

Evaluation of a Method for Improving Pedestrian Positioning Accuracy using Vehicle RSSI

Yuya Nishimaki

Hisato Iwai

Kenya Sato

Computer and Information Science
Graduate School of Science and Engineering
Doshisha University
Kyoto, Japan
email:yuya.nishimaki@nislabs.doshisha.ac.jp

Electrical and Electronic Engineering
Graduate School of Science
and Engineering
Doshisha University
Kyoto, Japan
email:iwai@mail.doshisha.ac.jp

Computer and Information Science
Graduate School of Science and Engineering
Doshisha University
Kyoto, Japan
email:ksato@mail.doshisha.ac.jp

Abstract—As the penetration rate of smartphones and tablet-type devices increases, various services using such location information are being used. In navigation applications, we can check our current location and how to get to a destination. Even if we are in a relatively new area, we can go anywhere using a navigation application. Other systems prevent traffic accidents by exchanging position information using vehicle-to-pedestrian communication. In these services and systems, especially for preventing accidents, accurate position information is critical. Currently, the Global Positioning System (GPS) is most frequently used as a positioning method to acquire position information outdoors, but its signals are influenced by the surrounding buildings in urban areas, reducing positioning accuracy. Therefore, in this paper, we propose a position estimation method using the Received Signal Strength Indication (RSSI) of vehicles and beacons for high and stable positioning accuracy outdoors. We applied a Kalman filter to RSSI and dynamically calculated the path loss index using vehicle-to-vehicle communication. We compared the positioning accuracy of our method and conventional methods by simulations and showed our method's superiority.

Keywords—position estimation; vehicle-to-vehicle communication; RSSI; path loss index.

I. INTRODUCTION

As the penetration rate of smartphones and tablet-type devices continues to increase, various services using their location information are being used. For example, we can check our current location on a map, look up a route from it to a destination, and get surrounding shop information and coupons. However, if the positioning error is too large, we might get lost or fail to get the information we want. In recent years, Intelligent Transportation Systems (ITS) have also been investigated that improve traffic safety, efficiency and driving comfort. For example, through vehicle-to-vehicle and vehicle-to-pedestrian communication, related work makes efforts to prevent vehicles from colliding with vehicles and pedestrians through exchange of information such as position and speed [1][2]. Since the large positioning error might lead to accidents, we need accurate position information of every involved pedestrians and vehicle to reduce traffic accidents and maintain safety. Among positioning systems that acquire position information which is important in such services and systems, Global Positioning System (GPS) is most frequently used. Its positioning accuracy ranges from several meters to

several tens of meters. But in urban areas that are littered with high-rise buildings, GPS signals are blocked by buildings and influenced by multipaths, further increasing the positioning error [3]. Since GPS accuracy is affected by the surrounding environment, achieving stable positioning is difficult.

In this research, we focus on a pedestrian whose positioning error is often larger compared to vehicles. We propose a method that uses vehicles to improve the outdoor positioning accuracy of pedestrians, since both vehicle-to-vehicle and vehicle-to-pedestrian communication will become more widespread due to ITS development. The rest of this paper is organized as follows. In Section II, we show conventional position estimation methods and their problems. In Section III, the proposed method is described. Simulation and evaluation results are presented in Section IV. Finally, Section V gives the conclusion.

II. CONVENTIONAL POSITION ESTIMATION METHOD AND PROBLEMS

A. GPS

In a GPS, which is the most widely used positioning method. A device receives signals with time information transmitted from multiple GPS satellites and estimates a position using pseudo distances obtained from the differences between transmission and reception times. In line-of-sight places and areas without high buildings around the target, since it can receive signals from many GPS satellites, GPS can estimate a position with error within a few meters. In non-line-of-sight places and urban areas with many high-rise buildings, GPS signals are influenced by shielding, reflection, and diffraction by obstacles. Sometimes positioning error becomes several meters to several tens of meters.

