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Location Tracking in Mobile Networks under Correlated Shadowing Effects

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Abstract—**Mobile location tracking based on the received signal strength (RSS) is known to be easily influenced by the shadowing effects in wireless propagation channels. In this paper, we exploit the correlation among shadowing losses at adjacent locations to improve the performance of location tracking. A location tracking algorithm consisting of a maximum likelihood estimator and a Kalman filter is proposed to jointly track the mobile location and the shadowing losses via the RSS. Under a shadowed propagation environment, the simulation shows that, without knowing the underlying mobility model but only the target's speed information, the shadowing tracking furnishes worthful information for the location tracking algorithm, and the proposed method thus provides acceptable performance both for the location and shadowing tracking.**

Keywords- Location Tracking; Correlated Shadowing; Kalman Filter; Maximum Likelihood.

I. INTRODUCTION

In modern wireless mobile communication networks, accurate location information of mobile stations (MSs) is essential for location-based applications. Mobility tracking therefore becomes one of the most important features to be considered in the development of wireless communication systems. In the last several decades, many wireless localization techniques were proposed and some of them have been applied to commercial applications for a long time. The most well-known technique is the Global Positioning System (GPS) [11] which can provide highly accurate location information, but has a critical limitation that requiring line-of-sight paths to the satellites. In addition to GPS, some other methods utilize the radio signals between a subscriber and a set of base stations (BSs) for localization, including the angle-of arrival (AOA) [1], time-of-arrival (TOA), time-difference-of-arrival (TDOA) [2], fingerprinting and received signal strength (RSS) [3]–[6] approaches. The AOA-based techniques, however, additionally require an antenna array system, greatly increasing the hardware complexity and cost. The fingerprinting approach needs to store a large amount of radio characteristic information and can generally be performed by BS units. For the TOA- and TDOA-based methods, an extra timing-synchronization mechanism is required and the localization performance is limited by the timing error due to the non-line-of-sight (NLoS) propagation effect.

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The RSS is the most easily gathered location-dependent information for both BSs and MS terminals. The RSS correlates highly with the propagation model, which has been deeply investigated and verified via many environmental experiments. It hence makes the RSS-based methods be widely utilized for geo-localization applications [3]–[6]. However, the chief defect of the RSS-based methods is the severe variation of the received signal strength due to the shadowing effects in the NLoS environments. One of the main techniques proposed to remove the shadowing losses is to pass the RSS through a moving-average filter [3], based on the assumption that the shadowing losses at different locations are assumed to be an additive white Gaussian noise (AWGN) process in dB unit.

Nevertheless, for real propagation environments, the shadowing losses at different locations are correlated and should be more precisely regarded as a correlated process. In [8] the author showed that between the experienced shadowing losses corresponding to two adjacent locations, there is a correlation coefficient inversely proportional to the spatial distance between the two locations. As a result, the moving-average method is no longer a good shadowing canceller for real propagation environments and the colored shadowing noise will significantly degrade the performance of location tracking, especially for an MS traveling with lower mobility. If the shadowing process can be predicted/tracked good enough, the outcome can be used as an assistant to the location tracking process and the localization performance can then be greatly improved.

In this work, we propose a location-shadowing tracking algorithm to overcome the correlated shadowing effects on location tracking in real propagation environments. The algorithm consists of a maximum likelihood (ML) location estimator and a Kalman filter (KF), taking charge of tracking the target's location and the shadowing losses, respectively. The shadowing tracking is mainly based on the spatial correlation property of the shadowing losses, manipulated by the speed of the desired target. Therefore, the proposed algorithm requires no more knowledge of the underlying mobility state model except the mobile's directionless speed, which can be obtained via various speed estimation techniques [7]. The simulation shows that the shadowing tracker indeed provides useful information to help the location estimation, attaining better performance.

The remainder of this paper is organized as follows. Section II presents the applied system and propagation models in detail. The proposed location-shadowing tracking algorithm is described in Section III. We show the simulation results in Section IV, and finally draw the conclusion in Section V.

