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Dynamic estimation of local mean power in GSM-R networks

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Abstract The dynamic estimation algorithm for Rician fading channels in GSM-R networks is proposed, which is an expansion of local mean power estimation of Rayleigh fading channels. The proper length of statistical interval and required number of averaging samples are determined which are adaptive to different propagation environments. It takes advantage of signal samples and Rician fading parameters of last estimation to reduce measurement overhead. The performance of this method was evaluated by measurement experiments along Beijing–Shanghai high-speed railway. When it is NLOS propagation, the required sampling intervals can be increased from 1.1λ in Lee's method to 3.7λ of the dynamic algorithm. The sampling intervals can be set up to 12λ although the length of statistical intervals decrease when there is LOS signal, which can reduce the measurement overhead significantly. The algorithm can be applied in coverage assessment with lower measurement overhead, and in dynamic and adaptive allocation of wireless resource.

Keywords GSM-R · Rician fading channel · Local power estimation · Propagation measurement

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1 Introduction

The high-speed railway has experienced rapid development in recent years, and it is a critical infrastructure transporting passengers, commodities, and goods. The primary consideration of high-speed railway infrastructure is safety, which has become increasingly dependent on the information and communication system. Since GSM-R networks are deployed for communications between train and railway regulation control centers in high-speed railway, it requires real-time measurement to ensure the reliability of the system [6, 9]. At the same time, it is necessary to make dynamic measurement due to the complexity of the radio propagation environments and the varied terrains along the high-speed railway route. It is crucial to lower the estimation overhead so that on-line measurement can be implemented to ensure the real-time reliability of GSM-R networks and the high-speed railway system.

The propagation measurement in mobile networks plays an important role in coverage assessment, dynamic channel allocation, power control and handoff algorithms [4, 14, 27, 28]. Propagation models and measurement methods for wireless communication channels were summarized in [3, 22], and a propagation prediction method was presented in [19] which is for the terrestrial point-to-area services in International Telecommunication Union (ITU) recommendations.

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These propagation models are widely used in wireless communication systems [21, 26], and specially in wireless systems of railway [23]. The authors in [2] and [17] proposed two kind of modified Okumura-Hata propagation prediction models respectively based on the least squares and Levenberg–Marquardt method. Most of the propagation measurement and prediction methods are focused on path loss and shadow fading [11, 20, 7], and multi-path fading is ignored which has a major impact on networks' performance. When multi-path fading is taken into account, it is crucial to get the accurate estimation of received signal power which indicates the link quality of wireless communication [10, 25]. For GSM-R networks, there are some specific requirements to ensure the real-time reliability and safety of high-speed railway systems:

(a) It is crucial to reduce the estimation overhead so that the on-line monitoring can be implemented and ensure the real-time reliability;
(b) It is necessary to make dynamic measurement due to the feature of propagation environments along the high-speed railway routes.

Lee's method proposed a standard procedure of local average power estimation, which determined the proper length and required sampling numbers for estimating the local average in the case of Rayleigh fading channels [15]. The Generalized Lee method [8] allows to estimate the local mean power without priori knowledge of the distribution function of fading channels, which is based on the measured samples of field data, but the optimum length of averaging interval is calculated using all the routes of the database with high overhead. Velocity adaptive handoff algorithms [4] get the amount of spatial averaging required for local mean estimation of Rician fading according to Lee's standard procedure by approximation, but it has too high overhead to be applied in real-time measurement.

Since GSM-R networks are deployed along the high-speed railway routes with varied terrains, the radio propagation environments are very complex, as is shown in Fig. 1. It is also obvious in Fig. 1 that the cell radius is normally designed short and the terrains are generally flat, so the multi-path fading should be characterized by Rician but not Rayleigh fading in this case. There are many Rician channels estimation methods such as Training-based Estimation [6], Maximum Likelihood [24] estimation, Expectation Maximization (EM) algorithm [16], and many other methods [1, 18]. The EM algorithm provides a complete iterative solution to the Rician parameters estimation in synthetic aperture radar images, which can also be applied in parameter estimation of Rician fading channels. Therefore, the high-speed mobility and Rician fading channels aggravate the real-time estimation of local mean power. The difficulties and challenges for dynamic estimation of local mean power in GSM-R networks are:

(a) Speed is 250–300 km/h for China high-speed railway;
(b) Terrains include mountains, viaducts, plains, etc.;
(c) Wireless interface is sensitive to propagation changes;
(d) Services should not be aggravated by measurement.

This paper combines Lee's method and EM algorithm to estimate the Rician fading channels in GSM-R networks. The basic procedure is same to the Lee's method of local mean power estimation, except that the multi-path fading is Rician distributed. This method takes advantage of the sampling signals and Rician fading parameters of last estimation to improve estimation accuracy and reduce measurement overhead. The determination of statistical interval length and averaging samples number are adaptive to different propagation environments, which strike a suitable balance between measurement accuracy and overhead.

To evaluate the performance of this algorithm, we developed the Um interface monitoring system for GSM-R networks, and measurement experiments were carried out along the Beijing–Shanghai high-speed railway. First, it is illustrated that the long-term and short-term fadings can be differentiated separately by the dynamic estimating algorithm. Next, it requires smaller sampling intervals in Lee's method than that of proposed method when it is None Line Of Sight (NLOS) propagation, which can be increased from 1.1 to 3.7λ. Finally, it does not need to make frequent sampling although the length of statistical interval decreases when there is Line Of Sight (LOS) signal, which can be set up to 12λ to reduce the measurement overhead.

The dynamic estimation algorithm can be used in coverage assessment with lower measurement overhead, and it can also be applied in real-time operating such as channel allocation, power control and adaptive handoff algorithms. Since Rician fading is the generalized model of multi-path fading channels, it can also be introduced into measurement of other wireless networks.

The rest of this paper is organized as follows. The propagation models including shadow fading and multi-path fading are given in Sect. 2. In Sect. 3, the measurement framework and basic procedures are presented. Section 4 demonstrates the dynamic propagation measurement of Rician fading channels. The algorithm design and implementation are illustrated in Sect. 5. In Sect. 6, the measurement experiments and performance evaluation are analyzed. Section 7 concludes the paper.

2 Propagation models

The received signal strength of Mobile Station (MS) is affected by many aspects, such as the transmit power of Base Station (BS), distance between MS and BS, and terrain of the radio propagation environments. In general, the propagation model can be expressed by:

