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Letter

Wireless Systems

Mobile radio bi-dimensional large-scale fading modelling with site-to-site cross-correlation

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SUMMARY

Wireless communication simulations are generally conducted using one-dimensional models for large-scale fading. While simple and with low computational costs, these models cannot produce correlated fading values for mobiles that are in nearby positions. To overcome this limitation, this paper presents a novel bi-dimensional large-scale fading model which introduces the spatial correlation present in real systems. Besides, it is also able to model the non-negligible cross-correlation among signals coming from different sites. Copyright © 2007 John Wiley & Sons, Ltd.

1. INTRODUCTION

As the complexity of wireless communication systems increases, the use of simulation tools to obtain initial assessments of system performance is becoming increasingly common. To conduct accurate and valid studies, a careful selection of the simulation models is required. The development and inclusion of precise large-scale fading models in simulation studies is an important issue. This fading effect, hereinafter referred to as either slow fading or large-scale fading, can significantly affect the dynamics of the signal variation at the receiving unit and, consequently, the coverage area and received signal quality.

Several experimental studies have shown that the statistical distribution of large-scale fading can be approximated by a lognormal law (e.g. [1]). To consider the spatial correlation properties of slow fading, Gudmundson [1] suggested a one-dimensional model of its autocorrelation function. Although this model has been extensively used in wireless communications testbeds and simulation studies, it is limited in the sense that it independently considers the slow fading for each mobile unit. This approach results in the large-scale fading experienced by receiver units that are in close vicinity to each other being uncorrelated, even if their surrounding obstacles are identical. As observed in different measurement campaigns (e.g. [2,3]) such lack of correlation does not happen in real networks. This observation is illustrated in Figure 1 for the measurements reported in [3]. Figure 1(a) shows two different urban paths followed in the measurement campaign realised within the framework of COST 231. Figure 1(b) illustrates the obtained slow fading values for both routes between the points A and B. As it can be observed, both measurement series, though taken in different moments, exhibit very similar slow fading values, hence highlighting the previously mentioned spatial correlation and reinforcing the need to model it. One possible way of doing so is through bi-dimensional maps, as considered in this paper.

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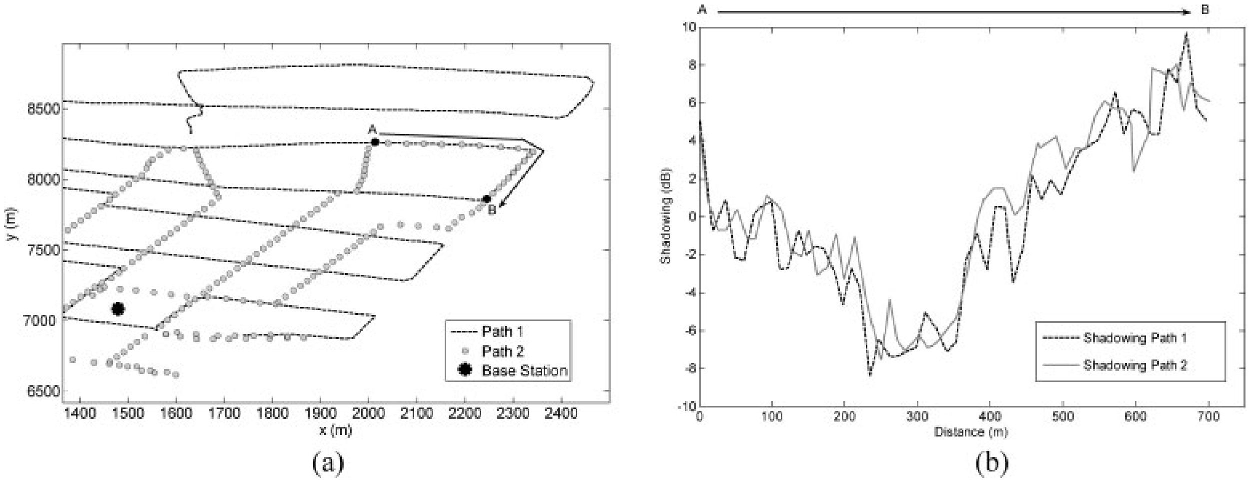

Figure 1. Slow fading experienced by two different mobiles connected to the same site (b) and moving from A to B along routes in (a).

