Challenges in Channel Measurement and Modeling for RF Localization Inside the Human Body

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ABSTRACT

In this invited paper, the authors introduce an overview of the fundamentals of radio frequency (RF) channel measurement and modeling techniques needed for localization inside the human body. To address these fundamentals, the authors use capsule endoscopy as an example application. The authors first provide the results of the Cramer Rao Lower Bound (CRLB) for received signal strength (RSS) based endoscopy capsule localization, inside the human body, using existing path-loss models for radio propagation. Then challenges demanding further research are highlighted for attaining more precise localization using the time-of-arrival (TOA) based ranging techniques.

Keywords: *Body Area Networks, Capsule Endoscopy, Cooperative Localization, Implant Localization, Radio Propagation, RSS-Based Localization, TOA-Based Localization, Wireless Health*

INTRODUCTION

In the past decade miniaturization and cost reduction of semiconductor devices has allowed the design of small low cost computing and wireless communication devices used as sensors in a variety of popular wireless networking applications and this trend is expected to continue in the next few decades. It is expected that a myriad of new applications designed around sensor technologies will emerge to stimulate a huge industrial growth. One of the most promising areas of industrial growth associated with this industry is the body sensor networks that are also referred to as the body area networks (BAN) (Yang & Yacoub, 2006).

These networks are expected to connect wearable and implantable sensory nodes together and with the Internet to support numerous applications ranging from traditional externally

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mounted temperature meters or implanted pace makers up to emerging blood pressure sensors, eye pressure sensors for glaucoma and smart pills for health monitoring and precision drug delivery.

To support the growth of this industry, recently the Federal Communication Commission (FCC) has allocated specific bands for Medical Radio Communication Services (MedRadio) (FCC, 2008) and the IEEE 802.15.6 is formed to address the standardization aspects of these emerging technologies. The IEEE 802.15.6 models the characteristics of the radio propagation inside and around the human body and defines wireless networking technologies for wearable and implanted sensor networks (Aoyagi, 2006). The standards recommend that the transmission power should be around 25 μW to keep the EM emissions at a healthy level (FCC, 2008).

Certainly for all BAN applications power efficient modulation and medium access control methods are needed in principle and a number of researchers are working on that topic (Kim, 2008). The important and the fundamental issue presented in this paper is the localization of objects inside the human body to assist the discovery of methods for navigating emerging micro-robots in wireless medical applications such as capsule endoscopy. This is a new field of research that is gaining some momentum in the recent years (Aoyagi, 2009; NIST, 2011).

Understanding the nature of signal propagation is the key to the design of precise localization for any wireless network (Pahlavan, 2005). Therefore, the first step in research is to start a measurement and modeling program to understand the nature of signal transmission inside the human body. Today, the existing literature in measurement and modeling for understanding the propagation in and around the human body is fragmented and it does not pay attention to localization inside the human body (Aoyagi, 2009). The IEEE 802.5.6 is working on creating a comprehensive channel model for different scenarios and frequency bands used for communication applications (Hagedorn, 2008). There is a need for research in understanding the behavior of RF signal propagation inside the human body for localization applications.

Localization techniques fundamentally work either based on the received signal strength (RSS) or the time of flight of the signal from the target device to the reference points (Pahlavan, 2005; Alavi, 2006; Ghaboosi, 2011). The channel model for localization and communication for the RSS-based systems are the same; however, for more precise TOA-based systems we need channel models that may be different from those traditionally designed for communication applications (Alavi, 2006; Pahlavan, 1998).

From an innovative research point of view, measurement and modeling of radio propagation inside and around the human body for RF localization applications offers unique challenges making this area very appealing for fundamental research. These challenges are raised by several specifics of the human body medium that are in principles different from the traditional indoor radio propagation challenges. Inside the human body is a non-homogenous liquid like environment for radio propagation and this poses a challenge for precise localization techniques using the time of flight of the signal between a transmitter and a receiver to estimate the distance. To localize a device inside the human body the infrastructure of the reference points are naturally mounted as sensors on the human body that constantly moves even when we are standing still.

To measure the characteristics of multipath arrivals and their effects on localization using time of arrival of the paths, we usually refer to statistical empirical modeling based on ultra-wideband measurements of the channel characteristics by placing antennas in different location of the application environment (Alavi, 2006). Placing antennas inside the human body for massive measurements is not practical and we need to resort to computational techniques or using Phantoms (Sayrafian-Pour, 2009) or dead body of animals for empirical measurements (Alomainy, 2009). The most popular computational methods for simulation of the radio propagations inside the human body are the Finite Element Method (FEM) (Askarzadeh,

2011) and the Finite Difference Time Domain (FDTD) (Kawasaki, 2008; Khan, 2011a). To validate the results of these simulation we need to match them with the results of empirical measurements based on body mounted sensors. Inside the human body, distances are on the orders of centimeters and it is desirable to have simulation techniques and measurement devices that have accuracies on the orders of centimeter that demands very fine grids for simulation using numerical techniques and extremely wide bandwidths for measurements of the characteristics using Phantoms or dead body animals.

In the rest of this paper we first use an existing model for path-loss inside the human body (Sayrafian-Pour, 2009) to calculate bounds on RSS-based RF localization for capsule endoscopy application (Cave, 2011). Then we address challenges for more precise TOA-based localization inside the human body by presenting some preliminary results and pointing to open issues demanding further research. These results address the effects of non-homogeneity of the human body on ranging inside the human body, measurement of the effects of the human body movements and accuracy of simulation of waveform transmissions inside the human body.

BOUNDS ON RSS-BASED LOCALIZATION

We begin by determining the bounds on the performance of RSS-based localization of a micro-robot inside the digestive system of the human body using known location of body mounted sensors. In the recent literature, there are a couple of path-loss models for inside the human body (Aoyagi, 2006; Sayrafian-Pour, 2009). We use the models presented in (Sayrafian-Pour, 2009) that provides the path-loss gradient and variance of the shadow fading needed for calculation of the Cramer Rao Lower Bounds (CRLB) for the variance of the RSS-based localization. For calculation of the bounds we have used 3D localization techniques needed for inside the human body, described in Ye (2011) and Wang (2011). These bounds are derived from the 2D bounds for traditional indoor geolocation applications described in (Patwari, 2005).

