Sensor Communications

The Application of Lognormal Mixture Shadowing Model for Body-to-Body Channels

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Abstract—In this work, a Lognormal mixture shadowing model based on a cluster concept is utilized in the modeling of body-to-body channels for different running and cycling activities. The mixture model addresses the inaccuracies observed using a unimodal distribution that may not accurately represent the measurement data set. Parameters of the mixture model are estimated using the expectation-maximization (EM) algorithm. The accuracy of the proposed mixture model is compared to other commonly utilized unimodal distributions showing significant improvement in representing the empirical data set. The measured data, as well as the developed model, can be used for accurate planning and deployments of wireless body-to-body networks for use in various sporting and other related activities.

Index Terms—Body-to-body (B2B) communications, wireless networks, Lognormal mixture shadowing, wireless body area networks (WBAN), fading distributions, sport, running, cycling.

I. INTRODUCTION

In recent years, there has been a growing interest on body-centric wireless communications because of their great potential applications in various domains such as health, entertainment, sports, or any other application that requires transmission of data from the human body [1]. Among other communication scenarios, the transmission could involve between a device mounted on one person to a device situated on another person in a different physical location. This kind of communication is known as body-to-body communications and is subject to time-varying shadowing effects caused by the movements of the human bodies at both ends of the communication link [2]. The successful design of such networks requires a good understanding of the propagation impairments affecting the wireless link.

The wave propagation characteristics of on-body and off-body channels have been extensively studied in the past, see [3], [4] for review. However, body-to-body propagation channels have not been extensively studied. Measurement data at 2.45 GHz was utilized in [2] to assess the impact of typical human body movements on the signal characteristics of outdoor body-to-body channels using flexible patch antennas. A modified log-distance path loss model that accounts for body shadowing and signal fading was proposed. Channel model characterization for indoor body-to-body scenarios based on 2.45 GHz measurements was reported in [5]. The shadowing and small-scale fading effects for line-of-sight (LOS) and non-LOS conditions were evaluated. Similar studies were also conducted in [6]–[8].

For body-to-body wireless networks, shadowing is the dominant propagation impairment causing partial or total blockage of the received signal due to environmental factors as well as due to the random (or periodic) movements of the body components at both ends of the communication link. Existing studies utilize a unimodal distribution (usually a Lognormal or Gamma distribution) to characterize the shadowing effects of body-to-body channels. However, such distributions may not be based on the actual underlying physical propagation process of such channels [9]. The Lognormal distribution is a widely accepted physical based model for modeling shadowing effects in wireless links [10]. However, our histograms of measurement data for different sports activity propagation scenarios of body-to-body channels show mixture and skewed distribution curves as also observed in other similar studies such as [5], [11]. This may suggest the existence of distinct scattering clusters for these type of channels that can be modeled utilizing mixture distributions. In addition to environmental effects, the movements of the different body components of the involved subjects at both ends of the communication link might contribute to distinct scattering clusters. This kind of clustering behavior cannot be accurately modeled using unimodal distributions.

In this work, a Lognormal mixture shadowing was used in modeling of body-to-body propagation channels under different sporting activities. The work aims to underline the potential improvement archived by the model, over the commonly used unimodal distribution approach, in representing body-to-body channels. The rest of the paper is organized as follows. Section II describes the measurement campaign, presenting the practical sensor nodes used as well as the investigated body-to-body propagation scenarios. Measurement data analysis and the proposed Lognormal mixture shadowing model is discussed in Section III. Conclusions are given in Section IV.

II. MEASUREMENT CAMPAIGN

The measurement campaign was conducted utilizing practical sensor nodes for characterizing the body-to-body propagation channel under various outdoor sporting activities. A transmitting and a receiving node were attached (using a small strip of Velcro) to the upper arm of two adult males of height 1.80 m and mass 80 kg (subject A), and 1.85 m height and 75 kg mass (subject B). Two different scenarios for running (average speed of 3.33 m/s) and cycling (average speed of 5 m/s) activities were considered. *Scenario 1)* subjects behind each other as shown in Fig. 1, and *Scenario 2)* subjects beside each other as seen in Fig. 2. The experiments were conducted in 500 meter outdoor stretch, which is a common running

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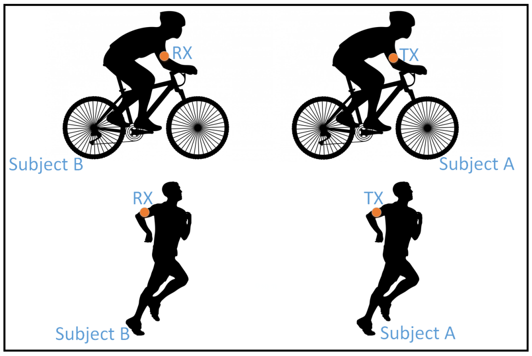

Fig. 1. Scenario 1: measurements for the body-to-body wireless network under running and cycling activities where one subject is behind the other [12].

