

Intelligent System Using Beacon Model for Autonomous Wheelchair

Shugo MIYAMOTO* Takamasa KOSHIZEN*

ABSTRACT

The system proposed is an intelligent system for autonomous wheelchairs using Bluetooth low energy beacons. A beacon model for estimating wheelchair position is generated by applying machine learning to received signal strength indicators from the Bluetooth low energy beacons. This beacon model reduces response lag for autonomous locomotion control, resulting in smooth driving and improving the destination arrival rate.

1. Introduction

In recent years, there is much talk about autonomous driving technology. With autonomous driving, vehicles will be capable of driving automatically without any human driving operation. The goals of autonomous driving are to help in resolving our social issues: reducing traffic accidents, mitigating traffic congestion, assisting in mobility for the elderly, and more. The key technology and a road map⁽¹⁾ for autonomous driving are given in Fig. 1. Autonomous driving can be categorized into 4 levels. Levels 1 and 2 center around advanced driver assistance systems (ADAS), level 3 is conditional autonomous driving, and level 4 is fully autonomous driving. Recently, in order to achieve autonomous locomotion equivalent to levels 3 and 4 autonomous driving, model predictive control (MPC) has been devised using machine learning^{(2), (3)}.

In terms of one social issue, elderly mobility assistance, elderly wheelchair usage is expected to increase in the future as the world accelerates toward a super-aged society. However, the elderly's action range is limited as they sometimes have trouble operating their wheelchairs as they wish. There are also concerns that those around the elderly will be burdened by having to assist in wheelchair locomotion. Thus, there is demand for autonomous wheelchairs applying autonomous driving technology.

The general approach in autonomous driving is to detect white lines or other partition with a camera and drive tracing that line. With wheelchairs, however, the traveled hallway or sidewalk will often have multiple

obstacles, making it difficult to draw lines. Also, traveling toward a destination will require wheelchair position to be estimated. Since GPS positioning cannot be used indoors, alternative means should be required. One such alternative is position estimation technology using received signal strength indicators (RSSI) from Bluetooth low energy (BLE) beacons⁽⁴⁾. BLE beacons are relatively low cost and have a good battery life. However, depending on where they are installed, BLE beacons are affected by electromagnetic interference, making precision the issue to address for use in autonomous locomotion control.

Thus, for the beacon model proposed in this research, the RSSIs from the BLE beacons are categorized with machine learning to generate a map of positional relationships. As a result, wheelchair position can be reverse-estimated in environments with electromagnetic interference. In parallel with cameras to detect obstacles, this proposed system is capable of bringing into play autonomous wheelchair locomotion. Proposals to date have combined a beacon model for estimating position with cameras for detecting wall corners and other obstacles for a smooth cornering control method with low acceleration and deceleration⁽⁵⁾. Given how using the beacon model allows for smooth autonomous wheelchair locomotion with low acceleration and deceleration change, lowered battery power consumption was also achieved⁽⁶⁾.

This paper will discuss the characteristics of the beacon model generated through machine learning and the travel stability when using this beacon model for autonomous wheelchair locomotion.

