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Experimental Evaluation on Maximum A Posteriori Location Tracking for Implantable Devices

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Abstract

Implantable medical devices that make use of wireless communications have so far attracted great attention. For efficient treatment based on wireless implantable devices, it is important to acquire their locations with high accuracy. In addition, considering an application example of wireless capsule endoscopy, motion control from outside and wireless power transmission need the endoscope location estimation in real time. This paper developed a real-time maximum a posteriori (MAP) location tracking system that can simultaneously estimate not only the location but also channel parameters for implantable medical devices. We then investigated achievable localization accuracy based on experimental evaluation under liquid phantom environment.

1 Introduction

Recently, implantable medical devices to realize efficient medical treatment have attracted much attention [1]. One of the promising medical devices is a wireless capsule endoscope, which includes a small camera and wireless communication function in order to make it easier to diagnose gastrointestinal conditions. In such medical treatments with implantable devices, it is important to estimate their locations accurately.

So far, several kinds of localization methods have been proposed, such as magnetic field-based, radio frequency (RF) wave-based, and acoustic-based technologies [2–5]. This paper pays attention to received signal strength indicator (RSSI)-based localization because RSSI can be measured by a fundamental function in modern wireless communication systems without any additional special devices [5,6].

To realize precise accuracy in RSSI-based implantable device localization, a maximum likelihood (ML) and maximum a posteriori (MAP) estimations were introduced in the related works. However, the performance evaluation was mainly considered through computer simulations and theoretical analyses. Furthermore, the theoretical analyses were limited to only the ML estimation [6], so that, the theoretical studies for the MAP estimation and the experimental evaluation were rarely discussed. In addition, there is another problem in the RSSI methods; the ML and MAP estimations need the channel parameter information in advance, which can represent the RSSI variation in the location estimation area [5].

In this paper, we aim to extend a MAP method to estimate not only the implantable device location but also the channel parameters. Then, we develop an implantable device location estimation system with the proposed MAP estimation. Finally, this paper carries out experimental performance evaluation under liquid phantom environment and demonstrates the performance improvement of the location estimation accuracy.

2 System Model and Implant Propagation Characteristics

2.1 System overview

In the location estimation system shown in Fig. 1, there are a medical implantable device inside a human body whose location is unknown so should be estimated and N receivers on the body surface whose locations are known in advance. Here, the receivers, namely RSSI detectors, measure RSSI data from 400 MHz-band implant communication signals transmitted by the implantable device, and afterwords, the measured RSSI data are sent to a laptop personal computer (PC) through 920 MHz-band wireless communications. As shown in Fig. 2, we estimate the three-dimensional implantable device location $\mathbf{u} = [x, y, z]^T$ based on N receiver positions $\mathbf{a}_n = [x_n, y_n, z_n]^T$, where the index n ranges between 1 and N. The implantable device transmits a packet to the receivers, and each receiver measures an RSSI P_n from the received packets.

2.2 Model of implant communication link

To accurately estimate the implantable device location with RSSI, a statistical model on the RSSI is required, which can well characterize the RSSI variation in the implant communication. From the investigation based on the finite difference time domain analysis, we came to the conclusion that the RSSI of the 400 MHz MICS-band signals can be well modeled with the following two-layered model [5]:

$$\overline{P_n} = \alpha r_n^{-\beta}, \quad p(P_n|r_n) = \frac{1}{\sqrt{2\pi}\sigma P_n} \exp\left[-\frac{\{\log P_n - \log \overline{P_n}\}^2}{2\sigma^2}\right] \tag{1}$$

where $\overline{P_n}$ and r_n indicate the average received power and the distance between the implantable device and the n-th receiver, respectively, and $p(P|r)$ is the conditional probability density function (*p.d.f.*) on P_n when r_n is given.

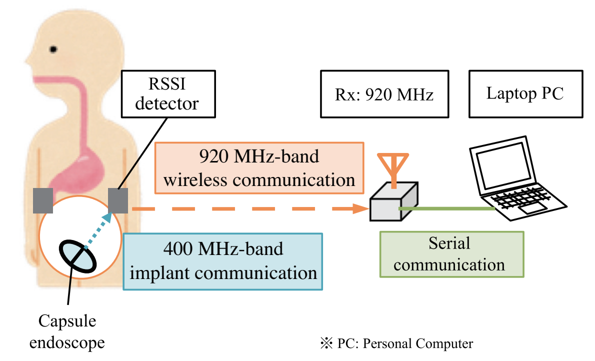

Figure 1. Overview of implantable device localization

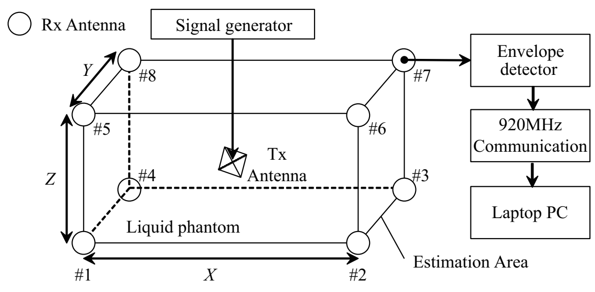

Figure 2. Location estimation system model

From (1), the channel parameters vector should be defined as $\mathbf{c} = [\alpha, \beta, \sigma]^T$ that is uniquely determined by individual human body characteristics.

