On-line and Dynamic Estimation of Rician Fading Channels in GSM-R Networks

Yongsen Ma, Chengnian Long Key Laboratory of System Control and Information Processing, Ministry of Education Shanghai Jiao Tong University Email: mayongsen, longcn@sjtu.edu.cn

Abstract—The on-line and 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 the sampling signals and Rician fading parameters of last estimation to reduce measurement overhead. The performance of this method was evaluated by measurement experiment along the 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 on-line and dynamic algorithm. And the sampling interval can be set up to 12λ although the length of statistical interval decreases 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.

I. INTRODUCTION

The high-speed railway has experienced rapid development in recent years, and it is a critical infrastructure transporting commodities, goods and passengers. 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 realtime measurement to ensure the reliablity of the system [4]. 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 realtime 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 [3] [9] [17] [18]. Propagation models and measurement methods for wireless communication channels are summarized in [2] [14], and a propagation prediction method was presented in [13] which is for the terrestrial point-to-area services in International Telecommunication Union (ITU) recommendations. [1] and [12] proposed two kind of modified Okumura-Hata propagation prediction models respectively based on the least squares and Levenberg-Marquardet method. Most of the propagation





(a) Viaduct

(b) Tunnel





(c) Shanghai Hongqiao Railway Station

(d) Qinghai-Tibet Railway

Fig. 1. Radio Propagation Environments and terrains of GSM-R Networks

measurement and prediction methods are focused on path loss and shadow fading, 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.

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 [10]. The Generalized Lee method [6] allows estimating the mean values without the requirement of a priori knowing the distribution function, which is based on measured field data samples, but the optimum length of averaging interval is calculated using all the routes of the database with high overhead. Velocity adaptive handoff algorithms [3] 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 realtime measurement.

Since GSM-R networks are deployed along the high-speed railway route with varied terrains, the radio propagation environments are very complex, as is shown in Fig. 1. It is also obviously in Fig. 1 that the cell radius is normally designed short and the terrain is generally flat, so the multipath fading should be characterized by Rician fading in this case. There are many Rician channels estimation method such as Training-based Estimation [5], Maximum Likelihood [15] method, and the Expectation Maximization (EM) algorithm [11]. The EM algorithm provides a complete iterative solution to the Rician parameters estimation in synthetic aperture radar images, which can also be applied in Rician fading channels' parameter estimation.

This paper combined 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 proper length of statistical interval and required number of averaging samples are adaptive to different propagation environments.

To evaluate the performance of this algorithm, we developed the Um interface monitoring system for GSM-R networks, and measurement experiment was carried out along the Beijing-Shanghai high-speed railway. Firstly, it is illustrated that the long-term and short-term fading can be differentiated separately by the on-line estimating algorithm. Next, it requires smaller sampling intervals in Lee's method than that of on-line method when it is NLOS propagation, which can be increased from 1.1λ to 3.7λ . Finally, 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 on-line and dynamic estimation algorithm can be used in coverage assessment with lower measurement overhead which is implemented in network planning, and it can also be applied in realtime dynamic channel allocation, power control and adaptive handoff algorithms. Since Rician fading is the generalized model of multi-path fading channels, the algorithm can also be introduced into measurement of other networks.

The rest of this paper is organized as follows. The propagation models and the basic measurement framework are given in Section II. Section III presents the procedure of online propagation measurement in the case of Rician fading. In Section IV, the on-line and dynamic estimation algorithm is evaluated in experiment and its measurement performance is analyzed in detail. Section V concludes the paper.

II. PROPAGATION MODELS AND MEASUREMENT PROCEDURES

The received signal strength of Mobile Station (MS) on the train in GSM-R networks 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 as follows:

$$p_r^2(x) = s(x)h(x) \tag{1}$$

$$P_r(x) = S(x) + H(x) \tag{2}$$

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, and then $x = \sqrt{d^2 + v_{train}^2 \cdot t^2}$ can be deemed as $x = v_{train} \cdot t$ 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 as (2) in dB values, where $P_r(x) := 10 \log(p_r^2(x))$, $S(x) := 10 \log(s(x))$ and $H(x) := 10 \log(h(x))$.

