Localization of Implanted Devices Combining TDOA, Particle Filter and Map Mapping with Intestine Modeling

Ayaka Nakamura*, Takumi Kobayashi*, Chika Sugimoto* and Ryuji Kohno*†
*Graduate School of Engineering Science, Yokohama National University, Japan
†Centre for Wireless Communications, Faculty of ITEE, University of Oulu, Finland
Email: *{nakamura-ayaka-bd, kobayashi-takumi-ch}@ynu.jp, *{chikas, kohno} @ynu.ac.jp, †ryuji.kohno@ee.oulu.fi

***Abstract*—In this paper, we propose a scheme to estimate the position of medical implanted device such as a capsule endoscopy in an intestine using combination among TDOA ranging/positioning, particle filter, and map information based on 2D/3D images taken by MRI or CT systems to compensate estimation error of implanted device position. The proposal scheme can perform reliable ranging and positioning by the compensation using the image which obtained by slicing small intestine, which we create with computer graphics and estimating the distance from the image by CNN.**

Keywords—implanted device, localization, TDOA, particle filter, SLAM

I. INTRODUCTION

Wireless information and communication technology (ICT) has been utilized in various fields such as body area network (BAN) for sensing and controlling medical implanted devices, an implanted microrobot and a capsule endoscopy. By using BAN to control implanted devices, it enables us to inspect in minimally invasive to the body.

We aim at remote diagnosis by wireless BAN, network cloud and AI data mining. For this aim, we have been collaborating with external institutes to establish a universal platform based on advanced ICT and data science for dependable network diagnosis and treatment. We are studying the effectiveness of it coordinating medical device regulatory science consortium with companies and institutes. Fig. 1 shows a case of rehabilitation.

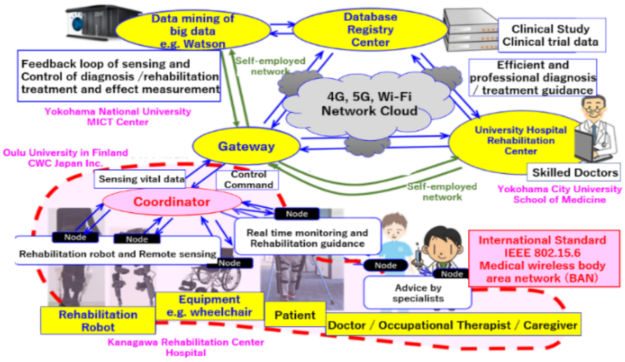

Fig. 1. Platform for Dependable Diagnosis and Therapy for Rehabilitation Based on BAN, Cloud and AI Server

The current capsule endoscopy moves according to the peristaltic movement of the small intestine for the purpose of observing the digestive tract. To resolve remained problems in such an implanted device and upgrade it we have been investigating an implanted microrobot that can run in the gastrointestinal tract appear. Such an implanted microrobot will enable to minimize invasion and to be extended to autonomous remote diagnosis and treatment. [1][2]

To realize it, the wireless information communication technology between wireless medical devices and the terminal communication worn outside the body plays an important role. It is thought that it is necessary to measure the accurate localization and tracking of an implanted device in various situations, such as use of position information when performing control in the remote treatment.

When estimating position, it is considered that an error may occur because images showing the inside of the small intestine cannot be acquired in real time if only CT and MRI images are used. Therefore, in this research, we focus on the real-time image from the camera built into the implanted device and recognize the environment around the implanted device.

II. ASSUMED ENVIRONMENT

A. Small intestine model

The small intestine consists of the jejunum and the ileum, the total length is about 6 m and the inside diameter is 3 cm. Assuming a capsule endoscopy as an implanted device moving in the small intestine, it will remain in the human body for about 8 hours. Thus, it is considered to remain in the small intestine for about 4 hours in half. [3]

It takes 4 hours to move the small intestine with a total length of 6 m, so the moving speed of capsule endoscopy is about 30 mm/min. Thus, it is supposed to move on the red line at 30 mm/min. The capsule endoscopy which was developed by Given Imaging performs uncompressed image transmission of about 2 frames per second from the body to the body using 2 MHz bandwidth of 433 MHz band. [4]

In the case of TDOA observation, it is assumed that radio waves from capsule endoscopy are emitted in units of 0.5 seconds. Simulation is performed with the straight line of 300 mm shown in Fig. 2. Thus, 300 units – 300 mm is basic, and 1200 mm is the basic unit when 0.25 unit.