3 Proposed Joint MAP Location/Channel Parameter Estimation Method

3.1 Conventional ML estimation

To estimate both the location and the channel parameters, we derive a log-likelihood function on not only the location $\mathbf{u}$ but also the channel parameter $\mathbf{c}$ for joint location/channel parameters estimation as

$$L(\mathbf{u}, \mathbf{c} = [\alpha, \beta, \sigma]^T) = \log l(\mathbf{u}, \mathbf{c}) = \log p(P_1, P_2, \cdots, P_N | \mathbf{u}, \mathbf{c}). \tag{2}$$

Assuming that P_n is statistically independent with $P_{n'}(n \neq n')$ *(local whiteness)*, we finally obtain

$$L(\mathbf{u}, \mathbf{c}) = \sum_{n=1}^{N} \left\{ -\log \left[\sqrt{2\pi}\sigma P_n \right] - \frac{\{\log P_n - \log \overline{P_n}\}^2}{2\sigma^2} \right\}. \tag{3}$$

The conventional ML location estimation gives $\hat{\mathbf{u}}$ and $\hat{\mathbf{c}}$ which maximize (3), where $\hat{(\cdot)}$ denotes the estimate of $(\cdot)$.

3.2 Proposed MAP estimation

Then, let us introduce a MAP estimation technique to the implantable device localization problem. The MAP estimation requires the logarithm of a conditional probability density function on $\mathbf{u}$ when $\mathbf{P}$ and $\mathbf{c}$ are given, namely, a posteriori probability density function on the implantable device location, which is given by

$$\log p(\mathbf{u}|P, \mathbf{c}) \propto \log p(P|\mathbf{u}, \mathbf{c}) + \log p(\mathbf{u}) = L(\mathbf{u}, \mathbf{c}) + \log p(\mathbf{u}) \tag{4}$$

where the first term $\log p(P|\mathbf{u}, \mathbf{c})$ can be calculated by the log-likelihood function defined in (3). Therefore, for realizing the MAP estimation, it is a key issue to obtain the second term $\log p(\mathbf{u})$, i.e., the prior probability on the location. In this paper, we employ a particle filter-based approach to acquire the prior probability. The particle filter with a sequential importance sampling (SIS) algorithm needs the definition of the state transition model and observation model [7]. Regarding the transmission model, we assume the random way point model that represents the capsule endoscope movement inside a small intestine [5]. On the other hand, the observation model is necessary for the update of each particle weight in the SIS algorithm. Defining i, m and $\overline{w}_{i,m}$ as the particle index, the time index and the normalized particles weights, respectively, the particle weight $w_{i,m}$ is updated as

$$w_{i,m} = \overline{w}_{i,m-1} p(\mathbf{P}_m | \mathbf{u}_{i,m}, \mathbf{c}) = \overline{w}_{i,m-1} l(\mathbf{u}_{i,m}, \mathbf{c}). \tag{5}$$

Here, $\mathbf{P}_m$ is the m-th measured RSSI vector defined as $\mathbf{P}_m = [P_{m,1}, P_{m,2}, \cdots, P_{m,N}]^T$, where $P_{m,n}$ denotes the RSSI measured at the n-th receiver with the time index m. Using the prior probability $p(\mathbf{u}_m)$ acquired by the particle filter algorithm, the proposed MAP method estimates the location and channel parameters that maximize (4), which thus result in

$$[\hat{\mathbf{u}}, \hat{\mathbf{c}}] = \arg\max_{\mathbf{u}, \mathbf{c}} \left[L(\mathbf{u}, \mathbf{c}) + \log p(\mathbf{u}) \right]. \tag{6}$$

3.3 Cramer-Rao lower bound analysis

In order to theoretically analyze the estimation accuracy, we derive the CRLB for the proposed MAP methods that provides the theoretical minimum error variance. The CRLB can be derived by the diagonal elements of the inverse of the information matrix defined as $\mathbf{J}_T = \mathbf{J}_F + \mathbf{J}_P$ [8], where $\mathbf{J}_F$ and $\mathbf{J}_P$ denote the Fisher information matrix and the priori information matrix, respectively:

$$\mathbf{J}_F = -E \left\{ \left[\frac{\partial}{\partial \mathbf{u}} L(\mathbf{u}, \mathbf{c}) \right] \left[\frac{\partial}{\partial \mathbf{u}} L(\mathbf{u}, \mathbf{c}) \right]^T \right\} \tag{7}$$

$$\mathbf{J}_P = -E \left\{ \left[\frac{\partial}{\partial \mathbf{u}} \log p(\mathbf{u}) \right] \left[\frac{\partial}{\partial \mathbf{u}} \log p(\mathbf{u}) \right]^T \right\}. \tag{8}$$

