Modeling of WLAN Beacon Signal Strength Measured in an Indoor Environment

Wenhui Zhang
University of Stuttgart, Institute of Communication Networks and Computer Engineering
Pfaffenwaldring 47, D 70569 Stuttgart, Germany

***Abstract**: In the fourth generation wireless networks, it is believed that wireless LANs (WLANs) will interwork with cellular systems to provide fast speed data services. The integration of WLANs and cellular systems calls for a careful design of handover decisions. In WLANs, the received signal strength (RSS) is used for handover decision, thus a thorough understanding of the characteristics of the RSS of beacons is important in the WLAN handover design. In this paper, measurements of the RSS of WLAN beacons in an indoor environment are presented, and based on theoretical analysis, Gamma random variables (RVs) are used to model the RSS variation from the average power, which fits the measurement data well. Correlation is observed in the variation, and new algorithms have been designed to generate correlated Gamma RVs.*

Keywords: WLAN, beacon, signal strength, correlated Gamma

I. Introduction

In recent years, WLANs have been deployed worldwide successfully, and it is very likely that WLANs will be used to interwork with cellular systems to provide fast speed data services in the fourth generation (4G) wireless networks, where handovers between WLAN cells and between WLAN cells and cellular cells are possible. Such a 4G network architecture is currently being developed by the IST project Mobility and Differentiated Services in a Future IP Network (Moby Dick) [1]. The integration of WLAN and cellular systems calls for a careful design of handover decisions [2]. In WLANs, the RSS of beacons are used for handover decision [3], thus a profound understanding of the characteristics of the RSS of beacons is important in designing good handover algorithms.

Mobile Radio propagation has two manifestations: large-scale fading and small-scale fading. Large-scale fading represents the average signal power attenuation or path loss over a large distance due to the spatial separation between the transmitter and the receiver, which can be described by the path loss models of Hata and Okumura [6]. Large-scale fading is also affected by terrain contours, which is called shadowing, and usually has a lognormal distribution. Small-scale fading refers to the dramatic changes in the signal amplitude and phase that can be experienced as a movement over a very small distance, which is usually modeled as a Rayleigh and Rician fading process [6].

In cellular systems, the fast fading effect is usually neglected in handover designs, because it can be averaged out over a certain distance [7]. Measurements show strong variations in the RSS of beacons due to the fast fading. But averaging out the fast fading effect in the WLAN handover process is difficult, because only a limited number of beacons can be measured during the handover decision process. The reason is that beacons are only sent at fixed intervals, say, a typical value is about 100ms, but the handover in WLAN environment requires a fast decision due to the limited coverage area and the corner effect. Thus, a thorough understanding of the fast fading characteristics in the RSS of WLAN beacons is crucial in the handover design. Measurements have been conducted for the propagation in WLANs in [4] [5], where path loss models were proposed, but the fast fading effect is not considered in both of the papers.

This paper aims to model the variation of the RSS of beacons of the 802.11b WLAN in indoor corridors, where handovers are likely to happen. In Section II, measurements of the RSS of beacons are presented. In Section III, modeling based theoretical analysis is given, which is corroborated by the measured data. In Section IV, new algorithms are suggested to generate correlated Gamma RVs.

II. Measurements

Measurements were carried out in corridors in an office building. The WLAN access point is Lucent Orinoco 802.11b access point sending beacons at an interval of 102.4ms, which is located near the ceiling at the crossing of two corridors. A laptop equipped with a SMC 2632W WLAN card is used to measure the RSS, of which the WLAN driver program has been modified to record the RSS of beacons in real time. A number of measurements have been carried out, and a representative example is illustrated in Fig. 1, referring to a movement first to the access point and then away from it. The

