A Resource Efficient Model of Spatially Correlated Shadowing in Semi-Mobile Ad-hoc Network Simulations

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***Abstract*—Over the past two decades several approaches for modelling (spatially) correlated shadowing in mobile communication environments have been proposed. One prominent implementation is the pre-generation of shadowing maps representing the shadowing loss for geographic locations. However, the majority of these models do only consider shadowing fluctuation with respect to only a single reference location of the non-mobile end of a communication link. Here, the amount of resources needed significantly increases in case multiple reference locations are required. In this paper a resource efficient approach for modelling spatially correlated shadowing in computer simulations for mobile (ad-hoc) networks reducing the complexity from $\mathrm{O}(n^2)$ to $\mathrm{O}(n)$ is proposed. Hence, it may advantageous specifically for complex computer simulations utilising hardware commonly available.**

***Keywords*-Mobile ad-hoc networks, simulation, channel models.**

I. Introduction

Computer simulation is a fundamental method used within the scientific community to evaluate concepts underlying new technologies. Stochastic discrete event simulation is a typical approach used in this scope to assess the performance of systems with a certain degree of confidence. When performing system level simulations certain details of a system need to be abstracted in order to achieve results within a finite amount of time. However, the process of abstraction requires careful consideration to ensure the overall system behaviour will not be adversely affected by the limitations and underlying assumptions of the abstraction. Additionally, the validity of results achieved by computer simulations strongly depends on the accuracy of simulation models and how closely they reflect the real system within its environment.

The simulation of communication networks often requires models of high complexity based on the amount of detail involved in modelling protocol layers. For the investigation of the performance of wireless networks a realistic representation of the physical layer and the channel conditions is essential [1]. The radio signal emitted by a node in a (mobile) wireless network is affected by transmission losses, which can be classified into three parts: a distance-dependent large-scale path loss, shadowing loss (long-term fading) due to large objects in the communication path such as hills or buildings, and non-shadowing loss (short-term fading) due to multi-path propagation (reflection and scattering) [2]. Using logarithmic (dB) values the total path loss can be expressed as

$$L_{i,j} = \gamma(d_{i,j}) + \theta_{i,j} + \chi_{i,j}, \tag{1}$$

where $d_{i,j}$ represents the Euclidean distance between nodes i and j, $\gamma(\cdot)$ is the large-scale path loss, θ is the shadowing loss, and χ represents the non-shadowing loss.

In system level simulations shadowing is sometimes modelled as an uncorrelated random process with a log-normal distribution. Although an uncorrelated process is easy to compute during simulation, spatial correlation has a significant impact on system performance [3], [4], [5]. Since shadowing loss is a spatially correlated quantity, the need for a realistic model including correlation arises in the performance evaluation of mobile ad-hoc networks (MANETs). Furthermore, omitting correlation can lead to significant drawbacks when investigating (closed) loop systems such as adaptive modulation and coding [6], [7] which exploit the correlated nature of the shadowing environment.

Over the past two decades several approaches for modelling correlated shadowing have been proposed. In 1991, Gudmundson described a one-dimensional model [8] for the autocorrelation function of shadowing. Graziosi and Santucci derived an extended correlation model [9] for the cross-correlation function of the shadowing contributions affecting the links between a mobile node and two base stations based on Gudmundson's autocorrelation model. A model for spatially cross-correlated shadowing in distributed radio access networks was presented in [5]. Patwari and Agrawal investigated the effects of correlated shadowing in [10] and introduced a joint shadowing model for links in a multi-hop network. The core idea behind this model is that losses from shadowing are attributed to an underlying spatial loss field [11], [12].

In addition to these publications several approaches based on pre-generated maps have been proposed. Forkel et al. introduced a method how to generate two-dimensional correlated shadowing using two-dimensional convolution [13].

