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Improvement of Software Defined Radio based RSSI localization with bias reduction ⋆

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Abstract:
In this paper, Received Signal Strength Indicator (RSSI) based localization, which attracts many interests because of its simplicity, is investigated. However, the accuracy of RSSI based localization is low because RSSI measurements are easily susceptible to human presence, multi-path effect, fading and even the change of temperature. In order to improve the performance of RSSI based localization, we propose a bias reduction algorithm. Another important contribution of this paper is that, instead of proving the effectiveness of the algorithm through simulation, a RSSI based localization system is developed using reconfigurable Software Defined Radios (SDRs) to verify the algorithm in practice. The results obtained from real-world experiments demonstrate that the proposed bias reduction algorithm can reduce the bias effectively, thus greatly enhancing the localization accuracy of the system.

Keywords: Bias; Localization; Received Signal Strength Indicator (RSSI); Software Defined Radio (SDR); Path-Loss-Exponent (PLE)

1. INTRODUCTION

Localization, also known as positioning, is to determine the position of targets at unknown locations, and it is a critical technology in numerous military and civilian applications, including surveillance, navigation, tracking, etc. Localization in wireless sensor network (WSN) is an important problem that attracts significant research interests. In WSN, measurements obtained by different technologies, such as Time Difference of Arrival (TDOA), Time of Arrival (TOA) and Received Strength Signal (RSS) Patwari et al. (2005), can be used to localize a target. Currently, Received Signal Strength Indicator (RSSI) based localization technology is becoming increasingly popular because of its ease of hardware implementation, inexpensive cost and less energy consumption Gorji and Anderson (2013). However, the weaknesses of RSSI based localization are also obvious because RSSI measurements are likely to be affected by the change of environment where the measurements are taken, such as temperature, humility, etc. Another factor that influences the accuracy of RSSI measurements is multi-path effect, which is caused by the reflection from ground, walls and ceilings. In addition, the variance of sensor hardware, antenna orientation and transmitter power, etc. also produce noise in RSSI measurements. Therefore, to achieve accurate localization using RSSI measurements is very challenging. Many methods have been proposed to enhance the accuracy of RSSI based localization, such as online calibration of the Path-Loss-Exponent (PLE) Mao et al. (2007), adaptive distance estimation using RSSI measurements Awad et al. (2007), etc. Apart from the influence from environment and hardware, during the process of target localization, a systemic error, or bias, arises and also affects the localization result. Bias exists because a localization process normally includes an application of a nonlinear transformation of noisy measurements to produce a desired estimated target position Ji et al. (2013).

Except the theoretical analysis, how to develop a practical RSSI based localization system is also an attractive problem. Most of existing RSSI based localization systems are implemented on specific hardware, such as CC2430 and PC wireless network cards Havinga et al. (2010), which have the problem of lack of flexibility in system design and compatibility of different products. In addition, they often use the same frequency (usually 2.4GHz) constrained by the hardware, such as WiFi (802.11) and Zigbee (802.15.4) Yang and Chen (2009), Zhang et al. (2011). However, 2.4GHz signal radiating sources widely exist in our daily work and living ambient, which may greatly interfere the accuracy of RSSI measurements of the signal on the same frequency. To avoid the disadvantages of traditional platforms, a RSSI based localization system is developed using Software Defined Radios (SDRs). SDR is an universal RF platform that aims to minimize the amount of specialized hardware required and implement the majority of components (and hence the desired functionality) in software. It provides great flexibility and adaptability in system design and implementation. In addition, SDR can cover wide range of frequency from DC to 6 GHz. Therefore, by choosing the frequency band on which there is few radiating sources, the interference from other signal sources can

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be reduced. In recent years, SDR has become a favorite platform for researchers to evaluate theoretical work in practice, such as to develop prototypes for researches on cooperative communication Zhang et al. (2010), distributed beamforming Rahman et al. (2012) and TDOA based localization system Wei and Yu (2013).