* R&D Center X

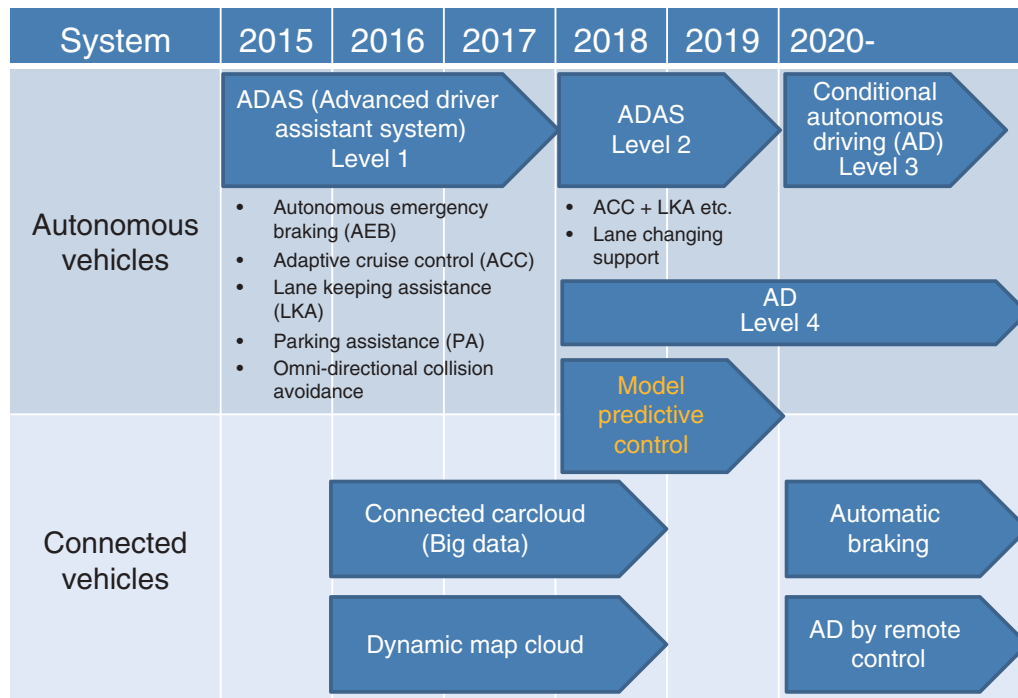


Fig. 1 Road map for autonomous driving

2. Development Aims

An example of RSSI is given in Fig. 2 which has shown where the wheelchair is located when it travels near the two BLE beacons. In the figure, the horizontal axis is for time, and the vertical axis is for RSSI. Conventionally, BLE beacons would be employed for position estimation by setting a RSSI threshold as given in Fig. 2(a) and judging that the wheelchair was approaching a nearby BLE beacon when the RSSI measured by the wheelchair in motion exceeded the threshold (a process called “checking in”). Depending on the environment, however, electromagnetic interference prevents the measured RSSI, makes the checking in between the wheelchair and the beacon inaccurate. This is illustrated in Fig. 2(b). Therefore, in our study, the beacon model was generated by pre-collecting the measured RSSIs for the travel environment on a tablet

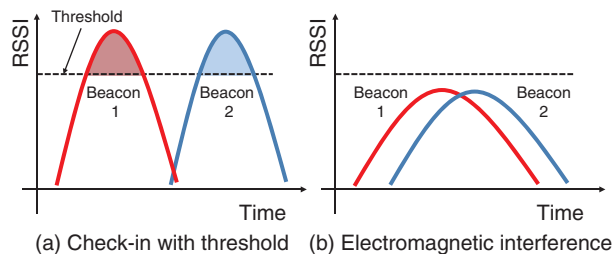


Fig. 2 Electromagnetic interference of two BLE beacons

device and then categorizing the RSSIs by training machine learning.

An overhead map of the indoor test course is shown in Fig. 3. In the map, the wheelchair test course is given by arrows, and the BLE beacon positions are given by the red diamonds. The BLE beacons were positioned around corners, near the elevator, and along the predetermined course.

The goal this time was to combine beacon model position estimation and smooth cornering to increase the stability rate of autonomous wheelchair locomotion. Here, the travel stability of an autonomous wheelchair is defined

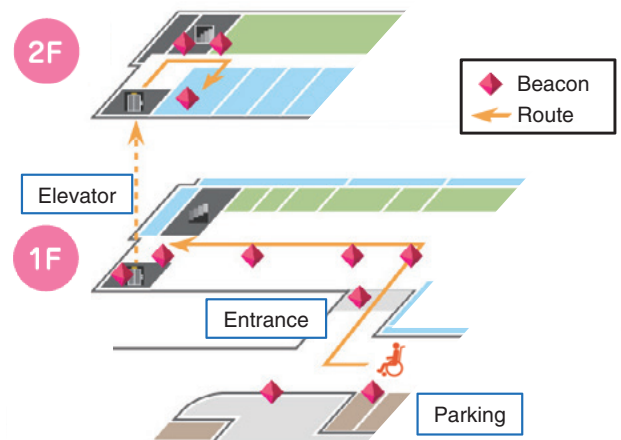


Fig. 3 Indoor map for preliminary experiment

as ability to reach the destination as set, and possible moves to reach the predetermined destination.

3. System Construction

3.1. Overview of Autonomous Locomotion Control

The wheelchair and BLE beacons used are shown in Fig. 4. The wheelchair is equipped with a tablet device for collecting RSSI information from the BLE beacons and a stereo camera for detecting obstacles. The BLE beacons are manufactured by Hosiden Corporation and measure 5 cm in diameter and weigh 28 g. The beacons use coin-shaped CR2450 batteries and can operate for approximately 1 year without battery replacement.