Besides, neglecting the slow fading spatial correlation present in wireless systems could result in significantly underestimating the performance of techniques that strongly depend on the radio link quality conditions (e.g. soft handover, macro-diversity or link adaptation) [4]. A proposal to overcome this limitation consists in generating bi-dimensional slow fading using methods based on sums of sinusoids [5]. However, this approach exhibits certain limitations in terms of spectral properties [6]. As a result, the work herein reported presents and analyses a different approach to generate correlated large-scale fading values.

Another aspect of slow fading modelling that is usually neglected is cross-correlation of signals transmitted from different base stations. Such cross-correlation effect, also highlighted in different measurement campaigns (e.g. [2,7]), is due to the fact that the random component of propagation loss consists of the sum of two components: one resulting from obstacles in the vicinity of the mobile unit and a second one from the specific surroundings of each base station. As a result, the fading phenomena affecting different signals received by a user from different base stations experience some correlation.

In this context, this paper presents a new bi-dimensional large-scale fading model capable of representing both spatial correlation and site-to-site cross-correlation that characterise the slow fading phenomenon. This model has been adopted within the reference scenarios for UMTS in the European Network of Excellence in Wireless Communications (NEWCOM).

2. LARGE-SCALE FADING MODEL

2.1. Mathematical description

Propagation loss experienced by the signal transmitted from base station i and received by a mobile unit can be expressed in decibels as:

$$L^i(t) = \bar{L}^i(t) + L^i_{\mathrm{SH}}(t) + L^i_{\mathrm{FF}}(t) \quad (1)$$

where $\bar{L}^i(t)$, $L^i_{\mathrm{SH}}(t)$ and $L^i_{\mathrm{FF}}(t)$ represent path loss, slow fading and fast fading, respectively.

The work reported in [1] established that the slow fading spatial autocorrelation can be expressed as a function of the distance shift Δr and a decorrelation distance d_{decorr}:

$$R(\Delta r) = e^{-\frac{\ln 2 |\Delta r|}{d_{\mathrm{decorr}}}} = 2^{-\frac{|\Delta r|}{d_{\mathrm{decorr}}}} \quad (2)$$

To consider the slow fading correlation in the bi-dimensional Cartesian coordinate system used to represent slow fading maps, (2) can be converted to:

$$R(\Delta r) = R(\Delta x, \Delta y) = 2^{-\frac{\sqrt{\Delta x^2 + \Delta y^2}}{d_{\mathrm{decorr}}}} \quad (3)$$

The influence of the surrounding environment over the large-scale fading results in the slow fading experienced by signals transmitted from different base stations and received at a single mobile station exhibiting some correlation. In particular, if we consider two base stations

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(i, j) such cross-correlation can be expressed as [7]:

$$R_{ij}(0) = \frac{E\left[L_{\mathrm{SH}}^{i}(t) \cdot L_{\mathrm{SH}}^{j}(t)\right]}{\sqrt{E\left[L_{\mathrm{SH}}^{i}(t)^2\right] \cdot E\left[L_{\mathrm{SH}}^{j}(t)^2\right]}} = \rho_{ij} > 0 \quad (4)$$

where ρ_{ij} typically has values between 0.3 and 0.5 [7].

2.2. Generation of cross-correlated slow fading between different radio links

The slow fading experienced by signals transmitted from a set of n base stations to a point (x, y) can be modelled as a set of n Gaussian random variables. It is assumed that these variables have the same standard deviation σ_{SH}. To make sure that these variables exhibit the cross-correlation present in real systems, the slow fading generation process has to ensure that for each pair of them (4) is valid for a given set of values $\{\rho_{ij}\}$. In this work, a fixed cross-correlation coefficient ρ is assumed for any pair of base stations, that is $\rho_{ij} = \rho$ for any pair (i, j).