In this paper, based on the analysis of the RSSI based localization algorithm, a bias reduction algorithm is introduced theoretically to reduce the localization bias. Moreover, the algorithm is implemented on a RSSI based localization system developed using SDRs. The experimental results show significant improvement on the localization accuracy of the system.

The rest of the paper is organized as follows: the RSSI based localization is reviewed in Section 2. Section 3 introduces the bias reduction algorithms in the target localization. In Section 4, system setting up is described and then real-world experiments are implemented. Conclusion and future work are presented in Section 5.

2. RSSI BASED LOCALIZATION

RSSI based localization can be divided into two categories: the distance estimation based and RSS profiling based technologies Mao et al. (2007). In this paper, we focus on the distance estimation one and without any further notice RSSI based localization means the one based on distance estimation. RSSI based localization is intended to measure the power decay of the signal transmitted by the electromagnetic source, and to transform the measured signal power loss into distance the signal travels in space. The distance estimate is then used to localize the signal source.

Consider a simple scenario with one stationary emitter as the target and K stationary sensors that measure the power level of the signal transmitted by the emitter at different locations. Without any further information, such as the direction of the target, the minimum number of K is 3 in 2D space ($n = 2$) and 4 in 3D space ($n = 3$). Define $\boldsymbol{x}_k = [x_k \ y_k]', k \in \{1, ..., K\}$ as the known position of the sensor at k-th location. Also, let $\boldsymbol{x_0} = [x_0 \ y_0]'$ be the unknown position of the emitter.

The received signal power at the k-th location can be expressed by a log-normal model as Pahlavan and Levesque (2005)

$$z_k = \bar{z}_k + w_k \tag{1}$$

where $\bar{z}_k$ denotes the mean received power, and w_k represents the log-normal shadow fading effect in a multipath environment. Here the received signal power data is measured in dB milliwatts. It is assumed that w_k is Gaussian distributed with zero mean and the correlation defined as follows:

$$E(w_{k_1} \ w_{k_2}) = \begin{cases} 0 & k_1 \neq k_2 \\ \sigma_w^2 & otherwise \end{cases} \tag{2}$$

where σ_w^2 is measured in dB milliwatts squared being the known variance. The received average power is a function of the distance between the emitter and the sensor, and the Path-Loss-Exponent (PLE). It has been shown in Pahlavan and Levesque (2005) that the received average power can be written in the following form:

$$\bar{z}_k = P_0 - 10 * \gamma * log_{10}(\frac{\eta_k}{d_0}) \tag{3}$$

with η_k being the Euclidean distance between the emitter and the sensor at the k-th location, viz

$$\eta_k = \sqrt{(x_0 - x_k)^2 + (y_0 - y_k)^2} \tag{4}$$

In (3), d_0 refers to the known reference distance at which P_0 is measured. The value of P_0 can be measured at the reference distance through experiments. The parameter γ is called the Path-Loss-Exponent (PLE), which measures the rate at which the received signal strength decreases with distance. The value of γ depends on the specific propagation environment, so it can only be determined empirically. A generic method based on the quantile-quantile (q-q) plot Hyndman and Fan (1996) is used to estimate the unknown constant γ.

Once the unknown parameters P_0 and γ are determined, the distance η_k between the sensor at the k-th location and the emitter can be estimated by measuring the received signal strength at that location according to equation (3). With adequate distance measurements between the target and the receivers, the location of a target can be obtained by solving the following formulation in noiseless case:

$$\boldsymbol{\eta} = \boldsymbol{f}(\boldsymbol{x}) \tag{5}$$

where the function $\boldsymbol{f}$ can be obtained analytically according to the geometry of the target and the sensors at known positions. For example, with three distance measurements in 2-dimensional space, the mapping $\boldsymbol{f}$ can be easily formulated as follows:

$$\eta_1 = f_1(x_0, y_0) = \sqrt{(x_0 - x_1)^2 + (y_0 - y_1)^2}$$
$$\eta_2 = f_2(x_0, y_0) = \sqrt{(x_0 - x_2)^2 + (y_0 - y_2)^2}$$
$$\eta_3 = f_3(x_0, y_0) = \sqrt{(x_0 - x_3)^2 + (y_0 - y_3)^2}$$

