A New Simulation Method for UAV Communication Channels Based on GPUs

Xujun Hu, Xiaomin Chen, Qiuming Zhu, Weizhi Zhong, and Bin Chen

Abstract—In this paper, an unmanned aerial vehicle (UAV) communication channel model is established by considering the propagation path loss, shadowing, and multi-path fading. Moreover, an efficient generation method for Gaussian random processes based on sum of sinusoids (SoS) theory is presented and is easy to realize by a graphics processing unit (GPU). Based on the proposed method, a new real-time generation method for multi-path shadowing composite fading is designed and implemented. The implementation results show that the proposed approach enables the easy generation of multi-path shadowing composite fading while reducing the processing time. Meanwhile, the impacts of flight altitude and communication scenarios on the performance of the UAV communication system are discussed. The results of this paper should have significant application value in UAV communication channel simulation.

Index Terms—UAV communication channel, SoS, GPU, channel simulation.

I. INTRODUCTION

Due to their simple structure and low cost, unmanned aerial vehicles (UAVs) have found a wide range of applications such as communications, emergency assistance, and environmental monitoring [1]-[2]. An UAV communication channel simulator, which can be easily used to analyze the performance of an UAV communication system, can not only reduce project costs but also accelerate development cycles. Therefore, research on UAV communication channel model simulation has become a hot topic because such studies can improve the efficiency and quality of an UAV communication channel simulator by using a graphics processing unit (GPU).

Channel fading includes shadowing and multi-path fading, which obey log-normal and Nakagami distributions, respectively [3]-[4]. Measured data for UAV communication channels in different scenarios are reported in [5] and [6], which show that shadowing and multi-path fading have a substantial influence on UAV communication channels. A three-dimensional geometric channel model is proposed for air-to-ground communication environments in [7]. In this work, the proposed model considers the air station and ground base station to be located at foci points of

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Q. Zhu is with the College of Electronic and Information Engineering, Nanjing University of Aeronautics and Astronautics, Nanjing, 211106, China, and the Institute of Sensors, Signals and Systems, School of Engineering & Physical Sciences, Heriot-Watt University, Edinburgh EH14 4AS, U.K. Q. Zhu is corresponding author. (e-mail: zhuqiuming@nuaa.edu.cn). a virtual bounding ellipsoid that corresponds to the delay of the longest propagation path. In addition, an extension to the geometric air-to-ground ellipsoidal radio channel model is proposed for predicting the performance of MIMO for lowaltitude air-to-ground systems in [8]. Furthermore, a statistical channel model for path loss, multi-path, and small scale characterization of UAV communication channels is developed in [9], and it can be extended to larger communication distances and flight altitude. However, the UAV communication environment is always complicated and changing. Thus, it is difficult to simulate UAV communication channels efficiently and accurately. Due to the high computing power of a GPU, it is necessary to use a GPU to accelerate the channel simulation. A design methodology for computing the time-varying coefficients of the fading channel simulators using GPUs is proposed in [10]. With the use of GPUs and the proposed methodology, it is possible for nonspecialized users in parallel computing to accelerate their simulation developments compared to conventional software. In addition, an efficient simulator implementation of a geometry-based spatial channel model on GPU is proposed in [11] and the channel coefficient generation, additive white Gaussian noise generation, input signal filtering and noise addition are optimized by making full use of the GPU's computing power. However, these fading channel simulators do not consider the influence of shadowing, while extensive measured data show that shadowing has a great influence on UAV communication channels, as reported in [5] and [6].

Overall, this paper proposes an UAV communication channel model. The channel model consider the propagation path loss, shadowing, and multi-path fading. In addition, an efficient generation method for Gaussian random processes based on sum of sinusoids (SoS) theory is presented and can fully utilize the parallel computing power of GPU. On this basis, a new real-time generation method for multi-path shadowing composite fading is implemented and validated.

The rest of this paper is organized as follows: In Section II, a typical UAV communication channel model is established. In Section III, the SoS theory for fading channel simulation is analyzed and a new real-time generation method for multi-path shadowing composite fading is presented. In Section IV, the real-time generation method is validated by simulations. Finally, the conclusions are presented in Section V.