B. RSSI-based position estimation

The positions of smartphones and tablet-type devices can be estimated by RSSI when receiving radio waves transmitted from such beacons as Bluetooth Low Energy (BLE) or WiFi [4][5]. As shown in Figure 1, when the target acquires the RSSI of Beacons 1 to 4, first, we calculate the distance between the target and each beacon from the RSSI and find the target's position by triangulation using the distance and the position of each beacon. We can calculate the distance from the RSSI

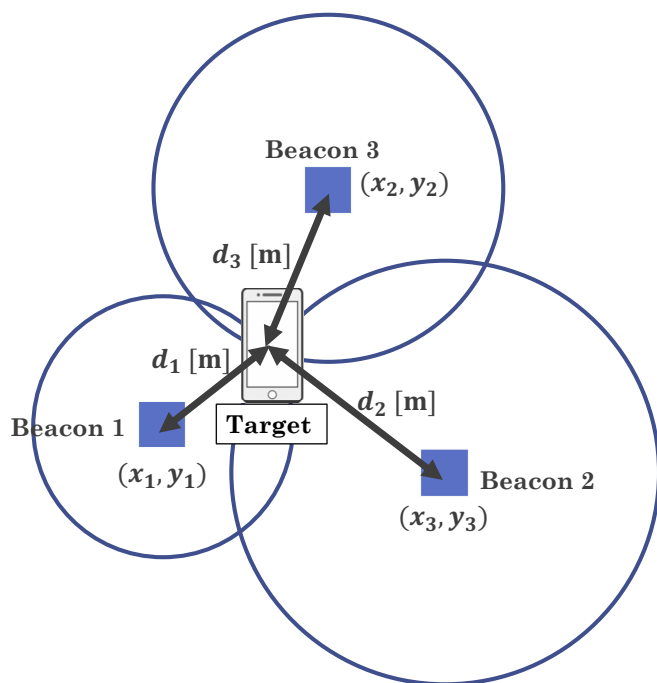


Figure 1. RSSI-based positioning

by a property through which RSSI is attenuated as the distance increases. In general, we can model RSSI's attenuation (as in (1)) to find the distance between the target and each node:

$$P(d) = A - 10n \log_{10} d. \quad (1)$$

Here, $P(d)$ is the RSSI [dBm] at position d [m] away from the transmission source, A is the RSSI [dBm] 1 m from the transmission source, and n is the path loss index. The path loss index is a value that represents the degree of attenuation of the radio waves based on the distance, and in the free space, $n = 2$. Here, RSSI attenuates in proportion to the square of the distance.

C. Problems when using RSSI

For an accurate position estimation using RSSI, the distance to each node must be accurately measured. However, since it is sometimes impossible to obtain the ideal RSSI in an actual environment, the distance calculated from the RSSI includes error. There are several causes for the error increase. One is that the path loss index is constantly changing due to the surrounding environment of the radio wave propagation. Another is that RSSI fluctuates. Although n in (1) is theoretically a constant value, it should be set dynamically because it is always changing, too. Also, RSSI does not always become a constant value even if the distance between the sender and the receiver is invariant. It varies with time due to the following factors:

- Fading

Fading, which is the RSSI fluctuation received by wireless communication, occurs during communication while moving by such mobile communication as mobile devices. In environments with many scattered materials, the radio waves transmitted from the sender are reflected, diffracted, and scattered