A simple and computationally fast solution for the stated problem is to generate $n + 1$ independent random Gaussian variable $\{G_0, G_1 \ldots G_n\}$ with zero mean and standard deviation equal to σ_{SH}. From these values, the slow fading experienced by the signals transmitted from each base station i can be generated as follows:

$$L_{\mathrm{SH}}^{i} = \sqrt{\rho} \cdot G_0 + \sqrt{1-\rho} \cdot G_i \quad (5)$$

With this approach, G_0 represents the common, receiver-position-dependent slow fading component while G_i models the base-station-dependent component. (5) guarantees that the slow fading generated L_{SH}^{i} follows a Gaussian distribution with zero mean and standard deviation equal to σ_{SH}. On the other hand, the cross-correlation factor between any pair (i, j) of slow fading values is equal to

$$R_{ij}(0) = \frac{E[L_{\mathrm{SH}}^{i} \cdot L_{\mathrm{SH}}^{j}]}{\sigma_{\mathrm{SH}}^2} = \frac{E\left[\rho \cdot G_0^2\right]}{\sigma_{\mathrm{SH}}^2} = \rho \quad (6)$$

given that G_0, G_i and G_j are independent random variables with zero mean.

The same procedure as represented by (5) could be repeated for each geographic location at which the slow fading should be generated. As a result, (5) can be rewritten as:

$$L_{\mathrm{SH}}^{i}(x, y) = \sqrt{\rho} \cdot G_0(x, y) + \sqrt{1-\rho} \cdot G_i(x, y) \quad (7)$$

2.3. Generation of spatially correlated slow fading

The procedure represented by (7) to generate slow fading maps does not guarantee yet the spatial correlation that mobiles experience.

The generation of slow fading maps verifying (3) can be performed using different methodologies. One possible approach to generate spatially correlated slow fading maps was reported in [5]. However, this procedure requires complex computations so as to select the sample frequencies needed to obtain valid approximations of the autocorrelation function. This paper proposes an approach consisting in applying a bi-dimensional filter to the slow fading maps previously generated using the procedure described by (7).

Generating random and independent slow fading samples produces 'white' slow fading, characterised by a null autocorrelation for non-zero spatial shifts. In order to introduce the auto correlation properties described by Equation (3), bi-dimensional filtering can be applied as follows. Let term $a(x, y)$ the spatially uncorrelated slow fading map described by (7) and $b(x, y)$ the desired spatially correlated slow fading map. $a(x, y)$ is considered as the filter's input and $b(x, y)$ as the filter's output, which can be expressed in the frequency domain as:

$$B\left(f_x, f_y\right) = A\left(f_x, f_y\right) \cdot H\left(f_x, f_y\right) \quad (8)$$

with H representing the frequency response of the filter that needs to be designed.

For white slow fading, the two-dimensional Fourier transform of the input slow fading map is flat. As a result, (8) can be rewritten as:

$$B\left(f_x, f_y\right) = k \cdot H\left(f_x, f_y\right) \quad (9)$$

The slow fading map $a(x, y)$ is characterised by its autocorrelation function being non-zero only at the coordinate system's origin. Consequently, its power spectral density is:

$$S_{\mathrm{aa}}\left(f_x, f_y\right) = \sigma_a^2 \quad (10)$$

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Now, the power spectral density of $b(x, y)$, given that the filter frequency response is known, can be obtained as:

$$S_{bb}(f_x, f_y) = S_{aa}(f_x, f_y) \cdot |H(f_x, f_y)|^2 \\ = \sigma_a^2 \cdot |H(f_x, f_y)|^2 \qquad (11)$$