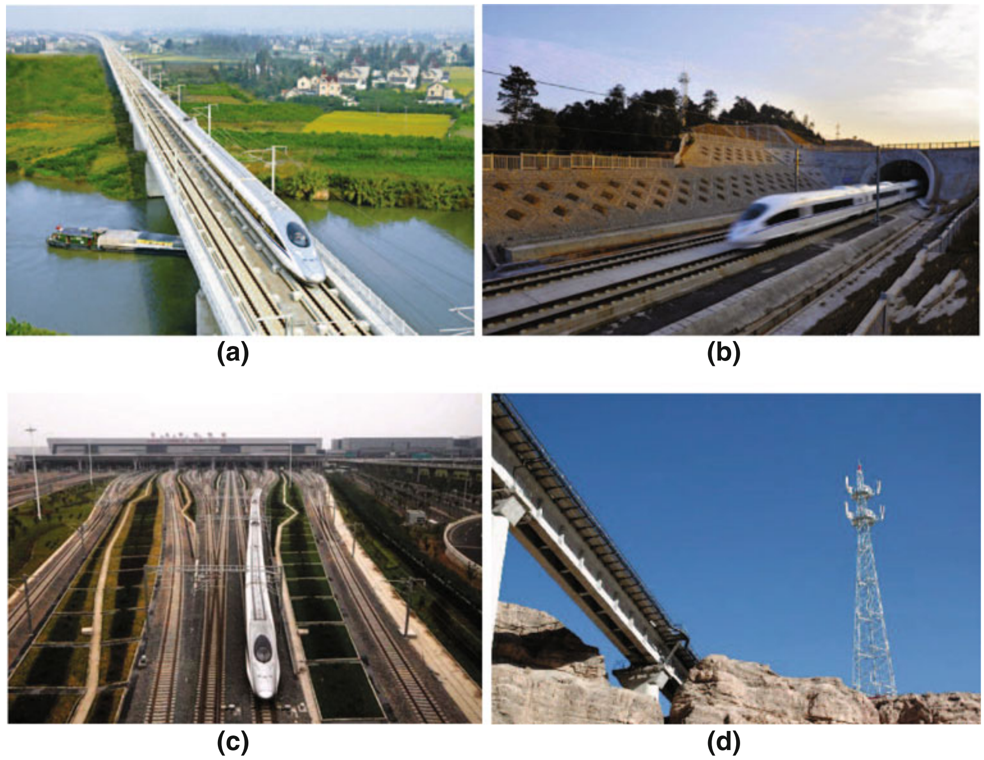


Fig. 1 Wireless propagation environments and terrains along GSM-R networks. **a** Viaduct. **b** Tunnel. **c** Shanghai Hongqiao Station. **d** Qinghai–Tibet Railway

$$p_r^2(x) = s(x)h(x), \quad (1)$$

where x is the distance between MS and BS which can also be replaced by time t. Since the distance d between railway track and BS is very short, which is usually <10 m as is shown in Fig. 2. Then $\Delta x = \sqrt{d^2 + v_{train}^2 \cdot \Delta t^2}$ can be deemed as $\Delta x = v_{train} \cdot \Delta t$ by approximation. $p_r^2(x)$ is the received signal square envelope which is composed of the local mean power $s(x)$ and multi-path fading $h(x)$. The model can also be expressed in logarithmic form in dB values:

$$P_r(x) = S(x) + H(x), \quad (2)$$

where $P_r(x) = 10\log(p_r^2(x))$, $S(x) = 10\log(s(x))$ and $H(x) = 10\log(h(x))$.

2.1 Shadow fading

Generally, $s(x)$ is can be modeled as a Gaussian process with mean $m(x)$ and variance σ_s^2

$$s(x) \sim N\left(m(x), \sigma_s^2\right), \quad (3)$$

where $m(x)$ is mainly affected by path loss. In [22], it gives a recommend model comprehensively considering the transmit power of BS, the receive sensitivity of MS, the distance between BS and MS, and the radio propagation environments, which can be simplified by:

$$M(x) = K_1 + K_2 \log(x), \quad (4)$$

where $M(x) := 20\log(m(x))$ is the logarithmic form of $m(x)$, K_1 denotes the transmit power of BS in which both antenna gains and cable losses are taken into account, and K_2 is the topographic factor which changes with different terrains [13, 17]. The spatial correlation function of $S(x)$ can be described by (5) based on the measured data of received signal strength in urban and suburban environments [12] as follows:

$$R_s(x) = \sigma_s^2 \exp\left(-\frac{\Delta x}{x_0}\right), \quad (5)$$

where σ_s is the variance of $S(x)$ which is typically between 4 and 12 dB, x_0 is the correlation distance which is normally vary from 10 to 500 m in different propagation environments [25], and Δx is the spatial distance which can be expressed as the velocity of MS and sampling interval by $\Delta x = v_{train} \cdot \Delta t$. In the model of shadow fading, the topographic factor K_2, shadow fading's variance σ_s and correlation distance x_0 are affected by different terrains, and they are essential to the section of hysteresis of handoff algorithms. The correlation distance x_0 and spatial distance Δx will affect the optimum accuracy of local mean power estimation.

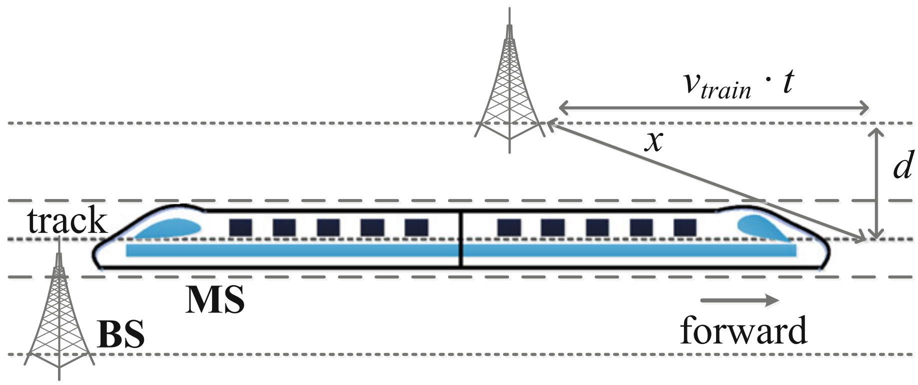


Fig. 2 The distance between MS and BS can be represented by $v_{train} \cdot t$ by approximation

2.2 Multi-path fading

The multi-path fading is the instantaneous fluctuation of received signal due to diffraction and scattering, so the received signal strength is a superposition of many contributions coming from different directions as the receiver moves. Since the phases are random, the sum can be described as a noise signal to the local mean power. In GSM-R networks, the cell radius is short and the terrains are generally flat. Hence, the multi-path fading contains LOS wave combined with NLOS components, which can be expressed by Rician fading:

$$h(x) = \underbrace{\frac{1}{\sqrt{1+K}} \lim_{M\to\infty} \frac{1}{\sqrt{M}} \sum_{m=1}^{M} a_m e^{j\left(\frac{2\pi}{\lambda}\cos(\theta_m x)+\phi_m\right)}}_{\text{NLOSComponents}} \tag{6}$$

where M is the number of independent scatterers, and λ is the wavelength. $\theta_m (m = 0, 1, \ldots M)$ denote the angles between plane waves and mobile station antenna, and $\phi_m (m = 0, 1, \ldots M)$ is the phase of each wave component. In Rician fading, the power of LOS and NLOS signals can be described by ν^2 and $2\sigma^2$. K is the ratio between the power in the direct path and the power in the other scattered paths, that is $K = \nu^2/2\sigma^2$. The received signal amplitude is then Rician distributed with parameters ν^2 and σ^2, and the resulting Probability Distribution Function (PDF) is:

$$f(y;\sigma,\nu) = \frac{y}{\sigma^2} e^{-\frac{y^2+\nu^2}{2\sigma^2}} I_0\left(\frac{y\nu}{\sigma^2}\right), \tag{7}$$

where $I_0(\cdot)$ is the zero-order modified Bessel function of the first kind. It can be deemed as Rayleigh fading when there is no LOS signal, i.e., $K = 0$. In this case, $h(x)$ and the PDF of received signal amplitude can be expressed as:

$$h(x) = \lim_{M\to\infty} \frac{1}{\sqrt{M}} \sum_{m=1}^{M} a_m e^{j\left(\frac{2\pi}{\lambda}\cos(\theta_m x)+\phi_m\right)}, \tag{8}$$

$$f(y;\sigma) = \frac{y}{\sigma^2} e^{-\frac{y^2}{2\sigma^2}}. \tag{9}$$

3 Measurement procedures

The procedures of propagation measurement in GSM-R networks is typically composed of the local mean power estimation, propagation prediction and model correction, as is demonstrated in Fig. 3. The received signal firstly passes through a linear or log-linear amplifier to get $p_r(x)$ or $P_r(x)$, and then is filtered by an averaging filter to get the local mean estimation $s(x)$ or $S(x)$. The estimation results can be used for coverage assessment, channel allocation, power control and handoff algorithms, which can achieve higher performance combined with dynamic measurement and propagation prediction of $m(x)$ or $M(x)$. The estimation accuracy is not only influenced by train's velocity but also by shadow fading and multi-path fading, and it can be improved by the correction of K_1 and K_2. In GSM-R networks, these steps should be implemented real-time to ensure the system's reliability.