A. Shadow Fading

Generally, s(x) can be deemed as shadow fading, which is commonly modeled as a Gaussian process with mean m(x) and variance σ_s^2 .

$$s(x) \sim N(m(x), \sigma_s^2) \tag{3}$$

where m(x) is meanly affected by path loss. In [14], 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 environment. The model can be simplified as (4).

$$M(x) = K_1 + K_2 \log(x) \tag{4}$$

where $M(x) := 20 \log(m(x))$ is the logarithmic form of m(x), K_1 denotes the transmit power of BS which both antenna gains and cable losses are taken into account, and K_2 is the topographic factor which changes with different terrains [8] [12]. The spatial correlation function of S(x) can be described by (5) based on measured data in urban and suburban environments [7].

$$R_s(x) = \sigma_s^2 \exp(-\Delta x/x_0) \tag{5}$$

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 10m to 500m in diffident environments [16], and Δx is the spatial distance which can be expressed as the velocity of mobile station and the sampling time 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 the hysteresis in handoff algorithms. The correlation distance x_0 and spatial distance Δx affect the optimum estimation accuracy of the local average power.

B. 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 usually designed short and the terrain is generally flat. Hence, the multi-path fading contains a possible Line Of

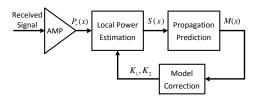


Fig. 2. Basic Procedures of Radio Propagation Measurement

Sight (LOS) wave, so that it can be expressed as Rician fading, which is composed of LOS and None Line Of Sight (NLOS) components:

$$h(x) = \underbrace{\frac{1}{\sqrt{1+K}} \lim_{M \to \infty} \frac{1}{\sqrt{M}} \sum_{m=1}^{M} a_m e^{j(\frac{2\pi}{\lambda} \cos(\theta_m x) + \phi_m)}}_{\text{NLOS Components}} + \underbrace{\sqrt{\frac{K}{1+K}} e^{j(\frac{2\pi}{\lambda} \cos(\theta_0 x + \phi_0))}}_{\text{LOS Component}}$$
(6)

where M is the number of independent scatterers, and λ is the wavelength. $\theta_m(m=0,1,...M)$ denote the angles between the plane waves and mobile station antenna, and $\phi_m(m=0,1,...M)$ is the phases of each wave component. In Racian 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 is:

$$f(y;\sigma,\nu) = \frac{y}{\sigma^2} e^{-\frac{y^2 + \nu^2}{2\sigma^2}} I_0(\frac{y\nu}{\sigma^2})$$
 (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 NLOS signal where K=0. In this case, h(x) and the probability distribution function of received signal amplitude can be expressed as:

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

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

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. 2. 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

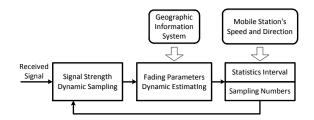


Fig. 3. On-line and Dynamic Estimation of Rician Fading Channels

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 realtime to ensure the system's reliability.

III. On-Line and Dynamic Estimation of Rician Fading Channels

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 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. Fig. 3 shows the basic estimation steps which mainly consist of the determination of proper length of statistical interval and required number of averaging samples.

A. Length of Statistical Intervals

For the propagation models presented in Section II, the estimation of s(x) can be calculated by the integral spatial average of h(x) as (10), and the variance of \hat{s} can be calculated by (11).

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

$$\sigma_{\hat{s}}^2 = \frac{1}{L} \int_0^{2L} (1 - \frac{\tau}{2L}) R_{p_r^2}(\tau) d\tau$$
 (11)

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 of the squared envelope of $p_r(x)$, and it can be derived from (6) and (7) by approximation [3] as follows:

$$R_{p_r^2}(\tau) = 4\sigma^2 \left[J_0^2(\frac{2\pi}{\lambda}\tau) + 2KJ_0(\frac{2\pi}{\lambda}\tau)\cos(\frac{2\pi}{\lambda}\eta\tau)\right] \quad (12)$$

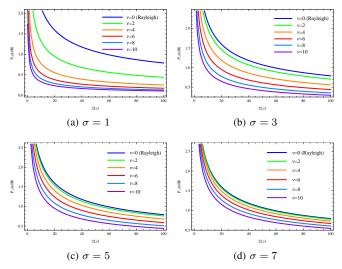


Fig. 4. Proper Length of Statistical Intervals

where $J_0(\cdot)$ is the zero-order Bessel function, and $\eta = \cos \theta_0$. Then $\sigma_{\hat{s}}^2$ can be calculated by substituting (12) into (11).