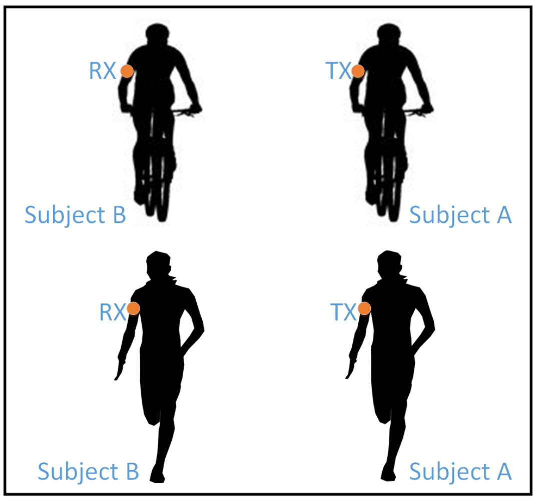

Fig. 2. Scenario 2: measurements for the body-to-body wireless network under running and cycling activities where subjects are beside each other [12].

and cycling route in Gjøvik, Norway. In all activities, the subjects tried to maintain a separation distance of 1 meter between them.

The test-bed is a programmable radio transceiver (CC2500) from Texas Instrument. The device was set to transmit a packet every 4 ms with constant transmission power of 1 dBm at a carrier frequency of 2.425 GHz. At the receiving end, the packet number together with its received signal strength indicator (RSSI) was stored on the MicroSD memory card. The nodes use horizontal polarized Wurth Electronik 7488910245 chip antenna. At least 25 kilo-samples for each scenario were collected, which is high enough for conducting statistical analyses. Details of the measurement campaign can be found in [12].

III. MEASUREMENT RESULTS AND ANALYSIS

A. Lognormal mixture shadowing

The received signal power at a given separation distance, d, from the transmitter that is subject to shadowing is defined in decibel scale as [10]

$$P_{\mathrm{RX}}(d) = P_{\mathrm{TX}} - 10n\log(d) + X_\sigma \tag{1}$$

where P_{TX} is the transmitted power, n is the path loss exponent, which shows the rate at which the received signal power decreases with distance. Parameter $X_\sigma \sim \mathcal{N}(0, \sigma^2)$, denotes the shadowing fading term with Normal distribution random variable (i.e., Lognormal distribution in linear scale) with zero mean and σ^2 variance. Defining, $X_\sigma = \ln(Y_\sigma)$, the Lognormal shadow fading implies $Y_\sigma \sim \mathcal{LN}(0, \sigma^2)$ [13].

The probability density function (PDF) of Lognormal mixture distributions can be described as

$$Y \sim f_Y(y) = \sum_{k=1}^{\infty} w_k \mathcal{LN}(\mu_k, \sigma_k^2) \tag{2}$$

where μ_k and σ_k^2 are the distribution parameters of the kth mixture component (for $k = 1, 2, \ldots$), parameter w_k is weighting proportion of the kth component such that $\sum_{k=1}^{\infty} w_k = 1$, and the Lognormal kernel PDF of the kth mixture is then given by

$$\mathcal{LN}(\mu_k, \sigma_k^2) = \frac{1}{y\sqrt{2\pi\sigma_k^2}} \exp\left[\frac{-(\ln y - \mu_k)^2}{2\sigma_k^2}\right] \tag{3}$$

