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Project	IEEE P802.15 Working Group for Wireless Area Networks (WPANs)
Title	UWB Channel Modeling for BANs based on ARMA Synthesis Method
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Re:	[This is in response to the Call for Contributions: Body Area Network (BAN) Channel Model Document IEEE P802.15-08-0033-0006]
Abstract	[This is a draft document that provides a UWB channel model for on body area networks based on the autoregressive-moving-average synthesis method]
Purpose	[The purpose of this document is to offer an alternative UWB channel model for on body area networks to be implementable in MatLab© code]
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Release	[The contributor acknowledges and accepts that this contribution becomes the property of IEEE and may be made publicly available by P802.15]

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CHAPTER 1

UWB Channel Modeling for BAN

1.1 Introduction

THE wireless channel for BANs determines the system performance limits in theory and in practice. Thus, understanding and modeling such channels becomes an important prerequisite for designing and evaluating physical and MAC layer proposals for TG6 BANs.

The last version of the IEEE 802.15.4a UWB channel model, considers a channel model for body area networks [1]. The IEEE 802.15.4a UWB channel model final report presents typical indoor and outdoor environments. However, measurements of the UWB channel around the human body indicated that some modifications are necessary in order to model body area network scenarios, accurately. Indeed, due to the short distance between sensors on a human body and the close proximity to the human body, the UWB-BAN channel model has different path loss, amplitude distribution, clustering, and inter-arrival time characteristics compared to other UWB scenarios.

Based on that 4a channel model, IMEC and NICT have proposed a modified 4a channel model for BANs. It consists basically of two components: diffracting multipath components around the human body expanding around 4 nsec, and clusters of multipath components due to reflections from nearby scatters including ground, walls, etc., expanding around 50 nsec. This second set of multipath components seem to follow a conventional UWB 4a channel model.

As UWB-BANs employ special antennas attach to the human body either wereable or on-body (patches), this proximity to the human body changes the antenna's characteristics. These phenomena are difficult to study as those depend from person to person and how antennas are handle. So, the effects of body and antennas into the propagation channel are not separated as in conventional channel measurements. The dynamics of both antennas and human body are characterized into one entity and embedded into the propagation channel. Thus, the reason of studying and characterizing a modified 4a channel model becomes obvious.

On the other hand, the UWB channel for BANs is assumed a linear system as in any other wireless channel. Thus, an alternative form of channel modeling is by linear prediction of the channel's transfer function obtained from measurements.

1.2 Linear Prediction

The background of this approach is that the concentration or spread of the power spectrum indicates the correlated or random structure of a signal. Thus, the power spectrum can be used to deduce the existence of correlated patterns or repetitive structures in the signal process. The literature is rich in spectrum analysis research works. In particular, linear model-based spectral estimation assumes a given signal $x(t)$ is modeled as the output of a linear system excited by a random, flat-spectrum excitation. Thus, the power spectrum of the model output is shaped entirely by the frequency response of the model. Hence, an input-output relation of a generalized discrete linear model is given by

$$x(m) = \sum_{k=1}^{P} a_k\, x(m-k) + \sum_{k=0}^{Q} b_k\, e(m-k) \tag{1.2.1}$$

where $x(m)$ is the model output, $e(m)$ is the input signal, $\{a_k\}$ and $\{b_k\}$ are the parameters of the model. Equation 1.2.1 is known as the autoregressive-moving average model (ARMA).

The frequency response of the model is given by

$$H(z) = \frac{B(z)}{A(z)} = \frac{\sum_{k=0}^{Q} b_k\, z^{-k}}{1 - \sum_{k=1}^{P} a_k z^{-k}} \tag{1.2.2}$$

with power spectrum

$$P_X(f) = P_E(f)\, |H(f)|^2 \tag{1.2.3}$$

Assuming the input signal $x(m)$ is white noise with unit variance, the input power spectrum is $P_E = 1$ and so the power spectrum of the model output is the square magnitude of the frequency response of the model

