SAR Analysis in Dispersive Tissues for In Vivo UWB Body Area Networks

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Abstract—In this paper, we present the impact on specific absorption ratio (SAR) distribution by dispersive media in wireless body area networks (BAN). For BAN systems, ultra-wideband (UWB) transmissions have received much attention because of its low power spectrum and its small antenna size. When we adopt the UWB technique to BAN systems, the SAR analysis is highly demanded for predicting the exposure level prior to experiments and products. It is well-known that the dielectric properties of human tissues have a great spectrum dependency, that renders a difficulty of an SAR analysis by electromagnetic field simulations through the finite–difference time–domain (FDTD) methods for wideband signals. For frequency–dependent analysis, the piecewise linear recursive convolution (PLRC) method is useful for dealing with the dispersive media. To employ the PLRC method, we re–formulate the dielectric spectrum properties of human organs approximating the so–called 4–Cole–Cole model. We reveal that we need to consider the dispersive effect of human tissues to analyze the SAR according to the UWB bandwidth.

I. INTRODUCTION

Wireless body area networks (BAN) are aimed at to facilitate our lives’ activities around the near–body environment no farther than a few meters, that is mainly implemented by wearable equipments and implantable devices. The wearable equipments typically exploit the communication channel outside the body or the on–body skin for data transmissions. Meanwhile, the implantable equipments make use of the communication channel inside the body tissues. The former scenario is categorized as ex vivo or in vitro communications, while the latter in vivo communications.

At present, most of the BAN applications are oriented for the ex vivo scenario because the development of body–friendly implantable devices has a number of technical issues to be tackled for a practical use: for example, we are highly demanded to guarantee that the devices cannot introduce any false operation that invades the body tissues. In [1], Halperin et al. have analyzed the security property of an implantable cardiac defibrillators (or, a pacemaker), which is designed to communicate wirelessly with a nearby external device to program the transmission schemes. In the literature, it has been confirmed that such a implantable device, which uses software–defined radio (SDR) techniques, can cause a serious malfunction because the transmission mode can be easily re–programmed from outside the body.

Nevertheless, in vivo communications have received much attention because it enables us to measure biological signals directly from inside the body, in particular for medical applications including patient monitoring, rehabilitations, anti–aging, diagnosing, surgery, etc. As one of examples, swallowable capsule endoscopes, which employ wireless communications technology to transmit high–resolution image data towards an external monitoring device, have been already adopted for clinical diagnosis. In the near future, it is envisioned that such in vivo communication devices will bring a substantial benefit for our health maintenance and will obtain a major popularity after the security and privacy problems are considerably overcome.

In order to realize secure in vivo communications, it is of great importance to analyze the possible level of risks caused by the radio waves against the body organs. For evaluating the radio frequency (RF) exposure level, the federal communications commission (FCC) recommends to measure a specific absorption ratio (SAR) in [2], which corresponds to an absorbed energy resulting into a temperature elevation of a specific tissue through the radio propagation. There are many literature reporting the SAR evaluations, e.g., in [3–7], where the finite–difference time–domain (FDTD) method [8–11] is exploited for electromagnetic field simulations. The FDTD method is useful for modelling the BAN channel along with the SAR evaluation, as in [12–22]. However, there has been existing few papers which focus on the in vivo scenarios for BAN channel models and SAR analyses. It is because the biological tissues have spectrum dependency as discussed in [23], that involves a high complexity for the FDTD analysis. In [5], it has been partially dealt with by using the single–pole Debye polarization model for the head tissues. However, the so–called 4–Cole–Cole model derived by Gabriel in [23] suggests that the simple Debye model may be insufficient to approximate the spectrum dependency of the body organs. It is particularly true when we use the ultra–wideband (UWB) techniques, whose signal bandwidth is very wide.

In this paper, we present an approximated 4–Cole–Cole model which is compatible to use the piecewise linear recursive convolution (PLRC) method for computationally–efficient FDTD simulations. We reveal that we need to take the dispersive property of the human tissues into consideration for evaluating the SAR distribution when we employ the UWB techniques. Through the use of the PLRC–FDTD method, we show an accurate SAR analysis for in vivo communications.

II. WIRELESS BODY AREA NETWORKS (W–BAN)

A. Ultra–Wideband (UWB) Communications

For in vivo communications, the UWB system is one of promising technologies for wireless transmissions. The signal bandwidth of the UWB communications spans a very wide
frequency range such as 1.5 GHz, that leads to a low spectrum power density. Because of the large bandwidth, the carrier frequency or the center frequency is inherently higher than several GHz. The fundamental advantage of the UWB for in vivo applications is twofold: 1) The low–power spectrum density feature may minimize the risk of the RF exposure for the body tissues, and 2) the high center frequency makes it possible to design a small antenna which results into downsizing of implantable devices.

