PAPER

Hybrid TOA/RSSI-Based Wireless Capsule Endoscope Localization with Relative Permittivity Estimation

Takahiro ITO[†a)], *Student Member*, Daisuke ANZAI[†], *Member*, *and* Jianqing WANG[†], *Fellow*

SUMMARY When using a wireless capsule endoscope (WCE), it is important to know WCE location. In this paper, we focus on a time of arrival (TOA)-based localization technique, as it has better location estimation performance than other radio frequency-based techniques. However, the propagation speed of signals transmitted from inside of a human body varies depending on which biological tissues they pass through. For this reason, almost all of conventional TOA-based methods have to obtain the relative permittivity of the passed biological tissues or the propagation speed beforehand through another measurement system, i.e., magnetic resonance imaging (MRI) or computational tomography (CT). To avoid such troublesome pre-measurement, we propose a hybrid TOA/received signal strength indicator (RSSI)-based method, which can simultaneously estimate the WCE location and the averaged relative permittivity of the human body. First, we derive the principle of RSSI-based relative permittivity estimation from an finite difference time domain (FDTD) simulation. Second, we combine the TOA-based localization and the proposed RSSI-based relative permittivity estimation, and add them to the particle filter tracking technique. Finally, we perform computer simulations to evaluate the estimation accuracy of the proposed method. The simulation results show that the proposed method can accomplish good localization performance, 1.3 mm, without pre-measurement of the human body structure information.

key words: WCE, localization, BAN, TOA, RSSI, particle filter

1. Introduction

In recent years, wireless body area network (BAN) techniques are often applied to medical and healthcare applications [1], [2]. The first major application in implant BAN is wireless capsule endoscopy system [3]. A wireless capsule endoscope (WCE) can help doctors to diagnose diseases in gastrointestinal tract with videos or photographs obtained by itself. WCE location information indicates the place where the videos or the photographs were taken, therefore doctors can notice which part has the disease. In the future, WCE location information may become useful to optimize the transmission power. However, since a WCE moves inside the gastrointestinal tract every moment, we do not know its location in advance. WCE location information is usable in various application; therefore, it is necessary to estimate location of a WCE sequentially.

Various kinds of location estimation methods have been widely studied, for example magnetic field-based [4], radio frequency (RF) wave-based [5], and acoustic-based [6] technologies. In these technologies, RF wave-based local-

ization is the most advantageous for WCE localization in terms of ease of implementation because it requires no specific device. Usage of no specific device can expect to contribute to miniaturization and low energy consumption. The most famous technology based on RF wave is global positioning system (GPS). However, the GPS technique does not support WCE localization because it requires a direct communication link between the WCE and satellites.

Some localization methods for the WCE with RF wave have been proposed. Received signal strength indicator (RSSI)-based WCE localization technology is often used because of simple construction [3], [5], [7]. In paper [7], cooperative localization algorithm with multiple capsules based on RSSI was studied. The algorithm proposed in [7] achieved the root mean square (RMS) localization error of 3 cm in the case with 10 capsules. This means that the existing method can estimate the position with smaller error than the WCE's size. Nevertheless, the estimation accuracy is not enough because a next generation WCE technology requires accuracy of several millimeters to support telesurgery with a WCE. On the other hand, time of arrival (TOA)-based WCE localization technology can realize more accurate location estimation according to the literature [8]. Generally, each biological tissue has different electrical constants, that is, the conductivity and the relative permittivity. Therefore, the method in [8] needs correct propagation speed information to reach a precise location accuracy. Pourhomayoun et al. (2014) developed an effective method for the WCE localization with RSSI and TOA [9]. The method directly calculate the WCE position focusing on the characteristic of spatial sparsity. While it can achieve a good localization performance, such as less than 1 cm, it still also requires relative permittivity distribution and boundary information of the human body. However, to obtain the relative permittivity information in advance, we have to use another measurement system, such as magnetic resonance imaging (MRI) or computational tomography (CT) which requires a lot of effort. For instance, MRI requires large equipment and very strong magnetic field, and CT uses X-ray to produce tomographic images. Of course, we can re-use the relative permittivity for the localization problem in the same situation as the relative permittivity measurement environment, that is, the relative permittivity is available only for the same patient. However, taking a realistic scenario into consideration, we need to do the WCE localization for many different patients. In that case, it is no longer be used again without re-calculation, which means that it is necessary to measure

---

(or estimate) the relative permittivity for each patient.

In this paper, we propose a novel hybrid TOA/RSSI-based method with a particle filter, which includes relative permittivity estimation. Here, the particle filter is widely used as a localization technique and may achieve precise localization accuracy using proper state transition model and sufficient amount of samples [10], [11], similarly on the WCE tracking [5], [12]. To avoid the above-mentioned troublesome pre-measurement of a human body structure, we first construct a relative permittivity estimation model based on RSSI information with a finite difference time domain (FDTD) method. The usefulness of FDTD analysis with numerical human body model including the effects of transmit/receive antennas has been shown in many papers [13], [14]. Then, we combine the TOA-based localization and the proposed RSSI-based relative permittivity estimation, and apply them into the particle filter tracking technique. While we have studied the TOA/RSSI-based WCE localization method [15], the validation was performed only with a 2-dimensional model, so it is insufficient to confirm the validity of the proposed method in a realistic WCE scenario, namely, the conclusions of literature [15] is really limited. Hence, in this paper, we validate the proposed method in a more realistic implant BAN scenario for a 3-dimensional anatomical human model considering antennas implementation.