$$P_x = |H(f)|^2 \tag{1.2.4}$$

1.3 Maximum Entropy Spectral Estimation

The power spectrum of a stationary signal is defined as

$$P_x(f) = \sum_{m=-\infty}^{\infty} R_{xx}(m)\exp(-j2\pi fm) \tag{1.3.1}$$

that is, the Fourier transform of the autocorrelation sequence R_{xx}. Notice that such autocorrelation is defined for time-lags in the interval $(-\infty, +\infty)$, but in practice such interval is finite $(-P, P)$. In parametric methods, R_{xx} is assumed zero for $|m| > P$ for which no measure or estimate values are provided. This assumption results in spectral leakage and so loss in frequency resolution. Thus, nonparametric methods are introduced to overcome this disadvantage based on the maximum spectral estimation. Indeed, the maximum entropy estimate is based on the principle that the estimate of the autocorrelation sequence corresponds to the most random signal, whose correlation values in $|m| \leq P$ coincide with the measured values.

In a future Appendix A, it is shown that the maximum entropy power spectrum estimate is obtained by maximizing the entropy of the power spectrum with respect to the unknown autocorrelation values, such that

$$\hat{P}_x^{\text{ME}} = \frac{\sigma^2}{A(z)A(z^{-1})} \tag{1.3.2}$$

That is, the maximum entropy power estimate is the power spectrum of an autoregressive model.

1.4 Autoregressive Power Spectrum Estimation

An autoregressive or linear prediction model is defined as

$$x(m) = \sum_{k=1}^{P} a_k\, x(m-k) + e(m) \tag{1.4.1}$$

where $e(m)$ is a random signal with flat spectrum and variance σ_e^2.

The power spectrum of an autoregressive process is given by

$$P_x^{\text{AR}}(f) = \frac{\sigma_e^2}{|1 - \sum_{k=1}^{P} a_k \exp(-j2\pi f k)|^2} \tag{1.4.2}$$

The AR model extrapolates the correlation sequence beyond the range for which estimates are available. That is, the AR model is nonparametric. By multiplying both sides of Equation 1.4.1 by $x(m-j)$, taking expectation and noticing that $e(m)$ is orthogonal to past samples $x(m-j)$, we obtain

$$R_{xx}(j) = \sum_{k=1}^{P} a_k \, R_{xx}(j-k) \quad ; \quad j \in \mathbb{Z}+ \tag{1.4.3}$$

Hence, given $P+1$ correlation values, Equation 1.4.3 can be solved to obtain the AR coefficients $\{a_k\}$. Equation 1.4.3 can be used to extrapolate the correlation sequence as well. Indeed, by assuming the system model is casual (zero for $n < 0$), the autocorrelation R_{xx} can be expressed in terms of the AR model parameters as

$$R_{xx}(m) = \begin{cases} \sum_{k=1}^{P} a_k \, R_{xx}(m-k) & m \geq 0 \\ \sum_{k=1}^{P} a_k \, R_{xx}(m-k) + \sigma_e^2 & m = 0 \\ R_{xx}^*(-m) & m < 0 \end{cases} \tag{1.4.4}$$

Thus, if $P+1$ correlation values are known ($R_{xx}(m)$ for $m = 0, 1, ..., P$), the filter parameters can be found by solving P linear equations given by

$$\begin{bmatrix} R_{xx}(0) & \ldots & R_{xx}(P) \\ R_{xx}(-1) & \ldots & R_{xx}(P-1) \\ \vdots & & \vdots \\ R_{xx}(P) & \ldots & R_{xx}(0) \end{bmatrix} \begin{bmatrix} 1 \\ a_1 \\ \vdots \\ a_P \end{bmatrix} = \begin{bmatrix} \sigma_e^2 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \tag{1.4.5}$$

Equation 1.4.5 is known as the Yule-Walker equations.

Then, the AR model provides a practical method for signal modeling. That is, if we want to represent a given random signal $x(n)$ by the AR model, the correlation $R_{xx}(m)$ can be estimated and used in Equation 1.4.5 to solve for the model parameters $\{a_k\}$.

1.5 Linear Modeling of Random Processes

In Equation 1.2.4 the shape of the power spectrum depends on the magnitude of the system frequency response. Thus, a random process with any desired 2nd moment characteristics can be reproduced by applying white noise to an appropriate linear filter. Such filter in the AR model is a recursive IIR with nontrivial denominator polynomial only. The idea is to employ an AR model to reproduce the random process of UWB channels.