B. SAR for RF Exposure Evaluation

Since the human body consists of water molecules for about 70%, the incident RF can cause a thermal increase in some specific organs. In order to limit the RF exposure, we should measure the SAR property as in [2], which is defined as

\[\gamma_{\text{SAR}} = \frac{\sigma E}{\rho},\]  

where \(\sigma\), \(E\) and \(\rho\) denote the tissue conductivity, the measured mean–square electric field, and tissue mass density, respectively. For reference, the mass densities \(\rho\) for the brain, skull and muscle are about 1030, 1850, and 1040 [kg/m^3], respectively.

For ex vivo communications, since the radio propagation is mainly through the air rather than the inside body, we generally use a phantom model, whose dielectric property is controlled to have approximately the same as that of the real body by using the homogeneous tissue–equivalent liquids, for the averaged SAR analysis. However, for in vivo communications, the partial SAR of different organs becomes more important because the radio wave mainly propagates through the body organs for data transmissions. As the dielectric parameters for the distinct organs differ from each other, we should use more detailed model to specify them. In addition, we should consider the spectrum dependence of the dielectric property, especially for UWB communications, because the very wide signal bandwidth with a certain GHz can be considerably fluctuated by the frequency dispersivity.

C. Dispersive Media of Body Tissues

It is well–known that the body tissues have dispersive media, whose dielectric property (permittivity \(\varepsilon\) and conductivity \(\sigma\)) highly depends on the frequency of the incident radio wave. For example, blood has a frequency–dependent dielectric property as follows: \(\varepsilon' \simeq 55\) and \(\sigma \simeq 1.9\) for 1 GHz, \(\varepsilon' \simeq 40\) and \(\sigma \simeq 13\) for 10 GHz, and \(\varepsilon' \simeq 6.2\) and \(\sigma \simeq 55\) for 100 GHz, where \(\varepsilon'\) being the relative permittivity. Due to a large bandwidth of UWB signals, it is expected that a severe estimation error may be observed for electromagnetic analysis of the SAR if we use a representative constant value of the dielectric property at the center frequency.

In [23], Gabriel has reported a thorough analysis of the dielectric properties of the body tissues over the wide spectrum range from several Hz to hundred GHz. In this literature, he has compiled a lot of existing measurement reports as well as the own experimental results. Another contribution derived in this literature is a development of an accurate spectrum model of the dispersive dielectric properties from the measured data sets. The spectrum model is referred to as the 4–Cole–Cole expression, which is written as

\[\varepsilon'(\omega) = \varepsilon_{\infty} + \frac{4 \Delta \varepsilon}{1 + (\omega \tau)\Delta \varepsilon} + \sigma_1 \frac{\omega \tau}{\varepsilon_0},\]  

where \(\omega, j = \sqrt{1}, \varepsilon_0 \simeq 8.85\) [F/m], \(\varepsilon_{\infty}, \sigma_1, \tau_1\) and \(\Delta \varepsilon_1\) denote the angular frequency, the imaginary unit, the vacuum permittivity, the permittivity in the THz frequency range, the ionic conductivity, the relaxation time and the drop in permittivity, respectively. The notation \(\chi_n(\omega)\) is termed the partial electric susceptibility. Each of the fitting parameters has been estimated by using the experimental data set available for 44 types of the particular tissues, e.g., aorta, bladder, blood, bone, cornea, heart, kidney, liver, tongue, trachea, uterus and lens cortex. For instance, the 4–Cole–Cole model parameters for blood have been obtained as 

\[\varepsilon_{\infty} = 4, \quad \sigma_1 = 0.7, \quad \Delta \varepsilon_1 = 56, \quad \Delta \varepsilon_2 = 5.2 \times 10^3, \quad \Delta \varepsilon_3 = \Delta \varepsilon_4 = 0, \quad \tau_1 = 8.377 \times 10^{-12}, \quad \tau_2 = 1.326 \times 10^{-7}, \quad \tau_3 = \tau_4 = 0, \quad \alpha_1 = \alpha_2 = 0.1, \quad \alpha_3 = \alpha_4 = 0.\]

It is verified that the fitted models for all the tissue types are very accurate for the frequency range between 1 MHz through 100 GHz.