$$\sigma_{\hat{s}}^2 = \frac{4\sigma^2}{L} \int_0^{2L} (1 - \frac{\tau}{2L}) [J_0^2(\frac{2\pi}{\lambda}\tau) + 2KJ_0(\frac{2\pi}{\lambda}\tau)\cos(\frac{2\pi}{\lambda}\eta\tau)]d\tau$$

$$\stackrel{\rho \triangleq \frac{\tau}{\lambda}}{=} \frac{s^2 (2L - \lambda) \lambda}{2(1+K)^2 L^2} \int_0^{\frac{2L}{\lambda}} [J_0^2 (2\pi\rho) + 2K J_0 (2\pi\rho) \cos(2\pi\eta)] \rho d\rho$$
(13)

where $\sigma_{\hat{s}}^2 \to 0$ as $2L/\lambda \to \infty$. \hat{s} can be considered as Gaussian distributed when 2L is large enough, and then the estimation error can be defined as $P_e := 10 \log_{10}((\hat{s} + \sigma_{\hat{s}})/(\hat{s} - \sigma_{\hat{s}}))$.

The above approach is also illustrated in [3], and the statistical interval 2L is determined by the estimation of K. To reduce the estimation overhead, EM algorithm [11] 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:

$$\nu_{k+1} = \frac{1}{N} \sum_{i=1}^{N} \frac{I_1(\frac{\nu_k z_i}{\sigma_k^2})}{I_0(\frac{\nu_k z_i}{\sigma_k^2})}$$
(14)

$$\sigma_{k+1}^2 = \frac{1}{2N} \sum_{i=1}^{N} z_i^2 - \frac{\nu_k^2}{2}$$
 (15)

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 proper length of statistics interval can be obtained in terms with ν^2 and σ^2 through $P_-e=1dB$, as is shown in Fig. 4.

B. 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 (14) and (15), and then the expectation and variance of r^2 can be calculated:

$$\bar{r^2} = E[r^2] = \frac{1}{N} E[\sum_{i=1}^{N} z_i^2]$$
 (16)

$$\sigma_{\bar{r^2}} = D[r^2] = \frac{1}{N^2} D[\sum_{i=1}^N z_i^2]$$
 (17)

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

$$E[\sum_{i=1}^{N} x_i^2] = \sigma^2 E[\sum_{i=1}^{N} x_{0i}^2]$$

$$= \sigma^2 E[\chi_N^2(\nu^2 \cos^2 \eta)]$$

$$= \sigma^2 (N + \nu^2 \cos^2 \eta)$$
(18)

$$D[\sum_{i=1}^{N} x_i^2] = \sigma^4 D[\sum_{i=1}^{N} x_{0i}^2]$$

$$= \sigma^4 D[\chi_N^2(\nu^2 \cos^2 \eta)]$$

$$= \sigma^4 (2N + 4\nu^2 \cos^2 \eta)$$
(19)

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

$$\bar{r}^2 = E\left[\frac{1}{N} \sum_{i=1}^N z_i^2\right] = \frac{1}{N} E\left[\sum_{i=1}^N (x_i^2 + y_i^2)\right]$$

$$= \frac{\sigma^2}{N} (N + \nu^2 \cos^2 \eta + N + \nu^2 \sin^2 \eta)$$

$$= \frac{\sigma^2}{N} (2N + \nu^2)$$
(20)

$$\sigma_{\bar{r}^2}^2 = D\left[\frac{1}{N} \sum_{i=1}^N z_i^2\right] = \frac{1}{N^2} D\left[\sum_{i=1}^N (x_i^2 + y_i^2)\right]$$

$$= \frac{\sigma^4}{N^2} (2N + 4\nu^2 \cos^2 \eta + 2N + 4\nu^2 \sin^2 \eta)$$

$$= \frac{\sigma^4}{N^2} (4N + 4\nu^2)$$
(21)

The estimation error can be defined according to the standard Lee method that $Q_e = 10 \log_{10}((\bar{r^2} + \sigma_{\bar{r^2}})/\bar{r^2})$, and Fig. 5 gives the relationship between the required number of

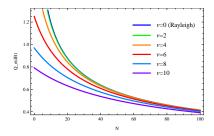


Fig. 5. Required Number of Averaging Samples

averaging samples and Rician fading parameter ν .

$$Q_{-}e = 10 \log_{10} \left(\frac{\bar{r^{2}} + \sigma_{\bar{r^{2}}}}{\bar{r^{2}}} \right)$$

$$= 10 \log_{10} \left(\frac{\frac{\sigma^{2}}{N} (2N + \nu^{2}) + \frac{2\sigma^{2}}{N} \sqrt{N + \nu^{2}}}{\frac{\sigma^{2}}{N} (2N + \nu^{2})} \right)$$

$$= 10 \log_{10} \left(\frac{2N + \nu^{2} + 2\sqrt{N + \nu^{2}}}{2N + \nu^{2}} \right)$$
(22)

The required sampling intervals Δd can be easily calculated through 2L/N, which determined the sampling frequency of on-line measurement. The sampling intervals Δd has a significant impact on the measurement accuracy and overhead. Note that Δd is the ratio of length of statistical interval 2Land 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.