Results of the analysis using cooperative localization bounds for endoscopic wireless capsule as it passes through the human gastro-intestine (GI) tract is reported in Ye (2011). In that work the CRLB variance limits on location estimators which use measured RSS are reported. Using a three dimensional human body model from full wave simulation software and log-normal models for RSS propagation from organ implants to body surface, we calculate bounds on location estimators in three digestive organs: stomach, small intestine and large intestine. We provide analysis of the factors affecting localization accuracy such as external sensor array topology and number of capsules in cooperation. The simulation results show that cooperation among pills inside the GI tract have the potential to reduce the location error significantly.

Path Loss Model for GI Tract Environment

The statistical implant to body surface path loss model used for calculating the CRLB of wireless capsule endoscopy (WCE) localization was developed by National Institute of Standards and Technology (NIST) at (Medical Implant Communication Service) MICS band (Sayrafian-Pour, 2009). The main components used for developing the model include: a three-dimensional the human body model, the propagation engine which is a three-dimensional full wave electromagnetic field simulator, the 3D immersive and visualization platform with implantable antenna. In the model presented in Sayrafian-Pour (2009), the path loss in dB at a distance d between the transmitter and receiver is statistically modeled by the following equation:

$$\begin{aligned} &L_p(d) \\ &= L_p(d_0) + 10\alpha \log(d / d_0) \\ &+S\,(d > d_0) \end{aligned} \tag{1}$$

Table 1. Channel parameters used for performance evaluation of RSS based cooperative localization

Implant to Body Surface	$Lp(d_0)$	α	σ_{dB}
Deep Tissue	47.14	4.26	7.85
Near Surface	49.81	4.22	6.81

where d0 is the reference distance, that is set to 50mm, and α is the path loss gradient which is determined by the propagation at different depths inside the human body. As we already mentioned, the human body tissue strongly absorbs RF signal. Therefore, we expect values of path loss gradient that are higher than two for the free space propagation. The random variable S in Eq. (1) is a log-normally distributed random variable representing the deviations caused by shadowing effect of human tissue. The parameters used by the model for the implant to body surface path loss modeling are summarized in Table 1. In this table we have two sets of parameters for path loss from deep and near surface implant to body surface and σ dB is the standard deviation of shadow fading S. According to the model developed in Sayrafian-Pour (2009), if the distance is less than 10cm, we use the near surface to surface path loss model, otherwise the deep tissue to surface model is used.

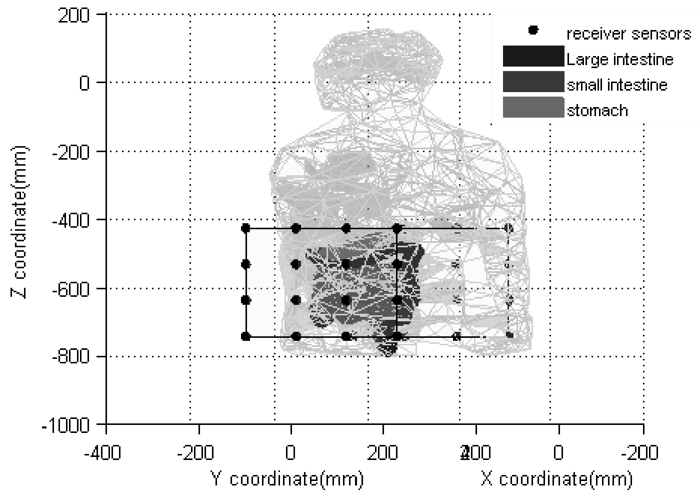
Simulation Results

We begin our analysis by evaluating the impact of the organ shape and location and the number of body mounted sensors as well as mobile capsule sensors inside the GI track on the localization accuracy of the RSS-based systems. For our first experiment, we use 32 body mounted sensors evenly mounted on two grids in front and back of the human subject with one capsule in a specific organs. Figure 1 shows the location of the sensors on the jacket with respect to the grid of points and location of the stomach, small intestine and large intestine inside the human body. We calculate the CRLB in a 3D grid inside each organ using 634 points in the stomach, 1926 points in the small intestine and 3334 points inside the large intestine.

Figure 2 shows three sets of results for performance evaluation of the RSS-based localization using 3D-CRLB described in Ye (2011). Figure 2(a) shows the CDF of the localization error for the capsule in the small intestine and stomach are smaller than error inside the large intestine. The median value of error for the small intestine and the stomach is approximately 45mm, while the median for the large intestine is approximately 50mm. The localization error for the capsule in the stomach has the lowest average value but distributed in a wider range compared to the errors in the other two organs. These observations can be explained by the geometric relationship between the sensor array and the organs. As we can see from Figure 1, the stomach is located in the upper part of the receiver sensor array system, and its volume is the smallest among the three organs. Therefore, the localization error varies more in the stomach environment. The points located in the upper part of the stomach have a larger localization error value as they are far from the center of the receiver array system, while the points in the lower part of stomach have a smaller localization error value. The small intestine is located in the center part of human abdomen cavity and the lumen is more centralized compared to the large intestine. Therefore, the localization error inside the small intestine is smaller than that in the large intestine.

Figure 2(b) represents the average accuracy of localization in each of the three organs as a function of the number of sensors mounted on the human body. In these simulations we used four different sets of body mounted sensors covering the same area with different densities

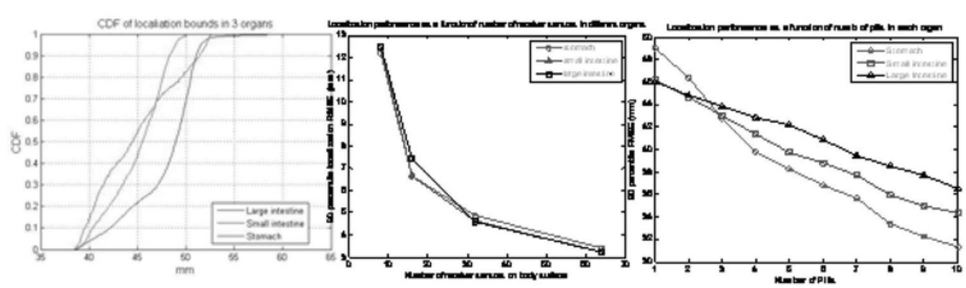
Figure 1. Typical simulation scenario for localization inside GI tract with 32 receiver sensors on the body surface



and we repeated the experiment for each set of sensor locations one thousand times for each organ. The localization error decreases significantly as the number of receiver sensors increase from 8 to 16 and from 16 to 32, but not as much when we increase the numbers from 32 to 64. The reason for this is the area of human torso is limited and 32 sensors already provide the density needed for localization. With 32 sensors we have an accuracy of around 5cm as the average error, using 64 sensors reduces error for approximately another cm. It is desirable to examine other methods to improve the accuracy. The simplest approach to improve the performance is to use multiple capsules using cooperative localization methods described in Ye (2011).