This paper is organized as follows. Section 2 presents the conventional TOA-based WCE localization methods. The derivation of the relative permittivity estimation model and performance evaluation on WCE localization with computer simulations are described in Sects. 3 and 4, respectively. Section 5 concludes this paper.

2. TOA-Based WCE Localization

2.1 System Model

We assume that receivers are put on a patient's body to receive signals transmitted from a WCE, and it obtains TOA and RSSI information from the received signals. The system overview of the WCE localization is shown in Fig. 1. We define 3-dimensional location of the WCE and the m-th receiver ($m = 1, ..., M$) as

$$\boldsymbol{r} = [x, y, z]^T \tag{1}$$
$$\boldsymbol{r}_m = [x_m, y_m, z_m]^T \tag{2}$$

where $(\cdot)^T$ indicates the transpose of $(\cdot)$. To localize the WCE based on a TOA technique, we range the propagation distance between the transmitter and the receiver according to travel time of the signal. The propagation distance to the m-th receiver d_m is expressed in the following equation:

$$d_m = |\boldsymbol{r} - \boldsymbol{r}_m| \tag{3}$$
$$= v\tau_m \tag{4}$$

where v and τ_m are the propagation velocity of the signal
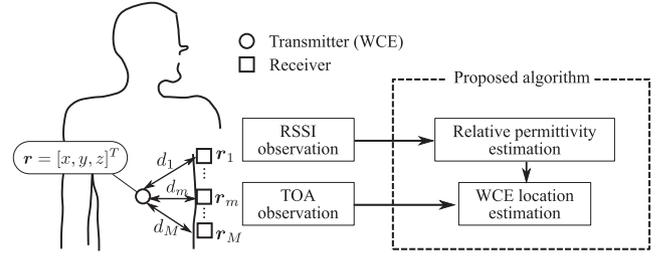
Fig. 1 System overview of WCE localization.

and the TOA acquired at the m-th receiver, respectively. Especially in free space, v is equal to the speed of light. Then, the WCE location is estimated by a localization system, for example a triangulation approach.

2.2 Variation of Propagation Signal Velocity in a Human Body

In implant BAN channels, the propagation velocity of the signal varies depending on the influence of various biological human tissues. The propagation distance of the signal which passed through a homogeneous tissue is given by

$$d_m = \frac{c}{\text{Re}\left[\sqrt{\varepsilon_r - j\frac{\sigma}{\omega\varepsilon_0}}\right]} \tau_m \tag{5}$$

where c, ε_r, σ, ω, and ε_0 are the velocity of light, the relative permittivity of tissue, the conductivity of tissue, the angular frequency, and the relative permittivity in free space, respectively.

2.3 Conventional TOA-Based WCE Localization

As a transmit signal, an ultra wideband (UWB) low-band signal (3.4–4.8 GHz) is used in this paper because it has advantages of high time resolution, low transmission power consumption and device miniaturization. The propagation distance can be approximated as follows because $\varepsilon \gg \sigma/\omega\varepsilon_0$ can be satisfied in UWB low-band [8].

$$d(\tau, \varepsilon_r) \approx \frac{c}{\sqrt{\varepsilon_r}} \tau. \tag{6}$$

For example, for muscle tissue at 4.1 GHz, the center frequency of the UWB low-band, the denominator $\text{Re}\left[\sqrt{\varepsilon_r - j\frac{\sigma}{\omega\varepsilon_0}}\right]$ in Eq. (5) and the approximated value $\sqrt{\varepsilon_r}$ represented in Eq. (6) are 8.38 and 8.36, respectively [16]. This means that regardless of neglecting the conductivity, the approximation by Eq. (6) can well represent Eq. (5) at such a frequency band. The WCE position is estimated by a least squares (LS) approach. Here, it requires the relative permittivity information to range the propagation distance. As we mentioned above, a human body consists of many kinds of biological tissues. Accordingly, because it is impossible to take all biological tissues into consideration, the conventional method [8] is to employ the averaged relative permittivity and the averaged propagation velocity as

Table 1 Conventional TOA-based WCE localization algorithm.

