Simulating Spatial Cross-Correlation in Vehicular Networks

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***Abstract*—Wireless channels are defined by the presence and motion of objects between and around the communicating stations. As parts of the environment change, so do the channels between stations that are nearby. While the impact of environmental changes on *individual channals* has been studies extensively, the spatial auto-correlation *across multiple channels*, which we will call *spatial cross-correlation*, has received little attention. These effects are important whenever protocols use multiple channels in real time, such as in multi-hop networks.**

This paper studies the trade-offs between different ways of simulating spatial channel cross-correlation in the context of vehicular networks. We compare independent stochastic, locally cross-correlated stochastic, and explicitly geometric models in terms of both their complexity and the network-level performance they induce. Our results generally favor the geometric approach. Geometric models have higher precision and lower complexity than cross-correlated stochastic models, although collecting the detailed input needed for geometric models can be expensive. As a result, we propose a hybrid approach that combines geometric and stochastic approaches, depending on whether the impact of physical changes has a major or more minor impact on the channels.

I. Introduction

The properties of wireless links are highly dynamic because the signal propagation environment changes as a result of movement in the environment. The performance of many wireless network protocols is sensitive to changes in wireless channel and consequently link properties, *e.g.*, transmit rate adaptation. Some protocols are also sensitive to how these changes are *correlated across multiple links*. Examples include routing protocols that adapt to quality of the links in multi-hop wireless network [1], [2] or protocols that rely on opportunistic overhearing of packets [3]. In a mobile environment with multiple wireless links, the changes of nearby links are not independent because the links share the same physical environment. Movement by objects, for example, is likely to impact all nearby links, although the precise nature of the impact will differ. We will refer to this phenomenon as spatial cross-correlation between wireless links. When such correlation is not accounted for properly, the diversity of adjacent links is often overestimated, which can lead to incorrect results, *i.e.*, the performance of techniques obtained in simulation may differ significantly from those obtained in the real world.

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This paper studies the trade-offs in terms of cost and accuracy of modeling spatial correlation for two common classes of channel models: geometric and stochastic models. Geometric models explicitly consider components of the physical space that are relevant to a channel, and directly derive the channel property. An example is the ITS Irregular Terrain Model point-to-point mode for path loss [4]. Since they explicitly represent the physical environment, geometric models automatically capture spatial correlation. While potentially very accurate, the drawback is that collecting the necessary detailed physical input can be time consuming or even impossible. Alternatively, stochastic models directly generate the desired channel property using a random process and some expected statistics, *e.g.* log-normal shadowing, Raleigh, Rician and Nakagami fading [5], [6]. Such models require far fewer parameters (*e.g.* a different K factor or maximum Doppler shift) and are often computationally simpler. They are generally less accurate, however, and crucially they do not capture cross-correlation unless it happens to arise from correlated *input* parameters.

Using line of sight (LOS) blocking in a vehicular network as an example, we compared the geometric and stochastic approaches in terms of cost and fidelity of capturing channel correlation. We found that stochastic cross-correlation models have very high computational complexity, although it may be manageable for sparsely-correlated networks. A simulation of a simple gossiping protocol in an urban environment with rich LOS blocking shows that stochastic models are less accurate than a geometric model. In contrast, explicit geometric modeling of the physical environment is also computationally simpler, but it introduces the new challenge of finding accurate *input* data for the model. We consequently suggest a hybrid approach in which correlation for channel effects caused by major physical effects, *e.g.*, buildings affecting LOS, is modeled geometrically, while those

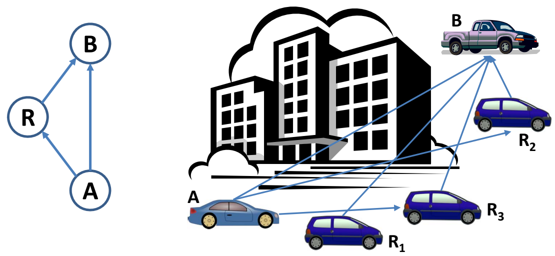

Fig. 1: Examples of Spatial Correlation across Links

caused by more minor effects, *e.g.*, cars affecting LOS, are modeled stochastically.