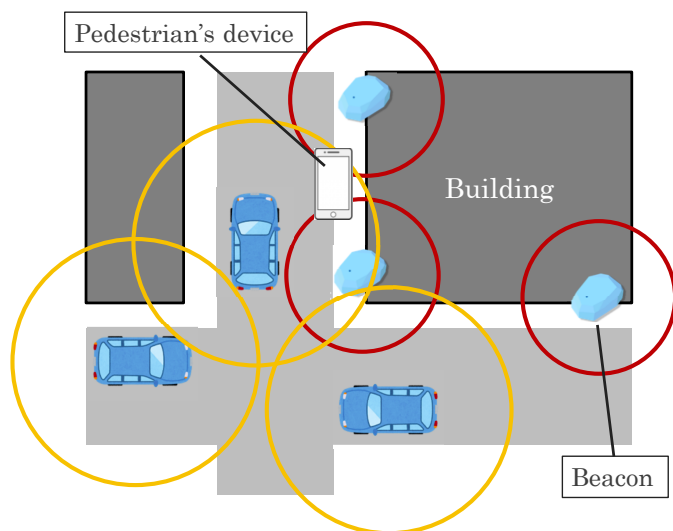


Figure 2. Outline

by buildings and moving objects, causing them to arrive at the receiver with a time difference. Interference of these radio waves also causes fading.

- Shadowing

This RSSI fluctuation, which occurs when a shielding object exists between a sender and a receiver, follows a lognormal distribution.

- Co-channel interference

This RSSI fluctuation occurs when a device using the same frequency band operates in the vicinity.

For accurate estimation of distance, it is necessary to reduce the influence of RSSI fluctuation and to use the dynamic path loss index.

III. PROPOSAL

A. Outline

In urban areas, positioning error might increase when GPS signals are blocked by buildings and influenced by multipaths. In this research, we propose a method to improve the positioning accuracy of outdoor pedestrians and outline it in Figure 2. We estimate a pedestrian's position using the RSSIs of vehicles and beacons on the road side. When we assume that the vehicle regularly transmits its own information to its surroundings, pedestrians can receive radio waves of vehicles in addition to beacons, allowing them to also use RSSIs from their vehicles to estimate their positions. However, the RSSIs of beacons and vehicles suffer from the problems shown in Section II-C. To solve them, we apply filtering to RSSIs and dynamically calculate the path loss index using vehicle-to-vehicle communication.

B. Presuppositions

- 1) All of the vehicle position information is accurate.
- 2) The pedestrian's device can receive 700-MHz band radio waves.
- 3) The vehicle regularly transmits its own information to the surroundings.

TABLE I. PARAMETERS FOR VEHICLES

Pedestrian state	$\hat{P}(0)$	Q	R
Stationary	1000	4.44	25.44
Moving	1000	5.37	27

TABLE II. PARAMETERS FOR BEACONS

Pedestrian state	$\hat{P}(0)$	Q	R
Stationary	1000	0.00046	19.0454
Moving	1000	5.41	13.3

C. RSSI filtration with Kalman filter

We used a Kalman filter as a filtering method to reduce the influence of fading, among variation factors mentioned in Section II-C. We applied it to the RSSI received by pedestrians from both the beacon and the vehicle, and did filtering using the following formulas. In the Kalman filter in the prediction step, we obtained RSSI's prior state estimate at the current time using the information of one time before. In the filtering step, we modified RSSI's prior state estimate by an observation value to find the posteriori state estimate:

- Prediction step

$$\hat{x}^-(k) = \hat{x}(k-1) \quad (2)$$

$$\hat{P}^-(k) = \hat{P}(k-1) + Q \quad (3)$$

- Filtering step

$$g(k) = \frac{\hat{P}^-(k)}{\hat{P}^-(k) + R} \quad (4)$$

$$\hat{x}(k) = \hat{x}^-(k) + g(k)(y(k) - \hat{x}^-(k)) \quad (5)$$

$$\hat{P}(k) = (1 - g(k))\hat{P}^-(k). \quad (6)$$

Here, $\hat{x}^-(k)$ and $\hat{x}(k)$ are prior and posteriori state estimates. $\hat{P}^-(k)$ and $\hat{P}(k)$ are prior and posteriori error variances, Q is a system noise variance, R is a measurement noise variance, $y(k)$ is a measurement value, and $g(k)$ is the Kalman gain. In this study, we set $\hat{P}(0)$, Q , and R to the values shown in Tables I and II. We determined them by simulation experiments in advance.