The basic consideration in local power estimation is the sampling frequency which is determined by the length of statistical intervals and number of averaging samples. The received signal strength of wireless propagation is influenced by the environments, so the local mean power estimation should be dynamic to the networks status, especially for GSM-R networks. Figure 4 demonstrates the time varying and location difference characteristics of received signal strength $P_r(x)$ in mobile wireless networks, which indicates the facts that: certain received signal

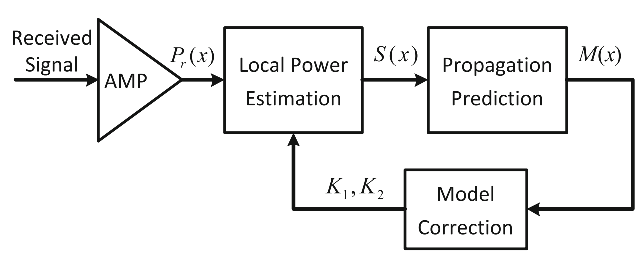


Fig. 3 Basic procedures of wireless propagation measurement

strength carve contains both long-term and short-term fluctuation in Fig. 4a; the overall received signal strength shows different characteristics for different routes in Fig. 4b. Since the received signal strength $P_r(x)$ is changing in both large and small time scale, the local mean power estimation should also be adaptive to this fluctuation.

A more detailed illustration is given in Fig. 5, which shows the estimation results with different sampling intervals. If the length of averaging interval is set too short, the rapid variations of signal strength will remain in estimation results. This will lead to unstable fluctuation of up-layer decisions, for instance the phenomenon of ping–pong handover when the received signal strength $P_r(x)$ is fluctuating around the threshold. On the other hand, it will lost some crucial information if the statistical interval length is chosen to be too long. As is shown in Fig. 5, the result overestimates the received signal strength when $\Delta t = 100\,\text{ms}$, especially when there is a sudden decline for received signal strength $P_r(x)$. This overestimation will lead to the decrease of quality of service that the system can provide according to current status.

Lee's method proposed a standard procedure of local average power estimation, which determined the proper length and required sampling numbers for estimating the local average. But Lee's method is conducted in the case of Rayleigh fading channels, which can not be adaptive to environmental changes. The Generalized Lee method allows estimating the mean values without the requirement of a priori knowing the distribution function, which is based on measured field data samples. However, the optimum length of averaging interval is calculated using all the routes of the database with high overhead. To make the local mean power estimation adaptive to dynamic progation environments with low measurement overhead, the on-line estimation algorithm is proposed which is analyzed in Rician fading channels. The basic process and analysis is presented in detail in the following section.

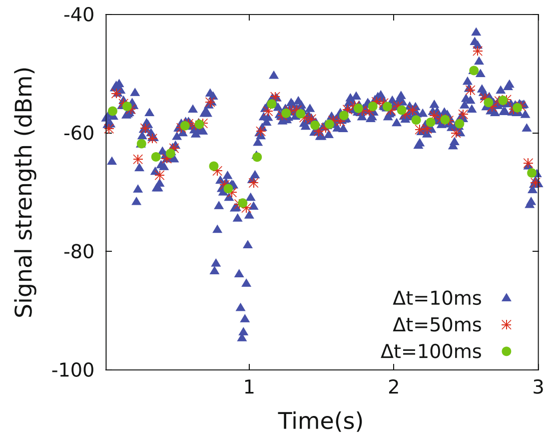


Fig. 5 Estimating with update periods of 50/100 ms will overestimate 20 % of received signal strength when there is a sudden decline

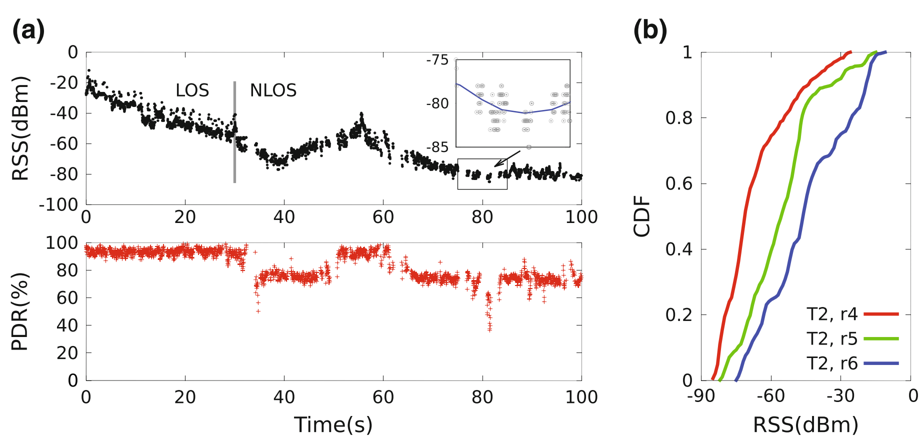
4 Dynamic estimation of local mean power

The proper selection of sampling interval is critical in local power estimation. If the sampling interval is set too short, the fast fading part will still be present in the long-term signal. But if the interval is chosen too long, the long-term fading will also be filtered out. Since GSM-R networks provide wireless communications for high-speed railway, it is crucial to make on-line propagation measurement with high accuracy and low overhead. The on-line estimation algorithm in this paper adopts the Lee's standard procedure in the case of Rician fading. It is mainly consist of the determination of proper length of statistical interval and required number of averaging samples.

4.1 Length of statistical intervals

The local mean power is estimated by the integrate averaging of sampled signal envelope $p_r(x)$ over a suitable length $2L$. The proper selection of $2L$ should be determined so that the long- and short-term signals can be separated accurately.

Fig. 4 **a** Time varying and **b** location difference characteristics of received signal strength in mobile wireless networks, composed of both of LOS and NLOS scenarios



For the propagation models presented in Sect. 2, the estimation of $s(x)$ can be calculated by the integral spatial average of $h(x)$ as (10)

$$\hat{s} = \frac{1}{2L}\int_{y-L}^{y+L} p_r^2(x)dx = \frac{s}{2L}\int_{y-L}^{y+L} h(x)dx, \tag{10}$$

where $2L$ is the length of statistical intervals. When $2L$ is properly chosen, the estimated mean $\hat{s}$ will approach the true value s, i.e., $\hat{s} \to s$. At the same time, the averaging of the short-term fading will be

$$\frac{1}{2L}\int_{y-L}^{y+L} h(x)dx \to 1. \tag{11}$$

To evaluate the measurement accuracy, the normalized error can be defined as follows:

Definition 1 The normalized estimation error of (10) can be calculated as follows:

$$P_e := 10\log_{10}\left(\frac{\hat{s}+\sigma_{\hat{s}}}{\hat{s}-\sigma_{\hat{s}}}\right), \tag{12}$$

where $\sigma_{\hat{s}}$ is the variance of $\hat{s}$.

For Rician fading channels, we can get the following theorem about normalized estimation error P_e.