In a non-parametric estimation, the use of symmetric kernels is preferred as they provide a convergent expansion according to the Mercer's theorem [14]. The expression in (3) is not symmetric, however, since the logarithm of each observation can be described as $x_i = \ln(y_i)$ (for $i = 1, 2, \ldots, N$, where N is the total sample number), a univariate Gaussian distribution with mean μ_k and variance σ_k^2 can be utilized. Thus, all samples of x_i can be modeled as a mixture of Gaussian distributions as

$$X \sim f_X(x) = \sum_{k=1}^{\infty} w_k \mathcal{N}(\mu_k, \sigma_k^2) \tag{4}$$

where the corresponding kernel PDF is given by

$$\mathcal{N}(\mu_k, \sigma_k^2) = \frac{1}{\sqrt{2\pi\sigma_k^2}} \exp\left[\frac{-(x - \mu_k)^2}{2\sigma_k^2}\right] \tag{5}$$

For a given shadow fading condition, an estimate of the actual PDF (with a measurable error) can be made utilizing a finite number of K Gaussian kernels and the resulting Lognormal mixture can be expressed as [13]

$$\widehat{f}_Y(y) = \sum_{k=1}^{K} w_k \frac{1}{y\sqrt{2\pi\sigma_k^2}} \exp\left[\frac{-(\ln y - \mu_k)^2}{2\sigma_k^2}\right] \tag{6}$$

In this work, the value of K was set to 4, as higher values did not bring further improvement in the results.

B. Results and comparisons

Figs 3 to 6 show the measured PDFs along with the estimated mixture of Lognormal distribution (6) with $K = 4$ (Lognormal-4). The expectation-maximization (EM) algorithm [13] was utilized to estimate the mixture model parameters and are given in Tables 1 and 2. Also shown are comparisons with unimodal distributions (Lognormal, Gamma, and Nakagami). We can observe that the measured PDFs (in all scenarios) exhibit mixture and skewed distribution curves, especially those of running activity as shown in Fig. 3 and Fig. 5. Such characteristics have also been observed in other similar studies, e.g., [5], [11]. With relatively stable transceivers achievable during cycling activity, the distinction between clusters is less pronounced, as seen in Fig. 4 and Fig. 6.

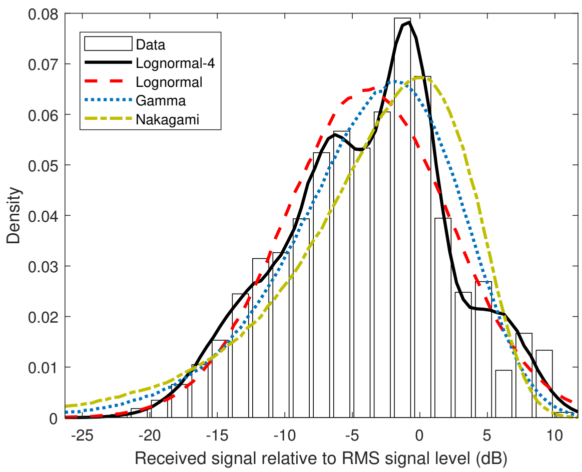

Fig. 3. Measured histogram and estimated PDFs for Scenario 1 running.

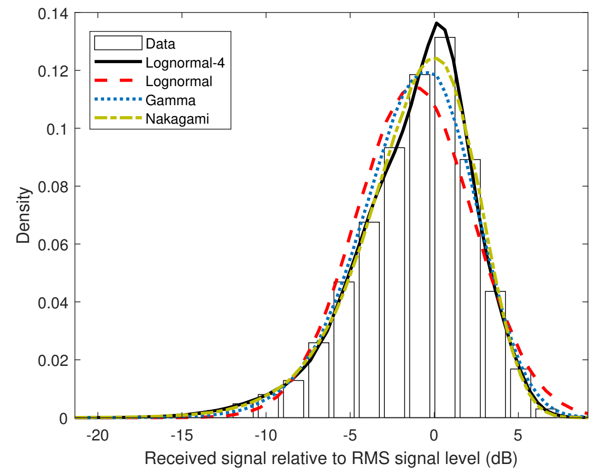

Fig. 4. Measured histogram and estimated PDFs for Scenario 1 cycling.