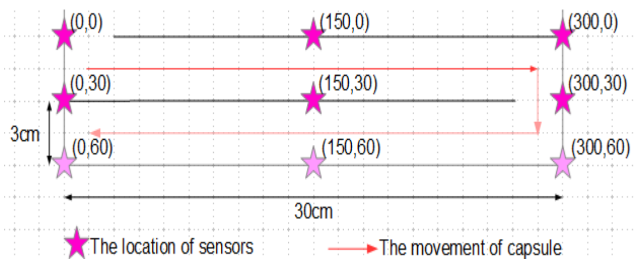

Fig. 2. Simple small intestine model

B. *Small intestine model which created by Blender*

Fig. 3 shows the model that reproduces Fig. 2 using open source 3D computer graphics software called Blender. We designed a small intestine with a horizontal width of 30 cm and an internal diameter of 3 cm.

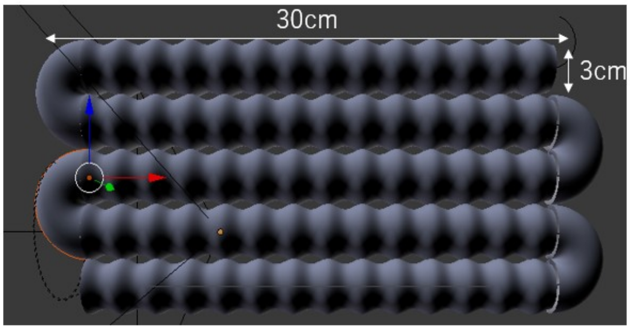

Fig. 3. Small Intestine model aiming real model

When the camera built into an implanted device has captured an internal small intestine with and without circular folds, an example of the resulting images is as follows.

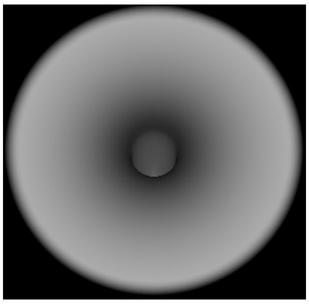

Fig. 4. Model

(with no circular folds)

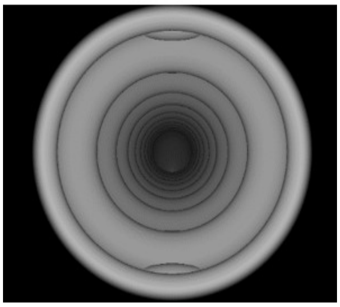

Fig. 5. Model

(with circular folds)

Fig. 6 is a graph which shows the position of the circular black edge in case of model with no circular folds like Fig. 4 from the image taken when moving from the straight line of small intestine to the curved line of it.

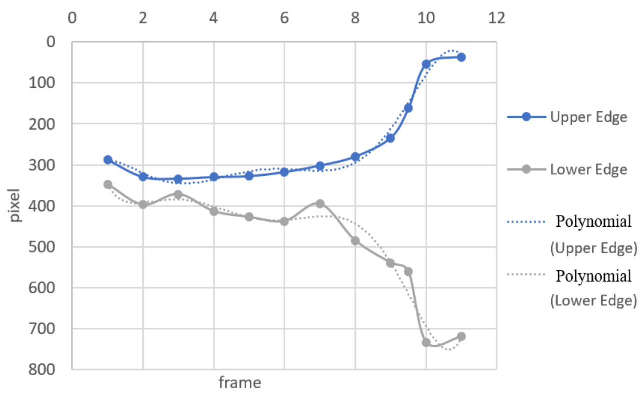

Fig. 6. Curve Recognition

The curve representing the position of the edge was approximated by a polynomial. Table I shows how the correlation coefficient varies when the degree of the polynomial changed. After that, we selected a polynomial of the minimum order which indicates that the correlation coefficient is 0.95 or more. In this case, the fifth order polynomial corresponds to the upper edge, and the sixth order polynomial corresponds to the lower edge. Each value of correlation coefficient and equation are as shown in TABLE I and TABLE II.