Theorem 1(Length of Statistical Intervals)

$$P_e := 10\log_{10}\left(\frac{\frac{2\sigma^2+\nu^2}{2\sigma^2}n + \sqrt{2(1+n)\int_0^n g\left(\frac{\nu^2}{2\sigma^2};\rho\right)d\rho}}{\frac{2\sigma^2+\nu^2}{2\sigma^2}n - \sqrt{2(1+n)\int_0^n g\left(\frac{\nu^2}{2\sigma^2};\rho\right)d\rho}}\right). \tag{13}$$

The detailed proof of Theorem 1 is listed in "Appendix" Sect. 8.1. Theorem 1 shows that the increase of P_e has logarithmical relationship with the ratio of ν^2 to σ^2. The proper length of statistics interval can be obtained in terms with ν^2 and σ^2 through $P_e = 1$ dB, i.e., $2L = f_{2L}(\lambda;\ \nu,\ \sigma)$ or $2L/\lambda = f_{2L/\lambda}(\nu,\ \sigma)$, as is shown in Fig. 6.

4.2 Number of averaging samples

Since it needs samples of received signal to sufficiently mitigate the effects of fading, the required number of averaging samples should be determined. The received power can be calculated by $r^2 = 2\sigma^2 + \nu^2 \approx \frac{1}{N}\sum_{i=1}^{N} z_i^2$ through (18) and (19), which will be presented in the following. The expectation and variance of r^2 can be calculated:

$$\bar{r^2} = E[r^2] = \frac{1}{N}E\left[\sum_{i=1}^{N} z_i^2\right], \tag{14}$$

$$\sigma_{\bar{r^2}} = D[r^2] = \frac{1}{N^2}D\left[\sum_{i=1}^{N} z_i^2\right]. \tag{15}$$

Similar to the normalized error of $\hat{s}$, we can have the following definition:

Definition 2 The normalized estimation error of $\bar{r^2}$ can be defined according to the standard Lee method that

$$Q_e = 10\log_{10}\left(\frac{\bar{r^2}+\sigma_{\bar{r^2}}}{\bar{r^2}}\right). \tag{16}$$

According to the properties of Rician distribution, we can get the following theorem about the number of averaging samples, which can be proven by non-central χ^2 distribution as shown in "Appendix" Sect. 8.2.

Theorem 2 (Number of Averaging Samples)

$$Q_e = 10\log_{10}\left(\frac{2N+\nu^2+2\sqrt{N+\nu^2}}{2N+\nu^2}\right). \tag{17}$$

Theorem 2 indicates that the number of averaging samples is only related to ν^2, but has no relationship with σ^2. Figure 7 gives the relationship between the required number of averaging samples and Rician fading parameter ν, i.e., $N = f_N(\nu)$.

4.3 Dynamic estimation of Rician factors

The required sampling intervals Δd can be calculated by the ratio of $2L$ to N, i.e., $\Delta d = f_{2L}(\lambda;\nu,\sigma)/f_N(\nu) = f_{\Delta d}(\lambda;\nu,\sigma)$, which can determine the sampling frequency of on-line measurement. Since Δd is closely related to the Rician fading parameters ν and σ, the Rician factor estimation has a significant influence on the overall measurement efficiency.

To reduce the estimation overhead, EM algorithm [16] is utilized to estimate the noise variance and the signal simultaneously. The Rician fading parameters ν^2 and σ^2 are determined by the signal samples and estimation results of last time as follows:

$$\nu_{k+1} = \frac{1}{N}\sum_{i=1}^{N}\frac{I_1\left(\frac{\nu_k z_i}{\sigma_k^2}\right)}{I_0\left(\frac{\nu_k z_i}{\sigma_k^2}\right)} z_i, \tag{18}$$

$$\sigma_{k+1}^2 = \max\left[\frac{1}{2N}\sum_{i=1}^{N} z_i^2 - \frac{\nu_k^2}{2}, 0\right], \tag{19}$$

where $I_1(\cdot)$ is is the first-order modified Bessel function of the first kind, N is the number of averaging samples, ν_k and σ_k are the estimation results of last recursion. The initial values are

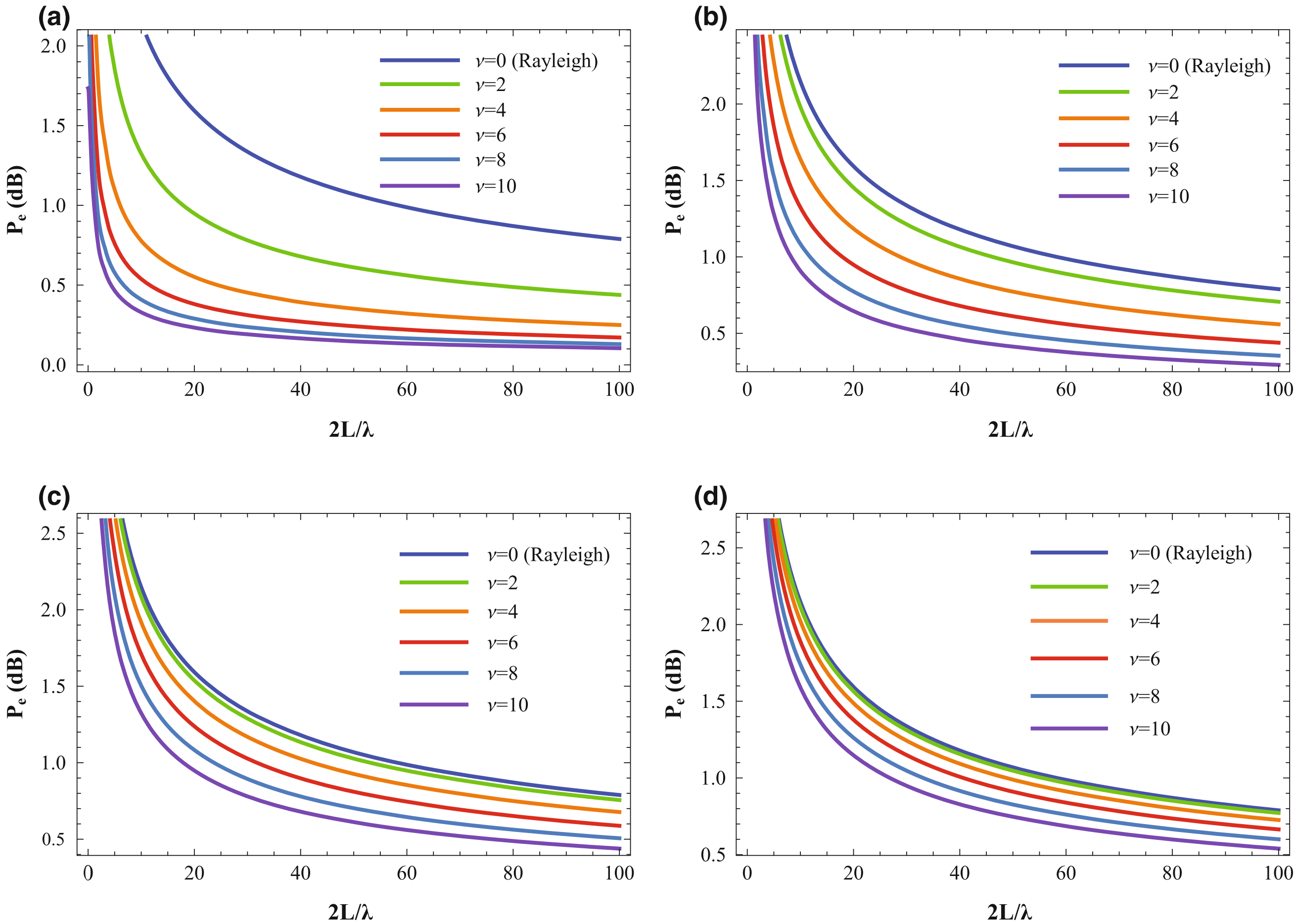


Fig. 6 Proper length of statistical intervals. **a** σ = 1. **b** σ = 3. **c** σ = 5. **d** σ = 7