II. SYSTEM AND PROPAGATION MODELS

Fig. 1 depicts the system scenario considered in this work. It is assumed that there are *b* BSs available for locating a target MS. By exploiting the RSSs from *b* BSs to the MS, localization algorithms can be performed either at the MS or at the BSs. The system time is divided into multiple epochs and the duration of each epoch is ΔT . In mobile radio environments, RSS depends on the path-loss, the shadowing effect and the fast multipath fading effect. Assuming that the fast fading effect can be suppressed via some smoothing procedures (e.g. by averaging RSS over several wavelengths), the path-loss and the shadowing effect become the two main portions of RSS. The shadowing effect is caused by obstructions in the propagation path, and will induce a large variation in the received signal strength in mobile radio environments. This variation is generally characterized, especially in outdoor environments, as a log-normally distributed random variable (RV).

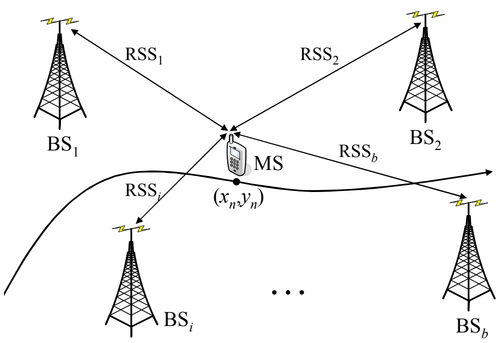

Figure 1. The system scenario.

At time epoch *n*, the RSS (in dB unit) from the *i*-th BS (BS$_i$) to an MS with the coordinate $\mathbf{z}_n = [x_n, y_n]^T$, is given by

$$s_{i,n} = \alpha_i - p_i(\mathbf{z}_n) + \varepsilon_{i,n} + w_{i,n} . \qquad (1)$$

In (1), α_i is a deterministic constant related to the parameters, including the transmission power of BS$_i$, antenna gains, carrier frequency and etc. $\varepsilon_{i,n}$ represents the shadowing loss between BS$_i$ and the MS experienced at time *n*, which is a Gaussian distributed RV with zero mean and variance σ_ε^2. The standard deviation σ_ε is an environment-dependent parameter, and is typically in the range of 5 to 12 dB. $w_{i,n}$ is introduced to exhibit the AWGN and the residual part of fast fading, which is approximated as an independently, identically distributed (i.i.d.) Gaussian RV with zero mean and variance σ_w^2 . $p_i(\mathbf{z}_n) = \beta_i \log(d_i(\mathbf{z}_n))$ denotes the distance-dependent attenuation, where β_i is the path-loss exponent and $d_i(\mathbf{z}_n)$ is the Euclidean distance between BS$_i$ and the MS at time *n*. Given a reference location $\mathbf{z}^*$ which is chosen near by $\mathbf{z}_n$, $p_i(\mathbf{z}_n)$ can be further linearized as [3]

$$p_i(\mathbf{z}_n) \approx p_i(\mathbf{z}^*) - \mathbf{h}_i^T(\mathbf{z}^*)(\mathbf{z}_n - \mathbf{z}^*) , \qquad (2)$$

where

$$\mathbf{h}_i(\mathbf{z}^*) = \frac{\beta_i}{2d_i^2(\mathbf{z}^*)} \frac{\partial d_i^2(\mathbf{z})}{\partial \mathbf{z}}\bigg|_{\mathbf{z}=\mathbf{z}^*} \qquad (3)$$

expresses the vector derivative with respect to $\mathbf{z}$ at $\mathbf{z} = \mathbf{z}^*$.

The shadowing loss $\varepsilon_{i,n}$ is in practical a location-dependent RV and will vary with time due to user mobility. The spatial correlation of the shadowing loss is modeled to be exponentially decayed with the increases in distance between any two separate locations [9]. The shadowing loss is therefore generally modeled as a first-order Gaussian Markov process [9]. The shadowing losses from BS$_i$ to the MS at locations $\mathbf{z}_{n-1}$ and $\mathbf{z}_n$ have a relationship represented as

$$\varepsilon_{i,n} = \zeta_{n-1}\varepsilon_{i,n-1} + (1-\zeta_{n-1})v_{i,n-1} , \qquad (4)$$