D. FDTD Electromagnetic Analysis for Dispersive Media

The FDTD method has been extensively applied to lots of research fields as one of accurate numerical calculus for electromagnetic analyses. The FDTD method computes the transient behavior of the electric field \(E\) and the magnetic field \(H\) in time domain by discretizing into a small–grid cell and a short time step, based on the Maxwell’s equations:

\[\frac{\partial D}{\partial t} = \nabla \times H - J,\]  

\[-\mu \frac{\partial H}{\partial t} = \nabla \times E + J_m,\]  

where \(\mu\), \(J\) and \(J_m\) denote the magnetic permeability, the electric and magnetic current sources, respectively. Here, the electric flux density \(D\) is given by the convolution as

\[D = \int_0^\tau \varepsilon(\tau) E(t - \tau) d\tau,\]

where \(\varepsilon(\tau)\) denotes the permittivity in time domain. Hence, when the electric property has no dispersivity (\(\Delta \varepsilon_n = 0\)), it simplifies into \(D = \varepsilon_0 \varepsilon_{\infty} E + \sigma_1 \frac{\varepsilon_0}{\varepsilon_0} E(\tau) d\tau\). Unless otherwise, we need to memorize all the time series of the electric field data \(E(t)\) from \(t = 0\) in the conventional FDTD method.

If the dispersive medium can be expressed by a summation of the Debye, Drude, and Lorentz polarization models, we can efficiently compute the convolution of (5) in a recursive...
manner, the technique of which is termed the recursive convolution (RC) scheme [8–10]. For instance, when we have a single–order Debye polarization, whose electric susceptibility is given as

$$\chi_n(\omega) = \frac{\Delta \varepsilon_n}{1 + j \omega \tau_n},$$

we can express its time–domain representation as

$$\chi_n(t) = \frac{\Delta \varepsilon_n}{\tau_n} e^{-t/\tau_n} U(t),$$

where $U(t)$ is the step function. The exponential characteristic enables us to recursively compute $\Phi$. Letting $\Phi(t) = \int \chi(\tau) E(t - \tau) d\tau$, we can write

$$\Phi(t + \Delta t) \simeq \Delta \varepsilon_n (1 - e^{-\Delta t/\tau_n})^2 E(t + \Delta t) + e^{-\Delta t/\tau_n} \Phi(t),$$

which is given by the zero–th order approximation of the convolution. It implies that we do not need to memorize all the sequence $E(t)$ if we recursively evaluate the recursive accumulator $\Phi(t)$. Likewise, a summation of the Debye, Drude and Lorentz polarizations is suited to evaluate the electromagnetic field for the FDTD method with the RC scheme. To improve the accuracy, we use the PLRC scheme [11], which uses the first–order approximation for the convolution.

III. SAR ANALYSIS

For narrowband signals, we usually approximate the dielectric property of a constant value, which is represented by the value at the center frequency. Meanwhile, we may need to consider the effect of the dispersive media to analyze the SAR distribution for wideband signals. The primary purpose of this paper is to show the difference of the SAR evaluation of the dielectric properties in body tissues, for UWB signals. We begin by describing an approximated version of the 4–Cole–Cole model for PLRC–FDTD analysis. Next, we present a realistic body model and UWB signalling. We then evaluate the SAR distribution for the case when an implantable communication device is deployed inside the body. We finally conclude that the increased bandwidth necessitates the consideration of the spectrum dispersivity.

A. Approximated 4–Cole–Cole Model

When we adopt the 4–Cole–Cole model to the PLRC–FDTD method, we encounter the implementation difficulty because there is no analytical representation in time domain of the partial susceptibility $\chi_n$ when $0 < \alpha_n < 1$. In the Gabriel report [23], the best fitting parameters $\alpha_n$ are chosen out of $\{0.0, 0.01, 0.05, 0.1, 0.15, 0.16, 0.18, 0.2, 0.22, 0.25, 0.27, 0.3\}$. Leveraging on the fact that any dielectric property can be well approximated by a sum of multiple Debye models in general, we re–formulate the 4–Cole–Cole model by a summation of $4L$ Debye polarizations as follows:

$$\varepsilon'(\omega) = \varepsilon_{\infty} + \sum_{n=1}^{4} \Delta \varepsilon_n \sum_{l=1}^{L} \frac{\beta_{n,l}}{1 + j \omega \tau_n \gamma_{n,l}} + \frac{\sigma_1}{j \omega \varepsilon_0},$$

where we optimize $\beta_{n,l}$ and $\gamma_{n,l}$. For simplicity, we put a constraint that $\sum_{l=1}^{L} \beta_{n,l} = 1$. Hereafter, we refer to this dispersive model as the $(4 \times L)$–Cole–Cole model. By excluding the exponent factors $\alpha_n$, we can simulate the PLRC–FDTD in a straightforward manner.

It is confirmed that the model with $L = 4$ can offer a good approximation for all the tissue types. For example, we illustrate the impact of $L$ to approximate the dielectric property of blood tissue in Fig. 1. In this figure, we plot the dielectric property of the 4–Cole–Cole model in (2) and the $(4 \times L)$–Cole–Cole model in (8) as a function of incident radio frequency. For the $(4 \times L)$–Cole–Cole model, we optimized $\beta_{n,l}$ and $\gamma_{n,l}$ to fit the 4–Cole–Cole curve in log–log domain. As shown in this figure, the curve of the $(4 \times 4)$–Cole–Cole model agreed well that of the original one, whereas $L = 1$ and $2$ have some visible approximation errors at specific frequency ranges.