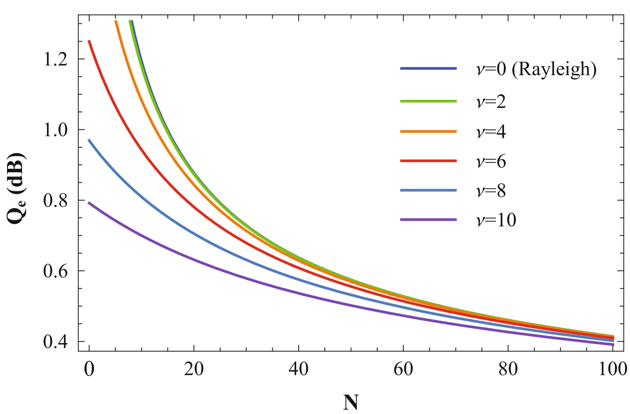


Fig. 7 Required number of averaging samples

$$v_0 = \left(2\left(\frac{1}{N}\sum_{i=1}^{N} z_i^2\right)^2 - \frac{1}{N}\sum_{i=1}^{N} z_i^4\right)^{1/4}, \tag{20}$$

$$\sigma_0^2 = \frac{1}{2}\left(\frac{1}{N}\sum_{i=1}^{N} z_i^2 - v_0\right). \tag{21}$$

Based on the estimated Rician channel parameters, the sampling frequency can be determined, which is in terms with λ, ν and σ. The procedure of dynamic estimation is shown in Fig. 8, in which the determination of $2L$ and N is the main component. Then the local mean power can be achieved by at least N signal strength samples, which is separated by distance Δd within a averaging window length of $2L$.

The sampling intervals Δd has an significant impact on the measurement accuracy and overhead. Note that Δd is the ratio of length of statistical interval $2L$ and number of averaging samples N, it does not necessarily mean frequent sampling when $2L$ gets short, for N may be very small at the same time as shown in Theorem 1 and 2.

5 Implementation

The algorithm design and implementation is presented in this section, which first gives a brief description of on-line measurement procedure and then demonstrates the software framework and development.

Algorithm 1 Dynamic estimation of local mean power of Rician fading channels

Input: v_{train}, r_i, ν_k, σ_k
Output: ν_{k+1}, σ_{k+1}, $2L$, N, Δd

//1. The initialization of ν and σ.
if begin-flag==true **then**
    $\Delta d \leftarrow$ Lee($2L_0$,N_0;λ);
    $\{\nu_{last},\sigma_{last}\} \leftarrow$ EM(Δd,N_0;r_i); //Equation(20),(21)
    $\{\nu_{now},\sigma_{now}\} \leftarrow$ EM(Δd,N_0;r_i;ν_{last},σ_{last}); //Equation(18),(19)
    if $(\nu_{now} - \nu_{last} > \nu_t)\&(\sigma_{now} - \sigma_{last} > \sigma_t)$ **then**
        $\{\nu_{next},\sigma_{next}\} \leftarrow$ EM(Δd,N_0;r_i;ν_{now},σ_{now}); //Equation(18),(19)
        $\{\nu_{last}, \sigma_{last}\} \leftarrow \{\nu_{now}, \sigma_{now}\}$;
        $\{\nu_{now}, \sigma_{now}\} \leftarrow \{\nu_{next}, \sigma_{next}\}$;
    end if
    $2L_{now} \leftarrow f_{2L}(\lambda; , \nu_{now}, \sigma_{now})$;//Equation(13)
    $N_{now} \leftarrow f_N(\nu_{now})$;//Equation(17)
end if
//2. On-line estimation of ν and σ, calculation of $2L$, N and Δd.
if operating-flag==true **then**
    for $i = 0; i < N_{now}; i++$ **do**
        $\{\nu_{next},\sigma_{next}\} \leftarrow$ EM(Δd,N_0;r_i;ν_{now},σ_{now}); //Equation(18),(19)
        $2L_{next} \leftarrow f_{2L}(\lambda; \nu_{now}, \sigma_{now})$;//Equation(13)
        $N_{next} \leftarrow f_N(\nu_{now})$;//Equation(17)
        $\Delta d_{next} = f_{2L}(\lambda; \nu_{now}, \sigma_{now})/f_N(\nu_{now})$;
        $\{\nu_{last}, \sigma_{last}\} \leftarrow \{\nu_{now}, \sigma_{now}\}$;
        $\{2L_{last}, N_{last}\} \leftarrow \{2L_{now}, N_{now}\}$;
        $\{\nu_{now}, \sigma_{now}\} \leftarrow \{\nu_{next}, \sigma_{next}\}$;
        $\{2L_{now}, N_{now}\} \leftarrow \{2L_{next}, N_{next}\}$;
        if $i == N_{last}$ **then**
            i=0;
        end if
    end for
end if

The dynamic estimation algorithm is given in Algorithm 1, which is based on the derivation and calculation introduced in the previous section. First, the initialization is conducted to calculate the initial value of Rician fading factors ν_0 and σ_0. It is calculated by EM algorithm with the statistical interval length $2L = 40\lambda$ and averaging sample numbers $N = 36$. Then ν_k and σ_k are estimated in every k-th compute cycles based on the estimation results of the last round. At the same time, the averaging factors $2L$ and N of next cycle are calculated based on the measurement samples and Rician fading factors. Finally, the sampling interval is determined by $\Delta d = 2L/N$, which can be converted into the time scale through the current velocity of train v_{train}. The process of received signal strength sampling and fading channels factors estimation are conducted in each compute cycle.

To get the received data and evaluate the measurement performance, we developed the Um interface monitoring system for GSM-R networks. As is illustrated in Fig. 9, the dynamic estimation algorithm is implemented on this platform and provides basic information to up-layer applications. The raw data of RSS is collected by GSM-R device, which is composed of the information of current cell and 6 neighbour cells. Then it is processed by the dynamic estimation algorithm to provide current network status and conduct next signal sampling. The system also provides RSS prediction based on the weighted averaging of signal samples, and gives warning information when the communication performance is lower than certain threshold. Since the system records the RSS of current and neighbour cells, the data can be used to make handover analysis and network optimization. Except the physical layer information, the system can also give quality of service of the link layer, including data traffic and voice service.