II. UAV COMMUNICATION CHANNEL MODEL

We consider the typical UAV communication systemshown in Fig. 1. The received signals include not only direct signals but also reflecting and scattering signals because of the influence of barriers on the transmitted signal. Considering the influences of propagation loss, shadowing, and multi-path fading, the received signals of the ground station can be modeled as

$$y(t) = \sqrt{\alpha(t)\beta(t)}\gamma(t)x(t-\tau) + n(t)$$
(1)

where x(t), y(t) are the transmitted signal of the UAV and the received signal of the ground station, respectively. τ represents the delays of the UAV communication links and $\alpha(t)$ denotes the path loss of the UAV communication links, which can be expressed in logarithmic form [12]

$$\alpha_{\rm dB} = 32.44 + 20\log(f_{\rm MHz}) + 20\log(d_{\rm km})$$
 (2)

where $f_{\rm MHz}$ is the carrier frequency expressed in MHz and $d_{\rm km}$ is the length of the communication link expressed in km. In addition, $\beta(t)$ is the shadowing of the UAV communication links. Usually, the shadowing follows a lognormal distribution, which can be expressed as [3]

$$f_{\beta}(x) = \frac{1}{\sqrt{2\pi\sigma_x x}} \exp\left[-\frac{\left(\ln x - \ln \mu\right)^2}{2\sigma_x^2}\right]$$
(3)

where μ is the mean power of fading, σ_x denotes the shadowing factor, and $\gamma(t)$ is the multi-path fading of the UAV communication links. The multi-path fading models primarily include the models of Rayleigh, Rice and Nakagami. One of the most popular and flexible models is the Nakagami model [13]-[15], which can be expressed as

$$f_{\gamma}(x) = \frac{2}{\Gamma(m)} \left(\frac{m}{\Omega}\right)^m x^{2m-1} e^{-\frac{m}{\Omega}x^2}$$
(4)

where $\Gamma(m), \Omega = E[x^2]$ are the Gamma function and the mean power of multi-path fading, respectively, and $m \ge 0.5$ denotes the Nakagami factor. The Nakagami distribution can be converted into Gaussian and Rayleigh distributions when *m* is equal to 0.5 and 1, respectively. Otherwise, the Nakagami distribution can be converted into the Rice distribution when m > 1. Therefore, the probability density function (PDF) of the multi-path shadowing composite fading can be expressed as



Fig. 1. Typical UAV communication system.

$$f(x) = \int_0^\infty f_{\gamma}(x|\Omega) f_{\beta}(y) dy$$
(5)

III. SOS SIMULATION MODEL AND GPU IMPLEMENTATION

A. SoS Simulation Model

Due to its simple structure and low complexity, the SoS simulation model has been widely used in fading channel simulation. According to the SoS simulation model, a Gaussian random process can be generated by summing multiple sinusoids, which is expressed as [16]

$$u_i(t) = \sqrt{\frac{2\sigma^2}{N}} \sum_{n=1}^{N} \cos\left(2\pi f_{i,d} \cos\alpha_{i,n} t + \varphi_{i,n}\right)$$
(6)

where *N* is the number of propagation paths and σ^2 denotes the variance of a Gaussian random process. In addition, $f_{i,d}$ is the maximum Doppler frequency and $\alpha_{i,n}, \varphi_{i,n}$ are the angle of arrival and the initial phase of the *n* th propagation path, respectively. Both $\alpha_{i,n}, \varphi_{i,n}$ are uniformly distributed over $[0, 2\pi)$ and they are mutually independent.

According to the properties of random variables, the shadowing process can be generated by a nonlinear transformation of the Gaussian random process $u_{k,0}(t) \sim CN(0,1)$ with mean 0 and variance 1, which can be expressed as

$$\beta(t) = e^{\sigma_x u_{k,0}(t) + \mu} \tag{7}$$

and the multi-path fading process can be generated by 2mGaussian random processes $u_i(t) \sim CN(0, \Omega/2m)$, which is expressed as [17]

$$\gamma(t) = \sqrt{u_{k,1}^2(t) + u_{k,2}^2(t) + \dots + u_{k,2m}^2(t)}$$
(8)

