An Ultra Wideband Communication Channel Model for the Human Abdominal Region

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Abstract—Long-term implantable devices communicating with receivers in the outer human body through a wireless interface are one of the most prominent applications of micro/nano-technology in medicine. Ultra wideband (UWB) interfaces have great potential for the communication links of these telemedicine applications due to their inherent low power consumption, high transmission rates, and simple electronics. Novel implant medical sensors and actuators operate in the abdomen at different depths, which makes an "abdominal" channel model essential for the proper design of the UWB communication interfaces of said devices. This paper presents a statistical model for the propagation of a UWB pulse through the abdominal region in the 1-6 GHz frequency band. For the development of this statistical model, numerical electromagnetic (EM) simulations were conducted using a digital anatomical model that includes the dielectric properties of human tissues; using this EM simulator, the channel responses of many in-body probes were computed. Based on the statistical analysis of the obtained data, we provide the mathematical expressions to calculate the path loss and shadowing at depths between 10-150 mm inside the abdomen. In addition, the channel impulse response (CIR) can be reproduced using a set of statistical formulas also provided. Our proposed model approximates very well the abdominal in-body channel properties, thereby eliminating the need for time-consuming and complex numerical simulations.

Keywords - channel model; implant devices; in-body communication; ultra wideband; wave propagation

I. INTRODUCTION

In modern telemedicine systems the physiological data of patients can be measured with the aid of electronic sensors located on and inside the human body [1]. The collected medical data is transmitted wirelessly to an external unit for processing, thereby enhancing the health monitoring, diagnosis, and therapy of the patients. Ultra wideband (UWB) technology has great potential for the wireless interface of these telemedicine applications, particularly for medical implant devices, due to its inherent low power consumption, high transmission speed, and simple electronics [2].

Accurate knowledge of the propagation channel is necessary for efficient design of UWB wireless communication systems.

Considerable effort has been devoted to the characterization of the propagation of UWB radio signals from on-body sensors; however, significantly fewer results are reported for the case of UWB implant devices. A number of path loss models for narrowband (NB) implant sensors are available in the literature [3]–[7], which regrettably are not suitable for modeling UWB propagation conditions. The IEEE 802.15.6 standardization group [8] has issued several propagation models for medical and nonmedical devices, both in-body and on-body, for wireless body area networks (WBANs). Nevertheless, the in-body channel models therein characterize NB applications, whereas the UWB models only characterize on-body communication channels.

The lack of a UWB channel model for implant sensor communications was overcome with the investigations reported in [9], [10]. In that work, the characterization of a UWB link in the 3.4-4.8 GHz frequency band is presented. The channel model was developed assuming 20 arbitrary locations of a transmitting implant device inside the human chest between 6-18 mm depth. Subsequently, our own research led to a more general UWB in-body channel model for the chest [11], which describes the propagation channel for depths between 5-120 mm in the 1-6 GHz frequency band.

Nevertheless, the highly inhomogeneous structure of the human body makes absolutely necessary the development of a customized model for different anatomical parts. Novel implant sensors and actuators such as pressure detectors in the bladder, implant automatic-insulin-release devices in the pancreas, etc. operate in the abdomen. Therefore, a UWB in-body channel model for the abdominal region is necessary for the design of the communication interfaces of said devices; this paper presents such a UWB in-body channel model.

In this work, numerical electromagnetic (EM) simulations were conducted using a digital anatomical model that included the dielectric characteristics of human tissues in order to obtain the channel response when a UWB pulse was propagated through the abdominal region. Then, the obtained information was processed to develop an easy-to-implement statistical channel model. Our proposed model allows computing the path loss and shadowing experienced by a UWB signal.
transmitted by an implant sensor in the abdomen at a depth between 10-150 mm. Moreover, we provide the statistical formulas to reproduce the channel impulse response (CIR) for the aforementioned depths.

The rest of the paper is organized as follows: Section II presents the in-body simulation scenario used for the numerical simulations. Section III presents the computational characterization of the channel and Section IV describes the statistical abdominal UWB channel model and its validation. Finally, our conclusions are drawn in Section V.