Let $\mathbf{I}$ and I_{ii} denote the inverse matrix of $\mathbf{J}_T$ and its i-th diagonal element, respectively. In this case, the minimum location error variance for the proposed MAP estimation σ^2_{CRLB} is written as

$$\sigma^2_{CRLB} = \min(var[x] + var[y] + var[z]) = I_{11} + I_{22} + I_{33}. \tag{9}$$

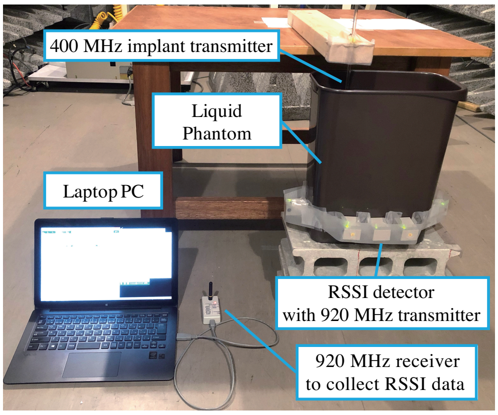

Figure 3. Experimental environment

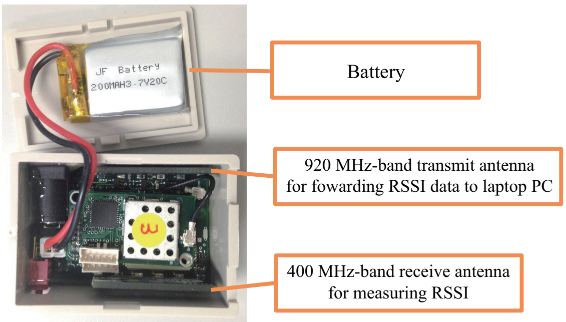

Figure 4. RSSI detector structure

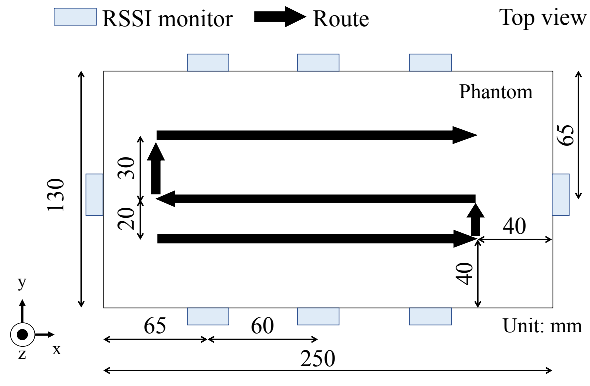

Figure 5. Movement path of transmit antenna

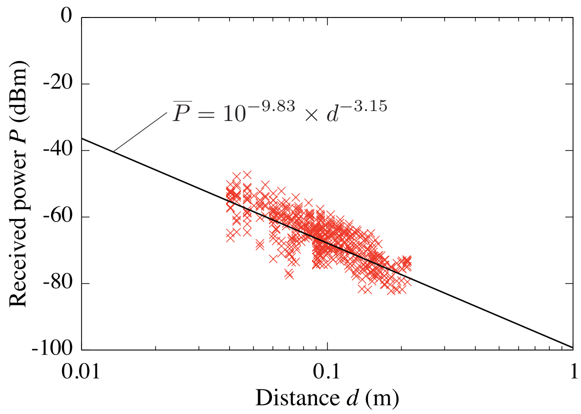

Figure 6. Measured RSSI on distance

4 Experimental Evaluation

4.1 Experimental setup

For evaluation of the performance for the prototype localization system with the MAP estimation, we conducted an experiment with liquid phantom in an anechoic chamber. Figs. 3 and 4 show the photograph of the experimental environment and the RSSI detector employed in the experiment, respectively. In Fig. 4, the RSSI detector has both 400 MHz-band antenna for implant communications and 920 MHz-band antenna for collecting measured RSSI data. The implant transmit antenna was moved inside the liquid phantom along the movement path shown in Fig. 5. The estimation area was assumed to a cuboid area, whose size was 25 cm (width) $\times$ 13 cm (depth) $\times$ 11 cm (height). We put 8 RSSI detectors on the tank of the liquid phantom to measure RSSIs from the 400 MHz-band implant communication signals. As for the transmit antenna, we used helical antennas whose resonant frequency was 400 MHz band. The relative permittivity and conductivity of the liquid phantom were 34.35 and 0.53 S/m, respectively, which were similar to the average dielectric constants of a human body.