Moreover, the PDF of Gaussian random processes based on the SoS simulation model can be expressed as [18]

$$\hat{f}_{u_i}(x) = 2 \int_0^\infty \left[\prod_{n=1}^N J_0\left(2\pi \sqrt{\frac{2\sigma^2}{N}}v\right) \right] \cos(2\pi v x) dv \qquad (9)$$

According to [19], when $N \rightarrow \infty$,

$$\lim_{N \to \infty} \left[J_0 \left(2\pi \sqrt{\frac{2\sigma^2}{N}} v \right) \right]^N = e^{-2(\pi v)^2}$$
(10)

The final result is derived by substituting (10) into (9) as

$$\lim_{N \to \infty} \hat{f}_{u_i}(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{x^2}{2\sigma^2}}$$
(11)

Therefore, the random process based on (6) is a Gaussian distribution $X \sim CN(0, \sigma^2)$ when $N \rightarrow \infty$, and the PDF of the random process based on (7) can be expressed as [18]

$$\hat{f}_{\beta}(x) = \frac{2}{\sigma_x x} \cdot \int_0^\infty \left[\prod_{n=1}^N J_0\left(2\pi\sqrt{\frac{2}{N}}v\right) \right] \cos\left(2\pi v \frac{\ln x - \mu}{\sigma_x}\right) dv (12)$$

When $N \rightarrow \infty$ and $\sigma^2 = 1$, the PDF of $\beta(t)$ is a log-normal distribution obtained by substituting (10) into (12).

Similarly, the PDF of the random process based on (8) can be expressed as [18]

$$\hat{f}_{\gamma}(x) = 2x \int_{-\infty}^{\infty} \left\{ \prod_{i=1}^{2m} \Xi \right\} e^{-j2\pi w x^2} \mathrm{d}w$$
(13)

where

$$\Xi = \int_0^\infty \int_0^\infty \frac{\cos\left(2\pi\nu\sqrt{y}\right)}{\sqrt{y}} \left[\prod_{n=1}^N J_0\left(2\pi\sqrt{\frac{2}{N}}\nu\right) \right] e^{j2\pi\nu y} dyd\nu \quad (14)$$

When $N \rightarrow \infty$, the PDF of $\gamma(t)$ is a Nakagami distribution, which is obtained by substituting (10) into (13).

To verify the accuracy of these derivations, we set the simulation parameters as $f_{i,d} = 48.4 \text{ Hz}$, m = 1, $\sigma_x = 1 \text{ dB}$. The simulated PDFs for composite fading under different values of *N* are compared with the theoretical distribution in Fig. 2, for 10⁶ samples. Compared with the theoretical results, the simulated PDF gradually approximate the theoretical results as the parameter *N* increases.



Fig. 2. Theoretical and simulated PDFs for composite fading in different values of $\,N$.



Fig. 3. GPU implementation for Gaussian random process generation.