II. NUMERICAL SIMULATION

The time-domain finite integration technique (FIT) was used to solve the Maxwell’s equations for our numerical simulations. An anatomical model of the human body based on the Visible Human Project of the National Library of Medicine (NLM) [12] was embedded in the FIT electromagnetic (EM) simulator. A voxel representation of the human body with a resolution of 2 mm was used. The dielectric properties of the human tissues, permittivity and conductivity, were provided by Gabriel [13] based on the Cole-Cole model, which describes the frequency dependent characteristics of the tissue materials. However, incorporating the highly complex material properties in the numerical simulation causes extremely long computational time. Previous investigations [14], [15] revealed that a simplified equation for describing the frequency dependent complex permittivity of human tissues can be obtained with a second-order polynomial, which precisely fits Gabriel’s data, by using

\[ \varepsilon_r(\omega) = \varepsilon'_r - j\varepsilon''_r = \varepsilon_\infty + \frac{\beta_0 + j\omega\beta_1}{\alpha_0 + j\omega\alpha_1 - \omega^2} \]  

where \( \varepsilon'_r \) and \( \varepsilon''_r \) are defined as the real and imaginary parts of the complex permittivity, \( \varepsilon_r(\omega) \), respectively. \( \omega \) is the angular frequency, \( \varepsilon_\infty \) is the permittivity at infinite frequency, and \( \alpha_0, \beta_0, \alpha_1, \beta_1 \) are fitting parameters that can be derived by fitting to Gabriel’s four-pole Cole-Cole data by using the Newton method and least square fitting. The fitting parameters are estimated for 18 different tissue materials in the abdominal region such as bladder, blood, fat, gall bladder, intestine, kidney, spleen, stomach, marrow, skeleton muscle and bones. The fitting accuracy using (1) was demonstrated in [14], [15].

The simulation scenario within the anatomical model of an adult male is illustrated in Fig. I. The abdomen is exposed to an incoming plane wave from the front. Electric and magnetic field probes are placed inside the abdomen within an anatomically shaped space of 150 mm depth, 140 mm width, and 300 mm height; the distance between contiguous probes is 10 mm, 20 mm and 50 mm, respectively, in the aforementioned sides of the space. The field probes are ideal frequency independent isotropic antennas with a specified polarization co-polar with the incident field polarization. The probe arrays do not have any coupling among them. Both vertical polarization (VP) and horizontal polarization (HP) of the electric field with respect to the standing body are considered. Perfectly matched layer (PML) absorbing boundary condition (ABC) is used for the simulations, thus the body environment reflections are disregarded. The first depth plane consists of the probes closest to the skin, placed 10 mm from the surface, and in each plane there are 48 probes. The arms and hands of the model are excluded from the EM simulation.

III. COMPUTATIONAL RESULTS

Using the model described above, a UWB Gaussian pulse with a 1-6 GHz bandwidth, shaped by a Hamming window, excited the plane wave. The total energy of the incident wave was normalized to unity so that the signal energy on the surface of the body was fixed at 0 dB J/m². The incident plane wave was excited either parallel to the x-axis (HP) or z-axis (VP), and the Poynting vector was calculated for the dominant direction into the body (\( S_y(t) \)). Then, the total energy density, \( E_t \), at each probe location could be computed by integrating the Poynting vector over the observation time,

\[ E_t(x, y, z) = \int_0^{t_{\text{max}}} |S_y(t)| dt, \quad 0 < t < t_{\text{max}}, \quad \text{J/m}^2 \]  

Fig. 1. Human body model used in the simulation scenario shown in the y-x, and y-z plane (from left to right). The plane wave propagates along the y axis as indicated by the arrow.
A. Power Delay Profile and Delay Spread

A multipath channel is characterized by its time dispersive properties such as excess delay spread and root-mean-square (RMS) delay spread, which are useful in assessing the potential for intersymbol interference (ISI) in high data rate transmissions. The intensity of a signal received through a multipath channel as a function of time delay, \( \tau \), is known as the power delay profile (PDP). Figure 2 shows the PDP of received UWB signals with HP at different depths. Notice that for the lower depths the PDP decays very rapidly, which indicates that the multipath components (MPCs) contribute only a small amount of power relative to the main path. Figure 3 shows the RMS delay spread for both VP and HP.

\[ P_{[dB]}(d) = P_{0[dB]} + m(d/d_0) + N(\mu(d), \sigma(d)) \]  

where \( d \) is the depth from the skin in millimeters, \( d_0 \) is the reference depth (10 mm), \( P_0 \) is the path loss intersection reference in dB, \( m \) is the gradient fitting constant and \( N \) is a normal distributed random variable, with mean value \( \mu \) and standard deviation \( \sigma \). A good fit to the average path loss is achieved with \( P_0=1.407 \) and \( m=3.397 \). Figure 4 shows the path loss at individual probes (circles), the average path loss (dashed line), and the fitted expression given by (3) (solid line). The shadowing distribution parameters for different depths are given in Table I.