The control portion of the proposed autonomous wheelchair locomotion is given in Fig. 5. Control is performed by combining position estimation with the beacon model and obstacle detection using stereoscopic vision.

For example, if the beacon model estimates the wheelchair position as being in a corner area, the stereo camera installed on the front of the wheelchair detects the wall and obstacles to the left and right, then finely adjust the amount of steering to make the wheelchair turn the corner. As error for traveling direction and distance are cumulative, the positional relationships between the BLE beacons and wheelchair are calculated and corrected with image processing.

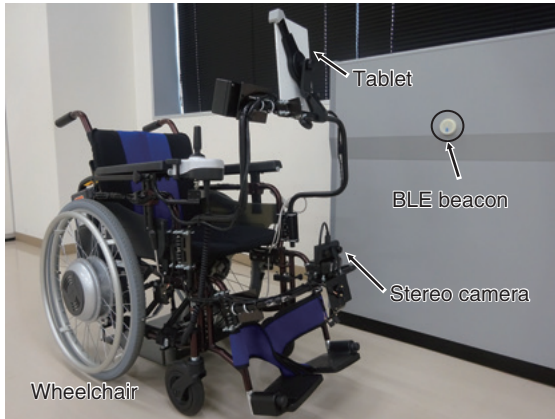


Fig. 4 Motorized wheelchair and BLE beacon

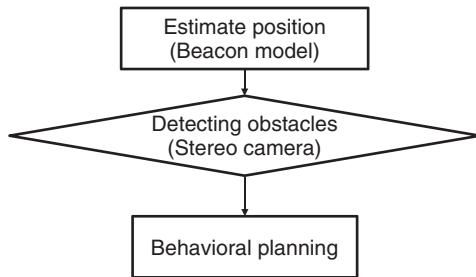


Fig. 5 Block diagram of autonomous wheelchair

These autonomous locomotion operations remain ongoing while travelling, and wheelchair operation is stopped when the position is estimated to be at the destination.

3.2. Beacon Model

The flow for autonomous locomotion control as given above requires estimation of the wheelchair position in order to form an action plan. This position can be estimated with the objective function $f(X; \theta)$ shown in Fig. 6. Here, as f is an unknown objective function, it is approximated by density function $P(X|L)$ as represented by Eqs. (1) and (2). μ_{jL} is the mean value, σ_{jL} is the covariance value, L is the position label, and α is the learning coefficient. Parameter θ is modeled after the normal distribution function (hereinafter the “beacon model”), derived by the algorithm⁽⁷⁾ for expectation maximization (EM), representing statistical machine learning.

$$P(X|L) = \sum_{j=1}^K \frac{\hat{\alpha}_{jL}}{(2\pi)^{1/2} \sqrt{|\hat{\sigma}_{jL}|}} \exp \left[-\frac{1}{2} (X - \hat{\mu}_{jL})^T \hat{\Sigma}_{jL}^{-1} (X - \hat{\mu}_{jL}) \right] \quad (1)$$

Where learning coefficient α is taken as satisfying the following constraints:

$$\hat{\alpha}_{1L} + \hat{\alpha}_{2L} = 1.0 \quad (2)$$

An image depicting the RSSIs and labels for BLE beacons in a corner area is given in Fig. 7. First, BLE

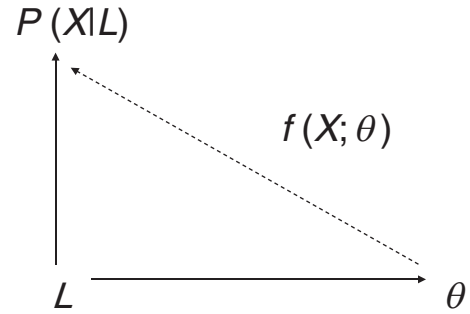


Fig. 6 Probability density function from label X

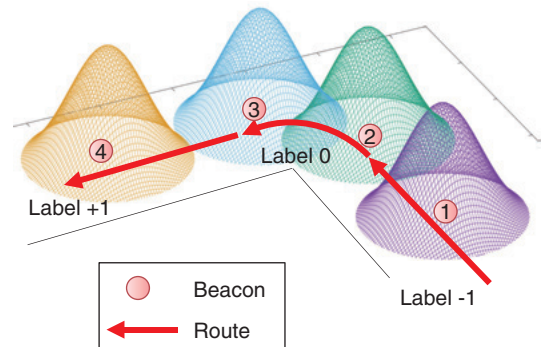


Fig. 7 Wheelchair position estimation with beacon models

beacons are positioned on the travel route, then RSSIs are pre-collected on the wheelchair's onboard tablet during travel for use as machine learning data. Next, the RSSI is artificially divided and labeled for 3 positions: before corner (Label -1), mid-corner (Label 0), and after corner (Label +1). These positions are derived by recording the cornering start and finish positions and times during travel and synchronizing them with the time axis for the collected RSSI. Based on these labeled RSSIs, the EM algorithm is applied to generate the beacon model.