The hardware and software architecture of Um interface monitoring system is shown in Fig. 10. The system's CPU module is RTD's CME137686LX-W including a 333 MHz AMD Geode LX processor with 128 kB L1 cache and 128 kB L2 cache, and the GSM-R module is COM161

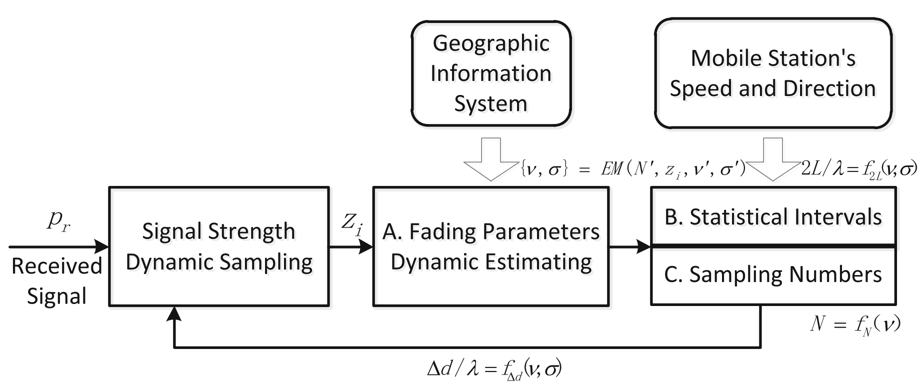


Fig. 8 On-line and dynamic estimation of Rician fading channels

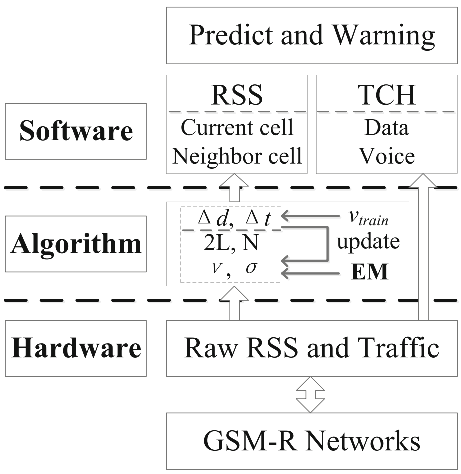


Fig. 9 Software framework and algorithm implementation

55RER-1 using Triorail's engine TRM:3a. The system's power supply, CPU and GSM-R modules are connected through PC/104 bus, and other peripherals through its specific interface. The hardware components are demonstrated in Fig. 10a. The software is independently developed by our research group, which uses Microsoft .NET Compact Framework written in C#, and it can run on various operating systems including Windows XP/Mobile/CE. The software interface is shown in Fig. 10b.

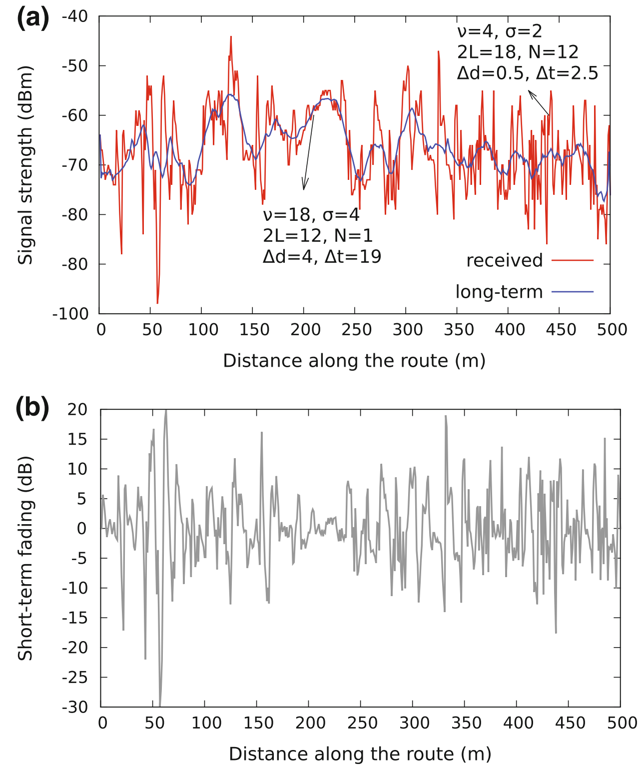


Fig. 11 Estimation results of local mean power. **a** Received signal strength and long-term fading. **b** Short-term fading

6 Evaluation

This section presents the measurement experiments and performance evaluation of on-line and dynamic estimation algorithm proposed previously. The received signal strength measurements, which is implemented by the Um monitoring system, were carried out along the Beijing–Shanghai high-speed railway, and the accuracy and overhead of the proposed algorithm is evaluated.

The measurement experiment is carried out by the Um interface monitoring system of GSM-R networks, as is shown in Fig. 10. The received signal strength was collected along the Beijing–Shanghai high-speed railway. Since the velocity of train is up to 300 km/h and the sampling interval is 500 ms limited by the length of

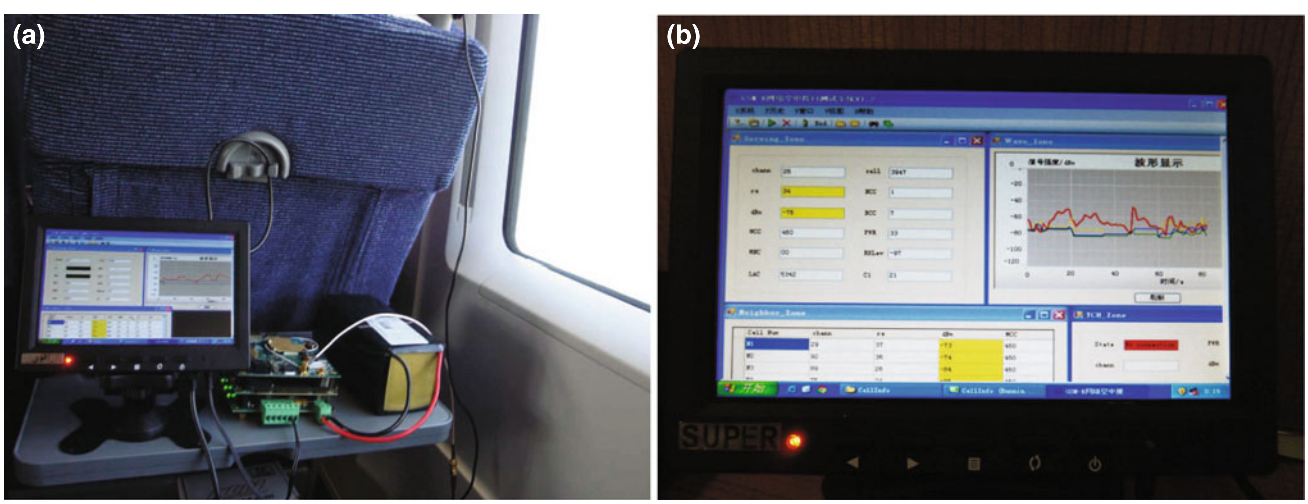


Fig. 10 Um interface monitoring system of GSM-R networks. **a** Hardware design. **b** Software development