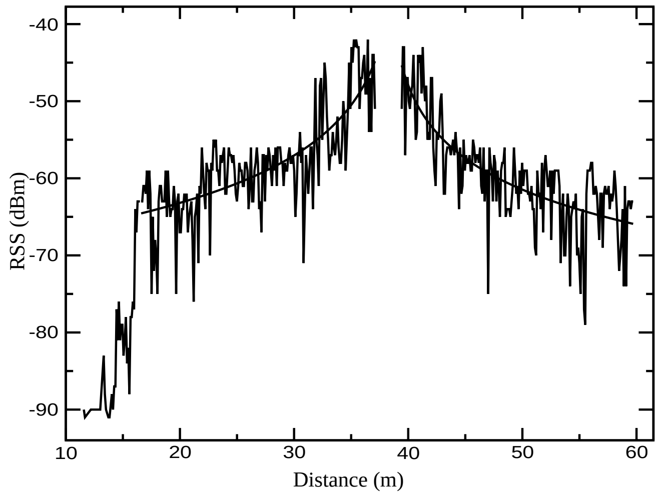

Fig. 1. Measured RSS of beacons best fitted with average power

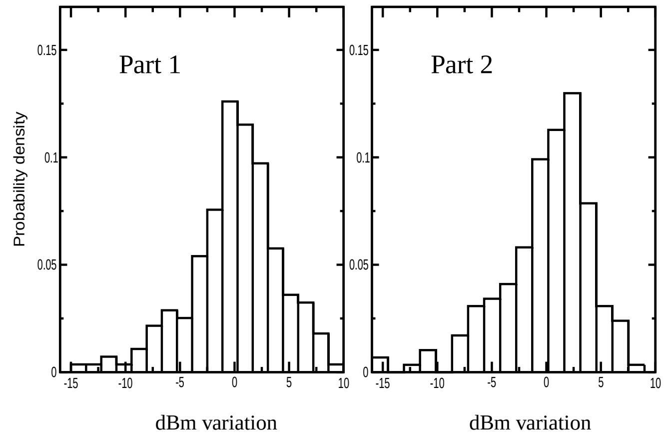

Fig. 2. Histograms of the variation of RSS about the average power

moving speed is at 1m/s, corresponding to receiving about 10 beacons per meter. The measurement data are split into a rising part (Part 1) and a falling part (Part 2), and the best fit lognormal curves are used to depict the corresponding distance-dependent average power due to path loss. The fast rising in the curve before 20m is due to the movement from a none line-of-sight (NLOS) corridor to a LOS corridor, where the corner effect leads to the fast rising of the RSS.

In order to study the characteristics of the RSS variance about the average power, histograms of the difference of the RSS are presented in Fig. 2. As can be seen from the figures, the probability density is neither Normal nor Lognormal distribution.

III. MODELING

It is well known that for a multipath-fading channel without LOS components, the received envelope is Rayleigh distributed; for a multipath-fading channel with LOS components, the received envelope is Rician distributed. The Rice factor *K* in the Rician distribution is used to characterize the ratio of the LOS components and the NLOS components. When the Rice factor *K* is zero, the Rician distribution becomes Rayleigh distribution [8]. Rician distribution is difficult to analyze because it has a Bessel function. Instead, the Nakagami distribution can be used, while it can closely approximate the Rician distribution, and the Rayleigh distribution is only a special case of Nakagami distribution. By using transformation method, the squared-envelope, or the power of Nakagami distributed RVs has a Gamma distribution [8], as follows

$$p(x) = \frac{m^m}{\Omega}\left(\frac{x^{m-1}}{\Gamma(m)}\exp\left(-\frac{mx}{\Omega}\right)\right) \tag{1}$$

where *m* is a function of Rice factor *K*, denoted by (2), Ω is the average received power, and $\Gamma(m)$ is a Gamma function.

$$m = \frac{(K+1)^2}{2K+1} \tag{2}$$

Compared with the density function of a standard Gamma distribution with parameters α and β, we can find from (1) that α is equal to *m*, and β is equal to Ω devided by *m*, and the mean value of the Gamma RVs is Ω. The Gamma distribution has some properties that are useful for our study: α is called *shape parameter*, which determines the shape of the probability density function, and β is called *scale parameter*, which only compresses or expands the distribution.