The main contributions of this paper are:

1) We present the design space for modeling spatial correlation across wireless channels.
2) We present a technique for adding such correlation to stochastic channel models, since they do not inherently provide it.
3) We analyze the complexity of the different modeling options and and compare their fidelity using a use case, LOS blocking in vehicular networks.

The rest of the paper is structured as follows. §II motivates the need for modeling channel cross-correlation. §III presents a design space for modeling spatial correlation, and we look at an example of modeling LOS blocking, including a novel correlated stochastic model, in §III. Next we present our analysis of simulation complexity and simulation results in §V and § VII. We discuss related work in §VIII, and conclude in § IX.

II. Channel Dynamics and Network Adaptation

Channel variations may require adaptation by protocols at all layers of the protocol stack. Most adaptive behavior targets the optimization of individual links, e.g., transmit rate adaptation to changing channel conditions or application-level strategies to deal with bandwidth variations. To properly evaluate such optimizations, it is sufficient that accurate channel models are used and that their inputs are set and changed in a way that reflects the target physical environment. However, for the evaluation of protocols that deal specifically with topology (e.g., routing) or that try to leverage spatial diversity, simulators also have to accurately model the spatial properties across groups of channels.

As a simple example, let us consider PRO, a Protocol for Retransmitting Opportunistically [3]. In PRO, if a transmission from a transmitter A to a receiver B fails (Figure 1), a relay node R can retransmit the packet on behalf of A, if it overheard the packet and has a better channel to B than A does. Evaluation in both a controlled and in-the-wild testbeds has shown that PRO can improve throughput, especially in environments with significant fading, which is not surprising since PRO leverages spatial diversity between channels A→B and A→R, and A→B and R→B. If those channels have very similar properties, PRO will have limited benefits.

The goal of this paper is to determine how to best model spatial correlation across channel in support of topology sensitive experiments. We specifically focus on vehicular networks which are challenging because of the high degree of mobility and rich channel dynamics. Let us consider how Line of Sight (LOS) conditions may affect PRO's performance in a vehicular network using Figure 1. In this scenario, the channel A→B is blocked by a building, meaning that a relay node might help. However, many potential relays *also* have a blocked LOS, either to the source A (e.g, relay R_2) or destination B (e.g, relay R_1). If the relay links are consistently blocked at the same times as the primary link (that is, if LOS blocking has high cross-correlation) the benefit of PRO will be reduced.

III. Modeling Spatial Correlation

This section classifies models by how their dynamics originate. We identify two classes of common channel models, geometric and stochastic, and discusses they can support spatial correlation. We will use the LOS property as a running example.

A. Spatial Auto- and Cross-Correlation Revisited

There is a key distinction between spatially-determined correlation of a single channel's properties as it moves over time (spatial auto-correlation) and correlation of nearby channels' properties at a given time (spatial cross-correlation). They reflect the same physical effects, but may require different modeling. Especially: Channel properties are commonly modeled with auto-correlated random sequences where the expected amount of change between samples is related to how far a station has moved in that time. This is true of essentially all fading models (though specific movement is often abstracted as speed, and the movement of *other* objects in the environment may be lumped in with the stations' movement), and also of many shadowing models, *e.g.* [7], [8]. Nothing in this approach creates cross-channel correlation: Under such a model, nearby or co-located channels will be completely statistically independent.

B. Geometric Models

At one extreme, in a purely deterministic model (e.g. distance-based path loss) the dynamics of the output (loss) follow directly from variation in the input (distance between transmitter and receiver), or else are not captured at all. For geometric models, the calculated channel properties are completely determined by input (environment details). Spatial auto- and cross-correlation are generated (or not) equally: The same physical features give rise to each. In the LOS example of Figure 1, if the same information about the location and size of physical objects (buildings, cars) is used consistently throughout the simulation, both kinds of spatial correlation will be captured, allowing for a realistic evaluation of protocols such as PRO.

C. *Stochastic Models*

At the other end, dynamics are entirely internal to the model. Rayleigh Fading is the classic example: The input parameters (station speed and carrier frequency) change slowly or not at all, and the output variation comes from an autocorrelated random variable. The underlying physical events (the positions of the objects whose motion is causing the fading) are not represented, but instead model inputs are chosen so the properties of the channel model output match those observed in the real world.