A. Channel Impulse Response

The channel impulse response can be viewed as a time-invariant linear filter. In other words, a sum of scaled and shifted copies of the original transmitted signal. The CIR may then be expressed as

\[ h(\tau) = \sum_{k=1}^{N} \beta_k \alpha_k \delta(\tau - \tau_k) \]  

where \( \beta_k \) and \( \alpha_k \) are the gain and delay of the \( k \)-th path, respectively, and \( \delta(\tau) \) is the Dirac delta function.

IV. Statistical Channel Model

The path loss for different depths was calculated by averaging the attenuation observed at the 48 probes in each of the 15 depth planes, i.e., a total of 720 probes. We found that the path loss can be expressed as a logarithmic function, which is common in on-body and free-space scenarios. Considerable path loss variations around the average was observed. This fading effect is referred to as shadowing, and is caused by the dielectric property variations of different tissues that affect each probe. We found that the shadowing in each depth plane is approximately lognormal distributed, which is also known to be the case in on-body and free-space scenarios [16]. A model of the average path loss at different depths including shadowing can be written as

\[ P_{[dB]}(d) = P_{0[dB]} + m(d/d_0) + N(\mu(d), \sigma(d)) \]  

where \( d \) is the depth from the skin in millimeters, \( d_0 \) is the reference depth (10 mm), \( P_0 \) is the path loss intersection reference in dB, \( m \) is the gradient fitting constant and \( N \) is a normal distributed random variable, with mean value \( \mu \) and standard deviation \( \sigma \). A good fit to the average path loss is achieved with \( P_0=1.407 \) and \( m=3.397 \). Figure 4 shows the path loss at individual probes (circles), the average path loss (dashed line), and the fitted expression given by (3) (solid line). The shadowing distribution parameters for different depths are given in Table I.

<table>
<thead>
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<th>Depth (mm)</th>
<th>( \mu, \sigma )</th>
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where $N$ is the number of MPCs to be included in the estimation, and $\alpha_k$ is the amplitude and $\tau_k$ is the time delay, respectively, of the $k$-th MPC. The polarity $\beta_k$ is a binary random variable, which takes the value +1 or -1 with equal probability. In order to estimate the CIR, deconvolution of a signal distorted by the channel is performed using the CLEAN algorithm [17]. Even though the CLEAN algorithm is limited to being a mathematical tool only, this method is still preferred because it produces a discrete CIR in the time domain when the signal template is known. In our case, by simulating a plane wave, the transmitted pulse, i.e., the known signal template, is not distorted by antenna effects. In other words, the CLEAN algorithm assumes that the channel response is a series of impulses consistent with the tapped delay line of (4) when $N \rightarrow \infty$. The CLEAN algorithm produces an unlimited bandwidth CIR by correlating the received signal with the transmitted signal (template). It iteratively finds the highest correlation peak, thus identifying the pulse amplitude and delay, and subtracts its power contribution from the original signal until the highest correlation peak is lower than a fixed threshold, chosen to be $20$ dB below the maximum peak in our case. In this way, the number of MPCs needed to model a distorted pulse is limited to a tractable number.

