Receiver positioning using received signal strength

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Abstract: In wireless positioning, estimating the location of a receiver is extremely challenging since the receiver does not transmit signal and it is invisible to sensors. To deal with the issue, we propose a *received signal strength* (RSS)-based method to position the receiver based on the signal from the corresponding transmitter. Our results indicate that the proposed method has about 20~40 meters positioning error in average, which reaches the same level of the positioning error as the conventional RSS-based Tx positioning methods.

Keywords: estimation, receiver, RSS, wireless positioning

Classification: Sensing

References

- [1] G. Mao and B. Fidan, *Localization algorithms and strategies for wireless sensor networks*, 2009.
- [2] X. Li, "RSS-based location estimation with unknown path loss model," *IEEE Trans. Wireless Commun.*, vol. 5, no. 12, pp. 3626–3633, Dec. 2006. DOI: [10.1109/TWC.2006.256985](https://doi.org/10.1109/TWC.2006.256985)
- [3] R. M. Vaghefi, M. R. Gholami, R. M. Buehrer, and E. G. Strom, "Cooperative received signal strength-based sensor localization with unknown transmit powers," *IEEE Trans. Signal Process.*, vol. 61, no. 6, pp. 1389–1403, Mar. 2013. DOI: [10.1109/TSP.2012.2232664](https://doi.org/10.1109/TSP.2012.2232664)
- [4] R. Zhang, "On active learning and supervised transmission of spectrum sharing based cognitive radios by exploiting hidden primary radio feedback," *IEEE Trans. Commun.*, vol. 58, no. 10, pp. 2960–2970, Oct. 2010. DOI: [10.1109/TCOMM.2010.082710.090412](https://doi.org/10.1109/TCOMM.2010.082710.090412)
- [5] E. Azzouz and A. Nandi, *Automatic modulation recognition of communication signals*, 2010.
- [6] B. Ramkumar, "Automatic modulation classification for cognitive radios using cyclic feature detection," *IEEE Circuits Syst. Mag.*, vol. 9, no. 2, pp. 27–45, Jun. 2009. DOI: [10.1109/MCAS.2008.931739](https://doi.org/10.1109/MCAS.2008.931739)
- [7] A. H. Sayed, A. Tarighat, and N. Khajehnouri, "Network-based wireless positioning: challenges faced in developing techniques for accurate wireless location information," *IEEE Signal Process. Mag.*, vol. 22, no. 4, pp. 24–40, Jul. 2005. DOI: [10.1109/MSP.2005.1458275](https://doi.org/10.1109/MSP.2005.1458275)
- [8] 3GPP TR 25.814, "Physical layer aspects for evolved universal terrestrial radio access (UTRA)," 2006.

1 Introduction

Positioning an unknown node has been extensively studied in the past decades [1], which is the essential technique for location-aware applications. Fig. 1(a) provides a conventional wireless positioning scenario: some fixed sensors with known locations (called anchors) measure the transmitted signal from an unknown node (called target), then they estimate the location of the target. In existing literatures, positioning algorithms include *received signal strength* (RSS) [2, 3], *time of arrival* (TOA), *time difference of arrival* (TDOA), *angle of arrival* (AOA), etc. However, they all belong to *transmitter positioning* technique since they treat the unknown transmitter as the target.

Fig. 1. System model.

In contrast, few contributions discuss *receiver positioning* technique since the receiver works in a passive way and it is invisible to sensors, i.e., the receiver does not transmit signal during the reception¹. Therefore, receiver positioning becomes extremely challenging. This significantly impedes the development of the location-aware applications.