thread GPU						
block n		block 0 $\sigma_x \rightarrow \mu \rightarrow \beta(t)$				
$u_{k,0}(t_{n,i})$ $u_{k,0}(t_{n,1})$ $u_{k,0}(t_{n,0})$		$ \underbrace{u_{k,0}(t_{0,i})}_{k,0} \underbrace{u_{k,0}(t_{0,1})}_{k,0} \underbrace{u_{k,0}(t_{0,0})}_{k,0} \underbrace{\clubsuit}_{k,0} \underbrace{F}_{k,0} \underbrace{F}_{k$	$\rightarrow r(t$			
$u_{k,1}(t_{n,i}) \dots u_{k,1}(t_{n,1}) u_{k,1}(t_{n,0})$		$\begin{bmatrix} u_{k,1}(t_{0,i}) & \dots & u_{k,1}(t_{0,1}) \end{bmatrix} = \underbrace{u_{k,1}(t_{0,0})}_{\bullet} \xrightarrow{\bullet} \underbrace{\bullet}_{\bullet} \xrightarrow{\bullet}_{\bullet} \underbrace{\bullet}_{\bullet} \underbrace{\bullet}_{\bullet} \xrightarrow{\bullet}_{\bullet} \underbrace{\bullet}_{\bullet} \underbrace{\bullet}_{\bullet$				
$u_{k,2}(t_{n,i}) \dots u_{k,2}(t_{n,1}) u_{k,2}(t_{n,0})$		$u_{k,2}(t_{0,i}) \dots u_{k,2}(t_{0,1}) u_{k,2}(t_{0,0}) \qquad \qquad$				
$u_{k,m-1}(t_{n,i}) \dots u_{k,m-1}(t_{n,1}) u_{k,m-1}(t_{n,0})$		$u_{k,m-1}(t_{0,1}) \dots u_{k,m-1}(t_{0,1}) u_{k,m-1}(t_{0,0})$				
$u_{k,m}(t_{n,i}) \dots u_{k,m}(t_{n,1}) u_{k,m}(t_{n,0})$	•••	$u_{k,m}(t_{0,i})$ $u_{k,m}(t_{0,1})$ $u_{k,m}(t_{0,0})$				
$u_{k,m+1}(t_{n,i}) \dots u_{k,m+1}(t_{n,1}) u_{k,m+1}(t_{n,0})$		$u_{k,m+1}(t_{0,i})$ $u_{k,m+1}(t_{0,1})$ $u_{k,m+1}(t_{0,0})$				
$u_{k,m+2}(t_{n,i}) \dots u_{k,m+2}(t_{n,1}) u_{k,m+2}(t_{n,0})$		$u_{k,m+2}(t_{0,i}) \dots u_{k,m+2}(t_{0,1}) u_{k,m+2}(t_{0,0}) $				
<u> </u>						
$\left[u_{k,2m-1}(t_{n,i})\right] \dots \left[u_{k,2m-1}(t_{n,1})\right] u_{k,2m-1}(t_{n,0})$		$u_{k,2m-1}(t_{0,j}) \dots u_{k,2m-1}(t_{0,1}) u_{k,2m-1}(t_{0,0})$				
$ \begin{bmatrix} u_{k,2m}(t_{n,i}) \end{bmatrix} \dots \begin{bmatrix} u_{k,2m}(t_{n,1}) \end{bmatrix} \begin{bmatrix} u_{k,2m}(t_{n,0}) \end{bmatrix} $		$\underbrace{u_{k,2m}(t_{0,i})}_{k,2m} \dots \underbrace{u_{k,2m}(t_{0,1})}_{k,2m} \underbrace{u_{k,2m}(t_{0,0})}_{k,2m}$				

Fig. 4. GPU implementation for composite fading process generation.

B. GPU Implementation

When simulating an UAV communication system, it is important to ensure the efficiency of UAV communication channel simulation. In addition, the number of propagation paths has a strong influence on the quality of UAV communication channel simulation based on SoS theory. However, the computational cost will increase sharply as the number of propagation paths increases. Therefore, it is challenging to ensure the efficiency and quality of UAV communication channel simulation.

Due to the high computing power of GPU, it is practical to use GPU to optimize the UAV communication channel simulation. In this paper, we construct a high-performance implementation of the composite fading process generation using NVIDIA's Compute Unified Device Architecture

(CUDA) programming framework. In Fig. 3, the GPU implementation for Gaussian random process generation is illustrated. The number of propagation paths, namely 2N, is equal to a positive integer power of two due to the construction of GPU. Suppose that the number of propagation paths is equal to 32. Then, 32×8 threads are assigned to each thread block. The threads in the same warp will be used in correlation calculations for each propagation path at the same instant, and the calculation results will be stored in shared memory. Finally, a Gaussian random process can be generated by summing all the calculation parallel reduction. results with In addition, $\omega_{i,n} = 2\pi f_{i,d} \cos \alpha_{i,n}$, $\varphi_{i,n}$, n = 1,...,2N will be stored in shared memory to accelerate the access speed.

Considering the details of thread scheduling and the size of global memory, the composite fading process can be generated based on the serial generation of Gaussian random processes in Fig. 4. As shown in Fig. 4, 2m Gaussian random processes will be serially generated and squared. Then, the temporary result can be obtained by summing all the calculation results and the multi-path fading process can be generated by calculating the square root of the temporary result. Meanwhile, the shadowing process will be generated by the nonlinear transformation of a Gaussian random process. Finally, the composite fading process will be generated by multiplying the multi-path fading process by the square root of the shadowing process.