Figure 2(c) illustrated the performance of cooperative localization as a function of number of capsules inside an organ with 32 body mounted sensors. Cooperative localization helps most in the stomach as the average localization

Figure 2. Results of performance evaluation using RSS-based localization inside the human body (a) accuracy within different organs (b) effects of number of sensors (c) effects of number of capsules



(a) (b) (c)

error in this organ drops faster with an increase in the number of pills in cooperation. The volume of stomach is more condense allowing more cooperative formations of capsules inside this organ. The error rate using cooperative localization drops another one to two cm when we use cooperative localization. To achieve more precise localization on the orders of millimeters one may think of TOA-based localization inside the human body that has its own challenges.

CHALLENGES IN PRECISE RF LOCALIZATION INSIDE THE HUMAN BODY

In the previous section we showed that using RSS-based localization one may achieve accuracies around a few centimeters inside the human body. Several factors affect more precise RF localization inside the human body. Localization inside the human body is based on the signal readings of the body mounted sensors. Since the human body is constantly moving relative location of body mounted sensors are constantly changing causing errors in accuracy of the localization. We need to understand the degree of movements and their effects on localization. To achieve more accuracy in localization we need to consider the TOA-based localization techniques (Pahlavan, 2005) and these techniques are very sensitive to the multipath behavior of the medium (Pahlavan, 1998). To model the multipath behavior inside the human body we need to measure the channel impulse response between sensors mounted inside and on the surface of the human body that is a very challenging task.

Our analysis of the accuracy of RSS-based localization systems inside the human body was based on the statistical model between the RSS and the distance that was presented in Sayrafian-Pour (2009). This model was derived from computer simulation for calculation of the RSS in different locations inside and on the surface of the human body. Measurement and modeling of the TOA requires measurement of the time of flight of signal inside the human body that is a far more complex problem and it is dependent on the bandwidth of the transmitted signal (Pahlavan, 2005). To model the TOA in a typical indoor area we use signals with different bandwidths to determine the time of flight for a given bandwidth, then we determine the distance by multiplying the time of flight with the speed of electromagnetic wave propagation in the air that is the same as speed of the light. The statistical model obtained this way relates the accuracy of TOA estimates to the distance and the bandwidth (Alavi, 2006). Repeating these experiences inside the human body becomes a far more complicated problem and we address that in the rest of this paper.

One of the fundamental differences between propagation inside the human body and the indoor propagation outside the human body is that the medium for propagation inside the human body is mostly liquids, which have substantially higher dissipation than the air which is the main medium for the indoor radio propagation. As a result, signals lose its strength much faster inside the body as it is compared with the outside body. Simple observation from Eq. (1) reveals that for short distances around 10cm on the average one loses around 60dB of the signal strength. With the same path-loss and at the same frequency of operation one can cover tens of meters in a typical indoor radio environment (Pahlavan, 2005). In addition, inside the human body offers a non-homogeneous environment with non-geometric boundaries for radio propagation, while indoor is a non-homogeneous environment with fairly geometric boundaries for radio propagation. Inside a typical indoor environment most of the propagation time is spent through the air and the second important medium are the walls that have geometric shapes.

These features allow us to construct simpler radio propagation mechanism such as ray-tracing to describe the radio propagation in indoor environment using ray optics methods (Pahlavan, 2005). Inside the human body is a non-geometric and non-homogeneous medium for radio propagation that will not allow application of simple ray tracing techniques.

Conductivity of the propagation inside different organs, bones and the mussel tissues are also widely different posing a challenge for the analysis of time of flight for the signal that is commonly used for ranging using TOA of the received signal.

Indoor environment is a very complex propagation mediums for localization as well (Pahlavan, 2005), but we can easily measure the wideband radio channel characteristics using a network analyzer and develop empirical statistical models for the TOA (Pahlavan, 1998). In radio propagation analysis inside the human body we cannot simply place antennas inside to collect empirical data for statistical radio propagation modeling. In indoor areas we use the time of flight of the signal to measure the distance between the transmitter and the receiver by multiplying the time of flight with the speed of radio wave propagation in the air that is the same as speed of light. Since the human body is a non-uniform liquid medium the speed of radio wave propagation is different from the speed of light and it also differs in various organs.

In the remainder of this section we present some preliminary results and point to open issues in three specific areas for research related to TOA-based localization inside the human body. First we discuss the effects of non-homogeneity of the human body on TOA-based localization, then we address effects of body motions and at last we discuss challenges for empirical measurements and computer simulations of the impulse response among in-body and body mounted sensors.

Effects of Non-Homogeneity of the Human Body

The most accurate ranging for localization used in popular localization applications such as Global Position System (GPS) is the TOA ranging. In traditional TOA localization applications the time of flight of a transmitted pulse with a sharp peak is measured at the receiver and distance is estimated by multiplying the time of flight with the velocity of propagation that is the same as velocity of light. This works because radio wave propagates in the air that is a homogeneous environment with a uniform permittivity. The human body is a non-homogeneous medium and permittivity of different organs are different and that causes a new source of ranging error. The ranging error is often caused by bandwidth limitation and SNR limitation. Further details of how the bandwidth limitation will influence the TOA ranging accuracy can be found in (Alavi, 2006). Propagation velocity inside the human body is expressed as a function of the relative permittivity (Kawasaki, 2008):

$$v(\omega) = \frac{c}{\sqrt{\varepsilon_r(\omega)}}, \tag{2}$$

where velocity is a function of permittivity and the permittivity is a function of the frequency of operation. On the other hand, the human body is formed by various organs with complex structures. Each organ has different characteristics of conductivity and relative permittivity. Inside the human body, received signal is also distorted through the multipath channel caused by the refraction at the boundary of different tissues. Therefore, TOA ranging inside the human body is very challenging.