1.6 UWB Channel Measurements

As it is well known, characterization of radio channels by measurements makes use of the linear property of such channels. Bello gave an exhaustive treatment of linear radio channels in [2]. Particularly, a frequency domain characterization can be obtained by an input signal $Z(f)$ localized in the frequency domain, i.e., $Z(f) = \delta(f - f_0)$ such that the input-output relationships are given by

$$W(f) = \int Z(f - v)\, H(f, v)\, dv \; = \int Z(f - v)\, G(f - v)\, dv \tag{1.6.1}$$

$$W(f) = H(f, f - f_0) = G(f_0, f - f_0) \tag{1.6.2}$$

where $H(f)$ and $G(f)$ are the input and output Doppler spread functions, respectively.

The time varying transfer function and associated input-output relationship are given by

$$T(f, t) = \int g(t, \xi)\, \exp(-j2\pi f \xi)\, d\xi \tag{1.6.3a}$$

$$w(t) = \int Z(f)T(f)\, \exp(2\pi f t)\, df \tag{1.6.3b}$$

If $Z(f) = \delta(f - f_0)$, then

$$w(t) = T(f_0, t)\, \exp(j2\pi f_0 t) \tag{1.6.4}$$

If the channel is slowly time varying

$$T(f, t) \approx T(f, t_0) \text{ for } |t - t_0| < 1/f_0 \tag{1.6.5}$$

so that

$$w(t) \approx T(f_0, t_0)\, \exp(j2\pi f_0 t) \tag{1.6.6}$$

which leads to

$$W(f) \approx T(f_0, t_0)\, \delta(f - f_0) = T(f_0, t_0)\, Z(f) \tag{1.6.7}$$

which is the input-output relationship in the frequency domain when the input has an impulse excitation. This quasi-static equation is measured by a vector network analyzer through the scattering parameter S_{21} for a two port radio channel.

NICT performed extensive channel measurements employing this technique to characterize BAN channels in different frequency bands. Furthermore, this technique has the advantage of calibrated measurements are performed relatively easy. Although, it has the serious disadvantage of a limited use of quasi-static channels. Indeed, as the VNA employs IF filtering, f_0 is replaced by the IF bandwidth, resulting in a stronger constrain for the time variability of the channel under measurement. Some other sources of errors and constrains might affect the measurements and need to be taken into account. Although those are out of the scope in this report.

The measurements for UWB channels were performed in the lower UWB band (3 GHz to 5 GHz) with central frequency of 4 GHz. The VNA recorded a snap shot of 801 sampling points with a sampling frequency of 2 GHz. The employed antenna is skycross, which was placed in different positions in a human body. Measurements took placed in an anechoic chamber and conventional hospital room. Those measurements and a preliminary UWB channel model (in the time domain) were presented in the Orlando meeting last March.

1.7 AR Modeling of UWB-BAN Channels

The channel's transfer function $H(f_n)$ can be obtained in the frequency domain in terms of the measured scattering parameter S_{21}. We can characterize the random nature of the UWB channel by an AR process modeling as

$$H(f_n, x) = \sum_{i=1}^{P} a_i\, H(f_{n-i}, x) \;+\; e(f_n) \tag{1.7.1}$$

where $H(f_n, x)$ is the nth sample of the $|S_{21}|^2$ measurement in the frequency domain at location x. $e(f_n)$ is a white process with distribution $\mathcal{N}(0, \sigma_e^2)$.

Notice that the 1st and 2nd order statistics of the UWB channel are captured in the AR model. The advantage of this modeling respect to conventional time domain approaches is that less parameters are required to generate a simulation program that resembles the statistical behavior of an UWB-BAN channel. The main drawbacks are that it does not provide information about the phase and it is not intuitive to understand.

A difference with similar approaches found in the literature is that the statistical correlation R_{xx} is not estimated from the measured data (sample correlation) by rather estimated by the data-oriented least squares criterion, where the sum of square terms of a conditional likelihood function is minimized.