In real-world situations, errors in distance measurements are inevitable due to radiating influence from other signal sources in the environment, reflection and the estimation of the function $\boldsymbol{f}$. Though when the usable number of measurements $N = n$, one can still obtain a target location estimate in effect by solving $\tilde{\boldsymbol{\eta}} = \boldsymbol{f}(\tilde{\boldsymbol{x}})$ (tilde denotes noisy measurements or estimates). However, generally when $N \geq n+1$, this equation will have no solution in the noisy case. The main idea of obtaining approximate estimate in this situation is to convert the localization problem to an optimization problem as follows and solve it using methods such as maximum likelihood, least square, etc. Foy (1976), Torrieri (1984).

$$\tilde{\boldsymbol{x}} = \arg\min_{\boldsymbol{x}} C(\boldsymbol{x}, \tilde{\boldsymbol{\eta}}) \tag{6}$$

where the cost function C is related to $\boldsymbol{f}$ and can be possibly formulated as follows:

$$C = \sum_{i=1} N[(f_i)^2 - (\tilde{\eta}_i)^2] \tag{7}$$

By solving the minimization problem, estimated positions of the unlocalized sensors can be obtained.

3. BIAS CORRECTION IN TARGET LOCALIZATION

In the target localization, due to 1) the non-linear of the mapping from target measurements to the target's location and 2) the measurements are noisy, bias is to be expected Ji et al. (2013). In practice these two factors are mostly present. In RSSI based localization, the noise in the distance measurements is inevitable because of inaccurate RSSI measurements and approximately estimated PLE of the environment. This motivates us to implement the bias reduction algorithm.

For the simplicity of notation, the Einstein summation convention is used: A repeated subscript and superscript is an implied summation, e.g. $u_i v^i = \Sigma_i u_i v^i = u^T v$. We define the bias as the difference between the expected value of $\boldsymbol{x}$ based on multiple mapping of measurements and the true target location:

$$E[\delta \boldsymbol{x}] = E[\boldsymbol{g}(\tilde{\boldsymbol{\eta}})] \neq \boldsymbol{x} \tag{8}$$

where $\boldsymbol{x} \in R^n$ denotes the location vector of a target, $\delta \boldsymbol{x}$ denotes the error in estimated target position, $\boldsymbol{g}$ denotes the localization mapping from the (noisy) measurements to the target position (estimates). $\tilde{\boldsymbol{\eta}}$ denotes the noisy measurements.

Since the noise always exists in the measurements in the real world, the target location estimate will be:

$$\boldsymbol{x} + \delta \boldsymbol{x} = \boldsymbol{g}(\boldsymbol{\eta} + \delta \boldsymbol{\eta}) \tag{9}$$

To determine the bias here we consider $x^\alpha = g^\alpha(\eta^i + \delta\eta^i)$. Assume the localization mapping $\boldsymbol{g}$ is well-defined for each point and there are derivatives of any order of g^α. Now g^α can be expanded by Taylor series and truncated at the second order term:

$$\begin{aligned} x^\alpha + \delta x^\alpha &= g^\alpha(\eta^i + \delta\eta^i) \\ &\approx g^\alpha(\eta^i) + g^\alpha_{,i}\delta\eta^i + \frac{1}{2} g^\alpha_{,ij}\delta\eta^i\delta\eta^j \end{aligned} \tag{10}$$

where $g^\alpha_{,i} = \frac{\partial g^\alpha}{\partial \eta^i}$ and $g^\alpha_{,ij} = \frac{\partial^2 g^\alpha}{\partial\eta^i\partial\eta^j}$. Hence the difference between the true position and the estimate is approximately:

$$\delta x^\alpha = g^\alpha_{,i}\delta\eta^i + \frac{1}{2} g^\alpha_{,ij}\delta\eta^i\delta\eta^j \tag{11}$$