Suppose *m* is constant during a movement, then the RSS at a certain place has a Gamma distribution with parameter α, which is constant during the movement, and mean value Ω, which depends on the mean path loss. Suppose the decimal value of the received power at that point is *X*, which has a Gamma distribution, and the mean power at that point is a constant *p*, clearly *p* is proportional to Ω. The variation *v* from the mean power in dBm and decimal value respectively is

$$v_{dBm} = 10\log X - 10\log p \tag{3}$$

$$v_{decimal} = 10^{\frac{10\log X - 10\log p}{10}} = \frac{X}{p} \tag{4}$$

So the variation *v* at that point also has a Gamma distribution with the same shape parameter α, but with a different mean value Ω/p, which is independent of the position.

We can use the Gamma distribution to model the received power and the difference with the average power. But the measured values are usually in dBm. The distribution of log *X*, when *X* has a standard Gamma distribution, is not being reported. But log *X* can be approximated by a Normal distri-

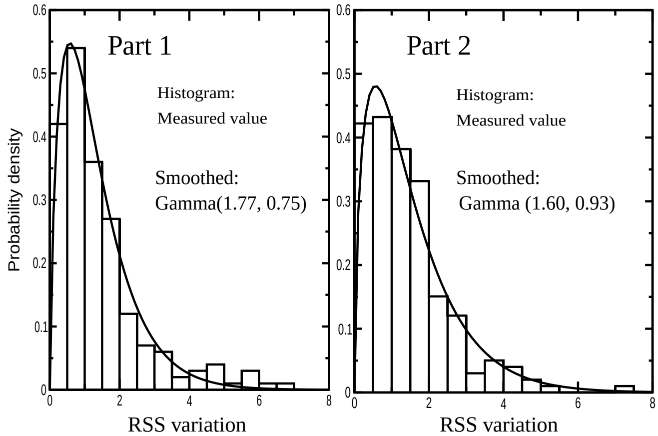

Fig. 3. Histogram of received decimal power variation

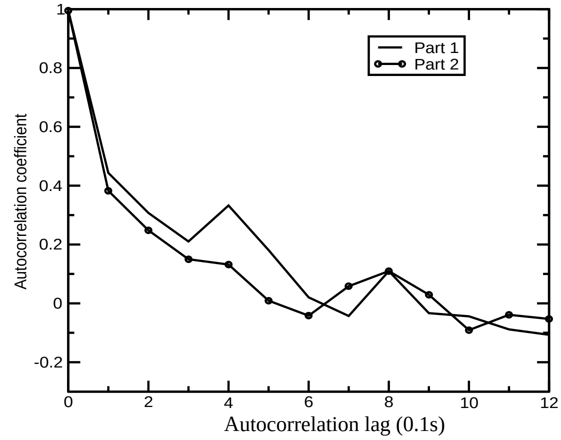

Fig. 4. Autocorrelation coefficient of received power variation

bution when α is sufficiently large [9]. Due to the complexity of the logarithm of Gamma RVs, Gamma RVs are used directly to study the RSS of WLAN beacons.

To verify the analytical results mentioned above, the histograms of the decimal difference is plotted for the two parts of data as shown in Fig. 3, and they are best fitted using Gamma probability distribution functions. Both parts show Rician fading due to LOS signals in the corridors, conforming with the assumption quite well. In addition, autocorrelation can be observed in the decimal variation, the autocorrelation coefficient is plotted in Fig. 4.