D. Calculation of dynamic path loss index

$$n_i = \frac{A - P(d_i)}{10 \log_{10} d_i} \quad (7)$$

$$n_k = \frac{\sum_{i=1}^m n_i}{m} \quad (i \neq k). \quad (8)$$

When vehicle k is communicating with m neighboring vehicles in vehicle-to-vehicle communication, the path loss index between vehicles k and i ($1 \leq i \leq m$) can be calculated by (7), which is obtained by transforming (1). Here, d_i represents the distance [m] between vehicles k and i , and $P(d_i)$ represents RSSI [dBm] from vehicles i . We assume that the vehicle-to-vehicle communication is within the line-of-sight and use RSSI exceeding $P(d_i) > -50$ dBm. Then with (8), we calculated the average value of the path loss indices for each surrounding vehicle within a certain time and use the result as the path loss index around vehicle k . The procedure

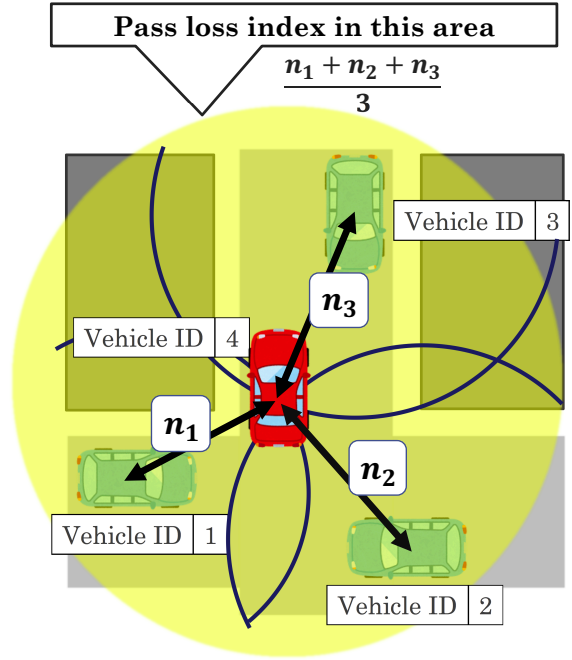


Figure 3. Example of calculation of dynamic path loss index

for dynamically calculating the path loss is described below, and Figure 3 describes the calculation example.

- 1) When a vehicle receives packets from a surrounding vehicle, it obtains the distance to the sender using the sender's position and its own position.
- 2) The vehicle obtains the path loss index between the sender and itself using (7) and stores the result and the sender's vehicle information in the vehicle information management table.
- 3) At the time of transmission, the vehicle calculates the average path loss index within the past 500 ms in the vehicle information management table by (8) and regards the average as the path loss index around itself.

E. Positioning algorithm

Next, we describe the algorithm that calculates the pedestrian's position using RSSI acquired from the beacons and the vehicles. If the pedestrian gets information of m ($m \geq 1$) nodes of the beacons and the vehicles, she can calculate the distance with each node from the RSSI by (9), which is obtained by transforming (1).

$$d_i = 10^{\frac{A - P_i}{10n}} \quad (1 \leq i \leq m). \quad (9)$$

The smaller an RSSI is, the larger is the variation and the error from the theoretical values [6]. Therefore, instead of using all the acquired RSSIs for position estimation, we set thresholds and in advance excluded those with large error from the theoretical value. We set the threshold and the parameters for distance calculation (Table III).

We also selected the RSSI depending on the state of the pedestrian and the vehicle.

- When pedestrian and vehicle are stationary

TABLE III. THRESHOLD AND PARAMETERS

Node type	Threshold	A	n (Path loss index)
Beacon	-81 dBm	-61 dBm	2.0
Vehicle	-50 dBm	-10.816 dBm	dynamic value

When determining the distance to the beacon or the vehicle, we used the maximum RSSI above the threshold received within the past 1 s. This is because the maximum RSSI is less influenced by fading than the others, and the distance error also becomes smaller.

