A Scalable Human Body Channel Modeling Technique for Networked Body Implants

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ABSTRACT
We describe an approach to modeling human body as a transmission medium for applications in implantable, networked sensors. The model is customizable, flexible and lends itself to digital computer simulation. The model views the human body as consisting of cubes (*elements*) of constant size. Each element is composed of a finite number of materials with composition profiles of materials assumed to be known. The proposed model does not require that all material types should have similar attenuation and fading distributions. The model can be applied to coarse or fine grained power requirements of implanted sensor network.

Categories and Subject Descriptors

B.1.2 Control Structure Performance Analysis and Design Aids

Simulation

General Terms
Algorithms, Measurement, Performance, Design,.

Keywords
Body channel, propagation model, implantable sensor network, human body as propagation medium.

1. INTRODUCTION
Recent developments in prosthetic and drug administration implants provide a clue to a future of medicine in which a virtual doctor will monitor human body *in-situ*. Automatically generated alert system could inform the primary care or first responders in case of emergencies. Power budget is among the outstanding challenges in designing such networks. While we talk about hours of usage per charge in smart phones, we would ideally not have to recharge batteries in implanted sensors and use techniques such as power scavenging [1] by converting, e.g., temperature gradient into power. This is practical only if the consumption levels are extremely low. It boils down to having a channel model that is not only extremely accurate but also extremely low in power requirement.

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However, given the variety of body types, variety of material composition and possibility of implants location to be anywhere in the body, a model with permanent values of parameters does not make sense. In this paper, we propose a model that uses a general baseline structure and then builds on individual body varieties, material characteristics of the signal path, material composition of the path and the location of the implants to be networked within the body. This flexible and scalable model can be applied in a customized way for networked sensors within the body making use of the modern computational power. The paper layout is as follows:

In Section 2, we discuss various approaches used for channel modeling for wireless network design. In Section 3, we focus on efforts of modeling signal propagation within the human body. Section 4 presents the proposed model. In Section 5, we discuss two computer simulation scenarios, for implants requiring coarse grain modeling and for the ones requiring a fine grain modeling. In Section 6, we discuss usage of simulation. In Section 7, we conclude the paper along with the future plan followed by references.

2. PROPAGATION MODELS
Extensive empirical research is available in modeling propagation conditions in wireless and dielectric media. Usually, the goal of these models is to determine the resources needed to provide a communications service between two devices when the channel is stochastic in nature. One of the resources is the transmit power required for given environment & receiver sensitivity. For most applications, the environments provide extremely random conditions. The approach taken to resolve this condition is by defining certain types of environments [2, 3], such as urban, sub-urban, rural, space, inside buildings, in busy square, etc. Then, empirical methods are employed to determine the signal attenuation and distribution of randomness in the signal, characterized as path loss and fading respectively. For most applications of wireless communications, delay spread and Doppler's bandwidth are also important. For more accurate measurements, and especially in antenna design, the electromagnetic wave propagation equations provide a better solution [4].

3. HUMAN BODY AS PROPAGATION CHANNEL
3.1 Limitations of Body Modeling
Human body departs from most environments studied for wireless communications in many ways [5]. The intractability of implanted systems perhaps stands out of all others. There are critical issues relating to supplying and continuation of power as well [6]. The impact of radiation on tissues is yet another debate that seems to be

unending and asks for lowest possible power levels. The variety of materials in various parts of body and variety of body types are other issues. Since this is an area where gamble is not an option, precision and accuracy are the only choice while designing a channel model for body.