where $\zeta_{n-1} = (\zeta_D)^{\Delta d_{n-1}/D}$, and Δd_{n-1} is the spatial distance between locations $\mathbf{z}_{n-1}$ and $\mathbf{z}_n$; ζ_D is the spatial correlation coefficient corresponding to a reference distance *D*; and $v_{i,n-1}$ is a Gaussian RV with zero mean and variance $\sigma_{v,n-1}^2 = (1+\zeta_{n-1})\sigma_\varepsilon^2/(1-\zeta_{n-1})$. This model has been verified to show good accuracy for spatial distances up to approximately 500m. The value of ζ_D is environment-dependent between 0 and 1. For $\sigma_\varepsilon \approx 7.6$ dB, ζ_D is estimated to be 0.82 at a distance of $D = 100$ m [8].

By using the vector form representation, the RSSs received from the *b* BSs at time *n* can be expressed as

$$\begin{aligned} \mathbf{s}_n &= \boldsymbol{\alpha} - \mathbf{p}(\mathbf{z}_n) + \boldsymbol{\varepsilon}_n + \mathbf{w}_n \\ &\approx \boldsymbol{\alpha} - \mathbf{p}(\mathbf{z}^*) + \mathbf{H}^T(\mathbf{z}^*)(\mathbf{z}_n - \mathbf{z}^*) + \boldsymbol{\varepsilon}_n + \mathbf{w}_n , \end{aligned} \qquad (5)$$

where $\mathbf{s}_n = [s_{1,n}, \cdots, s_{b,n}]^T$, $\mathbf{p}(\mathbf{z}_n) = [p_1(\mathbf{z}_n), \cdots, p_b(\mathbf{z}_n)]^T$, and $\mathbf{H}(\mathbf{z}^*) = [\mathbf{h}_1(\mathbf{z}^*), \cdots, \mathbf{h}_b(\mathbf{z}^*)]^T$ with each row vector defined in (3). In addition, the vectors $\boldsymbol{\alpha}$, $\boldsymbol{\varepsilon}_n$ and $\mathbf{w}_n$ are as well in the same vector construction.

III. PROPOSED TRACKING ALGORITHM

Fig. 2 shows the block diagram of the proposed location-shadowing tracking algorithm. The algorithm during each time-epoch is separated into two parts. The upper part is used for shadowing tracking and the lower part is used for location tracking. In addition, the Delay-block between the two parts

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represents a 1-tap delay. At the beginning of the n-th epoch, a predicted location $\hat{\mathbf{z}}_{n|n-1}$ based on the information received in the previous time epoch is available as the input for the KF-based shadowing tracker. For the first time epoch, epoch 0, an initial location information $\hat{\mathbf{z}}_0$ is required. By using the location prediction $\hat{\mathbf{z}}_{n|n-1}$ and the received RSS vector $\mathbf{s}_n$, the KF-based shadowing tracker can obtain a shadowing-loss estimation $\hat{\boldsymbol{\varepsilon}}_{n|n}$, which will then be fed into the ML location estimator. Subsequently, by using the shadowing-loss estimation $\hat{\boldsymbol{\varepsilon}}_{n|n}$ and the received RSS vector $\mathbf{s}_n$, the ML location estimator performs location tracking to obtain the location estimation $\hat{\mathbf{z}}_{n|n}$ of the target at epoch n. Furthermore, applying the estimated locations obtained at the present and previous $k-1$ epochs, i.e. $\{\hat{\mathbf{z}}_i\}_{i=n-k+1}^{n}$, joint with the mobile speed information, a prediction of the target location at the next time epoch will be drawn, denoted as $\hat{\mathbf{z}}_{n+1|n}$, which will be fed to the KF-based shadowing tracker for the tracking at the next time epoch. In the following, the details of the KF-based shadowing tracker and the ML location estimator will be described separately.