TABLE I: TIME CONSUMPTIONS OF THE GENERATION METHOD IN DIFFERENT SCENARIOS (IN MILLISECONDS)

	Hill	Mountain	Sea	
Mean	378.0	345.7	363.6	
Maximum	386.0	356.0	372.0	
Minimum	368.0	339.0	350.0	
Median	378.5	345.0	364.5	

IV. SIMULATION RESULTS

To compare the efficiencies of implementations of Gaussian random process generation on GPU and Central Processing Unit (CPU), the time consumptions of GPU and CPU implementations for generating the Gaussian random process $X \sim CN(0,1)$ with different values of N are provided in Fig. 5. As presented in this figure, the time

consumption of CPU implementation increases sharply as the number of propagation paths increases, while the time consumption of GPU implementation remains almost constant. When the number of propagation paths is small, the CPU implementation has better time performance than the GPU implementation because the GPU implementation must transfer the calculation results from global memory to host memory after Gaussian random process generation. Moreover, when the number of propagation paths is large, the time consumption of the GPU implementation is far less than that of the CPU implementation. Therefore, the speed of data transmission between global memory and host memory has a substantial influence on the time consumption of the GPU implementation, while the amounts of data and calculation have a strong influence on the CPU implementation.

To evaluate the accuracy of the new real-time generation method for multi-path shadowing composite fading, we set the simulation parameters of the UAV communication channel as $\sigma_x = 3.2$ dB, 3.9 dB, 4.2 dB and m = 10.3, 9.2, 9.6 for the scenarios of over a hill, mountain and sea, respectively [5]-[6]. The other simulation parameters are N = 128 and $\mu = 1$. The simulated envelopes and PDFs for composite fading are given in Fig. 6 and Fig. 7, where the number of simulated samples is 10^5 . As shown in Fig. 7, the simulated results are consistent with the theoretical distribution for the three scenarios. Based on the results in Fig. 6 and Fig. 7, the communication quality of the hill scenario is the best and that of the mountain and sea scenarios is the worse.

To evaluate the efficiency of the new real-time generation method for multi-path shadowing composite fading, the time consumptions of the generation method under the three scenarios are recorded in Table I. The scenarios in increasing order of time consumption are mountain, sea and hill. Based on the results in Fig. 4, the scenarios in increasing order of Nakagami factor are mountain, sea and hill as well. Increased Nakagami factor causes the number of propagation paths to increase. Moreover, the time consumption is approximated for the hill, mountain and sea scenarios, and a large part of the computation time is spent on data transmission between global memory and host memory.



Fig. 5. Time consumptions of GPU and CPU implementations.



Fig. 6. Simulated envelopes for composite fading in different scenarios.



Fig. 7. Theoretical and simulated PDFs for composite fading in different scenarios.



Fig. 8. Simulated ASER values for different scenarios and modulations.

For the UAV communication system, the flight altitude has a strong influence on the average symbol error rate (ASER). We assume that the UAV of the communication system is equipped with normalized omnidirectional antennas. The carrier frequency is 968 MHz. The ground station is below the UAV and equipped with normalized omnidirectional antennas. The ASER is simulated for all three scenarios in Fig. 8. As presented in this figure, the ASER gradually increases as the flight altitude increases under specific environments. When the flight altitude and modulation are constant, the ASER increases in the order of hill, mountain and sea. When the flight altitude is less than 500 m, the ASER using binary phase shift keying (BPSK) is less than 0.001, which means the UAV communication system exhibits satisfactory performance. When the UAV communication system uses quadrature phase shift keying (QPSK) signals, the flight altitude must be less than 300 m for satisfactory performance. In addition, when the flight altitude is constant, BPSK outperforms QPSK in specific environments.

V. CONCLUSIONS

In this paper, an UAV communication channel model is developed that considers the propagation path loss, shadowing, and multi-path fading. Moreover, a new realtime generation method for the composite fading process based on SoS theory is designed and implemented, which can fully utilize the parallel computing power of GPU. Finally, the GPU implementation for the real-time generation method is validated by simulations. The time consumption of the GPU implementation is recorded and analyzed. On this basis, the performance of the ASER using different modulations is analyzed. These results can aid in the simulation, optimization and evaluation of UAV communication systems.

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