B. Distribution of MPCs Amplitude and Delay

As can be seen by the power delay profile in Fig. 2, for depths less than 30 mm the power contribution from MPCs is negligible, and may be modeled by its path loss only. For depths above 30 mm the values of the $k$-th MPC’s normalized power has a distribution that fit well to a Rayleigh distribution with parameter $\sigma^P$. Whilst the first MPC component follows a complementary Rayleigh distribution $(1-R)$, the remaining $k$ components can be modeled with the regular Rayleigh distribution $R$. Within each depth, the value of $\sigma^R$ has the initial value $\Omega_d$ for the first MPC, and decays exponentially for every $k$ with a decay exponential $\Lambda_d$. Both the decay exponential and its initial value are dependent on the depth $d$, and can be expressed as linear functions

$$\Omega(d) = \omega_1 \frac{d}{d_0} + \omega_0 \quad (5)$$
$$\Lambda(d) = \lambda_1 \frac{d}{d_0} + \lambda_0 \quad (6)$$

The parameter $\sigma^R$ of the power distribution may therefore be expressed as a function of both $d$ and $k$ as

$$\sigma^R(d,k) = \Omega(d)e^{-(k-1)\Lambda(d)} + 0.01 \quad (7)$$

where $1 - \Omega\sqrt{\frac{1}{\pi}}$, according to the Rayleigh distribution, is the average power of the first MPC. A correction value of 0.01 is added for the asymptotic line of the exponential function.

The total delay of each of the MPCs is the sum of many small random delays caused by reflections and other propagation effects through the body’s complex geometry with its different dispersive materials. Therefore, the central limit theorem explains the observed Gaussian distribution of the total delay with mean value $\mu_d$ and standard deviation $\sigma_d$.

The mean value, $\mu_d^D(k)$, and standard deviation, $\sigma_d^D(k)$, of the $k$-th MPC’s delay distribution at a given depth $d$ can both be modeled as linear polynomials

$$\mu_d^D(k) = \rho_{d,1}k + \rho_{d,0} \quad (8)$$
$$\sigma_d^D(k) = \gamma_{d,1}k + \gamma_{d,0} \quad (9)$$

Table II shows the corresponding values for different depths. The suggested distribution parameters were acquired by applying the least square fitting method.

C. Model Validation

In order to validate our model, (4) can be reconstructed with $N$ independent Rayleigh distributed variables with parameter $(\sigma^P)$ for $N$ MPCs. The amplitude, $\alpha_k$, is the square root of the $k$-th MPC with a random polarity, $\beta_k$. The corresponding time delay, $\tau_k$, is generated as Gaussian values with parameters $(\mu^D_k, \sigma^D_k)$. Suggested values for $N$ and the parameters for (5),(6),(8), and (9) are available in Table II. The suggested values for $N$ provide the best representation of the CIR.

The standard procedure for validating a channel model is to compare its average power delay profile (APDP) and its RMS delay spread to those of the numerically simulated results. Since the temporal resolution of the MPCs is limited by the bandwidth of the pulse, the output is arranged in bins of 0.4 ns in size, which correspond to the resolution of the bandwidth of the transmitted pulse. Figure 5 shows the APDP and Fig. 6 shows the RMS delay spread comparison of the EM simulation and of the statistical model, respectively. A very good approximation was observed for all depths analyzed in this paper. It is important to mention that by using the adequate parameters, (5)-(9) can be used to model VP as well.

V. Conclusion

A computational analysis and a statistical model of the UWB in-body channel in the abdominal region for 1-6 GHz frequency band and 10-150 mm depth have been presented. The highly inhomogeneous structure of the human body suggests a model that takes the depth of interest into consideration. In the case of depths below 30 mm, the power contribution from multipath components is negligible; thus the channel might be characterized by path loss only. Deeper into the body, this contribution varies greatly with depth, and the time dispersive characteristics of the channel must be known in addition to path loss. An important contribution of this work is the statistical description of the channel impulse response for depths between 30 mm and 150 mm. The validation of the proposed statistical model shows that it approximates very well the channel impulse response acquired by deconvolution of distorted pulses obtained from a time-consuming numerical simulator. Therefore, our results will greatly ease the design and performance evaluation tasks of UWB interfaces for implanted sensors and actuators. Although this model is restricted to the abdominal area, the guidelines described in this paper can be used to develop UWB in-body
channel models for other anatomical parts. In future work, the same procedure will be applied to other anatomical models of different sizes for further refinement of our statistical channel model.

![Image of Fig. 5. APDP based on EM simulations and the statistical model](image-url)

![Image of Table II: Parameters of the MPCs distribution](image-url)

![Image of Fig. 6. RMS delay spread based on EM simulations and the statistical model](image-url)

Table II: Parameters of the MPCs distribution

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References