- When pedestrian is stationary and vehicle is moving

When obtaining the distance to the beacon, the process is the same as when pedestrian and vehicle are stationary. When calculating the distance to the vehicle, we use the latest RSSI among those received after the final position's estimation time.

- When pedestrian is moving

When calculating the distance to the beacon or the vehicle, we use the latest RSSI among those received after the final position estimation time.

We determined the pedestrian position using Weighted Centroid Localization (WCL) [6]. (10) to (12) show how to calculate the position by WCL. (x_i, y_i) is the position of the i th node that corresponds to the selected RSSI, and w_i is the weight, and we obtained the weighted average of the position of each node. The weight is the reciprocal of the distance obtained from RSSI, and the g value is 1.5 to minimize the positioning error in (12):

$$x_w = \frac{\sum_{i=1}^m x_i w_i}{\sum_{i=1}^m w_i} \quad (10)$$

$$y_w = \frac{\sum_{i=1}^m y_i w_i}{\sum_{i=1}^m w_i} \quad (11)$$

$$w_i = \frac{1}{d_i^g}. \quad (12)$$

IV. EVALUATION AND CONSIDERATION

A. Simulator

We used Scenargie as a simulator to evaluate our proposed method's performance. Scenargie is a network simulator developed by Space-Time Engineering (STE) [7]. By combining expansion modules, various simulations like LTE, vehicle-to-vehicle communication and a multi-agent simulation can be constructed. Since communication systems and evaluation scenarios are becoming more complicated, this ingenious simulation greatly reduces the effort required to create them. Examples include a GUI scenario creation, map data, the graphical information display of a communication system, and a radio wave propagation analysis function.

B. Evaluation Model

Since this research's goal is improving the positioning accuracy of pedestrians in urban areas, we did our simulation in an evaluation environment where pedestrians are surrounded by buildings. The simulation parameters are shown in Table IV, and its environment is shown in Figure 4. GIS-BASED-RANDOM-WAYPOINT in Table IV is a model where each

TABLE IV. SIMULATION PARAMETERS

Simulator	Scenargie2.1	
Simulation time	20 [s]	
Beacon intervals	5, 10, 15, 20 [m]	
Number of vehicles	0, 10, 20, 30, 40, 50, 60, 70, 80	
Vehicle mobility model	GIS-BASED-RANDOM-WAYPOINT	
Vehicle velocity	15 ~ 20 [m/s]	
Pedestrian velocity	Stationary, 2 [m/s]	
	Beacon	Vehicle
Transmission power	-21 [dBm]	19.2 [dBm]
Frequency bands	2.4 [GHz]	760 [MHz]
Communication intervals	500 [ms]	100 [ms]
Propagation model	TwoRayGround	ITU-R P.1411
Fading model	Rayleigh	

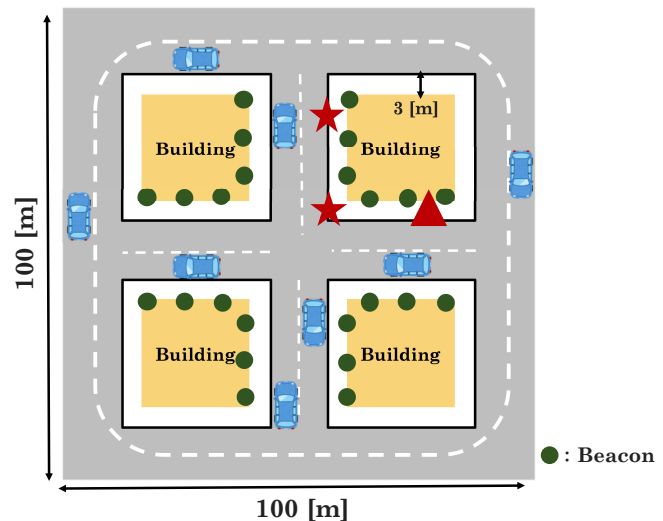


Figure 4. Evaluation environment

vehicle randomly determines a passing point, moves along the road, and passes through it. The ITU-R P.1411 model [8] is a radio wave propagation scheme that considers road map information. Since radio waves are attenuated based on the road's shape, this model closely resembles reality compared with a two-ray model using direct waves and reflected waves from the ground.