In this paper, we propose an RSS-based receiver positioning method under the scenario² that multiple transmitters communicate with a common receiver using *time division multiple access* (TDMA) protocol. In the proposed method, we treat the multiple transmitters as the anchors, and position the receiver by estimating the *transmitter-to-receiver* (Tx-Rx) distances, i.e., Anchor-Rx distances. It is reasonable to treat those transmitters as the anchors as the location of the transmitters can be obtained using the conventional transmitter positioning methods [1]. Regarding the Tx-Rx distance estimation, our method exploits the *close-loop power control*

¹Even though the receiver may feedback information to its transmitter, it goes through another frequency band in *frequency division duplex* (FDD) systems. Thus, the receiver is still invisible (or silent) to the sensors since the feedback channel may not be known to the sensors.

²Even though this letter considers the many-to-one scenario, the proposed method can also be used in the point-to-point scenario when the transmitter is moving. This is because during the geographic travel of the transmitter, the sensors can obtain multiple locations of the transmitter as well as the corresponding distances to the receiver.

(CLPC) between the transmitters and the receiver, which has been widely used in modern wireless communication systems. Under CLPC, the power adjustment of the transmitters actually carries the Tx-Rx distance information. Therefore, by measuring the transmission power of the transmitters, the sensors are able to estimate the Tx-Rx distances and then obtain the location of the corresponding receiver.

2 System model

Fig. 1(b) provides the system model of this paper, where M transmitters (labeled as Tx), a receiver (labeled as Rx), and N sensors are uniformly distributed on a disk with the radius R . Here, we denote l_i as the distance between the i -th Tx (denoted as Tx_i) and the receiver, and d_{ij} as the distance between the i -th Tx and the j -th sensor (denoted as Sensor_j). In particular, we assume that the Tx_i 's location and the corresponding Tx_i - Sensor_j distances d_{ij} are known to the sensors. Next, we provide the signal models for the Tx-Rx and Tx-Sensor links, respectively.

- **Tx-Rx Links:** We denote g_i and $q_i(k)$ as the path-loss and shadowing coefficients between the Tx_i and the Rx, where the former is modeled as $g_i = C/l_i^\alpha$ (C is a constant and α is the path-loss coefficient) and the latter follows log-normal distribution with the standard deviation of δ . Here, k ($1 \leq k \leq K$) is the index of independent shadowing. In static scenarios, we have $K = 1$ during the positioning. In time-varying scenarios, the shadowing coefficient varies with time, and then the Tx_i and the Rx experiences $K > 1$ independent shadowing coefficients during the positioning.

Let p_i as the transmission power of the Tx_i , then the average SNR of the Rx served by the Tx_i can be expressed as $\gamma_i(k) = p_i g_i q_i(k)$, where the variance of the noise at the Rx is normalized. When we consider the system with CLPC³, the Tx_i automatically adjusts the transmission power to meet a certain target SNR at the Rx, denoted as Γ ⁴. Then, the transmission power of Tx_i can be obtained by

$$p_i = \frac{\Gamma}{g_i q_i(k)}. \quad (1)$$

- **Tx-Sensor Links:** Similarly, we denote g'_{ij} and $q'_{ij}(k)$ as the path-loss and shadowing coefficients between the Tx_i and the Sensor_j , which follow the same model as in Tx-Rx links, then the average SNR at the Sensor_j can be expressed as

$$\gamma'_{ij}(k) = p_i g'_{ij} q'_{ij}(k), \quad (2)$$

where the variance of the noise at the Sensor_j is normalized. When adopting the path-loss model $g'_{ij} = C/d_{ij}^\alpha$ and substituting (1) into (2), we can rewrite (2) as

$$\gamma'_{ij}(k) = \Gamma \frac{q'_{ij}(k)}{q_i(k)} \left(\frac{l_i}{d_{ij}} \right)^\alpha. \quad (3)$$

³Since this paper focuses on proposing the basic idea of Rx positioning, we consider the perfect CLPC [4], where the quantization error and time delay are not considered.

⁴Even though Γ is the target SNR of the Rx, it can still be obtained by the Sensor_j using blind signal processing technique, e.g., recognizing the modulation level of the Tx_i 's signal and obtaining the corresponding target SNR [5, 6].