In order to have realistic inter-channel correlation, it must be modeled explicitly. This implies (a) determining the expected correlation properties among channels, and (b) applying this correlation to (time-series) models while maintaining their statistical properties. The primary example of this approach in practice is correlated fading for MIMO channels [9]. We present a harder example in § IV. As with MIMO, the approach which we explore here is to enforce correlation across the random variables which are implicit *inputs* to stochastic models, however with a discrete model that has a more complicated structure.

Between the two extremes, a stochastic model may have some environment-specific inputs. Examples include fading models that use some information about the physical environment, e.g., density of objects and degree of mobility [10]. If environment information and its changes are used consistently across "independent" channels, this may capture some or all of the covariance.

D. *Discussion*

Network simulators typically model channels by combining models for different features. When doing site-specific simulations, geometric models are preferred since they are more accurate, but collecting the models inputs can be expensive. For this reason, geometric and stochastic models are often combined. For example, [11] describes the models used for the vehicular channels on a suburban street. They include:

- Large-scale path loss is based on a geometric model (log-distance model).
- Fading caused by reflections off large objects (e.g., buildings) is based on a geometric model for a suburban street [10].
- LOS blocking by other vehicles uses a stochastic model.
- Scattering caused by small objects is based on a stochastic model.

The first two models correspond to the largest physical effects, so generating the inputs is realistic [12]. Collecting site-specific inputs for the last two properties would be very expensive, so a stochastic model is used. If we need to accurately model spatial correlation, an explicit model will be need will be needed for those, but not for the first two.

IV. Example: LOS Modeling

Shadowing is a reduction in signal strength caused by obstructions which absorb incident energy or reflect it away from the shadowed area. Shadowing occurs when obstructing objects – stationary or mobile – impinge significantly on the Fresnel zone around the dominant propagation path.

The *time and space scales* of shadowing makes it especially important for vehicular networks: Unlike small-scale fading, shadowing occurs on a time scale that network protocols can (and should) react to [13]. At inter-vehicle scales, shadowing is neither stable like large-scale path loss, nor effectively uncorrelated like fading.

A. *Shadowing vs. Line of Sight*

For the sake of this work, we consider a significant simplification: Treating shadowing by cars and buildings as a binary condition (Line-Of-Sight vs. Non-Line-Of-Sight). This is not entirely unreasonable at high frequencies [14]. We emphasize that the goal of this paper is not to propose or evaluate the LOS/shadowing models as such, but rather to use them as a test case for comparing simulation approaches. For this purpose, we choose a *discrete* model precisely because it is a common class of model which is also challenging from a correlation standpoint.

B. *Example: Geometric-Deterministic LOS Model*

We consider a simple geometric LOS model: The position of every vehicle in our simulated environment is modeled. Vehicles which are on the same road have an NLOS state if and only if another vehicle is on the same road between them.[1] Vehicles on different road segments but within 50 m of each other (that is, roughly, vehicles within the same intersection for the road sizes in this neighborhood) have an unobstructed LOS. Vehicles on different road segments between 50 m and 175 m (that is, on intersecting roads) have NLOS. (NLOS

[1] This model does not consider which lane any given vehicle is in; it may therefore have false positives when the "intervening" vehicle is not actually physically between the communicating pair.

propagation conditions near intersections are investigated in *e.g.* [15].) While this is in many ways a simplification, they key point is that LOS properties are directly derived from the environment, and the movement of cars relative to each other is explicitly considered.

C. Example: Stochastic Shadowing Model

Here, we briefly introduce a typical stochastic shadowing model based on [16], and shown in Figure 2. This is a two-state Markov model; the states considered are *LOS* and *NLOS*. The transition probabilities are p_1 and p_2. At initialization, each link randomly selects a starting state. For each state, the probability distribution over possible subsequent states is realized as a discrete random variable. Because each state in this model has only two possible next states, the discrete "next state" distributions are implemented as random variables r with a continuous distribution and a cutoff threshold. For example, if $current\_state = LOS$, $next\_state$ is $NLOS$ iff $r_i <= p1$.

