq. (3) and to enhance system tracking accuracy. In a static environment, the main factor that determines an adequate transmission rate is the toy car velocity. For a velocity in the range of 10 cm/s, a transmission rate of 10 Hz allots one measurement per centimeter.

Figure 19 describes the tracking accuracy achieved in the heart-shape trail with various transmission rates. The heart-shape trail demonstrates the significance of the transmission rate better than other trails, such as the circle, because of small variations along the trail that require precise tracking. Figure 19(a) shows the tracking results with a transmission rate of 1 Hz. The tracking is not consistent and there are variations...
Table II. A Comparison between the Experimental Results and the Theoretical Bounds for the Circle

<table>
<thead>
<tr>
<th>Location</th>
<th>Experimental Results</th>
<th>CRLB Bound</th>
<th>MLE Simulation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>x</td>
<td>y</td>
<td>Location</td>
</tr>
<tr>
<td>Mean Error (cm)</td>
<td>2.98</td>
<td>3.19</td>
<td>4.89</td>
</tr>
<tr>
<td>Standard Deviation (cm)</td>
<td>2.52</td>
<td>2.32</td>
<td>2.60</td>
</tr>
</tbody>
</table>

Fig. 20. Power levels measured by sensor nodes x and y at 8 different locations in the second experiment set (hand movement tracking).

6.4. Hand Movement Offline Phase
The human body affects the channel model in that the signal transmitted from the mobile node is partially absorbed in the body and partially reflected back to the medium. The reflection from the body and the body movement result in nonstationary channel conditions during the calibration process. Figure 20 shows the receive power measured at nodes x and y when a human body is present. A considerable difference in gain and dynamic power range can be seen between the two nodes. This difference can be explained by the strong reflection from the body in the direction of node y that enhanced the received power and increased the power level. Due to motion of the human body, the variability of the measurements at node x is much higher in comparison to the measurements used for the first experiment set, as shown in Figure 10. This variability demonstrates the nonstationary channel conditions in the direction of node x.
Enhancing RSSI-Based Tracking Accuracy in Wireless Sensor Networks

6.5. Hand Movement Tracking

During tracking, the hand moved in an arbitrary path in the 2D space determined by the two anchor nodes. Unlike the first experiment set, where the mobile node velocity was relatively constant and the channel conditions were close to LOS, in this experiment set, the mobile node moved in different velocities and the channel was not stationary due to the human body effect. The Polaris tracking system captured the hand movement during the experiment period. The RSSI measurements and the tracking system were synchronized by correlating the RSSI location estimation to the one of the tracking system over time. Figure 21 illustrates the tracking results of three experiments: a hand moving in horizontal movement, in a zig-zag pattern, and in a combination of horizontal movement and a circular pattern.

The location estimation mean errors were 10.77 cm, 7.88 cm, and 9.07 with standard deviations of 5.69 cm, 4.77 cm, and 3.0 cm, respectively. A comparison of these results to the CRLB bound and to the MLE simulation are shown in Table III. The CRLB bound is based on the system parameters and the standard deviation was derived based on the two nodes’ mapping tables. Both experimental and theoretical results were worse in this experiment set compared to the first one. Unlike the first experiment set, the location mean error in the second experiment set was slightly worse than the MLE simulation results. This difference can be explained by the dynamic changes in the channel during the tracking. The changes were caused by the presence of the body which were not taken into consideration in the MLE simulation since the simulation was based only on the static calibration noise. Still, as in the first experiment set, the standard deviation was significantly lower than the CRLB bound due to exploitation of the spatial-temporal channel correlations.

The distribution of the location estimation error is not uniform along the path. The nonuniform distribution can be explained by the statistical nature of the calibration, which is performed in one dimension for each sensor node, and cannot capture all of the channel variations in 2D. For example, in Figure 21(a), the right area has a lower estimation error compared to the left area. The low estimation error in the right area can be explained by the coincidence of the calibration points at a distance of 10–20 cm from the anchor node x with the channel path-loss model (the logarithmic fitting). The high variations at a higher distance of 30–60 cm caused an estimation bias. As a result,
the calibration accuracy and the overall location accuracy decrease in areas where the calibration varies from the channel model.

Figure 22 shows the tracking results of the hand moving in a zig-zag pattern for axes $x$ and $y$. The tracking results for each axis have a mean error of 4.33 cm and 0.19 cm and standard deviation of 6.74 cm and 4.55 cm for axes $x$ and $y$, respectively. The experiment results vary more slowly compared to the reference. This can be explained by the estimation bias and by the filters used in the data processing. Even with the relatively high estimation error due to the nonstationary channel conditions, the pattern of the movement is well-captured by the location estimations. As a result, RSSI-based tracking can be useful for tracking a movement pattern even in a dynamic environment.