TABLE I
CORRELEATION COEFFICIENT

Degree of equation	Correlation coefficient (Upper edge)	Correlation coefficient (Lower edge)
Quadratic	0.938	0.885
Cubic	0.947	0.914
Quartic	0.947	0.921
Quintic	0.969	0.939
Sextic	0.983	0.960

TABLE II
APPROXIMATE CURVE EQUATION

Edge	Equation
Upper edge	$y = 0.103x^5 - 3.1016x^4 + 33.634x^3 - 164.49x^2 + 356.79x + 61.323$
Lower edge	$y = -0.0534x^6 + 1.8141x^5 - 23.679x^4 + 150.57x^3 - 484.78x^2 + 746.72x - 41.819$

III. CONVENTIONAL METHOD

As a positioning method of sensors, the localization system using a signal reception time difference is known. However, in the case of the conventional linear search algorithm like TDOA, there is a possibility that the positioning accuracy deteriorates in a poor propagation environment. Thus, a few nodes receive a signal from a sensor to be located, and the estimation of state quantity by a particle filter is executed over two stages. [5]

A. *TDOA*

The localization method is mainly classified into a range-free method and a range-based method. The former method is a measurement method that can realize power saving and low cost, and Centroid measurement and DV-Hop measurement are representative examples. On the other hand, the latter method is performing localization by measuring the distance between the devices. For this reason, we use the range-based method with high positioning accuracy, specifically the TDOA localization method.

B. *Particle filter*

Particle filter is a type of sequential Monte Carlo method proposed for filtering and smoothing for high dimensional general state space model. First, the virtual particles are distributed according to the conditional distribution and the likelihood of each particle is calculated. Then, the particle with the highest likelihood is used as the estimation result. In this case, the likelihood represents the similarity between the observed value and the estimated value. The particle filter is a relatively simple method based on Bayes' theorem, and it is advantageous that the program is very simple and easy to install in the computer. [6]

If we repeatedly execute the particle filter algorithm, the weight of particles will be biased and the number of particles acting effectively decreases. Thus, we calculate the weight value between the particles, regenerate the particles and reset the weight when weight bias occurs to an arbitrary value. The following formula is used for the evaluation when it is judged whether the weight values are equal.

Effective Sample Size (ESS) is expressed as

$$\mathrm{ESS} = \frac{1}{\sum_{i=0}^{N}\left(w_t^{(i)}\right)^2} \tag{1}$$

where, N represents the number of particles and $w_t^{(i)}$ represents the weight of the ith particle at time t. When ESS equals N, it means that all particles have equal weights. When ESS equals 1, weight of all particles except one particle is 0.

The estimated vector $\hat{s}[k]$ including the estimated position and estimated direction is described by the following formula,

$$\hat{s}[\mathrm{k}] = \sum_{i=1}^{N_p} w_i[k]s_i[k] \tag{2}$$

based on the observation information, update with the likelihood function. The higher the similarity between the estimated value and the observation value is, the larger the likelihood function is set.

IV. PROPOSED METHOD

We propose a method for improving the positioning accuracy by combining the TDOA position estimation method using radio waves emitted from an implanted device and the position estimation method using the particle filter. In this case, assuming capsule endoscopy as an implanted device, it is unlikely that the device will exist other than the digestive device of the human body, if it deviates from the position assumed to move within small intestine, map matching is performed like car navigation system for using depth images. The flowchart of algorithm is as shown in Fig. 7.

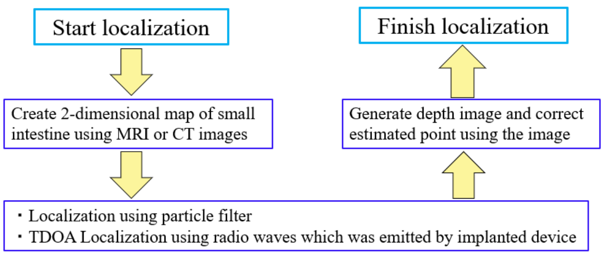

Fig. 7. Flowchart of algorithm

A. *Mapmatching*

Map matching is a technique of matching positioning information on the road considering localization information by TDOA as positioning information by GPS and image of small intestine as road map. This map matching technique is used in a car navigation system, and it is indispensable to obtain an accurate travel route to predict a correct destination.