The goal of our study in this area is modeling of the TOA ranging error caused by lack of information of the real propagation velocity inside the human body. The reference (Kawasaki, 2008) proposes a simple TOA localization algorithm for calculation of distances using TOA, by employing the average permittivity of all the tissue and organs to estimate the propagation velocity. This approach results a ranging error caused by non homogeneity of body as a medium for radio propagation. Here, we extend our previous results of 2D simulations reported in Ye (2011) to 3D to address this issue in details.

In RF localization literature (Pahlavan, 2005), the ranging error is defined as:

$$DME = d - \hat{d}, \tag{3}$$

where d is the actual distance and $\hat{d}$ is the estimated distance. Considering the total distance travelled through the body is added by the distance in each organ or tissue, the total distance can be expressed as:

$$d_{total} = d_1 + d_2 + ... + d_n, \quad (4)$$

where d_1 to d_n are the distances travelled in each organ or tissue. In reality, as proposed in Kawasaki (2008) we use average permittivity of the human body to estimate the average propagation velocity inside the human body, which is

$$\bar{v} = \frac{c}{\sqrt{\bar{\varepsilon}_r}} \quad (5)$$

Therefore, the estimated distance is expressed as:

$$\hat{d} = \hat{\tau}\,\bar{v} = (\hat{\tau}_1 + \hat{\tau}_2 ... + \hat{\tau}_n)\frac{c}{\sqrt{\bar{\varepsilon}_r}}$$
$$= \sum_{i=1}^{n} \frac{d_i}{v_i}\frac{c}{\sqrt{\bar{\varepsilon}_r}} = (\frac{d}{c/\sqrt{\varepsilon_1}} + \frac{d}{c/\sqrt{\varepsilon_2}}$$
$$+ .. + \frac{d}{c/\sqrt{\varepsilon_n}})\frac{c}{\sqrt{\bar{\varepsilon}_r}} \quad (6)$$

The difference between d_{total} and $\hat{d}$ is the ranging error that we refer to as DME in Eq. (3). This error between the actual distance and the distance measured by TOA and average velocity of the propagation is caused by using a single velocity rather than multiple velocities. To determine the statistics of this error, we simulated the effect of non-homogenous tissues on TOA ranging in a 3D torso environment, shown in Figures 3 through 5. We have selected approximately five hundreds random locations on the body and for each pair we have calculated the DME using Eqs. (3-6). The human organ's relative permittivity is a function of the operating frequency, we studied the TOA ranging error at MICs band for the center frequency of 405MHz, which is the reserved band for implant and in body applications. The average permittivity is calculated by weighting the permittivity of each organ according to their volume, the average permittivity is 46.35 in the torso environment. The permittivity and volume of different organs used for this simulation is shown in Table 2.

Figure 6 presents the results of simulation and the best fit Gaussian distribution to the results. The mean value of DME is -3.92mm, while the standard deviation of DME is 24.3mm. The mean value of DME is a negative value because the largest organ in the torso cavity are the lungs, which have a much smaller permittivity value than the average permittivity of human tissues. Hence, the signal propagates faster in the lungs than the average speed of signal propagation inside the human body. When we use the average propagation to calculate the estimated distance, the value is smaller than the real distance, because we underestimated the distance signal went through the lungs.

These values of DME need verification using empirical data or simulations of radio propagation inside the human body that is discussed later.

Effects of the Human Body Motions on Localization

The infrastructure of the localization reference points for the in-body localization is the body mounted sensors sensing the RSS or TOA of the signals transmitted from the capsule or any other in-body device. The relative location of these sensors changes with the human body motions and that has an impact on localization error inside the human body. To analyze the effects of these movements we need to measure the characteristics of the channel. Characterization of the channel is either based on narrowband measurements that are used for analysis of fluctuations of the RSS or based on wideband measurements that are used for the analysis of the performance of TOA systems (Pahlavan, 2005). Measurement of the TOA of the direct

Figure 3. Simulation scenario for 3D measurements of the DME due to non-homogeneity of the human body for radio propagation, front view

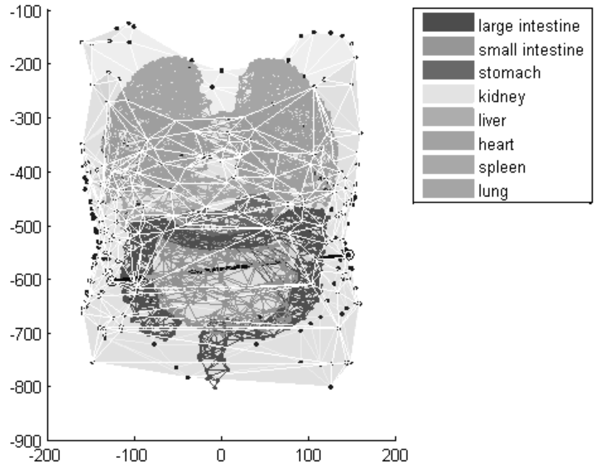
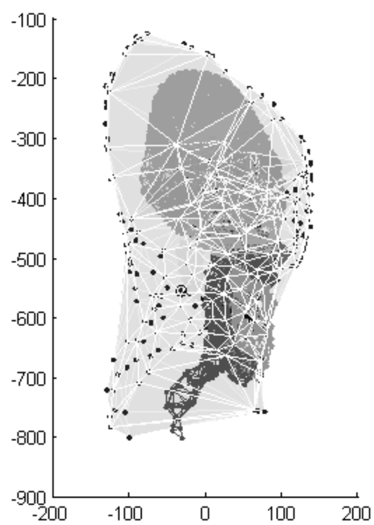
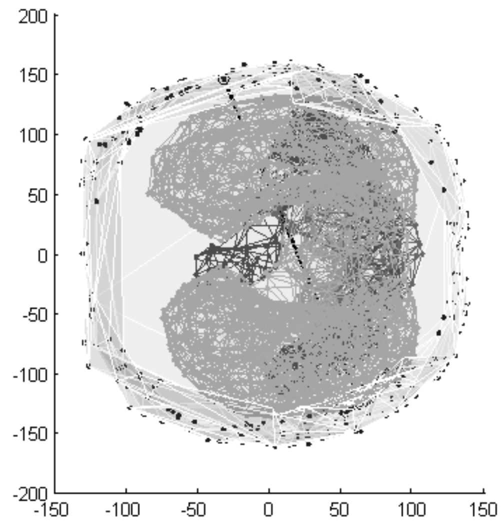


Figure 4. Simulation scenario for 3D measurements of the DME due to non-homogeneity of the human body for radio propagation, side view



path between the transmitter and the receiver when the path passes through the human body is very challenging because this path suffers from extensive loss and we may need to resort to computational techniques that we discuss in the following section. In this section we

Figure 5. Simulation scenario for 3D measurements of the DME due to non-homogeneity of the human body for radio propagation, top view



analyze the effects of the human body motions based on our narrowband measurements, more detailed description of the measurement system is reported in Fu (2011).