1.7.1 Order Selection

Selecting the order P might be a difficult problem. Monitoring the prediction error variance and model coefficients till they stabilized is difficult to achieve in practice. As result, other metrics have been proposed to estimate the order P. The four more known criteria are, The Akaike information criteria (AIC), criterion autoregressive transfer (CAT), final prediction error (FPE) and minimum description length (MDL). Discussion of the statistical properties of the these criteria is beyond the scope of this report.

1.8 Preliminary Results

The order was chosen as $P = 5$ after extensive trials. Thus, a UWB-BAN channel model can be implemented by an AR model in the form of a recursive IIR filter with parameters:
$a_1 = -1.3138$, $a_2 = 0.4829$, $a_3 = -0.0155$, $a_4 = -0.1518$, $a_5 = 0.0650$,
which is driven by a white process with variance $\sigma_e^2 = 4.853\text{x}10^{-12}$.

Notice that the power loss is included in the simulation model, but it can be extracted so that a conventional power delay profile can be obtained. *In a future update*, the simulation results will be compared in terms of resembling the RMS delay spread and other conventional channel model figures.

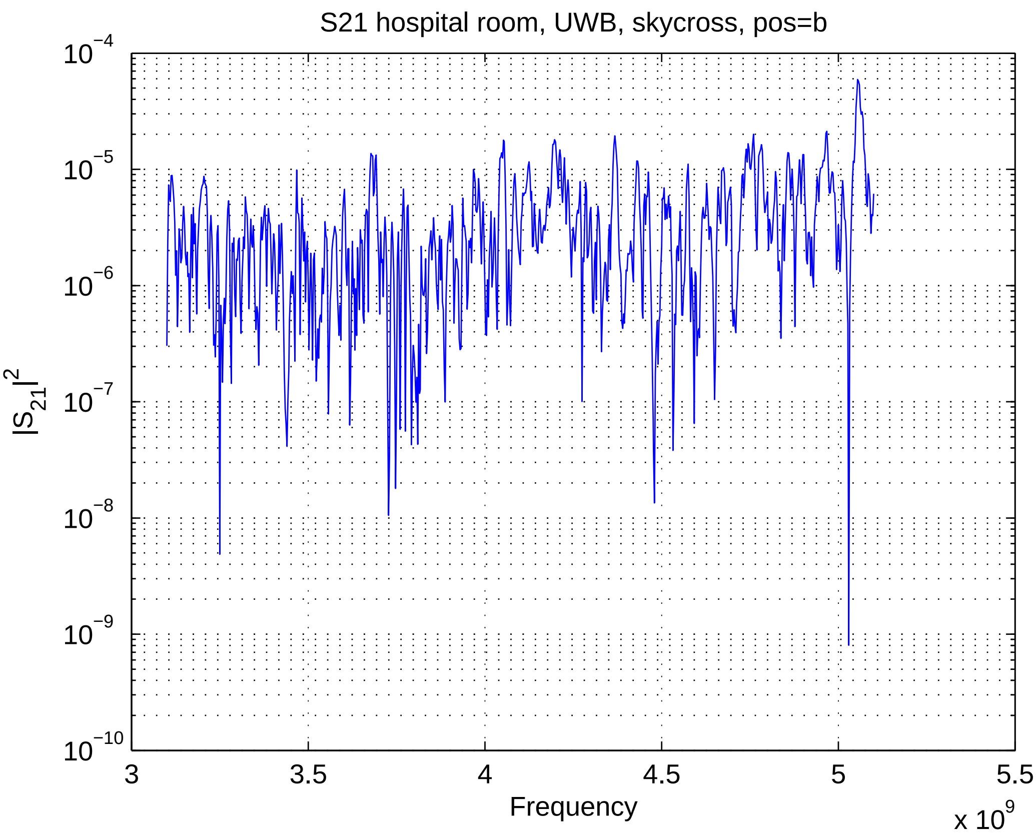

Figure 1.1: *Measured channel's transfer function in a hospital room and position b.*