In [14] Catrein and Mathar presented a model employing Gaussian random fields and isotropic correlation functions. A method for the generation of channel attenuation maps including both large-scale path loss and shadowing loss was presented in [15]. Wang et al. have shown that in a single mobility scenario the autocorrelation function of the shadowing for mobile radio networks can be well modelled by an exponential decay function. Furthermore they have proposed to approximate the joint spatially correlated shadowing fluctuation for peer-to-peer (P2P) radio links in dual mobility scenarios by the product of two autocorrelation functions (ACFs) in single mobility scenario [16], [17]. This approach can take the mobility of both the transmitting and receiving node into account.

The majority of the map-based models presented in this section do only consider shadowing fluctuation with respect to a single reference location of the non-mobile end of a communication link and their computational complexity may significantly increase in case multiple reference locations are required. Therefore, this paper contributes a resource efficient approach taking into account multiple reference locations while reducing the complexity in terms of (main) memory occupation from $\mathrm{O}\big(n^2\big)$ to $\mathrm{O}\big(n\big)$.

The remainder of this paper is organised as follows: Section II describes the proposed shadowing model and its applicability to mobile ad-hoc network simulations. Numerical results are presented in Section III showing the most important characteristics of the proposed model. Finally, Section IV concludes the paper.

II. Proposed Shadowing Model

A. Preliminary Requirements

As described in [15], the computational complexity of a model is a scaling factor which should not be neglected. To reduce computational requirements in system level simulations, a shadowing map realised as a lookup table is preferable. Overall, a correlated shadowing model has to meet the following constraints:

(i) Isotropic autocorrelation function (ACF), i.e. the statistical properties are independent of the direction of movement

(ii) ACF equal to Gudmundson's correlation model

(iii) Low computational complexity in terms of physical memory occupation during system level simulation

B. Generation of Correlated Shadowing Map

As the shadowing model presented in [13] exhibits relatively low complexity in generating the two-dimensional correlated shadowing maps by simply employing a two-dimensional convolution of a matrix of Gaussian random values and a correlation matrix, it serves as the basis for our enhanced approach. To achieve spatial correlation, Forkel et al. applied the normalised autocorrelation function

$$R(\Delta x) = e^{-\frac{|\Delta x|}{d_{\text{corr}}}\ln(2)} \tag{2}$$

from [8], where Δx represents the increasing distance in x-direction and d_{corr} is the decorrelation distance. However, we found that this model does not meet constraint (i).

In contrast to [13], we propose the use of an enhanced two-dimensional normalised autocorrelation function

$$R(\Delta x, \Delta y) = e^{-\frac{\sqrt{\Delta x^2+\Delta y^2}}{d_{\text{corr}}}\ln(2)} \tag{3}$$

for both negative and positive values of Δx and Δy. Applying the Fourier transform to (3) leads to the following relation

$$\mathcal{F}\left\{R(\Delta x, \Delta y)\right\} = PSD(\omega_1, \omega_2) = |G(\omega_1, \omega_2)|^2, \tag{4}$$

where $\mathcal{F}\{\cdot\}$ represents the Fourier operator, and $PSD(\cdot)$ and $|G(\cdot)|^2$ are the power spectral density and the squared magnitude spectrum, respectively.

Utilising a numerical frequency sampling filter design approach, a finite impulse response (FIR) filter can be devised for which the channel impulse response is equal to the inverse Fourier transformation of $G(\omega_1, \omega_2)$. After applying the FIR filter (which can be achieved by a two-dimensional convolution) to the uncorrelated Gaussian values of the map a shadowing map consisting of spatially correlated values is obtained.

Another approach for generating the shadowing map is to perform the calculation in the frequency domain by transforming both the two-dimensional ACF $R(\Delta x, \Delta y)$ and the uncorrelated Gaussian valued map using Fourier transform. We found the frequency domain approach actually shows better performance with respect to both accuracy and computation time.