In general, effects of the human body motion on RF propagation in and around the human body is a very important topic; because in most BAN applications sensors are mounted on the torso, hands and feet, while a body mounted relay with larger size is mounted on the hips with the belt. In most popular envisioned applications for BANs the relay is used for communication to external access points connecting the network to the backbone Internet. In this part of our research we analyze these movements using the characteristics of Doppler spectrum observed at the relay.

It is well known that an apparent change of frequency will occur in radar systems if there is a relative motion between the transmitter and the receiver and that change in frequency is referred to as Doppler shift of the channel (Pahlavan, 2005). The maximum Doppler frequency shift f_m is determined by the velocity of the movement v_c and the length of propagation wave $\lambda = \frac{c}{f_c}$ as $f_m = \pm \frac{v_c}{\lambda}$, where $c \approx 3 \times 10^8$ m/s is the velocity of light and f_c is the transmission center frequency. The

Table 2. Permittivity and volume, $\left[\varepsilon_r, v(cm^3)\right]$, of organs used for simulation of the effects of non-homogeneity of the human boy

Intestine (50.7,3936.3)	Stomach (67.8,357)	Gallbladder (52.3,12.4)
Lung (23.77,4320)	Heart (65.97,625.4)	Kidney (68,325.1)
Spleen (63.1,160.2)	Liver (51.15,1357)	Muscle (47.8,32403.4)

maximum value of f_m could be approximated from the Doppler spread B_D of the channel between the body mounted sensors. Narrow band channel measurement techniques are commonly used for analysis of the Doppler spectrum in wireless networks (Pahlavan, 2005).

The result of narrowband measurements at a frequency f_c is the time domain response, $H(f_c;t)$. The Fourier transform of the time domain data $H(f_c;t)$

$$D(\lambda) = \int_{-\infty}^{+\infty} H(f_c, t) e^{-j2\pi\lambda t} dt \quad (7)$$

is the so called Doppler spectrum $D(\lambda)$ of the channel. Figure 7 illustrates sample measurements of the time domain responses and associated Doppler spectrums for two sensors on the human body at 2.25GHz center frequency. Measurements are associated with the free space in Figure 7(a), where the antennas are in fixed location and there is no motion and associated Doppler spread. Figure 7(b) shows the measurements associated with body mounted sensors where the human subject is standing still. Fluctuations of power in the orders of a couple of dB and the associated narrow Doppler spread are due to essential movements of body from breathing and heart beats. Figures 7(c,d) illustrates the effects of walking and jogging on the Doppler spectrum. Here power fluctuation increases to 5-10dB and the spread of Doppler shift extends to up to 12Hz during jugging. For more details of measurements and more results one can refer to Fu (2011), where we measured the time domain response at 400MHz, 2.25GHz and 4.5GHz, respectively among the body mounted sensors for different human motions.

A more specific estimation of the Doppler spread is the RMS Doppler bandwidth (Howard, 1991), which is used to describe the Doppler shift by calculating the weighted signal power rather than simply an overall width of the spectrum. The RMS Doppler bandwidth is defined as

$$f_N = \sqrt{\frac{\int_{-\infty}^{+\infty} \lambda^2 D(\lambda) d\lambda}{\int_{-\infty}^{+\infty} D(\lambda) d\lambda}} \quad (8)$$

where $D(\lambda)$ is the Doppler spectrum defined in Eq. (7).

Figure 6. The CDF of DME and best fit Gaussian distribution

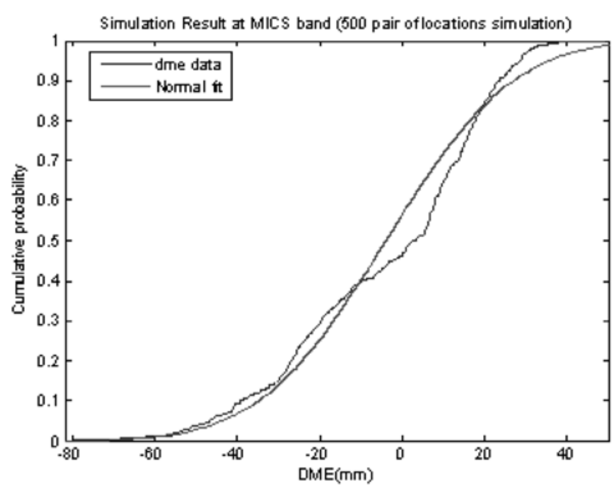


Figure 7. Doppler spread in time- and frequency-domain for different body motions (a) free space (b) stand still (c) walk on a spot (d) jog on a Spot