and its expectation result is denoted by

$$E(\delta x^\alpha) = g^\alpha_{,i}\Psi^i + \frac{1}{2} g^\alpha_{,ij}\Sigma^{ij}_\eta \tag{12}$$

where Ψ^i denotes the mean error and Σ^{ij}_η denotes the ij entry of the measurement error covariance matrix. Though in the theoretical analysis, the mean measurement error is assume to be zero mean, in practical situation this assumption is not necessarily satisfied. Apart from the influence of the imperfection of hardware and surrounding environment, in real-world experiments, we will not take very large number of measurements due to significate consumption of time and energy. That is why in equation (12) we remain the first term.

Here the expected value of δx^α which is $E(\delta x^\alpha)$ can be considered as analytical expression of the bias in localization. However, in (12), when considering, e.g. a scenario in R^3 involving a mixture of range and bearing measurements, to obtain the analytical expression of g^α becomes very challenging. Therefore, an alternative method to analytically express the derivatives of g^α is proposed to allow the computation of bias and its consequent reduction. Next we will present how to formulate $g^\alpha_{,ij}$ in terms of the known cost function C in (7), evaluated at $(\boldsymbol{x}, \boldsymbol{\eta})$, where $\boldsymbol{x} = \boldsymbol{g}(\boldsymbol{\eta})$.

Theorem 1. Let $C : R^D \times R^N \to R^D$ be a known smooth cost function for which a unique solution of the optimization problem (6) is available for all $\boldsymbol{\eta} \in \Theta \subset R^N$. Let $\boldsymbol{g}(\boldsymbol{\eta})$ denote the minimizing value of $\boldsymbol{x}$. Let $\boldsymbol{\omega}(\boldsymbol{x}, \boldsymbol{\eta}) = \frac{\partial C}{\partial \boldsymbol{x}^T}$. The following equations hold at every point $(\boldsymbol{x}, \boldsymbol{\eta}) = (\boldsymbol{g}(\boldsymbol{\eta}), \boldsymbol{\eta})$ for $\boldsymbol{\eta} \in \Theta$ and for all $a = 1, 2, ..., D$, $\alpha = 1, 2, ..., D$, $\beta = 1, 2, ..., D$, $i = 1, 2, ..., N$ and $j = 1, 2, ..., N$:

$$\omega^a_{,\alpha} g^\alpha_{,i} + \omega^a_{,i} = 0 \tag{13}$$

and by further differentiating equation (13) in respect to θ^j and can obtain:

$$\begin{aligned} \omega^a_{,\alpha} g^\alpha_{,ij} &= -[\omega^a_{,\alpha\beta} g^\alpha_i g^\beta_j + \omega^a_{,\alpha j} g^\alpha_{,i} + \omega^a_{,\beta i} g^\beta_{,j} + \omega^a_{,ij}] \\ &= -[g^\alpha_{,i} \ 1] \begin{bmatrix} \omega^a_{,\alpha\beta} & \omega^a_{,\alpha j} \\ \omega^a_{,\beta i} & \omega^a_{,ij} \end{bmatrix} \begin{bmatrix} g^\beta_{,j} \\ 1 \end{bmatrix} \end{aligned} \tag{14}$$

Assuming invertibility for all $\eta \in \Theta$ of the Jacobian matrix with (a, α) entry $\omega^a_{,\alpha}$, first derivatives of g^α can be expressed in terms of first derivatives of ω^α by (13), and second derivatives of g^α can be expressed in terms of first and second derivatives of ω^a by (14).

Proof. Because $\boldsymbol{g}(\boldsymbol{\eta})$ is a minimizer with respect to $\boldsymbol{x}$ of $C(\boldsymbol{x}, \boldsymbol{\eta})$, it is a zero of $\frac{\partial C}{\partial \boldsymbol{x}} = \boldsymbol{w}(\boldsymbol{x}, \boldsymbol{\eta})$, i.e.

$$\boldsymbol{\omega}(\boldsymbol{g}(\boldsymbol{\eta}), \boldsymbol{\eta}) = \boldsymbol{0} \ \forall \eta^i \tag{15}$$

Differentiating with respect to η^i yields (13). Equation (14) results from differentiation of (13) with respect to η^i.