However, in our case $S_{\mathrm{bb}}\left(f_x, f_y\right)$ is known, since it is the Fourier transform of the bi-dimensional autocorrelation function (3). As σ_a^2 is also known, we can easily obtain the Fourier transform of the filter impulse response $h(x, y)$ as the square root of $S_{\mathrm{bb}}(f_x, f_y)/\sigma_a^2$. After performing an inverse Discrete Fourier Transform, the definitive filter impulse response that verifies the slow fading variance properties requires normalising as follows:

$$\bar{h}\,(x, y) = \frac{h\,(x, y)}{\sqrt{E\left[(h\,(x, y) - E|h\,(x, y)|)^2\right]}} \qquad (12)$$

Once the filter is defined, the next step consists in applying it to the original slow fading map $a(x, y)$ that verifies (7). This process results in the final slow fading map including both spatial and site-to-site cross-correlation.

3. VALIDATION OF THE PROPOSED MODEL

Figure 2 compares the slow fading autocorrelation function (AF), along the first path considered in the COST 231 measurement campaign, for: measurements collected in the campaigns reported in [3], bi-dimensional maps proposed in this paper (2D), one-dimensional model from [1] (Gudmundson) and one-dimensional model from [8]

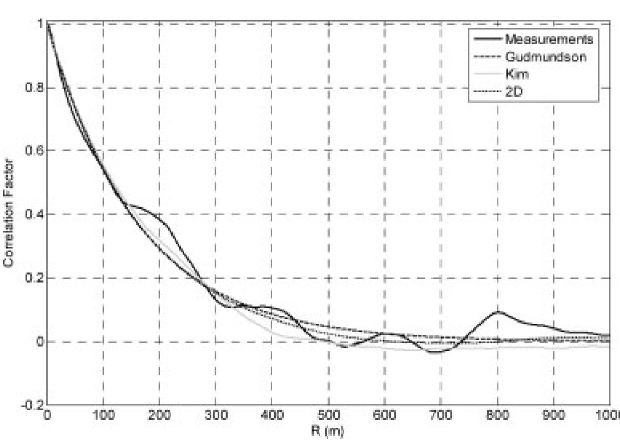

Figure 2. Comparison of the slow fading AF.

(Kim). It can be observed that, in all cases, the AF of the different models match fairly well with the AF measurements.

The proposed 2D slow fading model has also been compared to that proposed in [5]. For that purpose, the same configuration parameters have been considered. In particular, the slow fading standard deviation has been set to 1 dB and a correlation of 0.5 has been assumed for a distance of 7.5 m (these parameter values have been chosen merely to enable a fair and direct comparison between both models). The site-to-site slow fading cross-correlation factor has been set to 0.5. With the proposed 2D model, the achieved autocorrelation function average squared error with respect to the Gudmundson model is equal to 5×10^{-5}, which is two orders of magnitude lower than the best performance obtained in [5].[†] These values demonstrate that the 2D model outperforms the sum-of-sinusoids model reported in [5]. In terms of computational complexity, our approach requires calculating one Inverse Fast Fourier Transform more than [5], but it does not require performing either Monte-Carlo simulations or sum of sinusoids.

In terms of the cross-correlation, (6) already demonstrates the validity of the implemented model. However, simulations were conducted to obtain the Probability Density Function (PDF) of the cross-correlation factor for all the points of several bi-dimensional large-scale fading maps corresponding to different base stations. The obtained PDF exhibits a narrow distribution around the target value of 0.5, which further validates the implemented cross-correlation model.

4. SYSTEM-LEVEL EFFECT

To demonstrate the importance and need to develop accurate large-scale models, such as the one reported in this paper, this section analyses the impact of different models on a system's performance. To conduct this investigation, a powerful GPRS simulation platform modelling radio transmissions at the burst level has been used [9]. This simulation platform also emulates the operation of Link Adaptation (LA), an adaptive Radio Resource Management (RRM) technique that selects the most suitable transport mode (modulation and coding scheme) according to the

[†] The model proposed in [8] achieves very similar AF average square error values as the model proposed in this paper. However, our model considers bi-dimensional scenarios whereas the model in [8] is limited to one-dimensional scenarios.

Table 1. Simulation parameters.