B. *SLAM (Simultaneous Localization and Mapping)*

SLAM is a technology that simultaneously performs self-position estimation and environmental map creation. It is possible to grasp the shape of the surrounding environment based on the information acquired from the sensor and to perform self-position estimation from the shape data. This technology has been applied to automatic driving of topics in recent years and electric vacuum cleaners and the like. [7]

Since it is not possible to grasp the inside of the small intestine in the tomographic image by MRI or CT, self-positioning estimation is performed in combination with the image acquired from the camera built in an implanted device.

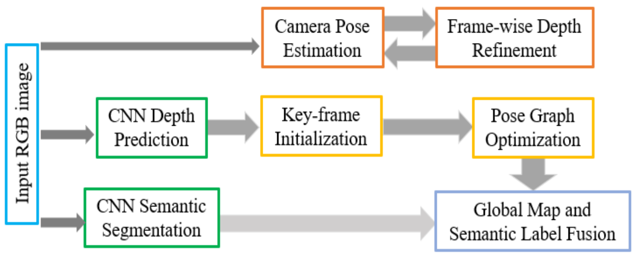

Fig. 8. Overview of CNN-SLAM

Especially, we focused on CNN-SLAM which is a method combining deep learning with SLAM. When we evaluate the image which created with Blender, it was evaluated by depth estimation. Only the key frame is extracted from the RGB image captured by the implanted device, and the distance image is estimated with the learned CNN. After that, the distance image is multiplied by the visual SLAM to perform three-dimensional restoration based on the motion parallax of the multiple frames. When learning CNN, we input RGB image and distance image as teacher data. The overview of this technique is as shown in Fig. 8. [8]

V. COMPUTER SIMULATION

A. *Condition of simulation*

Since TDOA causes observation error, the error is given in both x-axis direction and y-axis direction with a normal distribution with an average of 10 units and a standard deviation of 10 in the simulation. The implanted device moves at a constant speed at 3 cm/min on straight line, and it is assumed that the device emits radio waves every 0.5 seconds for TDOA measurement. The simulation parameters are as shown in Table III.

TABLE III
SIMULATION PARAMETERS

The location of sensor node	Node1(0,0), Node2(0,30) Node3(0,60), Node4(150,0) Node5(150,30), Node6(150,60) Node7(300,0), Node8(300,30) Node9(300,60)
Observation noise	Average 4 Standard Deviation 2 Normal random number
System noise	Average 2 Standard Deviation √2 Normal random number
The number of particles	100 [pcs]
The number of steps	1200 [times]
The movement speed of implanted device	30 [mm/min]

B. Result of depth estimation

When Fig. 4 is input as an input image, the distance image which obtained by estimating the distance with the learned CNN is as shown as Fig. 9. In this figure, graph legend shows depth information of input image. It means that the closer to blue it is shallow and the closer to yellow it is deep.

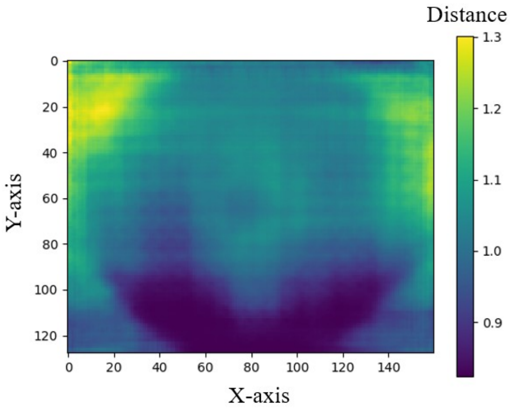

Fig. 9. Distance image

C. Simulation Result

When estimating position is performed using a particle filter, the average position of 100 particles is plotted and particles of the next cycle are generated from the particles of the previous cycle. In this case, there is no indicator for estimating the position of an implanted device. Thus, the next position is simply determined by a random number of a normal distribution, and a large deviation occurs in both x-axis direction and y-axis direction as shown in Fig. 10.