The condition of the theorem statement that the Jacobian matrix be nonsingular is not unreasonable; it is a sufficient, though admittedly not necessary, condition for the existence of a unique function $\boldsymbol{g}$.

From equation (14), we obtain the analytical expressions for the second derivatives of g^α. Substituting the formulas into equation (12) we can finally obtain the easily-calculated expressions for the bias.

In practical situations, we can obtain the inaccurate estimated position of the target by using existing localization algorithms. Then we can input the inaccurate target location into the obtained analytical expression for the bias. Finally we can improve the accuracy of the localization by subtracting the obtained bias, viz. $\tilde{\boldsymbol{x}} - bias_{\tilde{\boldsymbol{x}}}$. If necessary, one can input this target location into the expression for the bias as the argument at which second derivatives are evaluated, to improve the accuracy of the computed bias.

4. EXPERIMENTS

4.1 System setting up

As mentioned in Introduction, here we apply the bias reduction algorithm to improve the performance of the RSSI based localization system developed using SDRs. The SDR model we used is USRP N210 which is developed by Ettus Research. In the experiments, both of the emitter and receiver are developed using USRP N210s. A simple framework of the localization can be seen in Fig. 1. The emitter can transmit signals at a wide frequency bands (from 50MHz to 2.2GHz for this model) using bandwidth up to 40MHz. The parameters of the emitter are listed in Table 1. For simplicity, 1.2 GHz carrier signal (Sine wave) is transmitted as the signal source using omni-directional antenna. The receivers are tuned to the desired frequency and obtain M (M=102400) complex samples of the signal source. The sampling rate is set to 1M sps (sample per second).

The principle to obtain RSSI is described in Fig. 2. The SDR receiver obtains RF signal through its RF

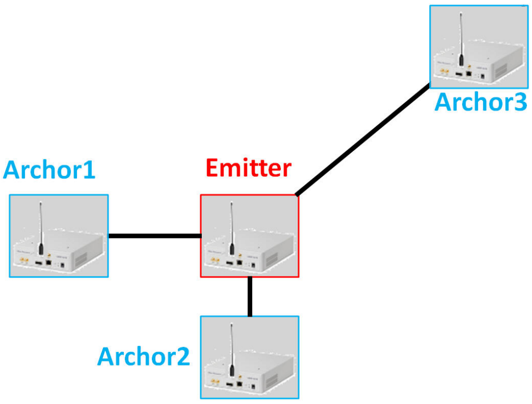


Fig. 1. Three receivers and one target

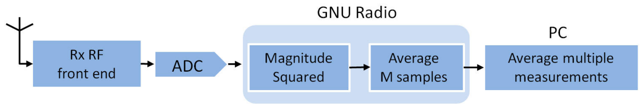


Fig. 2. Block diagram of RSSI measurement

front end and the signal is sampled by the 14-bit ADC. Then, the sampled signal is processed by GNU Radio and stored in the PC. The RSSI is calculated by obtaining the magnitude of the I/Q components of each samples, denoted by $I^2 + Q^2$, and averaging the magnitude of M samples in one measurement. To enhance the reliability of the measurements, measurements are implemented many times at one position and the average RSSI is obtained. The power of the emitter is unknown, but we found it is almost constant as long as the emitter are not switched off.

Table 1. Emitter parameters

Parameter	value
Central frequency	1.2GHz
Waveform	Sine
Bandwidth	1MHz
Sampling rate	1M Sps
Antenna	omni-directional

4.2 PLE estimation

The value of the PLE depends on the environment and it is determined by RSSI measurements at the corresponding distances in a specific environment. A 8m by 10m indoor area is used in the experiments. The emitter and receivers are placed on identical bar stools to reduce the influence of multi-path effect which is mainly caused by reflection of walls, ground and ceiling. In addition, for a particular transmitter power, the Signal-to-Noise ratio (SNR) drops when the spacing between the emitter and the receiver increases. To obtain high SNR, the gains of both the emitter and the receiver need to be large.