$$
\begin{aligned}
&\text{(Initialization)}\\
&\quad \varepsilon_{ave} = \frac{\sum_{k=1}^{K} \varepsilon_r d_k}{d_{all}} \;, \qquad v_{ave} = \frac{c}{\sqrt{\varepsilon_{ave}}}\\[4pt]
&\text{for } m = 1, ..., M\\
&\quad 1.\ \text{Observation}\\
&\qquad \text{TOA: } \tau_m\\
&\quad 2.\ \text{WCE localization with LS method}\\
&\qquad \tau_{m,\boldsymbol{r}} = d_m(\boldsymbol{r})/v_{ave}\\
&\qquad \hat{\boldsymbol{r}} = \arg\min_{\boldsymbol{r}} \sum_{m=1}^{M} [\tau_m - \tau_{m,\boldsymbol{r}}]^2
\end{aligned}
$$

$$
\varepsilon_{ave} = \frac{\sum_{k=1}^{K} \varepsilon_r d_k}{d_{all}} \tag{7}
$$

$$
v_{ave} = \frac{c}{\sqrt{\varepsilon_{ave}}} \tag{8}
$$

where K, d_k, and d_{all} are the number of regions, the length of the path via the k-th region, and the length of direct path, respectively. The conventional TOA-based WCE localization algorithm is summarized in Table 1. Here, note that this relative permittivity information in the k-th region is obtained by MRI or CT in the conventional method. This means that such information must be measured by troublesome pre-measurement with MRI or CT before diagnostic with a WCE, so it can be concluded that the conventional method is not suited for realistic WCE usage scenarios.

3. Proposed Hybrid TOA/RSSI-Based Localization with Particle Filter

In the proposed localization system, the WCE location and the relative permittivity are simultaneously estimated by using a proposed TOA/RSSI-based technique with the particle filter.

3.1 Proposed Relative Permittivity Estimation

3.1.1 Estimation Model

From Eqs. (5) and (6), it is clear that the TOA-based method needs the relative permittivity in order to estimate the propagation speed of the signal. In this paper, we estimate ε_r based on the RSSI information (RSSI means E as defined below). Because a human body is actually composed of various kinds of biological tissues, several lossy dielectrics exist between the transmitter (WCE) and the receiver. For simplification of the estimation problem, this paper assumes that there is one kind of biological tissue between the WCE and the receivers, which has the electric constants (namely, the relative permittivity and conductivity) averaged over the several lossy dielectrics. In this case, assuming that the transmitted signal radiates in a spherical wave form, the received electric field intensity (namely, the RSSI) at the m-th receiver E_m can be approximately expressed as

$$
E_m = f(\varepsilon_r) = E_0 \frac{A}{d_m} e^{-\alpha(\varepsilon_r) d_m} \tag{9}
$$
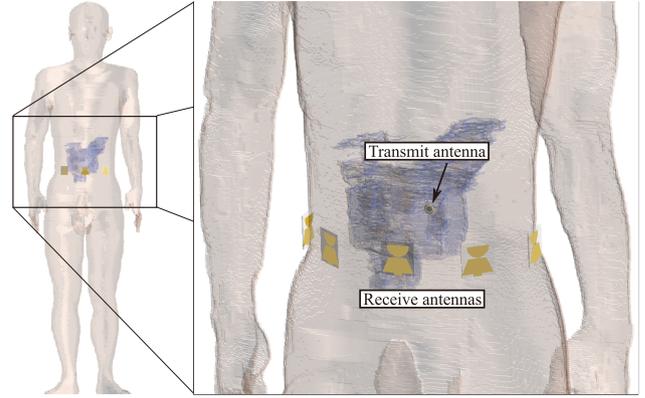
Fig. 2 Numerical human body model.

$$
\alpha(\varepsilon_r) = \omega \sqrt{\mu_0 \varepsilon_0 \varepsilon_r} \, \mathrm{Im} \left[1 - j\frac{\sigma}{\omega \varepsilon_0 \varepsilon_r} \right] \tag{10}
$$

where E_0, ω, μ_0, and σ are the transmit electric field intensity, the angle frequency, the magnetic permeability in free space, and the conductivity, respectively. A is a constant. Consequently, the averaged relative permittivity can be estimated from the electric field intensity acquired at m-th receiver E_m as

$$
\begin{aligned}
\varepsilon_m &= f^{-1}(E_m)\\
&= \frac{\sigma^2 \omega^2 \mu_0^2 d^4 - 4\left(\log\left[\frac{E_m}{E_0}d\right] - \log A\right)^4}{4\varepsilon_0 \omega^2 \mu_0 d^2 \left(\log\left[\frac{E_m}{E_0}d\right] - \log A\right)^2}
\end{aligned} \tag{11}
$$

where $f^{-1}(\cdot)$ indicates the inverse function of $f(\cdot)$ in Eq. (9). Here, we assume the conductivity σ as the two thirds of the muscle's value at the center frequency.

3.1.2 Validation for Relative Permittivity Estimation Model

We performed a computer simulation to validate the validity of an averaged relative permittivity to present the dielectric properties of a human body in our proposed relative permittivity estimation model. We used a numerical human body model shown in Fig. 2 developed by National Information and Communication Technology (NICT), Japan. The human body model consists of 51 tissue types. The transmit antenna of the WCE was assumed as a UWB loop antenna [17] inside the small intestine of the human body, and the receive planar imbalance dipole antennas were placed at five locations on the body surface as shown in Fig. 2. This receive antenna for UWB signals was also designed in the literature [17]. These antennas were located at the positions which suppose a realistic usage. Then, we calculated the received electric fields when we transmitted a UWB pulse from each transmission location by the finite difference time domain (FDTD) method.

Here, Eq. (9) can be transformed to

$$
\log\left[\frac{E}{E_0}d\right] = -\alpha(\varepsilon_r)d + \log A \tag{12}
$$

Fig. 3   Validation for relative permittivity estimation model.