The flow for the EM algorithm applied to the generation of beacon model is shown in Fig. 8. In statistics, the algorithm is a method for estimating the maximum likelihood of the parameters in a probability model and is used in cases where the probability model depends upon unobservable latent variables. The algorithm consists of two calculation steps: an expectation (E) step, represented by Eqs. (3) and (4), and a maximization (M) step, trained by Eqs. (5), (6), and (7). In the E step, the estimated likelihood of the probability model is calculated based on a distribution of the latent variables as currently estimated. Meanwhile, in the M step, the parameters needed to maximize the estimated likelihood as calculated in the E step are calculated. With the E step and M step recurring in alternation, if the probability model is taken as the mixed Gaussian function given by Eq. (1), the mean values μ_{jL} and covariance values σ_{jL} comprising the Gaussian functions can be estimated.

$$h_{ij} \equiv E [z_{ij} | x^i, \theta] \quad (3)$$

$$h_{ij} = \frac{a_j(t) / ((2\pi)^{n/2} \sqrt{|\Sigma_j(t)|}) \exp [-(1/2)(x^i - \mu_j(t))^T \Sigma_j(t)^{-1} (x^i - \mu_j(t))]}{\sum_{k=1}^G a_k(t) / ((2\pi)^{n/2} \sqrt{|\Sigma_k(t)|}) \exp [-(1/2)(x^i - \mu_k(t))^T \Sigma_k(t)^{-1} (x^i - \mu_k(t))]} \quad (4)$$

$$a_j(t+1) = \frac{1}{N} \sum_{i=1}^N h_{ij}(t) \quad (5)$$

$$\mu_j(t+1) = \frac{\sum_{i=1}^N h_{ij}(t) x^i}{\sum_{i=1}^N h_{ij}(t)} \quad (6)$$

$$\Sigma_j(t+1) = \frac{\sum_{i=1}^N h_{ij}(t) (x^i - \mu_j(t+1))(x^i - \mu_j(t+1))^T}{\sum_{i=1}^N h_{ij}(t)} \quad (7)$$

Taking the machine learned RSSI for BLE beacon 3, as measured in the Label 0 segment in Fig. 7, as an example, the relationship between the log likelihood and step number is given in Fig. 9. Log likelihood is a performance function for showing the convergence of learning. Here, looking to derive