IV. Generating Correlated Gamma RVs

From the previous study, correlated Gamma RVs are needed in the modeling of the RSS of WLAN beacons. Independent Gamma RVs can be generated using a method proposed by Cheng [11], but generating correlated Gamma RVs poses some challenges. Gudmundson has proposed Exponentially correlated Gaussian RVs for modeling the shadowing process in an suburban environment [10], where Exponentially correlated Gaussian RVs can be easily generated by filtering Gaussian RVs through a first-degree filter. But filtering Gamma RVs through a first-degree filter fails to produce Gamma distributed RVs. In [12], an algorithm has been derived to generate correlated Gamma RVs in the modeling of VBR video traffic in ATM, but the algorithm is complicated and is only an approximation. Here, new methods are designed to generate correlated Gamma RVs, which are very simple and accurate.

The Gamma distribution has a *reproductive property*: If X_1 and X_2 are independent RVs each having a Gamma distribution, with possible different values of α', α'' of α, but with common values of β, then $X_1 + X_2$ also has a Gamma distribution, with the same value of β, and with $\alpha = \alpha' + \alpha''$ [9]. Using this property, linearly correlated and exponentially correlated Gamma RVs can be directly generated by adding independent Gamma RVs.

A. Generating Linearly Correlated Gamma RVs

The linear correlation coefficient function is described as

$$r(m) = \begin{cases} \dfrac{n-m}{n} & m < n \\ 0 & m \ge n \end{cases} \tag{5}$$

where, n is called *correlation length*, and the autocorrelation will be zero if the distance m is greater than n. To generate Gamma RVs $X(1)$, $X(2)$, $X(3)$,... with the distribution Gamma (α,β), and with the autocorrelation function of (5), the following steps are taken:

1. Generate a series of n independent RVs with the distribution Gamma $((\alpha/n),\beta)$, denoted as X_1, X_2, X_3,..., X_n, and adding them together will get the first RV $X(1)$.

2. Replace X_1 in the series with a new RV X with the same distribution as X_1, and adding it to the rest of RVs in the series, and get the second RV $X(2)$.

3. Repeat step 2, that is, every time replace one of the old values by a new value of the same distribution and adding the series of n RVs to get a new RV.

We can find that each RV is the sum of n independent Gamma RVs, according to the reproductive property, the sum is a Gamma RV with the parameter (α,β). Adjacent RVs up to distance n have common components, so they are correlated. The proof of the autocorrelation function (5) is given in the appendix.

As an example, 10000 Gamma RVs with correlation lengths of 10 and 5, respectively, are generated and the histograms are shown in Fig. 5.

Adding the two sets of RVs with different correlation lengths will also give Gamma RVs. By adding individual RVs