First, let us show the measured RSSI data against the distance between transmitting and receiving antennas in Fig. 6. Also, Fig. 7 shows the *p.d.f.* on the measured RSSIs normalized by the average RSSI. As can be seen from both figures, the two-layered model used in the proposed method can well represent the RSSI variation in the experimental environment. Note that the channel parameters were obtained as $\mathbf{c} = [10^{-9.83}, -3.15, 1, 00]^T$.

4.2 Estimation accuracy

Fig. 8 shows the root mean square (RMS) location estimation errors for the proposed method. For comparison purpose, this figure also includes the localization performances for the conventional method which needs the channel parameters information in advance. These results demonstrates that the proposed MAP estimation has accomplished almost the same accuracy for the conventional method with known channel parameters in the computer simulations. We can also find that, in the experimental results, the proposed MAP estimation is superior to the ML estimation. Consequently, the proposed method can successfully estimate not only the location but also the channel parameters with good accuracy. Furthermore, the results for the computer simulation quickly converges to the theoretical lower bound. Importantly, the achievable estimation performance has been achieved to 5 mm.

Finally, let us discuss the accuracy of the parameters estimation in the experiment. Fig. 9 shows the experimental results of the normalized RMS errors for the parameters es-

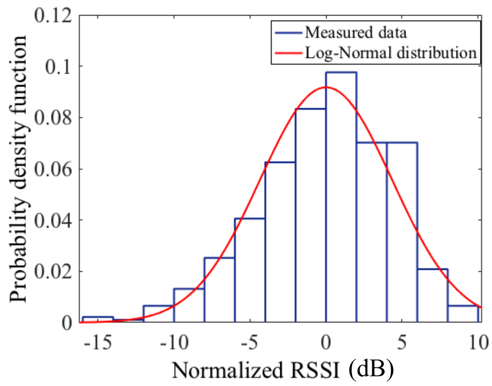

Figure 7. *p.d.f.* on normalized RSSI measured in the experiment

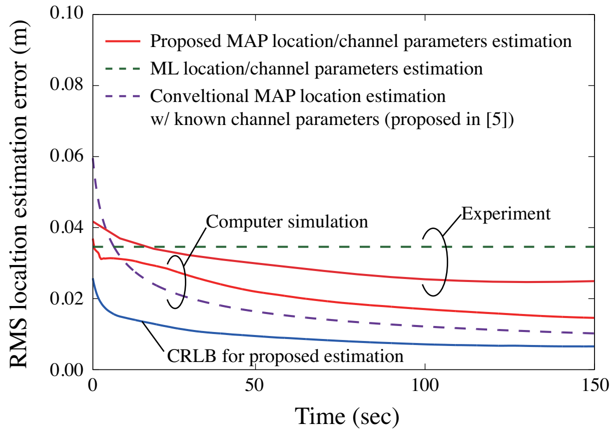

Figure 8. RMS location estimation performances for the proposed MAP localization method

timation. In the experimental results, the proposed MAP estimation can estimate all the channel parameters with the normalized RMS error of 0.5 below. As can be seen from both results in Figs. 8 and 9, we can conclude that the proposed MAP estimation has accomplished the location estimation accuracy of 20 mm with any prior knowledge of the channel condition, and furthermore, it is noted that the developed system should have a possibility to improve the accuracy to below 5 mm based on the CRLB analysis.

5 Conclusions

This paper has developed a real-time localization system for implantable devices with a MAP location/channel parameter estimation. Our evaluation results that the proposed method can accomplish good accuracy in the location and channel parameter estimation in the experiment, which should be satisfied for implantable medical applications, such as wireless capsule endoscopy systems.

6 Acknowledgements

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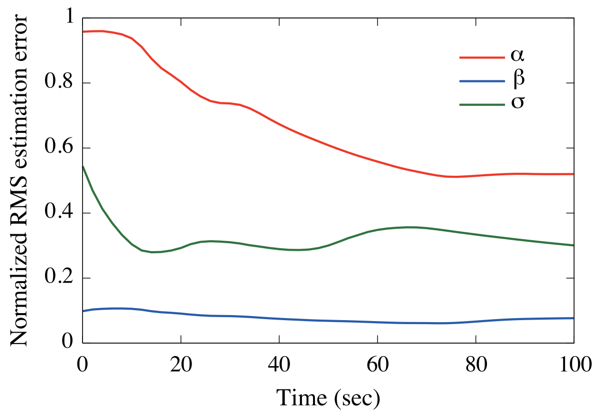

Figure 9. RMS parameter estimation performances for the proposed MAP localization method in the experiment

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