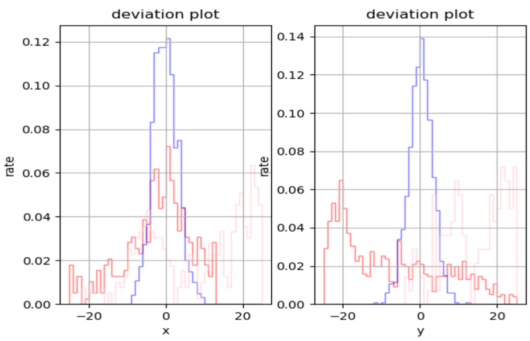

Fig. 10. Deviation plot (Particle filter)

This figure shows how much the estimation error of each value exists when the estimation error corresponding to the difference between the estimated value and the observed value is regarded as the evaluation index. That is, as the variance of the estimation error is small, shows the estimated value and the observed value is close value, the higher the estimation accuracy.

By generating a depth image, it is possible to acquire images inside small intestine unlike when only MRI or CT images are used, which is believed to lead to an improvement in accuracy of position estimation. Thus, it is assumed that the position can be estimated with higher precision than when measuring only with the radio waves emitted from implanted device, in the case of TDOA positioning.

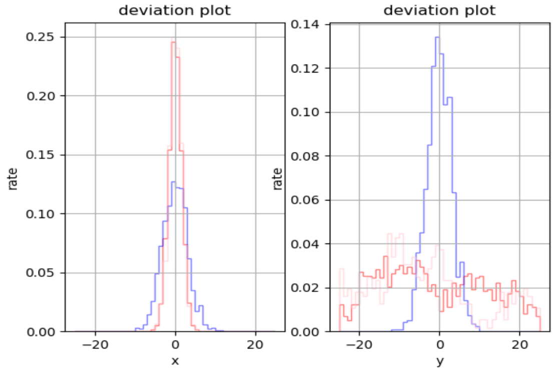

Fig. 11. Deviation plot (combining multiple methods)

Considering the localization in the x-axis direction, when the position estimation is further performed by combining the TDOA and the particle filter as compared with the case where only the TDOA is used, the variance of the estimation error becomes small, so it is represented as shown in Fig. 11.

VI. CONCLUSION

In this paper, we discuss two things. First is that we create small intestine close to real intestine model for considering curve recognition. Second is that we propose a method of generating a depth image from camera image using model which created and combining it with TDOA and particle filter.

Although it was not possible to obtain only a tomographic image of the small intestine in MRI or CT image, simulation was performed assuming that it is possible to acquire information inside small intestine by estimating distance image, which can improve accuracy of estimating position.

In future, we would like to consider the effectiveness of the algorithm which described in this paper.

REFERENCES

[1] N. Shiga, D. Anzai, and J.Wang, “A study on RSSI-Based Location / Direction Estimation for Wireless Capsule Endoscope” IEICE Technical Report MICT2017-47, pp.33-38, 2018

[2] Trung Duc Than, Gursel Alici, Hao Zhou, and Wihua Li, “A Review of Localization Systems for Robotic Endoscopic Capsules” IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL.59, No.9, SEPTEMBER 2012

[3] H.D. Hoeg, A. Brett Slatkin, “Biomechanical Modeling of the Small Intestine as Required for the Design and Operation of a Robotic Endoscope” IEEE International Conference on Robotics and Automation Symposia Proceedings, 2000

[4] K.Takizawa, K.Hamaguchi, “A Study on Wireless Video Transmission from an Implanted Device”, IEICE Technical Report, WBS2013-23, pp.13-18, 2010

[5] Y. Geng, Student Member, IEEE, and K. Pahlavan, Fellow, IEEE “Design, Inplementation, and Fundamental Limits of Image and RF Based Wireless Capsule Endoscopy Hybrid Localization”, IEEE TRANSACTIONS ON MOBILE COMPUTING, VOL.15, No.8, AUGUST 2016

[6] T. Higuchi, “Particle Filter” The Journal of the Institute of electronics, Information and Communication Engineers, Vol.88, No.12, pp.989-994, 2005

[7] J. Engel and T. Schöps and D. Cremers, “LSD-SLAM : Large-Scale Direct Monocular SLAM” European Conference on ComputerVision – ECCV2014, pp.834-849, 2014

[8] K. Tateno, F. Tombari, I. Laina, N. Navab, “CNN-SLAM: Real-time dense monocular SLAM with learned depth prediction” IEEE Conference on Computer Vision and Pattern recognition(CVPR), 2017