Tables 1 and 2 also show the mean error, standard deviation (STD) of error, and the root mean square error (RMSE) of the corresponding distributions compared to measured PDFs. The weighted mean relative difference (WMRD) expressed as a percentage was also included for easier comparison

$$\mathrm{WMRD} = \frac{\sum_{t=1}^{n} |F_t - A_t|}{\sum_{t=1}^{n} (F_t + A_t)} \times 100 \tag{7}$$

where A_t is the measured PDF, F_t is the estimated PDF, t is the fitted point and n is the total number of fitted points. In all cases, we can observe that the best estimation is achieved utilizing the mixture model. Naturally, the mixture model will give better results due to a large number of involved parameters. However, the improvements achieved here, especially for the case of running activity is significantly large, and hence suggest the existence of distinct scattering clusters for body-to-body propagation channels where in addition to the environment, the movements of the different body components of each person at both ends of the communication link contribute to distinct scattering clusters. Thus, utilizing a unimodal distribution may not describe the underlying propagation process, or give a good approximation of the channel in the body-to-body communication under sporting or other related activities.

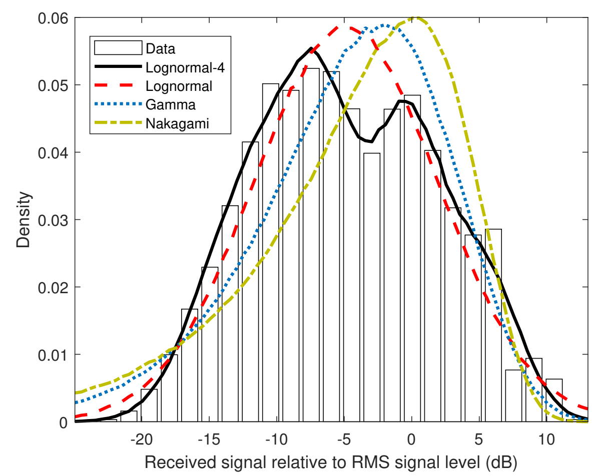

Fig. 5. Measured histogram and estimated PDFs for Scenario 2 running.

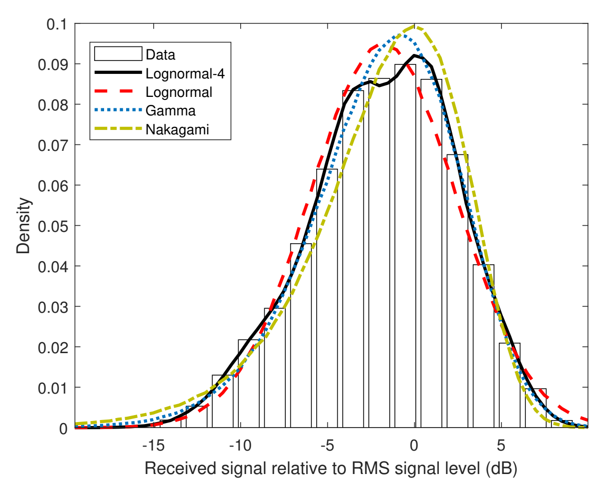

Fig. 6. Measured histogram and estimated PDFs for Scenario 2 cycling.

IV. CONCLUSION

Body-to-body wireless networks can support applications in various domains such as health, entertainment, sports, or any other application that requires the exchange of data among different persons. The design and reliable operations of such networks require accurate characterization of the propagation channel utilizing practical sensor devices. Inaccurate channel models may lead to poor decision making in the deployment of such networks resulting in unreliable communications. Inaccurate models may also result in poor energy efficiency of the wireless network.

In this study, the shadowing effects of body-to-body communications under various sporting activities are investigated using extensive measurements at 2.425 GHz. Running and cycling activities where the subjects are behind and beside each other are considered. Our histograms of measurement data for the different propagation

TABLE 1. Scenario 1: distribution parameters and error metrics for PDF estimation