The process of obtaining the PLE of this indoor area is described as follows: an emitter is fixed at one point, then a receiver is moved away from the emitter in a straight line by steps of half meter and the RSSI value is obtained at each point. 0.5m step is chosen because smaller steps, such as 0.1m or 0.2m, does not show obvious change of received signal strength. Fig. 3 shows the distribution of RSSI measurements at some training points, which obeys Gaussian distribution approximately. To determine the RSSI value, the average value is obtained from multiple measurements. At each training point, the measured RSSI values show small variance, which shows that the RSSI measurements obtained from SDRs are stable. The variance of RSSI measurements become larger gradually due to the drop of SNR when the distance between the emitter and the receiver increases.

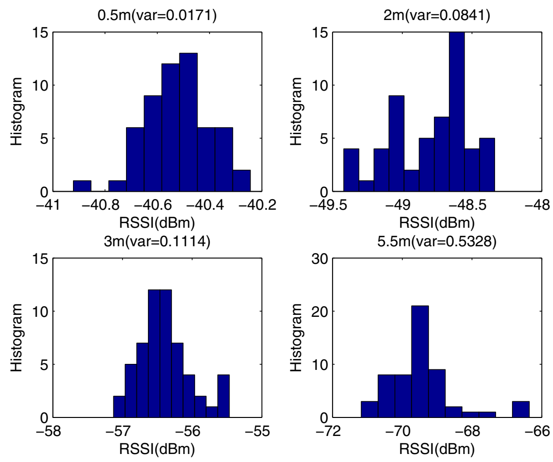


Fig. 3. Distribution of RSSI measurements

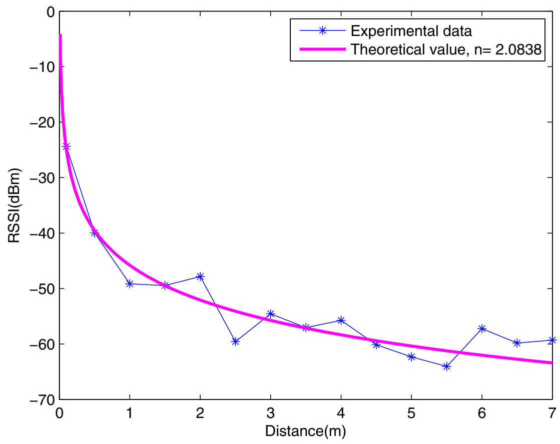


Fig. 4. PLE estimate of the indoor area

Fig. 4 shows the obtained RSSI-distance plot, in which some fluctuation can be seen, especially at 2m to 3m and 6m to 7m. In practical environment, however, the fluctuation is inevitable. Even though many tests are implemented at these abnormal points, the results are almost the same. This is determined by the reflection characteristics of the room. Rooms with different size or sharp will give different patterns of the fluctuation of RSSI-distance plot. To estimate the PLE γ, a fitting curve is obtained based on the average RSSI measurements at the corresponding distance. The approximated PLE of this room is 2.0838. This value is very close to the empirical value in the free space because the emitter and receiver are placed at the same height and in a line-of-sight condition.

Table 2. Error statistics of distance estimate(1)

Real distance(m)	Average distance measurement(m)	Variance(m)	Error ratio
1.89	1.7619	0.0015	6.78%
2	1.9068	0.008	4.66%
3	2.7992	0.0195	6.69%

4.3 Experimental results

Once γ and P_0 are estimated, the distances between the emitter and receivers can be calculated according to average RSSI measurements obtained by receivers at different locations. Then, one can estimate the location of the target by using the obtained distance measurements.

Three scenarios are considered to verify the performance of the bias reduction algorithm in RSSI based localization. In each scenario, the locations of anchors are known. The locations of targets are unknown and to be estimated. The SDR can be built as a receiver or an emitter by simply changing the software configuration. Therefore, the distance measurement in an anchor/target pair can be obtained by using the target as the emitter and the anchor as the receiver. The distance measurement in a target/target pair can be obtained by using one target as the emitter and the other one as the receiver.