C. Evaluation items

- Comparison of positioning error with conventional methods

Here, we label GPS as Conventional 1 and the method that only uses beacons as Conventional 2. Proposal 1 is our proposed method, and Proposal 2 does not adopt filtering and uses a static path loss index. In the simulator, since we cannot measure the GPS-positioning accuracy, we compared 15 m as GPS positioning error [3].

- Evaluation of beacon intervals

We evaluated the positioning error when the beacon interval increases in 5-m increments from 5 to 20 m. At this time, the number of vehicles was 50.

- Evaluation of number of vehicles

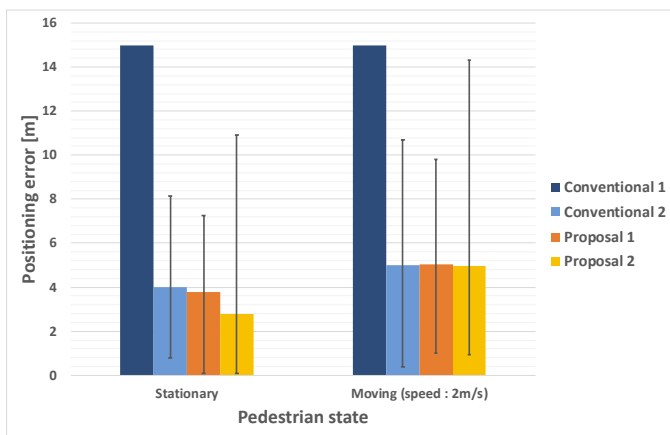


Figure 5. Average, maximum and minimum positioning error in conventional methods and proposed methods

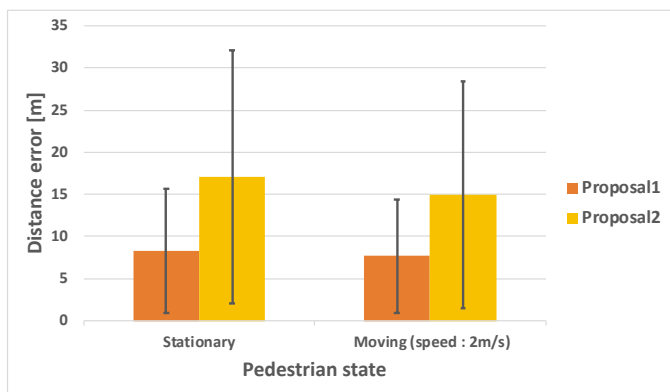


Figure 6. Distance error and standard deviation by pedestrian state of Proposal 1 and Proposal 2

We evaluated the positioning error when the number of vehicles increased from 0 to 80 in increments of 10. In this case, the beacon interval was 10 m.

Regarding the positioning error, when a pedestrian is stationary, we simulated at 5-m intervals between the stars shown in Figure 4 and calculated their average positioning error. We also simulated in a situation where the pedestrian is moving at a speed of 2 m/s from the top stars to the triangle in Figure 4 and calculated the average positioning error.