C. Applicability to Mobile Ad-hoc Network Simulations

The most realistic representation of correlated shadowing in an infrastructure-less mobile network is to provide a correlated shadowing value for each coordinate to every single point on the map. For a two-dimensional scenario, the total number of entries of such a four-dimensional lookup table is then given by

$$K = (M \times N)^2\,, \tag{5}$$

where M and N represent the map dimension in elements in y- and x-direction, respectively. Assuming a map where $M = N = 1,000$ and each map entry needs one byte of memory the total memory needed for a single shadowing map would be one terabyte. This amount of storage is typically not available in many of the usual computing platforms used by the research community and therefore an approach resulting in a much smaller amount of memory is required. The approach of modelling correlated shadowing by using pre-defined maps was originally developed for scenarios where at least one of the two communicating nodes is fixed. A typical representation of this scenario is a cellular communication network with fixed base stations and mobile nodes. Hence, the values within the shadowing map are calculated with respect to a certain point of reference, i.e. the position of the base station. In case of infrastructure-less networks such as MANETs, the shadowing map needs reformatting to keep memory requirements manageable as shown in (5).

To overcome issues with scaling computational complexity, i.e. exponential increase in required memory, we propose to apply an abstracted model following the concept of a spatial loss field describing the shadowing fluctuations. To achieve a further abstraction of the model described in [11], we propose to calculate the shadowing loss $\theta_{i,j}$ as the sum of the shadowing losses at both ends of a communication link between node i and node j. The total shadowing loss $\theta_{i,j}$ is then given by

$$\theta_{i,j} = \theta_{j,i} = \vartheta(x_i, y_i) + \vartheta(x_j, y_j), \tag{6}$$

where $\vartheta(x_i, y_i)$ and $\vartheta(x_j, y_j)$ are the values of the local shadowing for the two-dimensional position of nodes i and j, respectively. Since for our model shadowing fluctuation is described as a Gaussian random process

$$\mathcal{N}\left(\mu, \sigma^2\right), \tag{7}$$

where μ is the mean value and σ^2 represents the variance, it can be easily shown that this approach does not affect the characteristics of the random distribution.

Proof: As for the summation of stochastically independent variables from a Gaussian (or: *normal*) distribution the following interrelations apply:

$$\sigma^2 = \sigma_1^2 + \sigma_2^2 + \ldots + \sigma_n^2 \tag{8}$$

$$\mu = \mu_1 + \mu_2 + \ldots + \mu_n, \tag{9}$$

it is obvious that for $\mu = \mu_1 = \mu_2 = 0$ and $\sigma_1^2 = \sigma_2^2 = \sigma^2/2$ the utilisation of (6) does not alter the statistical characteristics of (7). ∎

Hence, the variance of the spatially correlated log-normal shadowing values in the map has to be adjusted to be equal to $\sigma_l^2/2$ to generate shadowing maps with a desired standard deviation σ_l for a link within a mobile network. According to (10), with the proposed approach the total number of map entries K remains at the same size as for the original two-dimensional map.

$$K = (M \times N) \tag{10}$$

As evident from (5) and (10) the proposed approach reduces the computational complexity from $\mathrm{O}(n^2)$ to $\mathrm{O}(n)$ and therefore this model can be easily applied to typical semi-mobile network simulations without increasing physical memory occupation.

D. Limitations of the Proposed Shadowing Model

As for all statistical models, some limitations apply to our shadowing model.

(i) The model is designed for two-dimensional deployments. However, it can be adapted to a three-dimensional model by creating a transformation of a three-dimensional autocorrelation function.

(ii) The proposed model is only valid for distances $d_{i,j}$ between nodes i and j which are larger or equal to the decorrelation distance d_{corr}. For $d_{i,j} < d_{\text{corr}}$ the variance σ^2 of the sum of the two shadowing values $\vartheta(x_i, y_i)$ and $\vartheta(x_j, y_j)$ will increase significantly due to the spatially correlation. To consider distances smaller than d_{corr} one can apply separate maps for each node. This way, the values in the different maps remain statistically independent of each other.