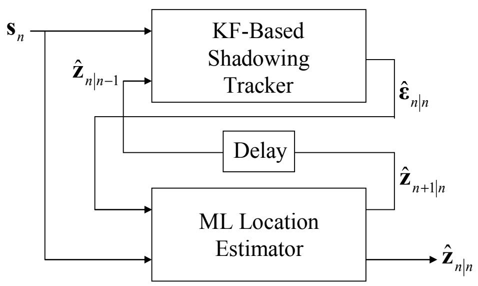

Figure 2. The joint location-shadowing tracking algorithm

A. KF-based Shadowing Tracking

Considering the shadowing losses $\boldsymbol{\varepsilon}_n$ as the desired signals which are going to be estimated, the corresponding RSSs $\mathbf{s}_n$ are thus the noisy observations of the shadowing losses, which are distorted by the unknown offsets $\mathbf{p}(\mathbf{z}_n)$ and a white noise vector $\mathbf{w}_n$. It infers a biased model distinguishing from the basic state-space model [10] in a conventional KF problem. At epoch n, based on the predicted location obtained from the ML location estimator at epoch $n-1$, i.e. $\hat{\mathbf{z}}_{n|n-1}$, the offsets $\mathbf{p}(\mathbf{z}_n)$ due to the path-losses are roughly removed via the following procedure that

$$\bar{\boldsymbol{\varepsilon}}_n = \mathbf{s}_n - \boldsymbol{\alpha} + \mathbf{p}(\hat{\mathbf{z}}_{n|n-1}) . \tag{6}$$

Denote the covariance of the prediction and estimation errors at epoch n as $\boldsymbol{\Sigma}_{n|n-1}$ and $\boldsymbol{\Sigma}_{n|n}$, respectively. We briefly describe the conventional KF procedure in the following.

- $\mathbf{K}_n = \boldsymbol{\Sigma}_{n|n-1}(\boldsymbol{\Sigma}_{n|n-1} + \sigma_w^2 \mathbf{I})^{-1}$.
- $\hat{\boldsymbol{\varepsilon}}_{n|n} = \hat{\boldsymbol{\varepsilon}}_{n|n-1} + \mathbf{K}_n(\bar{\boldsymbol{\varepsilon}}_n - \hat{\boldsymbol{\varepsilon}}_{n|n-1})$.
- $\hat{\boldsymbol{\varepsilon}}_{n+1|n} = \zeta_n \hat{\boldsymbol{\varepsilon}}_{n|n}$.
- $\boldsymbol{\Sigma}_{n|n} = (\mathbf{I} - \mathbf{K}_n)\boldsymbol{\Sigma}_{n|n-1}$.
- $\boldsymbol{\Sigma}_{n+1|n} = \zeta_n^2 \boldsymbol{\Sigma}_{n|n} + \sigma_{v,n}^2 \mathbf{I}$.

It is noted that the shadowing correlation coefficient is obtained by $\zeta_n = (\zeta_D)^{\vartheta_n \Delta T / D}$ for a given average mobile speed ϑ_n within epoch n.

B. ML Location Estimation

With the assistant information obtained from the KF-based shadowing tracker, the location tracker utilizes a batch of observations to perform ML-based localization estimation at each epoch. At epoch n, the present shadowing losses estimation output $\hat{\boldsymbol{\varepsilon}}_{n|n}$ and the previous $k-1$ outcomes, $\{\hat{\boldsymbol{\varepsilon}}_{n-k+1|n-k+1}, \cdots, \hat{\boldsymbol{\varepsilon}}_{n-1|n-1}\}$, of the shadowing tracker are first used to coarsely remove the shadowing effects of the k RSS vectors $\mathbf{S}_n = [\mathbf{s}_{n-k+1}^T, \mathbf{s}_{n-k+2}^T, \cdots, \mathbf{s}_n^T]^T$, which yields coarse estimation of the path-losses between MS and the BSs during epoch $n-k+1$ to epoch n, i.e.,

$$\bar{\boldsymbol{\varphi}}_n = [\bar{\mathbf{p}}_{n-k+1}^T, \bar{\mathbf{p}}_{n-k+2}^T, \cdots, \bar{\mathbf{p}}_n^T]^T , \tag{7}$$

where

$$\bar{\mathbf{p}}_i = \boldsymbol{\alpha} - \mathbf{s}_i + \hat{\boldsymbol{\varepsilon}}_{i|i} = \mathbf{p}(\mathbf{z}_i) + (\hat{\boldsymbol{\varepsilon}}_{i|i} - \boldsymbol{\varepsilon}_i) + \mathbf{w}_n . \tag{8}$$