3.2 Existing Work

Efforts have been reported in modeling human body and head. In [8], the authors have used tissue and geometrical variations properties in a galvanic coupling description of body. The model employs numerical simulations and measurements to characterize transmission of signals in individuals. In this more relevant work, the authors model the human body for intrabody communications. They have plotted E-field around the body and measured and simulated various characteristics including power spectrum density (PSD). In the both of the above papers, the frequency ranges used are below 100 MHz. However, IEEE 802.15.6 (medically implantable communications systems or MICS for short) target the FCC allocated band at 400 MHz [9] and there is enough interest in UWB to warrant a modeling study at this spectrum as well. In one of the latest work [10], the authors have used simulations to characterize the human body as a communications medium for implants network at higher frequency bands, including MICS (400 MHz), ISM (2.4 GHz) and UWB (3.1 GHZ+). The finite difference time domain (FDTD) mechanism used in this paper is the one researchers are looking up to as computational power is harnessed in desktop and smaller computing machinery. A frequency dependent FDTD has been employed in [11] along with matlab for determining the body signal propagation characteristics at the UWB band. In other related work on different frequency bands, one can find reference to ultrasonic frequencies [12]. The parameters that can be tuned in our case are the path-loss exponent and the variance of fading. It is reasonable then to start with some well-known values of the propagation characteristics of body materials and employ the standard path loss model, and then adjust the property values based on real data for each subject. Since not all materials in the body are expected to follow the same profile of change with time, each material has to be dealt with individually. With these assumptions, we are ready to describe our proposed model in the next section. Before ending this section, however, we will list modeling approaches in Table 1. The table is based on [2].

Table 1. Modeling approaches

Modeling Approach	Examples	Applicability to body modeling
Path loss models	Okumura, Hata	Accuracy issue
Small Scale Fading	Rayleigh, Ricean	Applicable with a good path-loss model
Impulse Response	Statistical Time Spread, SIRCIM	Measurement equipment issue
Joint Angle-Delay Estimation (JADE)	JADE-MUSIC, SI-JADE	Body movements issue

4. THE PROPOSED MODEL

In the proposed model, we depart from the traditional approaches in many ways:

(i). We assume that the body consists of cubes, called *elements*, of a constant size d_o. Value of d_o can be changed depending on the usage scenario. For example, for body areas relatively easier to approach surgically with homogeneous body composition, can have larger d_o in general. The difference between this assumption and FDTD is that d_o can be large depending on the body section, type of implant and its compatibility.

(ii). We assume that propagation characteristics of each material type are unique enough to warrant its own model. Transitions between materials can be accounted for separately from in-material propagation. Thus, the model will require two path loss exponents for muscle and bone and one for transition from one to the other, assuming the transition is symmetric. If γ_{kl} is the path loss exponent for propagation from material type k to l and vice versa, then γ_k is the same for within the material type k. In this way, the path loss exponent in our model consists of an $n \times n$ matrix $\boldsymbol{\gamma}$.

(iii). The second assumption allows us to model fading individually for each material type, which makes sense even if the distribution of fading is the same for all material types. Thus, $\boldsymbol{X}$ is the vector with components X_k ($k = 1, 2, \ldots n$) for the fading factor for material k with a standard deviation of $\boldsymbol{\sigma_k}$.

(iv). We assume that the path loss for the first d_o is known, not a deviation from other approaches.

Fig. 1 shows how the body element is viewed.

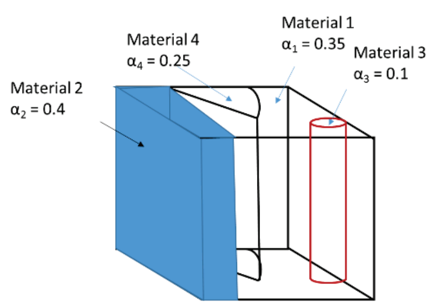

Figure 1. Body element as depicted by the proposed model.

In view of the above assumptions, the general model of the path loss is of the following form.

$$\boldsymbol{PL}(d,\lambda) = \boldsymbol{\alpha}.[\boldsymbol{A}(d_o) + \boldsymbol{B}(\lambda)] + 10.\ \boldsymbol{\gamma}.\log(R) + \boldsymbol{X} \qquad (1)$$

In Equation (1),

A(d_o) is the attenuation constant vector that depends on d_o and has components for different material types.