	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V
1	ID	chann	rs	dBm	MCC	MNC	BCC	C1	C2	chann2	rs3	dBm4	MCC5	MNC6	BCC7	C18	C29	chann10	rs11	dBm12
2	2011-9-25 14:35:06	2	11	−99	460	0	2	0	0	3	8	−102	460	0	2	−3	−3	23	7	−103
3	2011-9-25 14:35:07	2	9	−101	460	0	2	−2	−2	3	8	−102	460	0	2	−3	−3	23	7	−103
4	2011-9-25 14:35:08	2	9	−101	460	0	2	−2	−2	3	8	−102	460	0	2	−3	−3	23	8	−102
5	2011-9-25 14:35:09	2	8	−102	460	0	2	−3	−3	3	8	−102	460	0	2	−3	−3	23	8	−102
6	2011-9-25 14:35:10	3	9	−101	460	0	2	−2	−2	23	8	−102	460	0	0	−1	−1	2	7	−103
7	2011-9-25 14:35:11	23	9	−101	460	0	0	0	0	3	9	−101	460	0	2	−2	−2	2	6	−104
8	2011-9-25 14:35:12	23	10	−100	460	0	0	1	1	3	7	−103	460	0	2	−4	−4	2	7	−103
9	2011-9-25 14:35:30	23	10	−100	460	0	0	1	1	29	8	−102	460	0	0	−7	−7	2	8	−102
10	2011-9-25 14:35:31	23	11	−99	460	0	0	2	2	3	9	−101	460	0	2	−2	−2	29	8	−102
11	2011-9-25 14:35:32	23	11	−99	460	0	0	2	2	2	9	−101	460	0	2	−2	−2	29	8	−102
12	2011-9-25 14:35:33	23	10	−100	460	0	0	1	1	2	8	−102	460	0	2	−3	−3	548	8	−102
13	2011-9-25 14:35:34	23	10	−100	460	0	0	1	1	2	8	−102	460	0	2	−3	−3	548	8	−102
14	2011-9-25 14:35:35	2	10	−100	460	0	2	−1	−1	23	10	−100	460	0	0	1	1	29	7	−103
15	2011-9-25 14:35:43	29	8	−102	460	0	0	−7	−7	23	6	−104	460	0	0	−3	−3	548	5	−105
16	2011-9-25 14:35:44	548	7	−103	460	0	5	−4	2	29	6	−104	460	0	0	−9	−9	23	5	−105
17	2011-9-25 14:36:03	2	8	−102	460	0	2	−3	−3	23	7	−103	460	0	0	−2	−2	29	7	−103
18	2011-9-25 14:36:04	2	10	−100	460	0	2	−1	−1	23	7	−103	460	0	0	−2	−2	29	7	−103
19	2011-9-25 14:36:05	2	12	−98	460	0	2	1	1	29	8	−102	460	0	0	−7	−7	23	7	−103
20	2011-9-25 14:36:07	2	14	−96	460	0	2	3	3	23	9	−101	460	0	0	0	0	29	8	−102
21	2011-9-25 14:36:08	2	15	−95	460	0	2	4	4	23	10	−100	460	0	0	1	1	29	9	−101
22	2011-9-25 14:36:09	2	15	−95	460	0	2	4	4	29	11	−99	460	0	0	−4	−4	23	10	−100
23	2011-9-25 14:36:10	2	16	−94	460	0	2	5	5	23	12	−98	460	0	0	3	3	29	12	−98
24	2011-9-25 14:36:11	2	17	−93	460	0	2	6	6	23	13	−97	460	0	0	4	4	29	12	−98
25	2011-9-25 14:36:12	2	17	−93	460	0	2	6	6	29	15	−95	460	0	0	0	0	23	13	−97
26	2011-9-25 14:36:13	2	17	−93	460	0	2	6	6	29	15	−95	460	0	0	0	0	23	12	−98
27	2011-9-25 14:36:14	2	17	−93	460	0	2	6	6	29	15	−95	460	0	0	0	0	23	12	−98
28	2011-9-25 14:36:15	2	17	−93	460	0	2	6	6	29	15	−95	460	0	0	0	0	23	12	−98
29	2011-9-25 14:36:16	2	17	−93	460	0	2	6	6	29	15	−95	460	0	0	0	0	23	12	−98
30	2011-9-25 14:36:17	2	17	−93	460	0	2	6	6	29	16	−94	460	0	0	1	1	23	12	−98
31	2011-9-25 14:36:18	2	17	−93	460	0	2	6	6	29	16	−94	460	0	0	1	1	23	11	−99
32	2011-9-25 14:36:19	2	17	−93	460	0	2	6	6	29	16	−94	460	0	0	1	1	23	11	−99

Fig. 12 Measurement results of wireless propagation along Beijing–Shanghai high-speed railway. *Columns D–K* represent the measured data of current cell, including channel NO. (*chann*), RSS (*dBm*), Network Color Code (*NCC*), Base station Color Code (*BCC*), Cell Selection & Reselection criteria (*C1* & *C2*), etc. The other columns are the parameters of neighbour cells

Table 1 Summary of experiment results

Terrain	K (dB)	v	σ	$2L(\lambda)$	N	$\Delta d(\lambda)$	Δd(m)	v_{train}(km/h)		
								200	250	300
								Δt (ms)		
*NLOS**	0	–	–	40	36	1.1	0.367	2.20	1.76	1.47
Intensive	0	0	1	55	15	3.7	1.222	7.33	5.86	4.89
	2	4	2	18	12	1.5	0.500	3.00	2.40	2.00
	4	5.6	2	9	9	1.0	0.333	2.00	1.60	1.33
	6	6	3	20	7	2.9	0.967	5.80	4.64	3.87
	8	12	3	8	1	8.0	2.667	16.00	12.80	10.67
Open	10	18	4	12	1	12.0	4.000	24.00	19.20	16.00

* Calculated by Lee's method of local mean power estimation in the case of Rayleigh fading

measurement multi-frame, it requires repeated data collection to evaluate the estimation algorithm. Part of measurement results is demonstrated in Fig. 12, and the long-term and short-term fading are separated after on-line propagation estimation. As is shown in Fig. 11, the long-term and short-term fading are differentiated so that they can be analyzed separately. The long-term parts can be used to make propagation prediction by Maximum Likelihood (ML) or Minimum Mean Square Error (MMSE) estimator. On the other hand, the short-term variations are essential to the section of the hysteresis in handoff algorithms.

The estimation results is summarized in Table 1 in detail, and it gives the length of statistical interval and number of averaging samples according to different propagation environments. The types of different terrains are distinguished by Rician fading factor K, i.e., it is intensive area without LOS components when $K = 0$, and the propagation environment becomes more flat gradually along with the increase of K. The on-line estimation results are compared to Lee's method in the case of $K = 0$ which means the fading channels is Rayleigh distributed. It requires smaller sampling intervals in Lee's method compared to dynamic estimation, which can be increased from 1.1 to 3.7λ. The mean power in the direct path increase as the terrain becomes flat, so that the number of averaging samples is less than 5 when ν becomes larger than 10. So it does not need to make frequent sampling although the length of statistical interval decreases, which can be set up to 12λ to reduce the measurement overhead.

7 Conclusion

This paper proposed the on-line and dynamic estimation algorithm of Rician fading channels in GSM-R networks, which is influential for the real-time reliability of high-speed railway systems. We gave the basic procedures of the dynamic estimation algorithm which is similar to the Lee's standard procedure except that the multi-path fading channel is Rician distributed, for the cell radius is designed short and the terrain is generally flat in GSM-R networks. Then we discussed the determination of proper length of statistical intervals and required number of averaging samples, in which EM method is employed to reduce the estimating overhead and make the measurement adaptive to different propagation environments.

To evaluate the performance of the dynamic algorithm, the Um interface monitoring system is developed and extensive experiments were implemented along the Beijing–Shanghai high-speed railway. It is demonstrated that the long-term and short-term fading signals can be differentiated separately by the proposed estimation algorithm. In the end, the experimental results were summarized and compared to Lee's local power estimating method. It requires smaller sampling intervals in Lee's method than that of dynamic method when it is NLOS propagation, which can be increased from 1.1 to 3.7λ. Furthermore, it does not need to make frequent sampling although the length of statistical interval decreases when there is LOS signal, which can be set up to 12λ to reduce the measurement overhead.

The dynamic estimation algorithm can be not only used in coverage assessment with lower measurement overhead which is implemented in network planning stage, but also applied in real-time operating such as dynamic channel allocation, power control and adaptive handoff algorithms. Since Rician fading is the generalized model of multi-path fading channels, the dynamic algorithm can also be introduced into measurement of other wireless networks.