(iii) As the total shadowing loss $\theta_{i,j}$ of a certain link $l_{i,j}$ between nodes i and j is determined by equation (6) the resulting 'shadowing channel' is symmetrical for both the uplink (UL) and the downlink (DL). However, in some cases an asymmetrical channel behaviour is necessary. This can be achieved by simply using two shadowing maps, i.e. one for each transmission direction (UL/DL).

(iv) Finally, in case a single node is mobile while all its neighbours are static, the difference Δ_θ of the shadowing losses from node i to the set of neighbour nodes $\{j, k, \ldots, n\}$ is given by

$$\Delta_{\theta_{i,j}} = \Delta_{\theta_{i,k}} = \ldots = \Delta_{\theta_{i,n}}. \tag{11}$$

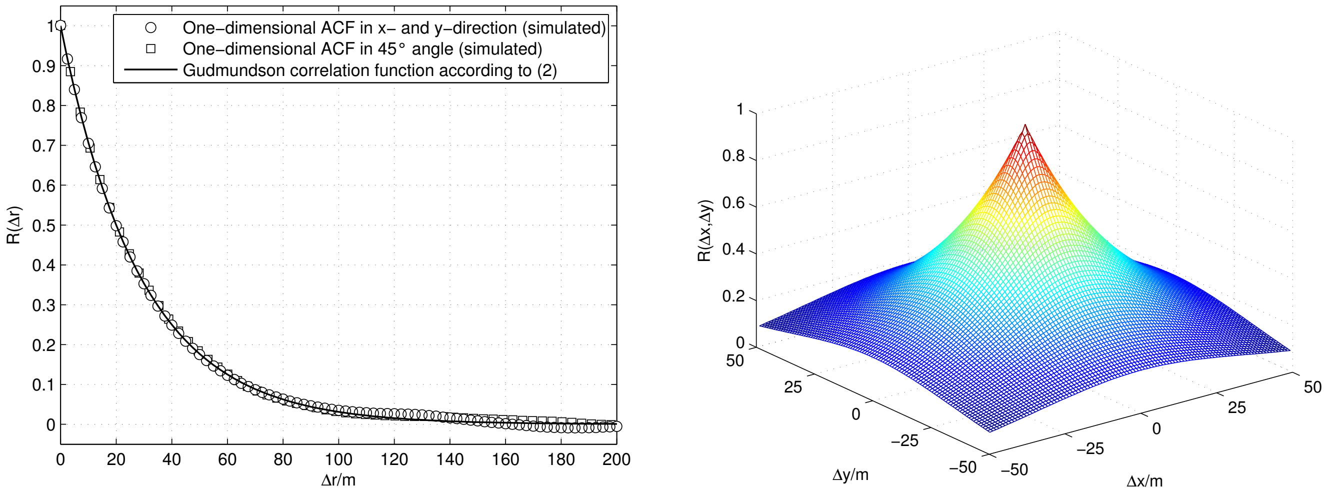
As the probability of such a scenario is low in mobile (ad-hoc) networks, we expect the effect of this on the average performance to be negligible.

III. Numerical Results

Figure 1 shows a detail from a spatially correlated shadowing map of size 2,500 m $\times$ 2,500 m with a resolution Δs of 2.5 m, a decorrelation distance d_{corr} of 20 m, a mean value μ of 0 dB, and a link standard deviation σ_l of 10 dB. In Figure 2 (a) the one-dimensional autocorrelation functions of the given map are depicted. The ACF along the x-axis as well as at a 45 degree angle follow the theoretical ACF given by Gudmundson. The related two-dimensional ACF shown in Figure 2 (b) is of isotropic shape and therefore we can claim the correlation to be independent from the direction of movement. Furthermore, as evident from Figure 3, the proposed approach shows an occupation of physical memory which is significantly reduced compared to a four-dimensional lookup table.