IV. MEASUREMENT EXPERIMENT AND PERFORMANCE EVALUATION

This section presents the experiment and evaluation of online and dynamic estimation algorithm proposed previously. Received signal strength measurements, which is implemented by GSM-R network monitoring system, were carried out along the Beijing-Shanghai high-speed railway, and the accuracy and overhead of the algorithm is evaluated in the following.

The measurement experiment is carried out by the Um interface monitoring system of GSM-R networks, as is shown in Fig. 6a. The system's cpu module is RTD's CME137686LX-W including a 333MHz AMD Geode LX processor with 128kB L1 cache and 128kB L2 cache, and the communication module is COM16155RER-1 using Triorail's GSM-R engine TRM:3a. The system's power supply, processor and comunication module are connected through PC/104 bus, and other peripherals through its specific interface. The software is independently developed by our research group, which uses Microsoft .NET Compact Framework in C#, and it can run on various operating systems including Windows XP, Windows Mobile, and Windows CE.

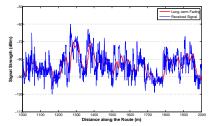
The received signal strength was collected along the Beijing-Shanghai high-speed railway, as is shown in Fig. 6b. Since the velocity of train is up to 300km/h and the sampling interval is 500ms limited by the length of measurement multiframe, it requires repeated data collection to evaluate the estimation algorithm.





(a) Um Interface Monitoring System (b) Experiment on High-Speed Railway

Fig. 6. Experiment along the Beijing-Shanghai High-Speed Railway



(a) Received Signal Strength and Long-term Fad-

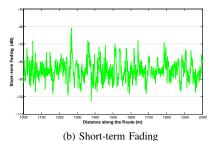


Fig. 7. Measurement Results

The measurement results is demonstrated in Fig. 7a, and the long-term and short-term fading are separated after online propagation estimation. As is shown in Fig. 7b, the longterm 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 I in detail, and it gives the length of statistical interval and number of averaging samples according to propagation environment. The type of different terrain is distinguished by Rician fading factor K, it is intensive areas without LOS components when K=0, and the propagation environment becomes more flat gradually along with the increase of K. The on-line estimating results are compared to Lee's method in the case of K=0 which means the fading channels is Rayleigh distributed, and it requires smaller sampling intervals in Lee's method. The 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, and it does not need to make frequent sampling

TABLE I SUMMARY OF EXPERIMENT RESULTS

								$v_{train}({ m km/h})$		
Terrain	K(dB)	ν	$ \sigma $	$2L(\lambda)$	N	$\triangle d(\lambda)$	$\Delta d(\mathbf{m})$	200	250	300
								$\Delta t(\mathbf{m}\mathbf{s})$		
NLOS*	0	-	-	40	36	1.1	0.367	2.20	1.76	1.47
Intensive areas	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 areas	10	18	4	12	1	12.0	4.000	24.00	19.20	16.00

^{*} Caculated by Lee's method of local mean power estimation in the case of Rayleigh fading

although the length of statistical interval decreases.

V. CONCLUSION

This paper proposed the on-line and dynamic estimation algorithm of Rician fading channels in GSM-R networks, which is influential in system's realtime reliability. We gave the basic procedure of this 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 interval 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 algorithm, measurement experiment was implemented along the Beijing-Shanghai high-speed railway. It is illustrated that the long-term and short-term fading can be differentiated separately by the on-line estimating algorithm. In the end, the experiment results were summarized and compared to the Lee's local power estimating method. It requires smaller sampling intervals in Lee's method than that of on-line method when it is NLOS propagation, which can be increased from 1.1λ to 3.7λ . It does not need to make frequent sampling although the length of statistical interval decreases when there is LOS signal, it can be set up to 12λ to reduce the measurement overhead. The on-line and dynamic estimation algorithm can be not only used in coverage assessment with lower measurement overhead which is implemented in network planning, but also applied in realtime dynamic channel allocation, power control and adaptive handoff algorithms. Since Rician fading is the generalized model of multi-path fading channels, the algorithm can also be introduced into measurement of other networks.