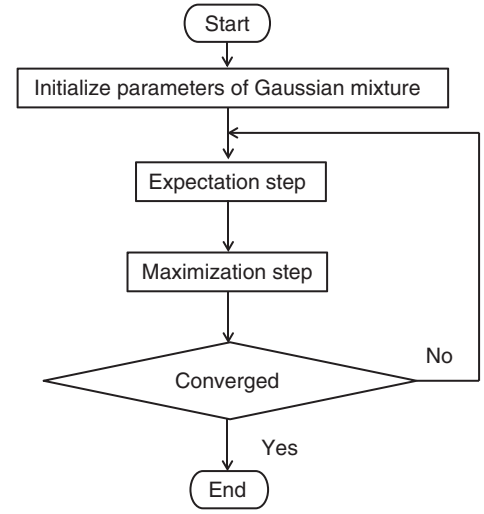


Fig. 8 Block diagram of EM-algorithm

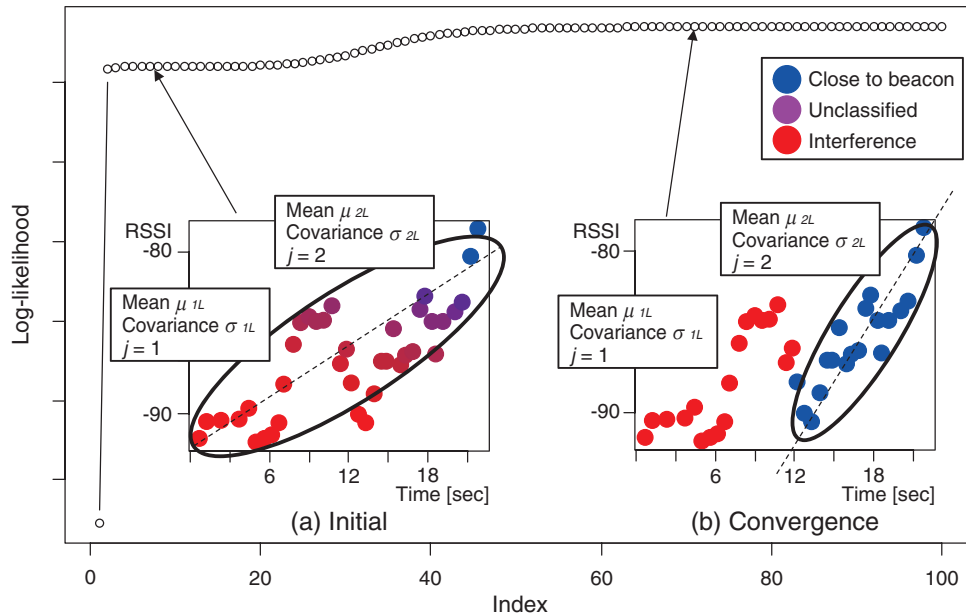


Fig. 9 Beacon models learned by machine learning and log-likelihood

the linear relationship between travel time and the RSSIs with machine learning, the two Gaussian functions contained in the ellipsoids of Figs. 9(a) and (b) were identified based on the Bayesian Information Criterion (BIC).

In Figs. 9(a) and (b), the blue RSSI dots represent the travel time range where the wheelchair is approaching the closest beacon. In the beginning of the learning process, RSSI data composition is not yet clearly categorized, as depicted in Fig. 9(a). Later, as shown in Fig. 9(b), the learning converges to group RSSI data composition into two categories. The RSSIs will interfere with each other due to multipath effects and other factors. Therefore, by using machine learning to selectively extract the RSSI corresponding to the travel time range for locomotion to the closest beacon, electromagnetic interference are expected to be greatly reduced compared to no separation, and model accuracy to be raised. As the relationship between the mutually interfering RSSIs and labels can be generated with the beacon model, this resolves the response lag in estimating positions with electromagnetic interference experienced by Kim⁽⁸⁾ et al.

4. Evaluation Results

A wheelchair was autonomously driven along the route from the overhead map in Fig. 3 from the parking lot to the destination on the second floor, estimating position with the beacon model. Next, the wheelchair was autonomously driven on the same route, this time estimating position using the threshold, to compare the rate at which the wheelchair reached its destination ($N=10$). The destination arrival rates were 90% with the beacon model and 10% with threshold judgments, showing the beacon model rate to be higher.

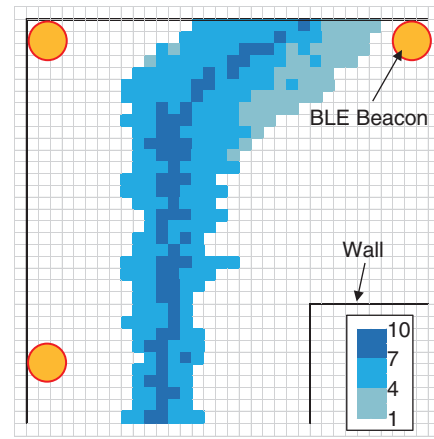
A frequency distribution chart for the travel path trajectories around corners is shown in Fig. 10. As seen in Fig. 10(a), the main factors in failure when traveling by threshold judgment were: 1) collision with the wall due to insufficient cornering control from delayed check-in judgment, and 2) collision with the wall due to inability to judge check-in, resulting in no cornering control. Meanwhile, as seen in Fig. 10(b), when traveling with the beacon model, cornering control was successful and had reduced control response lag. Further, the widened frequency distribution shows the deviation from the target travel path. Given that the frequency distribution for Fig. 10(b) is narrower than that for Fig. 10(a), using the beacon model was found to deviate less from the target travel path.