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Appendix Proof of Theorem 1 and 2

Proof of Theorem 1

The normlving the integral formualized estimation error P_e can be determined by $\hat{s}$ and $\sigma_{\hat{s}}$ according to Definition 1, and $\sigma_{\hat{s}}$ can be calculated by

$$\sigma_{\hat{s}}^2 = \frac{1}{L}\int_0^{2L}\left(1-\frac{\tau}{2L}\right)R_{p_r^2}(\tau)d\tau, \qquad (22)$$

where $R_{p\_r}^2(\tau) = E[p_r^2(x)p_r^2(x+\tau)] - E[p_r^2(x)]E[p_r^2(x+\tau)]$ is the autocovariance function of the squared envelope of $p_r(x)$. $R_{p\_r}^2(\tau)$ can be derived from Rician distribution (Eqs. 6, 7 in Sect. 2) by approximation [4] as follows:

$$R_{p_r^2}(\tau) = 4\sigma^2\left[J_0^2\left(\frac{2\pi}{\lambda}\tau\right) + 2KJ_0\left(\frac{2\pi}{\lambda}\tau\right)\cos\left(\frac{2\pi}{\lambda}\eta\tau\right)\right], \qquad (23)$$

where $J_0(\cdot)$ is the zero-order Bessel function, and $\eta = \cos\theta_0$ is the intermediate valuable. Then $\sigma_{\hat{s}}^2$ can be calculated by substituting (23) into (22), i.e.,

$$\begin{aligned}\sigma_{\hat{s}}^2 &= \frac{4\sigma^2}{L}\int_0^{2L}\frac{2L-\tau}{2L}[J_0^2(\frac{2\pi}{\lambda}\tau) + 2KJ_0(\frac{2\pi}{\lambda}\tau)\cos(\frac{2\pi}{\lambda}\eta\tau)]d\tau \\ &= \frac{\hat{s}^2(2L-\lambda)\lambda}{2(1+K)^2L^2}\int_0^{\frac{2L}{\lambda}}[J_0^2(2\pi\rho) + 2KJ_0(2\pi\rho)\cos(2\pi\eta)]\rho d\rho,\end{aligned} \qquad (24)$$

where $\rho = \tau/\lambda$ is the intermediate valuable and $\sigma_{\hat{s}}^2 \to 0$ as $2L/\lambda \to \infty$. $\hat{s}$ can be considered as Gaussian distributed when $2L$ is large enough. Then $\sigma_{\hat{s}}^2$ can be represented by the simple form as follows:

$$\sigma_{\hat{s}}^2 = \frac{2(n-1)}{n^2(1+K)^2}\int_0^n g(K;\rho)d\rho, \qquad (25)$$

where $n := 2L/\lambda$ represents the relationship between statistical intervals $2L$ and wireless prorogation wavelength λ, $g(K;\rho) := [J_0^2(2\pi\rho) + 2KJ_0(2\pi\rho)\cos(2\pi\eta)]\rho$ is the intermediate function.

Given the definition of normalized estimation error P_e in (12), it can be calculated by substituting (25) into (12) and solving the integral formula. Then P_e can be determined by

$$\begin{aligned}P_e &:= 10\log_{10}\left(\frac{\hat{s}+\sigma_{\hat{s}}}{\hat{s}-\sigma_{\hat{s}}}\right) \\ &= 10\log_{10}\left(\frac{n(1+K)+\sqrt{2(1+n)\int_0^n g(K;\rho)d\rho}}{n(1+K)-\sqrt{2(1+n)\int_0^n g(K;\rho)d\rho}}\right) \\ &= 10\log_{10}\left(\frac{\frac{2\sigma^2+v^2}{2\sigma^2}n+\sqrt{2(1+n)\int_0^n g\left(\frac{v^2}{2\sigma^2};\rho\right)d\rho}}{\frac{2\sigma^2+v^2}{2\sigma^2}n-\sqrt{2(1+n)\int_0^n g\left(\frac{v^2}{2\sigma^2};\rho\right)d\rho}}\right).\end{aligned} \qquad (26)$$

Proof of Theorem 2

According to the characteristics of Rician distribution, it can be expressed that $z_i^2 = x_i^2 + y_i^2$ where $x_i \sim N(v\cos\eta, \sigma^2)$ and $y_i \sim N(v\sin\eta, \sigma^2)$ are statistically independent normal random variables and η is any real number. Let $x_{0i} = x_i/\sigma$, then $x_{0i} \sim N(v\sin\eta, 1)$ and its sum subject to the non-central χ^2 distribution, that is $\sum_{i=1}^{N} x_{0i}^2 \sim \chi_N^2(v^2\cos^2\eta)$. For $E[\chi_n^2(\lambda)] = n + \lambda$ and $D[\chi_n^2(\lambda)] = 2n + 4\lambda$, the mean value and variance of $\sum_{i=1}^{N} x_i^2$ can be calculated by:

$$\begin{aligned} E\left[\sum_{i=1}^{N} x_i^2\right] &= \sigma^2 E\left[\sum_{i=1}^{N} x_{0i}^2\right] \\ &= \sigma^2 E\left[\chi_N^2(v^2\cos^2\eta)\right] \\ &= \sigma^2\left(N + v^2\cos^2\eta\right), \end{aligned} \tag{27}$$

$$\begin{aligned} D\left[\sum_{i=1}^{N} x_i^2\right] &= \sigma^4 D\left[\sum_{i=1}^{N} x_{0i}^2\right] \\ &= \sigma^4 D\left[\chi_N^2(v^2\cos^2\eta)\right] \\ &= \sigma^4\left(2N + 4v^2\cos^2\eta\right), \end{aligned} \tag{28}$$

and $E\left[\sum_{i=1}^{N} y_i^2\right] = \sigma^2(N + v^2\sin^2\eta), D\left[\sum_{i=1}^{N} y_i^2\right] = \sigma^4(2N + 4v^2\sin^2\eta)$ can also be calculated in the same way. Then the expectation of r^2 and its variance can be calculated by:

$$\begin{aligned} \bar{r^2} &= E\left[\frac{1}{N}\sum_{i=1}^{N} z_i^2\right] = \frac{1}{N}E\left[\sum_{i=1}^{N}(x_i^2 + y_i^2)\right] \\ &= \frac{\sigma^2}{N}\left(N + v^2\cos^2\eta + N + v^2\sin^2\eta\right) \\ &= \frac{\sigma^2}{N}\left(2N + v^2\right), \end{aligned} \tag{29}$$

$$\begin{aligned} \sigma_{\bar{r^2}}^2 &= D\left[\frac{1}{N}\sum_{i=1}^{N} z_i^2\right] = \frac{1}{N^2}D\left[\sum_{i=1}^{N}(x_i^2 + y_i^2)\right] \\ &= \frac{\sigma^4}{N^2}\left(2N + 4v^2\cos^2\eta + 2N + 4v^2\sin^2\eta\right) \\ &= \frac{\sigma^4}{N^2}\left(4N + 4v^2\right). \end{aligned} \tag{30}$$

Then the estimation error can be calculated according to (29) and (30) as follows:

$$\begin{aligned} Q_e &= 10\log_{10}\left(\frac{\bar{r^2} + \sigma_{\bar{r^2}}}{\bar{r^2}}\right) \\ &= 10\log_{10}\left(\frac{\frac{\sigma^2}{N}(2N + v^2) + \frac{2\sigma^2}{N}\sqrt{N + v^2}}{\frac{\sigma^2}{N}(2N + v^2)}\right) \\ &= 10\log_{10}\left(\frac{2N + v^2 + 2\sqrt{N + v^2}}{2N + v^2}\right). \end{aligned} \tag{31}$$

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