7. CONCLUSIONS AND FUTURE WORK

In this article we proposed a new RSSI-based tracking system that utilizes commonly available a priori knowledge about the environment. This new tracking scheme is optimized for networks like BSN, where the sensor nodes are deployed in close proximity and operate with an adequate power level and with a high transmission rate. An MMSE criterion for tracking, based on the coarse RSSI measurements and their correlation in space and time, was derived. A performance bound per path, which is based on the location estimation CRLB bound and a numerical simulation of the corresponding MLE, was derived. The sensor node transmission power level was chosen to maximize the RSSI dynamic range for better tracking accuracy. Effective processing techniques for efficient solution of the criterion were used. For performance evaluation, we conducted a series of experiments in an indoor environment for tracking a mobile node’s location on various paths with two anchor nodes. The results were compared to a performance bound per path which was based on the location estimation CRLB bound and a numerical simulation of the corresponding MLE.

The first experiment set was designed for tracking a toy car moving on a plastic trail. In this setup, the optimal transmission power was found to be $-11$ dBm. The maximal dynamic range was around 16 dBm per one centimeter in the distance. This dynamic range represents a coarse sensitivity around 5 cm for the tracking system. The optimal transmission rate for a mobile node with a velocity of 0.33 m/s was 20 Hz. A transmission rate of 5 Hz was found sufficient in our static environment with a small loss to its accuracy. A higher transmission rate is required when there are dynamic channel conditions with rapid changes of the mobile node’s location. The interpolation method we used managed to overcome a packet loss of up to 10%. The filter we chose was a LPF filter with a filter size equivalent to a spatial correlation (coherence distance) of 10 cm and a temporal correlation (coherence time) of 0.3 s. The location mean error and standard deviation, after applying the median filter, were reduced by 13.1% and
Enhancing RSSI-Based Tracking Accuracy in Wireless Sensor Networks

26.3\%, and after applying the LPF by 8.7\% and 9.4\%, respectively. The experimental standard deviation is better than the CRLB and MLE. The mean error was 5\% lower than the MLE estimation and the standard deviation was around 2 cm, which is lower by 13.1\% than both the CRLB and MLE standard deviations. The improved results can be explained by exploiting the spatial and temporal redundancy in successive RSSI measurements.

The second experiment set was designed for tracking the movement of a human hand in a dynamic environment. The configurations of the transmission power level, the transmission rate, and the filters were the same as in the first experiment. The tracking system provided in this case a location estimation with a mean error around 7 cm and a standard deviation of around 5 cm. The location mean error was slightly worse than the MLE simulation results since the simulation did not take into account the dynamic changes in the channel during the tracking. Still, similar to the first experiment set, the standard deviation was significantly better than the CRLB bound, due to exploitation of the spatial-temporal correlations.

Extension of the tracking system to a 3D environment is challenging and is planned to be carried out in the future. Tracking in 3D requires additional sensor nodes and adaptation of the localization algorithm. Systems that consist of isotropic antennas, where the antenna has the same intensity of radio waves in all directions, can use similar calibration and tracking phases as in 2D. When the antennas are not fully isotropic and have directionality, the RSSI measurements can vary inconsistently in different planes, for example, the RSSI measurements may be affected by the reflection of the signal from the ground. Therefore, the calibration process should be changed and also include additional information regarding sensor orientation, such as the height of the mobile node or its orientation.

Information from external devices about channel conditions, sensor nodes’ location, or orientation can further improve the accuracy of RSSI-based tracking systems. For example, a feedback from a camera, inertial sensors, or other devices can be used to adopt the adequate transmission power level during the tracking. External information can be also used to adopt the RSSI measurements to the dynamic channel. Combining the external information requires efficient synchronization of the RSSI measurements with the external information. Another prospective challenge is to combine the entire information obtained from different sensor nodes by using advance statistical methods, such as Kalman filtering, to mitigate over estimation bias and improve the location estimation accuracy.

The tracking system presented in this article can be used as a robust and economical solution for indoor tracking applications in areas such as BSN. The system is also beneficial for capturing the pattern of the movement for diagnosis.

ACKNOWLEDGMENTS

The authors would like to thank Ami Luttwak for his help in setting up the Polaris tracking system. The authors also thanks the anonymous reviewers for their valuable comments.

REFERENCES


ACM Transactions on Sensor Networks, Vol. 9, No. 3, Article 29, Publication date: May 2013.
Enhancing RSSI-Based Tracking Accuracy in Wireless Sensor Networks


ACM Transactions on Sensor Networks, Vol. 9, No. 3, Article 29, Publication date: May 2013.


Received February 2011; revised February 2012; accepted February 2012