Scenario 1 Firstly, the simplest scenario with three anchors and one target is considered (shown in Fig. 5(a)). The dashed line denotes the distance measurements between two nodes. Using the average distance measurements obtained by three anchors, the location of the target is estimated. In order to evaluate the localization performance we use the root mean square error (RMSE) which is calculated as follows:

$$RMSE = \sqrt{\frac{\sum_{k=1}^{m}(\boldsymbol{x_k} - \tilde{\boldsymbol{x_k}})^2}{m}}. \tag{16}$$

In Table 2, the real distance between the emitter and the receiver, the mean and variance of distance measurements, and the error ratio of the distance measurements to the true value are presented. The distance measurements show errors with non-zero mean and the largest error of 6.78%. Before the bias reduction algorithm is used, the RMSE of the localization result is 0.3521m. After the bias reduction algorithm is applied, the RMSE of target location estimate is reduced by 77.3% from 0.3521m to 0.08m (shown in Fig. 6(a)).

Scenario 2 In this Scenario, a more complex case is considered in Fig. 5(b), where three anchors are used to localize two targets and dashed lines denote the distance measurements between two nodes. The error statistics of the obtained distance measurements are shown in Table 3. While the distance measurement of 2m shows relatively larger error (19.29%), other measurements give errors less than 10%. As can be seen in Fig. 6(b), the RMSE of location estimate is also reduced by 79.7% from 0.4193m to 0.0853m for target $T1$ and by 67.2% from 0.2011m to 0.066m for target $T2$ respectively after our bias reduction algorithm is applied.

Scenario 3 Fig. 5(c) shows a more complex scenario, where we use three anchors to localize 4 targets. The error statistics of distance measurements are shown in Table 4.

Table 3. Error statistics of distance estimate(2)

Real distance(m)	Average distance measurement(m)	Variance(m)	Error ratio
4.5	4.7509	0.0792	5.58%
2	2.3857	0.0036	19.29%
3.4	3.2346	0.0157	5.97%
1.5	1.492	0.00074	1.84%
2.24	2.1298	0.0086	4.92%
2.04	2.0566	0.0031	0.81%

Table 4. Error statistics of distance estimate(3)

Real distance(m)	Average distance measurement(m)	Variance(m)	Error ratio
1	1.0002	0.00068	0.02%
2	1.7602	0.0073	11.99%
2.85	1.9362	0.0238	32.06%
1.34	1.226	0.0016	8.51%
2.26	1.5626	0.0206	30.86%
3.5	2.5968	0.0155	25.81%
3.23	3.3467	0.0206	3.61%
3.86	4.1787	0.1241	8.26%
3.95	3.816	0.0632	3.39%
3.2	2.8322	0.039	11.49%
2.3	1.8477	0.008	19.67%
4.7	4.1885	0.1833	10.88%

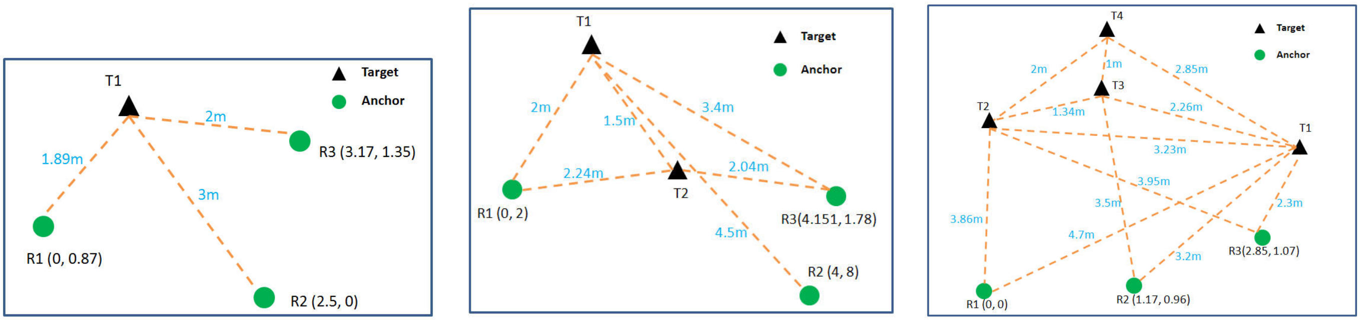
Similar to Scenario 2, some distance measurements show large errors, e.g. 2.85m, 2.26m, 2.3m and 3.5m. This is the combined influence of inaccurate PLE estimate and RSSI measurements at those distances, which are caused by the noise of the experimental platforms and environment.