Fig. 4   *cdf* of the normalized estimated relative permittivity.
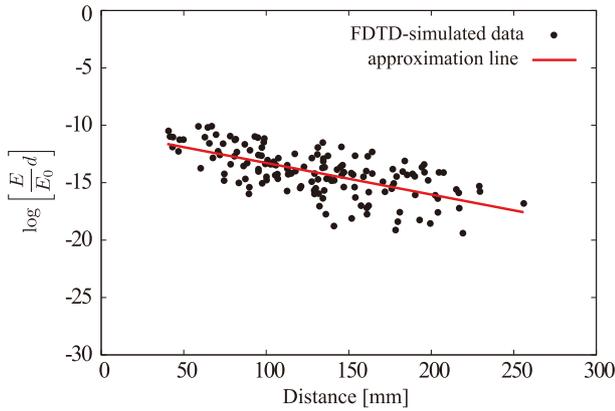
with the received electric field intensity E and the propagation distance d altogether. Equation (12) illustrates that $\log\left[\frac{E}{E_0}d\right]$ is proportional to the distance d. Figure 3 shows the FDTD-calculated results for the anatomical human body model with 51 tissue types and the fitted line using Eq. (12), both as a function of distance. From this result, the relationship between the distance and the received electric field intensity is well represented by Eq. (12), because the correlation coefficient between the FDTD-simulated data and the approximation line is 0.702. It should be noted that the constant A in Eq. (9) includes the effect of the antenna directivity and polarization, which can be estimated in advance. While we regard the complicated human body as an averaged biological tissue in Eq. (9), good accuracy for the averaged relative permittivity estimation can be accomplished based on the received electric field intensity.

Figure 4 illustrates the cumulative distribution function (*cdf*) against the estimated relative permittivity normalized by their average. Figure 4 also shows the log-normal distribution as a fitting curve. This implies that the distribution of the estimated relative permittivity can be expressed by the log-normal distribution, and this expression allows us to calculate the likelihood of each particles in the proposed particle filter algorithm. Here, the standard deviation of the approximated log-normal distribution is 1.23.

3.2 WCE Localization with Particle Filter

At the beginning, the proposed particle filter algorithm with the hybrid TOA/RSSI-based localization initializes N_p particles, which have a location vector, a velocity, a destination vector, a relative permittivity, and a weight. Then, it repeats the following four steps in an iterative manner to estimate the WCE location and relative permittivity.

3.2.1 Prediction Step

The states of the particles are decided by a state transition model. This paper assumes the random waypoint (RWP) model [5], [12] as the realistic transition model, which supposes peristalsis. In this paper, we define the process of the
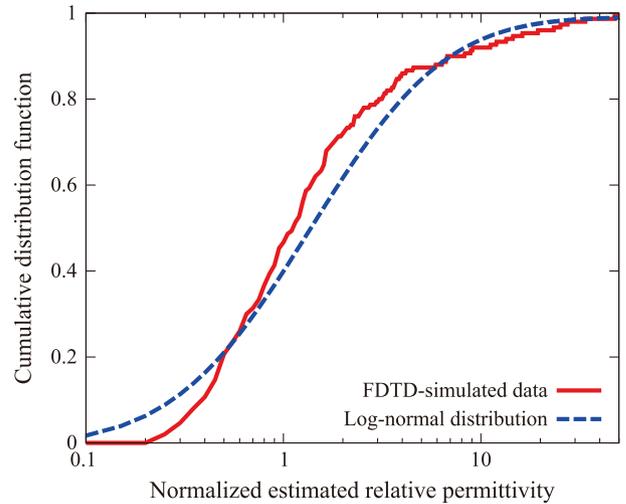
RWP transition as RWP($\cdot$). Furthermore, the i-th particle at the discrete-time index n has not only the particle location $\boldsymbol{r}_i[n]$ but also the relative permittivity information ε_i for each receiver (the subscript r is dropped without loss of generality in this section). When a particle reaches its destination, the particle is expected to linger in the bend of the small intestine for a random value of time, therefore it stops moving for the seconds decided by $\mathcal{U}(0, 20)$.

3.2.2 Update Step

In the update step, the weight of each particle $\tilde{w}_i[n]$ at the time index of n is updated as in the following way:

$$\tilde{w}_i[n] = w_i[n-1] \prod_{m=1}^{M} p(\tau_m, \varepsilon_m | \boldsymbol{r}_i[n], \varepsilon_i) \tag{13}$$

$$w_i[n] = \frac{\tilde{w}_i[n]}{\sum_{j=1}^{N_p} w_j[n]} \tag{14}$$

where $w_i[n]$ is the normalized weight of the i-th particle. ε_m is the relative permittivity estimated by Eq. (11) with the RSSI measured at the m-th receiver. The probability density function (*pdf*) in Eq. (13) can be decomposed into

$$p(\tau_m, \varepsilon_m | \boldsymbol{r}_i[n], \varepsilon_i) = p(\tau_m | \boldsymbol{r}_i[n], \varepsilon_i) p(\varepsilon_m | \boldsymbol{r}_i[n], \varepsilon_i). \tag{15}$$