IV. Conclusions

In this paper, we have derived a resource efficient model how to simulate two-dimensional spatially correlated log-normal shadowing. The proposed model fulfils the requirement of an isotropic (two-dimensional) ACF which is independent of the direction of movement. We have also shown how this model can be applied to simulations of



(a) One-dimensional autocorrelation functions.

(b) Two-dimensional autocorrelation function.

Figure 2. Investigation of the properties of the proposed model.

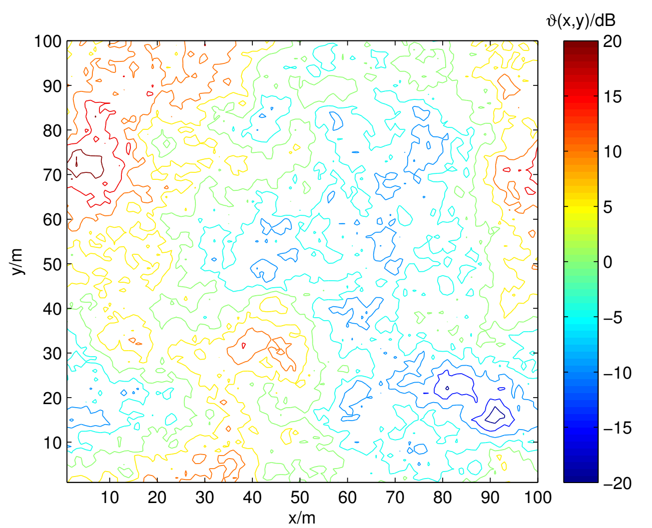


Figure 1. Detail from two-dimensional spatially correlated shadowing map ($A = 2,500$ m $\times$ $2,500$ m, $\Delta s = 2.5$ m, $d_{\mathrm{corr}} = 20$ m), $\mu = 0$ dB, $\sigma_l = 10$ dB.

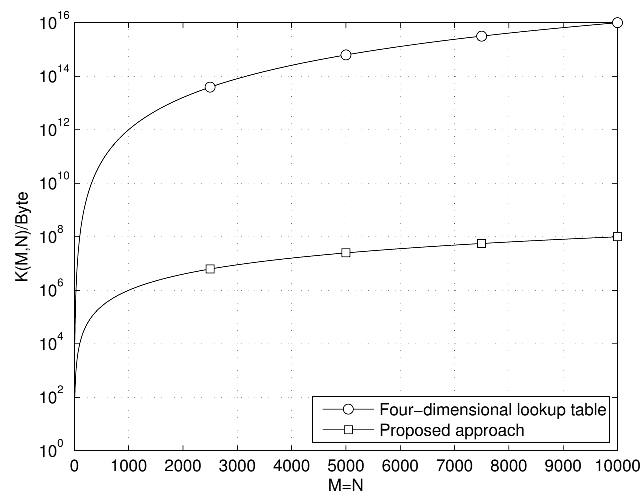


Figure 3. Physical memory occupation of the proposed model (assumption: one byte per map entry).

semi-mobile (ad-hoc) networks as the total shadowing loss is calculated by the sum of the shadowing losses at the positions of the transmitting and receiving node. It was shown, that in cases where variable positioning of both the static and the mobile end of a communication link is required, the proposed approach is significantly reducing the computational complexity to $\mathrm{O}(n)$ compared to the baseline of a four-dimensional lookup table having a computational complexity $\mathrm{O}(n^2)$.

Although the proposed approach is primarily designed for semi-mobile scenarios it may be applied to scenarios of complete mobility by on-demand loading of small maps created for every grid square. We expect this to be more resource efficient - especially in terms of main memory occupation - compared to a single map consisting of shadowing values for all combinations of grid squares. Hence, this approach may beneficial specifically for the simulation of scenarios of large geographical expansion and/or high resolution utilising hardware commonly available.

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