In this scenario, the initial localization results of the targets without the bias reduction algorithm being implemented also show larger errors than previous two scenarios, which is mainly caused by larger distance measurement errors at some points. Moreover, the factor like error accumulation also influences the localization accuracy in this more complex network. After the bias reduction algorithm is implemented, the results can still prove that the algorithm improves the localization accuracy largely. For target $T1$, $T2$, $T3$ and $T4$ in Fig. 6(c), the RMSEs of localization results drop by 55.4% to 0.602m, by 46.5% to 0.5047m, by 77.8% to 0.4929m and by 66.3% to 0.5406m respectively.

5. CONCLUSION AND FUTURE WORK

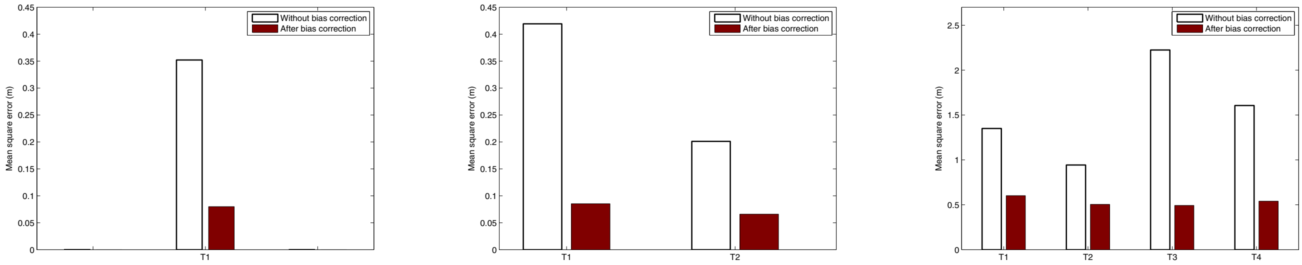
In this paper, a RSSI based localization system is developed using reconfigurable SDRs. To improve the performance of the localization system, a bias reduction algorithm is applied. To verify the performance of the algorithm in practice, indoor localization experiments are implemented with different number of emitters and receivers. The experimental results show that the bias reduction algorithm can reduce the localization error by around 50% to 80% and therefore the localization accuracy of the SDR based RSSI localization system is significantly enhanced.

Our future work is to further improve the localization accuracy of the SDR based RSSI localization system. From the perspective of system implementation, firstly, the RF parameters such as central frequency, bandwidth, RF gain and modulation scheme, etc. are easily changed as SDR is a reconfigurable platform. Therefore optimized parameter setting can be obtained to enhance the accuracy of RSSI measurements. Secondly, as discussed in the paper, PLE is important and thus methods to calibrate PLE



(a) Scenario 1 (b) Scenario 2 (c) Scenario 3

Fig. 5. Localization scenario: (a) 3 receivers and 1 targets, (b) 3 receivers and 2 targets, (c) 3 receivers and 4 targets



(a) Scenario 1 (b) Scenario 2 (c) Scenario 3

Fig. 6. Localization results: (a) one emitter, (b) two emitters, (c) four emitters

according to the reflection feature of the environment will be developed. In addition, to enhance the accuracy of localization estimate, apart from bias reduction, other optimized localization algorithms will be implemented.

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