Activity	Model	Parameters			Error mean	Error STD	RMSE	WMRD
Running	Lognormal-4	$\mu_1 = -0.0769$	$\sigma_1^2 = 0.0537$	$w_1 = 0.3531$	0.0001	0.0063	0.0062	3.60%
		$\mu_2 = -1.3645$	$\sigma_2^2 = 0.1563$	$w_2 = 0.2245$				
		$\mu_3 = 0.6879$	$\sigma_3^2 = 0.0920$	$w_3 = 0.2921$				
		$\mu_4 = -0.6476$	$\sigma_4^2 = 0.0793$	$w_4 = 0.1303$				
	Lognormal	$\mu = -0.4501$	$\sigma^2 = 0.5030$	-	0.0003	0.0143	0.0143	9.53%
	Gamma	$\alpha = 2.2387$	$\beta = 0.3619$	-	0.0002	0.0141	0.0138	9.88%
	Nakagami	$\mu = 0.6749$	$\omega = 1$	-	0.0005	0.0218	0.0214	9.88%
Cycling	Lognormal-4	$\mu_1 = -0.3353$	$\sigma_1^2 = 0.0663$	$w_1 = 0.3485$	8.4×10^{-6}	0.0017	0.0017	0.74%
		$\mu_2 = -0.6487$	$\sigma_2^2 = 0.2319$	$w_2 = 0.1273$				
		$\mu_3 = 0.0372$	$\sigma_3^2 = 0.0300$	$w_3 = 0.3690$				
		$\mu_4 = 0.3266$	$\sigma_4^2 = 0.0350$	$w_4 = 0.1551$				
	Lognormal	$\mu = -0.1350$	$\sigma^2 = 0.1607$	-	0.0002	0.0205	0.0200	9.49%
	Gamma	$\alpha = 7.0029$	$\beta = 0.1342$	-	3.9×10^{-5}	0.0118	0.0115	4.88%
	Nakagami	$\mu = 2.0019$	$\omega = 1$	-	1.5×10^{-6}	0.0062	0.0061	4.88%

TABLE 2. Scenario 2: distribution parameters and error metrics for PDF estimation

Activity	Model	Parameters			Error mean	Error STD	RMSE	WMRD
Running	Lognormal-4	$\mu_1 = -1.5353$	$\sigma_1^2 = 0.1391$	$w_1 = 0.2063$	4.6×10^{-5}	0.0051	0.0050	3.21%
		$\mu_2 = -0.9126$	$\sigma_2^2 = 0.1086$	$w_2 = 0.3216$				
		$\mu_3 = 0.4865$	$\sigma_3^2 = 0.1337$	$w_3 = 0.1964$				
		$\mu_4 = -0.1630$	$\sigma_4^2 = 0.1129$	$w_4 = 0.2757$				
	Lognormal	$\mu = -0.5596$	$\sigma^2 = 0.6158$	-	0.0003	0.0124	0.0122	8.60%
	Gamma	$\alpha = 1.8033$	$\beta = 0.4287$	-	0.0006	0.0183	0.0179	13.65%
	Nakagami	$\mu = 0.5581$	$\omega = 1$	-	0.0011	0.0262	0.0257	13.65%
Cycling	Lognormal-4	$\mu_1 = 0.4655$	$\sigma_1^2 = 0.0452$	$w_1 = 0.1297$	1.1×10^{-5}	0.0021	0.0021	1.06%
		$\mu_2 = -0.8142$	$\sigma_2^2 = 0.1180$	$w_2 = 0.2189$				
		$\mu_3 = 0.0993$	$\sigma_3^2 = 0.0356$	$w_3 = 0.2914$				
		$\mu_4 = -0.3385$	$\sigma_4^2 = 0.0552$	$w_4 = 0.3600$				
	Lognormal	$\mu = -0.2108$	$\sigma^2 = 0.2348$	-	0.0003	0.0105	0.0102	5.37%
	Gamma	$\alpha = 4.6427$	$\beta = 0.1950$	-	7.1×10^{-5}	0.0058	0.0057	2.98%
	Nakagami	$\mu = 1.3281$	$\omega = 1$	-	0.0001	0.0123	0.0119	2.98%

scenarios show mixture and skewed distribution curves as also observed in other reported similar studies. This suggests the existence of distinct scattering clusters for body-to-body propagation channels where in addition to the environment, the movements of the body components of the persons involved at both ends of the communication link contribute to distinct scattering clusters. A Lognormal mixture shadowing model for body-to-body channels under different running and cycling activities based on a cluster concept is proposed. The mixture model addresses the inaccuracies observed using a unimodal distribution that may not accurately represent the measurement data set. Parameters of the mixture model are estimated using the expectation-maximization (EM) algorithm. The accuracy of the proposed model is compared to other commonly utilized unimodal distributions showing significant improvement in representing the empirical data set.

The measured data, as well as the developed Lognormal mixture shadowing model, can be used for accurate planning and deployments of wireless body-to-body networks for use in various sporting and other related activities. Future works include conducting measurement campaign and analysis for varying distances between subjects.

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