Assuming that we establish a clear wireless communication link (namely, a certain level of SNR can be achieved), the effect of the sampling error should be dominant on the TOA measurement. In this case, taking the sampling error of TOA measurement into consideration, the former term of Eq. (15) is given by [18]

$$p(\tau_m | \boldsymbol{r}_i[n], \varepsilon_i) = \frac{1}{\sqrt{2\pi}\sigma_s} \exp\left[-\frac{(\tau_m - \overline{\tau}_{m,i})^2}{2\sigma_s^2}\right] \tag{16}$$

$$\overline{\tau}_{m,i} = \frac{\sqrt{\varepsilon_i}}{c} |\boldsymbol{r}_i[n] - \boldsymbol{r}_m|. \tag{17}$$

On the other hand, the latter term of Eq. (15) is assumed

Table 2 One cycle of proposed WCE localization algorithm.

Particle state: $\boldsymbol{r}_i, \varepsilon_i, w_i$
for $i = 1, ..., N_p, m = 1, ..., M$
1. Observation
   TOA: τ_m
   RSSI: E_m
2. Relative permittivity estimation
   $\varepsilon_m = f^{-1}(E_m)$
3. WCE localization
   Prediction: $\boldsymbol{r}_i[n] = \text{RWP}(\boldsymbol{r}_i[n-1])$
   Update: $\tilde{w}_i[n] = w_i[n-1] \prod_{m=1}^{M} p(\tau_m, \varepsilon_m | \boldsymbol{r}_i[n], \varepsilon_i)$
   Resampling:
   Estimation: $\hat{\boldsymbol{r}}[n] = \sum_{i=1}^{N_p} w_i[n] \boldsymbol{r}_i[n]$

as the following log-normal distribution as mentioned in above:

$$p(\varepsilon_m | \boldsymbol{r}_i[n], \varepsilon_i) = \frac{1}{\sqrt{2\pi}\sigma_e \varepsilon_m} \exp\left[-\frac{(\log \varepsilon_m - \varepsilon_i)^2}{2\sigma_e^2}\right] \quad (18)$$

where σ_e is the parameter of the log-normal distribution. From the FDTD simulation results in the previous section, σ_e of 1.23 has been obtained.

3.2.3 Resampling Step

As the particle filter algorithm iteratively processes, some of the normalized weights become negligible. When most of the normalized weights concentrate on a part of particles, resampling [5] is processed to avoid adverse effect occurs in terms of the sequential Monte Carlo method. If the parameter calculated from the weights of the particles is less than resampling threshold β_{thr}, new particles are generated as a copy of one of the remaining particle. Note that the resampling step of the proposed algorithm additionally employs one more procedure to add a little variation to the regenerated particle parameters in order to effectively avoid local optimization problem.

3.2.4 Estimation Step

The estimated location of the WCE is calculated as weighted average by

$$\hat{\boldsymbol{r}}[n] = \sum_{i=1}^{N_p} w_i[n] \boldsymbol{r}_i[n]. \quad (19)$$

Finally, one cycle of the proposed hybrid TOA/RSSI-based WCE localization algorithm is summarized in Table 2.

4. Performance Evaluation with Computer Simulations

4.1 Simulation Environment

In order to evaluate the performances of the proposed localization method, we performed computer simulations. In the computer simulations, we assumed that the WCE moves inside a small intestine according to the RWP model described
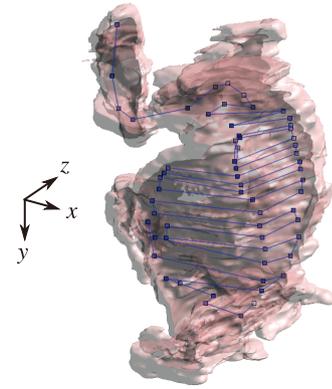
Fig. 5 Locus of capsule endoscope.

Table 3 Parameters of computer simulations.

Analysis area	$40 \times 40 \times 20$ cm
Time interval	0.1 s
Average speed of WCE motion	0.05 cm/s
Center frequency	4.1 GHz
Standard deviation of TOA observation distribution σ_s	62.5 ps
Conductivity σ	2.17 S/m

in the previous section, and the destination location of the transition model was determined based on the small intestine of the anatomical human model in advance as shown in Fig. 5. We put 8 receivers at each vertex of the cuboid which suppose a location estimation area. The received signals on these receivers were obtained based on the FDTD-derived statistical model, and were sampled with the sampling frequency of 8 GHz. In our simulations, we assumed that measured TOA followed a normal distribution whose standard deviation σ_s is half of the sampling interval 125 ps. Analysis area represent the possible range of the WCE location to be estimated. Besides, location estimation area was assumed to be filled with averaged biological tissue whose electrical properties were two thirds of muscle, namely $\sigma = 2.17$ [S/m] and $\varepsilon_r = 34.25$ at the center frequency of the signal according to the literature [19]. Finally, the computer simulation parameters are summarized in Table 3. We supposed a scenario that RSSI and TOA were acquired within every time interval, then the proposed particle filter outputs the estimated WCE location $\hat{\boldsymbol{r}}$ utilizing the acquired information.