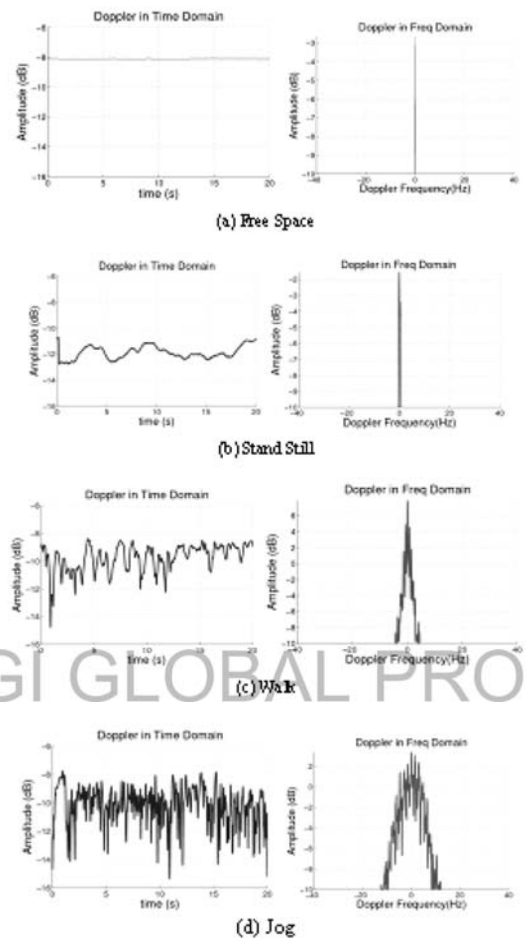


Table 3 provides the maximum Doppler shift and RMS Doppler spread for body mounted sensors across the human body torso for standing, walking and jogging motions (Fu, 2011). For the body surface mounted sensors, the measured Doppler spread of standing position is usually below 1Hz since the channel fading is caused by small body movements. In the walking and jogging motions, the Doppler spread varies around 4Hz and 9Hz, respectively. The RMS Doppler bandwidth is always below 1Hz for the standing still position, which shows a concentrated distribution of the received signal strength. For walking and jogging motions, RMS Doppler bandwidth is much larger than standing still position and the distribution is more dispersed in the frequency domain.

Another relevant parameter to Doppler spread is the coherence time which describes the dispersion of the fading channel in time domain. For standing still position, the signal is more stable and it holds for a longer duration, suffering from less temporal variations. For the jogging motion, the channel has a fast changing characteristic and suffers from more effects of fading. From our measurement reported in Fu (2011), the coherence time for standing, walking and jogging at 2.25GHz are 380 ms, 125.1

Table 3. Doppler spreads and RMS Doppler bandwidth for different body motions

Motion	Doppler Spread	RMS Bandwidth
Stand	0.826 Hz	0.8673 Hz
Walk	4.781 Hz	1.899 Hz
Jog	9.937 Hz	2.898 Hz

ms and 27.27 ms, respectively. These results relate the quantitative stability of the signal to different human motions. In communication applications coherence time is used to define maximum duration of a transmitted symbol so that the channel is constant for duration of transmission. In localization applications the coherence time determines the maximum time needed for measuring a localization metrics such as RSS or TOA before the channel characteristic is changed.

In this section we described how we could quantitatively measure the effects of different body motions using Doppler spectrum and coherence time. These results were based on narrow band measurements of channel characteristics that are obtained from measuring the RSS. The movements of the human body with different motions result in changes in the location of the sensors as well as polarization of the antennas and that will affect the estimate of their relative distance measured from RSS or TOA of the received signal. We can directly use these results for the analysis of the RSS based localization. For example, from Figure 7 we can observe that human motion can result up to 12dB of signal level changes. Using these values one can analyze the effects of the motion on RSS based localization algorithms. Analysis of the effects of movements on more precise TOA-based localization needs wideband measurement of the radio characteristics (Pahlavan, 2005) across the human body. As we will explain in the next two sections, measurement of the TOA through the human body has its own challenges that deserve further analysis.

Measurement of TOA of a Waveform Passing through the Body

In the last two sections we analyzed the effects of non-homogeneity on precise TOA-based localization inside the human body and we used empirical narrowband measurements on body mounted sensors to analyze the effects of body motions on variations of the signal strength. To further analyze the behavior of the TOA-based systems for in-body applications, we need empirical wideband data for measurement of the TOA of the signal that passes through the human body (Pahlavan, 2005). Measurements using antennas inside the human body is not practical and we need to resort to using phantoms or computer simulation of the radio propagation inside the human body. If these measurements are for the purpose of TOA estimations, problem will have its own particularities that will be discussed in this and the next sections.

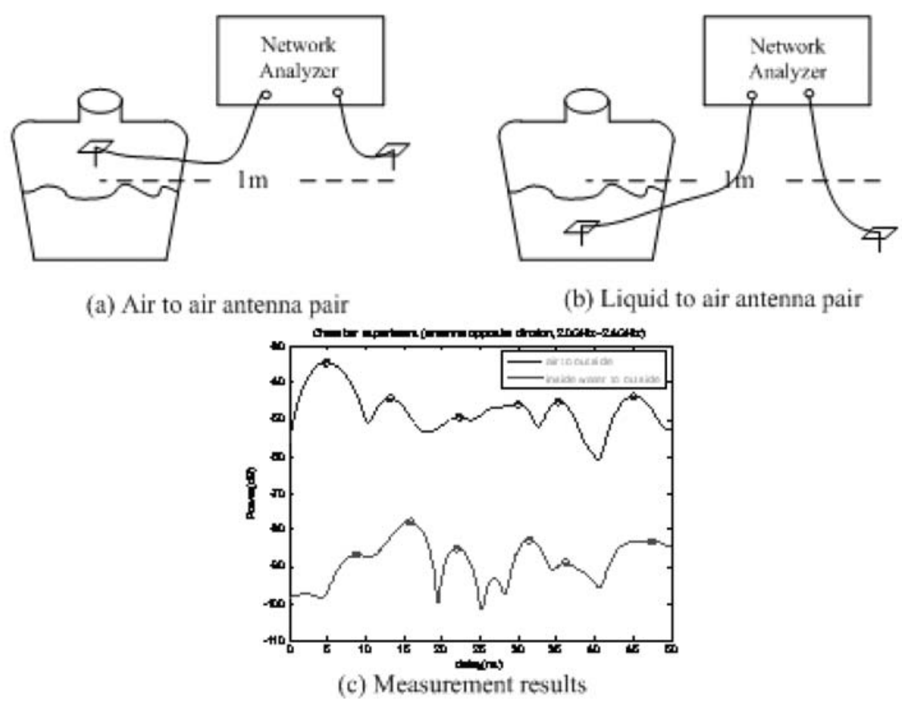
In this section, we start our discussions with a simple measurement inside a water filled hollow phantom using a network analyzer, shown in Figure 8. The bandwidth of this system is 100MHz and it operates at a center frequency of 2.4GHz. The TOA is estimated by taking the inverse Fourier transform of the frequency response of the channel, measured by the network analyzer, and detecting the first peak in time domain impulse response. The details of this measurement system are described in Pahlavan (2005) and Alavi (2006).