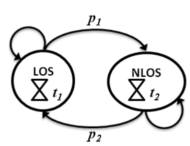

Fig. 2: Two-state Markov Shadowing Model

D. Spatial Cross-Correlation for the Stochastic Model

In the model just described, each link is modeled independently with individual streams of random variables as input. The correlation among multiple links is missing in this modeling process. For the purposes of this work, we *assume that the desired level of cross-correlation is known*. Determining the expected correlation is a major measurement and modeling undertaking in its own right. For this work, we use a very simple model, where correlation is a piecewise linear function of distance (measured from the "center point" of each link), ranging from 0.9 at 0 m to 0.01 at 1500 m. Distance-based correlation models (either auto- or cross-) have been successfully developed for small-scale fading [17], path loss [18], shadowing from stationary objects [19], and more.

In this model, input random variables r determine the next transition out of each state. To find the necessary *input* correlation among the random variables to produce a desired *output* correlation in the state, we solve for the stationary distribution of the Markov chain given p_1 and p_2 and numerically compute the input-output relation.

Consider a network of n connected links that are simulated independently with random variable streams r_l $l \in [1, n)$, where each l represents one link. The desired (input) correlation between link l_1 and link l_2 is denoted as $C(l_1, l_2)$. The pairwise correlation is described by an n by n correlation matrix C.

Given i.i.d. random variables for all links $R = [r(l)]$, the original correlation among inputs is $RR^T = I$. The task is to find $R_{corr} = [r_{corr}(l)]$ such that

$$R_{corr} R_{corr}^T = C \tag{1}$$

As elements of matrix C are chosen individually, there is no guarantee that C is a valid correlation matrix (C is symmetric, but not always positive-definite). A simple way to deal with this is to find the nearest correlation matrix $C_{near}$for C [20], [21]. Then, a corresponding R_{corr} can be found by computing an X through spectral decomposition of C_{near} such that

$$X^T X = C_{near} \tag{2}$$

The correlated input R_{corr} can then be derived by:

$$R_{corr} = RX \tag{3}$$

Each stream in $R_{corr} = [r_{corr}(l)]$ is now a linear combination of original n i.i.d. random inputs, and still preserves original statistics. Note that these computations will need to be repeated whenever the desired pairwise correlation changes.

V. Discussion on Complexity

In this section, we analyze and compare the modeling complexity of a network-wide simulation correlated wireless channels using the geometric and stochastic strategies discussed earlier in the paper.

A. Simulation Model

We assume a simulation of a network of N nodes that move around in a physical environment, and at most n ($0 \leq n \leq N$) nodes are within range of a node. Because simulators need only model links for which the end-points have a realistic chance of being within communication or interference range, the number of links to simulate drops from N^2 to nN links. n varies based on the node density and expected communication range.

As nodes move, both channel state and internal data structures must be updated. Not all movement events require all data to updated, however.

The most frequent events are updates of the channel state, which can then be used to calculate packet level errors and link state. We will denote the update frequency of the channels as f_c and the interval between updates as t_c, i.e., $f_c = 1/t_c$. The minimum frequency f_{c_min} at which channels must be updated depends on the speed of both the wireless devices and other objects in the environment. If exact fading state is maintained, this must be recomputed for a movement of even a small fraction of a wavelength. Other channel properties, such as path loss, LOS, and Doppler shift, will typically change more slowly. The update frequency f_c can usually be determined based on the maximum speed of objects in the environment.

Correlation matrices (when they exist) need to be updated when then the relative positions of nodes change "enough." Exactly what that means will depend on the model used, however it is expected that this rate $f_{corr} \ll f_c$.

B. Geometric Models

We denote by M the total number of objects modeled in the simulated environment, and the maximum number of objects to be considered when modeling a link is denoted as m. The per link cost associated with a geometric channel model includes two components: First, identifying the m objects that may impact the link, *i.e.*, that are within a certain range, thus can be done in $O(\log(M))$ time, as per [22]. Second, there will be an actual modeling complexity which depends on m; we'll denote this $C_g(m)$. For the model described in §IV, this is $\Theta(m)$. With geometric models, there is no extra cost for modeling spatial correlation across channels, it is already reflected in the overhead associated with modeling the objects. This gives a complexity of $O(nm)$, which is also $O(NM)$ in the common case.