According to the dynamics of the KF [10] in a generic Gaussian model, the output sequence of the KF-based shadowing tracker, $\{\hat{\boldsymbol{\varepsilon}}_{n-k+1|n-k+1}, \cdots, \hat{\boldsymbol{\varepsilon}}_{n|n}\}$, possesses Markovian relationships among its entries, which yields the cross covariance property between the estimation errors at epoch i and epoch $(i+j)$ given as

$$\begin{aligned} \boldsymbol{\Sigma}_{i+j,i} &= E[(\hat{\boldsymbol{\varepsilon}}_{i+j|i+j} - \boldsymbol{\varepsilon}_{i+j})(\hat{\boldsymbol{\varepsilon}}_{i|i} + \boldsymbol{\varepsilon}_i)^T] \\ &= \prod_{m=i}^{i+j-1} \zeta_m (\mathbf{I} - \mathbf{K}_{m+1}) \cdot \boldsymbol{\Sigma}_{i|i} . \end{aligned} \tag{9}$$

We then approximate $\bar{\boldsymbol{\varphi}}_n$ as multivariate-normal distributed vectors with means and variances given by $\boldsymbol{\mu}_n = [\mathbf{m}_{n-k+1}^T, \mathbf{m}_{n-k+2}^T, \cdots, \mathbf{m}_n^T]^T$ and

$$\boldsymbol{\Sigma}_{\boldsymbol{\mu},n} = \begin{bmatrix} \boldsymbol{\Sigma}_{n-k+1|n-k+1} & \boldsymbol{\Sigma}_{n-k+1,n-k+2}^T & \cdots & \boldsymbol{\Sigma}_{n-k+1,n} \\ \boldsymbol{\Sigma}_{n-k+2,n-k+1} & \boldsymbol{\Sigma}_{n-k+2|n-k+2} & \ddots & \vdots \\ \vdots & \ddots & \ddots & \\ \boldsymbol{\Sigma}_{n,n-k+1} & \cdots & & \boldsymbol{\Sigma}_{n|n} \end{bmatrix} + \sigma_w^2 \mathbf{I} \tag{10}$$

respectively, where $\mathbf{m}_i = \mathbf{p}(\mathbf{z}_i)$. Assuming that the mobility, including the mobile speed and direction, is almost invariant during epoch $n-k+1$ to n, the mean vector $\boldsymbol{\mu}_n$ can be linearized as follows based on the result in (5). Choosing an odd k and $\ell = (k-1)/2$ being the medium point between $n-k+1$ and n, a linearization of $\boldsymbol{\mu}_n$ is given as

$$\begin{aligned}\boldsymbol{\mu}_n &\approx \bar{\boldsymbol{\mu}}_n \\ &= [\bar{\mathbf{m}}_{n-\ell}^T - \ell\hat{\mathbf{H}}_{n-\ell}\Delta\mathbf{z}_n^T,\ \cdots,\ \bar{\mathbf{m}}_{n-\ell}^T,\cdots,\ \bar{\mathbf{m}}_{n-\ell}^T + \ell\hat{\mathbf{H}}_{n-\ell}\Delta\mathbf{z}_n^T]^T,\end{aligned} \tag{11}$$

where $\bar{\mathbf{m}}_{n-\ell} = \mathbf{s}_{n-\ell} - \boldsymbol{\alpha} + \mathbf{p}(\mathbf{z}_{n-\ell})$, $\hat{\mathbf{H}}_{n-\ell}$ denotes $\mathbf{H}(\hat{\mathbf{z}}_{n-\ell|n-\ell})$ in a brief form, and $\Delta\mathbf{z}_n = [\Delta x_n\ \Delta y_n]^T$ is the average spatial movement per epoch to be estimated.