We fill the phantom half way with water and measure the channel impulse response between an antenna inside the phantom and another at one meter distance outside the body. Since inside the human body is medium of a number of different liquids, this will be a simple modification. Figures 8(a,b) show two options for the measurement scenario and Figure 8(c) shows the results of the measurement for the two options of the scenario. The first path represents the direct path between the transmitter and the receiver and other paths are related to reflection from the water surface and other objectives in the close vicinity of the measurement location. When we move the antennas inside the water, the peak loses more than 50dB of its power and the TOA of the first path is shifted more than 2nsec. Attenuation is caused by the conductivity of the liquid that absorbs much more power than the free space propagation loss. The shift in the TOA is far more complex to measure because extensive attenuation of the direct path causes shifts in the location of peak of the first path caused by other arriving paths (Pahlavan, 2005).

Simulation of TOA of a Waveform Passing through the Body

Another alternative to measure wideband in-body radio propagations for the analysis of the TOA-based localization systems is to resort to computer simulations. The most popular method for the simulation of the radio propagations inside the human body in the current literature and available commercial products are the Finite Element Method (FEM) (Askarzadeh, 2011) and the Finite Difference Time Domain (FDTD) (Kawasaki, 2008; Khan, 2011a). To verify validity of these simulations we need to match the results with those obtained by wideband measurements of the channel characteristics through the human body using traditional frequency domain channel measurement systems (Pahlavan, 2005; Alavi, 2006). The

Figure 8. Measurement of the ranging error inside the human body using a hollow phantom (a) in the air (b) in the liquid (c) measurement results



results presented here are based on the FEM techniques described in Khan (2011b).

We validate the results of FEM simulations with the empirical wideband measurements using a signal with bandwidth of 100MHz at 900MHz center frequency. The measurement system is the same as the one described earlier. Both in the actual measurements and the FEM simulations, two dipole antennas were placed 50 cm apart and the frequency response of the medium between the antennas was measured. The empirical measurements were performed in an open laboratory environment and the boundaries of the FEM simulations were defined to imitate this environment. Both measurements and simulations produce the channel frequency response as a person with height 172 cm and weight 156 lbs was made to stand between the two antennas. The inverse Fourier transform of these frequency responses were then used to find the impulse response between the transmitter and the receiver. Figures 9 and 10 illustrate the impulse response for the channel for simulation and measurements with and without the human body in between the antennas (Khan, 2011b).

From the measurement taken without the body, the TOA of the first path was calculated to be 1.70 ns, which roughly translates to about 51 cm - an error of 1 cm from the actual distance. The same value from the FEM simulation came out to be 1.95 ns, which roughly translates to 58 cm, indicating an error of about 7 cm from the measurement. These two biases on measurements and simulation are not exactly the same because the simulation of the antennas is not exactly identical with the actual antennas. Since we are interested in measuring the actual distances affected by the body we can neglect the biases and normalize them to the actual distance. This approach is a common practice for all measurement and simulation techniques (Pahlavan, 2005). After normalization the TOA of the first path from measurements and simulations both represent 2nsec shift.

From Figures 9 and 10, the root mean squared (RMS) delay spread of the first three paths for the measurements without the body came out to be 4.12 ns and that of the simulation without the body came out to be 3.97 ns; a difference of just 0.15 ns. When the body was added to the measurement setup, the RMS delay spread was calculated to be 3.79 ns, the same value for the simulation with the body came out to be 3.32 ns; an error of about 0.47 ns. Hence even the RMS delay spread of the FEM simulation was very close to that of the actual measurements, suggesting that it is a valid mean to simulate the wideband profile of a channel.

The main issue with using FEM for these simulations is that it takes between one to five days to run one simulation and that is a tremendously long period of time when we need numerous simulations for statistical modeling of the behavior of the channel. To eliminate this problem we wrote a FDTD solver for the human body in MATLAB that is about sixty times faster than its FEM counterpart (Makarov, 2011).

Figure 11 shows the measurement scenario with multiple sensor locations and the results of FDTD simulation of body mounted sensors on locations a and b that are 5cm apart, in MATLAB. The body frame used for simulation is homogeneous with uniform dielectric constant and uniform conductivity of 1.56 and 0.5 Siemens/meter representing average muscle tissues. The absorbing boundary conditions were used for this simulation to isolate the path passing on the surface of the body from multipath arrivals from other objects surrounding the body (Khan, 2011a). The point source antennas were used to generate normalized plots of the channel impulse response independent form the antenna radiation pattern. As shown in the Figure 11, these antennas act as differentiators for the given 100MHz bandwidth used for the simulation. The TOA of the "first path" is at 0.2277 ns that represents 5cm distance plus 1.83cm of bias associated with the simulation.

To analyze the accuracy of simulation for TOA based localization a number of simulations, on the points shown in Figure 11, were carried out with the transmitter kept at position a and the position of the receiver varying from positions b to j. Figure 12 shows the plot of measured TOA versus the actual measured distances across the simulated homogeneous the human

Figure 9. Comparison of FEM simulations and empirical measurements: Electric field distribution on the human body

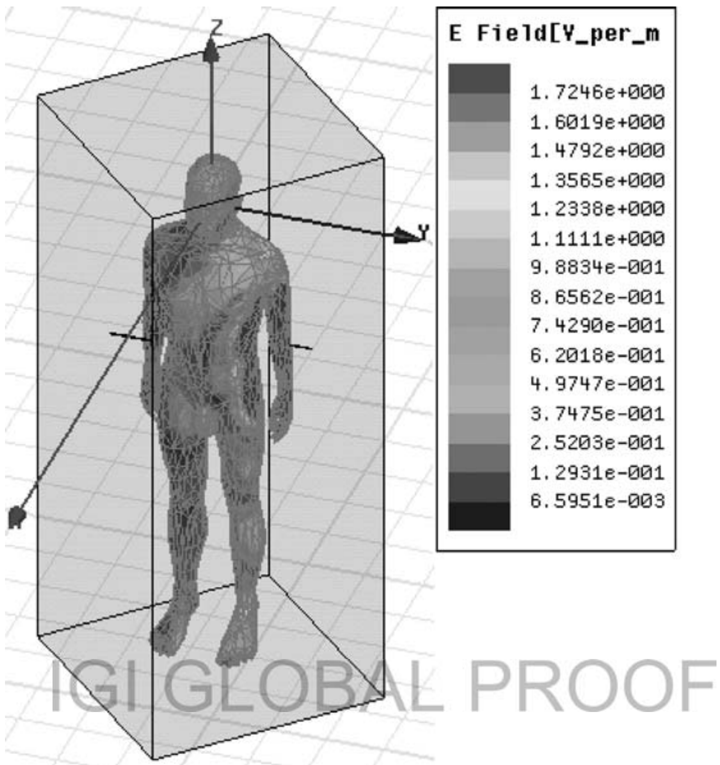


Figure 10. Comparison of FEM simulations and empirical measurements: Matching the impulse responses from measurement and FEM computer simulations