C. Stochastic Models

The costs are similar for stochastic models, except that when modeling correlation among multiple links, an additional step is required to calculate desired correlation properties. For example, the correlated simulation model described in § III considers the first-order spatial correlation, where all links in the vicinity of a given link are modeled collectively. In this case, there are three major steps: (a) calculate correlation coefficients in a correlation matrix, (b) spectral decomposition of the correlation matrix, and (c) calculate correlated random input. The first two steps occur with a frequency of f_{corr}, while the last step occurs with a frequency f_c.

Let n_{corr} be the maximum number of nodes in the correlated vicinity of a given link. The complexity of each of the above step is determined by the size of the correlation matrix (n_{corr} by n_{corr}). Therefore, the overall cost for all links combined is: n_{corr}^2 correlation coefficients for step (a). For step (b), a reasonable cost for eigenvector decomposition in Equation 2 is $O(n_{corr}^6)$ [23]. For step (c), the complexity is n_{corr}^2 for each link in Equation 3, thus $O(n_{corr}^4)$ for all links. Consequently, the overall complexity is dominated by the eigenvector decomposition, and requires $O(n_{corr}^6)$ time.

VI. NS-3 SIMULATION MODELS

A prototype of the proposed stochastic shadowing model with correlation was implemented in ns-3. We

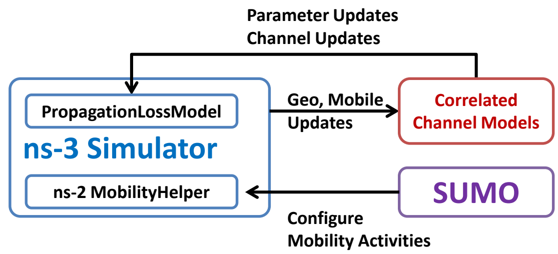

Fig. 3: Simulation Platform Overview

utilize this simulation model to evaluate realism of statistic shadowing models againt geometric models. Our simulation examines the performance of a "generic" gossiping protocol in an urban V2V network, compared across the different LOS models.

A. Gossiping Protocol

The protocol we use in the simulation is as follows: Each vehicle broadcasts status packets with a fixed interval of 100 ms. When a vehicle receives a new message in an incoming packet, it selectively re-broadcasts the new message with a certain probability (to avoid message flooding). Gradually, each message will spread throughout the network.

The primary performance metric for the gossip protocol is the delivery time of messages in the vehicular network, *i.e.*, how long it takes for vehicles to receive a new message. Our interest is not in the actual performance of this (admittedly very simple) gossiping protocol. Rather, we are interested in understanding the relative difference in performance of the gossiping protocol, when different models of spatial correlation across links are used.

B. Simulation Setup

A road network map was generated for a roughly 1.5 km x 1.5 km semi-residential region of a major U.S. city. Three-hundred vehicles are simulated; they move along roads following the true map, however the specific traffic load and vehicle routes are synthetically generated using MOVE [24] and SUMO [25]. A new message is generated every 0.01 s at one single vehicle in the center. Each simulation runs for 20 seconds, during which time the new message was always distributed to all vehicles that are reachable in the network. Wireless channels and networking were simulated in ns-3 [26], which was extended with the shadowing channel models described in § VI-C. The channel, PHY and MAC layer were implemented as a `YansWifiChannel` model with log-distance large scale path loss (exponent = 3.0) and Rayleigh [2] fading, in addition to our shadowing models.

[2]Note that ns-3 does not support Rician or more vehicular-specific fading models, unless one wishes to do symbol-by-symbol simulation with `PhySim-WiFi`.

C. Shadowing Models

We implemented the geometric and stochastic LOS models described below. Across all models, an additional shadowing loss of 8 dB is added to any NLOS (shadowed) link. We use the following three shadowing models, and a baseline "No obstructions" case without shadowing.

1) Geometric: The model described in § IV-B: Vehicle-vehicle obstructions are directly inferred from their positions; obstruction by buildings is assumed when vehicles are not on the same street or near an intersection.

2) Stochastic (Independent): In the stochastic model, links are modeled independently, so the shadowing properties of links are independent. The Markov two-state shadowing model described in § IV-A is implemented, and each link is associated with one instance of this model. The transition probability parameters are fitted to match the behavior of the geometric model as closely as possible; this is described in more detail in §VI-D.

3) Stochastic (Correlated): The stochastic LOS model is modified to enforce pairwise correlation as described in §IV-C.