4.2 Effect of Filter Parameters Regarding Localization Performance

Let us discuss the effect of the filter parameters before evaluating the localization performance. Figure 6 shows the root mean square (RMS) location estimation errors against the resampling threshold β_{thr} in the cases of the number of particle $N_p = 5000, 10000, 15000,$ and 20000. As illustrated in Fig. 6, the localization accuracy is insensitive to resampling threshold β_{thr}. From Fig. 6, we choose $\beta_{thr} = 0.06$ and $N_p = 20000$ as the optimal values for the localization performance.
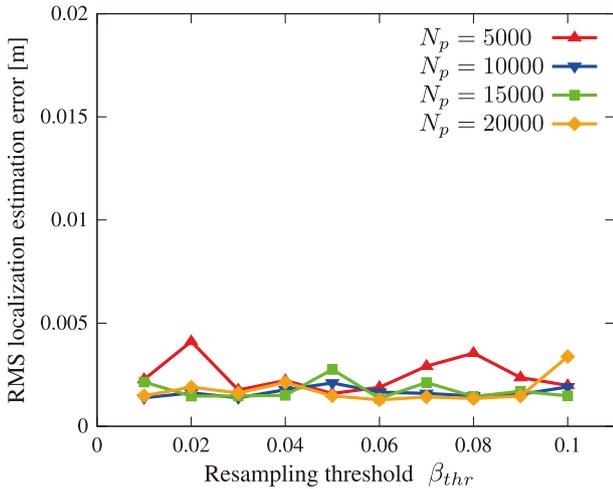
Fig. 6 RMS localization error against β_{thr}.
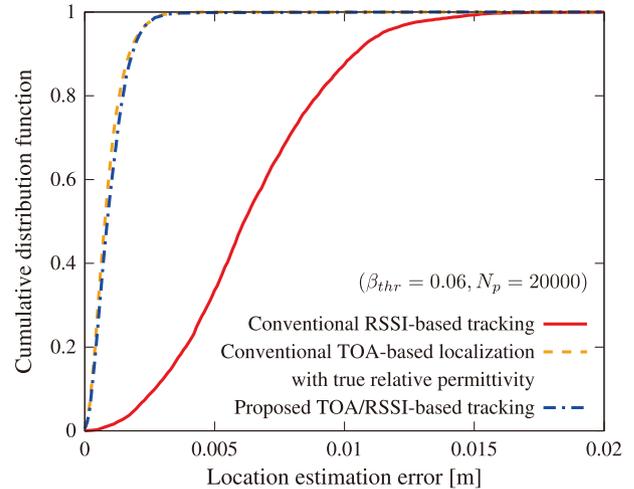
Fig. 8 cdf of location estimation error.
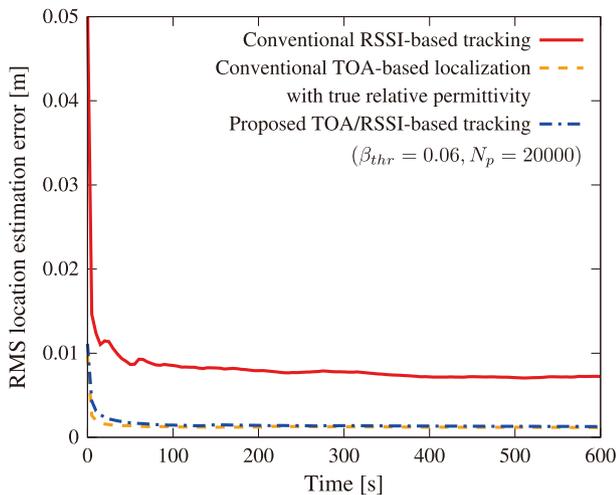
Fig. 7 RMS localization error against time.
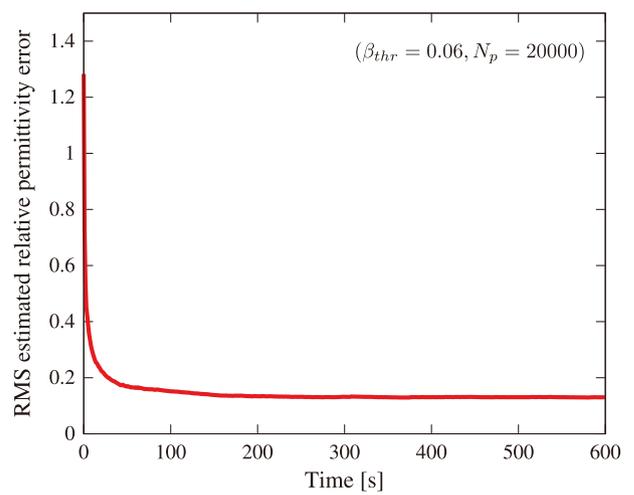
Fig. 9 RMS estimated relative permittivity error.