D. Comparison of positioning error with conventional methods

Figure 5 shows the positioning error of the pedestrian in the conventional and proposed methods. With the proposed method, the average positioning error decreased more for both stationary and moving pedestrians than in Conventional 1. Compared to Conventional 2, in Proposal 1 the positioning error in the moving situation hardly changed, but the average positioning error in the stationary situation was smaller. Moreover, the maximum positioning error became smaller both in the stationary and moving situations. Compared to Proposals 1 and 2, the average positioning error in Proposal 2 was smaller than in Proposal 1. However, the variation in the positioning error and the maximum positioning error in both the stationary

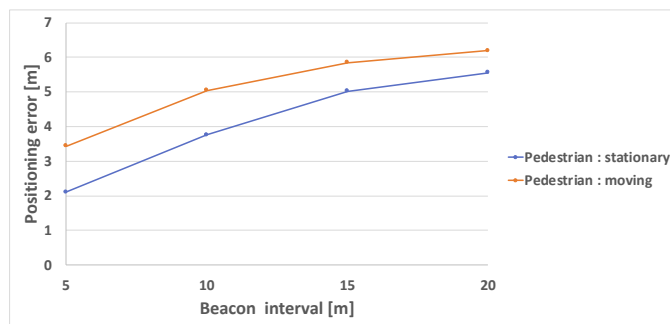


Figure 7. Relationship between beacon interval and positioning error

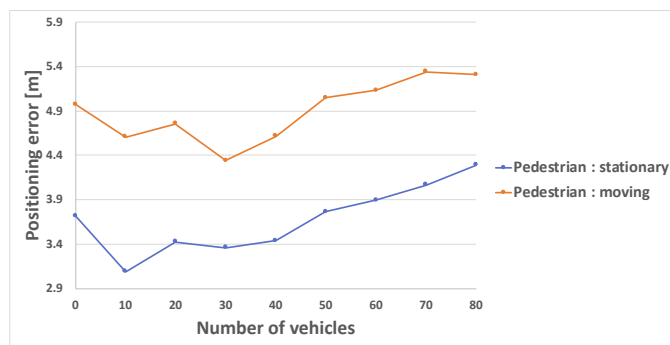


Figure 8. Relationship between number of vehicles and positioning error

and moving situations in Proposal 1 was smaller than in Proposal 2. Proposal 1 also decreased the distance error and the standard deviation of distance error as shown in Figure 6. Therefore, filtering RSSI and the dynamic path loss index effectively reduced the variation of the positioning error. We considered that the reason why Proposal 1 did not become smaller than Proposal 2 depends on the number of vehicles shown in Section IV-F.

E. Evaluation of beacon interval

Figure 7 shows the change in the positioning error with an increase in the beacon intervals. We found that the smaller the beacon interval is, the smaller is the positioning error. We also found that the larger the beacon interval is, the smaller is the amount of change in the positioning error.

F. Evaluation of number of vehicles

Figure 8 shows the change in positioning error with an increase in the number of vehicles. It did not become smaller as the number of vehicles increases, and it is the smallest when the number of vehicles is 10 in the stationary condition and 30 in the moving condition. This result was probably caused by using WCL for the position estimation. Because WCL calculates the weighted average of the position of vehicles and beacons, we can accurately estimate the position in a situation where the target is within a rectangle consisting of vehicles and beacons as shown in Figure 9. However, in the proposed method, we calculated positions using all the RSSIs that exceed the threshold in Section III-E. Therefore, since the available vehicle information increases when the number of vehicles

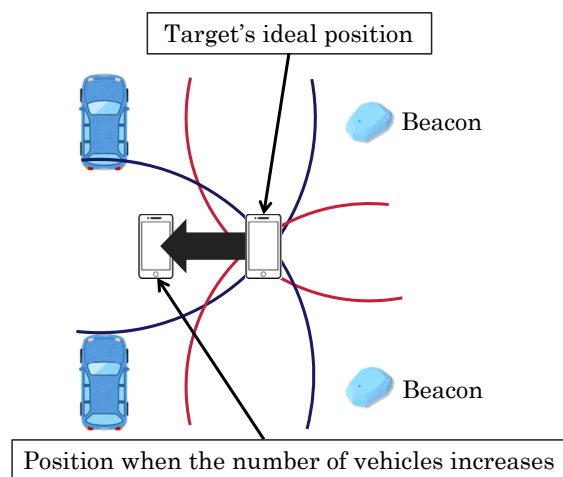


Figure 9. Ideal situation in WCL

increases, the estimated position is biased toward the vehicle side as shown in Figure 9 and that leads to poor accuracy.