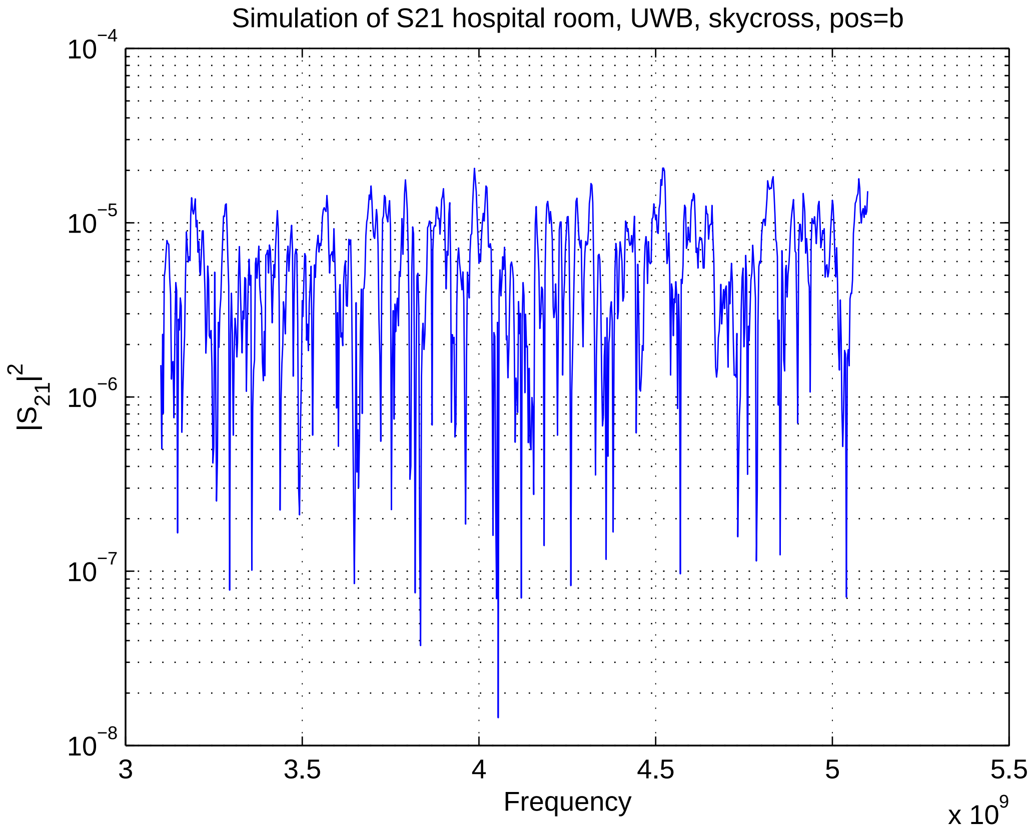

Figure 1.2: *Simulated channel's transfer function in a hospital room and position b.*