The ML estimator for $\Delta\mathbf{z}_n$, based on the observation vectors $\bar{\boldsymbol{\varphi}}_n$, is to minimize the concentrated log-likelihood function

$$L\left(\Delta\mathbf{z}_n \middle| \bar{\boldsymbol{\varphi}}_n\right) = (\bar{\boldsymbol{\varphi}}_n - \hat{\boldsymbol{\mu}}_n)^T \boldsymbol{\Sigma}_{\boldsymbol{\mu},n}^{-1}(\bar{\boldsymbol{\varphi}}_n - \hat{\boldsymbol{\mu}}_n). \tag{12}$$

With the information of the mobile speed, the constraint optimization problem is described as follows.

$$\begin{aligned}&\Delta\hat{\mathbf{z}}_n = \arg\min_{\Delta\mathbf{z}_n} L(\Delta\mathbf{z}_n | \bar{\boldsymbol{\varphi}}_n), \\ &\text{s.t.} \quad \|\Delta\mathbf{z}_n\|^2 = \Delta x_n^2 + \Delta y_n^2 = \vartheta_n^2,\end{aligned} \tag{13}$$

which is then solved by the Lagrange-KKT optimization method.

After obtaining $\Delta\hat{\mathbf{z}}_n$, the ML location estimator outputs two results, the location estimation at epoch n and the location prediction at epoch $n+1$ as follows.

$$\begin{aligned}\hat{\mathbf{z}}_{n|n} &= \hat{\mathbf{z}}_{n-\ell|n-\ell} + \ell\Delta\hat{\mathbf{z}}_n, \\ \hat{\mathbf{z}}_{n+1|n} &= \hat{\mathbf{z}}_{n-\ell|n-\ell} + (\ell+1)\Delta\hat{\mathbf{z}}_n.\end{aligned} \tag{14}$$

It is also noted that the initial location is assumed to be unknown and is estimated by the ML location estimator.

IV. Simulation Results and Discussions

The scenario used in the simulation is described in the following. We apply the COST231-HATA [9] path-loss model with a carrier frequency at 2GHz, a 10m BS antenna height, and a 1.5m MS antenna height. The number of BSs is 4, and their location vectors, from BS1 to BS4, are $[0,0]^T$, $[0,5]^T$, $[5,0]^T$, and $[5,5]^T$ in km unit, respectively. The standard deviation of shadowing is given as $\sigma_\varepsilon = 7.5$ dB, and the spatial correlation factor is $\zeta_D = 0.82$ at a distance $D = 100$ m. The standard deviation of the residual noise is set to be $\sigma_w = 3$ dB. The initial location of MS is $\mathbf{z}_0 = [1.8,3.5]^T$ (km) and the MS's movement per epoch is given as a constant vector $\Delta\mathbf{z} = [0.01, -0.01]^T$ (km) corresponding to a constant speed 0.014 km per epoch, equivalent to about 51km/hr for epoch duration $\Delta T = 1$ sec. The tracking duration is 30 epochs, and the observation length of the ML estimation is $k = 10$epochs.

Fig. 3 shows the exact trajectories and the output of the location tracker in the solid and dashed lines, respectively. During the first several epochs the tracking algorithm cannot converge to the exact path. However, it keeps providing a right direction to the correct locations and eventually converges to the desired trajectory. The slow convergence speed may be due to the estimation error of the shadowing and residual noise, and the lack of further mobility information, e.g. the dynamic mobility model of MSs. However, if the dynamic model is available, the ML location estimator can be easily replaced by a more suitable tracking algorithm, such as the KF, to achieve better performance.

In Fig. 4 and Fig. 5, comparisons are made between the exact and the estimated shadowing processes/path-losses values to assess the performance of the tracking algorithm for the shadowing loss. The subfigures in Fig. 4 show the shadowing effects corresponding to BS1 to BS4, where the dashed lines and the solid ones are the exact shadowing processes and the tracking output. In Fig. 5, four subfigures present the comparisons between the exact path-loss values, the estimated values, and the output of the moving-average-based method proposed in [3], in dashed lines, solid lines and double-dot-dashed lines, respectively, where the path-loss estimation is simply drawn by

$$\hat{\mathbf{p}}(\mathbf{z}_n) = \boldsymbol{\alpha} - \mathbf{s}_n + \hat{\boldsymbol{\varepsilon}}_{n|n}. \tag{15}$$

We also plot the composite signals of the path-loss and shadowing, i.e. $\mathbf{p}(\mathbf{z}_n) - \boldsymbol{\varepsilon}_n$ in the dotted lines, relating to the noisy path-loss values before shadowing cancellation. It is found that the moving-average-based method which is designed for averaging white noise cannot properly remove the correlated-shadowing effect. On the contrary, the KF-based shadowing tracker provides a good tracking performance such that it can act as a whitening filter to effectively suppress the correlated noise of RSSs.