D. Accuracy of Stochastic LOS Model

The uncorrelated stochastic line-of-sight model introduced in § IV-C has two free parameters: p_1 and p_2. They determine the expected duration of LOS and NLOS periods respectively:

$$E[T_{LOS}] = \frac{1-p_1}{p_1} \quad E[T_{NLOS}] = \frac{1-p_2}{p_2} \qquad (4)$$

We aim to isolate the effect of spatial variation and correlation: That is, to the extent possible *average link performance is held constant across models*, leaving the spatial and temporal differences as determinants of application-layer performance. Therefore, we configure p_1 and p_2 in this way: we select the $\frac{p_1}{p_2}$ ratio that produces a PDR which matches the actual link PDR property observed from geometric model from § IV-B.

Next, the exact p_1 is calculated from $E[T_{LOS}]$ and p_2 value is determined afterwards.

Figure 4 shows the distributions of the duration of LOS and NLOS states for links across all models considered. Note that the correlated and uncorrelated stochastic cases have the same distribution (as expected), and the geometric case is similar but not the same. The mean duration for each state is close across models (see Table I).

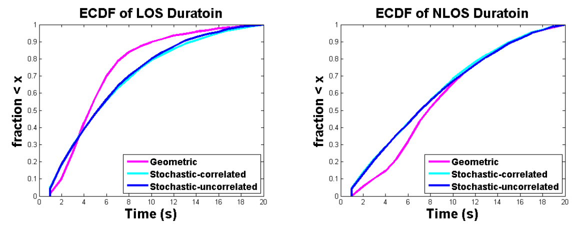

Fig. 4: ECDF of LOS and NLOS durations.

	Geometric	Stochastic
Packet delivery ratio	0.28	0.23
LOS probability	0.89	0.73
E[LOS duration] (s)	5.87	6.75
E[NLOS duration] (s)	9.09	8.35

TABLE I: Link-level Comparison of Shadowing Models.

VII. Results

The simulation results address two basic questions: *1. Do spatial patterns in link quality matter to application performance?* and *2. How well does a stochastic model with explicit spatial correlation approximate the effects of "real" spatial patterns?* We define application-layer performance as the time required for each participating node to receive the gossiped message. This section looks at both overall performance (the distribution of delivery time over all nodes) and delivery time relative to distance.

A. Overall Message Delivery Time

Figure 5 shows the cumulative distribution function of the delivery times over all nodes in the simulation. In addition to the three shadowing models already discussed, a baseline *no obstructions* case is included for reference. This shows the performance without any shadowing effects. In these results, the geometric model is the "reality" that the stochastic models were tuned to approximate; difference in application performance

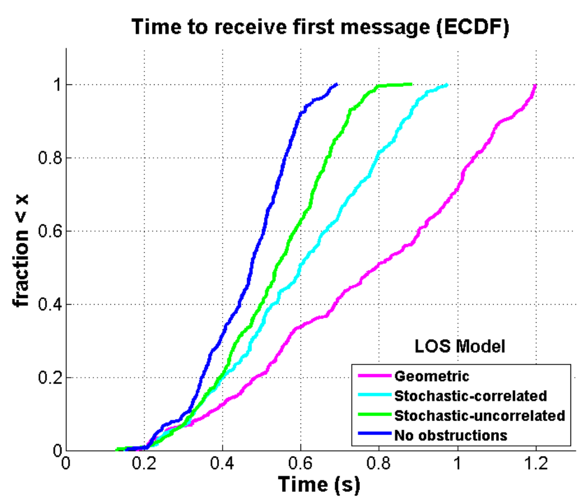

Fig. 5: End-To-End Delay

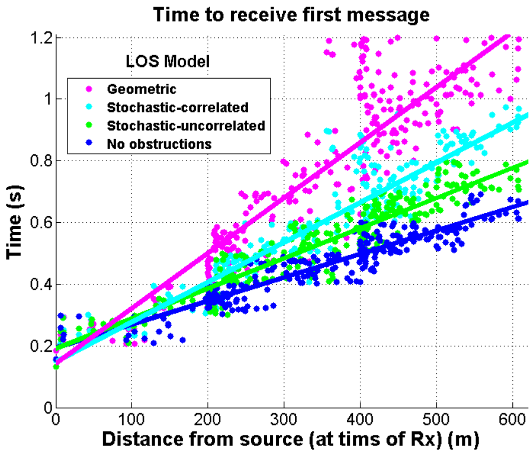

Fig. 6: Message Delivery Time

(whether higher or lower) is therefore a measure of inaccuracy in the stochastic models.