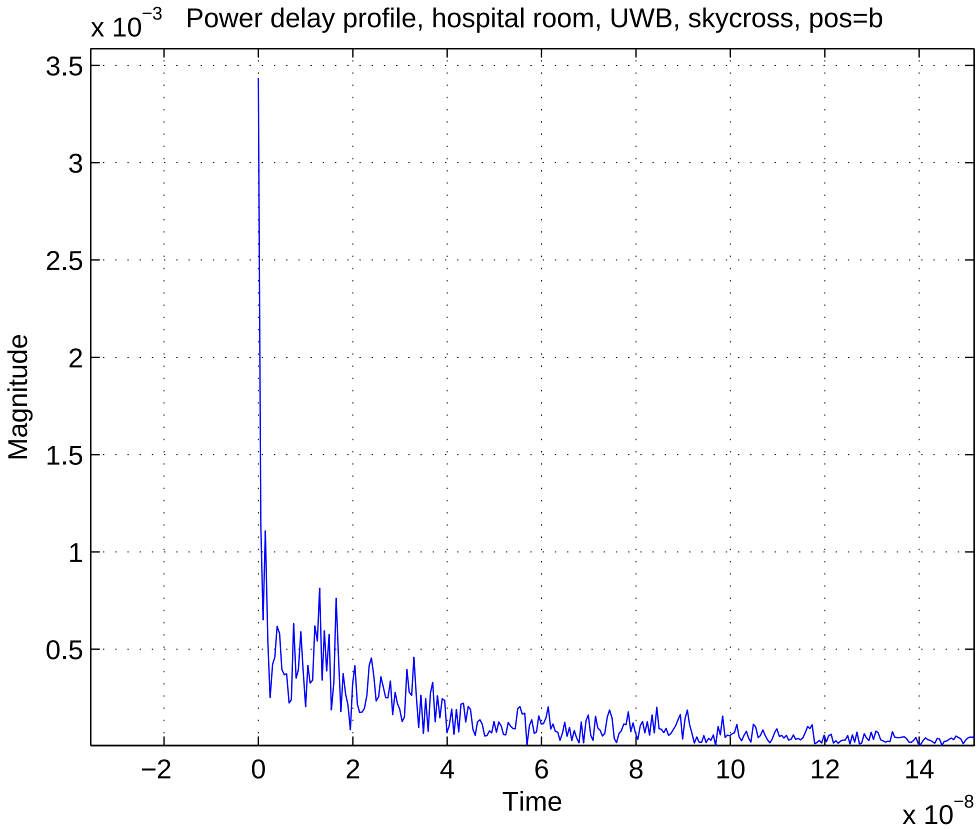

Figure 1.3: *Measured power delay profile in a hospital room and position b.*

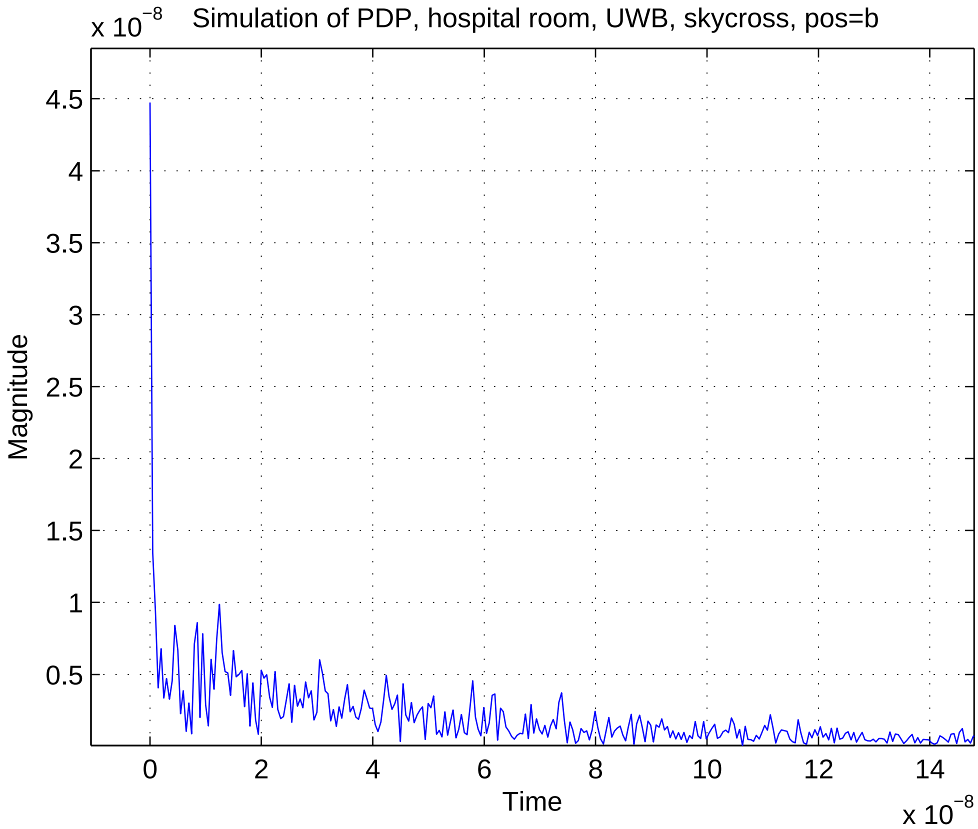

Figure 1.4: *Simulated power delay profile in a hospital room and position b.*

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