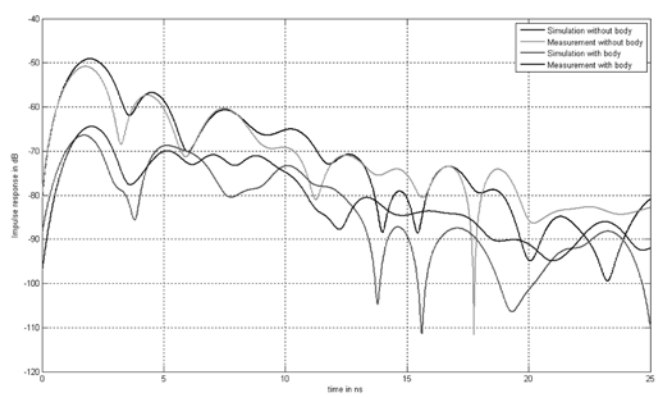
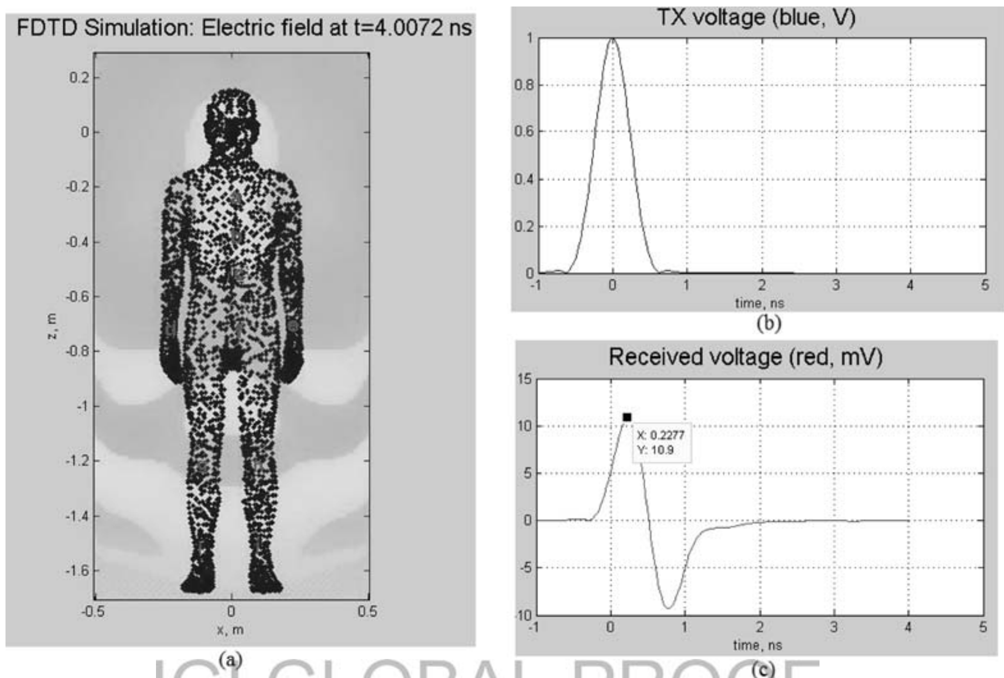
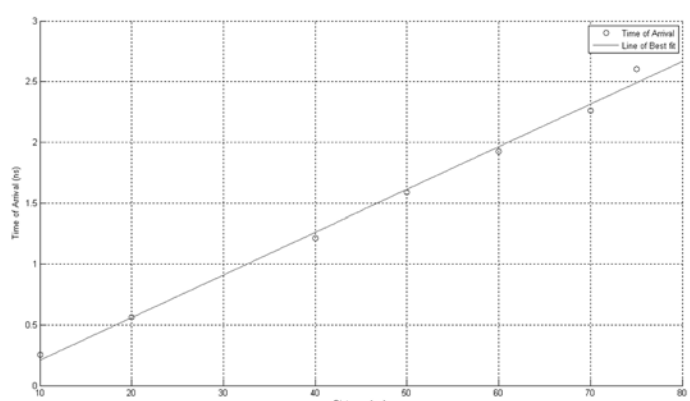


Figure 11. FDTD Simulations on MATLAB (a) Map of where the sensors were placed (b) Transmitted and (c) Received voltages vs. time



body and the best fit line to relate the TOA to the distance. The difference between the actual measurements and the best fit line are the DME caused by overall quantization errors embedded in the computational method. The variance of the DME obtained from this plot came out to be about 0.72 mm. The human body model used in the FDTD simulations was homogenous to isolate the effects of non-homogeneity from the computational error and simplify the simulation model.

Figure 12. Time of Arrival vs. distance for various sensor positions



SUMMARY AND CONCLUSION

In this paper we provided an overview of challenges in RSS- and TOA-based localization techniques inside the human body. We showed that using multiple micro-robots and RSS-based techniques one can use cooperative localization methods to achieve accuracies around a few centimeters. To find more accuracy we need to resort to TOA-based localization techniques that has its own challenges open for the future research. We showed that the effects of non-homogeneity of the human body can cause errors of up to a few centimeters in TOA based localization. We also showed that the human body motions can cause up to 12dB variations of the RSS among body mounted sensors and pointed to the fact that we need to find the effects of these variations on the TOA-based ranging. We argued that to verify the effects of non-homogeneity of the human body for radio propagation and to measure the effects of body motions on TOA-based localization we need to determine the impulse response of the channel between body mounted and implant devices. We then discussed challenges in measurement and simulation of waveform transmissions through the human body using FDTD and FEM techniques and determined that the simpler FDTD can have close to 1cm computational error. From these observations we suggested that analysis of radio propagation for localization inside the human body is rich with several useful and complex problems demanding future research.

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