B. Human Body Model and UWB Signalling

For the FDTD simulation, we make use of the human body models developed by magnetic resonance imaging (MRI) of a real male and female in [24]. We use the female model depicted in Fig. 2, where we show the vertical cross–section above a height of 40 cm. The anatomical model specifies the three–dimensional distributions of 51 tissue types in the body, whose height and weight are 160.8 cm and 53 kg, respectively. The resolution of the model is $(2 \text{ mm})^3$ cubic cell size. As an example, we evaluate the RF exposure level at some organs of the female model such as uterus and ovary when a communication device is implanted in bladder to sense biological signals for medical diagnosis of urologic diseases.

We consider the RF transmission based on the impulse radio (IR) UWB signalling. We suppose that the UWB pulse shaping is the $m$–th derivative of the Gaussian pulse, whose power...
The spectrum is expressed as

\[ p(\omega) = \frac{\sqrt{2}}{2^m \Gamma(m/2 + 1/4)} \left( \frac{\omega}{\omega_0} \right)^{2m} e^{-\frac{1}{4} \left( \frac{\omega}{\omega_0} \right)^4} \]  

(9)

where \( \omega_0 \), \( \Gamma(\cdot) \) denote the center angular frequency of the first derivative Gaussian pulse, and the Euler’s gamma function. The peak frequency of the power spectrum is \( f_c = \frac{(2m)^{1/4} \omega_0}{2\pi} \). We evaluate the impact of the SAR distribution by increasing the signal bandwidth (or the center frequency), for which we control the constant \( m \) in the FDTD simulations. In the simulations, we fix the central peak frequency at \( f_c = 8.75 \text{GHz} \), and consider the UWB bandwidth up to 4.0 GHz.

C. SAR Distribution

Here, we show the PLRC–FDTD result of the SAR distribution. Fig. 3 plots the SAR distribution of the horizontal cross–section at a height of 80 cm when an implantable communication device is located at a height of 82 cm inside the bladder. Fig. 3 (a) specifies some organs in the cross–section, whereas Figs. 3 (b) and (c) illustrate the maximum SAR distribution assuming a narrowband signal of 40 MHz and a wideband signal of 4 GHz, respectively. Since we fix the identical central frequency, the SAR distribution is not so different from each other. However, the increased signal bandwidth can make a difference in the SAR profile at some specific organs. This is illustrated in Table I, in which we list the maximum and average SAR values at ovary and uterus according to the signal bandwidth. As shown in this table, the increased bandwidth can increase the SAR at the organs.

D. Bandwidth Dependency

The above result of SAR distribution highly depends on the body model as well as the posture and the environmental situations. Our major concern in this paper is to find how different the SAR profile occurs whether we consider properly the dispersive model or just the constant dielectric model. We show the relative error ratio of the maximum SAR value at ovary between the constant dielectric model and dispersive \((4 \times 4)\)-Cole–Cole model in Fig. 4. We use the constant value for the dielectric properties of all the tissues obtained at the central peak frequency \( f_c \). As shown in this figure, the constant dielectric model incurs an estimation error with
an exponential increase according to the signal bandwidth, in comparison to the dispersive model. It suggests that we require considering a proper mode for dispersive media to analyze the SAR distribution when we use a very large bandwidth for in vivo UWB transmissions.

IV. Conclusion

In this paper, we evaluated the SAR distribution in human body tissues for in vivo UWB communications, in which implantable devices inside the body transmit biological data using a wideband radio signal. We consider the fact that the dielectric properties of the tissues have a spectrum dependency for wideband signals. To efficiently analyze the SAR profile in such dispersive media, we re-formulated the dielectric properties in a sum of 16 Debye polarizations based on the 4–Cole–Cole model, introduced by Gabriel, for human tissues. The increased signal bandwidth for UWB communications necessitates the proper consideration of the dispersive dielectric properties in body organs. Realistic measurements should be pursued as future work.

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REFERENCES


TABLE I

SAR VALUES IN OVARY AND UTERUS

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<tr>
<th>Bandwidth (GHz)</th>
<th>Ovary Max SAR (W/kg)</th>
<th>Ovary Ave SAR (W/kg)</th>
<th>Uterus Max SAR (W/kg)</th>
<th>Uterus Ave SAR (W/kg)</th>
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</table>

Fig. 4. Relative error ratio of maximum SAR profile at ovary between constant dielectric model and dispersive (4 × 4)–Cole–Cole model as a function of signal bandwidth.