3 RSS-based receiver positioning

3.1 Estimate the Tx-Rx distance

In this subsection, we first design a ML estimator to let each sensor obtain the Tx-Rx distance. To facilitate the derivation, we rewrite (3) using dB unit and then obtain the average SNR at the Sensor_{*j*} as

$$\gamma'_{ij[\text{dB}]}(k) = 10\alpha \log_{10}\left(\frac{l_i}{d_{ij}}\right) + q'_{ij[\text{dB}]}(k) - q_{i[\text{dB}]}(k) + \Gamma_{[\text{dB}]}. \quad (4)$$

Here, l_i is the unknown Tx-Rx distance to be estimated. $q'_{ij[\text{dB}]}(k)$ and $q_{i[\text{dB}]}(k)$ are independent shadowing coefficients, which follow normal distribution in dB unit, i.e., $q'_{ij[\text{dB}]}(k) \sim N(0, \delta^2)$ and $q_{i[\text{dB}]}(k) \sim N(0, \delta^2)$. Then, we have $q'_{ij[\text{dB}]}(k) - q_{i[\text{dB}]}(k) \sim N(0, 2\delta^2)$.

If the sensor can obtain K average SNR with independent shadowing coefficients, then we can obtain the K -dimension conditional *probability density function* (PDF) as

$$f(\gamma'_{ij[\text{dB}]}(1), \dots, \gamma'_{ij[\text{dB}]}(K)|l_i) = \prod_{k=1}^K \frac{e^{-\frac{\gamma'_{ij[\text{dB}]}(k) - 10\alpha \log_{10}\left(\frac{l_i}{d_{ij}}\right) - \Gamma_{[\text{dB}]}}{4\delta^2}}}{\sqrt{4\pi\delta^2}}. \quad (5)$$

Using the standard maximum likelihood distance estimator, then the Sensor_{*j*} can obtain the Tx-Rx distance as

$$\hat{l}_i = d_{ij} \cdot 10^{\frac{1}{10K\alpha} \sum_{k=1}^K (\gamma'_{ij[\text{dB}]}(k) - \Gamma_{[\text{dB}]})}. \quad (6)$$

Like other RSS-based distance estimators, the estimation in (6) is biased, i.e.,

$$\mathbf{E}\{\hat{l}_i\} = \mathbf{E}\left\{d_{ij} \cdot 10^{\frac{1}{10K\alpha} \sum_{k=1}^K (\gamma'_{ij[\text{dB}]}(k) - \Gamma_{[\text{dB}]})}\right\} = l_i \cdot e^{\frac{\delta^2}{K\xi^2}}, \quad (7)$$

where $\xi = 10K\alpha / \ln 10$. By modifying the estimator, we can obtain the unbiased estimation as follows

$$\hat{l}_i = d_{ij} \cdot e^{-\frac{\delta^2}{K\xi^2}} \cdot 10^{\frac{1}{10K\alpha} \sum_{k=1}^K (\gamma'_{ij[\text{dB}]}(k) - \Gamma_{[\text{dB}]})}. \quad (8)$$

3.2 Positioning the receiver

Once we obtain the Tx-Rx distance, positioning the receiver becomes easy. Here, we adopt the conventional linear method to estimate the Rx location [7]. Specifically, we first derive the positioning method for one sensor, denoted as Sensor_{*j*}, and then obtain the Rx location using N sensors.