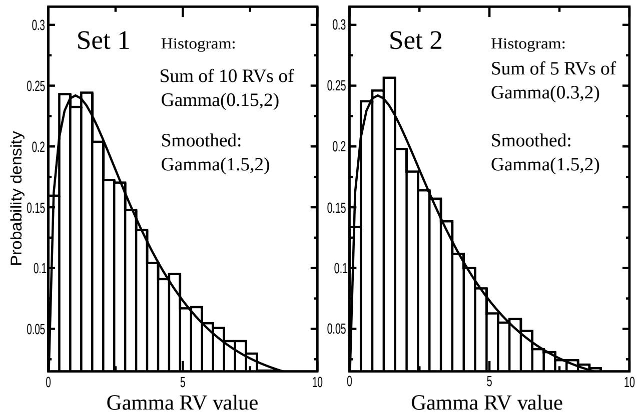

Fig. 5. Histograms of linearly correlated Gamma RVs

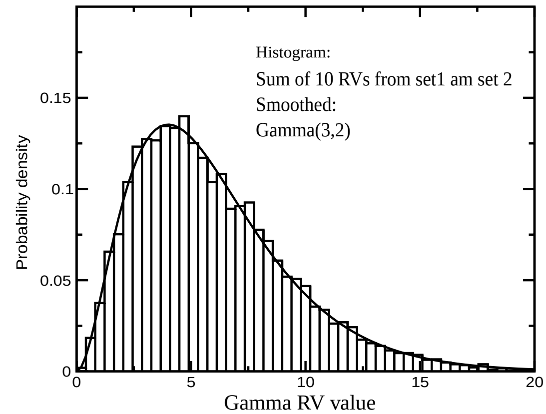

Fig. 6. Histogram of the sum of two sets of correlated Gamma RVs

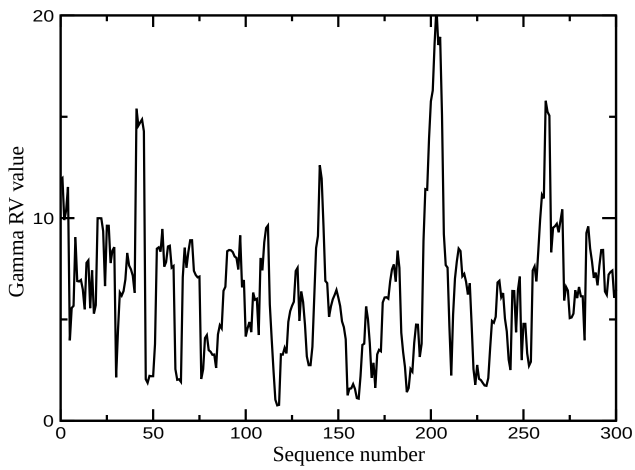

Fig. 7. Gamma RVs of sum of two sets of correlated Gamma RVs

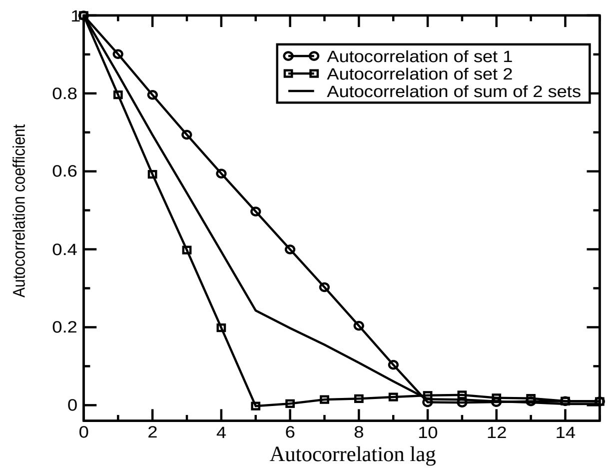

Fig. 8. Autocorrelation of linearly correlated Gamma RVs

from set 1 and set 2 together, we can get 10000 Gamma RVs with distribution Gamma (3, 2). The histogram is shown in Fig. 6, these RVs are plotted in Fig. 7, and their autocorrelations are shown in Fig. 8. In principle, if two linearly correlated Gamma RVs X_1 and X_2 are considered with the correlation length n_1, n_2 ($n_1 < n_2$), and the parameters $(n_1\alpha_1, \beta)$, $(n_2\alpha_2, \beta)$ respectively, $X_1 + X_2$ is also a Gamma distributed RV with parameters $(n_1\alpha_1 + n_2\alpha_2, \beta)$, and the autocorrelation coefficient function as follows

$$r(m) = \begin{cases} 1 - \dfrac{m(\alpha_1 + \alpha_2)}{n_1\alpha_1 + n_2\alpha_2} & m \le n_1 \\ 1 - \dfrac{n_1\alpha_1 + m\alpha_2}{n_1\alpha_1 + n_2\alpha_2} & n_1 < m \le n_2 \\ 0 \quad m > n_2 \end{cases} \tag{6}$$

The proof is similar as the proof of (5), and it can be easily extended to the sum of more linearly correlated Gamma RVs.