B(λ) is the vector for attenuation factor that depends on frequency of the signal,

$\boldsymbol{\alpha}$ is the composition vector for various materials such that $\Sigma\boldsymbol{\alpha_k} = 1$. As a special case when the transitions between materials are abrupt, the $\gamma_{ij} = 0$ for $i \neq j$, and Equation (1) becomes a set of linearly independent equations.

5. COMPUTER SIMULATION CASES

In this section, we will give two examples; one for coarse grain implementation and the other for fine grain implementation. In this paper, our main focus is on fine grain model.

5.1 Coarse Grain Model

The coarse grain model is for implants that are approachable to simple surgical procedure, or by considering each major limb as a propagation unit and applying to the limb as having uniform characteristics. Figure 2 shows a breakdown of human body into such propagation areas.

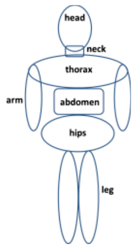

Figure 2. Coarse grain implementation example.

5.1.1 *Example – Hip Prosthetics*

An example of such implants is a network of coordinating hip implants for an athlete with artificial legs. The implants are in an area that are relatively easier to operate upon and are composed of a few material types. Depending on the location of sensors, the intervening material can be just a muscle. In this case, the matrix γ is a 2 x 2 or 3 x 3 matrix with only diagonal non-zeros for abrupt material boundaries. In some cases, such as brain implants, or implants for monitoring pregnancy, the interconnection will be within the same limb and a coarse grain model is good even with high accuracy. The grain in this case is defined by the scope of modeling, which is individual limb.

5.2 Fine Grain Model

We elaborate this model in greater detail and use the size limit of this paper mostly for the fine grain model. For areas that have more complex composition, are hard to reach and operate, a fine grain model can be adopted from Equation (1). Figure 3 shows how we scale this model as compared to the coarse grain. For ease of demonstration we have drawn Figure 3(a) in 2 dimensions. The third dimension can be incorporated easily as will be shown later in this section. Each element is designated by a bit pattern that also defines the resolution and location of the element. The model resolution is controlled by hierarchical layering of resolution reference axes. As shown in the figure, the first level divides the body into four parts, requiring two bits for designation of each element (quadrant). Therefore, if an application can tolerate a power variance given in one of these quadrants, a two-bit resolution can be used to identify the location of an element where the implant is located and propagation properties for that quadrant can be employed. The second layer of reference axes can narrow down the location to one-fourth of each quadrant area, further narrowing down the implant location and its neighborhood.

Figure 3(a) shows four hierarchies. To extend this to 3-D, one bit will be added to each layer, making it 12-bit for a four layer model. Each element in the fourth hierarchy is specified using 8 bits. In an 3M-bit body, there are $2^{(3M)}$ elements. For $M = 0$, the whole body is considered as one element and for $M > 0$, there are M hierarchies of grains or sections. For this reason, we called this model the *M-grain model.*

5.2.1 *How to Create an M-Grain Model*

It follows from the discussion above that an M-grain model views body as consisting of $n = 2^{3M}$ 3-D elements, each consisting of a composition of various materials. The following Lemma describes an important property of this model.

Lemma 1. If we know the material composition of all body elements for a given value of $M = \mu$, then we also know the composition of materials for all elements for values of M < μ.

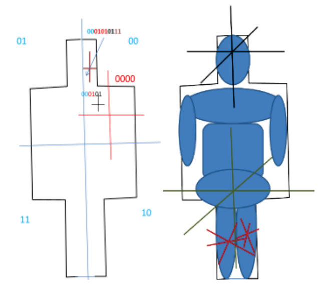

Figure 3 (a) Fine grain and (b) coarse grain comparison.