V. CONCLUSION

In recent years, efforts are made for improving pedestrian safety through vehicle-to-vehicle and vehicle-to-pedestrian communication. For preventing accidents, accurate position information is critical, but GPS has low positioning accuracy in urban areas. We proposed a position estimation method using RSSI of beacons and vehicles to improve the pedestrian positioning accuracy in urban areas. When estimating positions using RSSI, the RSSI fluctuation and the static path loss index lead to distance error. In our proposed method, we applied a Kalman filter to reduce the RSSI fluctuation. By calculating the path loss index using vehicle-to-vehicle communication, we dynamically dealt with the surrounding radio wave propagation environment. Filtered RSSI and the dynamic path loss index decreased the distance error and the standard deviation of distance error. We evaluated the positioning error of the conventional methods and the proposed method by simulations and determined that our proposed method reduced the positioning error. In the future, to further improve the positioning accuracy by WCL, based on the evaluation result of the number of vehicles, we will consider a method that selects appropriate RSSI for position estimation.

ACKNOWLEDGMENT

This work was supported in part by JSPS KAKENHI Grant Number 16H02814.

REFERENCES

- [1] M. Sepulcre and J. Gozalvez, "Experimental Evaluation of Cooperative Active Safety Applications Based on V2V Communications," in Proceedings of the Ninth ACM International Workshop on Vehicular Inter-networking, Systems, and Applications, ser. VANET '12. ACM, 2012, pp. 13–20, ISBN: 978-1-4503-1317-9, URL: <http://doi.acm.org/10.1145/2307888.2307893> [accessed: 2018-06-03].
- [2] J. J. Anaya, P. Merdrignac, O. Shagdar, F. Nashashibi, and J. E. Naranjo, "Vehicle to Pedestrian Communications for Protection of Vulnerable Road Users," in 2014 IEEE Intelligent Vehicles Symposium Proceedings. IEEE, 2014, pp. 1037–1042, ISSN: 1931-0587, URL: <https://ieeexplore.ieee.org/document/6856553/> [accessed: 2018-06-03].

- [3] M. Modsching, R. Kramer, and K. T. Hagen, "Field trial on GPS Accuracy in a medium size city: The influence of built-up," Proc. 3rd Workshop on Positioning, Navigation and Communication, 2006, pp. 209–218.
- [4] V. Varshney, R. K. Goel, and M. A. Qadeer, "Indoor Positioning System Using Wi-Fi & Bluetooth Low Energy Technology," in 2016 Thirteenth International Conference on Wireless and Optical Communications Networks (WOCN). IEEE, 2016, pp. 1–6.
- [5] Z. Jianyong, L. Haiyong, C. Zili, and L. Zhaohui, "RSSI Based Bluetooth Low Energy Indoor Positioning," in 2014 International Conference on Indoor Positioning and Indoor Navigation (IPIN). IEEE, Oct. 2014, pp. 526–533.
- [6] S. Subedi, G. R. Kwon, S. Shin, S. Hwang, and J. Pyun, "Beacon Based Indoor Positioning System Using Weighted Centroid Localization Approach," in 2016 Eighth International Conference on Ubiquitous and Future Networks (ICUFN). IEEE, July 2016, pp. 1016–1019.
- [7] "SPACE-TIME Engineering," URL: <https://www.spacetime-eng.com/en/> [accessed : 2018-06-03].
- [8] "ITU-R Recommendation P.1411-9," URL: https://www.itu.int/dms_pubrec/itu-r/rec/p/R-REC-P.1411-9-201706-I!!PDF-E.pdf [accessed : 2018-06-03].