B. Generation Exponentially Correlated Gamma RVs

The exponential correlation coefficient function is described as

$$r(m) = a^m \qquad 0 < a < 1 \tag{7}$$

To generate Gamma RVs $X(1)$, $X(2)$, $X(3)$,... distributed with Gamma (α,β) with the autocorrelation function of (7), the following steps are taken:

1. Find two smallest positive integers *m* and *n* that satisfy

$$a = \frac{n-m}{n} \tag{8}$$

2. Generate a series of *n* independent RVs with distribution Gamma $((\alpha/n),\beta)$, which are denoted as X_1, X_2, X_3,..., X_n, adding them together will get the first RV $X(1)$.

3. Replace *m* RVs in the series randomly with *m* new RVs x with the same distribution, and adding them to the rest of RVs in the series together will generate the second RV $X(2)$.

4. Repeat steps 3 to generate new RVs.

The autocorrelation of the generated RVs has a Gamma distribution with parameters (α,β) and the correlation coeffi-

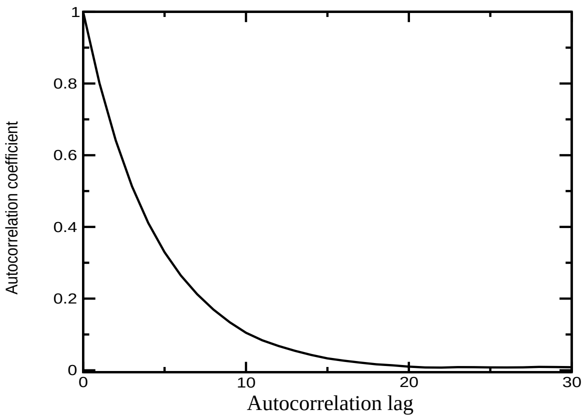

Fig. 9. Autocorrelation of exponentially correlated Gamma RVs

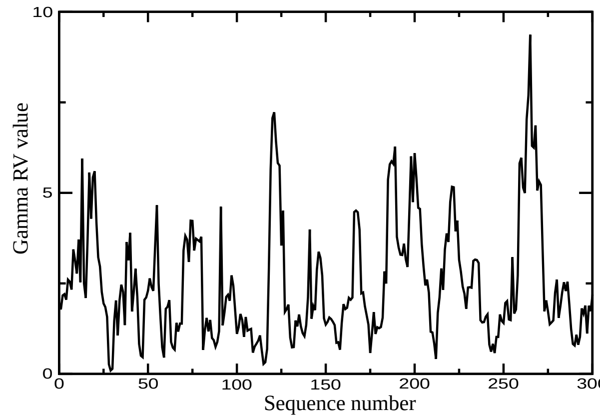

Fig. 10. Exponential correlated Gamma RVs

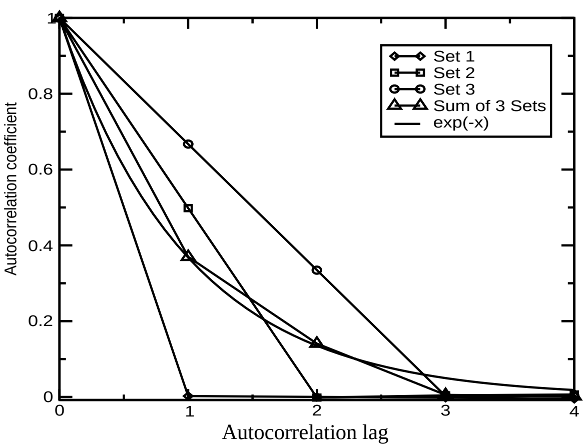

Fig. 11. Combination of linearly correlated Gamma RVs

cient function as specified in (7). This can be proved using the similar method as the proof of (5). For example, to generate exponentially correlated Gamma RVs with the correlation parameter *a* equal to 0.8, the values of *m* and *n* hold 1 and 5 respectively. In Fig. 9, the autocorrelation of the generated RVs is plotted, which is the same as the function of (7). The generated correlated Gamma RVs are plotted in Fig. 10.