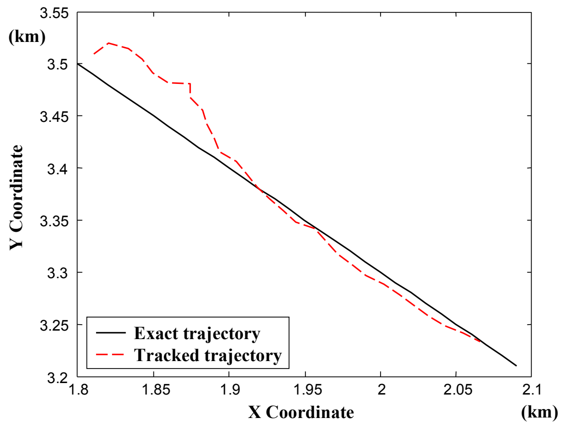

Figure 3. The location tracking results of the proposed algorithm.

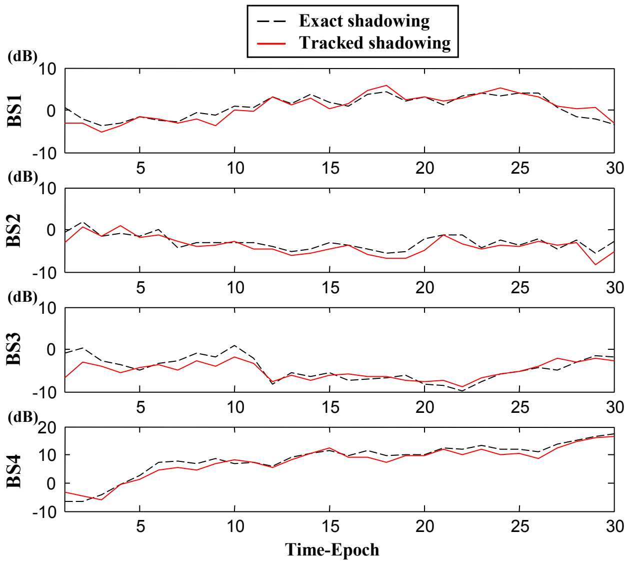

Figure 4. The shadowing tracking results corresponding to the four BSs.

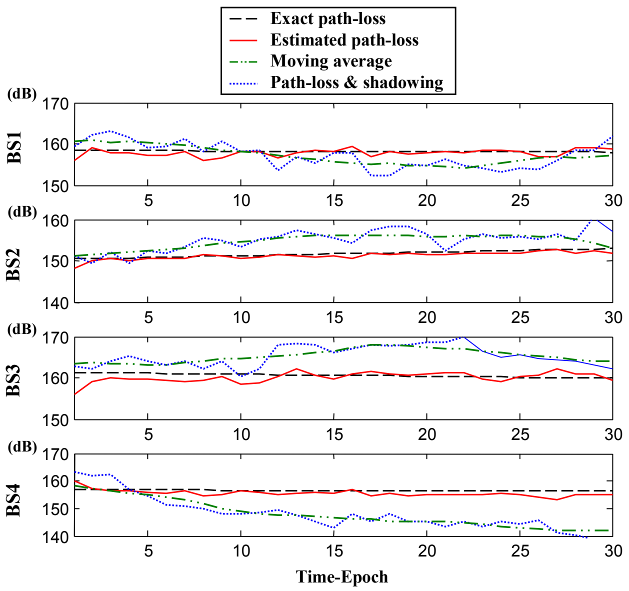

Figure 5. The estimated path-loss values corresponding to the four BSs.

V. CONCLUSION

Under real propagation environments, the correlated shadowing effects, which cannot be removed simply by a moving-average filter, yield inaccurate results of location tracking. The proposed location-shadowing tracking algorithm considers both shadowing and location dynamics and turns the shadowing processes from only noise sources into meaningful signals to help the location tracking. Moreover, the algorithm does not require the dynamic mobility model except the mobile speed, which is relatively easy to obtain. The simulation showed that the proposed algorithm conquers the correlated-shadowing problem and provides acceptable performance of localization.

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