Let (x_0, y_0) and (x_i, y_i) as the locations of the Rx and Tx_{*i*}, respectively, where $i = 1, 2, \dots, M$. We further let $D_i = x_i^2 + y_i^2$, then we have

$$\mathbf{H}\mathbf{X} = \mathbf{b}, \quad (9)$$

where

$$\mathbf{H} = \begin{bmatrix} (x_2 - x_1) & (y_2 - y_1) \\ \vdots & \vdots \\ (x_M - x_1) & (y_M - y_1) \end{bmatrix}, \quad \mathbf{X} = \begin{bmatrix} x_0 \\ y_0 \end{bmatrix}, \quad \mathbf{b} = 0.5 \begin{bmatrix} D_2 - D_1 - (l_2^2 - l_1^2) \\ \vdots \\ D_M - D_1 - (l_M^2 - l_1^2) \end{bmatrix}.$$

Once solving the equation (9), we can obtain the location of the Rx as

$$\hat{\mathbf{X}} = \begin{bmatrix} \hat{x}_0 \\ \hat{y}_0 \end{bmatrix} = (\mathbf{H}^T \mathbf{H})^{-1} \mathbf{H}^T \mathbf{b}. \quad (10)$$

When we consider N sensors that can share their distance estimations, they can obtain the average Tx-Rx distance by

$$\bar{l}_i = \frac{1}{N} \sum_j^N \hat{l}_i^{(j)}. \quad (11)$$

Substituting $\bar{l}_i$ into (10), we can obtain the Rx's location more accurately.

4 Simulation results

In this section, we demonstrate the performance of the proposed RSS-based receiver positioning method. Here, M Tx's, a Rx, and N sensors are uniformly distributed on the disk with the radius $R = 100$ m. In the simulation, the system bandwidth is $B = 10$ MHz, the power spectrum density of the noise is $N_0 = -174$ dBm, and the target SNR of the Rx is $\Gamma = 10$ dB. In wireless channels, $C = -128.1$ dB and $\alpha = 3.76$ are adopted according to [8]. Furthermore, 10^4 Monte Carlo trials are conducted for each simulation curve.

To evaluate the positioning performance, we define the *root-mean-square error* (RMSE) as $\text{RMSE} = \sqrt{(\hat{x}_0 - x_0)^2 + (\hat{y}_0 - y_0)^2}$.

Fig. 2. Impact of N and M on the RMSE of Rx positioning.

In Fig. 2, we consider the static scenario, where $K = 1$. We assume that the number of Tx's $M = 10$ in Fig. 2(a) and the number of sensors $N = 10$ in Fig. 2(b). From the two figure, we find that the number of Tx's (M) dominates the RMSE as the number of sensors (N) is larger than 5, i.e., $N \geq 5$. This is because we treat the Tx as anchor and more anchors result in a better performance. In addition, we compare the curves with different standard deviations of the shadowing. The RMSE reduces as the standard deviation δ decreases from 6 to 2. This is because the small δ introduces less uncertainty into the wireless channel.

Fig. 3 illustrates the RMSE of the proposed method versus the number of independent shadowing coefficients (K), where $M = 10$ Tx's and $N = 10$ sensors are considered. Here, when $K > 1$, it is the time-varying scenario, which means that

Fig. 3. Impact of K on the RMSE of Rx positioning.

each node experiences K independent shadowing coefficients during the Rx positioning. From the figure, the RMSE reduces as K increases from 1 to 20. The reason is that the uncertainty of the shadowing can be reduced by considering multiple independent shadowing coefficients. In particular, the proposed method has about 20~40 m positioning error, where the Rx is uniformly located on a disk with the radius 100 m. This means that the proposed Rx positioning method actually reaches the same level of the positioning error as the conventional RSS-based Tx positioning methods. For example, the method in [2] has about 6 m positing error, where the Tx is uniformly located on a disk with the radius 20 m.

5 Conclusions

In this paper, we proposed an RSS-based receiver positioning method to estimate the location of an unknown receiver. Different from existing RSS-based positioning, our method treated the associated transmitters as the anchors, and conducted the positioning by estimating the distances between the anchors and the receiver. The simulation results showed the effectiveness of the proposed method.

With our method, the location-aware applications can be extended to many scenarios. For example, a scenario where multiple wireless networks may share the same frequency band, the proposed method enables one system to locate the other base stations. This provides the crucial information for co-channel interference management.

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