Next, the rates of correct check-in judgments by the wheelchair were compared for beacon model judgments and threshold judgments. Given that the BLE beacons used in this research are normally used to estimate position within a range of 3 m, the correct check-in rate was calculated for when the wheelchair was stationary in positions 3 m away from the BLE beacons. Rates of correct check-in judgments in the corner areas ($N=30$) were roughly the same for beacon model judgments and threshold judgments, averaging 93%

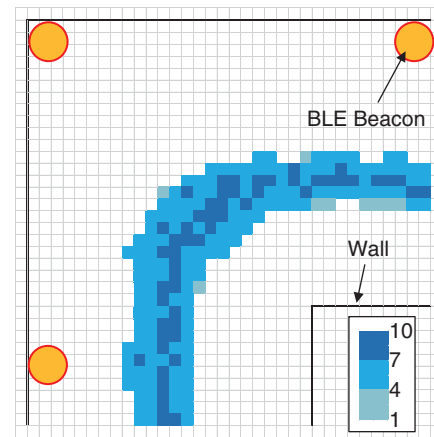
and 92%, respectively. From this, the generated beacon model was found to be estimating positions correctly.

Furthermore, the times taken until check-in judgment when traversing a certain corner section were compared between beacon model judgment and threshold judgment. Using 1 to represent the time required for threshold judgment, the mean values for the corner section ($N=30$) were 0.83 for the beacon model. Thus, check-in judgment times were shorter using the beacon model than when using the threshold. With a wheelchair traveling at 2 km/h, this is equivalent to cornering control starting approximately 800 mm earlier.

As the beacon model is generated from RSSIs for past trips using machine learning, by applying the beacon model to estimate wheelchair position, the wheelchair position is known in shorter time than if judged with a threshold. Therefore, this will presumably allow earlier detection for starting cornering control in corner sections and, as a result, increase destination arrival rates and lead to smooth driving with less deviation.



(a) Trajectory with threshold



(b) Trajectory with beacon model

Fig. 10 Comparison between trajectory with beacon threshold and with beacon model

5. Conclusion

This paper described an intelligent system for autonomous locomotion control of wheelchairs.

The findings are as follows:

- (1) By using machine learning to label BLE beacons used to measure signal strength and estimate position, wheelchair position can still be determined in the presence of electromagnetic interference. Because the beacon model is generated from historic data from past trips, it can judge check-in in shorter time than with threshold judgments, allowing it to cut response lag in wheelchair control.
- (2) The destination arrival rate is 10% when applying a threshold and 90% when applying the beacon model. The proposed approach is confirmed to have a higher destination arrival rate, driving the wheelchair with less deviation and higher travel stability.

References

- (1) Shima, T., Nagasaki, T., Kuriyama, A., Yoshimura, K., Sobue, T.: Fundamental Technologies Driving the Evolution of Autonomous Driving, Hitachi Review, Vol. 65, No. 9, p. 426-432, (2016)
- (2) Lima, P. F.: Predictive control for autonomous driving: With experimental evaluation on a heavy-duty construction truck, The PhD Thesis of KTH Royal Institute of Technology, (2016)
- (3) Naus, G. J. L., Ploeg, J., Van de Molengraft, M. T. G., Heemels, W. P. M. H., Steinbuch, M.: A model predictive control approach to design a parameterized adaptive cruise control, Automotive Model Predictive Control, Lecture Notes in Control and Information Sciences, Vol. 402, p. 273-284, (2010)
- (4) Sugino, K., Ozono, T., Shintani, T.: On Calibration for Device-free Localization based on Multiple Bluetooth Beacons, IEICE Technical Report, Vol. 115, No. 381, p. 1-6, (2015) (in Japanese)
- (5) Miyamoto, S., Matsumoto, T., Kawase, H., Higuchi, M., Torimoto, Y., Koshizen, T.: Autonomous Wheelchair Knows Its Position Throughout Beacon Model, The Society of Instrument and Control Engineers, The 4th Multi-symposium on Control Systems, (2017) (in Japanese)
- (6) Miyamoto, S., Koshizen, T., Matsumoto, T., Kawase, H., Higuchi, M., Torimoto, Y., Uno, K., Sato, F.: An Application Using a BLE Beacon Model Combined with Fully Autonomous Wheelchair Control, The 11th International Conference on Complex, Intelligent, and Software Intensive Systems, (2017)
- (7) Dempster, A. P., Laird, N. M., Rubin, D. B.: Maximum Likelihood from Incomplete Data via the EM Algorithm, Journal of Royal Statistical Society, Series B (Methodological), Vol. 39(1), p. 1-38, (1977)
- (8) Kim, Y. H., Lee, S.: A Method for Stable Indoor

Positioning using Beacons, Indian Journal of Science and Technology, Vol. 8, (2015)

■ Author ■



Shugo MIYAMOTO



Takamasa KOSHIZEN