4.3 Performance Evaluation

Figure 7 shows the RMS location estimation error for the proposed hybrid TOA/RSSI-based method, the conventional RSSI-based method [5] and the conventional TOA-based method with true relative permittivity information. As seen from Fig. 7, the achievable localization accuracy of the proposed method at 600 s is 1.3 mm and that of the conventional RSSI-based method is 7 mm. Namely, the localization performance of our proposed method is improved by around 80% compared with the conventional RSSI-based method. Besides, the accuracy of the conventional TOA-based method with true relative permittivity information is 1.2 mm. While our proposed method use no pre-measurement information of the relative permittivity, it achieves the same localization performance as that of the conventional TOA-based localization with true relative permittivity.

Figure 8 shows the cumulative distribution function

(cdf) on the location estimation error for the three methods. From the figure, the maximum location estimation error of the conventional RSSI-based method is around 15 mm. In contrast, that of the proposed method achieves the localization performance of less than 4 mm. The proposed method can achieve the same localization performance as the conventional TOA-based localization with true relative permittivity also in aspect of cdf. For example, when the cdf of the location estimation error is 0.8, the proposed method can accomplish the accuracy of around 1.5 mm.

Furthermore, Fig. 9 illustrates the RMS estimation error of the averaged relative permittivity on our method for 10 minutes. From Fig. 9, the RMS estimation error quickly converges to around 0.13. Considering the true value of the averaged relative permittivity of the human body, which is around 34.25 (two thirds of the average muscle parameter at 4.1 GHz), the proposed method realizes accurate relative permittivity estimation, so that, the proposed relative permittivity estimation can support the precise TOA-based localization in implant BANs.

Table 4 Performance comparison between the proposed and the conventional methods.

	Proposed	Kawasaki, 2009[8]	Pahlavan, 2012[7]	Ito, 2014[5]	Pourhomayoun, 2014[9]	
Localization technique	TOA/RSSI	TOA	RSSI	RSSI	TOA/RSSI	
Number of dimensions of estimated WCE location	3	2	3	3	2	3
Pre-measurement of model parameters (including relative permittivity information)	None	Required	Required	Required	Required	
Achievable RMS location estimation accuracy	1.3 mm	10 mm	30 mm	7 mm	6 mm	7 mm
The shortest distance between transceivers at the initialization	97.3mm	(Not available)	(Not available)	199mm	(Not available)	
Frequency bands	3.4–4.8 GHz	0–4.0 GHz	403.5 MHz	400 MHz	405.85–406.15 MHz	

Finally, we show the comparison between the localization performances for the proposed localization method and the existing conventional methods in Table 4. We note that all of the conventional methods in Table 4 took inhomogeneous biological tissue structure into consideration to realize the accurate localization method. Table 4 clearly demonstrates that only the proposed method does not require pre-measurement of model parameters including the relative permittivity information. Here, it should be noted that Pourhomayoun et al. (2014) [9] used both TOA and RSSI for the WCE localization, however, it has difficulties in a practical use because the number of dimensions of the estimation position is only two and it requires pre-measured boundary information of biological tissue layers.

Good precision of our method was mainly achieved by two contributors, namely, the use of UWB signals and applying the particle filter to the UWB-based localization. UWB signals have high time resolution so that we can reduce the location estimation error. The particle filter algorithm continuously tracks the location of WCE instead of estimating its instantaneous location based on all time-series TOA data.

As mentioned above, UWB-ranging between the transceivers need the relative permittivity values of the propagation path to get correct propagation speed information. If there is a mismatch on the relative permittivity, it is difficult to preciously estimate the distance between the transceivers. Moreover, there are many kinds of biological tissue on the propagation path so that it leads to a complicated relationship between the relative permittivity and the propagation speed. In this paper, we aimed to introduce relative permittivity estimation into the particle filter-based localization. For this purpose, we constructed a probability model of relative permittivity variation because the particle filter solves maximum a posteriori (MAP) estimation using the prior probability. Consequently, it can be concluded that the superiority of our proposed algorithm is to successfully apply the relative permittivity estimation to the particle filter-based localization, which allows us to high-precision localization without any troublesome pre-measurement on the patient.

5. Conclusions

This paper has proposed a hybrid TOA/RSSI-based WCE localization method without pre-measurement of relative permittivity information. First we constructed an RSSI-based averaged relative permittivity estimation, which is applicable to a human body model composed of various kinds of biological tissues. Then, we have showed the validity of the averaged relative permittivity estimation using the FDTD simulation together with an anatomical human body model. After that, we combined the TOA-based localization and the proposed RSSI-based relative permittivity estimation, and apply them into the particle filter localization algorithm. The results of our computer simulations have demonstrated that the achievable RMS location estimation error of our proposed method is 1.3 mm. Our proposed method approaches the estimation accuracy of conventional TOA-based WCE localization even without pre-measurement of the relative permittivity information.