We observe a substantial effect from spatial and temporal variation: The median packet delivery time is $0.52\,\mathrm{s}$ for the independent model $0.82\,\mathrm{s}$ for the geometric case; the Kolmogorov-Smirnoff (K-S) distance between the two distributions is 0.6. Recall from § VI-D and Table I that the probability of success for an arbitrary link at an arbitrary moment is very similar across the geometric and both stochastic models. In fact, the geometric model produced a slightly *better* PDR, along with lower overall perfomance. The Markov (stochastic) model has similar (but not identical) time-series behavior to the geometric case, suggesting spatial patterns as the primary difference.

We additionally note a significant difference between the correlated and independent stochastic model outputs: The K-S distance is 0.37. In this case, the degree of cross-correlation is the only difference between the models. The cross-correlated model is closer to the geometric model (in both median and variance) than the independent model is, but there is still a significant difference (K-S distance of 0.36).

B. Delivery Time Relative to Distance

Figure 6 is a scatter plot of message delivery times (y-axis) as a function of the distance between the receiver and the vehicle that originated the message.

If we draw a line to approximate linear regression of the delivery time vs. distance, the slope is proportional to the number of hops for a given distance. Geometric models impose constraints on connectivity as a result of LOS blocking due to buildings and vehicles, and as a result, more hops are required on average compared to the empty world model that ignores shadowing. Using stochastic shadowing model improves the level of realism somewhat relative to the empty world model, while adding spatial correlation brings the results even closer to those obtained with the geometric model.

Regarding the horizontal distribution of delay for a given distance, the results based on the geometric shadowing model have the widest range. The reason is that the geometric model captures spatial diversity in the most detail, e.g., consistently distinguishing between node pairs on the same road segment, near an intersection, or on parallel road. The diversity for a given distance indicates the spatial variation of link property (at the same distance). Since both the empty world and stochastically uncorrelated models are spatially independent (or homogeneous in all directions) by nature, the horizontal diversity range is minimum compared to other models. The stochastically correlated model falls in between.

VIII. Related Work

The spatial correlation of shadowing property among adjacent links have been frequently observed in wireless networks. Some measurement study specifically quantified the level of correlation versus distance in urban and suburban area [19], while others studies the correlated shadowing effects in multi-hop networks [8] and vehicular network [27]. Studies have shown the correlation in shadowing effects has significant impact on wireless protocol performance [28], specifically in vehicular networks [29]. Moreover, such correlation can even be utilized in discovery [30] and geographic mapping [18].

Two different types of stochastic correlated models have been proposed for wireless channels. One type is for large-scale path loss models [19], and the other type is for small-scale channel properties in MIMO [17]. Correlated stochastic shadowing models are not present in most wireless simulation platforms such as [26] and [31]. When evaluating adaptive protocols (such as PRO[3]) that are sensitive to spatial correlation, the spatial diversity, which is essentially the opposite side of correlation, could be mis-represented.

IX. Conclusion

This paper addresses challenges in modeling cross-channel correlation in wireless networks. For a V2V gossiping test case, we find that cross-correlation in (simulated) channel conditions *does* significantly impact observed protocol performance, affirming the importance of simulating such cross-correlation accurately. Stochastic channel models – including ones considering spatial autocorrelation of individual channels – will systematically underestimate cross-correlation between channels. For protocols which benefit from decorrelation (diversity) this may result in unrealistically good performance in simulation.

We compare two general approaches to simulation spatial cross-correlation: (1) Geometric models in which cross- and auto-correlation result automatically from the effects of explicitly-modeled objects, and (2) Stochastic models in which cross-correlation must be explicitly imposed. We find that, in addition to being less accurate, the second approach is unexpectedly computationally demanding, with complexity up to $O(n^6)$ in the number of nodes. This suggests that the first approach is generally preferable, except when the detailed environmental information it requires is not available, or link cross-correlation is sparse. We advise a hybrid approach of geometrically modeling large objects, which are generally more knowable and significant, while stochastically modeling the small and highly-variable.

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