Lemma 1 can be explained by taking an actual value with reference to Figure 3. We stick to 2-D example for ease of understanding. For the 2-D case, the number of elements will be modified to 2^{2M} for M-grain model. In Figure 3(a), if we know material composition of all sections for M = 3, then each element needs 6 bits ($b_0, b_1, b_2, b_3, b_4, b_5$) to be identified. Out of these 6 bits the left 4 bits constitute all the section IDs for M = 2. Thus, $(0, 0, 0, 1, b_4, b_5)$ is the second from top-right elements out of the 16 (red) elements for all values of b_4 and b_5. Figure 4 illustrates this.

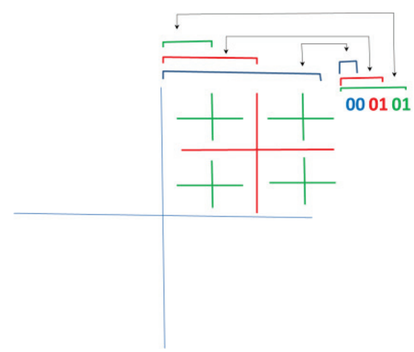

Figure 4. Lemma 1 demonstration for mapping from M=3 to M=2.

Lemma 1 leads to the conclusion that the resolution of the M-grain model can be scaled back to a lower resolution model by masking groups of d bits from the right side of the location IDs of the elements in a d-dimension. The following theorem is based on Lemma 1.

Theorem 1. In d-Dimension implementation of the M-grain model, the material properties of resolution layer $m < M$ are obtained by masking the right $(M-m).d$ bits of each element.

Proof: The proof of theorem 1 follows from lemma 1.

It may be noted that there is a difference between the coarse grain model and the low-resolution-layers fine grain model. In the coarse grain model we assume that each limb is designed as one or a few elements, thus requiring a different reference axis for each limb or organ according to convenience. A fine grain model can be applid to each limb of a coarse grain model. In the next section, we will discuss how to store the material properties in a computer to be used to create individual models.

6. SIMULATION USAGE

In a typical application of the model, following is a sequence of steps:

Step 1. The physician has a computer program that is based on Equation (1). The program employs, from a table, the material properties of various body parts that have default values.

Step 2. The physician enters the two body areas that are to host the implants in the computer. A general composition of the materials is available in the program. These can be manually changed by the physician depending on a physical exam.

Step 3. The physician enters the value for d_o in a unit of length and the longest length L_M to be considered to determine M. This satisfies an equation $(L_M/ d_o)^3 = 2^{3M}$. From this, the value of M is given by:

$$M = log_2(L_M /d_o) \text{ bits} \qquad (2)$$

The value of L_M is influenced by whether a limb or a part is considered in isolation or the whole body is considered. For some applications such as interconnection between heart sensor and diabetes sensor, multiple parts or whole body may be a better consideration for determining M. As a result of Equation (2), the total number of elements in the L_M length is 2^{3M}. The implicit assumption in deriving Equation (2) is that the body section of length L_M is a perfect cube, which is not the case for most part. However, the real purpose of this way of modeling is not be accurate about the location of boundaries, but to be accurate in modeling signal propagation within each body element through the use of proper material composition, and to be accurate in determining signal power received. For isotropic antennas propagation, the assumption of cubic element has the additional benefit that the model can be tested empirically by measuring power received at the body boundaries that occur at distances smaller than L_M and comparing it with the model. This is shown in

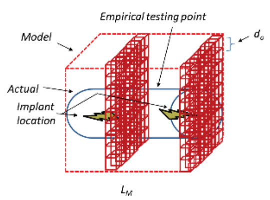

Figure 6. Difference between modeling and actual shape of body area can be used for empirical model verification.

Step 4. Solve Equation (1) typically employing numerical methods available extensively these days.

Step 5. The physician can determine the power source based on the solution of Equation (1), criticality of the situation, sensitivity of the receiver and experience. At this point a decision can be made and surgical operation can be planned.

It must be mentioned here that research on this modeling technique is ongoing and is expected to result in performance evaluation studies in near future.

7. CONCLUSION

We have presented a modeling technique to determine propagation channel characteristics of human body. The proposed method makes use of several available techniques with a new look to accommodate the body characteristics.

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