C. Combination of Linearly Correlated Gamma RVs

For some correlated Gamma RVs that are difficult to generate using the two methods mentioned above, the combination of linearly correlated Gamma RVs can be used to approximate the required functions. Two approximation methods are derived: the linear fit method and the numerical method. The linear fit method is to approximate a correlation function with the sum of several linear functions. Fig. 8 can be such an example.

Here an example is presented illustrating the use of the numerical method to approximate RVs distributed with Gamma (2, 1), and with the correlation function

$$r(m) = \exp(-m) \tag{9}$$

The first step is to calculate the value of each r(m), we can get r(1) = 0.3679, r(2) = 0.1353 and r(3) = 0.0498. Because r(3) is very small, the approximation can be done only for r(1) and r(2) without losing much accuracy.

Here, three sets of Gamma RVs X_1, X_2 and X_3 are used, each having a distribution of Gamma $(\alpha_1, 1)$, Gamma $(2\alpha_2, 1)$, and Gamma$(3\alpha_3, 1)$, and the correlation length of 1, 2 and 3 respectively. The following equations can be derived:

$$\begin{cases} 1 - \dfrac{\alpha_1 + \alpha_2 + \alpha_3}{\alpha} = r(1) = 0.3679 \\ 1 - \dfrac{\alpha_1 + 2(\alpha_2 + \alpha_3)}{\alpha} = r(2) = 0.1353 \\ \alpha_1 + \alpha_2 + \alpha_3 = \alpha = 2 \end{cases} \tag{10}$$

Solving the equations in (10), yields $\alpha_1 = 0.799$, $\alpha_2 = 0.1946$, and $\alpha_2 = 0.2706$. The sum of the three sets of RVs from X_1, X_2 and X_3 will give the required RVs. The autocorrelation of the 3 sets of RVs and the sum is shown in Fig. 11.

V. CONLUSION

In this paper, the measurement of RSS of WLAN beacons in an indoor environment is given. By mathematical analysis, the variation of the RSS from the average power has a Gamma distribution, which fits the measurement well. Correlation is observed in the variation of RSS. New algorithms using the reproductive property of Gamma distribution have been designed to generate linearly and exponentially correlated Gamma RVs. The combination of linearly correlated Gamma can be used to approximate other correlation functions.

VI. APPENDIX

Here the proof of the correlation coefficient function in (5) is outlined as follows

$$r(m) = \begin{cases} \frac{n-m}{n} & m < n \\ 0 & m \geq n \end{cases} \quad (11)$$

Proof: for RVs *x*, the autocorrelation is

$$R(m) = E\{X(n)X(n+m)\} \quad (12)$$

and autocorrelation coefficient is

$$r(m) = \frac{R(m)}{R(0)} \quad (13)$$

Suppose *m*<*n*, and using the method to generate linearly correlated Gamma RVs, we have

$$X(n) = X_1 + X_2 + \ldots + X_n \quad (14)$$

where X_1, X_2, X_3,..., X_n are independent Gamma RVs, it follows

$$X(n+m) = X(n) - \sum_{i=1}^{m} X_i + \sum_{i=1}^{m} X \quad (15)$$

Where is X is a new Gamma RV with the same distribution as X_1, X_2, X_3,..., X_n, hence (12) and (15) yields

$$R(m) = E\left\{X(n)\left[X(n) - \sum_{i=1}^{m} X_i + \sum_{i=1}^{m} X\right]\right\} \quad (16)$$

X(n) and X are uncorrelated and X(n) and X_i are correlated with the following relation:

$$E\{X(n)X_i\} = \frac{E\{X(n)X(n)\}}{n} \quad (17)$$

Because all X are independent and identically distributed, from (16) and (17), it follows

$$E\{X(n)X(n+m)\} = E\{X(n)X(n)\}\left(1 - \frac{m}{n}\right) \quad (18)$$

Finally, by combining (13) and (18), we obtain

$$r(m) = \frac{n-m}{n} \quad (19)$$

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