Acknowledgment

References

[1] J. Wang and Q. Wang, Body Area Communications, Wiley-IEEE, 2013.
[2] H. Li and R. Kohno, "Body area network and its standardization at ieee 802.15. ban," Advances in Mobile and Wireless Communications, pp.223–238, 2008.
[3] D. Fischer, R. Schreiber, D. Levi, and R. Eliakim, "Capsule endoscopy: The localization system," Gastrointestinal Endoscopy Clinics of North America, vol.14, no.1, pp.25–31, 2004.
[4] X. Wang, M.Q.-H. Meng, and C. Hu, "A localization method using 3-axis magnetoresistive sensors for tracking of capsule endoscope," Proc. 2006 International Conference of the IEEE Engineering in Medicine and Biology Society, pp.2522–2525, 2006.
[5] T. Ito, D. Anzai, and J. Wang, "Performance evaluation on RSSI-based wireless capsule endoscope location tracking with particle filter," IEICE Trans. Commun., vol.E97-B, no.3, pp.579–586, 2014.
[6] Y. Xu, W. Dandan, and F. Hua, "Underwater acoustic source localization method based on TDOA with particle filtering," Proc. 26th Chinese Control and Decision Conference (2014 CCDC), pp.4634–4637, 2014.
[7] K. Pahlavan, G. Bao, Y. Ye, S. Makarov, U. Khan, P. Swar, D. Cave, A. Karellas, P. Krishnamurthy, and K. Sayrafian, "RF localization for wireless video capsule endoscopy," Int. J. Wireless Inf. Networks., vol.19, no.4, pp.326–340, 2012.
[8] M. Kawasaki and R. Kohno, "Position estimation method of medical implanted devices using estimation of propagation velocity inside

human body," IEICE Trans. Commun., vol.E92-B, no.2, pp.403–409, 2009.

[9] M. Pourhomayoun, Z. Jin, and M.L. Fowler, "Accurate localization of in-body medical implants based on spatial sparsity," IEEE Trans. Biomed. Eng., vol.61, no.2, pp.590–597, Feb. 2014.

[10] J. Rodas, C.J. Escudero, and D.I. Iglesia, "Bayesian filtering for a bluetooth positioning system," Proc. 2008 IEEE International Symposium on Wireless Communication Systems, pp.618–622, 2008.

[11] D. Anzai, K. Yanagihara, K. Lee, and S. Hara, "Use of area layout information for RSSI-based indoor target tracking methods," IEICE Trans. Commun., vol.E94-B, no.7, pp.1924–1932, 2011.

[12] B. Moussakhani, R. Chavez-Santiago, and I. Balasingham, "Multi model tracking for localization in wireless capsule endoscopes," Proc. 4th International Symposium on Applied Sciences in Biomedical and Communication Technologies, ISABEL'11, pp.1–5, 2011.

[13] J. Wiart, A. Hadjem, M.F. Wong, and I. Bloch, "Analysis of RF exposure in the head tissues of children and adults," Phys. Med. Biol., vol.53, no.13, pp.3681–3695, 2008.

[14] J. Wang, O. Fujiwara, S. Kodera, and S. Watanabe, "FDTD calculation of whole-body average SAR in adult and child models for frequencies from 30 MHz to 3 GHz," Phys. Med. Biol., vol.51, no.17, pp.4119–4127, 2006.

[15] T. Ito, D. Anzai, and J. Wang, "Novel joint TOA/RSSI-based WCE location tracking method without prior knowledge of biological human body tissues," 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp.6993–6996, 2014.

[16] S. Gabriel, R.W. Lau, and C. Gabriel, "The dielectric properties of biological tissues: II. Measurements in the frequency range 10 Hz to 20 GHz," Phys. Med. Biol., vol.41, no.11, pp.2251–2269, 1996.

[17] Y. Morimoto, D. Anzai, and J. Wang, "Design of ultra wide-band low-band implant antennas for capsule endoscope application," 2013 7th International Symposium on Medical Information and Communication Technology (ISMICT), pp.61–65, 2013.

[18] S. Hara, D. Anzai, T. Yabu, K. Lee, T. Derham, and R. Zemek, "A perturbation analysis on the performance of TOA and TDOA localization in mixed LOS/NLOS environments," IEEE Trans. Commun., vol.61, no.2, pp.679–689, 2013.

[19] C. Gabriel, "Compilation of the dielectric properties of body tissues at RF and microwave frequencies," Technical Report: AL/OE-TR-1996-0037, 1996.

Daisuke Anzai received the B.E., M.E. and Ph.D. degrees from Osaka City University, Osaka, Japan in 2006, 2008 and 2011, respectively. Since April 2011, he has been an Assistant Professor at the Graduate School of Engineering, Nagoya Institute of Technology, Nagoya, Japan. He has engaged in the research of biomedical communication systems and localization systems in wireless communication networks.

Jianqing Wang received the B.E. degree in electronic engineering from Beijing Institute of Technology, Beijing, China, in 1984, and the M.E. and D.E. degrees in electrical and communication engineering from Tohoku University, Sendai, Japan, in 1988 and 1991, respectively. He was a Research Associate at Tohoku University and a Senior Engineer at Sophia Systems Co., Ltd., prior to joining the Nagoya Institute of Technology, Nagoya, Japan, in 1997, where he is currently a Professor. His research interests include biomedical communications and electromagnetic compatibility.

Takahiro Ito was born in Aichi, Japan, in 1990. He received the B.Eng. and M.Eng. degree from Nagoya Institute of Technology, Aichi, Japan in 2013 and 2015, respectively. He is currently pursuing the Doctoral Degree Program at Nagoya Institute of Technology, engaging in the research on localization in body area networks.