REFERENCES

- L. Akhoondzadeh-Asl and N. Noori. Modification and tuning of the universal okumura-hata model for radio wave propagation predictions. In Asia-Pacific Microwave Conference, 2007., pages 1 –4, Dec. 2007.
- [2] J.B. Andersen, T.S. Rappaport, and S. Yoshida. Propagation measurements and models for wireless communications channels. *Communica*tions Magazine, IEEE, 33(1):42–49, 1995.
- [3] M.D. Austin and G.L. Stuber. Velocity adaptive handoff algorithms for microcellular systems. *IEEE Transactions on Vehicular Technology*, 43(3):549–561, 1994.

- [4] G. Baldini, I. Nai Fovino, M. Masera, M. Luise, V. Pellegrini, E. Bagagli, G. Rubino, R. Malangone, M. Stefano, and F. Senesi. An early warning system for detecting gsm-r wireless interference in the high-speed railway infrastructure. *International Journal of Critical Infrastructure Protection*, 2010.
- [5] E. Bjornson and B. Ottersten. A framework for training-based estimation in arbitrarily correlated rician mimo channels with rician disturbance. *IEEE Transactions on Signal Processing*, 58(3):1807 –1820, March 2010.
- [6] D. de la Vega, S. Lopez, J.M. Matias, U. Gil, I. Pena, M.M. Velez, J.L. Ordiales, and P. Angueira. Generalization of the lee method for the analysis of the signal variability. *IEEE Transactions on Vehicular Technology*, 58(2):506 –516, Feb. 2009.
- [7] M. Gudmundson. Correlation model for shadow fading in mobile radio systems. *Electronics letters*, 27(23):2145–2146, 1991.
- [8] M. Hata. Empirical formula for propagation loss in land mobile radio services. *IEEE Transactions on Vehicular Technology*, 29(3):317–325, 1980.
- [9] K.I. Itoh, S. Watanabe, J.S. Shih, and T. Sato. Performance of handoff algorithm based on distance and rssi measurements. *IEEE Transactions* on Vehicular Technology, 51(6):1460–1468, 2002.
- [10] W.C.Y. Lee. Estimate of local average power of a mobile radio signal. *IEEE Transactions on Vehicular Technology*, 34(1):22–27, 1985.
- [11] T.L. Marzetta. Em algorithm for estimating the parameters of a multivariate complex rician density for polarimetric sar. In *Interna*tional Conference on Acoustics, Speech, and Signal Processing, 1995., volume 5, pages 3651–3654. IEEE, 1995.
- [12] A. Medeisis and A. Kajackas. On the use of the universal okumurahata propagation prediction model in rural areas. In *IEEE 51st Vehicular Technology Conference Proceedings*, 2000., volume 3, pages 1815–1818. IEEE, 2000.
- [13] E. Ostlin, H. Suzuki, and H.-J. Zepernick. Evaluation of the propagation model recommendation itu-r p.1546 for mobile services in rural australia. *IEEE Transactions on Vehicular Technology*, 57(1):38 –51, Jan. 2008.
- [14] T.K. Sarkar, Z. Ji, K. Kim, A. Medouri, and M. Salazar-Palma. A survey of various propagation models for mobile communication. *Antennas and Propagation Magazine*, *IEEE*, 45(3):51–82, 2003.
- [15] J. Sijbers, A.J. Den Dekker, P. Scheunders, and D. Van Dyck. Maximum-likelihood estimation of rician distribution parameters. *IEEE Transactions on Medical Imaging*, 17(3):357–361, 1998.
- [16] C. Tepedelenlioğlu, A. Abdi, G.B. Giannakis, and M. Kaveh. Estimation of doppler spread and signal strength in mobile communications with applications to handoff and adaptive transmission. *Wireless Communi*cations and Mobile Computing, 1(2):221–242, 2001.
- [17] N. Zhang and J.M. Holtzman. Analysis of handoff algorithms using both absolute and relative measurements. *IEEE Transactions on Vehicular Technology*, 45(1):174–179, 1996.
- [18] H. Zhu, Q. Yang, and K. Kwak. Performance analysis of fast handoff with mobility prediction. In *IEEE International Symposium on Commu*nications and Information Technology, volume 1, pages 75–78. IEEE, 2005.