Parameter	Value
Cluster size	4
Cell radius	1 km
Sectorisation	120°
No. of modelled cells (wrap-around)	25
Slots per sector	16
Users per sector	16
Traffic type	H.263 video: 6 users/sector; WWW: 6 users/sector; E-mail: 4 users/sector
Pathloss model	Okumura-Hata
Vehicular speed	50 km/h
LA updating period	20 ms

experienced channel quality conditions. The inclusion of LA has been considered as a suitable case study since its operation and performance can be significantly influenced by the channel quality variations and, therefore by the implemented radio channel models. The main simulation parameters are summarised in Table 1.

To demonstrate the importance of employing accurate large-scale fading models to conduct system-level studies, this section compares the performance obtained with the following three models: lognormal large-scale fading model with one-dimensional spatial correlation [1], bi-dimensional large-scale fading maps with spatial correlation but without site-to-site cross-correlation and bi-dimensional large-scale fading maps with spatial and site-to-site cross-correlations (a fixed 0.5 site-to-site cross-correlation has been considered). Figure 3 compares the system throughput performance obtained considering the three different slow fading models.

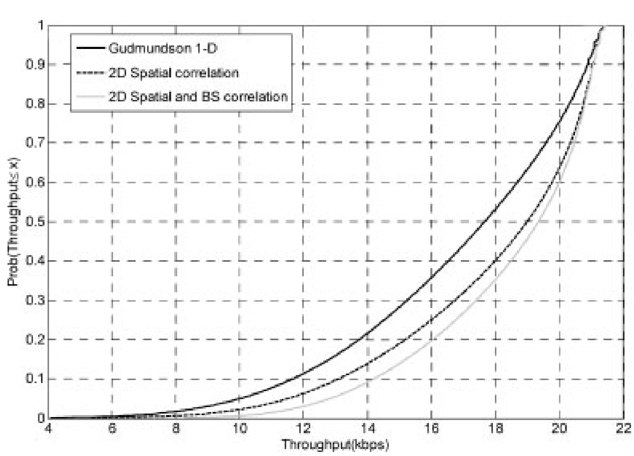

Figure 3. System throughput cumulative distribution function.

The figure clearly shows that using simple large-scale fading models results in an important underestimation of the system-level performance that could be obtained when employing LA. Such underestimation is a consequence of neglecting the inherent spatial and site-to-site correlation present in the large-scale fading. Since LA bases its transport mode selection on the experienced channel quality conditions, its operation is improved when such conditions are correlated. The results shown in Figure 3 also highlight that the spatial correlation has a more important effect on the system's performance than the modelled site-to-site cross-correlation.

The obtained results and previous observations are confirmed when analysing the percentage of data blocks transmitted using the optimal coding scheme according to the LA algorithm. When considering the large-scale fading model based on a bi-dimensional map including spatial and site-to-site cross-correlation, this percentage increases by 9.5% as compared to when large-scale fading is modelled using the one-dimensional lognormal model. The number of coding scheme changes per second also provides an indication on how well is LA adapting to the experienced channel quality conditions. The use of a bi-dimensional map including spatial and site-to-site cross-correlation results in a 23% reduction in this parameter compared to when using the one-dimensional lognormal model. These results further demonstrate that simple slow fading models are not able to properly capture the inherent spatial correlation properties present in real systems, which can result in a considerable underestimation of the system performance of adaptive radio interfaces.

5. CONCLUSIONS

This paper has presented a novel bi-dimensional large-scale fading model that is able to consider not only the spatial correlation characteristic of the slow fading phenomena but also the non-negligible cross-correlation between signals transmitted from different base stations. The proposed approach, based on two-dimensional filtering of 2D random slow fading maps, has been shown to exhibit good spectral properties. This paper has also shown that large-scale fading models can have a significant impact on a mobile's system performance, particularly when employing adaptive RRM techniques. Consequently, accurate slow fading models, such as the one proposed in this work, should be considered to appropriately conduct system-level investigations.

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